FINAL REPORT - SRDC PROJECT BSS257

GRUBPLAN2: DEVELOPING IMPROVED RISK-ASSESSMENT AND DECISION-SUPPORT SYSTEMS FOR MANAGING GREYBACK CANEGRUB

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BSES Sugarcane for the future

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EXECUTIVE SUMMARY

Greyback canegrub (*Dermolepida albohirtum*) is the single most important pest affecting the Queensland sugar industry. Greyback damage represents a loss of cane to the industry, a cost to growers and millers, and an ongoing source of disruption that continually drains research and extension resources in reactive responses to pest crises. Favourable conditions for greyback canegrub in the 2000 and 2001 seasons resulted in crop damage of just over 1 Mt of cane and a loss to the industry of about $38 million, not including the costs of premature replanting or dirt in the cane supply. Control measures are another financial burden, with these costing up to $400/ha. The inability to predict outbreaks means that huge cane losses are suffered during outbreak years, while control measures are used inefficiently during years when the risk of grub attack is low.

At the commencement of the project, we conducted case studies with selected growers to determine what factors were important in grower decisions and canegrub management. We also examined mill data to detect any relationships between canegrub damage and recorded factors such as crop class and harvest date.

To integrate available knowledge of greyback canegrub population dynamics, as an essential step for improving our ability to forecast future infestations, we conducted a comprehensive literature review. Quantitative information on relationships was then incorporated into population models written in the modelling software STELLA. These models can be used to explore the possible impact of different management strategies and to guide future research to address significant knowledge gaps.

To derive a statistical predictive model for greyback canegrub, numbers of canegrubs were monitored in a set of canefields in central and northern Queensland from 2003-2007. Canegrubs were counted annually in March-April under 20 cane stools in each field. Additional measurements were collected for apparent canegrub damage in these fields and in nearby fields, and for field and crop characteristics that we thought might influence each field's risk of canegrub attack. Canegrubs collected during these surveys were reared to adult to measure levels of known pathogens such as *Adelina* and *Metarhizium* in each field each year.

Analysis of the relationships between numbers of canegrubs, levels of infection of grubs by known pathogens, and various field-specific factors such as whether fields were fallow-planted or replanted and whether they were treated with insecticide, allowed statistical models to be developed that can help growers and their advisors to predict future canegrub infestations and plan management strategies accordingly. This analysis has also suggested management methods that may help to promote canegrub pathogens and alleviate canegrub infestations, such as zonal tillage, and these deserve further research.

We constructed a variety of statistical models to predict canegrub infestation levels 1 year in advance, with the choice of model depending on the availability of data. The most reliable models included information on current numbers of canegrubs in both individual fields and the district, as well as measurements of canegrub health as affected by known pathogens. However, predictions were also possible without some or all of these data,

provided there were good records of current levels of canegrub damage in individual fields and other factors that might pre-dispose fields to canegrub attack.

Economic decision aids were developed so that a risk analysis for canegrubs could be used to help make a management decision according to the costs and benefits of treatment. These aids were an improved version of the Best Management Practice (BMP) model previously developed by Macarthur Agribusiness, and a simpler economic spreadsheet to make decisions field-by-field depending on the predicted risk to each field in any given year.

We also identified a set of beetle feeding trees that can be used to record beetle activity in districts from Plane Creek to Mulgrave. Our databases which store the monitoring records of beetle activity on feeding trees and numbers of canegrubs and incidence of canegrub pathogens in canefields can be added to in future years to improve the industry's predictive capability.

We propose a framework at both a regional and a farm level for collecting the information required to allow growers to objectively assess the risk of canegrub attack in individual fields and make rational management decisions. These concepts have been promoted at field days and grower workshops each year, in a re-written version of the *GrubPlan* extension booklet, and communicated to industry advisors at discussion meetings in 2007 and 2008.

1.0 BACKGROUND

Greyback canegrub (*Dermolepida albohirtum*) is the most serious insect pest afflicting the Queensland sugar industry. It occurs from the Plane Creek mill area northwards. Various pesticide options are available, to be applied in plant crops, i.e. controlled-release products containing chlorpyrifos or imidacloprid (suSCon® Blue or suSCon® Plus, suSCon® Maxi), rice granules containing the fungal pathogen *Metarhizium* (BioCane™), and liquid imidacloprid (Confidor® Guard), or in ratoons, i.e. liquid imidacloprid products (e.g. Confidor Guard, Senator®). Non-pesticidal techniques are also available to mitigate damage. None of these options is sufficient on its own, and their effective integration depends on the assessment of the risk of grub damage to individual fields and economic analysis of the different management options.

Pesticides are mostly applied during July-December, at or soon after planting or harvesting, in anticipation of future grub infestations that may damage cane in February-April of the following year. Monitoring of greyback canegrubs is not practical before February-April, when they aggregate under cane stools. By that time it is too late to apply control measures as crops are large and inaccessible to machinery. Hence, numbers of greyback grubs found by monitoring in February-April are only useful if they help to predict the risk of damage in subsequent years.

There is not necessarily a direct link between greyback grub numbers in one year and risk of infestation in the next. The species has a life cycle occupying 1 year. Beetles leave canefields to feed on trees and may not return to the same field to lay eggs. In addition, the various life cycle stages are acted upon by both abiotic and biotic mortality factors. Cycles of greyback outbreaks and crashes have been observed in northern Queensland, and past research has indicated these may be caused by grub pathogens that build up in the soil. It is inefficient to apply costly pesticides when there is little or no likelihood of subsequent infestations, as may occur if the grub population is in decline.

A start was made in the *GrubPlan* program in 2001 to use risk assessment to develop whole-farm plans for greyback canegrub management. More than 900 growers and advisors undertook *GrubPlan* workshops. However, some issues needed to be addressed to take this program further and to improve growers' ability to assess risk:

- A suitable infrastructure for collecting the necessary information to assess risk was not currently available
- Useful variables to monitor should be identified
- A predictive model was needed to link current measurements of these variables with the likelihood of grub damage in subsequent years
- Economic analyses were needed to assess the costs and benefits of control options for different likelihoods of grub attack.

These considerations raise the level of complexity of the greyback canegrub data-gathering and decision-making process, and there may be opportunities for commercial monitoring and crop management services to benefit individual growers and the industry.

2.0 OBJECTIVES

The vision of the project was to provide industry with refined greyback canegrub management systems complete with risk-assessment and decision-support models that could ultimately be deployed at a commercial consultancy level. The outputs of the project would allow proactive management of greyback canegrub by growers and their advisors.

The specific objectives were to:

1. Continue to develop and refine pest management packages for greyback canegrubs, incorporating regional forecasting, farm monitoring, on-farm risk assessment, decision aids and economic analysis, with groups of growers or individuals.
2. Design and implement regional systems to monitor trends in greyback damage and management.
3. Develop and validate models that predict the probability of greyback infestations from one year to the next.
4. Determine the market acceptance and value of a greyback canegrub risk assessment and management program.

Each of these objectives was realised as outlined below.

Objective 1 - To continue to develop and refine pest management packages for greyback canegrubs, incorporating regional forecasting, farm monitoring, on-farm risk assessment, decision aids and economic analysis, with groups of growers or individuals.

A system was devised for a comprehensive district- and farm-level monitoring and prediction system for greyback canegrub. The components include:

- a regional system for assessing grub risk (see Objective 2)
- a methodology for monitoring farms for grubs, including sequential sampling plans
- sentry beetle-feeding trees identified by GPS location
- a plan for monitoring other factors that were shown to improve predictions of future grub populations
- a risk-assessment model incorporating these monitoring results (see Objective 3)
- a decision-tree for comparing grub management options
- an economic spreadsheet that evaluated the costs and benefits of insecticide treatment of ratoons at varying levels of grub risk, together with an improved version of the Macarthur Agribusiness Best Management Practice model with productivity data added for Mourilyan and Mackay
- a revised *GrubPlan* extension booklet.

Results were developed during the project in association with the *GrubPlan* program that interactively engaged groups of growers each year on the topic of greyback grub management.

Objective 2 - To design and implement regional systems to monitor trends in greyback damage and management.

A regional system was designed that combines a four-step annual cycle: quantitative records of beetle activity on sentinel trees (December-February), numbers of grubs in canefields (February-March), visible damage across the district as detected from the ground or by aerial surveillance (May-June), and district-wide cane loss (end-of-year). Each step provides additional information on annual grub status. This information is added to data from previous years to assess whether the overall grub trend is up, down or stable. Information would be released to growers at least twice each year:

- in February-March, to create awareness of canegrubs and to help growers to decide on the effort they should allocate to monitoring their own farms (more fields would be classed 'at-risk' and would be monitored by growers in high-risk years)
- in May-June, to help growers make field-by-field management decisions.

Actual damage the following year would be compared with forecasts as part of a continuous improvement program.

This monitoring cycle was conducted in the project in the Central, Herbert and Far Northern regions. In Mulgrave, the project involved an officer from Mulgrave Mill and the monitoring results were used to develop formal grub forecasts for that mill area. Results in other districts were presented at grub meetings and through print media.

Access databases were developed to store regional monitoring data for beetle-feeding trees and for canefields.

Objective 3 - To develop and validate models that predict the probability of greyback infestations from one year to the next.

To develop predictive models for greyback infestations, we collected almost 300 pairs of data comprising grub population estimates in fields for two successive years for the period 2003-2007. In addition, we obtained a range of other measurements:

- other measures of infestation levels in the monitoring fields – visible damage before harvest and presence of gaps after harvest
- crop measurements – those that were fixed for the crop cycle (e.g. soil texture, pH, GPS coordinates, distance to the nearest treeline, method of ground preparation, variety, suSCon use in plant cane), and those that varied annually (e.g. crop class, harvest date, cane height during beetle flights, Confidor use in ratoons)
- pest measurements – the level of infection of grubs by known pathogens in each field, and indications of infestation pressure from nearby fields (e.g. presence of visible damage in neighbouring fields, percentage of nearby old ratoons).

Two types of statistical models were developed for predicting grub numbers 1 year ahead, one for predicting actual grub numbers and the other for predicting grub density classes categorised as low (≤0.5 grubs/stool), moderate (>0.5-2 grubs stool) and high (>2 grubs/stool). In addition, models were developed for use in different circumstances depending on the availability of monitoring data, that is, the availability of estimates of grub densities for individual fields and/or for the district and estimates of the level of grub pathogens. The models for predicting actual grub numbers left considerable unexplained

variation in the data and showed some bias when predicting a validation data set, whereas models for predicting grub density classes appeared to perform better. In addition, the density-class models take account of the intrinsic uncertainty in the system by providing estimates of probability for the occurrence of each of the low-, moderate- and high-density classes.

Objective 4 - To determine the market acceptance and value of a greyback canegrub risk assessment and management program.

Growers we engaged individually during the project valued our monitoring results and took them into account when designing their grub management plans. The results were always of interest at *GrubPlan* meetings. However, we saw no evidence that growers would undertake this monitoring themselves, other than perhaps to confirm the presence of grubs under obviously damaged stools (and even then they are more likely to contact an industry advisor). Therefore, there may be an opening for a commercial service to provide this information to growers.

Growers at some group meetings were asked whether they would use a service that gave advice on grub monitoring and provided control recommendations for individual fields, for a cost. They were also asked how much they would be willing to pay for such a service, firstly, for the recommendations alone based on data they supplied, and secondly, for the additional work of someone doing the monitoring for them. Some growers in each district surveyed from plane Creek to Mulgrave recorded that they would use such a service, with a positive response from about half of the growers who experience grub problems. Given current costs of control measures of $200-$400/ha, and with farm insecticide bills sometimes running to tens of thousands of dollars each year, a commercial risk assessment and monitoring program should be commercially viable.

3.0 METHODOLOGY

3.1 Relationship with growers and productivity services

Productivity services and, in some cases, millers, were consulted in the mill-regions of Plane Creek, Mackay, Herbert, Tully, Innisfail, and Mulgrave, at the start of the project. All of the parties were favourably disposed to the objectives of the project and agreed to support the program, though their commitment varied. Mulgrave was particularly supportive, with a field officer (Gerard Puglisi) seconded part time to BSS257 to collect and collate field data in the Herbert, Tully, Innisfail and Mulgrave mill regions. Each of the mill regions had different levels of data collection and recording capacities. Similarly, some productivity services had greater access to mill data than others. There was also differences among mill-regions in how well their recording systems were set up and for how long they had been established. The data set available from Mourilyan for the years 1995-2001 was used to analyse damage trends across harvest weeks and crop classes (see later).

Productivity services in each mill area also submitted their district-wide estimates of canegrub losses and treatment details for each year, and these were collated to discern trends in grub status across regions. These estimates were obtained after the annual harvest and submitted usually by the middle of the following year.

This project followed the very successful *GrubPlan* campaign of 2001-2002 (Hunt *et al.*, 2002, 2003; Samson *et al.*, 2005). However, the nature of extension changed considerably in the sugar industry in the 12 months leading up to the commencement of the project. Raising discreet single-issue groups dedicated to the likes of canegrub management became impractical, as mill-regions adopted localised discussion-group meetings addressing issues of concern to members on a needs-basis. Hence, this project opted to fit in with this new extension thrust, to avoid any district sensitivities and especially to eliminate duplication. In the first 6 months of the project, Warren Hunt, Keith Chandler and Peter Samson participated in more than 20 local discussion groups throughout Central and Northern areas on the issue of greyback grubs. To complement this, *GrubPlan* workshops were conducted in March-May of each year 2003-2007 according to demand.

3.2 Intensive monitoring sites

3.2.1 Canegrub monitoring

Monitoring sites were selected across the Central and Northern regions. Site selection involved identifying fields of plant, first- and second-ratoon cane that could be monitored over the next 4 years of the project. The main determinant of site selection was whether the field had a history of greyback damage. Table 1 details the distribution of fields of different crop classes and the overall totals of fields from region to region. Some of these fields were ploughed out during the monitoring program, and new fields were added, so that about 100 fields were monitored each year of 2003-2006 with a smaller number monitored in 2007.

Table 1 Distribution of monitoring fields across the Queensland sugar industry at the 2003 harvest

Mill region	Plant cane	First ratoon	Second ratoon	Total
Plane Creek	1	2	3	6
Mackay	1	6	4	11
Herbert	11	10	12	33
Tully-Innisfail	6	6	6	18
Mulgrave	10	13	12	35
Total	**29**	**37**	**37**	**103**

Twenty stools were sampled in each field on almost all sampling occasions. Two different sampling schemes were used, corner and transect (Fig. 1). The corner scheme was used for all sampling outside the Central region. Sites in the Central region were sampled with either scheme, depending on the year. A block of soil about 40 cm x 40 cm x 30 cm deep was dug beneath a cane stool at each of the approximate positions shown in

the figure. Grubs were identified to species and instar and then placed into individual tubes or cups with a small amount of soil.

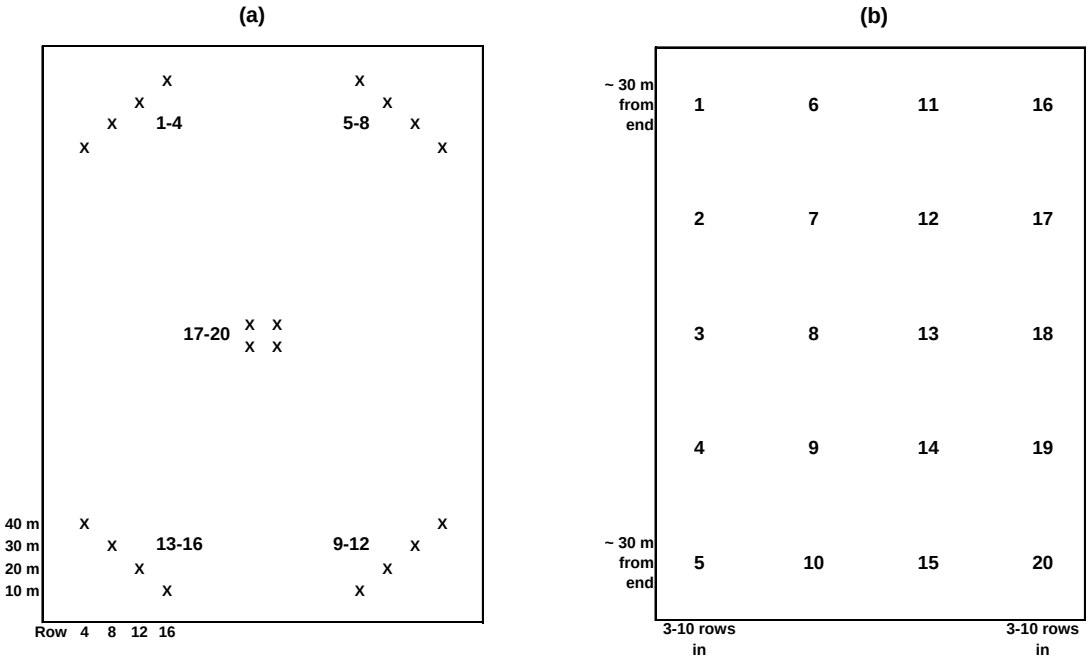


Figure 1 Corner (a) and transect (b) sampling schemes used for greyback canegrub

Sampling was intended to estimate both the grub density in each field and the level of infection by pathogens, especially *Adelina* sp., *Metarhizium anisopliae* and *Paenibacillus popilliae*. As we were only able to sample once each year, we chose a time of sampling that was late enough to allow grubs to be large, easily visible and aggregated under stools, but not so late that many had already been killed by pathogens and decomposed. On advice from David Dall of CSIRO Entomology, we aimed to collect most samples in March when all larvae had completed the first instar, the stage when larvae are presumed to acquire *Adelina* infection (Robertson *et al*., 1998) (Table 2). Robertson *et al*. (1998) detected *Adelina* infection in greyback canegrubs collected as all three instars, but infection was less frequent in those collected as first instars: the percentage of larvae killed by *Adelina* and the days to death post-collection were 19% and 67 d, 30% and 53 d, and 28% and 40 d for larvae collected in successive instars, with the mean age to death of field-collected larvae estimated to be 92-115 d post-hatching.

Table 2 Sampling dates and details of greyback grubs collected each year from monitoring sites in the Central region (Mackay, Plane Ck) and in northern Queensland (Herbert, Tully-Innisfail, Mulgrave)

Region	Year	Range of sampling dates	No. of grubs in each instar		
			I	II	III
Central	2003	5 March - 2 April	4	19	30
	2004	10 - 18 March + six sites in May	6	170	579
	2005	17 March - 15 April	0	13	105
	2006	18 - 24 April	0	25	120
	2007	30 March – 19 April	1	16	77
Northern	2003	27 February – 9 April	2	67	22
	2004	9 March – 6 April	5	80	155
	2005	4 - 21 April	0	23	591
	2006	16 March – 5 April +one site in May	9	181	118
	2007	26 March – 12 April	4	38	91

Grubs from each region were reared at the BSES pathology laboratory at Tully to check for the presence of diseases and to measure grub survival to adulthood. Each grub was 'bled' and the haemolymph examined for pathogens such as *Adelina* and milky disease. Grubs collected in 2003 were reared at ambient temperature in soil with carrot slices as food. Grub development was very slow over winter and survival was poor. An experiment was done in 2004 to compare different rearing media. Peat proved to be a much more suitable medium than soil (Table 3), probably due to its ability to absorb excess moisture while maintaining good aeration. All grub rearing in 2004-2007 was done in peat. Grub survival was good from 2004 onwards, allowing us to estimate not just the proportion of grubs infected with pathogens but also the proportion developing successfully to adult. A reverse cycle air-conditioner was installed in the rearing room in 2004 to maintain a temperature of 25°C over winter and allow an earlier estimate of grub survival. Incidence of pathogens was calculated as the number of infected grubs detected during rearing as a percentage of the number of grubs received alive at the laboratory.

Table 3 Success of grub rearing in three different media at Tully in 2004 (*n* = 18 in each)

Medium	No. adults in November
Tully soil	1
Peat (Searles)	14
Peat (Kiwi)	11

Mean numbers of grubs/stool (x) required transformation to allow statistical analysis of their relationship to other measurements and observations. The common transformation of $\log_{10}(x+1)$ was judged as too severe (see report Appendix 11). An alternative of $x^{0.35}$ was considered, based on the variation in the data as described by Taylor's power law (Section 4.9), but the eventual transformation chosen was $\log_{10}(x+0.05)$ (see Appendix 11).

3.2.2 Related measurements and observations

3.2.2.1 Spatial relationship of fields

The latitude-longitude coordinates at the centre of each monitoring field were obtained from existing records or by reference to GoogleEarth.

3.2.2.2 Soil texture and pH

Soil samples were collected from each monitoring field in 2007. Texture (sand/silt/clay proportions) was determined by an hydrometer method, while pH was measured using a glass electrode.

3.2.2.3 Visible grub damage

Damage in each monitoring field and in neighbouring fields (within about 0.5 - 1 km) was inspected from the ground in May-June of each year, by driving along headlands and water furrows (winch tracks or tow paths) and marking damage on farm maps. Damage was intended to reflect infestations in the current year, as evidenced by yellowing leaves and by stools sprawling or tipping and being easily pulled from the soil, and was rated on a scale from 0 to 3:

0, no visible damage
1, small patches of yellow or stressed cane;
2, stool tipping and yellow leaves, stools easily pulled from ground;
3, extensive patches of dead cane, no roots remaining.

3.2.2.4 Gaps in cane rows

Gaps of greater than 60 cm between cane stools were counted in five, 10 m lengths of row in a set portion of each field in summer (November-February) of each year. Because gaps measured in ratoon fields must reflect the history of fields from planting onwards, and not just events in the immediately preceding years, we also calculated the change in the number of gaps from year-to-year as a more current measure of 'gappiness'.

3.2.2.5 Cane height during beetle flights

Height of cane to the top visible dewlap (TVD) was measured annually at five points in each monitoring field in summer near the time when beetles were expected to fly in 2003-2005, but no measurements were done in 2006 (Table 4). In addition, we thought that the height of cane relative to the height of cane in surrounding fields may have been a better indicator of grub risk than height *per se*. To speed up data collection, heights of each monitoring field and its immediate neighbours were measured to the top of the canopy, where the leaves bend over to form a solid visual mass, at one point in each. These measurements were done at the same times as those to TVD in each year in the Central region but only in 2004-2005 in northern Queensland. There was a good correlation between both measurements in the monitoring fields in each year:

Central 2003 Canopy (mm) = 1.27*TVD (mm) + 742 (R^2 = 0.74)
Central 2004 Canopy (mm) = 2.16*TVD (mm) + 237 (R^2 = 0.89)
Central 2005 Canopy (mm) = 3.13*TVD (mm) + 154 (R^2 = 0.89)

Northern 2004 Canopy (mm) = 4.63*TVD (mm) + 4 (R^2 = 0.56)
Northern 2005 Canopy (mm) = 3.97*TVD (mm) + 21 (R^2 = 0.81)

We calculated the difference between the canopy height of each monitoring field and both the average height of neighbouring fields and the height of the tallest neighbouring field.

Table 4 Dates of measurements of cane height in each region each year

Year	Central	Herbert	Innisfail-Tully	Mulgrave
2003	4-17/2/2004	4/12/2003	2/12/2003	27/11/2003
2004	6-7/12/2004	30/11/2004	19/11/2004	16/11/2004
2005	13-15/12/2005	12-13/12/2005	12-14/12/2005	9-16/12/2005

3.2.2.6 Other insect and crop measurements

Details of field preparation for the current crop (destruction of previous crop by cultivation or herbicide, replant or fallow plant, any legume rotation) and annual insecticide use (suSCon products or Confidor Guard) were obtained from the growers. Annual harvest dates were supplied by the mills, although dates could not be obtained for all fields. The shortest distance for each field to the nearest treeline was determined by inspection in association with farm maps. The percentage of the area of nearby canefields (within a 400 m radius of the perimeter of each field) that contained crops older than first ratoon was measured on farm maps for each year. Limited data were obtained on beetle activity by rating feeding damage on a set of sentinel trees.

3.3 Other grub-sampling data

Mean numbers of greyback canegrubs counted in the untreated plots of insecticide trials using small plots (typically about 100 m^2) were collated for samples collected from 1995-2006 in trials from the Central Region north, including the Burdekin. The number of grubs in different crop classes was analysed and compared with results from our intensively monitored whole-fields.

4.0 RESULTS

4.1 Review of current knowledge of greyback population dynamics

This report is attached as Appendix 6.

Apparent knowledge gaps include:

- Effect of rainfall and other climatic factors on adult emergence and fecundity
- Proportion of females that mate and then successfully oviposit
- Dispersal distance and direction of beetles (and what proportion oviposits in the same field from which they emerged)
- Reasons why adult beetles are attracted to certain fields and not others
- Role of cane height in crop attractiveness in non-Burdekin areas
- Egg and larval survival rates under different soil moistures, temperatures and soil types
- Decline in grub densities over time in the absence of pathogens and at different grub densities
- The role of larval combat as opposed to dispersal
- Rates of transmission of pathogens from infected grubs to new hosts
- Impact of tillage on pathogen levels in soil.

4.2 Descriptive population models for greyback canegrub

Simulation models were developed for greyback canegrub by Frank Drummond from the University of Maine using the modelling software STELLA. Frank emphasises that these models are a quantitative literature review rather than a predictive population model, because some important relationships are not included due to lack of empirical data.

The initial model attempted to model greyback canegrub dynamics within a single canefield (Appendix 11). The variables and relationships in this model are shown schematically in Figure 2. The output from various runs is also given in Appendix 11.

There are some relationships about which we have limited data, but which are likely to be critical to the outcome of simulation runs. These include:

1. An upper limit to the number of grubs that a stool can support, as a function of canegrub instar and plant size
2. Density-dependent movement of grubs to adjacent stools resulting in avoidance of cannibalism
3. Linkage with a sugarcane model
4. Transmission of specific disease causal organisms, the relationship between density and transmission, and the persistence of inoculum as it relates to inter-year carryover of disease
5. Adult behaviour, e.g. mating frequency of adult females, and dispersal and movement of adults at the landscape level.

Some of these factors can be represented in a model and simulations can be conducted in order to assess the potential significance of the interactions, but it is always preferable if

the range of likely values for parameters can be arrived at so that simulations are realistically grounded.

An expanded model was then developed to include movement of adults within or among canefields. The population is distributed into eight sub-populations with variable interchange between them (Fig. 3). This particular model was designed to evaluate population dynamics of greyback canegrub on a multi-field scale, where some fields are protected by insecticide and some are unprotected. Although the model has been completed, there has not been time within this project to evaluate fully the impact of different treatment scenarios. A user guide is given in Appendix 12.

A copy of all models is held by Peter Samson at BSES Mackay.

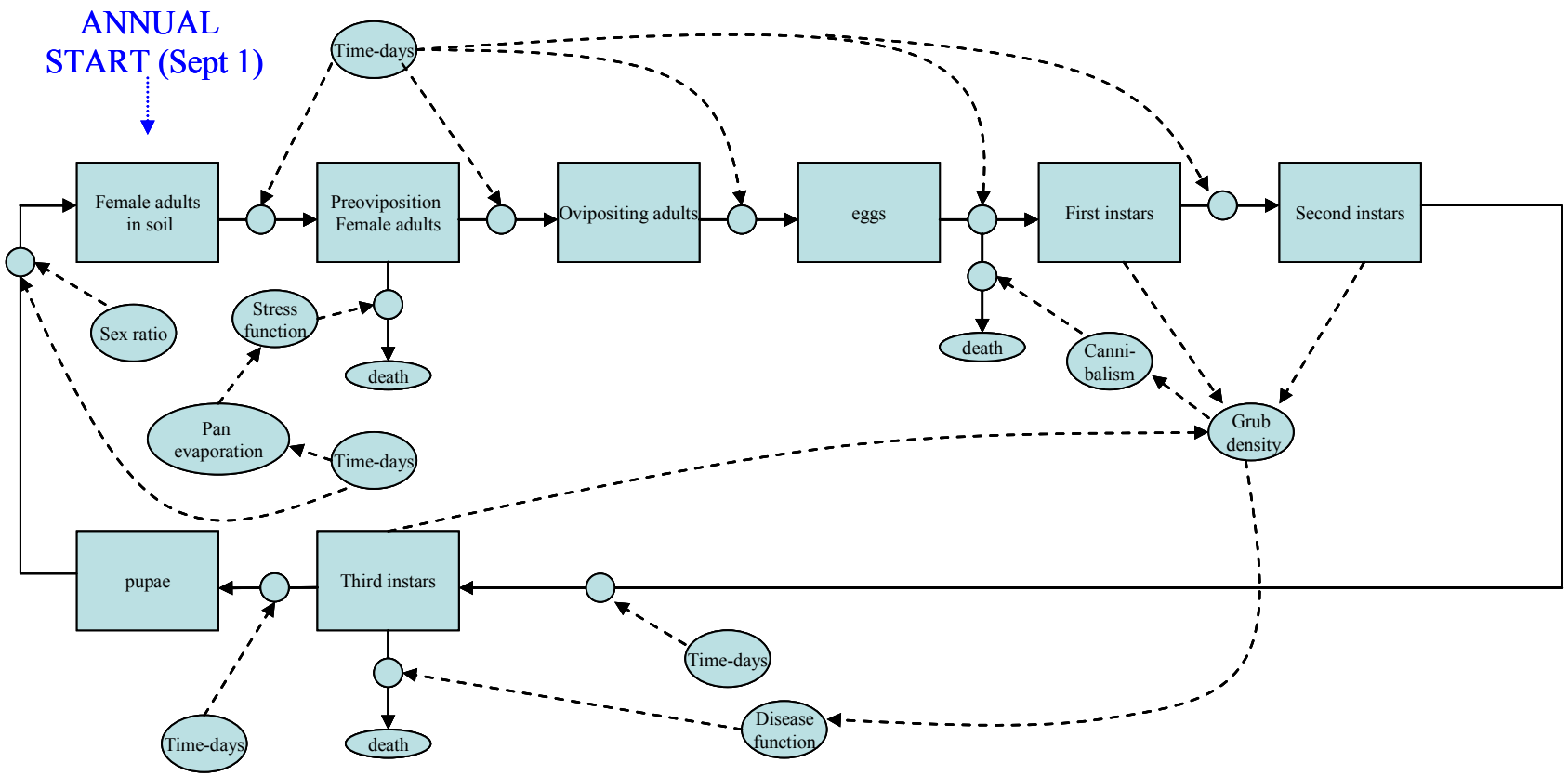
4.3 Regional trends in grub numbers and damage, 2003-2007

4.3.1 Annual pest data returns from productivity services

Regionally based damage data were collected for the 2002 harvest season and compared to the damage in 2001 (Table 5). A downward trend in most of the industry provided some assurance for the 2003 crop. Damage data for the 2003 harvest season also showed a static or downward trend compared with the previous 2 years. Results were similar in 2004, except for the Central region, where there was an increase in losses compared with the previous three years. The area treated against canegrubs in Far North Queensland had been declining since 2001, when there was a spike of treated area in response to huge grub losses in that year. In Central Queensland, however, the area treated in 2004 was greater than in previous years.

At the time of this report (May 2008), canegrub data for 2005 had not been received from Tablelands, Babinda-Mourilyan-South Johnstone, the Burdekin or Plane Creek, despite several requests and reminders. Data for 2005 are compared with previous years in Table 5, for those regions where there was at most one missing set of mill data. The area recorded as affected in the Central region continued to increase, even though Plane Creek data are not included in the 2005 records. The area treated also increased. Losses remained low in the Herbert with a static area treated, much below the spike of treatment in 2001-2 following huge grub losses in 2001.

Each year it has become increasingly difficult to obtain these data in a timely manner. There are one-off reasons for the poor response to the supply of data for 2005 – the cyclone early in 2006 and the smut incursion – but staff losses are also partly to blame. In previous decades, data were collated by BSES in preparation for the annual May conference of the Cane Protection and Productivity Boards. That conference and the Boards themselves are now defunct. With structural changes within the various productivity services, this type of routine monitoring is receiving less attention. While individual productivity services still have access to their own data for each year, failure to submit data to BSES means that data are not collated across the industry, losing valuable information on long-term trends.



key:

solid lines = flows of individuals
dashed lines = information flows
= state variables

= rate regulators
= converters (control variables)
= population sinks (death)

Figure 2 Schematic of simulation model for greyback canegrub in a single field

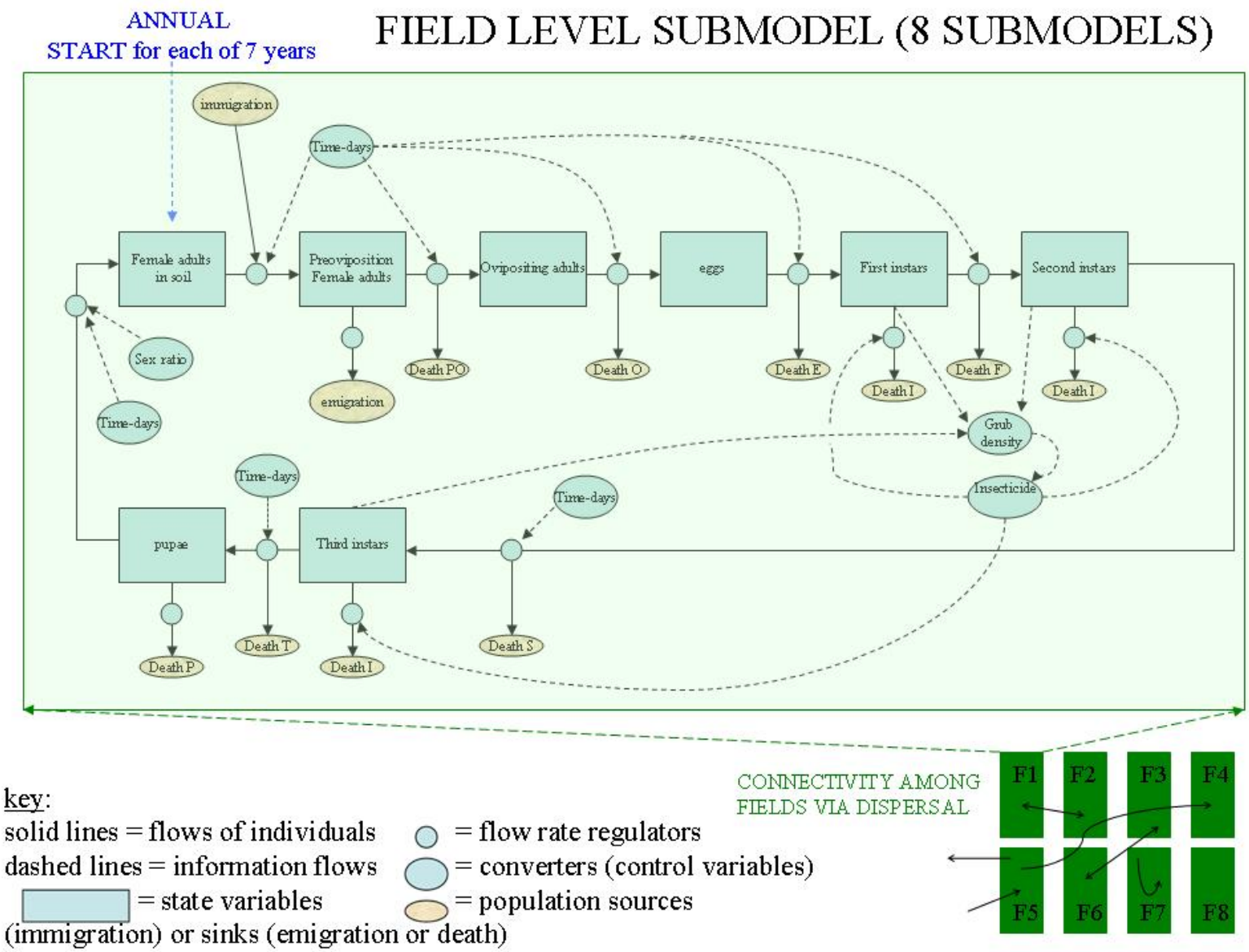


Figure 3 **Schematic of simulation model for greyback canegrub in multiple fields**

Even if these data are supplied on time, however, they always have a particular flaw for predicting future grub risk: they are a year out-of-date. In addition, as a tool for predicting risk, they are limited because only highly visible acute damage is detected in most cases, and not the early indications of grub build-up that may indicate increasing risk for the following year. A more immediate system is needed for monitoring trends.

Table 5 Regional damage by canegrubs 2001-2005 harvest seasons

Year	Mossman-Babinda incl. Tablelands	Innisfail-Tully	Herbert River	Burdekin	Central	Total
Hectares damaged						
2001	6640	3820	6800	6745	475	24480
2002	1700	870	1140	1605	1300	6615
2003	1075	960	1155	1065	600	4855
2004	1100 [a]	1085	790	1895	2320	7775 [a]
2005	na [c]	na [c]	540	na [c]	2655 [b]	na [c]
Tonnes cane lost						
2001	175200	75700	231420	257640	6030	745990
2002	28700	16720	33060	45150	31990	155620
2003	22170	12700	26600	36160	8890	106520
2004	21000 [a]	11880	21310	41000	51070	153440 [a]
2005	na [c]	na [c]	15500	na [c]	44590 [b]	na [c]
Hectares treated						
2001	7620	4180	6440	8765	3660	30665
2002	5705	2705	5750	5160	2570	21890
2003	4470	2020	2465	3970	2525	15450
2004	2490 [a]	1730	2720	3295	4005	15785 [a]
2005	na [c]	na [c]	2720	na [c]	4320 [b]	na [c]

[a] Data missing for Tableland.
[b] Data missing for Plane Creek.
[c] Data missing from more than one mill area.

4.3.2 Use of aerial imagery to detect damage

The Burdekin has a system whereby the productivity service photographs grub-prone blocks from the air in May each year. The photographs are then used to help growers make decisions on grub management, based on visible damage. This system has considerable merit, but is not done elsewhere.

Some progress was been made in the Mackay district to develop a more proactive approach to grub damage estimation. John Markley of Mackay Sugar examined the spectral image of fields known to be damaged in 2003, using the satellite image collected annually by Mackay Sugar for yield estimation. Badly damaged fields were distinguishable from undamaged fields (Fig. 4). In 2004, much of the damage that we recorded from ground surveys could be detected by John in the satellite image, analysed

according to some measure of vigour. However, 2005 'vigour' maps showed many false positives when they were taken out into the field. Problems with the current satellite image include its poor resolution and the limited opportunities to obtain a suitable image while the sky is clear. If successful, a system of aerial detection of damage would be immensely useful for Mackay and other regions. The aim would be to detect not just badly damaged fields that are a risk to neighbouring fields, but also fields with light damage that might become worse the following year. This system would also allow detection of damage in time for a useful risk forecast for the following year, and for suitable management options to be implemented.

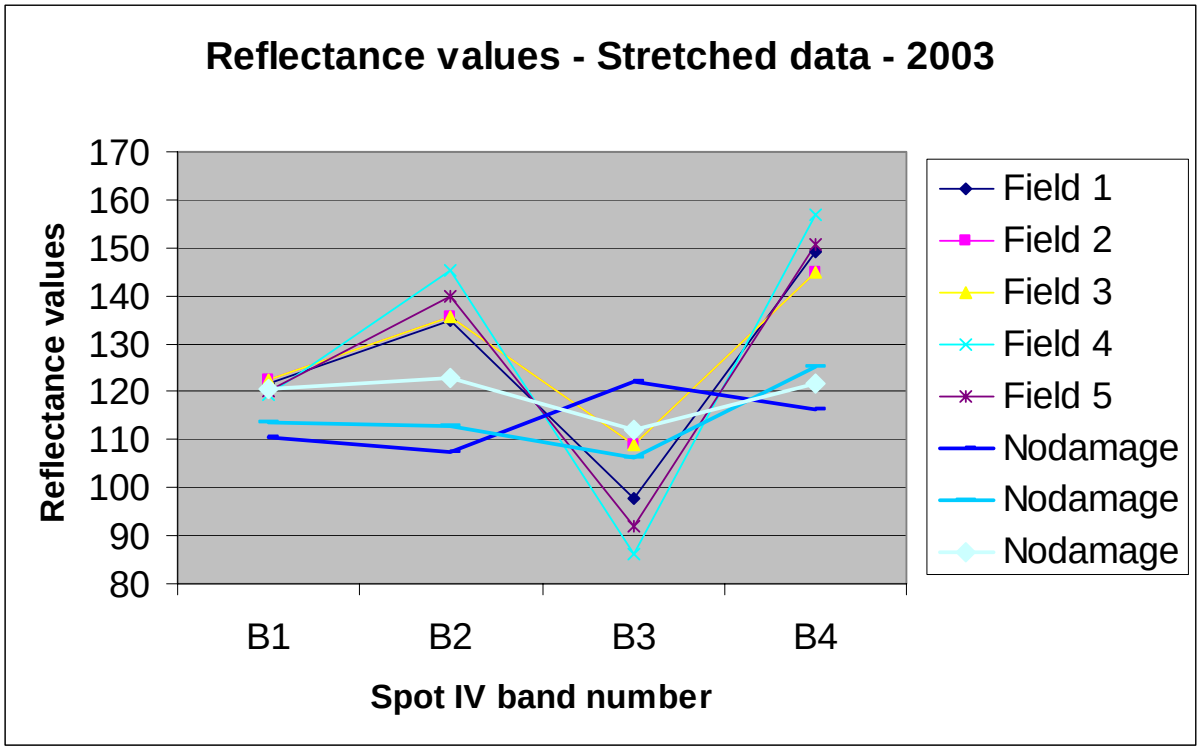


Figure 4 **Reflectance patterns for five damaged fields and three undamaged fields at Mackay in 2003**

We flew over our grub monitoring sites in the Central region in 2005 and 2006 and obtained aerial photographs of each of the monitoring blocks and its neighbours. It was much easier to judge the extent of infestations from the air than from the ground. Particularly noteworthy was how quickly the photographs were obtained, and we were able to inspect blocks on 10-12 farms covering Mackay-Sarina-Gargett in about 2 hours and at a cost of a few hundred dollars. There is an opportunity for growers to use such a system independently of their productivity services, perhaps as individuals, as a group of neighbours, or through a consultancy service, to help with management of canegrubs and perhaps with other management issues on their farms.

4.3.3 Beetle activity

Adult activity could provide an estimate of population trends. Beetle feeding can be detected for months on palm trees in particular, and can be rated according to severity.

In 2004, low crop damage mirrored the conclusions drawn from prior observations of generally low grub numbers, low incidence of gappy ratoons, and low incidence of beetle flights and beetle feeding activity. More specifically at Mulgrave, increasing beetle activity and the highest grub populations coincided with the greatest intensity of damage in the Aloomba sector for the 2003 crop. In addition, slightly greater beetle activity and grub numbers overall, and especially in the Green Hill and Highleigh/Sandy Creek sectors in January-May 2004, corresponded with the majority of damage at Mulgrave in the 2004 crop. At Mourilyan, there was generally increased beetle activity overall and although there were no damaging grub populations at monitoring sites, there were at least two severely damaged fields (Ah Shay) that had displayed incipient damage signs (gappy ratoons) after the previous crop. At Ingham, increased beetle activity overall from December 2003 and February 2004 was mirrored by consistently greater grub numbers in the monitoring sites and more damage overall in the 2004 crop than in the previous crop year. In the Burdekin region, substantial late beetle flights detected on January 29 at Giru were followed by severe damage that expressed later than usual. Working retrospectively at some of these sites, intensity of extensive beetle activity on *Livistona* palms corresponded with dispersion of damage (Aguirresarobe, Giru, and the Graham Lyons and Stevens farms off the Giru-Clare road).

A set of beetle feeding trees was identified covering all regions, including the Burdekin, and the intensity of apparent greyback beetle feeding was recorded during late 2007-early 2008 (e.g. Fig. 5). Approximately 300 groups of trees (each group sometimes comprising multiple species or several individuals of the same species) were identified by GPS coordinates. These trees were not used in analysis of the 2003-7 monitoring data, but they do form a set of sentry trees for future data collection.

Figure 5 Beetle-feeding marks on a fig tree near Proserpine, February 2008

It was sometimes difficult to assess the amount of feeding on trees such as figs that had dropped damaged leaves and produced new ones. However, midribs with the lamina removed could usually be found beneath such trees, together with beetle remains (elytra etc.).

There is not universal agreement on the usefulness of recording beetle feeding damage. The link between beetle flights and subsequent canegrub numbers is not straight-forward, and previous attempts to relate beetle activity to canegrub infestations have been unsuccessful (Ward and Robertson 1999). Beetle numbers and canegrub numbers must logically be related at some population density or spatial scale – if there were truly no beetles in a district then there could be no grubs the following year – and failure to see relationships in previous studies may reflect our inadequate knowledge of the dispersal patterns of adults and interactions among their progeny. Nevertheless, data on beetle activity are easy to collect and could help to develop a picture of greyback infestation trends across a district and from year-to-year, once sufficient records are available. It was clear during the survey in 2007-8 that beetle feeding was intense on some trees (particularly cluster figs) where grub damage has been recorded recently, whereas, not surprisingly, feeding was absent from other areas not known to be currently infested with greyback canegrub. Beetle activity was not used in this project to develop predictive models for greyback canegrub. However, a comprehensive data set of beetle feeding may allow patterns of damage intensity to be discerned over time or over different spatial scales, and which could be linked with past or (more usefully) future infestation levels. At the very least, observance of beetle activity is a way of maintaining awareness of greyback canegrub among advisors and growers, particularly as the symptoms are easily observed and recorded.

4.3.4 Grub sampling – successive estimates from the same fields

2003 was our first year of grub monitoring and we sampled 102 fields. Grub numbers were low everywhere; the largest mean number of greybacks per stool was 0.8 (Table 6).

We sampled 107 sites in 2004, including 96 of the sites that had been sampled in 2003. There was a huge increase in grub numbers in the 16 monitoring fields in the Central region from 2003 to 2004. In 2003, the average grub density across all fields was 0.2/stool, with the highest density in any one field being 0.8; corresponding figures for 2004 were 2.4 and 11.8, respectively (Table 6). Grub densities in other regions were similar to or higher than the 2003 figures.

Our monitoring result for the Central region farms (Mackay-Sarina) in 2004 was in agreement with subsequent reports of crop damage in May, with many farmers from Proserpine to Sarina reporting much greater damage than in 2003. This provides evidence that our monitoring fields were acting as sentries to detect damage trends. Grub extension effort was ramped up to counter this grub threat in the Central region (see attachments in Appendix 3). Our observations also indicated an increasing greyback risk in other regions.

We sampled 101 sites in 2005, 92 of which had been sampled the previous year. Grub numbers appeared to have stabilised in the Central region in 2005 following the huge

increase the previous year (Table 6). However, this was due in part to the most susceptible of our monitoring fields having been ploughed out in 2004 due to extreme grub damage. Grub numbers increased in Far North Queensland, particularly in Tully and Mulgrave.

72 sites that had been sampled in 2005 were able to be sampled in 2006 (Table 6). Some sites had been ploughed out, while a few could not be sampled due to the effects of cyclone Larry and the prolonged wet season in northern Queensland. Grub numbers had not changed much from the previous year in each region, in contrast to the considerable changes in numbers measured from 2003 to 2004 and 2004 to 2005.

Only 37 sites that had been sampled in 2006 were able to be sampled in 2007 (Table 6). Many of the fields that had been sampled in 2006 had been subsequently ploughed out and were either fallow or had been planted with insecticide, so were not worth sampling in 2007. Grub numbers appeared to fall in 2007 compared with the previous year in most regions; the slight increase in the Herbert was from a very low base in 2006 (Table 6). Some of the ratoon crops sampled in 2007 had been treated with liquid imidacloprid (Confidor Guard) in 2006. Extensive treatment of sugarcane ratoons may be depressing greyback populations, both in the treated fields and probably on a wider scale as well.

Table 6 Comparison of greyback grub numbers in 2003-2004, 2004-5, 2005-6 and 2006-7; note that only fields that were sampled in consecutive years were included in annual means

Region	No. sites	Year 1		Year 2		Trend
		No. with grubs	Mean no./stool (max. mean)	No. with grubs	Mean no./stool (max. mean)	Year 2/ Year 1
2003-4						
Central	16	11	0.16 (0.8)	15	2.38 (11.8)	14.5
Herbert	27	2	0.01 (0.2)	9	0.05 (0.8)	5.8
Tully-Innisfail	18	8	0.05 (0.3)	15	0.20 (1.2)	4.2
Mulgrave	35	18	0.06 (0.4)	27	0.18 (1.0)	3.2
2004-5						
Central	12	12	0.56 (2.5)	11	0.49 (1.1)	0.87
Herbert	28	10	0.05 (0.6)	13	0.05 (0.4)	1.1
Tully-Innisfail	17	13	0.20 (1.2)	17	0.39 (1.6)	2.0
Mulgrave	35	27	0.18 (1.0)	28	0.60 (2.7)	3.4
2005-6						
Central	10	8	0.49 (1.1)	10	0.73 (2.7)	1.5
Herbert	23	15	0.08 (0.4)	14	0.10 (0.4)	1.2
Tully-Innisfail	15	15	0.33 (1.4)	14	0.29 (0.6)	0.87
Mulgrave	25	18	0.53 (2.7)	22	0.33 (1.9)	0.61
2006-7						
Central	3	3	0.12 (0.2)	2	0.07 (0.2)	0.57
Herbert	14	7	0.09 (0.4)	6	0.18 (0.9)	2.0
Tully-Innisfail	7	6	0.25 (0.6)	6	0.07 (0.2)	0.29
Mulgrave	13	10	0.28 (1.9)	8	0.10 (0.6)	0.37

In the Central region, only three of the ratoon fields that had been sampled in 2006 were available to be sampled as ratoons in 2007 (Table 6). Therefore, an additional 20 fields were sampled for the first time in 2007. Some fields sampled in 2007 in northern Queensland had also not been sampled in 2006 because of the effects of cyclone Larry. These data can be used to examine future trends in 2008, but there are no corresponding density estimates from the same fields in 2006. To allow full use of all sample data, annual means for grub density in each region and corresponding changes in grub density from year-to-year were re-calculated using all available grub counts (Table 7). As would be expected, this method of calculation gives rather different estimates from the method used previously, where annual means were calculated using only the data from fields where grub counts had been obtained in two successive years (compare with Table 6). The revised data set indicates a general fall in grub populations in most regions from 2006 to 2007 (Table 7).

Table 7 Comparison of greyback grub numbers in 2003-2004, 2004-5, 2005-6 and 2006-7, with all sampled fields included in annual means

Region	No. sites	No. with grubs	Mean no/stool (max. mean)	Trend Yr 2/Yr 1
2003				
Central	16	11	0.16 (0.8)	-
Herbert	27	2	0.01 (0.2)	-
Tully-Innisfail	18	8	0.05 (0.3)	-
Mulgrave	35	18	0.06 (0.4)	-
2004				
Central	22	21	1.87 (11.8)	11.7
Herbert	31	12	0.07 (0.8)	7.0
Tully-Innisfail	19	15	0.19 (1.2)	3.8
Mulgrave	35	27	0.18 (1.0)	3.0
2005				
Central	13	11	0.45 (1.1)	0.24
Herbert	36	20	0.08 (0.9)	1.1
Tully-Innisfail	17	17	0.39 (1.6)	2.1
Mulgrave	35	28	0.60 (2.7)	3.3
2006				
Central	10	10	0.73 (2.7)	1.6
Herbert	23	14	0.10 (0.4)	1.3
Tully-Innisfail	16	15	0.30 (0.6)	0.77
Mulgrave	25	22	0.33 (1.9)	0.55
2007				
Central	23	18	0.20 (1.4)	0.27
Herbert	16	7	0.23 (1.2)	2.3
Tully-Innisfail	7	6	0.07 (0.2)	0.23
Mulgrave	18	12	0.15 (0.7)	0.45

We would expect that estimates of trends in grub population densities from year to year would be more precise when based on mean densities in a set of fields sampled in successive years, rather than in a set of fields that changes each year. However, attempting to sample the same 'sentry' fields in successive years can be logistically difficult if some of the fields have lodged or are waterlogged. In addition, effort in sampling sentry fields in any year is wasted if those same fields are then ploughed out or treated with insecticide before the next sample the following year. The latter circumstance is becoming increasingly common. A better plan to monitor regional trends might be to sample the same fields in successive years where possible, but to bring in additional fields to make up the numbers if the chosen fields are no longer suitable for sampling. For example, there seems little point in sampling fields protected by insecticide in any given year. All data should be used to estimate means if use of successive sampling data is too restrictive.

In 2008, it is unlikely that a comprehensive set of data comparable to that for 2003-7 will be collected from all regions. Two GGIPs in Mulgrave and near Mackay will help with sampling of some fields in their respective regions, though perhaps not the same fields that we have sampled in previous years. The future for regional monitoring of canegrub populations in the Herbert and Innisfail-Tully regions is uncertain.

4.3.5 Regional forecasts

A combination of methods – changes in district-wide losses and treated area over several years, beetle feeding indices, and quantitative estimates of grub numbers in a selection of fields – can be used as a early warning system to promote awareness of the need for grub management, either to increase management input in a rising grub trend or to relax management (and cost) at times of low risk (see Chandler article, Appendix 5).

Mulgrave Mill used concepts developed in this project to produce formal grub forecasts for distribution to growers. The involvement in the project of Gerard Puglisi, at that time working with Mulgrave Mill, has been instrumental in establishing the project in that district. Mulgrave annually issued an analysis of the grub threat for the coming year, based on the monitoring results (Appendix 4). Results in other districts have been presented at grub meetings and through print media (e.g. Appendix 3).

4.4 Effect of some variables on damage in Mourilyan

Sufficient grub damage data were available for the Mourilyan mill area on a block-by-block basis to investigate trends in grub damage in relation to two possible predictor variables, harvest date the previous year and crop class. Data had been collected by George Bujega and analyses were carried out by Alicia Magnanini, both of Innisfail-Babinda Productivity Services Limited.

There was no apparent decrease in damage frequency with later harvest (Fig. 6), unlike the trend that has been demonstrated in the Burdekin region.

The distribution of damaged blocks classified by crop class in ratoons followed the same pattern as total blocks (Fig. 7), suggesting no influence of ratoon age on the likelihood of damage. However, damaged plant cane blocks were under-represented compared with the total number of plant cane blocks, both fallow-plants and replants, in all years except 1999 and 2000 (Fig. 7). This suggests that damage was less likely in plant crops, presumably reflecting the influence of treatment of plant crops with suSCon Blue and, perhaps, an effect of crop replacement. Data were not available to analyse suSCon-treated and untreated plant crops separately.

4.5 Utility of historical data from insecticide trials for developing a risk assessment model

Mean numbers of grubs did not differ significantly among crop classes in untreated plots in insecticide trials conducted in non-Burdekin (mainly Innisfail) or Burdekin regions and sampled between 1995 and 2006 (Table 8). These data show much higher grub populations in the plant crop than do the data collected from our intensively monitored fields (see later), perhaps because they were deliberately chosen as having a high grub risk. However, numbers did not increase in ratoons. The dynamics of greyback canegrub populations may differ between small plots surrounded by treated cane, as in the insecticide trials, and whole fields, as in our intensively monitored fields.

Table 8 Grub numbers in different crop classes using the data from untreated plots in small-plot insecticide trials

Crop class	Non-Burdekin		Burdekin	
	n	Grubs/stool ± SE	n	Grubs/stool ± SE
Plant	34	0.31 ± 0.08	26	1.04 ± 0.17
1R	34	0.51 ± 0.10	26	0.84 ± 0.22
2R	22	0.30 ± 0.12	13	0.72 ± 0.32
P		0.071		0.203

Other measurements that might aid in assessing risk of grub attack, such as presence of nearby damage or levels of grub pathogens, were not collected in conjunction with these trials. We do not believe that such historical data are useful for developing a suitable risk-assessment model.

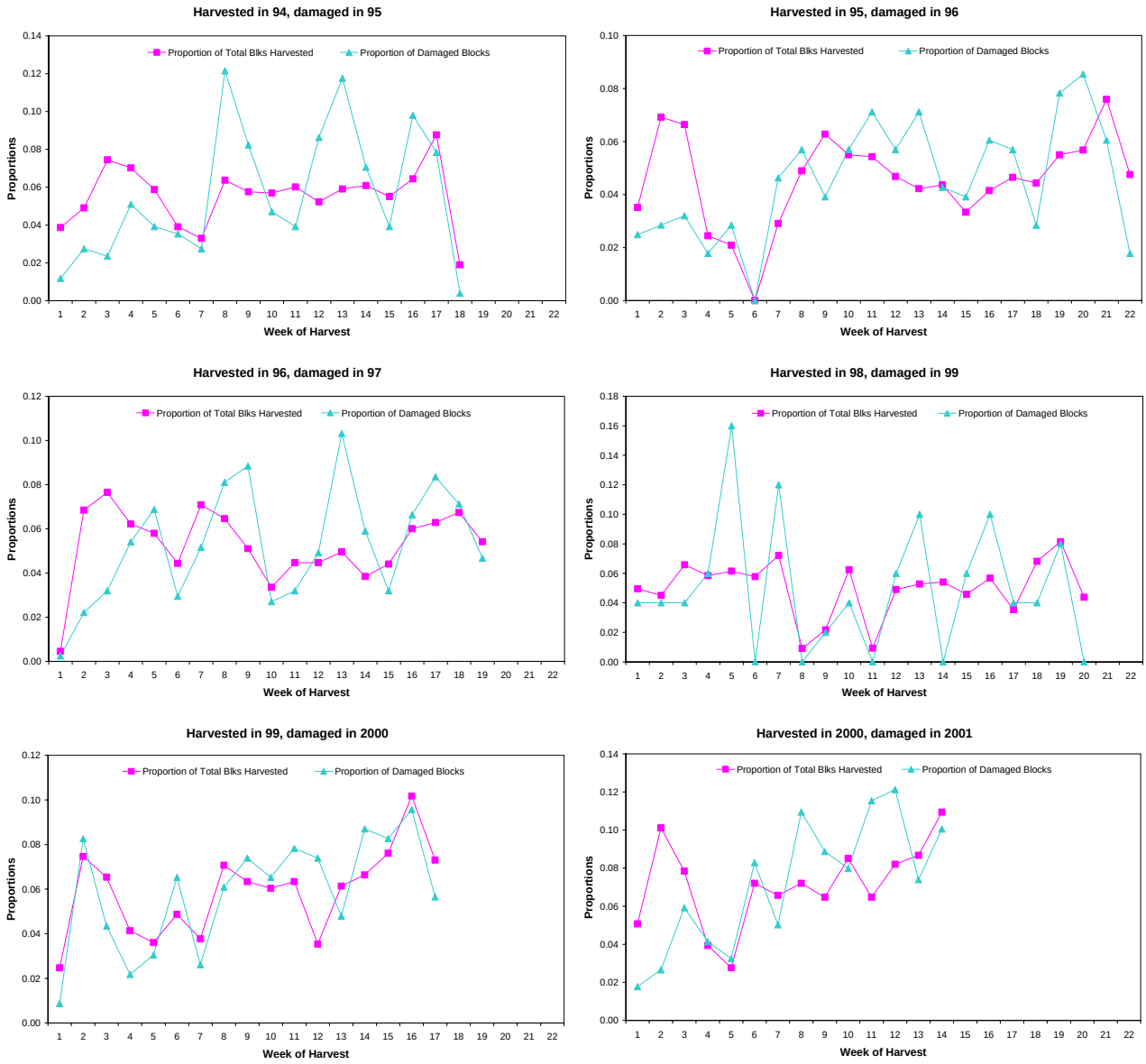


Figure 6 **Proportion of blocks harvested weekly and the proportion of blocks damaged by greyback canegrubs the following year at Mourilyan, both classified by harvest week for each year 1994-2000**

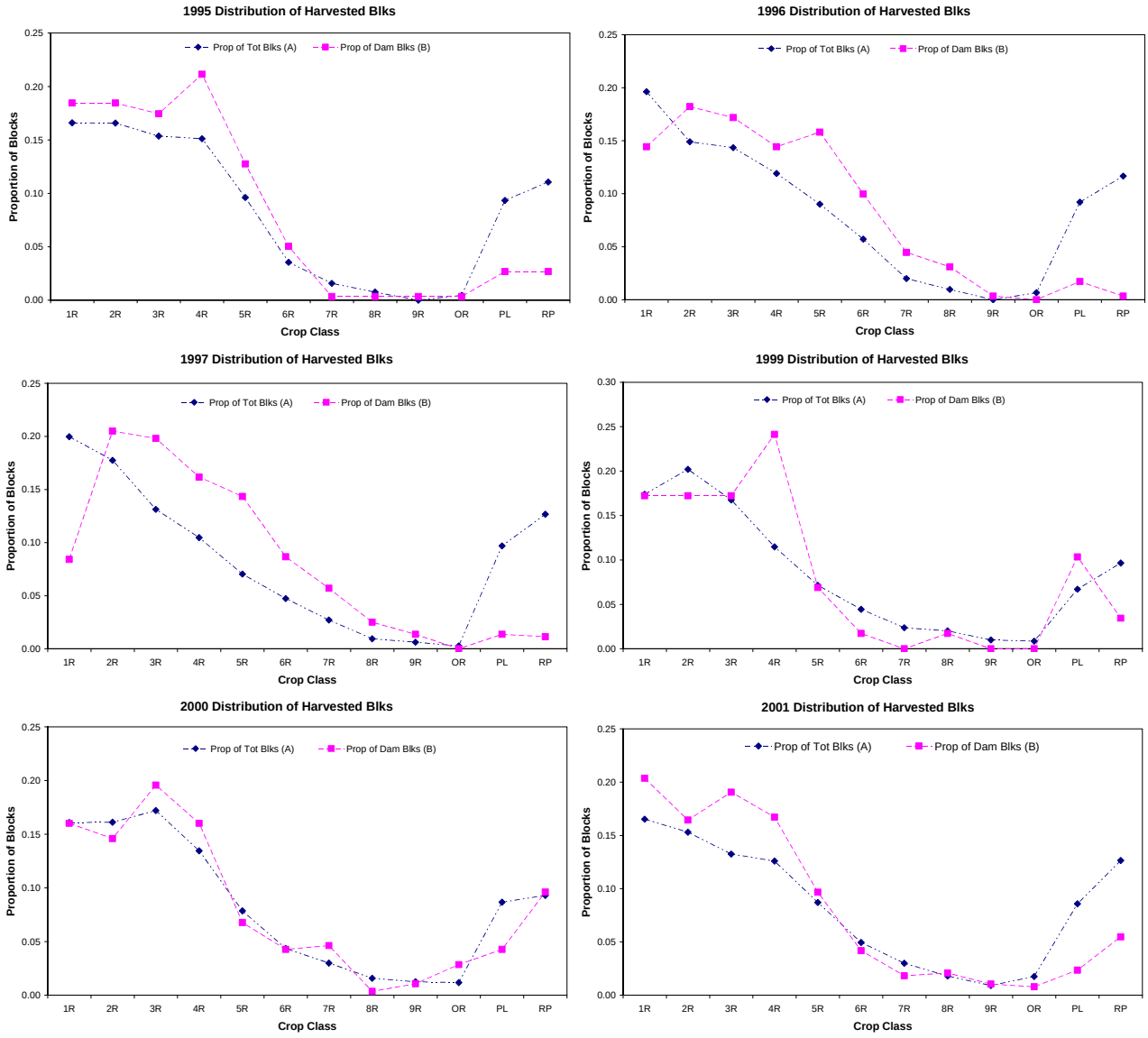


Figure 7 **Proportion of total blocks and the proportion of blocks damaged by greyback canegrubs at Mourilyan in each crop class for years 1995-2001**

4.6 Factors related to grub numbers in individual fields

Apart from the analysis of spatial relationships among fields (Section 4.6.9), the analyses described below were conducted by Peter Samson using *Statistix 8*. Some similar analyses were conducted by Frank Drummond, but they are reported elsewhere (Appendices 10 and 11).

4.6.1 Grub numbers in the same fields in the previous year

In three pairs of years, 2003-4, 2004-5 and 2005-6, there was a relationship between numbers of canegrubs found in successive years in the same fields, although there remained considerable unexplained variation in the data (Fig. 8). There was no apparent relationship in 2006-7. These relationships are explored in greater detail in Table 9. A linear regression using numbers of grubs explained between 10% and 36% of the variation in numbers of greyback grubs in the following year, for each combination of region and year, except for 2006-2007.

The apparent link between grub numbers in successive years can be interpreted in several ways. One is that each field is to some extent independent of others, and beetles tend to return to the field from which they emerged, either actively by some 'homing instinct' or passively because that field happens to be near their aggregation sites or is attractive for some other reason. Alternatively, grub counts from a particular field may simply be an estimate of grub density for that field's neighbourhood, which is made up of many fields, and may be a useful predictor of risk not just for that field but for all nearby fields. If the latter, this would reduce the sampling effort needed to develop risk-assessment plans for farms, as a sample from only a small number of fields might be enough to estimate risk to all nearby fields for the following year. Our data are not sufficient to explore these possibilities further, although the 'global predictive models' developed in Section 4.8 include average grub densities district-wide as one of the predictor variables.

Table 9 Goodness of fit of linear regressions between mean numbers (log-transformed) of greyback canegrubs in canefields and numbers in the same fields the previous year

Grub year	R^2 (P, n) for each combination of region and year		
	Central	Northern	Both
2004	0.268 (0.040, 16)	0.175 (<0.001, 80)	0.296 (<0.001, 96)
2005	0.374 (0.035, 12)	0.258 (<0.001, 80)	0.290 (<0.001, 92)
2006	0.123 (0.32, 10)	0.176 (<0.001, 63)	0.178 (<0.001, 73)
2007	0.195 (0.71, 3)	0.068 (0.14, 34)	0.069 (0.12, 37)
All	0.101 (0.043, 41)	0.177 (<0.001, 257)	0.193 (<0.001, 298)

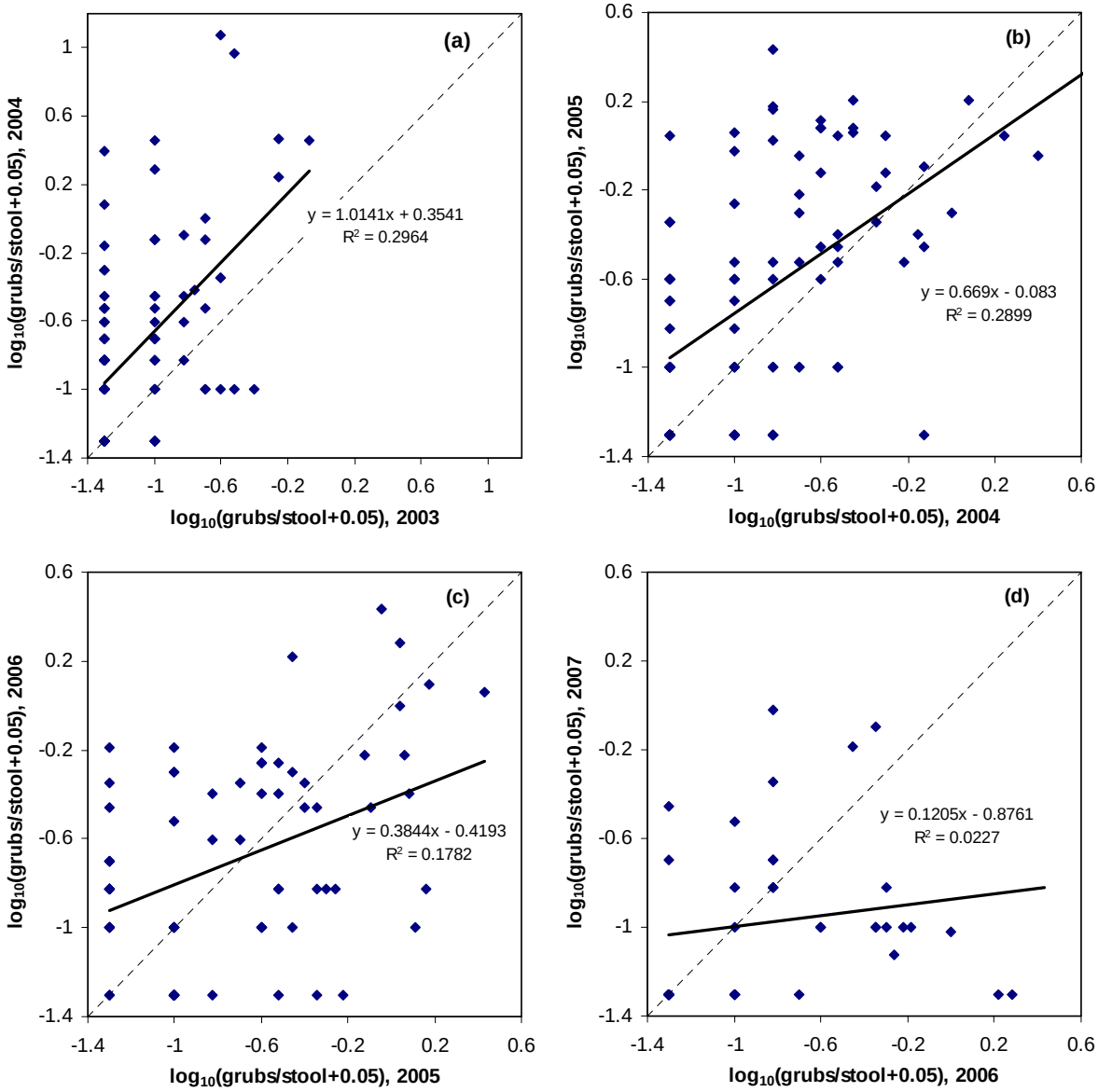


Figure 8 **Numbers of greyback canegrubs in successive years 2003-7 in canefields sampled annually from Plane Creek to Mulgrave (excluding Burdekin)**

4.6.2 Other measures of current infestation levels – visible damage and gaps

There were highly significant ($P < 0.001$) relationships between grub density measured in 2004, 2005, and over years 2004-2007 combined, and damage rating (scale 0-3) the previous year (Table 10). However, no relationship was detected for grub density in 2006 and 2007 and prior damage rating. There was also a highly significant ($P < 0.001$) relationship between grub density in 2006 and both the number of gaps measured in 2005 and the increase in gaps from 2004-5 (Table 10). These relationships indicate that, in some years, visible damage before harvest or number of gaps after harvest could be useful predictors of future grub risk; fields with apparent damage in those years were more likely

to have higher grub populations the following year. There was a weak ($P = 0.06$) negative relationship between grub density in 2005 and number of gaps the previous year, which may be spurious.

Table 10 The goodness of fit of linear regressions between various measures of crop damage and the density of canegrubs (log-transformed) in each field the following year

Grub year	R^2 (*P*, *n*, sign of slope) for each combination of measurement and year		
	Damage rating	Gaps	Gap increase
2004	0.143 (<0.001, 96, +)	0.001 (0.73, 94)	na
2005	0.185 (<0.001,93, +)	0.040 (0.057, 90, -)	0.001 (0.85, 83)
2006	0.014 (0.33, 73)	0.109 (0.005, 70, +)	0.114 (0.004, 70, +)
2007	0.048 (0.16, 43)	0.075 (0.13, 32)	0.037 (0.33, 28)
All	0.100 (<0.001, 305, +)	0.001 (0.66, 286)	0.002 (0.52, 181)

4.6.3 Crop class and treatment with insecticide

Numbers of grubs in first-, second- and third-ratoon crops differed significantly between fields that had been treated or not treated with suSCon products (mainly suSCon Blue) in the plant crop, when all fields were considered and using grub density measurements for each year from 2003-2007 (Table 11). The mean grub density for fields without suSCon tended to be skewed by data from the Central region, which had high grub densities in some years, particularly 2004 (see Table 6), and included mainly untreated fields (41 of 64 grub density measurements in the Central region were from fields without suSCon, compared with only 52 of 361 observations for regions further north). To test the generality of the apparent effect of suSCon treatment, the analysis was repeated without the Central region data. In this case there was a statistically significant difference in grub numbers between treated and untreated fields only in the first ratoon crop, although there was an indication that treated fields had lower grub numbers in second and third ratoons (Table 12).

Table 11 Grub numbers in different crop classes in fields with and without suSCon products applied to the plant crop, across all regions

Crop class	No suSCon		suSCon		*P* of difference[a]
	n	Grubs/stool ± SE	n	Grubs/stool ± SE	
Plant	8	0.03 ± 0.01	30	0.02 ± 0.01	0.30
1R	20	0.44 ± 0.16	64	0.08 ± 0.02	0.001
2R	31	0.49 ± 0.12	91	0.17 ± 0.04	0.001
3R	25	1.56 ± 0.57	79	0.27 ± 0.04	<0.001
4R	12	0.40 ± 0.12	56	0.28 ± 0.05	0.32
5R+	4	0.06 ± 0.05	22	0.20 ± 0.07	0.53
Total	100	0.68 ± 0.16	342	0.18 ± 0.02	<0.001

[a] By Kruskal-Wallis one-way non-parametric analysis of variance.

Table 12 Grub numbers in different crop classes in fields with and without suSCon products applied to the plant crop, excluding fields in the Central region

Crop class	No suSCon		suSCon		*P* of difference[a]
	n	Grubs/stool ± SE	n	Grubs/stool ± SE	
Plant	6	0.03 ± 0.02	30	0.02 ± 0.01	0.33
1R	11	0.23 ± 0.10	57	0.08 ± 0.02	0.04
2R	15	0.42 ± 0.15	76	0.15 ± 0.04	0.08
3R	9	0.47 ± 0.16	71	0.25 ± 0.04	0.08
4R	7	0.15 ± 0.09	53	0.29 ± 0.06	0.39
5R+	4	0.06 ± 0.05	22	0.20 ± 0.07	0.53
Total	52	0.28 ± 0.06	309	0.18 ± 0.02	0.06

[a] By Kruskal-Wallis one-way non-parametric analysis of variance.

Considering only those fields not treated with suSCon products in the plant crop, numbers of grubs did not differ significantly among crop classes in either the Central region or in the other regions combined (Kruskal-Wallis one-way ANOVA, $P = 0.10$ in both analyses). However, there was a tendency for plant crops to have fewer grubs than ratoon crops (Table 13).

Table 13 Grub numbers in different crop classes, in fields that did not receive suSCon products in the plant crop

Crop class	Central region		Other regions	
	N	Grubs/stool ± SE	n	Grubs/stool ± SE
Plant	2	0.03 ± 0.03	6	0.03 ± 0.02
1R	9	0.70 ± 0.33	11	0.23 ± 0.10
2R	16	0.56 ± 0.19	15	0.42 ± 0.15
3R	16	2.17 ± 0.86	9	0.47 ± 0.16
4R	5	0.74 ± 0.18	7	0.15 ± 0.09
5R+	0		4	0.06 ± 0.05

Mean numbers of greyback grubs did not differ significantly between the 37 fields that had been treated with Confidor Guard the previous year and 406 untreated fields (0.17 ± 0.05 and 0.31 ± 0.04, respectively; $P = 0.53$ by Kruskal-Wallis test). Fields that were treated with Confidor Guard would have been high-risk fields, that is, fields that were expected to have large numbers of grubs the next year, and this might have masked any apparent effect of treatment. The difference between numbers of grubs (log-transformed) in successive years also did not differ significantly between the 22 fields that had been treated with Confidor Guard the previous year, and for which successive population estimates were available, and 276 untreated fields (-0.010 ± 0.021 and 0.044 ± 0.009, respectively; $P = 0.15$ by Kruskal-Wallis test). However, limited data are available to statistically evaluate the effect of Confidor Guard, as its use was limited during most of the study. Based on the results of numerous insecticide trials, there is no doubt that it

reduces grub numbers the year after treatment, compared with numbers in its absence, by 60-80% (Chandler 2003; Samson *et al*. 2006).

In summary, this analysis shows that treatment of plant crops with controlled-release products must be considered as part of a risk-assessment model. The protection afforded extends to at least the first ratoon in our data set, and perhaps longer. Confidor treatment must also be considered. Ratoon age does not seem critical in the absence of suSCon protection. Plant crops may tend to have lower infestation levels than ratoon crops, but were poorly represented in our data set.

Table 14 Goodness of fit of linear regressions between mean numbers (log-transformed) of greyback canegrubs in canefields and different measures of insecticide protection, for grub density measurements collected from 2003-2007 (n = 81 and 362 in CQ and NQ)

Data	Insecticide Variable [a]	Central Queensland		Northern Queensland		Both	
		R^2	*P*	R^2	*P*	R^2	*P*
2003-7	suSCon P	0.125	0.001	0.011	0.044	0.075	<0.001
	suSCon ≤1 yr	na		0.045	<0.001	0.044	<0.001
	suSCon ≤2 yr	0.058	0.031	0.088	<0.001	0.094	<0.001
	suSCon ≤3 yr	0.097	0.005	0.093	<0.001	0.108	<0.001
	suSCon ≤4 yr	0.087	0.008	0.038	<0.001	0.070	<0.001
	Protect ≤2 yr	0.077	0.020	0.071	<0.001	0.086	<0.001
	Protect ≤3 yr	0.114	0.002	0.088	<0.001	0.112	<0.001

[a] suSCon variables represent all fields treated with suSCon-products in the plant crop (suSCon P) or fields treated within 1, 2, 3 or 4 years; Protect ≤2 yr and Protect ≤3 yr represent fields treated with suSCon within 2 or 3 years, respectively, plus fields treated with Confidor the previous year

The utility of different treatment parameters for use as the independent variable in a multivariate analysis of the data to develop a risk-assessment model is explored in Table 14. Considering only data from Central Queensland, the suSCon variable that explained the greatest variation in grub numbers was that describing whether or not fields had received treatment in the plant crop (suSCon P). Replacing 'suSCon P' with variables describing different periods since suSCon application, from 1 to 4 years, gave lower values of R^2. In contrast, 'suSCon P' gave a low R^2 for the Northern Queensland data, and the suSCon variable that removed the greatest variation in the grub data was that describing application within the previous 3 years. The combined data were strongly influenced by the Central Queensland data with high grub populations (see Table 6). These results reflect the differences between regions reported earlier for numbers of grubs in suSCon-treated and untreated fields of different crop classes (see Tables 11, 12). One would not expect a very protracted period of efficacy of suSCon Blue, the main suSCon-product used in the study, as its label registration is only for one year against greyback canegrub, although 2 or perhaps 3 years' protection might be expected under ideal conditions (good distribution of granules in soil, low soil pH and moderate grub pressure). Therefore, the result of the analysis for Northern Queensland seems closer to reality than that for Central Queensland.

4.6.4 Cropping system

To estimate any effect of cropping system on greyback canegrub, we first calculated the mean numbers of canegrubs over the monitoring period for each field, as the cropping system did not change from year to year. Numbers were significantly lower in fallow-planted fields than in replant fields, and in fields where the last ratoon of the previous crop cycle had been killed by herbicide rather than cultivation (Table 15). The sprayed-out fields usually received full cultivation at some time before planting, and only 10 fields were prepared by zonal tillage (cultivation of the rows only). Mean numbers of canegrubs did not differ significantly between fields prepared either by zonal tillage or conventional tillage (Table 15). Canegrub numbers also did not differ significantly between fields with or without a legume rotation prior to the current crop of cane (Table 15).

Table 15 Grub numbers in fields with and without different cultural practices before planting, using data from all regions and years combined

Cultural practice	No		Yes		*P* of difference[a]
	n	Grubs/stool ± SE	n	Grubs/stool ± SE	
Replant	72	0.25 ± 0.05	42	0.52 ± 0.18	0.022
Sprayout	69	0.46 ± 0.11	39	0.16 ± 0.04	0.003
Zonal tillage	99	0.36 ± 0.08	10	0.34 ± 0.08	0.062
Legume	85	0.36 ± 0.09	26	0.33 ± 0.09	0.79

[a] By Kruskal-Wallis one-way non-parametric analysis of variance.

We also compared mean numbers of canegrubs among the four combinations of replant or fallow-plant and sprayout or cultivation. Replanted fields would all be expected to be cultivated, although four were reported to be sprayed out. Mean numbers of grubs differed significantly among practices ($P = 0.009$ by Kruskal-Wallis test), with the fallow-plant sprayout fields having significantly fewer grubs than replant cultivated fields (Table 16).

Table 16 Grub numbers in fields with four different combinations of methods of fallowing and of killing the old crop, using data from all districts and years combined

Fallowing system	n	Grubs/stool ± SE
Replant with cultivation	35	0.57 ± 0.21 a
Replant with sprayout	4	0.36 ± 0.22 ab
Fallow-plant with cultivation	33	0.36 ± 0.08 ab
Fallow plant with sprayout	35	0.14 ± 0.03 b

Means followed by the same letter were not significantly different by Kruskal-Wallis multiple comparison test.

It is possible that one or more of these cultural practices may have had a direct effect on greyback canegrub populations. In particular, replant fields may tend to have a direct

carry-over of populations from one crop cycle to the next in the absence of a fallow period, leading to the higher populations observed. Legume crops grown in rotation with cane may harbour grub populations (unpublished data) but this was not reflected in increased grub numbers in the following cane crop.

Cultural practices may also have indirect effects on grub populations via effects on natural enemies. The average percentage infection of grubs with *Metarhizium* was greater where the previous crop had been killed with herbicide rather than cultivation, while infection by both *Metarhizium* and *Adelina* was higher in fields prepared with zonal tillage rather cultivation across the whole paddock (Section 4.6.8). Conservation of pathogens with reduced tillage could help explain the lower grub densities in sprayout fields that were observed above.

4.6.5 Soil characteristics – texture and pH

The mean percentage of each texture fraction in soil samples collected from fields in 2007 was (range in parenthesis): sand, 56% (19-78%); silt, 19% (6-38%); clay, 25% (14-60%). There was not a significant linear relationship between the percentages of any of these fractions and canegrub density averaged over years for each field (Table 17).

Table 17 Goodness of fit of linear regressions between the percentages of each soil fraction and soil pH, and the mean density of canegrubs (log-transformed) in each field (*n* = 120), with data combined across regions

R^2 (*P*, sign of slope)			
Sand	**Silt**	**Clay**	**pH**
0.005 (0.46)	0.011 (0.25)	0.000 (0.86)	0.093 (<0.001,+)

The mean pH of soil samples collected in 2007 was 5.1 (range 4.7-7.0). The linear relationship between pH and grub density was highly significant ($P < 0.001$) with a positive coefficient (Table 17), indicating more grubs at higher pH. A possible mechanism is the known deleterious effect of high pH soil on the efficacy of suSCon Blue (Chandler *et al.* 1998; Robertson *et al.* 1998). Alternatively, there may a negative effect of increasing pH on known pathogens of greyback canegrub, particularly *Adelina* (see Section 4.6.8). This analysis must be interpreted with some caution, however, as soil pH was only measured once, in 2007, and actual values in preceding years are unknown.

4.6.6 Cane height during beetle flights (including harvest date)

Cane heights, both height to TVD and canopy height, appeared much larger in the Central region in the summer of 2003/4 than in all other years and regions because the measurements were done unusually late (February 2004) (Table 18). No heights are available for 2006.

Table 18 Range of mean cane heights (to TVD) and canopy heights (mm) of monitoring fields in each region each year (see Table 4 for dates of measurement)

Year	Central	Herbert	Innisfail-Tully	Mulgrave
TVD				
2003	858-1920	58-234	96-686	70-675
2004	184-724	108-354	78-400	122-304
2005	90-495	98-472	0-652	117-581
Canopy				
2003	1700-3200	na	na	na
2004	550-1810	150-1590	250-1670	350-1800
2005	300-1680	70-3000	0-2300	330-2240

Table 19 Goodness of fit of linear regressions between various measures of cane height and the density of canegrubs (log-transformed) in each field the following year

Grub year	R^2 (*P*, *n*) for each combination of region and year		
	Central	Northern	Both
TVD			
2004	0.091 (0.26,16)	0.084 (0.009,81)	
2005	0.014 (0.71, 12)	0.001 (0.78,79)	
2006	0.009 (0.80, 10)	0.014 (0.37,60)	
Canopy height			
2004	0.239 (0.06,16)	na	
2005	0.022 (0.65, 12)	0.001 (0.74,79)	
2006	0.007 (0.82,10)	0.002 (0.77,62)	
Canopy height relative to tallest neighbour			
2004	0.132 (0.17,16)	na	na
2005	0.028 (0.61,12)	0.020 (0.22,76)	0.008 (0.41,88)
2006	0.045 (0.56, 10)	0.032 (0.16,62)	0.029 (0.15,72)

Mean grub density (log-transformed) in 2004 in Northern Queensland was significantly related to height of cane to TVD measured during the previous summer (Table 19). The slope was positive, indicating a greater grub population in those fields with taller cane, a result that would be expected based on previous work in the Burdekin region (Horsfield *et al.* 2002; Ward 2003). However, there was no significant relationship in other years or in the Central region in any year. No relationships were statistically significant using canopy height or canopy height relative to the tallest neighbouring field (Table 19). Only the relative data were combined across regions for analysis, but again there were no significant relationships. There is anecdotal support for infestations being more likely in taller cane, even outside the Burdekin, but this is often in ratoons that have been cut early for plants rather than during the crushing season (see Section 4.12.1).

Even if cane height at the time of beetle flight was a useful predictor of future infestations, it is impractical to use in a predictive model, as by then it would be too late in the year to

apply most control measures. As an alternative to measuring cane, we obtained dates of harvest from the relevant mills for each monitoring field in each of 2003-2005 (heights were not measured in 2006). We expected that cane height at the time of beetle flights would decrease with later harvest. While this was the general trend of the data, and there was a good fit between regressions of harvest data and cane height in some regions, in other regions and years the relationship was poor to non-existent (Table 20). The reason for this is unclear. Weather conditions and supply of irrigation during the harvest season influences speed of ratooning, and early-cut fields may grow slowly under dry conditions, allowing late-cut fields to catch up in ratoon growth. Errors in reporting of harvest date cannot be ruled out.

Table 20 Goodness of fit of linear regressions (R^2) between harvest date (expressed as the proportion of the harvest season completed when each field was harvested) and mean cane height (to TVD) and canopy height of monitoring fields (see Table 4 for dates of measurement)

Year	Central	Herbert	Innisfail-Tully	Mulgrave
TVD				
2003	0.376	0.164	0.512	0.088
2004	0.718	0.135	0.295	0.189
2005	0.750	0.312	0.851	0.514
Canopy				
2003	0.283	na	na	na
2004	0.604	0.092	0.474	0.097
2005	0.648	0.003	0.808	0.634

4.6.7 External infestation pressure – nearby damage or nearby old ratoons, distance to treeline

Six linear regressions between grub density in monitoring fields (log-transformed values) and the number of nearby damaged fields (within 400 m) the previous year had significance values (*P*) less then 0.10, for years and major regions (Central, Northern) individually or combined (Table 21). The slopes were positive in all cases. Six regressions were significant with distance to nearest damaged block as the independent variable, although none of these was for the Central region. All had negative coefficients. Eight regressions were significant with maximum severity of nearby damage (< 400 m) as the independent variable, all with positive coefficients.

The presumption with these variables was that the number of canegrubs in a field would be promoted by the presence of nearby infestations the previous year, in which case regressions should have been positive for two of the variables (number of nearby damaged fields and maximum severity of nearby damage) and negative for the other, distance to nearest damaged block. That is what we observed.

There was only one statistically significant relationship ($P<0.10$) using the proportion of nearby old (unprotected) ratoons as the independent variable, with an unexpected negative

coefficient (Table 21). This variable is a very rough measure of possible external infestation pressure, as old (unprotected) ratoons may not be infested by canegrubs.

Table 21 Goodness of fit of linear regressions between various measures of possible external infestation pressure and the density of canegrubs (log-transformed) in each field the following year

Grub year	R^2 (*P*, *n*, sign of slope) for each combination of region and year		
	Central	**Northern**	**Both**
No. nearby damaged blocks			
2004	0.292 (0.031,16,+)	0.085 (0.009,80, +)	0.336 (<0.001,96,+)
2005	0.020 (0.89,12)	0.196 (<0.001,81,+)	0.096 (0.003,93,+)
2006	0.010 (0.79,10)	0.011 (0.41,63)	0.006 (0.51,73)
2007	0.750 (0.33,3)	0.005 (0.65,40)	0.003 (0.73,43)
All	0.083 (0.07,41,+)	0.003 (0.34,264)	0.002 (0.41,305)
Distance to nearest damaged block			
2004	0.017 (0.63,16)	0.105 (0.003,80,-)	0.154 (<0.001,96,-)
2005	0.010 (0.76,12)	0.145 (<0.001,81,-)	0.163 (<0.001,93,-)
2006	0.102 (0.37,10)	0.012 (0.40,63)	0.029 (0.15,73)
2007	0.920 (0.18,3)	0.006 (0.63,40)	0.002 (0.76,43)
All	0.039 (0.21,41)	0.061 (<0.001,264,-)	0.097 (<0.001,305,-)
Maximum severity of nearby damage			
2004	0.183 (0.10,16,+)	0.031 (0.12,80)	0.243 (<0.001,96,+)
2005	0.064 (0.43,12)	0.131 (<0.001,81,+)	0.139 (<0.001,93,+)
2006	0.005 (0.85,10)	0.016 (0.32,63)	0.040 (0.09,73,+)
2007	0.750 (0.33,3)	0.009 (0.56,40)	0.002 (0.80,43)
All	0.116 (0.029,41,+)	0.038 (0.002,264,+)	0.128 (<0.001,305,+)
Proportion of nearby old ratoons			
2004	0.011 (0.65,16)	0.050 (0.064,69,-)	0.009 (0.37,91)
2005	0.065 (0.40,12)	0.000 (0.88,74)	0.001 (0.82,87)
2006	0.002 (0.90,10)	0.002 (0.76,51)	0.010 (0.45,61)
2007	na	na	na
All	0.033 (0.23,38)	0.000 (0.88,194)	0.002 (0.49,239)
Distance to treeline			
Average	0.000 (1.00,23)	0.025 (0.12,97)	0.027 (0.07,120)

We did not conduct separate annual analyses with distance to treeline as the independent variable, as the value of this variable did not change between years. Instead, we calculated a single average grub density for each field and attempted to relate this (log-transformed) to the distance to treeline. Linear regressions were not statistically significant for either the Central or Northern regions or for both combined (Table 21). This result does not support the hypothesis that fields closer to treelines, which may serve as aggregation sites for beetles, are more likely to receive grub infestations. However, all fields monitored in this study had a predisposition to greyback canegrub attack, as they were chosen for their previous history of greyback infestations, and a stronger relationship between grub numbers and distance to the treeline may have been obtained had we monitored a random sample of fields in each region.

4.6.8 Pathogens

4.6.8.1 Annual incidence of pathogens

Adelina, Metarhizium and milky disease were recorded in greyback canegrubs from few fields in 2003 and 2004 (Table 22). Survival of grubs to adult in 2003 could not be estimated due to overheating of the rearing incubator late in the year.

Table 22 Pathogens recorded in greyback canegrubs from monitoring fields each year

Region	Fields where grubs examined		Fate of grubs % (no. fields where pathogens present)				
	No. sites	No. grubs	*Adelina*	*Metarhiz -ium*	Milky disease	Death, cause?	Adults
2003							
Central	10	51	0	2 (1)	0	na	na
Herbert	4	30	33 (2)	0	0	na	na
Tully-Innisfail	5	15	7 (1)	20 (1)	0	na	na
Mulgrave	13	25	16 (2)	0	0	na	na
2004							
Central	21	540	0 (0)	0.4 (2)	0.4 (2)	25	74
Herbert	7	21	14 (1)	0 (0)	0 (0)	14	72
Tully-Innisfail	13	37	5 (1)	3 (1)	0 (0)	32	60
Mulgrave	21	71	17 (2)	0 (0)	3 (2)	27	53
2005							
Central	11	122	1 (1)	3 (4)	0	38	58
Herbert	15	37	8 (3)	0	0	60	32
Tully-Innisfail	15	103	28 (7)	17 (6)	0	31	24
Mulgrave	28	317	22 (13)	5 (10)	2 (2)	27	44
2006							
Central	10	125	4 (4)	3 (3)	2 (2)	45	46
Herbert	11	33	18 (3)	6 (2)	0	39	36
Tully-Innisfail	13	63	17 (5)	14 (5)	2 (1)	41	25
Mulgrave	19	123	40 (10)	7 (7)	1 (1)	33	20
2007							
Central	17	83	5 (3)	8 (4)	0	40	48
Herbert	7	73	22 (5)	3 (1)	0	25	51
Tully-Innisfail	6	10	40 (4)	0	0	40	20
Mulgrave	11	51	8 (4)	2 (1)	2 (1)	47	41

Adelina was recorded in 24 of the 69 fields where grubs were collected in 2005, a large increase from the four fields where it was detected in 2004 (Table 22). *Metarhizium* was observed in grubs from 20 fields, again a large increase from the single field where it was detected the year before (Table 22). More grubs died from unknown causes in 2005 than 2004. This is difficult to interpret, as differences in conditions during grub collection and during rearing may vary from year to year and could affect rearing success.

The percentage of grubs that produced adult beetles was lower in 2005 than in 2004, in all regions (Table 22). This was due at Mulgrave, Innisfail and Tully to an increased incidence of *Adelina* and *Metarhizium*, and at Innisfail to an increased number of grubs dying from unknown causes. Reduced numbers of adults produced by grubs from the Herbert and Central regions was associated with increased deaths from unknown causes; mortality from identified pathogens was no higher than in 2004 in these areas.

The percentage of grubs infected by pathogens in 2006 was mostly similar to 2005, except for a high level of *Adelina* infection in Mulgrave (Table 22). As in 2005, more grubs died from unknown causes and fewer successfully produced adults than in 2004. The level of infection of grubs by identified pathogens remained extremely low in the Central region, although *Adelina* and *Metarhizium* were found in grubs from four and three of ten sampled fields, respectively. Over all regions, the proportion of fields where *Adelina* and *Metarhizium* were detected was similar to 2005: 22/53 fields (42%) and 17/53 fields (32%), respectively, in 2006 compared with 24/69 fields (35%) and 20/69 fields (29%) the previous year.

The percentage of grubs infected by known pathogens in 2007 was low in the Central region, as had been the case in every year since 2003 (Table 22). The frequency of infections by *Adelina* and *Metarhizium* in the Herbert was similar to 2006. The rate of *Adelina* infection appeared to be high in Innisfail-Tully but this was estimated from only 10 grubs. In Mulgrave, the proportion of grubs infected by *Adelina* was surprisingly low, after infection levels had seemed to be increasing up to 2006. Over all regions, the proportion of fields where *Adelina* was detected was similar to 2006 – 13/28 fields (46%) and 22/53 fields (42%), respectively – but the proportion of fields where *Metarhizium* was detected, 2/28 (7%), was much lower than in 2006 (17/53 fields, 32%). However, these numbers have to be considered in the light of the lower average number of grubs in 2007 in most regions, which reduces the likelihood of detecting pathogens in grubs from any particular field.

Over the 5 years of the study, there has been a trend for the incidence of *Adelina* and *Metarhizium* to increase in the Central region, but from a very low base, and the rate of infection by *Adelina* in particular was still much lower than in other regions in 2007 (Fig. 9, Table 22). Incidence of *Adelina* seems to be increasing in the Herbert, as also is the average density of grubs. As noted earlier, the apparently high incidence of *Adelina* in Innisfail-Tully in 2007 is poorly estimated because of the small number of grubs examined. In Mulgrave, incidence of *Adelina* peaked in 2006 and declined enormously in 2007, perhaps in response to declining grub densities. Incidence of *Metarhizium* in each region was erratic and only ever exceeded 10% in Innisfail-Tully (Fig. 9, Table 22).

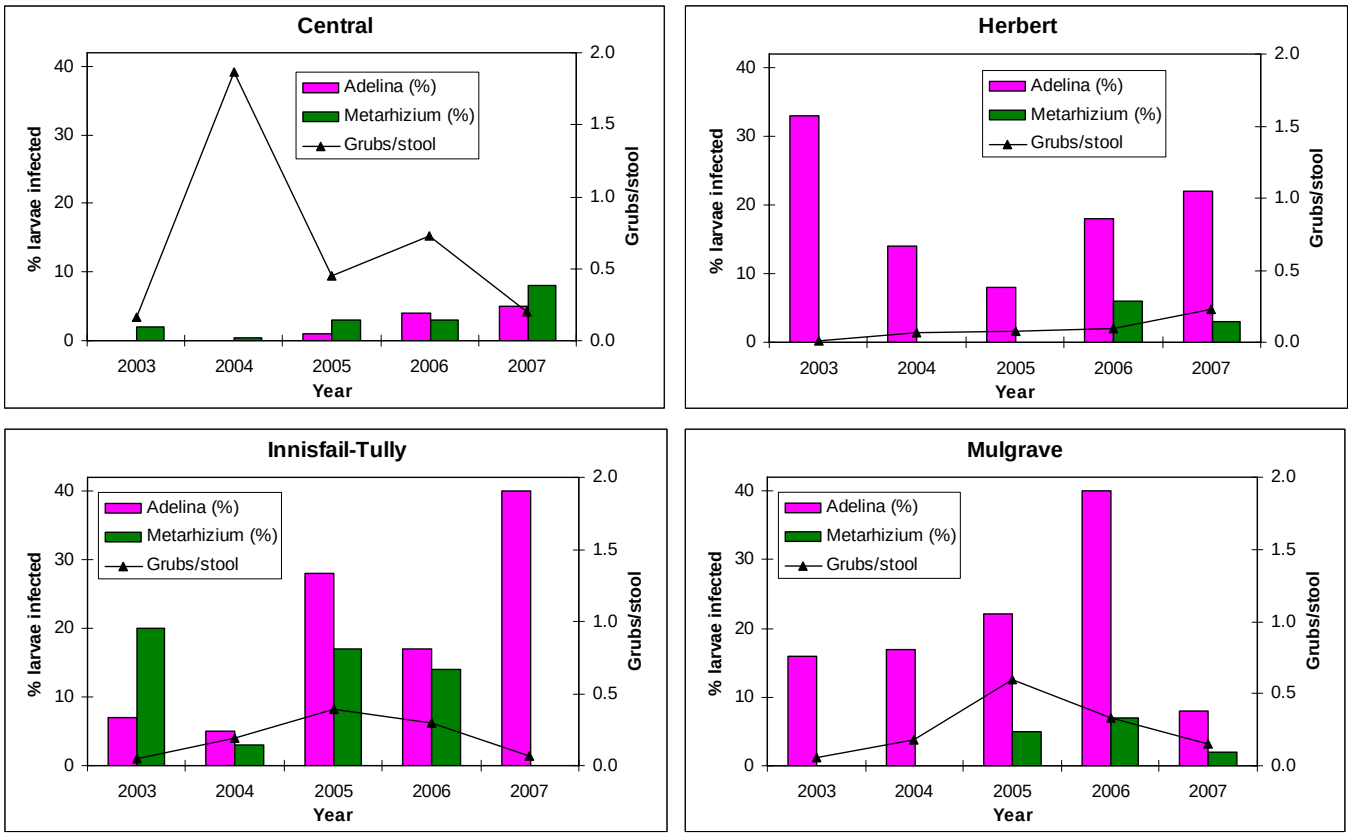


Figure 9 **Frequency of infection of greyback canegrubs by *Adelina* and *Metarhizium*, and the average canegrub density in the sampled canefields, in each region from 2003-2007**

4.6.8.2 Dynamics of *Adelina* and *Metarhizium*

As the incidence of *Adelina* differed considerably between the Central region and all other regions (Fig. 9), relationships between levels of *Adelina* infection and numbers of greyback canegrubs were considered separately for the Northern region (Mulgrave, Innisfail-Tully and Herbert combined) and for the Central region.

In the Central region, there were no significant relationships between levels of *Adelina* infection and canegrub density in individual canefields in the same year (Table 23), probably because *Adelina* infection was so uncommon. In the Northern region, however, the percentage of canegrubs diagnosed with *Adelina* was significantly related to the density of canegrubs in each field in every year except 2007 (Table 23). The relationship was positive in all cases, with slopes of 28, 40, 27 and 45 in each of 2003-2006. For all data from the Northern region (2003-2007), the percentage infection with *Adelina* was related to grub density in the same year as $26.9 + 24.8*\log_{10}(\text{grubs/stool}+0.05)$. This is consistent with the hypothesis that levels of *Adelina* are variable and density-dependent, responding to increases in host density and declining when host numbers decline (Robertson *et al.* 1998).

Table 23 Relationships between the percentage of reared greyback canegrubs that were infected with *Adelina* and the density of canegrubs (log-transformed) in each field in the same year, by linear regression weighted according to the number of individuals examined for disease

Year	Central region			Northern region		
	R^2	*P*	*N*	R^2	*P*	*n*
2003	na			0.192	0.042	22
2004	na			0.277	<0.001	41
2005	0.225	0.14	11	0.104	0.014	58
2006	0.073	0.45	10	0.315	<0.001	43
2007	0.014	0.68	15	0.098	0.147	23
All	0.028	0.17	67	0.111	<0.001	187

Relationships between levels of *Adelina* infection and log-transformed numbers of greyback canegrubs in the following year were examined for the Northern region fields only, as infection was rare in the Central region. A statistically significant relationship was detected in 2006 only, with a slope of -0.0079 (Table 24).

Table 24 Relationships between the percentage of reared greyback canegrubs that were infected with *Adelina* and the density of canegrubs (log-transformed) in each field the following year, by linear regression weighted according to the number of individuals examined for disease

Year	Northern region		
	R^2	*P*	*n*
2003	0.025	0.50	20
2004	0.007	0.62	39
2005	0.067	0.094	43
2006	0.374	<0.001	20
All	0.000	0.94	122

Fewer than two fields were recorded with *Metarhizium*-infected grubs in either the Central region or the Northern region in 2003 and 2004 (Table 22), so no analyses were performed for these years. In 2005-2007, the percentage of canegrubs diagnosed with *Metarhizium* in individual canefields was not significantly related to the density of canegrubs in each field in any single year in either region (Table 25). The statistically significant negative relationship using all data from the Central region was not convincing, and could have been an artefact of combining data across years. The results are consistent with *Metarhizium* causing a background level of mortality that is not density dependent (e.g. Robertson *et al.* 1998).

Table 25 Relationships between the percentage of reared greyback canegrubs that were infected with *Metarhizium* and the density of canegrubs (log-transformed) in each field in the same year, by linear regression weighted according to the number of individuals examined for disease

Year	Central region			Northern region		
	R^2	*P*	*n*	R^2	*P*	*n*
2005	0.003	0.87	11	0.006	0.58	58
2006	0.014	0.74	10	0.018	0.40	43
2007	0.028	0.55	15	0.096	0.15	23
2003-2007	0.071	0.030	67	0.000	0.88	187

There was no significant relationship between the percentage of *Metarhizium* infection and grub numbers (log-transformed) the following year in 2005 or 2006 in the Central region or the Northern region, or in data combined over years (Table 26). Too few positive fields were recorded in 2003 or 2004 or in 2006 in the Central region to conduct a useful analysis for those years individually.

Table 26 Relationships between the percentage of reared greyback canegrubs that were infected with *Metarhizium* and the density of canegrubs (log-transformed) in each field the following year, by linear regression weighted according to the number of individuals examined for disease

Year	Central region			Northern region		
	R^2	*P*	*n*	R^2	*P*	*n*
2005	0.104	0.44	8	0.048	0.16	43
2006	na			0.001	0.90	20
2003-2007	0.000	0.93	32	0.019	0.13	122

As an alternative analysis, we compared the grub population trend from year-to-year in fields where pathogens were recorded as either present or absent. We used infection records from the Northern region for the years 2005 and 2006, when the frequency of fields with infected grubs was relatively high (see Table 22), and only for fields for which there were grub population estimates in successive years. In most years and regions, the fields with *Adelina* or *Metarhizium* present had lower average rates of grub increase than those where these pathogens were not detected (Tables 27, 28), although there were statistically significant differences ($P < 0.05$) only for *Adelina* data combined over regions in 2006 (Table 27) and for *Metarhizium* data for Innisfail-Tully and combined regions in 2005 (Table 28). It is noteworthy that, for most years and regions, fields recorded with these pathogens had a higher average grub density in the same year than fields where they were not found. This could be a real effect, as hypothesised earlier for levels of *Adelina* infection, or it could be an artefact of the screening procedure, as we were more likely to detect pathogens in fields where we were able to collect more grubs for examination. If the latter, this might tend to bias the estimates of the population trend. In fact, the mean numbers of grubs in fields were mostly similar for fields where either pathogen was detected or not detected the previous year (Tables 27, 28), and the three significant

relationships described above were not statistically significant if the population trend was replaced with actual grub numbers (log-transformed) in the second year.

Table 27 Trend of grub numbers in successive years in fields where *Adelina* infection was or was not recorded in 2005 and 2006, for fields in the Northern region

Year 0	Area	*Adelina* detected	No. of fields	*Adelina* in Year 0 (%)	Mean grubs/stool (max. mean)		Grub trend[a]	*P*[b]
					Year 0	Year 1		
2005	Mulgrave	No	9	-	0.56 (1.2)	0.43 (1.9)	-0.168	
		Yes	9	48	0.93 (2.7)	0.38 (1.2)	-0.501	0.08
	Innisfail-Tully	No	7	-	0.26 (0.8)	0.27 (0.6)	-0.003	
		Yes	6	47	0.51 (1.4)	0.29 (0.5)	-0.064	0.94
	Herbert	No	9	-	0.09 (0.3)	0.06 (0.4)	-0.217	
		Yes	3	46	0.27 (0.4)	0.22 (0.4)	-0.142	0.51
	Combined	No	25	-	0.31 (1.2)	0.25 (1.9)	-0.140	
		Yes	18	47	0.68 (2.7)	0.32 (1.2)	-0.296	0.32
2006	Combined	No	15	-	0.20 (0.6)	0.18 (0.8)	-0.104	
		Yes	5	54	0.66 (1.9)	0.05 (0.1)	-0.733	0.028

[a]$\log_{10}$(grub/stool [Year 1] + 0.05) – $\log_{10}$(grubs/stool [Year 0] + 0.05)
[b]By Kruskal-Wallis test

Table 28 Trend of grub numbers in successive years in fields where *Metarhizium* infection was or was not recorded in 2005 and 2006, for fields in the Northern region

Year 0	Area	*Met.* detected	No. of fields	*Met.* in Year 0 (%)	Mean grubs/stool (max. mean)		Grub trend[a]	*P*[b]
					Year 0	Year 1		
2005	Mulgrave	No	13	0	0.77 (2.7)	0.44 (1.9)	-0.305	
		Yes	5	26	0.68 (1.5)	0.32 (1.2)	-0.412	0.35
	Innisfail-Tully	No	8	0	0.15 (0.3)	0.31 (0.6)	0.204	
		Yes	5	35	0.73 (1.4)	0.23 (0.5)	-0.409	0.039
	Combined	No	33	0	0.39 (2.7)	0.28 (1.9)	-0.143	
		Yes	10	30	0.71 (1.5)	0.28 (1.2)	-0.410	0.045
2006	Combined	No	14	0	0.20 (0.6)	0.16 (0.8)	-0.114	
		Yes	6	23	0.59 (1.9)	0.10 (0.4)	-0.605	0.082

[a]$\log_{10}$(grub/stool [Year 1] + 0.05) – $\log_{10}$(grubs/stool [Year 0] + 0.05)
[b]By Kruskal-Wallis test

4.6.8.3 Effect of agronomic factors on *Adelina* and *Metarhizium* incidence

The incidence of the pathogens *Adelina* and *Metarhizium* among greyback canegrubs collected from each field was estimated as the numbers of infected individuals as a

percentage of the total number examined over the period 2003-2007. The influence of soil factors was analysed by linear regression weighted according to the number of individuals examined. The incidence of *Adelina* was negatively related to soil pH, with each increase in pH of one unit being associated with an average decrease in infection of 10% (Table 29). This is a different conclusion from that of Sallam *et al.* (2003), who found no relationship between *Adelina* incidence and soil pH. We found no relationship between *Adelina* and soil texture components. In contrast, the incidence of *Metarhizium* was significantly related to soil texture but not to pH (Table 29). The percentage of *Metarhizium* was higher in fields with less sand and more silt or clay. Each decrease in sand content of 10% was associated with an average increase in infection of 2%.

Table 29 Goodness of fit of linear regressions between the percentages of each soil fraction and soil pH, and the percentage of canegrubs infected with *Adelina* or *Metarhizium* in each field (*n* = 106), by linear regression weighted according to the number of individuals examined for disease

Pathogen	R^2 (*P*, sign of slope)			
	Sand	Silt	Clay	pH
Adelina	0.004 (0.53)	0.003 (0.60)	0.003 (0.55)	0.069 (0.006,-)
Metarhizium	0.072 (0.006, -)	0.074 (0.005, +)	0.035 (0.05,+)	0.013 (0.25)

Weighted linear regressions were also carried out with the presence or absence of various cultural practices as the independent variable. *Adelina* infection was positively associated with the implementation of zonal tillage and with legume rotations, while *Metarhizium* infection was positively associated with sprayout of the old crop and zonal tillage (Table 30).

Table 30 Goodness of fit of linear regressions between the presence or absence of different cultural practices before planting and the percentage of canegrubs infected with *Adelina* or *Metarhizium* in each field (*n* = 99), by linear regression weighted according to the number of individuals examined for disease

Pathogen	R^2 (*P*, sign of slope)			
	Replant	Sprayout	Zonal tillage	Legume
Adelina	0.013 (0.27)	0.005 (0.50)	0.073 (0.007,+)	0.046 (0.032,+)
Metarhizium	0.008 (0.38)	0.070 (0.011,+)	0.088 (0.003,+)	0.010 (0.32)

An alternative examination of these data was done by comparing average levels of infection between fields with each cultural practice present or absent, while omitting all data where fewer than four grubs were examined for disease. This rather arbitrary number was chosen to exclude those data points where percentage infection would be very poorly estimated. By this analysis, infection by both *Adelina* and *Metarhizium* was significantly

greater in fields prepared with zonal tillage, and *Adelina* infection was also significantly greater following a legume rotation (Table 31).

Table 31 Percentage of canegrubs infected with *Adelina* and *Metarhizium* in fields with and without different cultural practices before planting, including only fields for which at least four individuals were examined for disease during 2003-2007

Pathogen	Cultural practice	No		Yes		*P* of difference[a]
		n	Disease% ± SE	n	Disease% ± SE	
Adelina	Replant	41	12 ± 2	32	17 ± 4	0.64
	Sprayout	54	13 ± 2	18	14 ± 4	0.70
	Zonal till.	64	13 ± 2	9	26 ± 5	0.013
	Legume	56	13 ± 2	19	20 ± 4	0.039
Metarhizium	Replant	41	7 ± 2	32	4 ± 1	0.27
	Sprayout	54	4 ± 1	18	9 ± 3	0.35
	Zonal till.	64	4 ± 1	9	11 ± 4	0.048
	Legume	56	6 ± 1	19	4 ± 2	0.18

[a] By Kruskal-Wallis one-way non-parametric analysis of variance.

It must be noted here that the independent variables that we examined may be confounded with other factors not included in the analyses, for example, they may not be equally common in all regions, and the results do not prove causal relationships. However, the apparent effects of the different cultural practices are in agreement with would be expected if conventional intensive cultivation is presumed to be harmful to soil-borne pathogens of canegrubs. In that case, sprayout of old ratoons with consequent reduction in tillage operations, and zonal tillage of the row only, would be expected to encourage pathogen infections in the new cane crops.

4.6.8.4 Mortality due to unknown causes

Each year from 2004 onwards, a considerable number of greyback canegrubs have died during rearing before maturing to adults, for unknown reasons (see Table 22). To assess the influence on mortality of our standard rearing and pathogen assessment procedures, greyback canegrubs collected from a canefield near Mackay in 2007 were reared at two centres, at Tully using the standard procedure, including haemolymph extraction for detecting disease organisms, and at Mackay. Haemolymph was not extracted at Mackay and grubs were disturbed as little as possible during feeding (every 1 or 2 weeks). General rearing procedures were otherwise similar at each centre, using peat medium and with carrot slices supplied as food.

Two batches of greyback canegrubs were collected from the canefield, on 1 May and 14 May 2007. Each batch was separated into two groups to be reared at either centre. The numbers successfully reaching adult or dying during rearing did not differ significantly between centres for Batch 1, Batch 2 or the combined batches (Table 32, P = 0.07, 0.58 and 0.51 by the Fisher exact probability test for 2 x 2 tables). The overall success of adult production, 60% at Mackay and 53% at Tully, was similar to that recorded for all other

sites at Mackay combined in 2007 (48% from Table 22). Thus, there was no evidence that any particular procedure at Tully, such as haemolymph extraction, was increasing mortality. However, this does not exclude the possibility that mortality may be artificially inflated by the rearing conditions applying at both centres.

Table 32 Results of rearing two batches of greyback canegrubs (from a canefield at Mackay) at two centres, Mackay (minimal handling of larvae during rearing) and Tully (with haemolymph extraction and regular examination for disease symptoms)

Batch	Centre	No. adults produced (%)	No. died (%)	Total
1	Mackay	11 (69)	5 (31)	16
	Tully	4 (29)	10 (71)	14
2	Mackay	15 (56)	12 (44)	27
	Tully	17(65)	9 (35)	26
Both	Mackay	26 (60)	17 (40)	43
	Tully	21 (53)	19 (47)	40

4.6.8.5 Summary of pathogen effects

There was evidence that *Adelina* infection in individual fields acts in a density-dependent manner in response to canegrub density in the same year, whereas *Metarhizium* infection appeared to be independent of current grub density. This is in agreement with the conclusions of previous work (e.g. Robertson *et al.* 1998). There was also some evidence that levels of *Adelina* influenced the rate of increase in grub populations among fields, but not in every year. However, analysis of possible effects of pathogens on grub population dynamics in individual fields is constrained by limitations of the data. This is likely to always be a problem with a monitoring program at a field level, especially when grub numbers are low, unless a great deal of effort is put into collecting sufficient grubs to examine. The role of pathogens on region-wide trends of grub populations is still uncertain. It may be noteworthy that the Central region, with an extremely low incidence of pathogens, had very high grub populations in the monitored fields, especially in 2004 (see Fig. 9). It could also be hypothesised that declining grub populations in Innisfail-Tully and Mulgrave since 2005 as seen in Figure 9 have been influenced by increasing levels of *Adelina* in these regions. However, such effects, if real, were rarely detected in the comparisons of grub and pathogen dynamics among individual farms.

4.6.9 Spatial relationships among fields

To test for a linear relationship between canegrub numbers as a function of the separation distance among fields, we first determined the distance between all pairs of canefields from their latitude and longitude coordinates. A series of permutation Mantel tests were then conducted (1000 randomisations per test) in order to assess the degree of association

(linear correlation and regression) between separation distance and difference in canegrub density, for each pair of fields.

The analysis suggests that in three of four years there was a significant inverse relationship between the distance between canefields and their similarity of canegrub density, although only in 2004 was the association close to moderate in strength (Table 33). The overall sign of the slope suggests that as distance increased, so did the difference in canegrub density between sites; that is, neighbouring sites were more likely to have similar canegrub densities in any year.

Table 33 Association between distance and similarity in canegrub density for pairs of canefields monitored in each of years 2003-2006

Year	Proportion of variance explained by distance (R^2)	*P*
2003	0.014	0.043
2004	0.146	0.001
2005	0.0007	0.282
2006	0.032	0.004

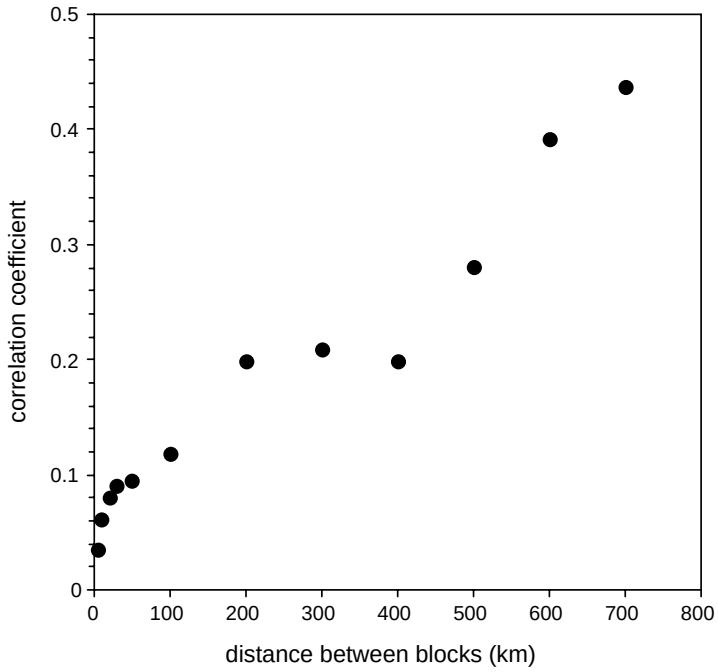


Figure 10 Correlation between difference in canegrub numbers between pairs of canefields each year and the distance between those fields, for fields separated by maximum distances from 5 km to 700 km

Further analysis was done by repeating Mantel tests with data pooled across years, but on subsets of the data representing fields separated by distances up to 5 km, 10 km, 20 km,

30 km, 50 km, 100 km, 200 km, 300 km, 400 km, 500 km, 600 km and 700 km. Figure 10 suggests that the correlation between distance and dissimilarity of canegrub density became stronger as canefields that are further apart were added to the data set. Fields separated by large distances were usually in different canegrowing regions.

The mechanism of this spatial structure is unknown and is not necessarily related to any particular property of greyback cane beetle behaviour, such as dispersal. Differences in weather, farmer production practices or grub pathogens could impose spatial relationships, which could operate over different distances as suggested by Figure 10; e.g. at a small scale (< 10 km) and then at a moderate to large scale. These analyses suggest that district- or region-specific variables may be important when attempting to predict canegrub populations in individual fields.

4.6.10 Summary

The following factors were related to subsequent numbers of greyback canegrubs in at least part of the data set:

- grub numbers in the same fields
- apparent damage in the same fields
- number of gaps
- insecticide treatment
- replant or fallow-plant
- method of killing the previous crop – herbicide or cultivation
- soil pH
- cane height
- damage in nearby fields
- *Adelina* infection
- district or region.

Some of these relationships were weak and may have only been detected in a single year or a single region.

The occurrence of infection by *Adelina* and *Metarhizium* was investigated in some detail. The following factors were related to the percentage of greyback canegrubs infected by either pathogen:

- *Adelina* and the density of canegrubs in the same year
- *Adelina* and soil pH
- *Metarhizium* and soil texture
- both *Adelina* and *Metarhizium* and zonal tillage before planting
- *Adelina* and legume rotation
- *Metarhizium* and method of killing the previous crop
- *Adelina* and region (Central or Northern).

It should be noted again that many of the independent variables in the analyses were themselves correlated, and, in any case, significant correlations may not necessarily indicate causal relationships.

4.7 Relationship between grub infestation and yield

4.7.1 Grub numbers and visible damage in monitoring fields

Fields in which grubs had been found did not always show signs of grub damage later in the year (pre-harvest) (Table 34, damage rating of zero). Not surprisingly, the median number of grubs was usually higher in those fields with higher subsequent damage ratings.

As an indicator of the number of fields that were ploughed out by growers after grub infestation, we examined the number of fields available for sampling after different levels of grub infestation the previous year. The number of fields available for sampling in the second year fell considerably when the number of grubs the previous year exceeded 1 per stool, and very few were sampled when the preceding year's infestation exceeded 2 grubs per stool (Table 35).

Table 34 Grub populations per stool associated with different damage ratings later in the year (0 = no damage to 3 = severe damage) in Central and Northern regions

Rating	Central			Northern		
	Median	1st quartile	3rd quartile	Median	1st quartile	3rd quartile
2003						
0	0.00	0.00	0.05	0.00	0.00	0.00
1	0.50	0.25	0.50	0.05	0.00	0.10
2	0.20	0.05	0.80	0.13	0.01	0.15
3	0.05	na	na	0.35	na	na
2004						
0	0.30	0.05	0.65	0.00	0.00	0.05
1	0.15	0.05	1.90	0.15	0.05	0.23
2	0.20	0.08	0.59	0.30	0.10	0.70
3	2.85	2.40	9.20	0.68	na	na
2005						
0	0.30	0.03	0.76	0.05	0.00	0.20
1	0.30	0.25	1.05	0.20	0.05	0.40
2	0.35	na	na	0.58	0.21	1.09
3	1.05	na	na	1.55	na	na
2003-5						
0	0.08	0.00	0.41	0.00	0.00	0.05
1	0.28	0.20	0.64	0.10	0.05	0.20
2	0.23	0.08	0.61	0.25	0.10	0.70
3	2.80	1.48	6.05	0.45	0.28	1.90

Table 35 Number of monitoring fields sampled in successive years following different levels of canegrub infestation in the first year (Year 0)

Number of grubs per stool, Year 0	No. of fields sampled, Year 0	No. of fields sampled, Year 1	% of Year 0 fields sampled in Year 1
<0.2	210	187	89
0.2-0.5	52	47	90
0.5-1	20	14	70
1-2	19	11	58
2-3	6	2	33
>3	2	0	0

4.7.2 Grub numbers and subsequent yield in insecticide trials

Data from trials of Confidor (liquid imidacloprid) applied to ratoon crops (Chandler 2003; Samson *et al*. 2006) were examined for relationships between grub numbers and subsequent crop yield.

It was expected *a priori* that grub numbers would be more closely related to yield loss expressed as a percentage rather than an absolute amount, and the relationship would plateau at high grub densities. The resulting relationship did appear curvilinear (Fig. 11a), although the quadratic term was not statistically significant (P = 0.096). There was no relationship between the reduction in CCS of untreated plots compared with treated plots and numbers of grubs in untreated plots (Fig. 11b, R^2 of linear regression= 0.11, P = 0.25). The average loss of CCS in untreated plots over all trials infested with greyback canegrubs was 0.9 units.

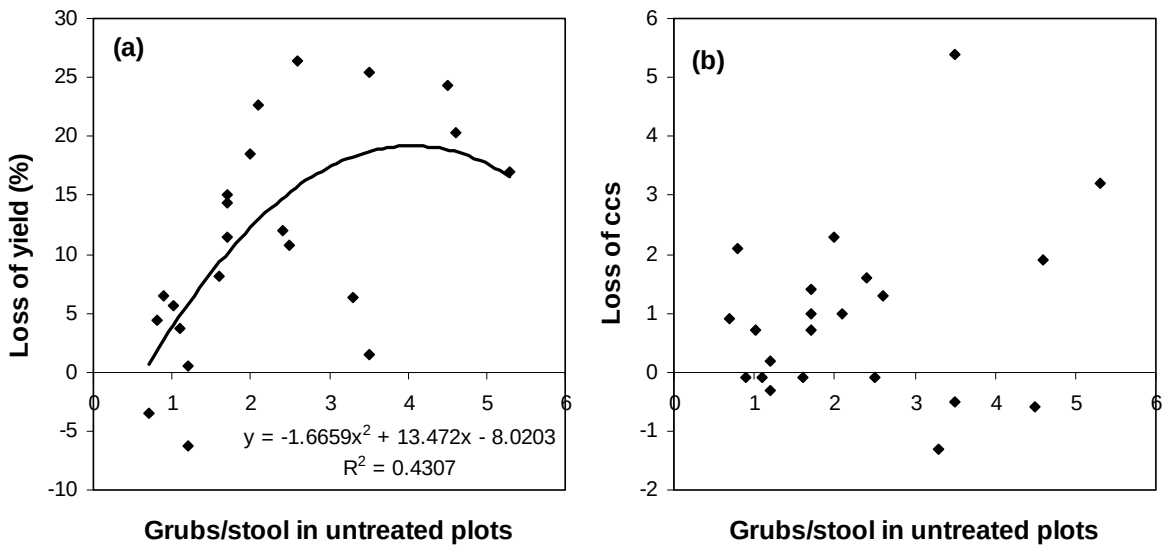


Figure 11 Reduction in (a) cane yield (as a percentage), and (b) CCS, of untreated control plots compared with plots treated with liquid imidacloprid the previous year (Chandler 2003; Samson *et al*. 2006)

Greyback grub infestations not only affect crop yield at the next harvest, but they also may harm ratooning and subsequent yields for the remainder of the crop cycle. There is a lack of data to describe this effect. However, numbers of ratoon shoots were measured in two Confidor trials reported by Chandler (2002). Numbers of ratoon shoots were significantly related to crop yield at the previous harvest, with slopes of greater than 1 (Fig. 12). For every percentage fall in cane yield from a base of 100 t/ha, there was a corresponding drop in ratoon shoots of 2.3% in Kelly 1999 (Fig. 12a) and 1.8% in Kelly 2001 (Fig. 12b).

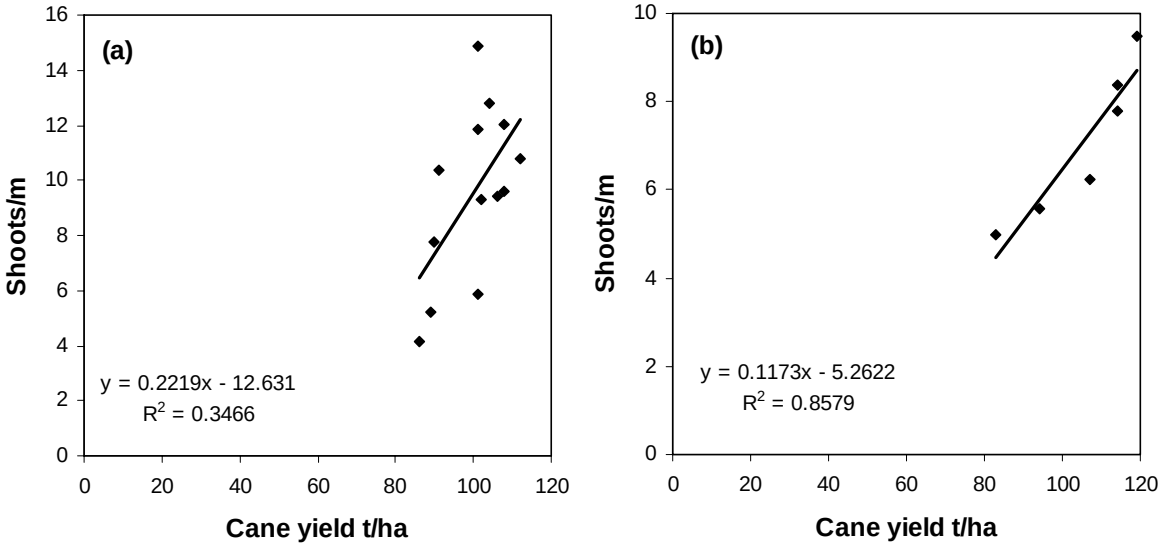


Figure 12 Relationship between crop yield and numbers of ratoon shoots after harvest following application of liquid imidacloprid the previous year, in two trials, (a) Kelly treated 1999, (b) Kelly treated 2001 (Chandler, 2002)

4.8 Models of grub risk

4.8.1 Types of predictive models

The development of predictive models is detailed in the reports of Drs Trevor Jackson and Frank Drummond, attached as Appendices 8-11. The final models reported below were extracted from the 2008 report of Frank Drummond (Appendix 11).

Two types of models were developed, which we named 'global' and 'regional'.

1. Global models were developed to be used in all regions with only field-specific predictors such as estimates of grub density in that particular field and estimates of grub damage in that field and in nearby fields
2. Regional models included field-specific predictors but also included regional averages of additional predictors such as regional grub density and regional *Adelina* infection levels. These regional predictors were intended to account for

inter-region differences in grub density in a way that was biologically meaningful, rather than simply using coded variables representing the regions themselves.

Models were constructed to cover a range of scenarios that might be expected in practice, when the full suite of predictor variables related to grub density or grub pathogens may not be available. These scenarios are (Table 36):

1. When only field-specific predictors are available (global model)
2. As 1, but without an estimate of grub density (global model with no grub predictor
3. When both field-specific and regional predictors are available (regional model)
4. As 3, but without an estimate of field-specific grub density (regional model with no field-specific grub predictor),
5. As 4, but without an estimate of regional *Adelina* infection levels (regional model with no regional *Adelina* predictor).

Table 36 Predictors that were available to be included (subject to statistical significance) in five modeling scenarios

Predictors potentially in model	Possible combinations of predictors and models				
	1	2	3	4	5
Field-specific grub density	✓		✓		
Regional average grub density			✓	✓	✓
Regional average *Adelina* %			✓	✓	
Other significant field-specific predictors	✓	✓	✓	✓	✓

Further, two types of statistical analysis were used, linear multiple regression to predict grub density and discriminant analysis to predict grub density class.

A validation data set was used to test the robustness of each model. Initially, we had planned on using the 2007 data as a validation data set, but the data were characterised by a unique structure in that there was no relationship between the previous year's log grub-density (2006) and the log grub-density in 2007 (Section 4.6.1). This appeared to represent a decline in greyback grub densities across all regions. In fact, all of the 2007 sites that were to be used for validation had extremely low grub densities (<0.35 grubs/stool), with more than 80% being characterised by densities ranging from 0.0 to 0.1 grubs/stool. Therefore, the 2007 data were used to build the final model along with the previous four years of data and a new validation data set was derived. The new validation data set consisted of thirty pre-selected sites that were representative of the five regions and the four years (2003-2007). These sites were not used for model construction and parameter estimation.

4.8.2 Prediction of grub densities

Linear multiple regression was used to construct final models for predicting log(grubs/stool + 0.05) one year in the future relative to the predictors. Five models were estimated. All variables were selected by a combination of stepwise procedures (mixed and backward elimination strategies), assessment of co-linearity by removing variables

individually from the models to assess changes that might occur in other predictor coefficients, and assessment of predictor correlation matrices. Evaluations of the models were based upon the corrected coefficient of determination and inspection of predictions of the validation data set with their true or observed estimates of log grub density.

The final model coefficients are listed below (see Appendix 11 for validation results for each model).

Table 37 Parameters for regression model 1: global model with a field-specific estimate of grub density, R^2 = 0.324

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-0.759865	0.20333	-3.74	0.0002
replant (=0)/fallow (=1)	-0.161643	0.054472	-2.97	0.0033
plant (=0) or ratoon (=1)	0.4173001	0.191445	2.18	0.0302
suSCon (3 yrs) Confidor (1 yr) =1	-0.117801	0.055407	-2.13	0.0345
log grubs (yr0) +0.05	0.3974251	0.065683	6.05	<0.0001
max. severity damage <400 m (yr0)	0.1405794	0.030424	4.62	<0.0001

Table 38 Parameters for regression model 2: global model without any estimate of grub density, R^2 = 0.251

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.178882	0.218125	-5.40	<0.0001
replant (=0)/fallow (=1)	-0.154416	0.058075	-2.66	0.0083
ratoon plant (=0) or ratoon (=1)	0.4395422	0.207788	2.12	0.0354
suSCon (3 yrs) Confidor (1 yr) =1	-0.180092	0.057566	-3.13	0.0020
severity of damage year(0)	0.103807	0.046387	2.24	0.0261
max. severity damage <400 m (yr0)	0.14943	0.036254	4.12	<0.0001

Table 39 Parameters for regression model 3: regional model with a field-specific estimate of grub density, R^2 = 0.364

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-0.803918	0.20914	-3.84	0.0002
replant (=0)/fallow (=1)	-0.153186	0.054096	-2.83	0.0050
plant (=0) or ratoon (=1)	0.5806165	0.186943	3.11	0.0021
log grubs(yr0) +0.05	0.4023771	0.063264	6.36	<0.0001
severity of damage (yr0)	0.1462237	0.038018	3.85	0.0002
region % *Adelina*	-0.009927	0.002458	-4.04	<0.0001
(max. severity damage <400 m (yr0)-0.77255)*(region % *Adelina*-16.1451)	-0.007205	0.002283	-3.16	0.0018

Table 40 Parameters for regression model 4: regional model with no field-specific estimate of grub density, R^2 = 0.275

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.238698	0.214194	-5.78	<0.0001
replant (=0)/fallow (=1)	-0.171745	0.056976	-3.01	0.0028
plant (=0) or ratoon (=1)	0.5834284	0.200277	2.91	0.0039
severity of damage (yr0)	0.2104231	0.038897	5.41	<0.0001
region grubs	0.1669365	0.080078	2.08	0.0381
region % *Adelina*	-0.009233	0.002576	-3.58	0.0004
(max. severity damage <400 m (yr0)-0.75191)*(region % *Adelina*-16.5153)	-0.008643	0.002519	-3.43	0.0007
(severity of damage (yr0)-0.56107)*(region grubs-0.2642)	-0.246551	0.09063	-2.72	0.0070

Table 41 Parameters for regression model 5: regional model with no estimate of regional *Adelina* infection or field-specific grub density, r^2 = 0.229

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.369839	0.213518	-6.42	<0.0001
plant (=0) or ratoon (=1)	0.4678179	0.207181	2.26	0.0247
suSCon (3 yrs) Confidor (1 yr) =1	-0.165473	0.056437	-2.93	0.0037
severity of damage (yr0)	0.17737	0.037298	4.76	<0.0001
region grubs	0.2910185	0.102502	2.84	0.0049
(max. severity damage <400 m (yr0)-0.75273)^2	0.0949768	0.025025	3.80	0.0002
(max. severity damage <400 m (yr0)-0.75273)*(region grubs-0.2608)	-0.145422	0.069887	-2.08	0.0384

Summary

Five regression models were developed for use in different prediction scenarios. In general, the ability to use field-specific estimates of grub density enhanced prediction. In addition, the use of regional variables such as regional grub density and/or regional *Adelina* infection level improved prediction (as measured by the corrected coefficient of determination). Removal of field-specific estimates of grub density from the models drew in other predictors that are presumably correlated with those estimates: field-specific severity of damage (model 2, Table 38) or regional grub density (model 4, Table 40).

Inspection of the coefficients in the models indicates that a higher grub density is favoured by each of the following, when no interaction terms are present:

- replant instead of fallow plant
- ratoon crops rather than plant crops
- lack of insecticide protection (defined as suSCon within 3 years or Confidor last year)
- greater density of grubs in the field the previous year

- higher severity of damage in the field the previous year (scale of 0-3)
- higher severity in nearby fields the previous year (scale of 0-3)

and, as a regional average in regional models 3 and 4:

- lower infection by *Adelina* the previous year

and, as interaction terms in regional models 3 and 4:

- higher severity of damage in nearby fields the previous year when regional *Adelina* is low (< approx 16%), with the effect reversed when regional *Adelina* is high
- higher severity of damage in the field the previous year when regional grub density is low or moderate (< approx. 1.2/stool), with the effect reversed at higher regional grub densities.

The influence of the predictor 'region grubs' in regional models 4 and 5 is complex because of its interaction with other terms. In model 4, a greater regional grub density results in prediction of a higher grub density in a field if the apparent severity of damage in the field is 0 or 1 but a lower grub density if damage severity is greater than 1. In regional model 5, the interaction of variables is complex and non-linear, but generally a higher grub density is favoured by a greater density of grubs in the region the previous year provided maximum severity of nearby damage is less than 3, and by a higher severity of damage in nearby fields the previous year provided regional grub density is low to moderate.

The straightforward effects above are intuitively appealing, and follow from the analysis of individual predictor variables discussed earlier in Section 4.6. The biological interpretation of some of the interaction terms is less obvious and the results less convincing. If possible, these relationships should be re-visited when more data are available over a longer time period.

One unfortunate aspect of all of the regression models is a bias in prediction of the validation data set. This bias is due in part to our inability to develop a transformation that corrects the problems with a left-truncated distribution (0 as a minimum and a large number of very-low-density sites). Correction of the bias was attempted by modelling the residuals, but while this did eliminate the bias, it produced a model with a very low explanatory power (see Appendix 11). It can be better to know the bias and have a more accurate predictor. In all of these models, low-density sites were over-predicted and high-density sites were under-predicted with a continuous linear trend in the bias as density increased (Fig. 13). Therefore, it is believed that these models can be useful, but interpreted with caution and knowledge of bias. It is recommended that the discriminant models (described below) be used in conjunction with the regression models.

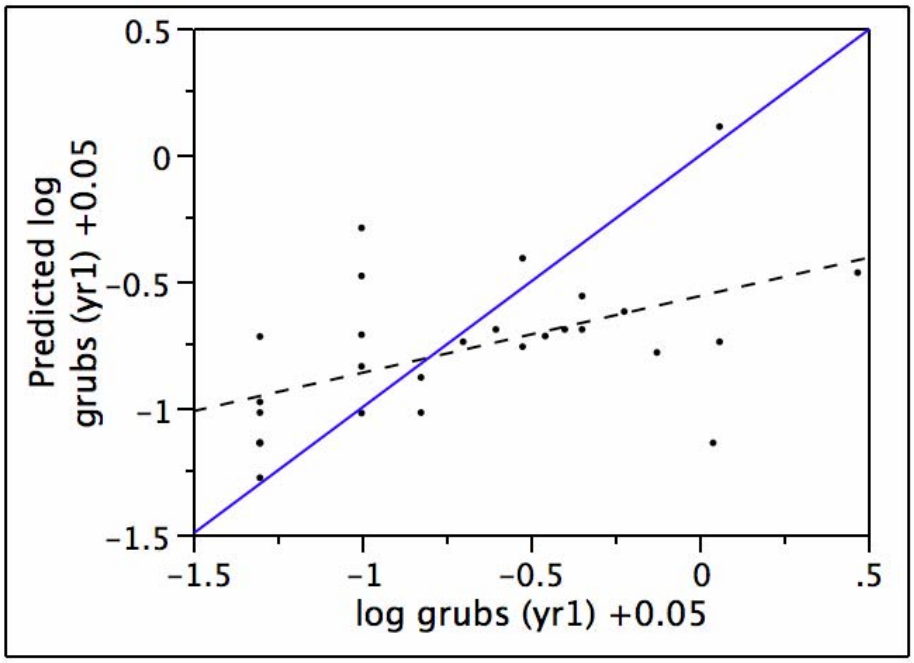


Figure 13 **Relationship between the observed and predicted of the independent validation data set (n=29) for model 1, global model with an estimate of cane block grub density. The dashed line is the relationship between observed and predicted derived from the model and the solid line is the line of perfect prediction (slope = 1)**

4.8.3 Prediction of grub-density classes

4.8.3.1 Definition of grub-density classes

To develop statistical models of grub risk, we assigned measured grub densities to infestation categories that were intended to reflect the expected amount of crop damage that they would cause. We wished to develop three categories, low, where there was no yield consequence, moderate, where yield was reduced but the crop was able to complete its normal cycle, and severe, where the effect on ratooning was so severe that immediate ploughout was required after the next harvest.

To estimate the severe category, we examined:

1. Grub densities in those monitoring fields rated as severely damaged in pre-harvest visual inspection. The median grub density in these fields was 2.8 per stool in the Central region and 0.5 per stool in the Northern region (Section 4.7.1). (We suspect the difference between regions could result from the severe damage suffered in the North in 2001, which was confounded with current damage in years from 2003 onwards.)

2. Grub densities in those monitoring fields that were ploughed out after the next harvest. The number of surviving fields declined steeply once grub density exceeded 2 per stool (Section 4.7.1).
3. The relationships between grub numbers, yield, and subsequent ratooning in insecticide trials. Assuming that continued ratooning of fields would become uneconomic once shoot loss exceeded 20%, and using the calculation that this would equate to a yield reduction due to grub damage of 10% (half of the ratooning effect, Section 4.7.2), the grub density at which this would occur would be 1.8 per stool (Section 4.7.2).

There was general agreement from all three calculations that a grub density of about 2 per stool would cause severe effects on the crop, which may be sufficient to require ploughout following harvest.

To estimate the moderate category, we examined:

1. Grub densities in those monitoring fields rated as moderately damaged in pre-harvest visual inspection. The median grub density in these fields was about 0.3 grubs per stool in both Central and Northern regions (Section 4.7.1).
2. The relationship between grub numbers and yield in insecticide trials. The curvilinear relationship crossed the x-axis at about 0.6 grubs/stool (Section 4.7.2).

Based on these results, we assumed the moderate infestation category would be represented by grub densities of 0.5 per stool and above, up to 2 per stool.

Densities below 0.5 grubs per stool were assumed to have no significant effect on crop yield at the coming or future harvests.

4.8.3.2 Frequency of occurrence of grub density classes

We sampled fields that were thought to be prone to greyback canegrub infestations and, of the 137 fields we sampled, we found grubs in all but 12 at some time during the study. Over the 5 years 2003-2007 we obtained a total of 443 estimates of grub density for the 137 fields. Of these estimates, 150 were zero while 293 included at least one greyback grub under 20 stools. The frequency of occurrence of each grub density class was:

Low (≤0.5 grubs/stool)	380 fields (86%)
Moderate (>0.5 – 2.0 grubs/stool)	54 fields (12%)
High (>2.0 grubs/stool)	9 fields (2%).

Thus, moderate infestation levels were uncommon and severe infestations of more than 2 grubs per stool were rare.

However, these average frequencies of occurrence did not apply in every region in every year. In the Central region, for example, the frequency of occurrence of each grub density class from 2003-7 was as follows (81 estimates in total):

Low (≤0.5 grubs/stool)	59 fields (73%)
Moderate (>0.5 – 2.0 grubs/stool)	14 fields (17%)
High (>2.0 grubs/stool)	8 fields (10%).

And considering only 2004 in the Central region, moderate-heavy infestations were relatively common (22 estimates in total):

Low (≤0.5 grubs/stool)	11 fields (50%)
Moderate (>0.5 – 2.0 grubs/stool)	4 fields (18%)
High (>2.0 grubs/stool)	7 fields (32%).

These results reinforce the need for a grub prediction system. This system should be dynamic, allowing for changes in risk profile from region to region and year to year.

4.8.3.3 Discriminant models to predict grub density classes

Fisher-discriminant functions were used to develop a series of equations using a multivariate approach to predicting grub density classes. Discriminant functions are additive linear functions of predictor variables that are parameterised to minimise the errors when predicting the density classes. The discriminant functions were parameterised based upon rules of thumb of good practice. Independent suites of predictors were selected, since highly correlated sets of predictors tend to be less effective at predicting classes. We also limited the number of predictors so that there were no more predictors than the number of data points/30 (thus one predictor for every 30 data points). Thirty is somewhat arbitrary, but is generally considered a reasonable sample size for estimating mean responses. Manual backward stepwise selection was used to explore simultaneous fitting of variables and their co-linearity. In addition, univariate analysis of variance was used to test that each predictor independently was a significant predictor of at least one density class. Multiple analysis of variance (Wilks lambda) was used to assess the potential of the entire suite of predictors as a means of discerning at least one class from the other two. Plots from canonical discriminant analysis (an ordination technique developed for inspecting multivariate models in two-dimensional space) were also inspected on occasion to evaluate the overlap of class confidence intervals.

Validation was assessed by 3x3 contingency tables that were set up to determine the percentage of correct classification for each of the three density classes. A field was predicted as being either a low-, moderate- or high-density field according to the class with the highest likelihood in the predictive model. These 3x3 tables were constructed for both the data used to build the model and the validation data set. Table 42 lists the % correct classification for both data sets using 18 different models.

Table 42 The percentage of fields predicted to fall into each of three infestation classes tabulated against their observed classes, using different types of predictive models (see text), for both the validation data set of 30 fields and (in parenthesis) for the data used to develop the models

Model type (numbers in brackets refer to models in text)	Observed classes	Global models (include only variables measured for individual fields)			Regional models (include some variables averaged over region)		
		≤0.5	>0.5-2	>2	≤0.5	>0.5-2	>2
Grub density for field as #/stool, no pH (1,5)	≤0.5	61 (70)	35 (19)	4 (11)	61 (73)	35 (20)	4 (7)
	>0.5-2	40 (25)	60 (59)	0 (16)	40 (25)	60 (64)	0 (11)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density for field as #/stool with pH of soil (1a, 5a)	≤0.5	65 (71)	30 (19)	5 (10)	61 (72)	35 (20)	4 (8)
	>0.5-2	40 (25)	60 (59)	0 (16)	40 (25)	60 (66)	0 (9)
	>2	0 (14)	100 (0)	0 (86)	0 (14)	100 (0)	0 (86)
Grub density not estimated for field, no pH (2,6)	≤0.5	74 (72)	22 (15)	4 (13)	65 (69)	31 (24)	4 (7)
	>0.5-2	40 (39)	60 (41)	0 (20)	40 (33)	60 (57)	0 (10)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density not estimated for field, with pH (2a,6a)	≤0.5	74 (70)	22 (19)	4 (11)	65 (69)	30 (24)	4 (7)
	>0.5-2	40 (39)	40 (44)	20 (17)	40 (33)	60 (59)	0 (8)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
As above, *Adelina* not estimated for region, no pH (7)	≤0.5				65(68)	31 (23)	4 (9)
	>0.5-2				40 (33)	60 (59)	0 (8)
	>2				0 (14)	100 (14)	0 (72)
Grub density for field as <> 0.5/stool no pH (3, 8)	≤0.5	70 (69)	26 (19)	4 (12)	70 (69)	26 (24)	4 (7)
	>0.5-2	40 (30)	60 (50)	0 (20)	40 (30)	60 (57)	0 (13)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (14)	0 (72)
Grub density for field as <> 0.5/stool with pH (3a, 8a)	≤0.5	70 (70)	26 (20)	4 (10)	70 (68)	26 (24)	4 (8)
	>0.5-2	40 (30)	60 (52)	0 (18)	40 (30)	60 (57)	0 (13)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
As above, *Adelina* not estimated for region, no pH (9)	≤0.5				70 (69)	26 (23)	4 (9)
	>0.5-2				40 (30)	60 (57)	0 (13)
	>2				0 (14)	100 (14)	0 (72)
Grub density for field as Yes/No, no pH (4,10)	≤0.5	48 (57)	48(31)	4 (12)	57 (68)	39 (25)	4 (7)
	>0.5-2	20 (18)	80 (61)	0 (21)	40 (30)	60 (59)	0 (11)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density for field as Yes/No, with pH (4a, 10a)	≤0.5	48 (58)	48 (33)	4 (9)	57 (68)	39 (24)	4 (8)
	>0.5-2	20 (18)	80 (64)	0 (18)	40 (30)	60 (59)	0 (11)
	>2	0 (14)	100 (0)	0 (86)	0 (14)	100 (0)	0 (86)

The effect of an estimate of grub density, either as grubs/stool or a density class (≤0.5 or >0.5 grubs/stool) or presence and absence, was important in the global models (Table 42), although both damage severity in the block and a neighbourhood estimate of damage tended to be surrogates for grub density. To a lesser extent, soil pH was also a significant predictor.

The regional models tended to be marginally better than the global models although there were exceptions to this, as seen in the models where presence/absence was used as the grub density estimate within the cane block. In this case, the global model was better at predicting moderate density sites, whereas the regional models were better at predicting the low-density sites. When there was no block-level estimate of grub density, global models were better at predicting low-density sites whereas regional models were much better at predicting moderate density sites. A regional estimate of *Adelina* infection improved prediction of high-density sites in the model building data set when there was no block-level grub density estimate, but this was a fairly minor improvement and was not seen when estimates of grub density were used.

Coefficients for each of the 18 models whose output is summarised in Table 42 are given in Appendix 11. Those coefficients are repeated below for five models that we think are most likely to be used in practice (Tables 43-47). Although pH was a significant predictor, its contribution was minor and values of pH may be difficult to obtain for all fields on a farm, so we did not consider those models here. For fields where a good estimate of grub density is obtained, we believe that models 1 (global) or 5 (regional) would be the first choice, to make maximum use of the density estimates. It will be impractical to fully sample (20 stools) every field of interest on a farm, so we also consider model 6 (regional), where there is no estimate of grub density for a particular field of interest but there are regional estimates of both grub density and *Adelina* infection. Lastly, we consider models applicable to a rapid estimation technique of grub presence/absence in individual fields, i.e. models 4 (global) and 10 (regional).

Table 43 Coefficients for discriminant model 1: global model with a field-specific estimate grub density

Classification Function Coefficients

	Predict density class (3) 0.5,2		
	1	**2**	**3**
suSCon (3 yrs) Confidor (1 yr)	1.547	.504	.721
log grubs(yr0) +0.05	-7.176	-4.944	-6.540
severity of damage year(0)	1.116	1.595	1.076
max severity damage <400 m year(0)	1.383	1.570	3.948
(Constant)	-5.632	-4.143	-8.957

Fisher's linear discriminant functions

Table 44 Coefficients for discriminant model 5: regional model with a field-specific estimate grub density

Classification Function Coefficients

	Predict density class (3) 0.5,2		
	1	**2**	**3**
suSCon (3 yrs) Confidor (1 yr)	0.778	-0.211	0.389
log grubs(yr0) +0.05	-8.907	-6.791	-6.961
severity of damage year(0)	1.433	1.976	1.097
max severity damage < 400 m year(0)	1.035	1.100	3.996
region grubs	5.360	5.785	1.218
region % *Adelina*	0.200	0.182	0.090
(Constant)	-8.549	-6.988	-9.381

Fisher's linear discriminant functions

Table 45 Coefficients for discriminant model 6: regional model without a field-specific estimate of grub density, without soil pH

Classification Function Coefficients

	Predict density class (3) 0.5,2		
	1	**2**	**3**
suSCon (3 yrs) Confidor (1 yr)	1.601	0.375	0.946
severity of damage year(0)	0.415	1.153	0.249
max severity damage < 400 m year(0)	0.943	1.018	3.967
region grubs	1.924	3.156	-1.462
region % *Adelina*	0.172	0.165	0.078
(Constant)	-3.543	-4.052	-6.378

Fisher's linear discriminant functions

Table 46 Coefficients for discriminant model 4: global model with a field-specific estimate of grub presence (present/absent)

Classification Function Coefficients

	Predict density class (3) 0.5,2		
	1	2	3
suSCon (3 yrs) Confidor (1 yr)	2.421	1.352	1.568
grub presence/absence	2.522	3.815	2.726
severity of damage year(0)	0.030	0.510	0.017
max severity damage < 400 m year(0)	0.676	0.968	3.280
(Constant)	-2.553	-3.788	-6.606

Fisher's linear discriminant functions

Table 47 Coefficients for discriminant model 10: regional model with a field-specific estimate of grub presence (present/absent)

Classification Function Coefficients

	Predict density class (3) 0.5,2		
	1	2	3
suSCon (3 yrs) Confidor (1 yr)	1.822	0.773	1.338
grub presence/absence	2.625	3.740	3.285
severity of damage year(0)	-0.117	0.470	-0.344
max severity damage < 400 m year(0)	0.942	1.040	3.931
region grubs	1.207	2.122	-2.381
region % *Adelina*	0.181	0.172	0.078
(Constant)	-4.152	-5.336	-7.292

Fisher's linear discriminant functions

Most of the predictors that had been used in the regression models were also the best predictors in the discriminant functions, with few exceptions. The common predictors for the various discriminant functions were an estimate of canegrub density in a cane block, insecticide protection, severity of grub damage within the cane block, and the maximum severity of grub damage in neighbouring blocks (within 400 m). Ratoon age and whether a block was fallowed were not significant at the $P<0.05$ level when used in these discriminant models, unlike the regression models discussed previously.

Considering prediction of only the low and moderate density classes, inspection of the coefficients in the models indicates that the higher grub density class is favoured by each of the following:

- lack of insecticide protection (defined as suSCon within 3 years or Confidor last year)

- greater density of grubs in the field the previous year (as grubs/stool or presence/absence)
- higher severity of damage in the field the previous year (scale of 0-3)
- higher severity in nearby fields the previous year (scale of 0-3)

and, as regional averages in regional models 5, 6 and 10:

- greater density of grubs in the region the previous year
- lower infection by *Adelina* the previous year.

The influence of the predictors did not always follow the above pattern when separating moderate- and high-density classes. As pointed out in Appendix 11, it is difficult to draw strong conclusions about the way the variables work in concert. In addition, the high-density class was represented by very few fields in the data set and so there is presumably considerable uncertainty attached to the coefficients for distinguishing this class.

4.9 Spatial pattern of grub counts within fields, and sampling plans

4.9.1 Comparison of grub counts at different stool positions

Mean numbers of grubs were compared between stools dug from the corners and the centre of fields in the corner sampling scheme (samples 1-16 compared with 17-20 in Fig. 1a), and between stools dug from the inner and outer transects (samples 1-5 and 16-20 compared with 6-15 in Fig. 1b), for fields where at least one grub was counted. Numbers did not differ significantly between the two different groups of samples within each scheme (Table 48). Thus, we cannot recommend a method of targeted sampling that would maximise the chance of detecting grubs. (Incidentally, these results also show the need to treat the whole of most fields in those cases where treatment is warranted, rather than just the perimeter as has been done by some growers in an attempt to save money.)

Table 47 Comparison of mean numbers of greyback canegrubs in samples taken from different positions in two sampling schemes (see Fig. 1)

Corner sampling (*n*=218)		Transect sampling (*n*=33)	
Position	**Mean ± SE**	**Position**	**Mean ± SE**
Corners	0.30 ± 0.02	Outer	0.98 ± 0.25
Centre	0.42 ± 0.06	Inner	1.13 ± 0.36
P [a]	0.35	P [a]	0.90

[a] By paired *t*-test of site means transformed as ln(x+1)

We also compared mean numbers of grubs between samples taken from pairs of corners close to and distant from treelines when these were adjacent to one end or side of the monitoring fields. Grub numbers were not significantly different between these locations within the fields (Table 49).

Table 49 Comparison of mean numbers of greyback canegrubs in samples taken from field corners close to and further from treelines (*n*=55)

Proximity to trees	Mean ± SE
Near	0.22 ± 0.04
Distant	0.26 ± 0.05
P [a]	0.72

[a] By paired *t*-test of site means transformed as ln(x+1)

4.9.2 Mean-variance relationship – Taylor's power law

The relationship between the mean and variance for all data collected over 4 years is shown in Figure 14. Fields in which a single larva was collected have been omitted from the analysis, as the mean and variance of such samples are necessarily equal. The data fits well the linearised form of Taylor's power law (TPL), $\ln s^2 = \ln a + b \ln \bar{x}$, where s^2 is the variance and $\bar{x}$ is the mean of the sample data. Estimated parameter values are rather different from values reported elsewhere for greyback grub and for some southern canegrub species, but similar to values reported for picticollis canegrub (Table 50).

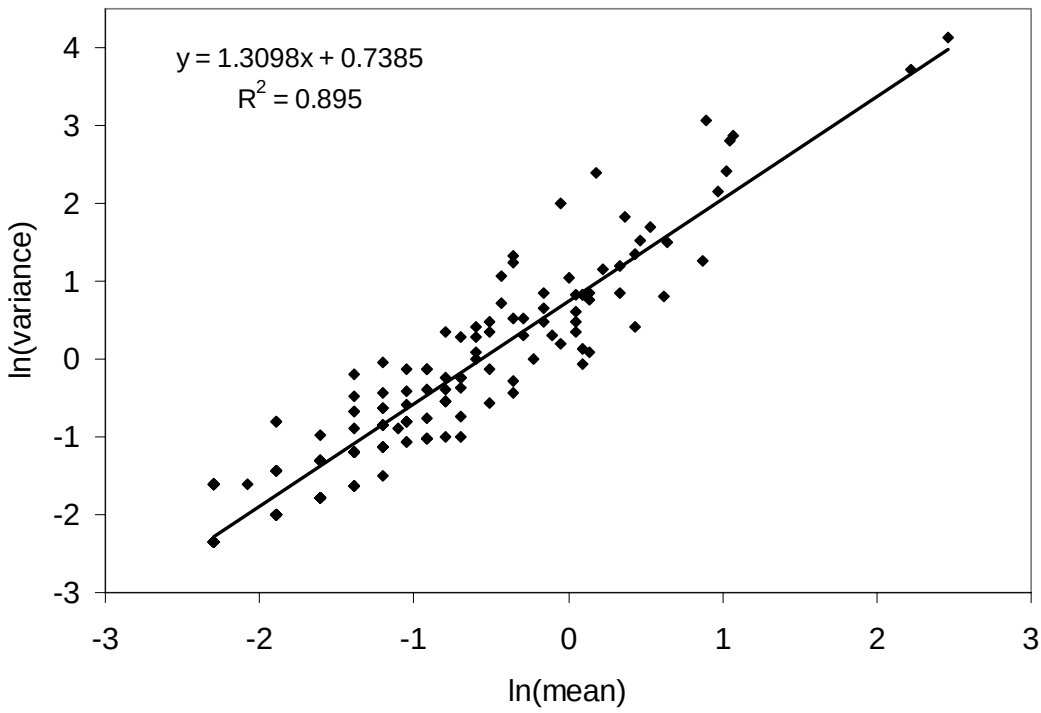


Figure 14 Taylor's power law fitted to counts of greyback canegrub over 4 years in canefields from the Central region to Mulgrave

Table 50 Parameters of Taylor's power law for our data and for other data sets from canefields

Species	ln*a*	*b*	R^2	Source
Greyback canegrub	0.74	1.31	0.90	This report
Greyback canegrub	0.43	1.13	0.83	Walker *et al.* unpublished
Picticollis canegrub	0.68	1.27	0.91	Allsopp and Bull (1989)
Five other southern spp.	0.33	1.12	0.91	Allsopp and Bull (1989)

Although a linear relationship was a good fit to the mean-variance data, there was a significant departure from linearity (*P* of quadratic term = 0.040). However, the increase in R^2 over a linear relationship was miniscule (0.897 compared with 0.895).

4.9.3 Parameters of Taylor's power law in different data sets

We compared the linearised form of TPL among data sets grouped by three different classifications, by sampling scheme, by year and by region. We compared regression lines for all data (omitting singletons) and, because the range of data differed considerably among categories within these classifications, we also compared regressions when extreme means were omitted from analyses.

There was a significant difference in the elevation of TPL calculated from two different sampling schemes (Table 51). However, there was a large difference in the range of means used in calculating the relationship for each scheme. There was no significant difference between parameters of TPL for each scheme if only data with means in the range 0.20-2.65 were included (Table 51).

Table 51 Parameters of Taylor's power law for greyback canegrub data collected by two different sampling schemes

Scheme	n	Average mean	Range of means	Parameters of TPL	
				Intercept	Slope
Corner	159	0.43	0.10-2.65	0.63	1.25
Transect	23	1.82	0.20-11.79	0.90	1.32
Comparison of lines: variances, *P* = 0.15; slopes, *P* = 0.45; elevations, *P* = 0.014					
Using only means in range 0.20-2.65					
Corner	104	0.59	0.20-2.65	0.67	1.35
Transect	19	0.80	0.20-2.45	0.84	1.25
Comparison of lines: variances, *P* = 0.14; slopes, *P* = 0.53; elevations, *P* = 0.053					

There was also a significant difference in the elevation of TPL among each of four years (Table 52). This difference was maintained even when data were constrained to cover a similar range of mean counts, i.e. 0.10-1.40 (Table 52).

Table 52 Parameters of Taylor's power law for greyback canegrub data collected in each of four years

Year	n	Average mean	Range of means	Parameters of TPL	
				Intercept	Slope
2003	26	0.26	0.10-1.40	0.46	1.12
2004	57	0.93	0.10-11.79	0.99	1.38
2005	56	0.63	0.10-2.65	0.57	1.27
2006	47	0.41	0.10-1.85	0.66	1.30
Comparison of lines: variances, *P* = 0.69; slopes, *P* = 0.15; elevations, *P* = 0.001					
Using only means in range 0.10-1.40					
2003	26	0.26	0.10-1.40	0.46	1.12
2004	48	0.31	0.10-1.10	1.08	1.45
2005	52	0.55	0.10-1.40	0.53	1.24
2006	45	0.35	0.10-1.20	0.71	1.33
Comparison of lines: variances, *P* = 0.75; slopes, *P* = 0.10; elevations, *P* = 0.008					

The variances associated with TPL varied significantly among the five sampling regions, both in the full data set and when data was constrained to means no greater than 1.40 (Table 53). Inspection of the individual regressions showed a very low residual variance associated with the Tully data. If the Tully data were omitted, there was no significant difference among the TPL lines for the other four regions for means up to 1.40 (variances, *P* = 0.41; slopes, *P* = 0.76; elevations, *P* = 0.13).

Table 53 Parameters of Taylor's power law for grub data collected in each of five regions

Year	n	Average mean	Range of means	Parameters of TPL	
				Intercept	Slope
Mulgrave	75	0.49	0.10-2.65	0.62	1.24
Innisfail	28	0.26	0.10-0.60	0.55	1.27
Tully	15	0.56	0.10-1.55	0.78	1.41
Herbert	26	0.33	0.10-1.40	0.55	1.12
Central	42	1.28	0.10-11.79	0.88	1.34
Comparison of lines: variances, *P* = 0.005; slopes, *P* = 0.30; elevations, *P* = 0.08					
Using only means in range 0.10-1.40					
Mulgrave	71	0.41	0.10-1.25	0.64	1.25
Innisfail	28	0.26	0.10-0.60	0.55	1.27
Tully	14	0.49	0.10-1.40	0.80	1.42
Herbert	26	0.33	0.10-1.40	0.55	1.12
Central	32	0.45	0.10-1.05	0.71	1.20
Comparison of lines: variances, *P* = 0.017; slopes, *P* = 0.46; elevations, *P* = 0.22					

In summary, the slopes of regressions of log-transformed means and variances, Taylor's power law, did not differ significantly among categories of sampling data classified by

different procedures. The slope is considered to be an index of aggregation of the organism. However, the elevation of regression lines, considered to be a sampling factor, differed significantly among years, even when regressions were calculated using data covering a similar range of values.

4.9.4 Precision of population estimates and sequential sampling plans

The parameters of TPL were used to derive sequential sampling plans for greyback grubs. As there was no way to allow for the apparent difference in elevation among years detected in the previous section, we used the parameter values derived from the data set incorporating all years, ie ln$a$ = 0.7385 (a = 2.093) and b = 1.3098.

We determined the number of samples (n) needed to estimate population density with fixed precision p, the standard error as a proportion of the mean, using the formula:

$$n = a\,\bar{x}^{(b-2)}/p^2.$$

We chose a precision level of 0.25, which should allow detection of a doubling or halving of the population (Southwood 1978, p. 7).

The sample size we used in our monitoring, 20 stools per field, would estimate the mean with a precision of 0.25 provided means were above about 2 grubs per stool (Fig. 15). Mean density was less than this in most of our samples and precision of these population estimates is predicted to be below 0.25.

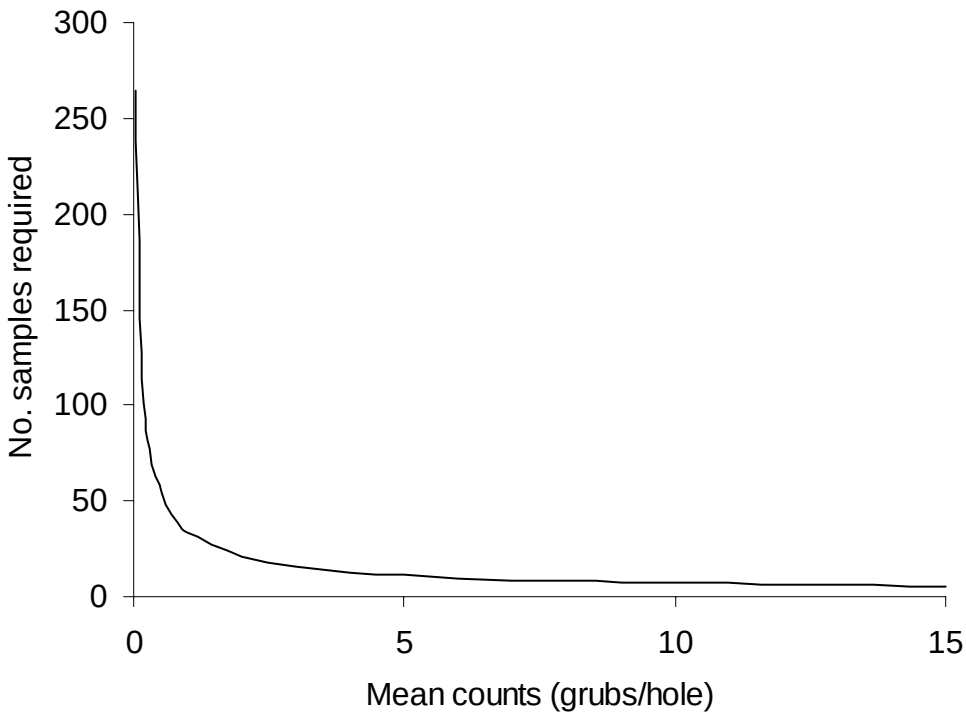


Figure 15 **Number of samples (n) required to estimate mean greyback grub density with a standard error of 25% of the mean, for different mean counts ($\bar{x}$) ($n = 2.093\,\bar{x}^{-0.69}/0.25^2$)**

To implement a monitoring program that aims to estimate mean grub density, it should be possible to reduce the number of stools sampled at very high grub densities while still maintaining the precision level of 0.25. The total number of grubs T that must be counted in samples to maintain a fixed level of precision was estimated as:

$T = (an^{1-b}/p^2)$^$(1/(2-b))$ (Green 1970).

Five stools should be the minimum sample size, spread over several places in a field, to ensure that the sample is representative. The number of grubs that would need to be counted to allow sampling to stop before 20 stools were dug is listed in Table 54.

Table 54 Total numbers of greyback grubs that need to be counted in samples to allow sampling to stop before 20 stools have been dug, while maintaining a precision of the estimate of population density of 0.25 ($T = (2.093*n^{-0.31}/0.25^2)$^$(1/0.69)$)

No. stools dug	Total grub count needed to stop sampling	Corresponding mean grub count/stool
5	79	15.7
6	72	12.1
7	68	9.7
8	64	8.0
9	60	6.7
10	58	5.8
11	55	5.0
12	53	4.4
13	51	3.9
14	50	3.5
15	48	3.2
16	47	2.9
17	45	2.7
18	44	2.5
19	43	2.3
20	42	2.1

To implement a monitoring program for making decisions, stop lines were calculated according to Iwao's sequential decision rule (Iwao, 1975) and the parameters of TPL:

upper boundary = $nC + z_\alpha \sqrt{naC^b}$

lower boundary = $nC - z_\alpha \sqrt{naC^b}$

where C is the critical density about which a decision is to be made and z_α is a standard normal deviate (we used 1.5).

Stop lines for estimating a critical density of 0.5 grubs per stool are given in Figure 16. If the total number of grubs moves above the upper line then a decision can be made that canegrub density exceeds 0.5 per stool and sampling can stop. Conversely, if the total number of grubs falls below the lower line then the decision is made that density is less than 0.5 grubs per stool, and again, sampling can stop. As long as the total number of

grubs remains between the upper and lower lines, no firm decision can be made and sampling should continue.

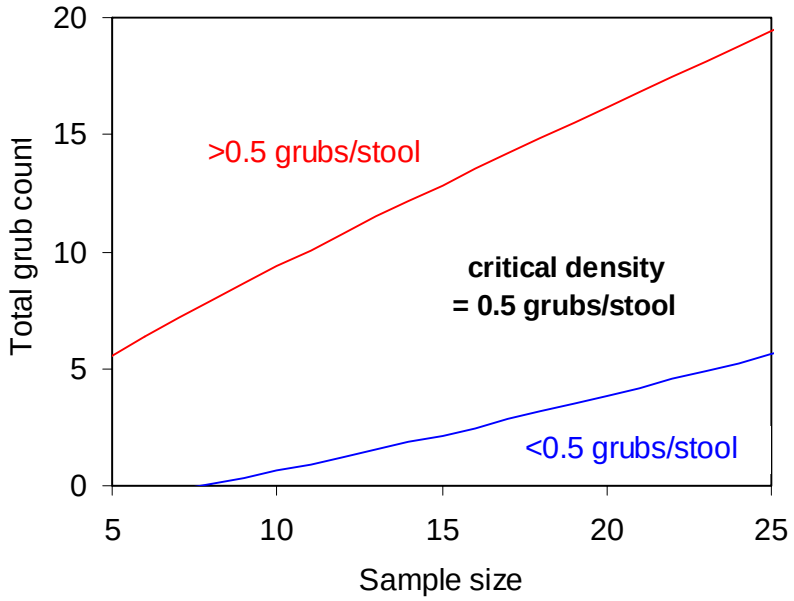


Figure 16 Stop boundaries for a decision on greyback grub density, greater or less than 0.5/stool; boundaries are $n*0.5 \pm 1.5*\sqrt{(n*2.093*0.5^{1.3098})}$

In practice, sampling cannot continue indefinitely and 20 stools are about the maximum that could realistically be dug from a field. If the total grub number remains in the inconclusive zone of Figure 16 after digging 20 stools, a conservative decision should be made that density is greater than 0.5 per stool.

4.10 Economic decision aids

4.10.1 BMP model

One of the outputs of this project was to be an improved Best Management Practice economic model as developed by Macarthur Agribusiness. In particular, productivity data for Mulgrave, Mourilyan and Herbert mill areas were to be included in the model which formerly contained only Burdekin data.

Due to unfamiliarity of the current project team with the BMP model, we employed Hugh Macintosh of IQ Agribusiness, Toowong, as a consultant. Hugh worked with Mohamed Sallam from 18-20 October 2004 to run through some real-world scenarios with farm data. They were assisted by Michael Porta (grower and variety officer) and Jeff Smith (BSES farm manager). Hugh developed an addendum to the original Program Manual as a guide to data entry, as well as a review of the model which highlights some apparent shortcomings; this is attached as Appendix 7. This addendum should be of considerable use to anyone using the BMP model.

Difficulties were experienced in accessing suitable data to extend the model to non-Burdekin regions. The required data are tonnes cane, tonnes sugar and area harvested for different years, harvest weeks within years, varieties and crop classes. We were unable to obtain suitable data for two mill areas specified in the project proposal. Some data were obtained for the Herbert but included only Q124 and did not distinguish ratoons of different ages. For Mulgrave, we obtained yields for 1992 onwards, but were advised that there are no corresponding records for area harvested.

However we did obtain data for the Mourilyan mill area and for the four mills at Mackay (the latter supplied by Andrew Higgins, CSIRO Sustainable Ecosystems). Due to the size of the productivity data sets, separate models were created for each district. The original Mourilyan data set included 42,819 records covering the years 1992-2003, while the Mackay data included 329,972 records covering 1994-2001 and four mills, in both cases too many for the 30,385 limit in the model. These numbers of records were reduced to 8,322 and 14,431, respectively, by deleting records that were incomplete (e.g. missing week of harvest, area or CCS), were experimental or mixed varieties, covered harvested areas less than 0.2 ha, or had apparent yields of less than 10 or greater than 300 t/ha. Records were averaged for each combination of mill, year, variety, crop class and harvest week using Microsoft Access. The data were pasted into the relevant columns in the Data worksheet. A separate model was created for each district after Burdekin data were deleted from the original model. Look-up tables were updated with the new mill and variety names.

Thus, there are now three models available, the original Burdekin data set plus Mourilyan and Mackay; these can be obtained from Peter Samson. The Mourilyan and Mackay data sets can probably be used for other districts in northern and central Queensland.

Answers to Questions 16 and 17 of the Wizard in the Mourilyan and Mackay BMP models contain a list of farm activities and a calendar of operations carried over from the Burdekin model. These were left in so that a new user does not have to start from the beginning, but they would need to be updated to suit individual circumstances when the models are run.

Once data were entered, difficulties were encountered when setting up and running the model. We concluded that the model is cumbersome for the purpose of evaluating grub-management strategies.

We also question whether the model is at the appropriate level for the risk assessment being attempted within this project. The BMP model considers inputs at a farm level – the proportion of the farm subject to damage, the percentage loss in CCS and yield in damaged areas, and the percentage of fields treated. Benefit cost analyses are compared in three scenarios: No Damage (no pest or disease constraints), Damage (pest and disease constraints exist but no treatments are applied), and Treatment (constraints exist and treatments are applied). We think that a simpler model that could be applied on a field-by-field basis depending on risk would be more suitable for use in a system where different control decisions will be made annually dependent on results of a monitoring program.

4.10.2 A simple year-to-year spreadsheet

A simple spreadsheet was developed using Excel, to incorporate the economic factors that will convert the grub risk model into a decision-making tool.

Grub risk categories were defined in Section 4.8.3 as low (less than 0.5 grubs per stool), moderate (0.5 to 2 grubs per stool), and high (2 grubs per stool and above). The consequences of each category on crop yield were assigned as follows:

- Low: no yield effect.
- Moderate: 10% loss of cane yield every year until the end of the crop cycle and loss of 1 unit of CCS at the next harvest only.
- High: 50% reduction in cane yield and loss of 2 units of CCS; the crop is then assumed to be ploughed out because of intolerable damage. This level of loss of cane yield is higher than measured in insecticide trials (Section 4.7.2) but is in agreement with some estimated losses in case studies (Appendix 2) and will lead to more conservative treatment decisions.

The spreadsheet in fact allows values of loss of cane yield and CCS to be entered by the user, but the assumptions of crop cycle length are fixed, i.e. a moderate infestation does not alter the crop cycle while a high infestation necessitates ploughout.

Examples of the main page of the spreadsheet, with data entry and output, and the associated chart of cumulative gross margins, are given on the following pages.

Predicted return from one-year control of greyback canegrubs with insecticide (e.g. imidacloprid liquid)

BSES QCROPS

BSES

Costs of operations for plant cane or for ratoons

Plant cane $	$1,500	/ha
Ratoon cane $	$400	/ha

Harvest revenue/cost data

Sugar price $	$250	/t sugar
Harvest cost $/t	$6.30	/t cane
Levies $/t	$0.48	/t cane

How will the field be prepared for the next crop cycle?

Replanted or fallow planted?	replanted

Field data - expected yield without canegrubs

Expected ratoons from field (maximum of 5)?		4 R
Expected yield without damage?	t/ha	ccs
Enter plant crop data -	100	13
Enter first ratoon data -	100	13
Enter second ratoon data -	100	13
Enter data for third ratoon and older -	100	13

Expected yields for this crop cycle

Crop age at coming harvest (0=plant crop)?		0 R
Expected yields at next 5 harvest(s) until ploughout after 4 R?		
	t/ha	ccs
Enter data for next harvest -	100	13
+1 year -	100	13
+2 years -	100	13
+3 or more years -	100	13

Canegrub treatment data

Cost of chemical $/ha	$150	/ha
Application cost $/ha	$30	/ha

Grub risk estimates

Likelihood of no damage each year	50 %
Likelihood of light damage next year	40 %
Likelihood of severe (ploughout) damage next year	10 %

Fields are replanted after ploughout

EXPECTED RESULT

Risk $/ha	-$543
Treatment cost $/ha	-$180
Average return $/ha	$363

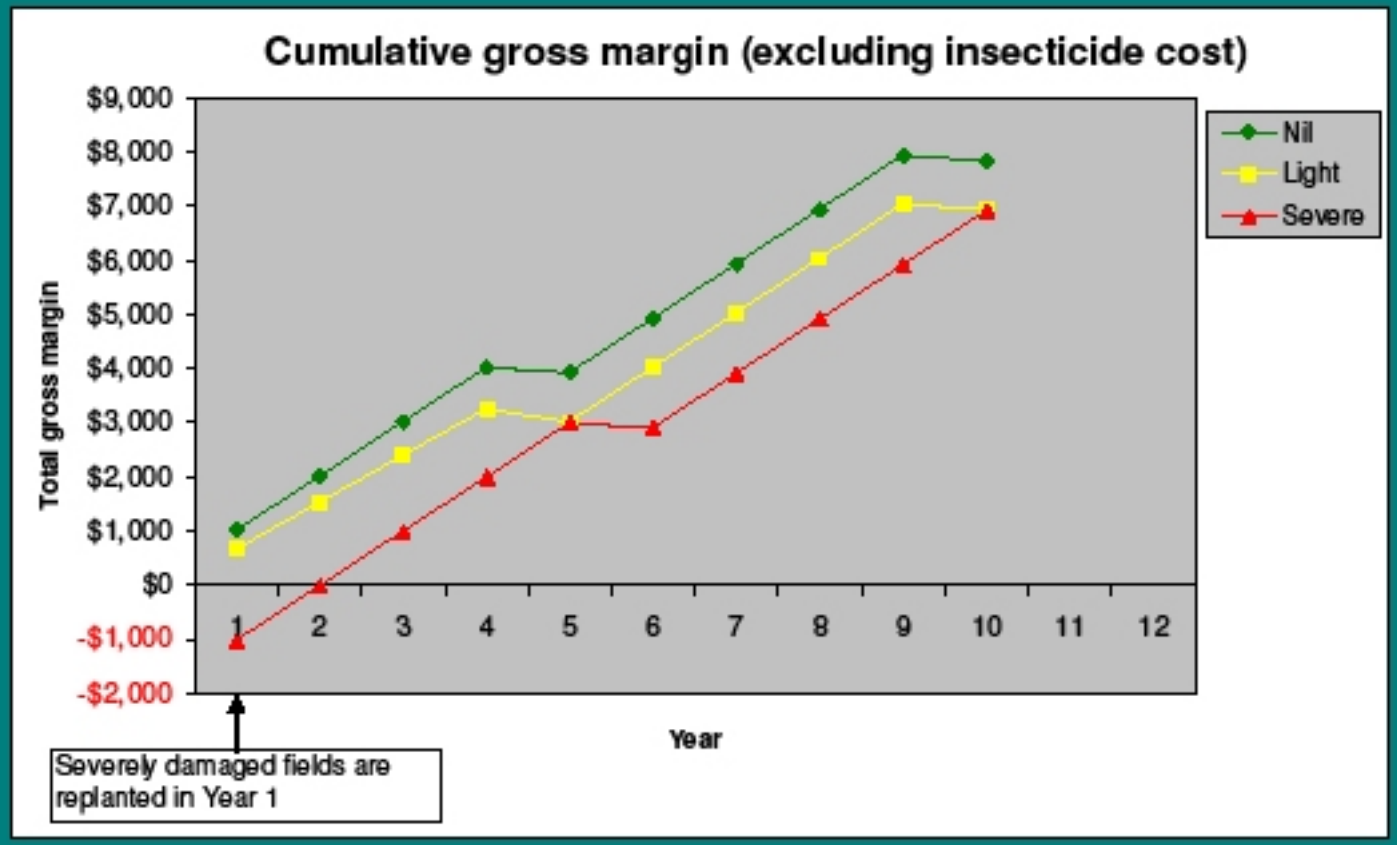
The expected result is the likely $ return on insecticide treatment, determined by the risk profile entered for the field and economic variables. Due to the nature of risk, the actual result in a given year may differ from the expected one.

This expected result is based on the analysis at right - the consequences of different categories of damage and the likelihood of each outcome actually occurring.

View chart

Cost-benefit analysis per hectare for different outcomes

	Possible damage next year		
	Nil	Light	Severe
Consequence ($)	0	-$905	-$1,807
Treatment cost ($)	-$180	-$180	-$180
Nett return on treatment ($)	**-$180**	**$725**	**$1,627**
Likelihood (%)	50	40	10



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4.11 A commercial monitoring and risk assessment program

4.11.1 Possible market acceptance

Growers at group meetings were asked whether they would use a service that gave advice on grub monitoring and provided control recommendations for individual fields, for a cost. They were also asked how much they would be willing to pay for such a service, firstly, for the recommendations alone based on data they supplied, and secondly, for the additional work of someone doing the monitoring for them.

Some growers in each district recorded that they would use such a service (Table 55). Support was highest in Plane Creek, Burdekin and Herbert; these growers were part of new farming systems groups and were relatively 'switched-on'. Overall, about half of the growers who experience grub problems said they would use the service.

Table 55 Numbers of growers who recorded that they would employ a user-pays service for canegrub management advice for individual fields

District	Total no. of responses	Responses from growers with canegrubs	
		No.	No. who would use service
Plane Creek	13	12	7
Mackay	26	14	4
Burdekin	10	8	5
Herbert	4	4	3
Tully	10	9	3
Innisfail	21	14	5
Mulgrave	19	17	9
Total	103	78	36

When given a range of cost possibilities for the service, the amount growers stated that they would be willing to pay was, not surprisingly, skewed towards the lower end of the range (Table 56). Less than $10 per field is not a realistic charge for monitoring fields if any grub digging is involved. However, a significant number of growers said they would be willing to pay more than $30 per field for each of grub monitoring results and field-specific recommendations.

Table 56 Numbers of growers who recorded that they would pay each range of costs in a user-pays service to give field-specific canegrub recommendations and to collect the necessary monitoring data

Service	No. of growers willing to pay each $ amount			
	<10	10-30	30-50	>50
Field-specific advice	15	11	5	1
Grub monitoring	14	10	5	4

4.11.2 District- and farm-level monitoring and prediction systems

4.11.2.1 Framework for suitable monitoring systems

Our analysis of monitoring data collected from 2003-7 indicates that it is possible to assign a probability value to the risk of canegrub infestations in the following year, so as to evaluate the economics of different management options, provided that adequate information is available. Of greatest importance is the current status of canegrub infestations (numbers, damage and infection by pathogens) in a particular field, in nearby fields, and in the district. The more information that is available on current infestation status, the greater will be the reliability of future predictions. This could include a range of spatial scales: field-level (e.g. insecticide and disease effects), farm- or neighbourhood-level (beetle movement and dispersal), and district-level (climatic factors that affect abiotic mortality, e.g. Horsfield *et al*. 2008).

We propose a monitoring framework operating on two levels: a district-wide monitoring system to benefit all growers, and a farm-level system that will enable management decisions to be made for individual farms and fields (Fig. 17).

District-wide monitoring

At the district level, the system would aim to:

- Create awareness of greyback canegrub trends in the district and help growers to decide on their monitoring requirements for the coming year (by February-March, depending on the district)
- Provide information on the status of canegrub infestation in the district and the trend compared to previous years, to feed into growers' decisions on canegrub management (by May-June, depending on district and seasonal conditions)
- Create a formal system of data collection, storage and retrieval that could be used to identify relationships and improve canegrub forecasting in future years.

Monitoring would be an on-going cycle each year, involving quantitative records of beetle activity on sentinel trees, canegrub numbers in representative fields, visible damage across the district, and estimated district cane loss (Fig. 17). Each step in the monitoring program would provide additional information on annual canegrub status in the district. This information would be added to data from previous years to assess whether the overall canegrub trend was up, down or stable. A formal data storage and retrieval system would allow trends to be easily examined and ensure data were not lost. Information would be released to growers at least twice each year:

- in February-March, to create awareness of canegrubs and to help growers to decide on the effort they should allocate to monitoring their own farms (in high-risk years, more fields would be classed 'at-risk' and would be monitored by growers);
- in May-June, to help growers make field-by-field management decisions.

Actual damage the following year would be compared with forecasts as part of a continuous improvement program.

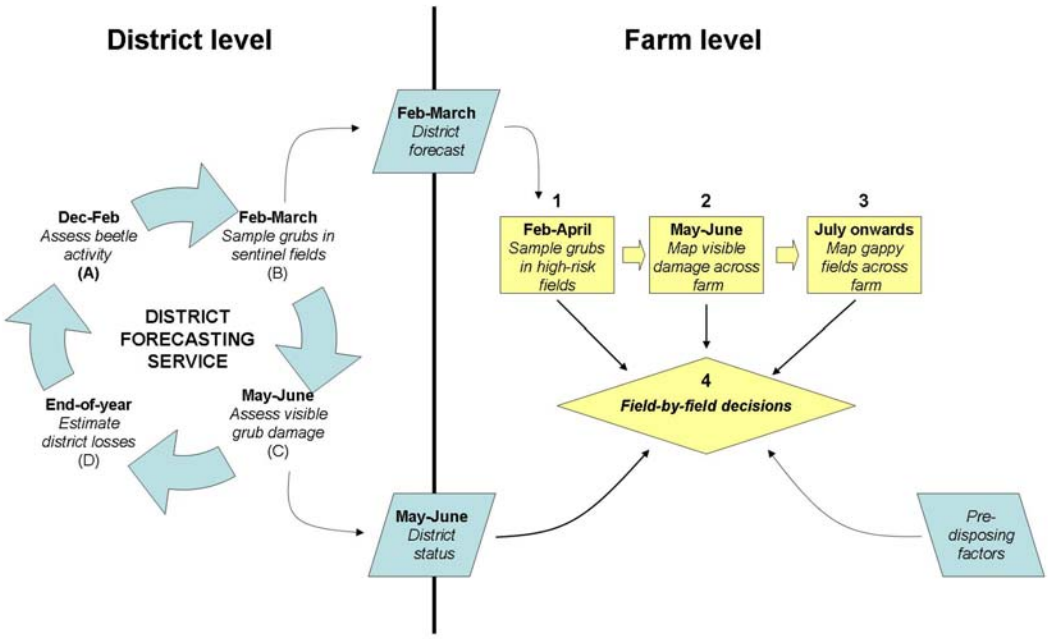

Figure 17 Proposed steps in a monitoring system to help growers manage greyback canegrub

Details of each step in the proposed system (Fig. 17) are:

A. Beetle activity

The link between beetle flights and subsequent canegrub numbers is not straightforward, and previous attempts to relate beetle activity to canegrub infestations have been unsuccessful (Ward and Robertson 1999). Beetle numbers and canegrub numbers must logically be related at some population density or spatial scale – if there were truly no beetles in a district then there could be no grubs the following year – and failure to see relationships in previous studies may reflect our inadequate knowledge of the dispersal patterns of adults and interactions among their progeny. Nevertheless, data on beetle activity are easy to collect and could help to develop a picture of greyback infestation trends across a district and from year-to-year, once sufficient records are available. Anecdotal reports of beetle flights may be useful, but we also propose a formal system of annual observations of beetle activity on feeding trees. Such a system can be made semi-quantitative by rating the amount of damage on trees and by having a systematic pattern of sentinel trees throughout the district. About 300 groups of feeding trees were identified as part of this project (Section 4.3.3).

B. Canegrub numbers

Sampling canegrubs provides evidence of infestations in years when no damage symptoms are visible, especially at low canegrub densities. Canegrub sampling can provide advance warning of the early stages of a build-up in canegrub density across a district, at least one year before it might be detected by observations of damage to cane. This early warning is a critical step to prevent the periodic canegrub outbreaks that plague the industry, such as the outbreak in northern Queensland in 2001 (Samson *et al.* 2005).

C. Visible damage

A map of damage through the whole district can serve two functions:

- visible damage should be a component of a district-level system to examine both current canegrub status and also the change from previous years, whether up or down;
- growers can be supplied with records of damaged fields on their farms to help them make management decisions, e.g. a change in harvest scheduling to minimise cane loss from damaged blocks and the need for insecticide treatment of neighbouring blocks that might be infested by beetles emerging from the damaged fields.

Aerial photography is used very effectively by the productivity services in the Burdekin to identify and map canegrub damage.

D. District losses

Records of cane loss due to canegrub damage are already collected in most districts as part of annual pest data collection. They are backward-looking and are not, on their own, an adequate basis for a pro-active canegrub management strategy. However, they are a useful indicator of the success or otherwise of the canegrub management strategies employed in the district, they can help detect trends in canegrub populations and damage, and, depending on the severity of the economic, environmental and social impacts, they form a basis for setting industry priorities for RD&E.

Farm-level monitoring

At the level of individual farms, monitoring would aim to collect sufficient information on current canegrub status to allow informed decisions on future canegrub management.

We suggest that canegrub damage, expressed as both visible symptoms in cane before harvest and gaps in ratoons after harvest, should be assessed farm-wide and mapped every year. In addition, in fields considered at risk of canegrub attack, some stools should be dug to determine if an infestation is already present. Information should be sought on the district-wide canegrub status. Decisions on canegrub management for each field should be based on this canegrub information together with other factors that may pre-dispose fields to canegrub attack.

Details of each step in the proposed monitoring procedure are (see Fig. 17):

1. Canegrub numbers

Knowledge of the infestation level in a field this year adds to the accuracy of predictions of infestations next year. However, sampling every block on a farm is not practical. We suggest a multi-stage procedure; firstly, identifying fields that might be at risk, then prioritising those fields in order of risk, and thirdly, sampling a selection of the high-risk fields until a decision can be made to continue sampling additional fields or stop.

Various models are available to estimate the risk of grub infestations next year, depending on what information is available for each field. The most reliable predictions can be developed for fields where an estimate of grub density is available in the current year. However, other estimates of current infestations can be used, including current grub density class (<>0.5 grubs/stool), presence or absence of grubs (under a maximum of 20 stools), or level of visible damage (see Section 4.8).

Figure 18 **Aerial photographs of a farm near Mackay taken in May 2005 and 2006. The bay of Q185$^{\Phi}$ circled was sampled in both years with average grub densities of 0.3/stool (second ratoon) and 1.6/stool (third ratoon), respectively; the aerial photographs show the increase in damage and also reveal damage appearing in 2006 across the road to the right side of the photograph**

2. *Visible damage*

A map of damage across the farm serves many purposes (e.g. Fig. 18):

- The presence of light damage symptoms in a field may indicate the presence of canegrubs, which should be checked by examining a few stools for root pruning – these fields may need treatment to prevent damage increasing next year
- The presence of severely damaged fields may indicate the need for a change in harvest scheduling to minimise crop and stool losses in those blocks
- Severely damaged fields will produce beetles later in the year, and are a major risk factor for neighbouring blocks
- Several years of sequential mapping may allow growers to identify parts of their farms that are consistently at higher risk than others.

The presence of nearby damage is a critical predictor in models developed to estimate risk of greyback grub infestations (Section 4.8).

3. Gappy ratoons

Gaps in ratoons may indicate the presence of canegrubs, particularly if the gaps were not present the previous year. If canegrubs were the cause, then root and stubble damage will be apparent on those stools that remain.

4. Field-by-field decisions

With information on the current distribution of canegrub infestations, together with other factors that may pre-dispose certain fields to canegrub attack (e.g. crop class), growers can quantitatively assess the risk to individual fields (Section 4.8) and plan their management accordingly. Other factors that are not currently included in the quantitative models, such as cane height at the time of beetle flight, can also be considered qualitatively when making management decisions.

Given the predicted likelihood of grub infestations next year (light/moderate/heavy), the expected return on insecticide treatment this year then depends on economic factors – the expected number of harvests during what remains of the cropping cycle, expected yields, the cost of replacing crops if they are prematurely ploughed-out due to damage, the sugar price, and the cost of treatment. We have developed a spreadsheet to help growers evaluate expected return on ratoon treatment for different values of these variables and for different levels of grub risk (see Section 4.10.2).

4.11.2.2 Databases for storage of monitoring data

Two Access databases, one for beetle feeding trees and one for canefields, have been developed to store the monitoring data collected during this project. These databases can be used to store and retrieve the results of future district-level monitoring.

4.12 Communication and adoption

4.12.1 Case studies

GrubPlan project staff and assisting extension officers conducted 11 case-study interviews early in the project, as an additional reference point for assessing what aspects of individual grower's grub plans worked for them, and as a means of collecting anecdotal evidence about trends observed on farms. Only growers who had participated in previous *GrubPlan* workshops were interviewed. Ideas and issues discovered from talking with farmers assisted in moulding subsequent *GrubPlan* workshops and related activities. Summaries of these case studies are given in Appendix 2.

Grower testimonies indicated that the damage in the 2001 greyback outbreak started to appear in the first half of 1999. This damage increased exponentially over the 2000 and 2001 seasons. Some signs of increasing grub activity were observed before this (Appendix 2, Cases 10 and 11) and one grower (Case 5) felt that rat damage in the preceding years may have masked signs of increasing grub activity in the Herbert region. This supports the BSES philosophy that canegrub outbreaks do not appear overnight; there is usually a lead-in period or build-up of the population once conditions suit their increase.

The case studies indicated that there may be a correlation between reduction in plant crop insecticide protection (suSCon Blue), and a trend of increasing damage. A number of growers indicated a run-down or complete absence of suSCon Blue in their crop management regime in years leading up to the 2001 outbreak (e.g. Cases 1, 3, 4, 8 and 10). Growers who had maintained a regular regime of suSCon Blue still incurred a level of damage on their farms but not at the same extreme levels as those with a complete absence of the product in their crop cycle. Many growers also commented that they had not previously experienced the capacity of greyback canegrub to destroy an area, and even though they had seen some early signs of damage, they underestimated the effects of the pest and so failed to put strategies into place to minimise their risk. Growers also reached a better understanding about the vulnerability of different blocks on their farms. Some knew the areas on their farms that did occasionally get attacked but had not known what proportion of their farms might be prone to greyback impact.

During the *GrubPlan* workshop series in the Herbert in mid-2001, BSES was heavily criticised for promoting the concept of trap-cropping. There was a general grower rejection of the concept that beetles flew to higher cane, and the rain-fed systems in the Herbert would not allow for effective manipulation of beetle movement by altering harvesting or planting sequence. In the case-study interviews, there was testimony of the failure of early harvest and forage sorghum trap-cropping efforts, perhaps due to insufficient height difference from the surrounding fields. However, many interviewees across the regions did concede that they had seen evidence of trap effects with blocks of cane cut early as a plant-source, with some instances in early-cut ratoons (e.g. Cases 2, 3, 8, 9, 10, 11). One grower (Case 11) did aggregate large numbers of grubs into an early-cut and irrigated block of plough-out cane.

There was also evidence of the resistance of growers to monitoring fields for grubs (e.g. Cases 7 and 9), although checking for beetles seemed acceptable (and certainly easier) (e.g. Cases 8 and 9). At least one grower (Case 7) valued the results of grub monitoring supplied to him by Mulgrave Mill, and there may be an opening for a commercial service to provide this information to growers.

In the Herbert case studies, attempts were made to look at gross margin analysis on individual plant cane blocks, as well as a comparative economic assessment of trials that had been undertaken with participants. The aim was to provide a handle on the affordability of using the different crop protection products. This exercise demonstrated a number of key issues:

1. Plant crop protection with suSCon Blue is largely cost-effective even in low price years such as 2002
2. BioCane can be cost-effective in northern rain-fed Herbert cane growing systems, but only in lower-risk field situations
3. Confidor Guard is a useful tool when there is a high risk of greyback damage, and when crops are sufficiently high yielding or when the sugar price is sufficiently high to justify its expense. In lower price years or when rain-fed crops may yield poorly due to drought, its advantages are marginal. (Note that the price of Confidor Guard and generic imidacloprid products has fallen substantially since these case studies were undertaken.)

4.12.2 Communications with growers and productivity services

4.12.2.1 2002

GrubPlan workshops were run in 2002 but the participation rate was substantially reduced compared with 2001. Unlike 2001, *GrubPlan* workshops were run in the first half of 2002 as greyback damage became visible (March-June). The workshops ran to a similar process as the 2001 program with individual farm plans prepared by growers following a self-assessment of their risk and a brief revision of the available IPM approaches.

Overall attendance by growers was down compared to 2001. Burdekin attendance was at 25% of 2001 (100 compared to 401). In non-Burdekin areas, *GrubPlan* only attracted 32% of the numbers of growers that attended in 2001 (164 compared to 506).

Some of the comments returned in evaluations might assist us in understanding these trends:
"Grubs are no longer a problem, they have gone away".
"I can't afford to apply treatments with the current low sugar price".
"I now know what to do, and I don't need to attend follow-up workshops".

The third point was encouraging as it indicated that trainers were achieving an increase in understanding, skills and practice change in industry. However, it is realistic to expect future impacts if management is relaxed. Therefore, even though damage estimates and grower surveys indicated strong levels of achievement with the 2001 *GrubPlan* program, maintaining future motivation and momentum within industry will be challenging.

The only deviation from the downward trend in participation was in the Central region, where an outbreak developed. Few of the 2001 participants returned for ongoing *GrubPlan* workshops in 2002. However, there were newcomers to the program, many of whom incurred destruction of whole or part of blocks of cane to greyback canegrub in 2002. For many of these growers it was the first time they had seen serious greyback damage. Four workshops were run in the Mackay district in 2002, training 49 growers and rural industry advisors.

Gross margins were prepared on different control options within the *GrubPlan* IPM program and presented at *GrubPlan* workshops in the Atherton Tableland, Mulgrave, Innisfail and Herbert regions in 2002. These examples were derived from real trial results, and were sourced from BSES, Bio-Care, Bayer and Crop Care work. The objective was to demonstrate the net cost-benefit effects of different treatments over successive years within a crop-cycle. In particular, they demonstrated to workshop participants that, where a definite risk of infestation exists, there is generally a benefit for the outlay on control measures. Where there was limited risk, the benefit could be cancelled out completely. A key message in this work was to <u>only</u> deploy treatments in areas that were under a moderate to high level of risk. Another point was to highlight that the cost of any treatment employed to manage canegrubs needed to be assessed over the lifespan of a crop, not just in the year of application or even within the product's efficacy period. The true benefit of a treatment lies in its ability to provide the grower with the ability to farm through a crisis or risk period with canegrubs. Thus there will be periods of time when growers can minimise their reliance on canegrub treatments.

Another segment attempted at some 2002 workshops was to use the current BMP (Macarthur) Model to demonstrate some comparisons between farms where risk management treatments were used versus those that had a reliance on ploughing out and replanting. The message was where and how canegrub impact reduced cash flows and increased indebtedness over time. Scenarios were not easy to develop in the package, which seemed to have serious shortcomings with respect to simulation of real-life situations and ease of use.

4.12.2.2 2003

A total of 103 growers from Mulgrave, Innisfail, Tully, Herbert, Tablelands and Plane Creek participated in *GrubPlan* training workshops and farm walks in 2003. The Burdekin did not run *GrubPlan* activities. There was a significant reduction in interest in 2003 compared to 2001, mainly because of reduced levels of grub damage throughout much of northern Queensland.

A potential problem with the application of a complete IPM program by growers for the 2003/4 season was uncertainty regarding the availability of the ratoon insecticide treatment Confidor, with registration pending but not yet granted. Warren Hunt (then project leader) organised an emergency use permit application for the use of Confidor which was submitted by CANEGROWERS on behalf of the industry to the APVMA.

Early detection of damage was a key theme promoted at meetings and farm walks in 2003. Growers who attended gave positive feedback on the significance of this principle. *GrubPlan* Risk Management and Planning Guides were distributed at these meetings as on-going reference tools for whole-farm planning. Cost-benefit analyses were covered both in formal presentations and sometimes less formally in small group discussions and farm walks. Cost-benefit analysis was also a central theme in the process, aiming to demonstrate that where risk was present, investment in IPM approaches did yield both an immediate benefit in the following season, and potentially further benefits during the crop cycle once the infestation peak had passed.

4.12.2.3 2004

By 2004 there was a cultural resistance among growers to carrying out formalised mapping in a workshop environment, which needed to be taken seriously. The technique of mapping used in the 2001 and 2002 series was beneficial as a training approach, but should not be overdone as many growers can feel awkward in a classroom-type environment. Using farm walks in some of the training, with the particular theme of recognising early signs of damage, was seen by growers as a useful and refreshing change from the previous method.

Six greyback workshops were held in the Central region during May-June, at Proserpine, Mt Ossa, Eton, Gargett, Sarina and Koumala, with about 150 growers attending. A training workshop was also held for advisory staff from BSES Limited, MAPS and local consultants. The format covered grub biology and control options as in previous years but with considerably more emphasis on monitoring and risk assessment. These workshops did not develop individualised farm plans but instead participants were given a generic farm map on which they drew in their control strategies for a hypothetical pattern of

damage. Volunteers were then asked to display their plans through a document projector. This initiated a lively debate and was a valuable learning tool; it particularly demonstrated the diversity of control options that people would develop when faced with the same problem, particularly with regard to trap cropping and ratoon treatments. Several informal canegrub discussions were also included in shed meetings. There was heightened interest in greyback canegrub in the Central region due to increased damage compared with 2003, which had been forecast based on grub monitoring earlier in the year, together with the availability of new control options, Confidor Guard and suSCon Maxi/Confidor CR.

Eleven meetings with about 90 growers total were held in the Burdekin in 2004, covering control options, monitoring and planning. As with the Central region meetings, planning was done using a generic map and hypothetical damage. The Productivity Services in the Burdekin conduct aerial surveys of grub damage and growers rely heavily on this for their monitoring rather than conducting their own ground-level surveys.

In the Herbert, HCPS Ltd cooperated to arrange four large grub meetings with more than 60 growers attending. The format covered:

- Potential for lower-cost grub control
- The trend in grub population densities from monitoring in 2003-4 and predicted risk for the 2005 crop
- Actions that growers should take to identify at-risk fields (monitoring)
- How to decide where best to invest limited resources

From these meetings, 20 growers indicated willingness for further on-farm consultations and desire to develop a grub management system for their farm and district. Subsequently (early June), 10 meetings were held with these 20 participants as individuals or in small neighbourhood groups, to assess their individual situation and to plan follow-ups to help them through the process of collecting observations, making decisions and generally increasing the flexibility of their grub strategy to align risk management with the need to cut input costs.

At Tully, two grub-prone grower groups were addressed as part of meetings covering various topics. Two growers agreed to participate in further activities similar to the Herbert.

A group of about 10 growers was addressed at Green Hill in Mulgrave, but unfortunately the most affected growers were unable to attend due to a conflict with other activities. One attendee and three non-attendees are already sampling for grubs and tying in risk assessment with forward planning.

Mulgrave Mill developed a risk forecast for greyback canegrub in 2005. This is attached as Appendix 4.

4.12.2.4 2005

Eight Herbert River growers who are not part of the regular grub-monitoring program were engaged during regular visits to discuss local monitoring results and/or conduct site-specific monitoring, and to discuss options for farm-specific grub management plans. In addition, two growers from the regular monitoring program (White, Kangas) and five additional growers have been engaged in less frequent visits to discuss grub-management

planning options. One of the above growers will be dropping out of cane production and a larger grower (Brian Johnson, Abergowrie Rd) will now become a 'potential client', having shown interest in our activities.

None of the farms on which we had issued low-risk prognoses during 2004 experienced any noticeable damage for the 2005 crop. One grower (Hartwell), whom we had considered slightly at risk in mid-2004, had no damage in the 2005 crop. Damage became obvious in 2004 and 2005 on one farm (Kangas) where our monitoring had indicated an escalating risk; this grower has continued to ratoon but treated those fields with Confidor Guard, which (unfortunately) included our monitoring fields. We were able to convince one grower (Leonelli) in 2004 that it was safe to ratoon a healthy field again for 2005 rather than plough it out.

Two growers (Leonelli, Wallis) are using risk-assessment processes to decide on treatment options, and both avoided treating cane planted in 2005, comfortable in the knowledge that the fields could be treated as ratoons if the risk increases. Neither treated ratoons in 2005. These growers are actively looking at crop growth and ratooning for early signs of damage and at beetle flights on key feeding trees that have been identified. Regrettably, both declined to conduct digging surveys in their crops. One has had an attitude change, formerly being a 'routine-treatment' grower, and the other retains the attitude of restricting insecticide treatment for 'crisis-years' and is building his capacity for using risk-assessment to identify potential crises and to take evasive action.

Five growers (Celotto, Irlam, Mackee, White, and Hartwell) persist with routine treatment of plant cane, a decision process that is proving hard to displace. However, they are listening with interest to monitoring advice (both for grubs and beetles) and may reconsider in 2006. Predicted low priority for Confidor Guard treatment in 2005 was discussed during our visits, and none of these growers treated ratoons in 2005. They all prefer to grow no more than four ratoons, then to fallow, giving grub populations little chance to multiply and minimising any need to resort to ratoon treatments. Alternatively, Kangas treats plant cane but attempts to grow many (6-8) ratoons, and is using risk-assessment to decide when and which ratoon fields to treat with Confidor Guard.

4.12.2.5 2006

In the main, efforts in 2006 concentrated on developing the outputs necessary to complete the project. However, results of annual monitoring in 2006 in comparison with previous years were discussed with grower groups in far north Queensland. The reaction from a couple of growers was "grubs are gone, we can forget about them and hit them when they come back". It was pointed out that this would only work if there was an adequate monitoring program underway, and that numbers may rise again without them noticing. There is no real argument about this, and most growers understand that they need to continue to treat strategically but, in the absence of a systematic monitoring program, it is inevitable that the intensity of treatment is going to fall and grub numbers will eventually increase again.

4.12.2.6 2007

Meetings were held in 2007 with productivity services and BSES extension from Mulgrave (8 February), Mackay (15 March), Herbert (21 March) and Plane Creek (26 March). This covers the main districts that have been involved in the project. The outputs of the project were summarised, emphasising the way district- and farm-level monitoring systems could be used to improve grub management. Although there were no objections to the concept or desirability of the monitoring framework proposed (see Section 4.11.2), there was little indication that these districts had the resources to adopt comprehensive district-level monitoring systems. The time and effort required for sampling grubs is the main sticking point. However, there are opportunities to collect and store data on other parts of the grub monitoring system (beetle activity, visible damage, crop loss estimates) in a more systematic manner than is currently done.

4.12.2.7 2008

Final meetings were held with productivity services and BSES extension from the Burdekin (31 March), Herbert (1 April), Tully (2 March), Innisfail (2 March), Mulgrave (2 March), and Plane Creek, Mackay and Proserpine combined (16 May), to present outputs that could be used by advisory staff.

4.12.3 Decision aid tree for risk management

At the start of the project, a pamphlet incorporating decision-aid-trees was developed as a guide for growers who were considering their management options with greyback (Appendix 1). 200 copies were produced and distributed to extension staff working with grower groups in central and northern mill-regions.

4.12.4 Revised *GrubPlan* booklet

The original *GrubPlan* booklet was produced in 2001 as the resource pack for *GrubPlan* workshops that began that year, in response to a severe outbreak of greyback canegrub. Attendance at a *GrubPlan* workshop was a prerequisite for use of the then-new insecticide Confidor under an Emergency Use Permit.

The original *GrubPlan* booklet presented the '4 pillars for grub management': suSCon Blue/Plus, BioCane, Confidor for ratoon treatment, and trap cropping. Several more pillars have been added since 2001:

- Confidor Guard, as well as generic liquid imidacloprid products, now have full registration for ratoon application;
- Confidor Guard is now registered for plant crops as well as ratoons;
- BioCane is registered for application at-planting as well as at fill-in;
- a new controlled-release granule is registered for plant crops, suSCon Maxi;
- a new type of product with insecticide contained in a peat granule, GrubGuard, is available under permit for plant crops.

In addition, much more is now known about assessing the risk of greyback attack, for making good management decisions, as a result of work in BSS257.

Therefore, a new booklet was developed in early 2007. It includes these extra control options, and covers monitoring and risk assessment in much greater detail than the original. One thousand copies were printed and distributed to each region in 2007, and a PDF is also available on the BSES website. The booklet was officially launched by Robert Troedson at the BSES Activate Breakfast on 4 October 2007.

4.13 Consultants' reports

4.13.1 Dr Trevor Jackson 2004

Dr Trevor Jackson from AgResearch, NZ, visited from 22-26 March 2004. He flew into Mackay, inspected greyback-infested cane and then travelled with Peter Samson to Home Hill to join Keith Chandler and Mohamed Sallam. The group inspected infested cane and feeding trees in the Burdekin, discussed grub issues and data collection with Ron Kerkwyk of Herbert Cane Productivity Services Ltd and discussed the project with former Chief Investigator Warren Hunt. The group was joined at Tully by Gerard Puglisi of Mulgrave Mill and a formal planning meeting was on 24-25 March. While at Tully, Trevor spent considerable time in the BSES laboratory at Tully advising on grub rearing and pathogen detection and identification. Trevor then flew out of Cairns on 26 March.

Trevor Jackson's recommendations included the following:

- It is important to define easily monitored indicators of population growth and potential damage. The reliability of such indicators must be validated with field observations and analysis against data base information.

- Better prediction is required in areas of sporadic outbreaks. Emphasis should be placed on the role of abiotic factors (weather and soil type) in these areas. Matrix models could assist with analysis.

- In areas of persistent attack, biotic indicators may be of more value. Key areas for research include studies of female beetle behaviour, role of plant root vigour in susceptibility to damage and further research on diseases.

- Simple indicators of outbreaks are required. Remote sensing should be further evaluated.

- Better understanding of the benefits of prophylactic treatments will assist decision-making. The availability of curative treatments will increase the benefit of short-term predictions.

- Data should continue to be collected to build reliable data bases for the industry. Such data can be incorporated into matrix models which will be useful in analysis of factors underpinning outbreaks and also for presenting to assist decision-making protocols.

His full report is attached as Appendix 8.

4.13.2 Dr Frank Drummond 2005, 2007, 2008

Dr Frank Drummond of the University of Maine visited from 8-12 August 2005 to work with the project team and he also participated in the SRDC review of the project on 11 August. He met again with the project team at Meringa from 5-9 February 2007. His last visit was for 2 weeks from 21 January-1 February 2008, when he worked with Peter

Samson at Mackay to finalise modelling aspects of the project. His reports from each visit are attached as Appendices 9, 10 and 11, respectively.

5.0 OUTPUTS

The project outputs as detailed in previous sections are summarised below:

- A review of knowledge of population dynamics of greyback canegrub and a variety of simulation models describing key relationships
- Additional knowledge of the interaction between canegrub populations, agronomic factors, and canegrub pathogens, which may help to promote natural biological control of canegrubs
- A quantification of the influence of risk factors on the likelihood of infestations of greyback canegrub
- A framework for collecting the necessary monitoring data to enable risk predictions
- Tools for assessing risk and making management decisions:
    - beetle-feeding trees identified by GPS location
    - databases for storing regional monitoring data
    - statistical models for predicting grub populations
    - an economic spreadsheet for converting risk to a cost-benefit analysis
    - an improved user guide for the existing Best Management Practice (BMP) economic model that had been developed in an earlier SRDC-funded project by Macarthur Agribusiness, together with additional productivity data from Mourilyan and Mackay included in the model
    - a revised *GrubPlan* extension booklet.

6.0 INTELLECTUAL PROPERTY

Intellectual property arising from this project is contained within the models used for predicting greyback risk and population dynamics and within the revised *GrubPlan* booklets. All are protected by copyright.

7.0 ENVIRONMENTAL AND SOCIAL IMPACTS

Implementation of the findings of this research will have positive environmental and social benefits through better targeting of canegrub insecticides and reduced cane losses caused by unforeseen canegrub infestations.

8.0 EXPECTED OUTCOMES

The project has shown that it is possible to improve canegrub management by appropriate monitoring of canegrub populations and their damage and certain other risk factors.

The major obstacle to implementation of this strategy is the collection of the necessary data. Sampling of grub populations, in particular, is not done routinely by growers or their advisors, apart from occasional excavation of stools to confirm that grubs were the cause of obvious crop damage. It is difficult to see how this situation will change, other than through a user-pays consultancy. However, even in the absence of quantitative grub estimates, it is still possible to derive reasonably good predictions of future grub infestations using current estimates of visual damage on a field-by-field basis. Such estimates can be obtained relatively simply by growers for their own farms or by industry organisations operating at a district level.

The need for monitoring has been and will continue to be promoted at *GrubPlan* workshops, while the various risk-assessment tools developed in the project are available to growers and their advisors.

9.0 FUTURE RESEARCH NEEDS

- The data used to develop the predictive statistical models in this project covered a relatively short period of 5 years. It would be highly desirable to re-evaluate these models in the future, with more data covering a longer time period. A longer time series of data could also be used to explore the joint dynamics of populations of canegrubs and canegrub pathogens in different regions (e.g. will the incidence of *Adelina* and *Metarhizium* increase over time in the Central region) and the effect of environmental factors on both.

- The detection of canegrub damage is critical for the strategic implementation of management strategies. An efficient means of detecting and geo-referencing damage, perhaps by aerial imagery, and of transmitting that information to growers, would greatly enhance growers' ability to make good management decisions.

- Insufficient time was available within the project to fully explore the implications of the multi-field simulation model developed by Frank Drummond. This should be done.

- The review of greyback population dynamics and associated simulation modelling highlighted a number of knowledge gaps that could impact on pest management, and these were discussed earlier in the report. One critical gap is our knowledge of the dispersal behaviour of adults of this highly mobile pest.

10.0 RECOMMENDATIONS

- Make the decision tools that were developed within the project available to interested growers and industry staff
- Continue to promote concepts developed within the project at *GrubPlan* workshops

- Test and fine-tune the proposed monitoring and decision-making strategies with growers on selected farms (this is currently being done as part of SRDC-funded GGIPs in the Mackay and Mulgrave districts)
- Explore the implications of simulation models developed for greyback canegrub and develop those models further
- Revisit the statistical predictive models when more data are available.

11.0 LIST OF PUBLICATIONS

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12.0 ACKNOWLEDGMENTS

This project was initially led by Warren Hunt, then of BSES Limited, who established the project framework and began its implementation. Gerard Puglisi, formerly of Mulgrave Mill, gave great assistance throughout. I also acknowledge the contribution to the project by fellow BSES entomologists Mohamed Sallam and Keith Chandler. The staff of various productivity services assisted with aspects of the work, especially for Mourilyan Mill. Several consultants – Frank Drummond, Trevor Jackson and Hugh Macintosh – contributed enormously. QDPI&F staff of FutureCane, particularly Mark Poggio, helped with economic analyses. Andrew Higgins of CSIRO Sustainable Ecosystems supplied productivity data for Mackay. Funding from SRDC and QDPI&F is gratefully acknowledged.

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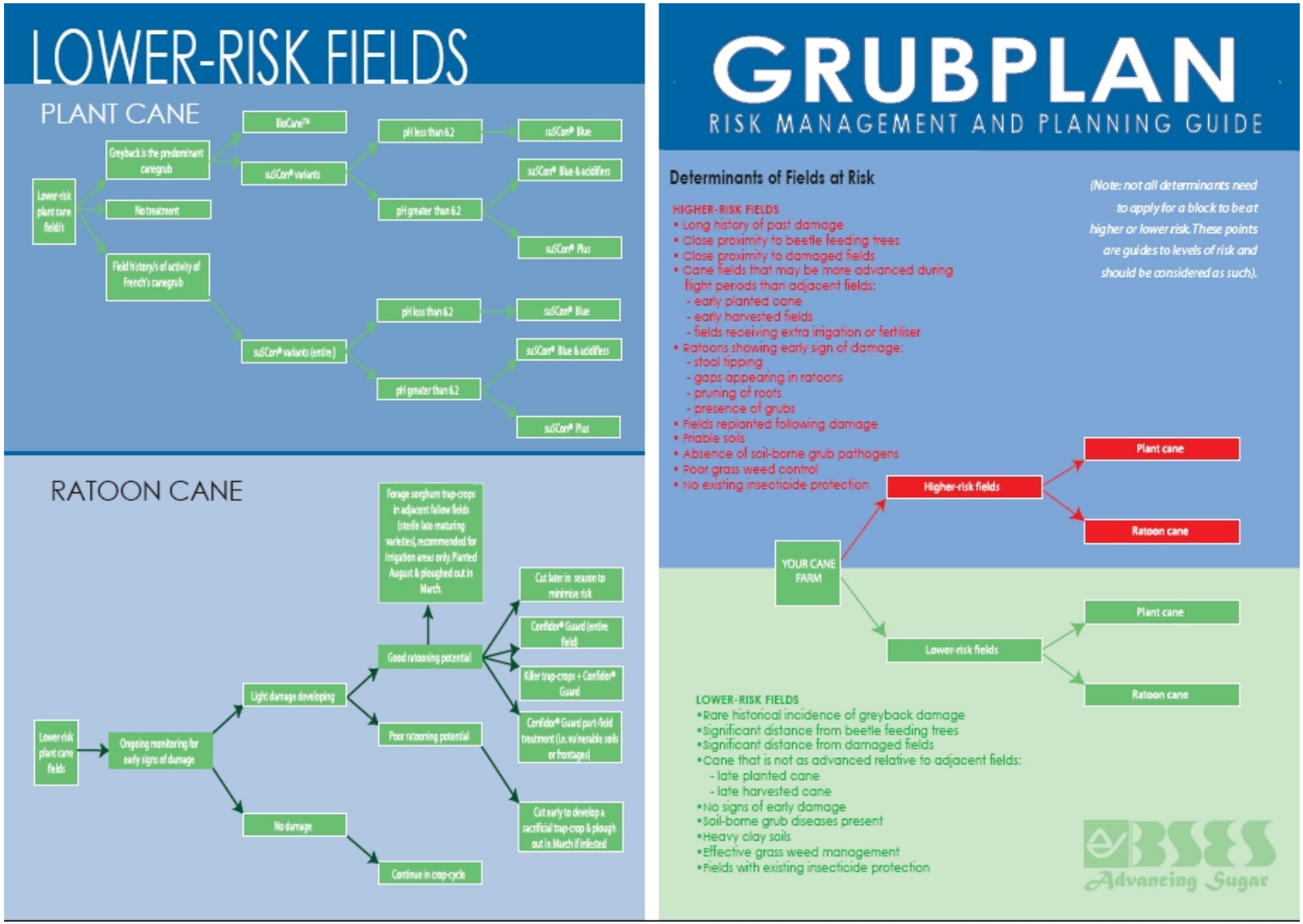
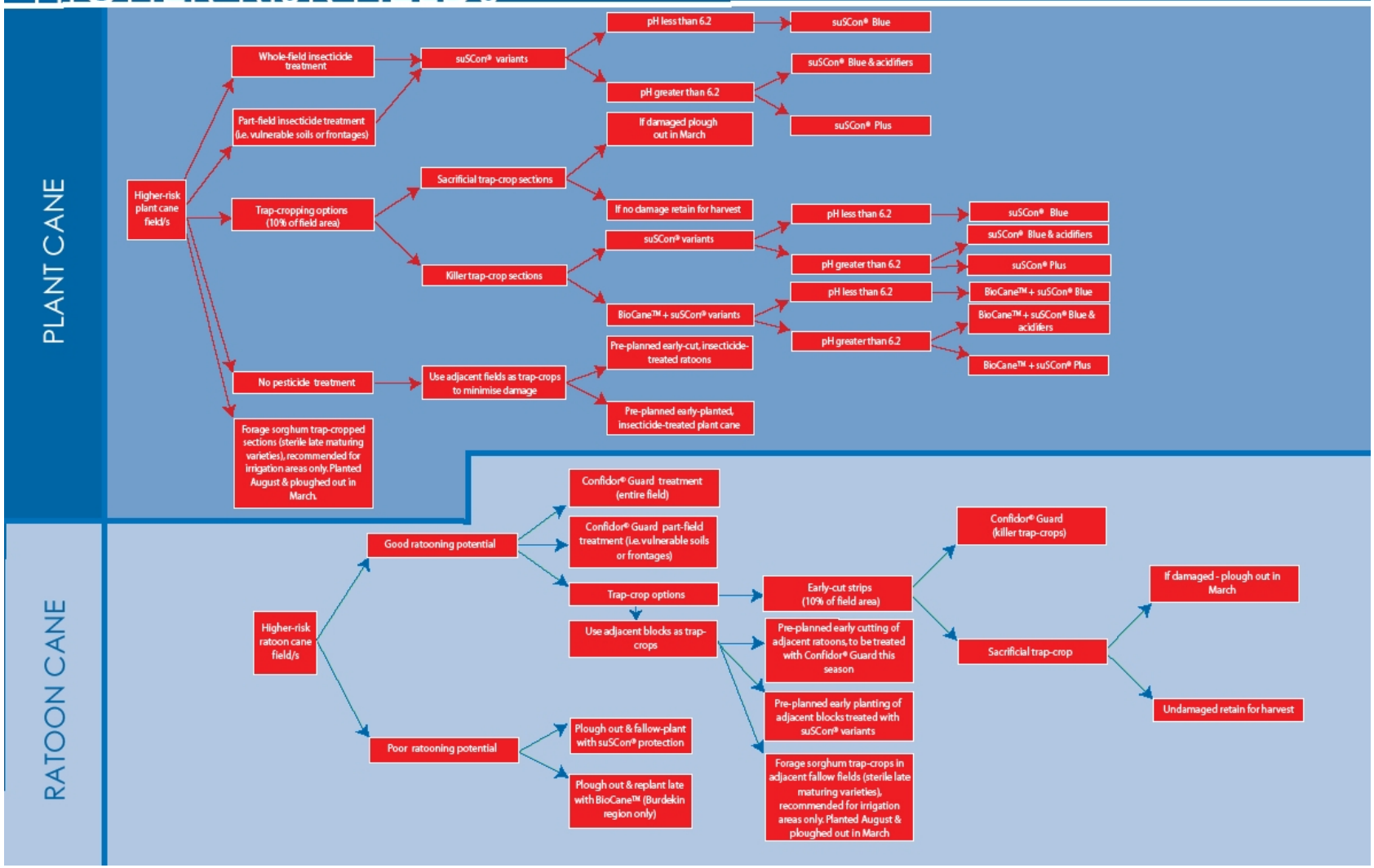
APPENDIX 1 – DECISION TREE



HIGHER-RISK FIELDS



APPENDIX 2 – 2002 *GRUBPLAN* CASE STUDIES

Introduction

The purpose of these case studies was to learn from cane farmers how they managed the 1999-2002 greyback outbreak: what worked for them and what didn't, trends they observed and things they learned through their own experience in applying risk management strategies. Growers who had participated in the *GrubPlan* workshop series were interviewed. Ideas and issues discovered from talking with farmers would assist in moulding future *GrubPlan* workshops and related activities.

Herbert River Region 25-26 September 2002

By: Warren Hunt BSES IPM Coordinator & Kylie Webster, Extension Officer.

Case study 1 – Eda Vella, Abergowrie.

Eda operates a farm of 53 ha in the Abergowrie district of the Herbert. It borders the Herbert River and is comprised largely of alluvial loams.

History has demonstrated that the majority of the farm is prone to greyback damage. The first damage in the current outbreak appeared in 1999. This damage was sporadic, but by the year 2000 all but 6 ha of the farm was experiencing some level of greyback damage. This represented nearly 90% of the farm area. Damage first appeared in the older ratoons (third ratoon plus). Eda believes there was a relationship between the decline of their use of suSCon® Blue and the subsequent rise in damage. The Vellas had all but eliminated their use of suSCon® Blue until 2000, when they were forced by the severity of the damage to replant 28.3 ha of the farm, but this time with suSCon® Blue protection. In 2001 and 2002 Eda has used suSCon® Blue in both fallow-plant and replant blocks, some applied at planting and in other fields applied into the half-open drill. Damage is hard to find on the Vella farm in 2002.

Table 1 Economics of Vella's 2000-2001 plant crop vs hypothetical damage at the 2001 sugar price of $320/t

	suSCon® treated plant crop (harvested 2001)	Crop estimate without treatment
Tonnes cane/ha	104	45
CCS	13.5	9.8
Income $/t cane	27.94	17.28
Production cost $/t cane	16.85	23.64
Gross margin $/t	**10.98**	**(-6.44)**

Eda is able to provide an account of her gross margin for applying suSCon® Blue treatment to her 2001 harvested plant crop compared with hypothetical estimates of damage she might have incurred if she had not protected her crop, based on the damage trend on her farm in 2000 and other neighbouring farms in 2001 (Table 1).

A sensitivity analysis revealed that on Eda's farm in 2001, a plant crop below 10 CCS and less than 70 t/ha would have been unprofitable. Bearing in mind the amount of damage incurred in much of the Abergowrie district in 2001, the hypothetical damage impact outlined in the table is not unreasonable. Eda's investment in plant crop protection appears to have been a good one.

Eda has also participated in trials of Confidor® 200 SC in ratoons in 2000 and 2001. These have proven to be successful exercises and she will continue to use Confidor® as a tool to protect valuable and vulnerable ratoon blocks in higher-risk years. Eda also sees Confidor® as a measure she can use in trap-crop situations. Currently, Eda has two blocks, second ratoons for 2003, that were early-cut and are well ahead of adjacent cane. These fields (which are next to each other), are located close to beetle feed trees on the river and may be prone to damage. One of these blocks will be treated with Confidor® in October-November, and one left untreated (ear-marked for fallow and plant 2004). These fields may be useful comparisons of the level of canegrub activity next season.

The variety used in the Confidor trial was Q179$^{\phi}$ 1st Ratoon. Confidor® was applied at a rate of 2.1 L/ha stool, either by stool-splitting or side dressing. The stool-split treatment in this small strip trial produced the best tonnes sugar (Table 2), but the trial was not replicated.

Table 2 Results of Vella's Confidor® strip trial 2001

	Untreated	Side-dressed	Stool-Split
Cane (t/ha)	86	96	132
CCS	15.7	15.1	15.1
Sugar (t/ha)	13.5	14.6	20.0
Value of sugar ($/ha) [a]	4326	4656	6387
Difference less cost of Confidor	**N/A**	**(-20)**	**1711**

[a] @ $320/t

This trial demonstrates that, under the 2001 sugar price and growing conditions, Vellas gained an advantage by using Confidor® in a stool-split treatment in their risk management strategy.

Eda believes that a risk management strategy is a necessary step in aiming to achieve cost-effective greyback management. It would be financially unviable to attempt a total pesticide-based protection program for the entire farm over every crop class in every year.

Case study 2 - Brendan and Liz Sheahan, Abergowrie

The Sheahans operate two farms totalling 90.7 ha of assigned area. They experienced little greyback grub damage. Their only damage was on the home farm on the Herbert River where they first saw 3 ha in a fourth ratoon block mildly affected in 2000. This damage to the block intensified in 2001, forcing them to replant it in 2001 with suSCon® Blue protection. This block has since experienced no damage in 2002. None of the

blocks adjacent to the damaged field expressed any sign of damage even though soil types were fairly similar. The damaged block had been cut very early in the 1999 and 2000 harvests and adjacent blocks cut late in the season. The Sheahans expect that beetles migrated from damage in adjoining farms and from isolated fig trees in the area and possibly found the difference in height of their early-cut block of cane attractive.

Since 2001, the Sheahans have decided to apply suSCon® Blue at planting on both of their farms, even on blocks that had not experienced damage to date. They decided that they needed to implement this risk management as some adjoining blocks on neighbouring farms had either seen recent damage or were continuing to show damage symptoms.

In areas where damage has occurred, the Sheahans will be aiming to strategically harvest blocks with the aim of shifting beetles into treated stands of cane. Along the same lines, they will aim to cut older unprotected blocks late to minimise the risk to those blocks, while minimising their overall crop protection cost.

Case study 3 - Ross Blanco, Blackrock

The Blanco's farm on the Herbert River has 51 ha assigned to cane. Probably 30% of the farm (mainly alluvial soils and some sandy ridges) is prone to greyback canegrubs. Damage first commenced in 1999 with 7.4 ha showing signs of damage. In 2000 and 2001 this increased to 12.6 and 13.3 ha respectively. Ross says that he had ceased using suSCon® Blue in 1993 as he felt the expense could not justify the returns as no greyback damage was evident.

Since this outbreak has occurred, Ross has relied principally on suSCon® Blue applied at planting as his means of mitigating greyback damage. He finds that this has been successful but is concerned with the lack of longevity of the product for greyback control. He has not intentionally used trap-cropping and probably won't, but he does qualify this by saying he has seen damage on his farm where beetles were attracted to early-cut plant sources.

An economic analysis on Ross's farm indicates that application of plant cane protection, though expensive, still leaves a gross margin that is in the black even at a low sugar price (Table 3).

Table 3 Economics of treating Blanco's plant crop with suSCon Blue at two different sugar prices, $320/t in 2001 and $245/t in 2002

	2001 harvest results @ $ 320/t	**Hypothetical result @ $245/t**
Tonnes cane/ha	90	90
CCS	15.9	15.9
Income $/t cane	34.85	26.82
Production cost $/t cane	21.08	21.08
Gross margin $/t	**13.77**	**5.73**

Ross participated in a BSES Confidor® trial. Confidor® was applied at a rate of 2.2 L/ha, either stool-split or side dressed, and the crop was then harvested on 8 August 2001. The variety used in the trial was Q157 1st Ratoon. In one replicate the stool-split treatment appeared to perform better than the side-dressed treatment while this result was reversed in the second replicate; the untreated strips performed poorly in both replicates (Table 4). This was a difficult trial to visually pick trends and results are difficult to explain. However, in three out of four treatments Confidor® did deliver a financial advantage in the 2000-2001 season, compared to doing nothing. Despite reasonably positive outcomes, Ross doesn't think he will use Confidor® in ratoons as the he believes the level of productivity on his blocks could not justify its expense. At 2002 prices ($245/t sugar) this attitude would probably be justifiable, but at 2001 prices, Ross gained more from using Confidor® in most treatments than if he had chosen to leave these areas untreated.

Table 4 Results of Blanco's Confidor strip trial 2001

	Side-dressed	**Stool-split**	**Untreated**	**Side-dressed**	**Stool-split**	**Untreated**
Cane (t/ha)	88	94	77	81	67	70
CCS	16.3	16.4	16.9	17.1	16.2	16.3
Sugar (t/ha)	14.3	15.4	13.0	13.8	11.3	11.4
Value of sugar ($/ha)[a]	4614	4918	4166	4403	3616	3638
Difference less cost of Confidor	**82**	**386**	**N/A**	**399**	**(-388)**	**N/A**

[a] @ $320/t

Case study 4 - Geoff Morley, Lannercost

Geoff Morley's Lannercost farm totals 224 ha of assignment, some of which is located on the banks of the Herbert River. Damage in the current outbreak first became apparent in 2000. Geoff estimates that 46 ha were affected. This represented nearly 21% of the area of the farm. Damage intensity in some blocks was extreme, with 80-90% reductions in yields as stools rolled completely out of the ground. Main areas affected were alluvial silts, red soil ridges, and some light clays.

Geoff had never used suSCon® Blue until 2000, as up until then he had never seen serious, sustained greyback impact. He never thought that greyback canegrubs could be so catastrophic.

Geoff trialled forage sorghum as a trap-crop in the latter half of 2001 with little success. Digging in early 2002 found little presence of grubs. Another discouraging point was that Geoff had received poor advice on the selection of the variety of forage sorghum to plant. The variety he used was an early maturing viable-seed type, which that encouraged an infestation of rodents as well as an ongoing weed problem, rather than a later maturing sterile variety.

As part of an ongoing regime to manage greyback risk, Geoff will continue to use suSCon® Blue in any plant blocks in high-risk areas. Where damage intensity is less

severe, he is considering use of BioCane™, largely because of its potential longevity in the soil. Geoff has trialled BioCane™ in recent years in high-risk areas and recognises that the product is not suited for those situations (see below). In years where greyback damage is intensifying, Geoff has used Confidor® in valuable or vulnerable ratoon situations and would consider doing so again on a needs basis.

Geoff believes that consecutive heavy November rains in 1999 and 2000 may have synchronised beetle flights, allowing for better survival. In years where he might observe a similar occurrence, he says he would upgrade his vigilance in crop protection and monitor crops for early signs of damage.

BSES conducted trials at Morley's during the recent greyback outbreak. Peter Samson and Errol Sander (Mackay BSES) with assistance from Kylie Webster conducted cane grub counts in treatments of all BioCane™ sites in the Herbert on 21-22 March 2001. The only trial giving satisfactory grub numbers was the Morley trial with the varieties Q179$^{\phi}$ and Q174$^{\phi}$. This trial was subsequently harvested on 17 July 2001. Yields were greater in the BioCane-treated strips than in the untreated strip in Q179$^{\phi}$, but suSCon® Blue appeared to give a better result in both varieties (Table 5).

Table 5 Results of Morley's plant cane protection strip trial 2001

	Q179$^{\phi}$ Untreated	**Q179$^{\phi}$ BioCane ½ rate**	**Q179$^{\phi}$ BioCane**	**Q179$^{\phi}$ suSCon**	**Q174 $^{\phi}$ Untreated**	**Q174 $^{\phi}$ BioCane**	**Q174 $^{\phi}$ suSCon**
Cane (t/ha)	69	83	88	113	95	95	106
CCS	14.4	14.3	14.7	13.6	15.1	14.9	15.9
Sugar (t/ha)	9.9	11.9	12.9	15.3	14.3	14.2	16.9

The Q179$^{\phi}$ untreated- and BioCane™-strips were ploughed out in 2001 due to poor ratooning and heavy grub damage. Grub damage in the Q174$^{\phi}$ was not as high in comparison to the heavy damage suffered by the Q179$^{\phi}$. The Q174$^{\phi}$ sections were subsequently treated with Confidor® in late 2001; resulting yields are given in Table 6. Due to the gaps suffered by heavy grub damage in the plant cane, results reflect those recorded for the harvest of the plant crop; Confidor® is efficacious, but it cannot resurrect dead cane. As a result, it is no surprise that the suSCon® Blue treatment continued to perform the best. The take-home message is that spending money on the right inputs to meet the risk can and does pay a return.

Table 6 Results of Morley's Confidor® strip trial 2002; Confidor 200SC was applied at 1 L/ha in 2001

	Untreated 2000 2001	Untreated 2000 Confidor 2001	BioCane 2000 Confidor 2001	BioCane 2000 Untreated 2001	suSCon 2000 Untreated 2001
Cane (t/ha)	83	98	111	93	138
CCS	17.3	17.4	16.0	17.7	16.5
Sugar (t/ha)	14.3	17.1	17.7	16.4	22.8
Value of sugar ($/ha)[a]	3494	1492	4346	4028	5593
Difference less cost of Confidor	N/A	(-2169)	685	543	2009

[a] @ $245/t

Case study 5 - Vince Balanzategui, Stone River

Vince has 125 ha of assignment located on the alluvial flats and sandy terraces of the Stone River district. He feels that most of his farm is greyback-prone (80% plus), having experienced damage at some time in most blocks. The only exception is some heavy clay soil on his river flats. He has a regular regime of suSCon® Blue treatment. The first greyback damage in the current outbreak appeared in 1999. He feels that many people did not detect the increase in greybacks as their presence was masked by the severe rat damage that was occurring in much of the Herbert district in 1999. His damage peaked in 2001 with around 16 ha expressing greyback impact. Vince believes that he was lucky to avoid worse damage, but fortunately, he had all of his plant cane protected (constituting 16 % of the area of the farm), and his crop rotation had another 21% of the farm in fallow.

Vince confesses that he learned a lot in the recent outbreak. Certain varieties appear to be less tolerant of greyback pressure than others, and he may decide to plant more tolerant varieties in the future. He also learned that he needed more effective coverage of his suSCon® Blue in order to maximise its longevity and efficacy. He experimented with trap-cropping using an early-cut ratoon. Irrigation of the trap area in September when it was well advanced and late-cutting of the adjacent fields still did not result in a significant height difference between crops, and he feels this is the reason why the trap may have failed. Vince won't rush back into trap-cropping at this point.

Vince has been able to make protection of his plant crops a viable proposition. An example is given from a representative block of his 2000-2001 plant crop; even at the 2002 price he is covering his operational expenses (Table 7).

Table 7 Economics of treating Balanzategui's plant crop with suSCon Blue at two different sugar prices, $320/t in 2001 and $245/t in 2002

	2001 harvest results @ $ 320/t	**Hypothetical result @ $245/t**
Tonnes cane/ha	100	100
CCS	15.0	15.0
Income $/t cane	32.36	24.83
Production cost $/t cane	19.23	19.23
Gross margin $/t	**13.02**	**5.60**

Case study 6 - Victor Cervellin, Bambaroo

Victor has 95 ha on his home farm assigned to cane. There is a long history of greyback damage on this farm. Like many other farms in the Herbert, this damage is located around remnant rainforest areas along creek lines and on the slopes adjoining the range at the rear of the farm. Prevailing soil types are light sandy soils and red loams. Victor first observed damage in the current outbreak in 2000, principally in older ratoons.

His damage peaked in 2001 with 10.2 ha affected by greyback canegrubs. There is a regular regime of suSCon® Blue use on the farm. He applies it either at planting or at fill-in. Victor has also used Confidor® and BioCane™ in BSES trials as well as on a commercial basis. He will probably continue to use BioCane™ in low- to moderate-risk situations on his farm and will reserve Confidor® for valuable ratoons should they became prone to potential greyback damage.

Victor has attempted to use standing sacrificial trap-crops in two locations in the last season, but has found no success in doing so. This could be because of a natural decline of grub populations in his locality.

A strip trial comprising 1st Ratoon Q179(b) Q138 was harvested on 2 August 2002 (Table 8). The whole field had been treated with BioCane in 2000 and then with two rates of Confidor 200SC or left untreated in 2001. The crop was very drought-stressed with minimal canegrub damage, making interpretation difficult. No cane was lodged. The economic assessment clearly indicates that there is no advantage in applying Confidor® unless there is a good chance of greyback damage, along with sufficient crop yields and/or sugar price to justify its expense.

Table 8 Results of Cervellin's Confidor® strip trial 2002 – different rates in 2001 superimposed on BioCane treatment in 2000

	Q138 2 L/ha	Q138 1 L/ha	Q138 Untreated	Q179$^{\Phi}$ Untreated	Q179 $^{\Phi}$ 2 L/ha	Q179 $^{\Phi}$ 1 L/ha
Cane (t/ha)	54	59	59	58	55	54
CCS	14.2	14.3	13.6	12.7	14.4	13.7
Sugar (t/ha)	7.7	8.4	8.1	7.4	8.0	7.3
Value of sugar ($/ha)[a]	1887	2070	1975	1823	1962	1798
Difference less cost of Confidor	(-422)	(-72)	N/A	N/A	(-195)	(-192)

[a] @245/t sugar

Far North Queensland November 2002
By: Steve Garrad BSES Extension Officer – Innisfail

Case Study 7 - Viv Weinert, Mulgrave

Viv has two farms at risk from canegrubs; one beside the town of Fishery Falls (still the home farm), and the other near Aloomba that he acquired in the 1980s and calls Banna. He has a third farm across the Mulgrave River that is rarely damaged by canegrubs and he does not apply suSCon on some blocks.

Viv had Keith Chandler (BSES), Alan Morton (Mulgrave CPPB) and Frank Steene (Cane Inspector, Mulgrave Mill) at his farm discussing and preparing a grub management plan for him in 2000. The plan was later computer mapped by Gerard Puglisi of Mulgrave Mill. This was used as a training opportunity by Keith to develop the concepts used later in the series of *GrubPlan* workshops in 2001.

Viv's worst damage was in 2001. Much of it was in older ratoons of Q124 and Q113 on Banna where 10 to 15 t cane/ha were lost. The rest of the farm experienced moderate losses of about 5 t cane/ha. Banna has only the plant blocks relatively unaffected so about 70% of the farm has some level of grub damage. Fishery has 40-50% of the farm with some level of grub damage. 2000 and 2001 seasons had sizable patches and even plant Q181$^{\Phi}$ with suSCon® Blue on Fishery showed significant damage. A block of Q124 2R had six grubs/stool (including one tipped stool with nine grubs). As a result, Viv wanted details on how to use Confidor®.

Viv implemented a plan to manage greyback grubs on his farm. Monitoring by Gerard Puglisi of Mulgrave Mill supplied considerable data. Viv refers to these often, including where Confidor® had been applied to see whether the practice reduced grub numbers. However, it represents a lot of data that is also confusing. There were 8 blocks checked on the farm in 2000, 15 in 2001 and 1 in 2002. Low numbers were found in each block, especially on the Fishery farm. Viv believes that, by referring to monitoring results, he is able to map his risk in the next season. Generally though, Viv is not demonstrating any greater keenness to look for grubs (or indications of their presence) than any other farmer. There was no further monitoring after Mulgrave Mill ceased the service. Viv has limited time and the apparent decline of the pests made monitoring a low priority.

In addition to using suSCon® Blue and Confidor®, Viv had several trap crop options across a range of varieties highlighted on his plan. He applied extra urea &/or molasses, cut in the first round (or cut late but beside fallow), and sometimes put on extra irrigation, in an attempt to make the cane significantly more advanced. Confidor® was applied in most of the trap crops. Unfortunately the dry season of 2001 followed by low grub pressure in 2002 resulted in little difference between the trap crops and adjoining cane. Viv is aware of how he can inadvertently set up some blocks as trap-crops with early planted/harvested cane (especially Q174[(b)]). In particular, the Fishery farm has several blocks that are alongside (and even surrounded by) fallow land. These are being considered for Confidor® treatment this year, even though Viv has concerns with being able to afford the chemical. The Banna farm also has early-harvested old ratoons that are potentially a trap/at risk. Since there is only one more crop from these fields, they are not worth treating. Forage sorghum is not an option that Viv wishes to attempt.

Viv contracted another grower (Yusaf Mohamed) who had an excellent set-up in his tractor for 2-row Confidor side-dress application. Applying suSCon® Blue at fill-in is another job to do, at a time when Viv is looking to do less in the cane, and his machinery does not modify easily for the task. He was advised in the discussion to dig in his first ratoons to measure the depth to the band of suSCon® Blue to check that the placement is correct before committing himself fully to the system.

Viv is reviewing how to treat blocks of moderate risk and sees a potential for BioCane™. Since most of the worst-damaged blocks are in older ratoons, Viv intends to put these blocks into fallow rather than plough out and replant.

One conclusion reached with Viv is that each grower needs to annually monitor for grubs in a reasonable proportion (e.g. 75%) of valuable blocks that may be at risk, such as 2nd ratoon, and perhaps a lesser proportion of each other crop class, depending on the management options available. However, since growers do not attach a priority to monitoring pests, growers may need a service of someone providing them with an annual nucleus of information with the grower then responsible for filling-in the gaps. There has been no follow-up of Viv's management plan in 2002 (though feedback will be achieved in the 2003 *GrubPlan* series). Vic felt that this could become part of a formal service if people are prepared to pay for it.

Case Study 8 – Alf Nucifora, Murray Upper c/o Tully

Alf attended the first discussions on canegrub control in August 2001 run by Derrick Finlayson, Tully BSES. This was one of the earliest versions of *GrubPlan* and did not have individual farm mapping and planning unless requested. The initial *GrubPlan* workshop worked through a group model. Tully held a *GrubPlan* review in February 2002 which Alf also attended and this was where he actually used farm planning as a decision tool in canegrub IPM. One management plan was developed for Alf's individual situation at the review in early 2002.

The farm has previously suffered some damage from both greyback and French's canegrub, but not enough for Alf to commence using suSCon® Blue. Damage levels increased to impact heavily in 1999 when Alf ploughed out 12 ha acres of second ratoon

cane and cut the remainder of damaged cane as late as possible. He admits the late harvesting of damaged cane made little difference and production continued to fall, dropping from 12000 t cane to 8000 t. The damage appeared to be widespread over the farm with no apparent pattern. Alf's farm is an indicator of grub presence in the district due to its elevation in the landscape and proximity to feeding-trees.

Alf quickly included suSCon® Blue into his planting program after the high damage of 1999. Alf generally continues to use late harvesting of the areas with a history of grub damage.

Alf came to the *GrubPlan* workshops aware of the research being done on grub control and hoping that there would be a new product that would prevent such losses in productivity.

Alf believes that the blocks planted and harvested earliest are the ones at highest risk. The blocks on the flats are planted to early maturing varieties and subsequently harvested early in the season. The blocks higher up the slope where damage is concentrated are being planted to later maturing varieties and harvested later in the season.

Alf is prepared to monitor for beetle flights (mostly by observing what is attracted to his backdoor light at night) and monitor for grubs including digging in the cane after Christmas and walking through the plant cane and looking for gaps. He now tries to manage the risk rather than aim for complete annihilation. This includes careful planning to set up some cane (Q174[Φ] suitable for early harvesting) as a trap crop, which will be surrounded by a legume fallow or late-cut cane. The parts of the farm most at risk (due mostly to time of harvest) are usually the next to be fallowed. Alf is becoming more confident that he can move the pattern of grub damage around on his farm. Early planting is still preferred for maximising production and replanting is avoided, but where it is necessary it is completed as early as possible.

Of the insecticides, Alf will continue to use only suSCon® Blue. He believes it works well for him and that it is worth the (considerable) expense. One of the first Confidor® trials in the area was on his farm by the productivity services and BSES. The results did not convince Alf that it was worth the investment in his ratoons at the current sugar price (while it remains at or below $250/t sugar). The application technology for Confidor® also seems too time-consuming, conflicting with his other major farming activity (watermelons).

Bio-Cane™ was also trialled on Alf's farm but the product's expense and handling requirements have not encouraged him.

The damage Alf suffered in 1999 and 2000 added up to 4000 t cane lost which translated to about $180000 over the two years. By spending about $14000/year on suSCon® Blue, Alf is confident that he is well on the way to getting his productivity back to 12000 t cane/year. This season, when the grub pressure is low, Alf sees the expense as insurance that he will budget for and not cut back on. By easing out of the huge replant situation he was in after the grub damage, Alf can afford the expense of using suSCon® Blue to protect the cane.

Case Study 9 – Steve Ah Shay, Innisfail

Steve has three adjoining farms in an area near Innisfail known for its high risk of canegrub damage. While the whole farm is seen at risk (about 124 ha), about half the farm is at a higher risk with mapping of actual damage over the last 5 years covering about 35 ha. Steve lost over 4000 t of cane to the pest in the 2001 season, dropping from 11800 to 7700 tonnes of cane with a drop in CCS of nearly a unit. Steve's worst-affected blocks in 2001 were older ratoons of Q127 and early ratoons of Q135 where 15 to 25 t of cane/ha were lost. The rest of the farm experienced moderate losses of about 5 t cane/ha. There is about 40% of the farm with some level of grub damage and almost all of this is under ratoons, some of which are to be ploughed out and replanted or fallowed within a year.

Steve participated in the first round of *GrubPlan* Workshops in 2001. Confidor® was a new chemical and Steve wanted to have the option of applying it to his farm. Steve attended the *GrubPlan* review a year later in (2002) to learn more about canegrubs and any further developments. The plans developed by Steve were used to some extent on his farm. Steve observed, however, that few growers follow any plan completely because many other factors go into making decisions on the ground on a daily basis.

Steve normally applies suSCon® Blue at the time of planting (around the setts) and believes that it is much better for his situation than applying at fill-in. However, Steve did not apply suSCon® Blue to any plant cane this year. Confidor® was applied to specific parts of the crop last season. The use of the chemical has yet to prove to Steve that the benefits from its use outweigh its cost. No Confidor® will be applied this year.

Steve has observed beetle preference for higher cane. Cane that was cut early (such as where a break was cut for later harvester access) often showed obviously greater levels of grub damage. Other factors such as weather, variety and soils come into consideration also. Q127 shows the damage worst on Steve's farm, with Q135 the next most susceptible cane. Damage is usually not associated with nearby feed trees (several clumps of fig trees and coconut trees are dotted about the farm).

Steve has had several blocks set up as trap crops across a range of varieties. These were either old ratoons to be ploughed out later, or sections cut in the first round with Confidor® applied. He sees their use as opportunistic at present, to be used when other things (such as growing conditions, block history, age of ratoons) look favourable in achieving markedly advanced growth over surrounding blocks. Steve is keen to see more work done on trap cropping as a means of killing as many canegrubs as possible. The dry season of 2001 followed by low grub pressure in 2002 showed little difference between the trap crops and adjoining cane.

Steve monitors by observing the numbers of adults flying at this time of year. Steve has seen low numbers of greyback beetles from early this November. The BSES office conducted some digging for grubs early this year, showing higher numbers in the old ratoon trap crop (1.2 grubs/stool) than in the surrounding younger cane (0.7 grubs/stools). However Steve is not interested in sampling for grubs himself. Steve has limited time and the apparent decline of the pests makes monitoring a lower priority.

Central Region 17-18 October 2002
By: Warren Hunt IPM Coordinator BSES

Case study 10 - Fritz Attard, Eton

Fritz has a cane assignment of 165 ha. Around 10% of his farm is prone to greyback impact, principally on sandy alluvial soils and light clays. Fritz first saw signs of greyback damage in 1998 and it has been increasing steadily in area and intensity on his and neighbouring farms since then. He has been successfully using suSCon® Blue since 1999, but prior to that had no need to use any form of plant cane protection. He has participated in *GrubPlan* workshops and has also used Confidor® to successfully protect some vulnerable young ratoons.

Fritz is also trialling trap-cropping in a fallow block of 5.6 ha that recently suffered heavy greyback infestation. He is using Jumbo® and Superdan® forage sorghum and Jap Millet, and intends to bale the crop before seed-set in January for hay. This will be sold onto a lucrative drought market. The area will then be ploughed in and fallow-planted May-June with suSCon® Blue protection.

Fritz has confidence in the behaviour of beetles to move into advanced crops. He saw a recent situation where a plant source area cut in April 2001 was badly damaged in 2002 because as it was much more advanced during the beetle flight period.

In 2002, Fritz harvested his own Confidor® demonstration trial (unreplicated). Yield was much greater where Confidor was applied, 131 t cane and 22.4 t sugar, than in the untreated area, 102 t cane and 17.0 t sugar.

Fritz has attended *GrubPlan* workshops for the second year running, and sees value in developing a plan, principally because it offers an opportunity to achieve a level of management whilst minimising costs.

Case study 11 – John Hemmens, Proserpine

John operates a 5000 t assignment on 72 ha, at the southern end of the Proserpine mill area. John has been farming for 12 years and had no prior experience with greyback canegrub impact or management prior to 2001. On reflection, he had seen signs of possible grub build-up with an over-abundance of bandicoot diggings in 1999-2000. In 2001, greyback canegrubs affected around 18 ha of his farm, reducing cane production by about 1000 t. Most this damage was located within 300 m of riparian areas, namely the O'Connell River. On consulting his father-in-law he learnt that this farm had seen serious damage in the past within the same general area.

John attended a *GrubPlan* workshop in 2001. He strongly believes that if he had not sought professional advice through the *GrubPlan* process he would be in a much worse position. John is only seeing limited indications of greyback damage on his farm in isolated locations. John believes he had received a lot of poor advice from neighbours regarding the pest, and the capabilities of the different management tools available. He

feels that the knowledge he gained about the lifecycle and behaviour of the pest in the *GrubPlan* training was critical in making effective management decisions.

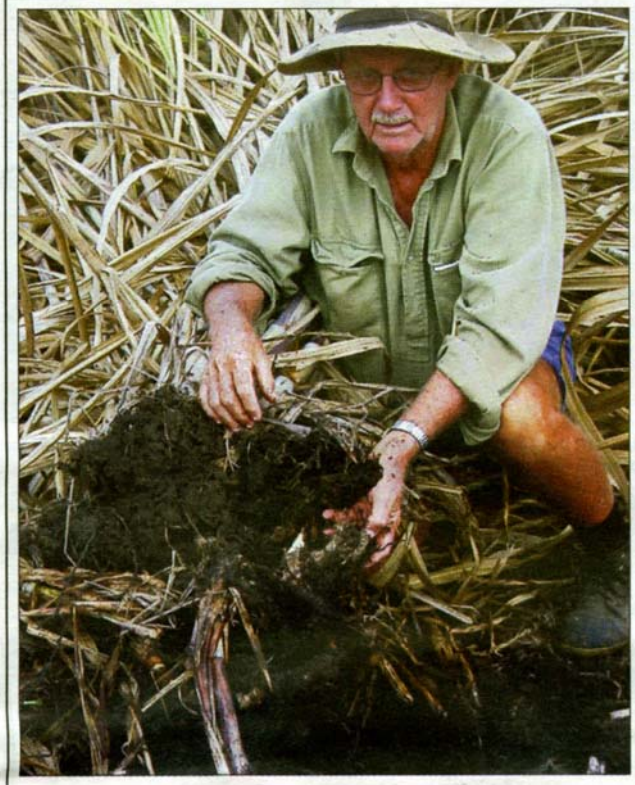
Understanding beetle behaviour has helped John understand why areas he has cut early for plant source in the last two seasons have incurred greater damage. Additionally, the bulk of his damage in 2001 was located on the mid-slopes with Q138, an aggressive ratooning variety.

John used suSCon® Blue as his principal management tool. He applied the treatment both at the planting and fill-in stages. He prefers application at fill-in though he admits he has not seen any differences between treatment types. John applied suSCon® Blue to every block of plant cane on his farm in 2001. In retrospect he admits he probably did not need to treat such a large area and is intending to rationalise suSCon® Blue treatment to prone riparian areas only.

John is also considering a change of varieties in prone areas, i.e. going for cane with a good solid stool that is also later maturing, hence trying to avoid an early-cut situation in his prone fields. John also used a plough-out trap-crop in his most vulnerable area on his farm. He deliberately cut two small blocks (approximately 1 ha total) early in 2001, and watered them so that they would be well advanced compared to adjacent cane during the beetle flight periods. In mid-January he sprayed the blocks out with glyphosate, and then ploughed the area out some four weeks later. The ploughed area yielded a vast quantity of greyback grubs (identified by John after consulting his *GrubPlan* manual). He feels that he can strategically employ this method in the future to trap and destroy greyback canegrubs in his prone fields.

APPENDIX 3 – MEDIA RELEASES

MACKAY BUSH Telegraph
FOR FARMERS & CONTRACTORS PHONE 07 4957 0405
Tuesday, May 4, 2004 Email: bushtelegraph@dailymercury.com.au 50 cents



Grub numbers up

CANE grower Stan Durnsford inspects greyback cane grub damage at his Wagoora property last week. The BSES is alerting growers to increased numbers of grubs and beetles in Mackay district cane fields this year. Story, Page 4. Picture: Contributed.

On The **Land**

Growing concern for greyback grubs

GREYBACK canegrubs are making a comeback.

And all signs are pointing towards this year being a bad one.

BSES Limited's senior entomologist Peter Samson said canegrubs had been increasing in the Mackay district for the past few years.

"BSES is working to develop a forecasting system for greyback so growers can take preventative action early.

"The system is not yet fully developed, but the signs are disturbing locally," Mr Samson said.

"We have been monitoring grub numbers in a set of fields throughout central and northern Queensland."

There are 16 fields being monitored in the Mackay-Sarina area, with 20 stools dug from each field, each year.

Last year the number of grubs in the local fields averaged 0.2 a stool; this year the average is 2.4, with some fields averaging more than 10 a stool.

"These fields were not randomly chosen throughout the district. They were chosen on farms with a history of greyback, so some greybacks were expected. However, the massive increase since last year is a concern," Mr Samson said.

"Reports are also coming in from field staff and growers that there is a lot of greyback damage around."

Mr Samson said for growers, it was too late to get rid of the grubs in infested fields.

"But some decisions will need to be made soon, such as when should fields be cut? And, should suSCon Blue be applied to plant crops?

"There will be other decisions later in the year, like should fields be ratooned, replanted or fallowed? Should ratoon crops be treated with Confidor and, if so, which ones?"

Good decisions would only be possible if growers knew which of their fields were infested, because these fields were the ones that would produce beetles at the end of this year and then give rise to next year's infestations, in the same fields or in fields nearby.

"So, a slow drive around the farm at this time of year is very worthwhile. Stools that are looking poor, yellowing or tipping should be checked. If a grower can pull the stool out with his hand, then grubs are the likely culprits," Mr Samson said.

"Check the roots and stubble — pruned roots and gouged stubble are a real give-away. Growers will also find grubs at shallow depth until mid to late May. "Dig out a few stools with a shovel. Mark on a farm map where grubs and damage are found, so that this information can be used in planning later in the year.

"A key point is to not just look at fields where the damage is obvious. Early signs of damage are more subtle, but indicate a developing problem that shouldn't be ignored."

Bush Telegraph 17 May 2004

Grub monitoring in district's fields

GREYBACK canegrubs have been on the increase in the Mackay district in the past few years.

BSES Mackay has been monitoring a group of fields in the central region, and grub numbers in these fields are higher than in 2003.

Farmers have a range of control options for greyback in both plant and ratoon crops.

These are used in a preventative fashion, so advance warning of grub outbreaks is an advantage, allowing farmers to put control strategies in place before they get out of hand.

Identifying at-risk fields is vital, particularly now when the sugar price is low relative to the cost of treatments.

Determining the presence of grubs:

Look for damage symptoms and give suspect stools the "pull test".

Dig underneath stools and look for grubs or root pruning after harvest by inspecting ratoon stools beside gaps for root loss and for gouging on stubble.

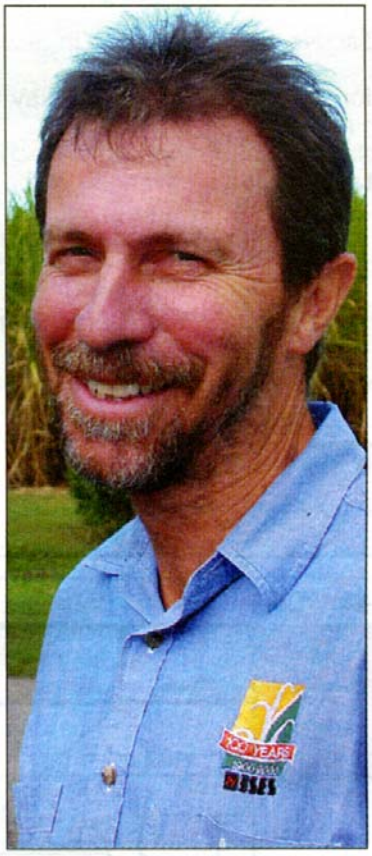
BSES Mackay is involved in two greyback canegrub projects:

❑ To develop a forecasting and risk-prediction model so that grub treatments can be targeted to high-risk years and high-risk fields.

The aim is to spend money on grub control when needed, and conversely, to not spend money when it is not needed or when the return will not justify the expense.

❑ To assess the risk of grub infestations and to develop appropriate treatments for fields planted to new farming systems (legume rotations, controlled traffic, minimum tillage planting).

Information on these projects will be available at the field day. — DR PETER SAMSON.



DR PETER Samson, senior research cfficer.

Sugar Times 25 May 2004

Grubs up for farmers

Instances of grey back grub damage are increasing around the Central District, with the BSES and other groups out to inform growers how to control them and determine why they are so prevalent.

BSES Senior Entomologist Dr Peter Sampson said reports from growers around the area indicated the infestations did seem to be higher this year than last.

While he said it was too late to do anything about the grubs that were already in the cane, positive steps could be taken to avoid the pests next season.

"Any grubs that are in the cane now will be hungrily feeding - what's important is for growers to inspect their land and identify which areas are infested and take action following the harvest," Dr Sampson said.

He added the BSES was currently working on a forecasting model, which may explain why the grubs are worse in some years than others.

"There is a range of factors that come into play with the grubs - whether the cane is plant or ratoon plays a part. Part of it could also be environmental, but we are not definitely sure."

A number of workshops on how to manage the grubs will be held this week, with the first at the Gargett Bowls Club at 8am on May 27, followed by the North Eton Bowls Club at 1pm and the Mt Ossa Community Hall at 8am on May 28.

Guest speakers include Dr Sampson, Pat English of Bayer and Andrew Horsfield of Crop Care.

• *Stan Durnsford inspects grub-damaged cane near Wagoora.*

APPENDIX 4 – GREYBACK FORECASTS FOR MULGRAVE MILL AREA

Mulgrave Cane News

NO. 10 SEPTEMBER 2003

BSES
Sugarcane for the future

Manager – Field & Productivity	Trevor Crook	4043 3362	0418 196 340
Field Officer	Alan Hopkins	4043 3342	0408 877 641
Field Officer	Allan Morton	4043 3390	0419 738 441
Field Officer	Richie Falla	4043 3390	0417 566 803
Field Officer	Frank Steene	4043 3342	0409 491 298
Senior Extension Officer	David Calcino	4056 1255	0419 679 472
Extension Officer	David Wallis	4056 1255	0407 968 572

'SUGAR PRODUCTION IS AS MUCH A LOGISTICAL BUSINESS AS AN AGRICULTURAL BUSINESS'.
(Mike Clowes – Swaziland Sugar Assoc.)

WITH THE COST OF HARVESTING AND TRANSPORT OF CANE APPROACHING THE COST OF CANE PRODUCTION ITSELF, THERE HAS NEVER BEEN A BETTER TIME TO SEEK WAYS TO IMPROVE HARVEST EFFICIENCY. AS A RESULT, HARVEST PAYMENT SYSTEMS ARE COMING UNDER THE SPOTLIGHT.

There has been industry-wide interest in adopting a harvest payment system that reflects the actual cost of harvesting each farm or block. This interest has grown from the need to introduce incentives, which more closely reflect commercial reality.

One payment system, which has been adopted by some operators in the industry, pays a lower base-harvesting price with an actual fuel cost added on. This system rewards efficient operations and farming practices that reduce fuel usage such as improving farm layout and/or haul roads.

The hourly rate system is also under consideration throughout the industry. Similar to most other contract machinery businesses, this system also rewards growers for improving their on farm harvest efficiency.

For three seasons now the Rossi harvesting group has adopted a payment system that applies a sliding scale to the standard flat price per tonne contract rate. For example, farms that yield 80t/ha will pay the standard price per tonne. The contract price per tonne is varied with the average yield for each farm. Put simply, the higher the yield (up to 100t/ha) the lower the harvesting price and the lower the yield the higher the harvesting price. This system recognises that harvesting costs are lower in bigger crops and much higher when crops are poor.

With every system there are advantages and disadvantages (the current system included). However a payment system can be tailored to the needs and characteristics of each harvesting group. This is a matter entirely between the contractor and growers. However there has never been a greater need to introduce incentives for efficient practices.


Mark, Chris & Tony Rossi of Rossi Harvesting discuss the harvest payment scheme with grower Robert Rossi Jnr.

GREYBACK CANEGRUBS – WILL THEY BE VISITING YOU THIS CHRISTMAS?

It was reported in the May *Mulgrave Cane News* that canegrub numbers appeared to be low in the 2003 crop. It seems that this assessment was a little premature for some areas and the Deeral and Aloomba districts in particular. However the important question to address is the likely infestation in each block during the 2004 wet season.

Now that the harvest is past the half way mark, growers and field staff are able to properly assess the trends in grub damage and populations. This is a critical step in the process of cost effective grub management. The table on the back of this newsletter aims to provide farm managers with an indication of the trends in their local area and the likely infestation risk for the 2004 crop. Farm managers should consider this advice in conjunction with the enclosed ***Grubplan – Risk management and planning guide*** to plan their grub control program for future crops.

In 2003 canegrubs devastated farms not previously known to be grub prone. Don't be complacent, keep a watch for the early signs of a change in greyback activity and adopt the management practice appropriate to the situation.


A HBM bean seeder mounted on a fertilizer box

INDUSTRY SEEKS EMERGENCY USE PERMIT FOR CONFIDOR®

Confidor®, the liquid insecticide previously used to control greyback canegrubs in ratoons is currently awaiting full registration. However the window of opportunity is closing as the ratoons get too big for coulter application. Industry representatives have decided to apply for an emergency use permit to maintain access to this important canegrub management tool. Success of the application is uncertain at this stage and growers are advised to check with the field office or BSES before using this product.

FALLOW MANAGEMENT STRATEGIES

With the sugar price for 2003-2004 looking to be low for a second consecutive year growers are continually looking to reduce costs further. An opportunity to reduce costs by spraying-out the cane crop with a Glyphosate based product is an option worth considering. Some growers will be reaching the plough-out round within their sequence in the next month or so and it is now time to consider fallow management strategies.

The practice of spray-out greatly reduces erosion and soil runoff from fallow land. Despite some of the sensational media reports regarding damage to inshore reefs some growers are significantly reducing the risk of erosion and combining the practice with direct drilling of legumes into the old stool area.

This technique delivers the double advantage of reducing the risk of erosion from fallow land whilst enjoying the well-known benefits that legumes provide. Further savings can be achieved by reducing fertilizer costs in the plant crop due to nitrogen fixed by legumes.

Pictured left is a relatively cheap modification of a HBM bean seeder mounted on the back of a fertilizer box. After the cane is sprayed out soybeans are direct drilled behind coulters through the trash blanket either side of the stool.

Increased adoption of legumes into the farming system can only support cane farmers efforts to conduct environmentally responsible management whilst remaining profitable and sustainable.

GREYBACK CANE GRUB THREAT FOR THE 2004 CROP BY DISTRICT

NOTE:- Monitoring refers to 1) Beetle flights, 2) Grub number per stool (Feb to April) and 3) Cane and stool damage observed during the harvesting season.

FOCUS GROUP	District	Current Status	Risk trend for 2004 Crop	Comments
		(Low - Moderate - High)	Increasing - Static - Decreasing	
NORTH BARRON	***West Cairns / Redlynch***	Low	Static	Some farms with no insecticide (suSCon) use. Monitor the most susceptible blocks for early signs of infestation.
	Barron Delta	Low	Static	Nil insecticide (suSCon) used. Monitor the most susceptible blocks for early signs of infestation.
PINE CREEK	***Pine Creek***	Low - Mod	Increasing	Damage likely to occur in unprotected blocks. Maintain monitoring and adopt integrated grub management program
GREENHILL	***Greenhill***	Low - Mod	Static	Reduction of old ratoons has contributed to the decreased infestation. Due to recent history, management practices and monitoring should be maintained
INLET	***Lower Wrights Ck***	Low	Static	Monitor for early signs of infestation on lighter soils in unprotected blocks.
	Redbank	Low	Increasing	Early warning call for farms with patches of lighter soils and no recent history of insecticide (suSCon) use.
SANDY CREEK	***Sandy Creek***	Mod	Static	Due to history of damage, management practices should be maintained. Ie:- Maintain monitoring and adopt integrated grub management program
HIGHLEIGH	***Highleigh***	Low	Static	Monitor for early signs on lighter soils in unprotected blocks.
MACKEY CREEK	***Mackey Creek***	Low	Static	Monitor for early signs on lighter soils in unprotected blocks. Especially adjacent to creeks and feeding trees
MERINGA	***Meringa***	Low	Decreasing	Reduction of old ratoons has contributed to the decreased infestation. Due to recent history, management practices and monitoring should be maintained
SAWMILL POCKET	***Sawmill Pocket***	Low	Static	Due to history of damage, management practices and monitoring should be maintained
BEHANA	***Behana Gorge / Quingilli***	Mod	Static	Due to history of damage, management practices and monitoring should be maintained. Ie:- Mitigate the damage using an integrated grub management program.
ALOOMBA	***Mulgrave Flats***	Low	Static	Monitor for early signs on lighter soils in unprotected blocks.
	Kenny rd and Bennett rd localities	Mod - High	Increasing	Damage likely to occur in unprotected blocks. Maintain monitoring and adopt integrated grub management program
	Banna	Low - Mod	Static	Damage likely to occur in unprotected blocks. Maintain monitoring and treat accordingly
LITTLE MULGRAVE	***Red soil***	Low	Decreasing	Due to recent history, management practices and monitoring should be maintained
	Alluvial soil	Low	Increasing	Damage may occur in unprotected blocks. Maintain monitoring and treat accordingly
SOUTH MULGRAVE	***Deeral***	Mod - High	Increasing	Damage likely to occur in unprotected blocks. Maintain monitoring and adopt integrated grub management program
	Fishery / Mt Sophia	Low - Mod	Static	Management practices and monitoring should be maintained. Ie:- Maintain an integrated grub management program.

Unprotected blocks - Blocks with no suSCon applied or older than 2nd ratoon

Mulgrave Cane News

No. 12 October 2004

Manager - Field & Productivity	Trevor Crook	4043 3362	0418 196 340
Field Officer/Transport Coordinator	Alan Hopkins	4043 3360	0408 877 641
Senior Field Officer	Richie Falla	4043 3342	0417 566 803
Field Officer	Gerard Puglisi	4043 3307	0428 671 529
Field Officer	Frank Steene	4043 3342	0409 491 298
Senior Extension Officer	David Calcino	4056 1255	0419 679 472

BSES
Sugarcane for the future

Greyback Canegrubs – What risk do they pose to your next crop?

Now that the harvest is nearing completion, growers and field staff are able to properly assess the trends in grub damage and populations. This is a critical step in the process of cost effective grub management. The table on the back of this newsletter aims to provide farm managers with an indication of the trends in their local area and the likely infestation risk for the 2005 crop. Farm managers should consider this advice in conjunction with their own observations and plan a grub control program for future crops.

We all know the devastation that canegrubs are capable of and the economic loss which can result. Don't be complacent, keep a watch for the early signs of a change in greyback activity and adopt the management practice appropriate to the situation.

The sugar industry now has access to a range of insecticides. Each of these products has its strengths and weaknesses and is best used as a component of an integrated management plan for each farm. Don't hesitate to consult the advice of Productivity Services, BSES, Bayer or Cropcare staff when constructing your management plan.

New Canegrub Insecticide Registered for Sugarcane

(Article by Mitchell Faint, Research and Development Specialist - Bayer CropScience 0408 264 539)

The Australian cane industry now has full registered access to the world's biggest selling insecticide, Confidor. Since the active ingredient in Confidor, (imidacloprid) was first discovered by Bayer it has become very extensively used in agriculture throughout the world. For sugar cane, Confidor will be available in two formulations; as a controlled release (CR) granule for use against greyback grubs in plant cane, and as a liquid for application into ratoons against greyback and Childers grubs.

The controlled release granules will be marketed as **Confidor CR granules by Bayer CropScience and as SuSCon Maxi by Crop Care** after a joint development program by the two companies to speed up a solution for a developing crisis in canegrub management. Confidor CR applied in plant crops will provide two years control and is **not** affected by high soil pH nor accelerated biodegradation conditions in the soil. The **liquid formulation, Confidor Guard** gives a solution in ratoons for the first time, providing one seasons control. Registration for Confidor CR, Confidor Guard and SuSCon Maxi has been approved in the last few months.

The slow release granule can be applied after planting in a very similar manner to currently available granular insecticides, at either the first working stage, at cutaway or at drill fill-in. Current granular insecticide application equipment can also be used with generally a minor adjustment to the flute rollers only. For microband boxes, an 18 paddle roller is recommended and are available free from your local reseller. The granule is applied at 15 kg/ha as a standard rule, with a lower rate of 10 kg/ha suitable only for low risk areas.

The new granular CR products (Confidor CR & Suscon Maxi) are different in many ways to the organophosphate chemicals which have been in use in SuSCon Blue and SuSCon Plus. Grub control using the old chlorpyrifos products requires accurate placement as canegrubs had to come into direct contact with the chemical in the soil. It is also critical with these products to ensure adequate soil cover so that losses through volatilisation doesn't waste product unnecessarily. In soils with high pH, results can be compromised.

In contrast, Confidor CR/Suscon Maxi is suitable on both alkaline and acid soils, without the need to add acidifying fertilisers for high pH soils. The active ingredient has practically no losses into the vapour phase so volatilisation issues do not exist for these products. The new imidacloprid based CR products (Confidor CR granules or SuSCon Maxi) can provide more flexibility in grub control as the active is able to move short distances through the soil and is also plant systemic so that it can be taken up into the cane roots. This means that Confidor CR/Suscon Maxi can control canegrubs by ingestion of treated soil and roots as well as by direct contact in the soil. It can also have a dramatic anti-feeding effect on the grubs resulting in reduced feeding on cane roots. The infected grubs do not gain weight and do not appear to successfully develop into beetles.

Yield responses in field trials have been exceptional with the CR products and also with the Confidor Guard applications in ratoons.

Ideal conditions to knock out Guinea Grass

Ratoon stools of Guinea Grass can rob vital nutrients and moisture from sugar cane and cause harvesting problems later in the year. The weather conditions currently being experienced (i.e. hot and dry with low humidity), present an excellent opportunity for growers to carry out some effective control measures. A tank mix of Daconate® and Diurex 900WG® at 3.0 l/ha and 2.0 kg/ha respectively, has been shown to provide effective control of ratoon stools of guinea grass in cane. A repeat application will be necessary 3-4 weeks after the initial application for best results.

Mitchell Faint of Bayer CropScience explains to growers the results of a Nutgrass herbicide trial on the Mill farm

GREYBACK CANE GRUB THREAT FOR THE 2005 CROP BY DISTRICT

NOTE:- Monitoring refers to 1) Beetle flights, 2) Grub number per stool (Feb to April) and 3) Cane and stool damage observed during the harvesting season.

FOCUS GROUP	District	Current Status (Low - Moderate - High)	Risk trend for 2005 Crop Increasing - Static - Decreasing	Comments
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HIGHLEIGH	***Highleigh***	Low	Static	Monitor for early signs on lighter soils in unprotected blocks.
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SAWMILL POCKET	***Sawmill Pocket***	Low	Static	Due to history of damage, management practices and monitoring should be maintained
BEHANA	***Behana Gorge / Quingilli***	Mod	Increasing	Due to history of damage, management practices and monitoring should be maintained. Ie:- Mitigate the damage using an integrated grub management program. Untreated blocks / farms may result in increased damage.
ALOOMBA	***Mulgrave Flats***	Low	Static	Monitor for early signs on lighter soils in unprotected blocks.
	Kenny rd and Bennett rd localities	Mod	Static	Due to history of damage, management practices should be maintained. Ie:- Maintain monitoring and adopt integrated grub management program
	Banna	Low - Mod	Static	Due to history of damage, management practices and monitoring should be maintained
LITTLE MULGRAVE	***Red soil***	Low	Decreasing	Due to recent history, management practices and monitoring should be maintained
	Alluvial soil	Low	Static	Damage may occur in unprotected blocks. Maintain monitoring and treat accordingly
SOUTH MULGRAVE	***Deeral***	Mod	Static	Management practices and monitoring should be maintained. Ie:- Maintain an integrated grub management program.
	Fishery / Mt Sophia	Low	Static	Management practices and monitoring should be maintained. Ie:- Maintain an integrated grub management program.

Unprotected blocks - Blocks with no insecticide applied or older than 2nd ratoon

APPENDIX 5 – BULLETIN ARTICLES AND FIELD DAY POSTERS

BSES Bulletin issue 2: 2004, pp. 9-11.

Chemical and biological weapons – saving money while managing canegrubs with insecticides

> Peter Samson

Insecticides are only one component of successful canegrub management. However, they represent a major weapon in the arsenal - and they are certainly among the most expensive. With sugar prices currently low, many farmers are looking at ways to reduce insecticide costs. In this article, Dr Peter Samson helps you ask some questions about your own farm situation to see how you can manage the risk of canegrub damage as inexpensively as possible.

Weigh the risks, enjoy the benefits

Insecticides are like insurance. Striking the right balance makes sound economic sense: you want to make sure you have a good idea of the genuine value of what you're insuring, sensibly appraise the risks it's facing, and find a policy that will protect it with premium payments that aren't going to break the bank. To protect your crop against canegrub damage, you have to appraise accurately the value of the crop against the risk of attack for each field. Studies show that it is possible to identify quite accurately the years and fields most likely to be at risk, provided that relevant monitoring and risk-assessment are carried out.

There are two key issues to think about when considering the chemical component of your canegrub management plan:

1) Will the return justify the expense? That means spending money if you need to, and *not* spending it if you don't have to!

2) If you do need insecticides, ensuring that you get the most from them by making certain that conditions are right for the products to be effective.

Planning according to risk

Greyback canegrubs

From Sarina north, greyback canegrub is the grub of greatest concern to sugarcane growers. After a couple of years with only low levels of damage from this pest, in 2004 we are noticing that the presence of grubs and damage is rising. In districts where this trend has begun, damage is likely to get worse if farmers do not protect plant cane that is at risk, or if they keep old ratoons that are now unprotected and showing initial signs of damage.

Which plant cane fields should be treated for protection against greybacks? Replant fields that suffered grubs in the last crop cycle, or fields that are near infestations in neighbouring fields, are at high risk of grub attack. The more infested crops nearby, the greater the risk. Early, fallow-planted fields are especially vulnerable. Plant cane fields at high risk should be a priority for treatment with suSCon® Blue or an alternative.

Extra yield (tonnes cane) and revenue from application of suSCon® Blue in four trials in far north Queensland.

Increase plant crop (t)	Increase first ratoon	Total increase (t)	Increased revenue / ha @ $210/t sugar
12	31	43	$572*

**Cost of suSCon® Blue has not been deducted.*

Note the large benefit in first ratoons, partly as a flow-on from reduced damage in the plant crop. It is still worthwhile treating with suSCon® Blue at low sugar prices, provided that high-risk crops are correctly identified.

Canegrubs can devastate crops if left unchecked, leading to poor yield and forced plough-out. Stan Durnsford shows this crop north of Mackay has been attacked by greyback grubs.

But does the whole field need treatment? Grubs are usually worst in free-draining, loamy soils, so if there is also a heavier, slower-draining soil in a section of the block, or if history shows that parts of a field tend not to attract grubs, then the applicator could be turned off in those sections. Experience in Mackay, Ingham and the far north has shown that damage often starts in parts of fields nearest to creek lines. Treating only these sections is a cost-saving option in hard economic times.

It is possible that Confidor® Guard will be registered and available for greyback canegrub control in ratoons this year. Consider applying Confidor® Guard to young ratoons if grub damage is beginning to appear in a field, because experience suggests it will only get worse. Also consider Confidor® Guard if there are bad infestations in one or more adjacent fields. The risk is higher if the ratoons are from early-harvested blocks. However, it is not worth trying to protect badly damaged or weakly growing, old ratoon fields because the income they generate won't justify the cost of the treatment. Confidor® Guard should only be considered when protecting productive ratoons that you intend keeping for two years or more.

Other species of canegrubs

The risk posed by negatoria and French's (frenchi) grubs is currently low. Being two-year grub species, numbers build up more slowly than greybacks. If damage from either of these grub types has not been seen on your farm recently, or if it is very isolated, then treatment of plant cane against these grubs could be wound back.

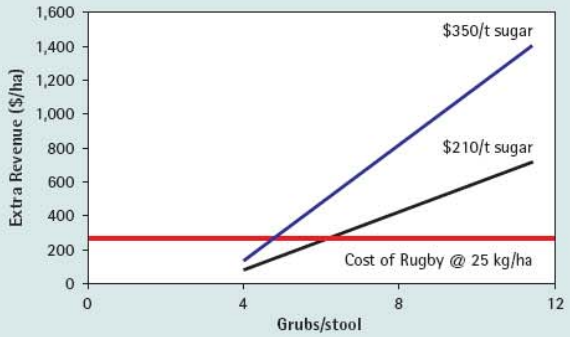
If grubs appear in ratoon crops, Rugby® 100G is a control option that you can consider for some species. A needs-only treatment is possible for negatoria, southern one-year and Childers canegrubs in southern Queensland. Near Mackay, many of the frenchi-type grubs are actually negatoria and can be treated with Rugby® as well.

Rugby® is a knockdown treatment that can be restricted to sections of fields where grubs are known to be present - but timing of treatment is critical to success. Damage by negatoria and Childers grubs usually starts in September, whereas southern one-year (which is usually confined to sandy soils) generally causes problems just after Christmas. Rather than wait for damage symptoms to become obvious before considering treatment, the best tactic is to *dig!* Get out a shovel and check in your ratoon crops for grubs. Early detection and treatment will result in quicker and larger growth responses in your cane and a better dollar return.

Good planning lets products work

If you need grub control with insecticides, it must not be an afterthought; these products are too expensive to waste. Planning ahead gives products the best chance to perform. Modern pesticides are sensitive chemicals - you have to

The break-even point for use of Rugby® against different densities of Childers grubs in ratoons, calculated from yields at the next harvest in nine trials, at two different sugar prices.



The break-even point (where the response lines cross the red line) has been calculated as the grub density at which the value of the extra cane due to treatment equals the cost of Rugby® product (excluding application costs). The threshold number of grubs at the break-even point did not change much with sugar price - the threshold was about 5 grubs/stool at $350/t and 6/stool at $210/t. Above the threshold, it was still worthwhile using Rugby® even with a low sugar price. Additional benefits of treatment, such as better ratooning after harvest and delay in need for replanting, have not been factored into this analysis, but must also be considered when making decisions about grub control.

make certain that conditions are right if you are to get the best performance from them. It pays to plan ahead to make sure that the row profile and soil pH will be suitable when the time comes for application. If conditions aren't right, then you are better off not treating and saving the money!

Approximate costs of grub control products per hectare		
Applied to plant cane		
suSCon®Blue (21 kg/ha)	$290	most species
suSCon®Plus (40 kg/ha)	$430	greyback
BioCane® (33kg/ha)	$280	greyback
Applied to ratoon cane		
Rugby® (20-25 kg/ha)	$210 - $260	negatoria/ Childers/ southern 1 year
Confidor® Guard	N/A	not yet registered

suSCon® Blue

Surveys show that many fields have suSCon® Blue far too close to the surface. This is money wasted because chlorpyrifos, the active chemical in suSCon® Blue, is lost from the soil as vapour (volatilisation) if granules are too close to the surface for a long period. But neither must the granules be too deep, or grubs will not come in contact with them, and a band of adequate width is also vital to have a good chance of contacting grubs. For the best results, granules should be in a band 15-20 cm wide and 15-20 cm deep after the row is hilled up and the soil has packed down. There are several application methods on the suSCon® Blue label. Select the method and time of application so that granules end up 15-20 cm deep.

A quick and easy way to decide which method to use is to dig down to the setts in a couple of ratoon fields. Measure sett-depth and then use the suSCon® label to decide on an application method to get the right placement. Remember that if you are planning to apply suSCon® after planting into the open furrow, then there will already be some soil over the setts. So if the setts are 20 cm deep after hill-up, and if there is usually 5 cm of soil over the setts at planting, then the final depth of granules won't be more than 15 cm, and it could be less if you drag more soil into the furrow before application. Also look at the depth of any suSCon® band in these ratoons. Is it at the right depth? If not, then change the application method or the hill-up procedure for future plant crops.

Soil pH greater than 6.2 can cause the chlorpyrifos from suSCon® Blue to break down prematurely, reducing the effective life of the product from years to months. suSCon® Plus, which has a sulphur coating, can be used against greyback in soils with a naturally high pH, but it is expensive. Alternatively, farmers suffering greyback can use BioCane™, particularly in fields that are at low to moderate risk, because this biological product is not affected by pH.

Incorporating large quantities of lime close to planting can cause problems with subsequent suSCon® Blue application, so get a soil test before liming. If immediate treatment is necessary, avoid applying a large amount that would result in a pH of 6.2 or above. Apply a small amount (0.5 t/acre or 1.25 t/ha) to plant cane and perhaps more in later ratoons, depending on the need. If lime has already been applied and pH is already 6.2 or above, then don't use suSCon® Blue; try suSCon® Plus or BioCane™ for greyback, or monitor and use Rugby® as required for other species.

BioCane™

BioCane™ contains living fungal spores that can infect greyback grubs, but they are sensitive to heat. BioCane™ must be kept cool (<12°C) while in storage and must never be applied during the hottest part of the day. Once applied, at least 100 mm of compact (settled) soil must cover the granules immediately. Optimum position in the soil profile is the same as for suSCon® products.

Rugby® 100G

Rugby® granules should be applied behind coulters through the ratoon stool for most species, and must be irrigated or receive substantial (more than 25 mm) rainfall after application.

Monitoring - saving dollars and making sense

Correctly identifying at-risk fields is vital when sugar prices are low relative to the cost of treatments.

- For greyback, determine the presence of grubs by looking for damage symptoms in April (give suspect stools the "pull test") and digging 10-20 stools and looking for grubs or root pruning. Also, after harvest, dig out ratoon stools beside gaps and inspect for root loss and for gouging on stubble. These signs could indicate trouble the following year, especially if present in many fields on the farm.
- For two-year grubs (eg Childers, negatoria) dig 5-10 stools in each high-risk (unprotected) valuable field in spring. Consider immediate treatment with Rugby® if you find more than 2-3 negatoria or 5-6 Childers grubs/stool.

Money can be saved with grub control, particularly by targeting products to certain fields or parts of fields. However, it is not as simple as just stopping treatment cold, because canegrubs can do devastating damage to unprotected crops. In these tough times, the real benefit of close monitoring and risk-prediction is that it allows you to limit expensive treatment only to areas where it is needed, while future grub infestations can be headed off by timely and effective treatment.

If you need to know more about effective canegrub control, contact your local BSES extension officer.

BSES Bulletin issue 6: 2005, pp. 10-12.

A system to lessen cost of controlling grub damage?

> Keith Chandler

Growers must cut costs in a low-price sugar market. But canegrubs are on the upsurge and the need for cheaper and more effective grub control has never been greater. This article outlines systems to substantially reduce input costs while effectively controlling grub damage. BSES Limited is seeking growers and producer support groups who want help to develop and manage local grub control systems.

Some canegrowers feel that to cut costs for grub control is an unacceptable risk, and they currently pay a high price for their standard routine. Many others take significant risks with no treatment—most would not take that risk if the sugar price were higher. However, neither group consistently uses any system to assess whether or not to act in advance to prevent or control grub damage outbreaks.

Currently, growers do not have sufficient information on which to make annual, cost-effective grub-management decisions. Essentially they have to guess what to do or gamble on doing nothing.

Could growers benefit from being aware of the current level of grub risk?

Most growers agree that widespread, timely management prevents major uncontrolled grub outbreaks, thus ensuring each grower's own crops and avoiding endangering their neighbour's.

Grub-affected growers say, 'If only I'd known this (grub damage) was about to happen, I'd have done—(something else)'! Others observe that, although they spent 'a fortune' protecting some plant crops, there was no infestation, and so the money and insecticide were probably wasted.

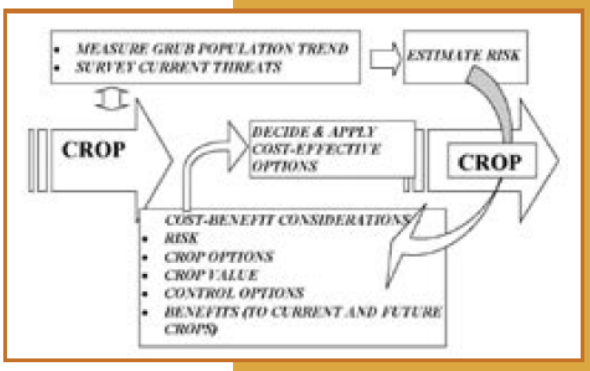
Such views suggest those growers believe the key to more effective canegrub management is to be sufficiently aware of the current risk, so that they know when and where to use (or not to use) the various control options.

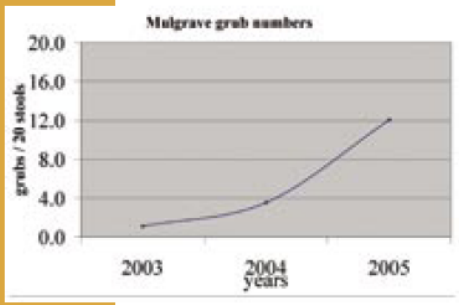
New possibilities

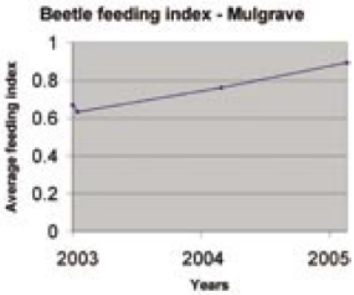
In line with the grower opinions outlined above, BSES has invested in long-term research to develop the background for grub control strategy planning systems. The system depicted in the flow chart *(below)* comprised information-gathering on population trends and probability of damage, followed by application of that data to assess: 1) the risk relative to the value of the crops and their potential loss and 2) the specific type and level of intervention needed.

Such systems help growers to make rational decisions about if, when and where to use a

> *Such systems help growers to make rational decisions... and to attain a cost-effective strategy to minimise grub damage.*







variety of treatments and/or crop management tactics, and to attain a cost-effective strategy to minimise grub damage.

What's new?

As a result of past and current BSES programs the industry now has greater capacity to monitor canegrub pests, to predict the risk of grub damage, and to choose suitable controls from a range of options. Identifying population trends and predicting risk for greyback canegrub damage are both reasonably effective. Monitoring Childers canegrub, another major species, is possible and practical.

BSES was also closely involved in recent registrations of a range of new insecticide products that have led to the release of several improved control options. Advances in procedures (e.g. for cost-benefit analysis) will further improve systems. So it is now more appropriate than ever for growers to begin using new systems and to develop and adopt new strategies for more cost-effective damage control.

So, what's proposed?

BSES, with support from Sugar Research and Development Corporation (SRDC) and suppliers of the insecticide products registered for control, is carrying out pilot projects to combine monitoring and damage prediction processes into local grub management strategies with a range of both new and old products and/or crop management tactics.

Case study at Mulgrave Mill

Mulgrave Mill Productivity Service's officer Gerard Puglisi has been helping since 2003 to develop a monitoring system for greyback canegrub. Information collected in April each year since 2003 (see graphs) on canegrub numbers under semi-mature cane shows a steeply escalating population trend; similar to the trend before disastrous damage in 2000-2001. Also, an index of the characteristic marks made by greyback beetles on palms, especially coconuts and to a lesser extent Alexandria palms, shows a steady rise since 2003.

Implications for Mulgrave growers in 2005 are: First, find exactly where grubs are; and where needed plan and carry out the most cost-effective and suitable management options to protect the 2006 crop. The surest method to locate greyback grubs is by digging between 10 and 20 sugarcane stools per field: between March and May.

Second, Do NOT WAIT until extensive damage occurs before starting to implement control measures! As numbers build up beetles will spread, putting at risk fields up to at least 500 m away.

When deciding control strategy, consider a range of facts and options rather than restricting control to the same routine and options as in previous years. The following advice is worth considering:

- Some practices (e.g. ploughout-replant) actually increase risk.

Note the offer from BSES to collaborate with producer groups and support groups, to help them begin to operate their own population trend monitoring, risk assessment and grub control strategy development systems. With first-hand experience, the benefits from such a system are obvious.

- Other crop options (e.g. minimum tillage legume fallow) may be beneficial.
- Effective options are not always insecticides.
- New control options and insecticide products are now available.
- The cheapest option may not be the most cost-effective.

Starting to establish a system

For all grub species, and particularly for greyback canegrub, it would be better for growers to combine into locality-based groups, with the services of a 'local expert'. Information from individual farms, although important, is generally insufficient to predict trends and risk situations.

So, prediction systems should combine data from a wide range of farms in a district. The 'local expert' needs to develop enough local knowledge and understanding so that this information can be used to plan farm-specific control tactics with the most cost-effective options. A local grub management system group could be operated in-house with existing industry support structures (for example, productivity services) or may eventually be contracted on a fee-for-service basis.

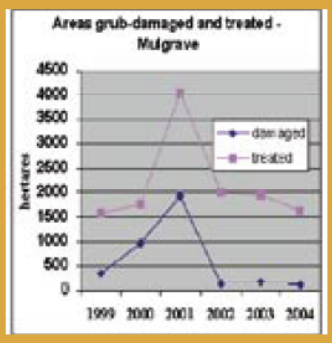
Growers in Childers grub areas on red soils at Childers and Bundaberg have an immediate opportunity to implement an effective grub control management system. Monitoring for damage-prone fields is certain—a matter of going and digging.

Current trials indicate that monitoring can be easily carried out in autumn and/or in spring. By noting in autumn that grub damage could become a constraint, growers would have plenty of time to plan cost-effective options to manage Childers grub.

Grub damage in the Mulgrave district has been very low since 2002 (see graph).

However, the area protected has fallen, and the monitoring (above) indicates numbers of grubs are again increasing rapidly. In general, damage is becoming highly probable for the 2006 & 2007 crops.

Now is the year to reduce the pressure; 'nip it in the bud'. A monitoring system could locate 'at risk' fields and allow growers to efficiently manage them to prevent a population explosion.



Growers and producer groups interested in developing systems to improve cost-effectiveness and efficiency of grub management are invited to call the author Keith Chandler at BSES Bundaberg on 41325235 or 0429 749146; or Dr Peter Samson at BSES Mackay on 49545100 or 0407 629076; or Dr Mohamed Sallam at BSES Gordonvale on 40561255 or 0417 749153

Mackay BSES Field Day poster, 2005

GREYBACK CANEGRUB MANAGEMENT

Greyback canegrubs are a continuing problem near Mackay. Some farms are suffering damage for the first time in many years. Monitoring grub presence and treating accordingly is vital, particularly for farms without a management program already in place.

Dr Peter Samson, BSES Limited, Central

Unprotected fields are at great risk of greyback attack next year if:

- They show initial damage symptoms this year.
- They are replanted over current grub damage.
- There are infestations nearby (particularly if they are early-plant or early harvested fields).

To assess extent of current infestations and risk of attack next year:

- Look for damage symptoms across the farm in April-May (give suspect stools the "pull test"). Don't miss small patches in otherwise healthy fields – they are a warning for next year.
- Dig some stools in April-May and look for grubs or root pruning.
- After harvest, dig out ratoon stools beside gaps and inspect for root loss and for gouging on stubble.

These signs could indicate trouble next year, especially if present in many fields.

Products available for managing greyback canegrub

suSCon® Blue – controlled-release chlorpyrifos. Works well if placed in a band of adequate width and depth in soil, and provided soil pH is less than 6.

suSCon® Plus – controlled-release chlorpyrifos with sulphur coating, formulated to counteract effect of high soil pH. More expensive than suSCon Blue.

suSCon® Maxi/Confidor® CR – new controlled-release product containing imidacloprid. Not affected by pH. May be less sensitive to placement than suSCon Blue.

BioCane™ – a biological control product containing the fungus *Metarhizium anisopliae*. Specific to greyback grub; harmless to beneficial organisms in soil.

Confidor® Guard – a liquid formulation of imidacloprid for application to ratoons.

BSES

For further information contact your local BSES Limited Office.

Mackay BSES Field Day poster, 2005

PREDICTING GREYBACK CANEGRUB ATTACK

Peter Samson, BSES Limited

There are options for treating greyback canegrub in both plant crops and ratoons.

To decide on whether treatment is needed, growers must predict what greybacks are likely to do next year and maybe the year after as well.

GREYBACK DAMAGE

Damage shows up March-May.

To develop methods for predicting greyback grubs from year-to-year, BSES Limited staff have been sampling greyback populations in about 100 fields from Sarina to Cairns each year since 2003.

☞ **The best predictor so far is the number of grubs in fields the previous year.**

- In most fields where there were grubs in one year, they were present in similar or greater numbers the following year.
- However, if grubs were absent, then it was unlikely that a severe infestation would develop the following year (only a 3 in 100 chance).

Grub numbers this year	Chance of grubs next year		
	Few grubs (less than 0.2/stool)	Moderate grubs (up to 1/stool)	High grubs (more than 1/stool)
Zero	87%	10%	3%
Low (less than 0.2./stool)	53%	33%	14%
Moderate (up to 1/stool)	20%	44%	36%

Monitoring is a key to predicting greyback grub numbers, to ensure grub damage is avoided by applying treatments when risk is high, and to save money by not applying treatments when risk is low.

BSES Sugarcane for the future

Australian Government Sugar Research and Development Corporation

BSES QCROPS Growing your bottom line

APPENDIX 6 – REVIEW OF POPULATION DYNAMICS OF GREYBACK CANEGRUB

Mohamed Sallam, BSES Limited, Meringa

Introduction

The greyback canegrub (*Dermolepida albohirtum*) is the most devastating sugarcane pest in Australia, with estimated annual losses of up to $10 million and with periodic outbreaks where losses may reach $40 million in damage and management expenses (Chandler 2002). Greyback canegrub occurs from Mossman to Sarina in Queensland in a wide range of soil types including loam soils along the Burdekin and Herbert rivers and red volcanic soils between Tully and Mossman (Allsopp *et al.* 1993). The greyback canegrub has a one-year lifecycle and the larval stage has three instars that feed on the sugarcane root mass in the soil, leading to reduced growth, stool tipping and ultimately plant death (Allsopp *et al.* 1993). Knowledge of grub behaviour and dynamics is available in the literature; however, information is scattered in many sources. This manuscript attempts to collate all existing information on greyback population ecology, with the aim of understanding factors governing their dynamics in nature. This knowledge should improve our capability to predict changes in grub dynamics and possible population outbreaks. Ultimately this information will provide growers with decision-support tools and enhanced means of managing the pest effectively.

D. albohirtum biology and life cycle

The adult stage

Detailed information on greyback biology and life cycle is available from Jarvis (1933). Adult *D. albohirtum* beetles fly following the first fall of spring rain, which normally starts in October. Beetles will emerge until January and in some cases they keep emerging until March, but this depends on the onset of spring rain; if rain is late (January) then beetles may still be emerging in March, but if rain comes early (October) then flight will cease around December. In areas relying on rain, a fall of 38-50 ml of rain can trigger emergence, and beetles may not emerge at all until it rains (Buzacott 1947). Alternatively, irrigation was found to trigger adult emergence in areas mainly relying on irrigation such as the Burdekin (Robertson & Walker 2001).

The sex ratio of adults in the field is normally around 1:1 when beetles start emerging, but it gradually becomes female-biased (70-80% females) (Bell 1934; Mungomery & Buzacott 1935).

Beetles emerge from different fields and head towards aggregation/feeding trees, where they feed for 10–14 days, and this is considered crucial to their subsequent fecundity (Illingworth & Dodd 1921). Females fly back to fields to lay eggs, and can fly up to 1.6 km (Mungomery & Buzacott 1935). There are anecdotal observations that some females may have a “homing instinct” where a proportion heads back to where they originally came from so that damage keeps recurring in the same spot. This is based on the persistence of local grub infestations from year to year rather than direct observations of adult behaviour. Another proportion of the population is likely to disperse, and may end up ovipositing in unexpected spots such as under nearby lawn, other crops such as pawpaws, peanuts and dead corn stubble, or even in fallowed fields (Sallam & Burgess, unpublished; Chandler, personal communication). Adults live for about 8 weeks, and longevity is negatively

correlated with temperature with females tending to live longer than males (Illingworth & Dodd 1921; Jarvis 1933).

There is ample evidence to show that adult greyback beetles prefer to fly to tall crops. Logan *et al* (2000a) showed that early-planted and early-cut cane is more frequently damaged by greyback than other classes of cane in the Burdekin. This led to the development of the "trap crop" concept. A trap crop is a section of a field that was either planted or harvested earlier than the rest of the crop, and so stands out in comparison to the rest of the crop at the time of beetle flight. Trap crops, in several cases, were shown by Horsfield *et al* (2002) to harbour more grubs/stool compared to adjacent blocks in selected areas in the Burdekin region. In addition, Ward (2003b) shows a negative relationship between date of planting or harvesting and subsequent damage in the Burdekin, and concluded that sugarcane height is a primary determinant of where adult beetles lay their eggs. Moreover, Illingworth (1918) and Mungomery (1949) reported that egg-laying females may be preferentially attracted to tall and dense sugarcane crops. However, this relationship has not been proven beyond doubt outside the Burdekin.

The egg stage

Females lay 23-36 eggs at depths between 20-37.5 cm, and eggs hatch in 10-14 days (Illingworth & Dodd 1921; Jarvis 1933). Females may lay fewer eggs in drier or heavier soils. Ward (2003a) showed that, in a choice experiment, female beetles laid fewer eggs in a heavier silty clay soil than in light loam and silty loam soils, and that hatchlings suffered higher mortality in the silty clay soil. Ward (2003a) also recorded higher egg mortality at field capacity than at lower moisture content in silty clay soil; moisture content did not affect egg mortality in lighter loam and silty loam soils. The same author also noted that adult females retained more eggs when they were introduced to silty clay soil in a "no-choice" experiment compared to other lighter soils.

Generally females tend to lay the majority of eggs (24 eggs) in one occasion and in a single cell; they could come back and lay more, but the second batch will contain fewer eggs (5–10 eggs) (Jarvis 1933). Illingworth & Dodd (1921) noted that some females may be able to oviposit several lots of 20–25 eggs over their life span. However, they made the assumption that gravid adult females found on trees in February (3 months after the first emergence took place) had already laid eggs. This may not have been the case because these females may have emerged late and were relatively fresh when they were examined by the authors.

The larval stage

Larval durations for first, second and third instars are 4 weeks, 4-5 weeks and 7 months respectively (Jarvis 1933), with grubs showing faster development in lighter soil types (Illingworth & Dodd 1921). When first instar grubs emerge, they make their way towards the soil surface (Illingworth & Dodd 1921). Robertson & Walker (2001) showed that first instars are more laterally dispersed than later instars, with later stages aggregating gradually towards the stool area during the first 2–4 months of development. These authors inferred that larvae feed on organic matter and fine roots as first instars before they move towards the centre of the row as they develop into second and third instars and travel deeper in the soil profile. This agrees with Illingworth & Dodd (1921) who also recorded that second instar larvae descend in soil and aggregate under the cane stool.

Very saturated, water-logged soils cause high mortality of hatchlings, and grubs are more destructive in well-drained land (Illingworth & Dodd 1921). Ward (2003a) suggested

that heavy silty clay soils become more difficult for grubs to burrow in as they get wetter. However, there is evidence that third instar grubs are capable of surviving prolonged water-logging conditions. Robertson & Walker (2001) also showed that larvae can be found at shallower depths when soil is saturated. Illingworth & Dodd (1921) noted that grubs move upwards in the soil profile under very wet conditions, and in some cases come out of the soil completely and hide under trash or plant material. Moreover, Jarvis (1933) put individual third instar grubs in glass test tubes containing water and then removed them after varying time intervals. Several grubs were able to survive for up to 32 hours, with a few grubs surviving for 41 hours under water.

The average grub number/stool in canefields varies significantly due to several factors, including time of year, pesticide use, soil type, cane cultivar, soil moisture, grub pathogens and infestation pressure in a particular year. Several estimates of grub numbers/stool are available in the literature. Jarvis (1933) estimated an average of 70,000 grubs per acre, which approximately translates to 6-7 grubs per stool. He also estimated a mortality rate of 5-6% in the late larval stage due to "parasitic and predaceous insects and other enemies". Ward & Robertson (1999) recorded a range of 3-6 grubs/stool as the ultimate number of grubs that eventually settle around a stool towards the end of the season. Other studies record up to 14 grubs/stool late in the season (Volp 1947), while the unusually high mean figure of 30 grubs/stool was recorded by Bell (1934) in a number of fields during the early part of 1934.

It is possible that fields with a high presence of weeds could have a greater larval carrying capacity than weed-free fields (Ward & Robertson 1999). This has also been observed by Jarvis (1933), who noted that a luxuriant growth of weeds among the stools is strongly attractive to egg-laying females.

Most studies on grub numbers are conducted during March-May. This measures the functional number of grubs that damage cane, but the figure that determines the following beetle population will be the number present in September–October. A decline in grub densities is expected to occur later in the season but is difficult to quantify. This is due to the difficulty of finding late larval stages or pupae in August–September as grubs dig deep in soil in preparation for pupation. It is well established that grub densities decline in soil over time (Robertson *et al* 1997a; Robertson & Walker 2001), and this could be due to dispersal, combat mortality, or death due to pathogens and other unknown natural mortality factors. This was also shown by Bell (1934), who reported a gradual decline in grub numbers during winter months.

Illingworth & Dodd (1921) stated that grubs mainly feed on organic matter, and when they do not get their requirements from soil they start attacking cane roots. Hence, the authors concluded that grubs are only excessively destructive to sugarcane when it is growing in soils deficient in organic matter. However, it is now known that first instar larvae require living roots for survival (Logan and Kettle 2002). It is possible that damage to cane growing in rich soils could be masked by vigorous growth of the crop.

Pupal stage

By May–June, fully grown third instar grubs stop feeding and start digging deeper in the soil in preparation for pupation. Jarvis (1933) found third instar larvae preparing to pupate at depths as great as 60 cm, but pupae are more frequently found between 15–40 cm below the surface depending on soil type and soil moisture. Jarvis (1933) also recorded that the pupal duration is between 4-5 weeks. The same author gives varying pupating depths ranging from 10 to 60 cm depending on soil type. For example, the pupal chamber could be shallow in sandy loams or in light soils with a clay or stony sub-soil, while it tends to be deeper in

volcanic soils. In addition, pupae can be found at a shallow depth if the soil was still moist during July–August at the time when third instars started to pupate. However, very dry conditions afterwards (August–December) will result in high mortality among these shallow pupae (Buzacott 1947). Much deeper pupation depths of up to 120 cm and more were recorded by Girault (1914) and Illingworth & Dodd (1921).

Logan & Kettle (2007) estimated the developmental zero for pupae to be 12.0^{o}C and the thermal constant to be 476 D^{o} , with pupal duration ranging from 26–75 days at 30°C–18°C respectively. Simulation of development using temperatures recorded hourly at different depths indicated that pupal development would take 2-10 days longer at 20 cm than at 40 cm depth depending on location and date. When pupation was simulated in late August, as is likely in the field, pupal development at 40 cm depth took 48-56 days at Ayr and 58-62 days at Sarina. Illingworth & Dodd (1921) noted that grubs pupate faster in well-drained soil.

Adult beetles are formed by October. Adults usually remain in the pupal cell for up to 4 weeks, and they may also emerge but remain "arrested" in surrounding soil for weeks until rain comes (Illingworth & Dodd 1921; Jarvis 1933).

Impact of climatic conditions on greyback populations

The impact of climatic conditions on grub dynamics is an area of debate. The following is an attempt to collate all historical observations with more recent studies to understand the possible effect of climate on the different life stages.

Adults

There are several historical observations on the impact of temperature and rain on beetle emergence and fertility. Long continued dry weather will sometimes cause very heavy mortality among adult beetles (Jarvis 1933; Bell 1936). Mungomery (1931) stated that “droughty conditions, if prolonged into late spring and summer, may cause beetles to die in their cells, or they may be so weakened that reproduction does not take place”, while Buzacott (1947) reported an unusual number of dead beetles being ploughed up during an exceptionally hot and dry 1946-1947 summer. Also, Bell (1935) asserted that “the great reduction in damage in the far northern section of the cane belt can be attributed mainly to the abnormally hot and dry weather conditions which prevailed during the latter part of 1934, and in the early months of 1935. This hot weather had the effect of killing most of the beetles that had emerged during November, whilst those that were still in their pupal cells underground were unable to emerge”. Bell (1935) added that “when a fall of rain eventually did occur in late January, the beetles were too weak to oviposit, and a further period of dry weather likewise accounted for them”. The same author recorded isolated small grub spots during that very dry season, and these were attributed to local thunderstorms which had occurred during late September and October. In addition, Volp (1947) reported heavy mortality among gravid females due to dry and hot soil conditions. The same author also attributed lower fertility among females collected in February (compared to those collected in January) to prolonged dry soil conditions during the adult emergence season, which may have caused female sterility. Mungomery (1952) stated that “The very dry spring and early summer had a profound effect on populations of the greyback beetle by almost entirely eliminating major flights in the Mulgrave. Further depression of the populations appears to have been affected by desiccation of the eggs and early larval stages”. Bell (1938) reported large beetle emergence following heavy rainfall in the Burdekin and along the Townsville–

Ingham line. However, dry conditions followed and significant damage was only seen in irrigated fields, while unirrigated fields remained comparatively grub free.

Eggs

Wilson (1956) stated that "temporary depletion of grub populations was experienced in some years prior to the use of BHC due to desiccation of the eggs when the soil rapidly dried out in the intense summer heat, after beetle emergence and oviposition had been stimulated by an initial, brief, heavy rain". Similar remarks were also made by Illingworth & Dodd (1921) who confirmed the severe negative impact of soil dryness and high temperature on adult longevity and egg viability.

Pupae

Buzacott (1947) attributed the shallow depth at which larvae pupated in 1946 to very dry conditions that made it difficult for larvae to move any deeper in soil, and resulting in high mortality during summer months as the drought continued. Similar observations were also made by Mungomery (1947). It is probably the case that extreme dry or wet weather conditions might result in shallow pupation depth.

Climate and damage

Horsfield *et al* (2008) correlated a number of climatic factors with subsequent grub damage using data collected between 1987-2003 in the Burdekin district. Of the climatic variables evaluated, only pan evaporation was significant, and it was inversely related to the subsequent area of grub damage. On the contrary, Robertson *et al* (1997a) regressed the area of canegrub damage against annual rainfall in the preceding 1, 5 and 10 years and against seasonal rainfall over the period from 1921 – 1994 in the Innisfail and Tully districts, and found no relationship between rainfall and subsequent grub damage. The authors therefore attributed significant declines in grub populations to disease epizootics.

In an attempt to explain the role of climatic conditions on grub populations, it is hypothesised that a considerable amount of rain will cause the homogenous bulk emergence of a regional population, including grubs surviving outside sugarcane fields (i.e. in river banks and under wild grasses etc.) and therefore would result in the emergence of a "critical mass" of beetles, and this will enable successful mating and will ensure an abundance of egg-laying females (Chandler, personal communication). Irrigation alone, alternatively, is usually conducted in separate fields and on separate days, and this may cause beetle emergence to become unsynchronised, therefore reducing the egg-laying capacity in an area with beetles emerging in low densities. However, it is obvious that studying the impact of rainfall alone does not show a clear correlation with subsequent grub numbers or ultimate crop damage (Robertson *et al.* 1997a; Horsfield *et al.* 2008). Alternatively, pan evaporation, which combines the effects of both rainfall and temperature as well as solar radiation and wind, may better explain the impact of climatic conditions on beetles' survival and fecundity. However, it needs to be stated that Robertson *et al.* (1997a) and Horsfield *et al.* (2008), by using historical crop damage data rather than grub numbers (which are not available), assume a strong positive correlation between grub numbers and subsequent damage under all climatic conditions. With the absence of solid data demonstrating this relationship, and bearing in mind the impact of dry weather on the crop itself which may reduce its tolerance to grubs, further work is required to demonstrate the impact of pan

evaporation directly on actual grub densities, especially in areas mainly relying on rain fall rather than regular irrigation.

Role of grub diseases and natural enemies

Grub pathogens

Canegrub larvae are prone to a number of pathogens that could in some cases be responsible for complete destruction of local populations. The most frequently encountered diseases are those caused by the fungus *Metarhizium anisopliae*, the protozoan *Adelina* sp., and the bacterium *Paenibacillus popilliae* which causes milky disease. Other less common diseases are caused by the protozoan *Nosema* sp. and unidentified entomopox viruses (Dall & Logan 2001). In addition, high larval mortality is usually encountered in grubs from FNQ for unknown reasons (Sallam *et al.* 2003) and further work is required to identify and account for the factors responsible for this unexplained mortality.

Of the detectable diseases, *Adelina* sp. stands out as a density-dependent factor responsible for regulating grub numbers (Robertson *et al.* 1998). *Adelina* is a disease frequently encountered in FNQ where it is responsible for variable rates of mortality up to 100%. Robertson *et al.* (1998) showed that over half of the variance in annual mortality in certain plots at Tully (FNQ) could be explained by the level of incidence of *Adelina* alone. The same authors suggested that *Adelina* infection levels are strongly influenced by grub density, with high pathogen incidence following high grub populations causing the grub population to crash, which then negatively impacts on subsequent *Adelina* levels. They monitored a block at Tully for 4 years (1995-1998), and showed a steady decline of *Adelina* infection from 40% to 5%, coincident with the decline in grub numbers from an average of 1.5 to 0.1 grubs per stool. This agrees with Sallam *et al.* (2003) who recorded complete disappearance of the disease from the same block. Sallam *et al.* (2003) attributed this to either the sharp decline in grub numbers during 1995-1998 following a peak in 1994, or soil disturbance resulting from plough-out of the plot, or possibly a combination of these two factors.

Sallam *et al.* (2003) also recorded a higher rate of *Adelina* survival and carry-over under grass-covered soil compared to that under bare fallow. They attributed this to a combination of higher soil moisture and relatively cooler temperatures under cover.

It has been suggested, based on the absence of *Adelina* in the more alkaline Burdekin soils, that high pH soils may not favour the pathogen. However, Dall & Logan (2003) and Sallam *et al.* (2003) found no clear relationship between disease incidence and pH or levels of organic matter in soil. Soil moisture proved to be a crucial factor in the persistence of *Adelina* in soil while soil dryness is detrimental to the pathogen. Dall & Logan (2003) showed that 85% of *Adelina* cadavers (maintained for 20 months under adequate moisture conditions and used as a disease inoculum) were able to infect new grubs, compared to only 22% when the inoculum was kept in dry conditions prior to the test. This could explain the abundance of the disease in the 'super-wet' belt of FNQ. This, however, does not explain the frequent abundance of *Adelina* at Mutarnee south of Ingham, where very dry winters occur and soil moisture drops significantly between seasons.

In the Burdekin, factors such as burning crop residues, long-term intensive cultivation, high soil temperature, and frequent and abrupt changes in soil moisture as a result of irrigation cycles could be important in limiting the occurrence of *Adelina*. The *Adelina* pathogen is also very rarely encountered in Mackay. It might be the case that moist rainforest soils in FNQ are conducive to *Adelina* occurrence, and this may have resulted in a

long term association between the grub species and *Adelina* and led to well established levels of the pathogen in that region. However, more work is needed to examine this theory.

Another frequently encountered disease, especially in FNQ, is that caused by the soil-dwelling fungus *Metarhizium anisopliae*. Different strains of the fungus infect different grub species, with the specific isolate FI-1045 infecting greyback canegrub larvae (Robertson *et al.* 1997b; Samson *et al.* 1999). The fungus can be grown on rice grains, and this is used as the method to mass-produce it commercially. Isolate FI-1045 is currently available under the name BioCane™. Application of BioCane™ gives moderate rates of grub control (50-60%), with the possibility of an increase of infection in subsequent crops when cadavers act as a source of infection (Logan *et al.* 2000b). *Metarhizium* spore levels following BioCane™ application decline in soil if not augmented by conidia from infected grubs, and may fall below a level capable of grub suppression 3 years after initial treatment (Milner *et al.* 2003). The same authors determined a mean monthly decay rate of spore viability to be between 0.0309 and 0.0835 (mean = 0.0512, or about 60% per year). The exact level of *Metarhizium* spores in soil that will result in good grub control is unknown. However, under laboratory conditions, Milner *et al.* (2002) showed that an average LC_{50} of FI-1045 was 9 x 10^4/g of soil against third instar grubs. Bearing in mind the controlled nature of laboratory work, higher spore levels/g of soil will most certainly be needed in the field to have the same impact on the grub population.

Sallam *et al* (2006) determined *Metarhizium* spore levels in soils at varying depths from different regions in Queensland with a history of BioCane™ application. Across all plots, Innisfail and Tully showed a significantly higher spore abundance than Bundaberg, with the highest spore count recorded in Tully (6.35 x 10^5 spore/g of soil), while the Burdekin had significantly lower counts than all other locations and the lowest spore level was recorded there (3.7 x 10^2 spore/g of soil). It is possible that harvesting cane by burning negatively impacts on spore levels in Burdekin soils, while soils in Tully and Innisfail are probably more conducive to spore viability due to trash retention, high moisture levels and natural richness in organic matter (Lai-Fook *et al.* 1997; Samson and Milner 1999; Sallam *et al.* 2003). It is not clear if the alkaline nature of the Burdekin soils has a negative impact on spore levels compared to the more acidic soils of Tully, Innisfail and Bundaberg, especially when no clear impact of soil type or pH on *M. anisopliae* spores has been proven in Australia or elsewhere (Bidochka *et al.* 1998; Milner *et al.* 2003).

Metarhizium spores were more frequently found 10-30 cm below the soil surface, possibly indicating where grubs are mostly active (Sallam *et al.* 2006). Similar observations were made by Samson *et al.* (2002), who recorded the highest spore levels at depths between 20-40 cm in a BioCane™ trial plot in the Burdekin, where the majority of *Metarhizium* cadavers and late third-instar grubs were found.

Unlike *Adelina*, *Metarhizium* does not act in a density-dependent manner. In an area naturally rich in *Metarhizium* (Tully), it is responsible for a more or less fixed mortality rate (20–30%) over time, despite changes in grub density (Sallam *et al.* 2003).

Sallam *et al.* (2003) recorded that *Metarhizium* spores exhibit a degree of tolerance to soil disturbance, enabling the fungus to act as a long-term regulating factor of low-to-moderate grub populations.

A third disease, milky disease, caused by the bacterium *Paenibacillus popilliae*, kills a small proportion (2-5%) of third instar grubs late in the season in far north and central regions (Sallam, unpublished data). The role of this disease in regulating grub populations is unknown.

Predators

A number of animal predators attack both the beetle and larval stages. Illingworth (1921) and Illingworth & Dodd (1921) give a long list of natural predators that include birds, bandicoots, lizards, frogs, rats, flying foxes and even hogs and dogs. They refer to two species of Ibis (*Carphibis spinicollis* and *Ibis molucca*) as very useful predators of grubs. The same authors also list several insect predators such as the larvae of the Asilid fly (*Promachus doddi*), the larvae of a giant Elaterid beetle (*Agrypnus mastersi*), a Pentatomid bug (*Amyotea hamata*) and the omnivorous ant (*Pheidole megacephala*). The combined impact of these predators is unknown but is probably not significant.

Parasitoids

Illingworth (1921) and Illingworth & Dodd (1921) list a number of parasitic wasps belonging to the families Scoliidae and Thynnidae; however, no established records of the latter family are available to support their role as parasitoids of greyback grubs. Illingworth (1921) refers to two Scoliids, *Campsomeris tasmaniensis* and *C. radula,* as useful parasitoids of the larval stage of *Dermolepida albohirtum*. Female wasps dig deep in soil and lay an egg on the scarab larva after paralysing it. Illingworth (1921) and Illingworth & Dodd (1921) give varying rates of parasitism ranging between 25 – 60% at Meringa (FNQ). These authors refer to a number of hyper-parasitoids that may negatively impact on the effectiveness of the digger wasps. In addition, the wasps require an abundance of flowering plants to feed on before they are capable of laying eggs, and are rarely encountered in areas lacking in nectar sources. It also seems, based on observations by Jarvis (1926), that these wasps are not host-specific, and they may exploit other scarab larvae for their development. The wasps are very rarely encountered in the field in recent times, and therefore unlikely to have any impact on the grub population (Sallam, unpublished data).

Parasitisation of adult beetles by an unidentified Tachinid fly has been noted by several authors (Illingworth 1921; Illingworth & Dodd 1921; Jarvis 1933). Jarvis (1925) refers to an incidence where he collected 200 adult beetles of which 31% produced the adult Tachinid. However, the impact of parasitism on subsequent grub population is probably insignificant.

Larval combat or dispersal?

In their work on density-stabilising mechanisms acting on canegrubs in soil, Ward & Robertson (1999) found no correlation between adult numbers, caught in intercept traps as well as light traps, and subsequent grub numbers in the same or adjacent fields. The same authors also noted that adult mortality is largely replaceable, with grub populations arriving at a similar density per plant late in the season despite significant variations in numbers of egg-laying adult beetles. They attributed this to larval combat that increases with an increase in grub density. This would explain why targeting adult beetles to control the pest has always proven futile (Bell 1938, 1940, 1943). However, Logan & Kettle (2002) did not find any evidence of larval combat between first instars, with availability of food being a critical factor in early-instar survival. They recorded high mortality (87%) with a high larval density in combination with a low abundance of food in laboratory containers, compared to a mortality rate of 53% when food was abundant. In addition, they noted that groups of six first instar grubs dispersed quickly within the first 48 hours of introduction, with fewer than two larvae remaining in the zone of introduction, thereby avoiding aggressive combat. It might be the case that larvae compete in conditions of very high densities per plant, a

condition which will limit the availability of food. Larval combat may inflict a degree of mortality, but it may also lead to active dispersal among competing grubs to avoid high mortality levels. When a number of large larvae are confined in a closed arena in the laboratory, high mortality usually results due to aggressive combat. However, this has not been proven beyond doubt in a field condition, and therefore requires more work to be confirmed. Yet, in the absence of larval combat, two fundamental questions still stand: 1) how can similar larval densities establish early in the season from a much lower beetle population in FNQ compared to that in the Burdekin; and 2) how can similar grub densities per plant in the Burdekin and FNQ result in very different beetle numbers in the following season?

In an attempt to reconcile the contrary positions taken by Ward & Robertson (1999) and Logan & Kettle (2002), it is probably the case that larval combat is not the only factor contributing to density stabilisation. I hypothesise that, due to high larval mortality in FNQ, larval densities decline over time until the beetle stage, while populations in the Burdekin suffer far less mortality due to the absence of key pathogens and densities of immatures remain high until the beetle stage. Bell (1934) asserts that, to estimate the probable beetle population emerging in a given area, it is necessary to conduct the diggings during the pre-pupal, pupal and early beetle stage, which is during the months of August–September. Work by Ward & Robertson (1999) relies on grub counts taken in March–April, but these may not be the final grub densities. The functional density from which the adult population eventuates is what is in the soil just prior to emergence, which is bound to be less than the number recorded earlier in the year, and is also bound to be a higher figure in the Burdekin compared to FNQ. In addition, while grub infestation in FNQ is usually patchy and scattered, the Burdekin suffers greater wide-scale infestations that would result in a significantly higher beetle population. It is proposed that, even though the density per stool remains similar in localised areas on a farm or "micro-population" level, beetle densities on a larger regional scale are bound to be significantly higher in the Burdekin compared to FNQ, resulting in larger areas of infestation with a higher grub "macro-population".

In the absence of density dependent mortality, reducing the beetle population by any percentage (for example, via chemical control) would be expected to reduce the subsequent grub population by the same proportion. If this were the case, why did control strategies targeting adults fail to reduce subsequent grub populations? If we hypothesise that larval combat does not take place in the field, then chemical control of adult beetles in the Burdekin (where density-dependent pathogens are absent) should result in an equal degree of reduction in larval numbers. However, no beetle killing method is capable of significantly reducing the overall beetle population on a regional scale. Based on an average figure of 1 adult beetle/plant with 10,000 plants/ha, an infested average area in the Burdekin of 4000 ha will produce 4×10^7 adult beetles. It would be unrealistic to assume that any method of adult control would be capable of significantly reducing this high number.

Role of pesticides

Pesticides are an effective means of grub population suppression. The history of greyback canegrub damage patterns can be divided into three distinct eras, (I) Pre 1947, when no effective control measures were available and there was widespread crop damage; (II) 1947-1987, when widespread usage of organochlorines (OCs) brought canegrubs under control; and (III) Post-1987, an era marked by the loss of OCs and the introduction of less persistent synthetic and biological insecticides (Logan & Allsopp 2000; Logan 2001).

During Period I, grub control relied on the use of fumigants in combination with tolerant varieties (Jarvis 1933; McDougall 1940). However until the introduction of OCs in

1947, growers were unable to effectively control greyback and suffered widespread damage and significant losses. During Period II, there was widespread and routine use of 'Gammexane' (gamma-isomer benzene hexachloride), and heptachlor. These products were relatively cheap and persisted well in soil, and effective control of canegrubs was achieved in all cane growing districts in Queensland for almost forty years (Logan & Allsopp 2000). Towards the end of Period II, increasing environmental pressure led to the banning of organochlorine usage in sugarcane, and suSCon® Blue, a controlled-release organophosphate formulation, was introduced. However suSCon® Blue proved to be ineffective at providing long-term control of greyback in the alkaline soils of the Burdekin. Work by Chandler (1997) and Robertson *et al.* (1998) showed that alkaline hydrolysis and microbial degradation result in accelerated breakdown and premature loss of the active ingredient chlorpyrifos from suSCon® Blue granules. This led to multiple control failures against greyback grub in the Burdekin, which in turn resulted in a rapid reduction in suSCon® Blue application due to lack of confidence in the new product. Significant outbreaks of canegrub damage through the 1990s and early 2000s are documented as a result of lack of insecticide application and multiple failures of suSCon® Blue in the Burdekin. Currently, a number of controlled-release and knockdown insecticides are available for canegrub control. Alternative management methods emerged more recently such as trap cropping and altering of planting and harvesting dates (Ward 2003a; Horsfield *et al.* 2002; Ward & Cook 1997). Robertson *et al.* (1995) highlighted the need for a comprehensive decision-support system for canegrub management which takes into consideration alternative grub management strategies, sequential sampling and Economic Injury Levels guidelines to ultimately develop reliable cost–benefit analysis schemes. An Integrated Pest Management approach was compiled, incorporating all farming practices that contributed to reducing grub damage while using insecticides strategically, and delivered to industry in 2001 under the training program "GrubPlan". This approach proved successful in combating grub populations, and is increasingly gaining favour among cane growers (Hunt *et al.* 2002; 2003, Samson *et al.* 2005).

It is widely accepted that, while OCs gave 90–95% control of greyback grubs and lasted for several years, suSCon® Blue gives 80-90% control in plant cane, with the possibility of achieving some control in first and second ratoons (50-60% and 20-30% respectively) depending on soil conditions and product placement in the field; high soil pH impacts negatively on its effectiveness. Another controlled-release granule (suSCon® Maxi), which contains imidacloprid as the active ingredient, gives 85–90% mortality in plant cane and possibly 70% and 40–50% mortality rates in first and second ratoons respectively. Imidacloprid liquid (e.g. Confidor® Guard) gives 85-90% mortality the year after treatment of plant or ratoon cane, with impact uncertain in subsequent years (Chandler *et al.* 1993; Chandler, personal communication).

Role of farming systems

There is evidence that greyback grub populations suffer relatively higher mortality under green cane trash blanketing (GCTB) in comparison to populations under burnt cane (Robertson *et al.* 1995; Robertson & Walker 1996; Allsopp *et al.* 2002). Trash retention was also found to increase densities of the earthworm (*Pontoscolex corethrurus*) and improves the diversity of soil fauna (Robertson & Bakker 2004). In addition, Allsopp *et al.* (2002) showed that grub numbers were higher under "invasive farming strategies" such as the combination of intensive cultivation + suSCon application + harvesting by burning. This may be attributed to high disease incidence under "softer farming strategies" such as GCTB and reduced tillage of soil. In addition, Robertson *et al.* (1999) showed that pesticide

application will suppress grub numbers initially but ultimately results in population outbreaks. The authors attributed this to the fact that pesticides, by rapidly reducing pest numbers, also disrupt the natural cycle of the range of entomopathogenic pathogens, thus making it difficult for natural control to resume its course of action. Incidences of population outbreaks of canegrubs could possibly be minimised if systems conducive to beneficial pathogens were to be implemented on a wide regional scale (Robertson 1998). Other agricultural practices, such as the use of tolerant varieties, manipulating of planting and harvesting dates, thorough management of weeds and improving soil health are all expected to contribute to a long term suppression of grub populations (Robertson *et al.* 1995; Robertson 1998). Independent reviews compiled by Potter (1997) and by Dent (1997) emphasised the importance of long term strategies that integrate all aspects of pest control and crop management. The current review agrees with previous reports that relying on one method of control, though effective on the short term, does not offer a long-term suppression of the pest's populations. Integrated Pest Management and comprehensive Crop Management strategies are required to maintain a sustainable level of grub population suppression.

Conclusions

Greyback canegrub dynamics are governed by a complex of factors that include climatic conditions, soil types, pathogen levels, farming practices and pesticide use. As none of these factors is acting separately, attempts to model greyback dynamics will have to account for the collective impact of all the different factors. With all the knowledge currently available on grub biology and ecology, more research is required to study numerous aspects of greyback canegrub biology and behaviour. Areas of research to be addressed can be listed as follows:

- Emergence rate of adults under different climatic conditions and rainfall.
- Proportion of females that mate and then successfully oviposit.
- Dispersal distance and direction of beetles (and what proportion oviposits in the same field from which they emerged).
- Reasons why adult beetles are attracted to certain fields and not others.
- Role of crop height in attractiveness to beetles in non-Burdekin areas.
- Egg and larval survival rates under different soil moistures, temperatures and soil types.
- Decline in grub densities over time in the absence of pathogens at different grub densities.
- The role of larval combat as opposed to dispersal.
- A quantitative description of disease transmission and inoculum production and survival for different pathogens.
- Impact of tillage on pathogen levels in soil.

More work is required to address these gaps to ultimately improve management of greyback canegrub.

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APPENDIX 7 – BMP MODEL REVIEW

IQ

AGRIBUSINESS
- Thought for Food -

COMMERCIAL-IN-CONFIDENCE

BSES BEST MANAGEMENT PRACTICE MODEL REVIEW

DATA ENTRY PROCESS AN ADDENDUM TO THE "PROGRAM MANUAL"

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1. INTRODUCTION

- The BSES engaged IQ Agribusiness (IQ) to assist with the interpretation and application of the Best Management Practice Impact Model (BMP Model, Model). This Model was originally developed as part of the SRDC funded CP2002 Best Management Practice project (CP2002).
- BSES Meringa are using the Model as part of a project to assess the impact and control options for grey back cane grub.
- The process began in mid- October 2004, and included:
  - Auditing and attempting to use and understanding the Model
  - Approximately four (4) hours interviewing two (2) BSES employees, who also farm cane, to assess the Model's application under 'field' conditions
  - Further work to extract and interpret the Model output and, in doing so, to identify difficulties in interpreting the Model questions.
- While completing this work, IQ was asked to provide an assessment of the Model and its suitability for use in evaluating various pest management options. This Review has been conducted without reference to the CP2002 Project Brief, thus IQ cannot, and was not asked, to conclude whether the Model satisfactorily meets the terms of the CP2002 Project Brief.
- This Report provides information to guide the data entry process and to assist with interpreting the model output. Though not required in the original Project Brief, this Report also provides an assessment of the deficiencies of the BMP model.
- The first part of this Report follows the order of the questions in the Data Entry Wizard used in the BMP Model.
- This Report should be read in conjunction with the "Program Manual" provided with the BMP Model.

2. DATA ENTRY

2.1 Productivity Data

- Before the model can be used in a new Mill Area it is necessary to upload productivity data for the:
  - **Mill Area** (e.g. Mourilyan, Proserpine, etc)
  - **Sub-Area** within a Mill Area (e.g. White Rock, Cattle Creek, etc)
  - **Farm** within a Mill Area or Sub-Area (e.g. R. Down, J. Howard, etc)
  - **Block** within a farm (e.g. Block 10, Block 38, etc)
  - **Sub-Block** within a Block on a particular farm (e.g. Sub-block A, etc).
- Given the time required to complete the data entry, it is unlikely that entering data and conducting analysis at the Block or Sub-Block level can be justified.
- In most situations Mill Area data should be sufficient. Farm level productivity data is only likely to be required if a particular farm is involved in an ongoing research project.

- The model uses historical productivity data as the basis to predict future production for a given area (mill area, sub-area, farm, etc). Thus, the more historical data that is entered the more reliable will be the forecast of future production. The model will work with one year of data, though five years of data is probably a minimum to achieve a meaningful output.
- Data must be uploaded into the Worksheet labelled **"DATA"**. Data must only be entered into those columns shown in BLUE – these are columns:
  - S – "Mill"
  - T – "Year"
  - U – "Variety"
  - V – "Class/Code"
  - W – "Year Week"
  - Y – "Tonnes of cane"
  - Z - "Area Harvested"
  - AB – "Tonnes of Sugar".
- Once all the available data has been entered into these columns, it is necessary to copy the formulae in the remaining columns so that each row of data has formulae in all the relevant columns on either side.
- **NOTE 1** - in the Model provided for the review, some of the data entry columns were shown in Black rather than Blue. If you are unsure if data should be entered in a particular column, simply place the cursor on a cell in that column – if the cell contains a **number** (e.g. 83.97) rather then a **formula** (e.g. =AA1907/AB1907), then it is safe to enter data into the column.
- **NOTE 2** – the area available for data entry is limited to **30,387 rows** so it may be necessary to delete some datasets in order to enter new data, particularly if the new data is at the Block or Sub-Block level and covering a number of years. Take care to only delete data that is not relevant to the particular Mill Area or Farm being analysed (e.g. Burdekin data may be deleted in order to enter Mourilyan data).
- **NOTE 3** – After entering new data it will be necessary to update the LOOK UP tables to include the new Mill Area, Sub-Area, Farm, Block or Sub-Block details. To do this, go to cell **A1** in the Worksheet titled **"LU"**. In Columns A & B you will see a table – in the first column of this table ("Districts") there are a list of names of Mill Areas or Sub-Areas – simply type the name of the new Mill Area (or Sub-Area, etc) into this table. If you deleted old data from the "Data' worksheet, you may also delete the corresponding Mill Area (or Sub-Area, etc) name from the "Districts" table in the "LU" worksheet.
- Further detail on the specific data required is shown on Page 20 of the Manual under the heading "Farm Specific Productivity Data". Refer to **Note 4** below as well.

2.2 Question 1 - District or Farm Data

2.2.1 District

- By selecting the check box **"Use all districts"**, the model will use all the data in the model (e.g. the whole of QLD) to calculate future production for the farm in

question. Typically one should choose a particular Mill Area (e.g. Mourilyan) that is relevant to the farm being analysed, rather than the Use All Districts option.

2.2.2 Year

- The "**Year**" box allows the user to select the year to be used as the basis for calculating future productivity. In most cases you should choose the "**Use all years**" option as this will give the most reliable projections of productivity.

2.2.3 Use Farm Specific Data

- The user should only choose this option if planning to use data for a particular farm rather than relying on Mill Area data for estimating future productivity. Unless the farm data is very accurate and covers a minimum of five years, users would be best advised to use Mill Area data rather than Farm Specific Data.
- **NOTE 4** – Cell E258, headed "Week" refers to the Year Week in which the cane was harvested. Some mills use Harvest weeks as the reference point, however the BMP Model uses Year weeks so care is needed to ensure that any data being entered refers to Year Weeks rather than Harvest Weeks.

2.3 Question 2 - Name

- This is self explanatory.

2.4 Question 3 – Total Farm Area

- It is **not** necessary to enter the **total** farm area provided that the **Non-Arable** area is shown as **zero** (0) percent in Question 9 (Cell D260). If the user enters only the arable area in Question 3, rather than the total farm area, they **must** show the Non-Arable area as zero (0) percent in Question 9.

2.5 Question 4 – Starting Year for Projection

- This simply refers to the first year from which the user wishes to begin the cashflow calculation. The further forward this is from the current year, the greater will be the discount applied to the cashflows to bring them back to a current year value.
- Typically, the Starting Year will be the current year or the next year (e.g. at the moment it would probably be 2005 (i.e. the 2004/05 financial year).

2.6 Question 5 – Days of Harvest

- This is a **critical** piece of data for the model. The number of harvest days per week will affect the season length (i.e. more harvest days/week = a shorter season and vice versa).
- The data entered must be between 0 and 7.
- **Note 5** – it is important to exercise care when entering this data as the Days of Harvest will affect the season length and has a dramatic impact on profitability. For example: In the Test Scenario modifying the number of harvest days from 0.5 per week to 1 per week reduced the NPV of each of the options (No Damage, Damage and Control) by more than 50%. Thus, the absolute value of the NPV

under any of the three options is less important than the relativity between the three options.

The Model's reliance on this piece of data presents a fundamental flaw as the Model is not sufficiently flexible to accommodate situations where a grower does not harvest cane every week during the season. Further, the Model does not reflect the industry reality whereby a grower completes the harvest over a number of rounds during the season.

2.7 Question 6 – Harvest Costs per Tonne

- This is self explanatory.

2.8 Question 7 – Sugar Prices

- This is self explanatory (sugar price is expressed in A$ per tonne).

2.9 Question 8 – Variety Selection

- This table is used to select the varieties that are grown on the farm being analysed. The availability of historical data for a variety will determine the reliability of the output for that variety on the farm being analysed. Thus, if the farm is growing a very new variety with little or no historical production data, the model will be unable to predict the future production from that variety.
- One can delete varieties from the table by putting the cursor in the cell containing the variety to be deleted, then clicking on the "Delete Variety" button.
- To add varieties one must:
  - select the desired variety from the drop down menu
  - click the "Add Variety" button
  - move the cursor in Column B so that it is beside an empty cell in Column C in the table
  - press ENTER on the keyboard.
- **Note 6** – the list of varieties shown in the Drop Down menu is drawn from the range **F1-G48** in the **"LU"** worksheet. It will be necessary to update this list from time to time. This can be achieved by deleting, from **Column F**, those varieties that are no longer required and adding the names of new varieties in their place.

2.10 Question 9 – Define the Ratoon Structure

- The user allocates cane production across six (6) **crop classes** (including Fallow) in the **starting year** of the Model. The Model requires the user to nominate the percentage of the arable area that will be devoted to each Crop Class in the starting year.
- It is important that the user **only enters data for the starting year**. Changes to the crop structure, in later years, can be made in Question 10.
- **Note 7** – Once cane production has been allocated to a Crop Cycle (or Class), that area of crop (effectively an area of land on the farm) remains in that Crop

Cycle for the **duration** of the Model timeframe (e.g. crop allocated to Fallow in the first year of the Model continues to be referred to as the **"Fallow Crop Cycle"** even after crop has been planted in that area of land), unless the cycle is altered in Question 10. This is a significant point as it is different from the standard industry practice of naming crops by their Crop Class (i.e. Ratoon 1, Plant, Stand Over, etc). **Follow the colours in the table to trace the Crop Cycles across the life of the analysis.**

- **Note 8 –** If the user entered the **total** farm area (including non-arable land) at Question 3, it is important to enter the percentage of non-arable land in Cell **D260** of Question 9.

2.11 Question 10 – Modify the Ratoon Structure

- Take care when entering data to this table. If an area of crop is being changed from one "Crop Cycle" to another one must add the area (enter a positive percentage) to the new Crop Cycle **and** subtract (enter a negative percentage) it from the old Crop Cycle. As in double entry book-keeping, the positives and negatives must balance in **each** year.
- The user needs to think in terms of **Crop Cycles** as defined in the Model, rather than in terms of crop classes as in the case in a practical farming situation. Thus, if in the starting year, an area of 10% of the farm is allocated to the **Fallow Crop Cycle**, then in the following year the area is planted to Q124 (for example), this area of crop is still referred (in the Model) to as the **Fallow Crop Cycle**, despite the fact that the farmer will refer to it as plant cane. This can be a confusing detail to new users of the Model.
- Obviously, an area of crop can only be moved to **Fallow** (by ploughing out an area) or **Plant** (by planting an area). **Caution** – the term 'Fallow' and 'Plant' in this case do not refer to the **Fallow Crop Cycle** or **Plant Crop Cycle** referred to in the Model. An area of land from any **Crop Cycle** can become fallow or plant cane but it will remain a part of the **Crop Cycle** to which it was originally allocated.
- The second table in this Question simply calculates the area (ha) devoted to each Crop Cycle after the crop structure has been modified.
- **Note 8** – after altering the Crop Cycle in the top table in Question 10, the Total row (Row 292) should show zero percent (0%). Similarly, the Total Row in the second table (Row 305) should show the area of the farm as entered in Question 3.

2.12 Question 11 – Varieties by Crop Class

- Again the user needs to think in terms of **Crop Cycles** as defined in the Model, rather than in terms of Crop Class as is common in the industry.
- Except for the **Fallow Crop Cycle** the purpose is to define the area allocated to each variety in a particular Crop Cycle, in the **starting year** of the analysis, as a percentage of the total area allocated to that Cycle. In the case of the Fallow Crop Cycle, the user must allocate varieties that will be planted, next year, in the currently fallow ground.

- **Note 9** – the figures in **Column P317-P325** and in **Row D328-N328** must each add to 100%.
- **Note 10** – the variety structure entered for each Crop Cycle will remain **fixed** for the duration of the analysis. That is, the variety structure for each Crop Cycle cannot be changed part way through the analysis.

  This assumption that the data is fixed for the duration of the Model duration, both here and in other Questions, is a fundamental flaw in the Model as it does not reflect the practical reality of the industry.

2.13 Question 12 – Proportion harvested early, mid or late.

- The Model calculates the production for a particular farm, based on the average yields and CCS for different periods in the harvest (early, middle, late). Thus, the proportion of crop allocated to each of these harvest periods in Question 12 will affect the profitability calculated by the Model.
- It is important to remember that the crop cycles shown in the top row of the table refer to the **Crop Cycles** defined in the Model, **not** to crop class as defined in the industry. Thus, the term **Plant Cycle** refers to all cane that was designated as Plant Cane in the starting year of the Model analysis (i.e. shown in a white cell in Question 9) – it **does not** refer to plant cane as the industry defines it.
- The allocated proportions for each variety in each Crop Cycle will endure for the life of the analysis.

2.14 Question 13 – Season Length.

- This is self explanatory. Refer to **page 12** of the Program Manual for additional instructions.
- Once entered, the Season Length will remain constant for each year of the projection.

2.15 Question 14 – Area exposed to damage

- This is a critical part of the Model – again it is also potentially confusing due to the reference to Crop Cycles as opposed to crop class (industry terminology). Users must continue to think in terms of **Crop Cycle** as defined in the Model. Thus, the term 'Fallow' refers to the **Fallow Crop Cycle** defined in the Model **not** to fallow land (the land will only be fallow in the first year of the Model analysis) as recognised by farmers.
- The area exposed to damage will be a function of soil type and seasonal conditions. Thus, it is feasible than an area of the farm (e.g. that area devoted to the Plant Crop Cycle) is not exposed to damage because of the heavy soil in that part of the farm. In this case, the area exposed to damage would be recorded as zero (0%). It is equally possible that the area of land defined as the Fallow Crop Cycle is exposed to damage because of the soil type (the only year that the exposure is zero will be in the starting year when there is no crop planted in this are of land).
- **Note 11** – it is critical that users think in terms of **Crop Cycle** as defined in the Model rather than in crop class as defined by the industry.

2.16 Question 15 – Change in CCS and yield due to damage

- This is another critical area of the Model. Ideally, the data entered here will be based on research results for a particular area or farm.
- It is important to be as accurate as possible in estimating the impact of pest damage as this will directly affect the relative profitability of a pest treatment.
- Figures entered here are used to calculate the profitability of a farm under the "Damage" scenario, assuming that no treatment is applied. The impact of the damage is measured in terms of the reduction in CCS and Yield compared with an 'average year' (calculated from the productivity data entered into the Model). The Model assumes that the average reflects a year with no pest or disease damage.

2.17 Question 16 – Define activities used on farm

- This section feeds into the cost calculations to estimate the profitability of various scenarios. Basically, the object of this question is to define all the activities that occur on the farm in order to produce a sugar crop.
- Entering data into this table is a time consuming task but accuracy is important.
- The example model contains a range of possible activities. For simplicity, these activities should be used as the basis for future analyses. The user can leave the activity name in Column B and simply leave Columns D, F, H, J blank if that activity is not used on the particular farm being analysed.
- The way that this table is laid out requires that data be entered for every activity separately even though some activities are carried out jointly (e.g. Planting and Insecticide application at Planting will be recorded as separate activities even though they are done together). In this case it is important to note that the use of a Machine, Implement, Consumables and Labour is only applied once so as to avoid any double counting. **Note** - that **Contract** activities are considered to be Consumables for the purpose of data entry.
- It may be necessary to modify the list and price of Consumables, Machinery, Labour and Implements. This is done via the **"LU"** worksheet starting in:
  - Cell AR 1 for Consumables
  - Cell AY 1 for Labour
  - Cell BE 1 for Machinery
  - Cell BL 1 for Implements.
- **Note 12** – be sure to include the application rate in Column K of the **"Def Act"** worksheet.

2.18 Question 17 – Build the Calendar of Operations used on the farm

- The data from this question is used to calculate the timing of cashflows and the total costs.
- The user must build the Calendar of Operations (COO) by selecting the Operation (activity) from the drop down menu shown in Cell D3 of the **"COO"** worksheet, then clicking the "Operation Code" button directly above the menu.

The Model will ask (in the bottom left hand corner of the screen) the user to ***'select the destination then press ENTER or choose PASTE'***.

- At this time, the cursor will be in a blank cell in Column D – using the arrow keys, the user should move the cursor **one Column to the left** then press **ENTER**. Once the Model has re-calculated the new data, the previously blank cell in Column D will show the activity that was selected from the drop down menu.
- The COO is built by working down Column D entering a new code for each activity that is performed.
- It is likely that some activities (e.g. irrigation, or harvesting) will appear more than once in the COO as these activities are carried out more than once during the season.
- After completing the list of operations, the user must then complete **Columns I, J and K** in the "COO" worksheet. Column I is used to show the month in which an activity is undertaken (January is 1, December is 12). Where an activity is undertaken in more than one month, the activity will be shown more than once in Column D and a different number will be entered in Column I to show the different months in which the activity is undertaken.
- Column J shows the **Crop Class** to which each of the activities is applied (ignore the Column heading if it refers to 'Ratoon') – the user now needs to think in terms of **crop classes** as defined by the industry rather than in **Crop Cycles** as defined in the Model.
- Column K simply allows the user to specify how much of a particular crop class is treated with a particular activity (i.e. irrigation, harvesting, herbicide, etc).

2.19 Question 18 – Define pest and disease management treatments

- There are two parts to this question:
  - The first table in the **"Control"** worksheet requires the user to enter all the possible treatments for the pest or disease being assessed. The critical part of this is to enter accurate data for the impact that each treatment has on each **crop class** (as opposed to Crop Cycle). Ideally the data entered here will be drawn from research conducted in the area where the farm is located. Be sure to include data for both Yield and CCS, and to record the number of years for which the treatment remains active (**see Note 13 below**)
  - The second table allows the user to choose which of the treatments (or combination of treatments) shown in the first Table is to be applied. The Model will calculate the benefit:cost of each of the selected treatments or combination of treatments. **The user will need to run the Model several times to evaluate all the treatment options. Either print the results or save each run of the Model as a separate file so that the results can be compared.**
- In completing the second Table the user will need to revert back to thinking in terms of Crop Cycles as defined in the Model rather than in terms of crop classes. For example – assume that the Model period begins in 2004 and that Confidor CR is applied to each Crop Cycle (as opposed to crop class) at planting. Thus, Confidor CR will be applied to each **Crop Cycle** as follows:

Crop Cycle	2004	2005	2006	2007	2008
Fallow Crop Cycle		Confidor CR			
Plant Crop Cycle	Confidor CR				
Ratoon 1 Crop Cycle					
Ratoon 2 Crop Cycle					Confidor CR
Ratoon 3 Crop Cycle				Confidor CR	
Ratoon 4+ Crop Cycle			Confidor CR		

- The above table illustrates the year in which each of the **Crop Cycles** will be planted afresh.
- Thus, in completing the second Table on the "**Control**" worksheet, the user must be careful to refer back to the tables completed in questions 9 and 10 to ensure that the treatments are applied in the correct year to the correct **Crop Cycle**.
- **Note 13 –** In completing the first Table, the user must enter data representing the **percentage** increase in CCS and Yield compared with doing nothing (i.e. the 'Damage' scenario). There is no facility for the user to enter an absolute response to a treatment. Thus, if the Damage scenario lead to a 100% Yield or CCS reduction in one or more crop classes, the Model would not be able to calculate the profitability of the various treatment options. This is a fundamental flaw in the Model.

2.20 Question 19 – Define the calendar of operations for pest and disease management treatments

- This table is based on the data entered into the second Table in Question 18.
- The user must revert back to thinking in terms of crop class rather then Crop Cycle, and must complete Columns I, J, K, L.
- Using the example shown above, we know that:
  - Confidor CR is applied to all plant cane (Column J = Plant)
  - It is applied in 2004, 2005, 2006, 2007, 20008 (Column L = each of the years entered one below the other).
- Column I simply requires the month in which the cane is planted (and, thus when Confidor CR is applied).
- Column K requires the user to enter the proportion of plant cane that is treated with Confidor CR. **Note** that the proportion treated may vary between Crop Cycles (due to soil type, etc), so the proportion treated may vary for each year of treatment.

2.21 Question 20 – Overhead costs

- The example model contains a number of overhead items in the "**OH**" worksheet. This list can be amended simply by typing additional items in Column D (Rows 143 – 160). The user may also wish to alter the costs shown in Column E.
- Once the list of overhead costs has been completed, the user simply needs to indicate the month in which the expense is paid (rather than when it is incurred) by entering a "**1**" in the appropriate Cell in the range F143 – Q160.

2.22 Question 21 – Owner's Wages

- These items are only really required if the user wishes to make comparisons between different businesses.
- The data required is self explanatory.

2.23 Question 22 – Asset Values

- These items are only really required if the user wishes to make comparisons between different businesses.
- The data required is self explanatory.
- Data may have to be gathered from the farm owner's Balance Sheet.
- The user may also need to alter the list and value of the plant and equipment. This can be done in the "**M&I**" worksheet .

2.24 Question 23 – Annual Discount Rate

- This is a financial concept that refers to the rate at which expected future cashflows are discounted to bring them back to current dollars, so that an accurate comparison may be made between various options.
- The rate of 12% used in the Model is adequate for the time being.

3. OUTPUTS

- The results are presented as Cashflow, Gross Margin and Benefit:Cost.
- These results are shown in the "**CF**" worksheet.
- The most useful results are shown in the Benefit:Cost chart at **Cell A402** in the "CF" worksheet. This chart shows the relative value of the three scenarios – No Damage (where the crop is not damaged), Damage (where the crop is damaged and not treated), and Treatment (where the crop is damaged but treatment is applied).
- Generally, if the NPV of the Treatment option is higher than the Damage option, then the treatment is worth applying.

4. MODEL REVIEW AND EVALUATION

4.1 Overview

- Overall, and after no specific training in its use other than via the "Program Manual", the Model was found to be extremely difficult to understand and use. Specifically:
    - The file is extremely large, causing even quite new and powerful computers to perform very slowly, with occasional system 'freezing'

- The "Program Manual" is unclear, appears incomplete and provides insufficient examples to anticipate anything more than the simplest of applications
- A user will need to devote around 3-4 hours to enter their specific data into the Model. In addition, the project manager (or equivalent) will need to devote at least this much time to upload the required historical production data, on a mill area, or farm basis. With this total time requirement (and even without the other usability issues) it is difficult to see the Model being used in anything other than a research environment
- The level of detail required by the Model is unnecessary, and it is highly likely that a similar result to that intended from the BMP Model, could have been achieved using a much simpler approach
- While Microsoft Excel is widely available, given the complexity and size of the BMP Model, one must question whether Excel was the most suitable programme in which to build the Model. IQ is unable to determine whether alternative programmes/languages were considered before the Model was built
- The Model may have been more practically applicable, and possibly a little easier to use, had it been linked to Mill GIS databases containing farm areas, soil type and productivity data
- The overall impression is that the model, in its current state, is incomplete. This impression is underpinned by the presence of some spelling errors and inconsistent formatting in the model, and the fact that there has been no effort to lock the Model's underlying code or to fine-tune the navigation issues.

- There are some useful features incorporated into the Model, including:
  - The ability to specify a range of treatment options
  - The application of historical data to predict future production. If sufficient data is available, this can be driven from a Block, Farm or Mill area perspective.

4.2 Some Specific Issues

- In addition to those identified elsewhere in this report, some specific issues encountered during the review process include:
  - The Model seems to have been developed using a relatively small data set from a particular production area with larger than average farms. The model is not sufficiently flexible to handle the range of production scenarios that will exist in other production areas. For example, the model does not allow for the situation where a grower does not harvest cane every week during the season (Question 5)
  - The Model does not have the flexibility to accommodate many common industry scenarios. Other common scenarios can only be evaluated by running numerous iterations of the model.

- There is some double entry of data required – for example, in Questions 9 and 10 relating to ratoon structure (this could probably have been handled in one table) and in Question 17, relating to the Calendar of Operations
- There is insufficient explanation of how to use complex data entry tables (e.g. in Questions 11 and 12)
- Some of the terminology used in the Model is inconsistent with the general industry terminology (eg. Ratoon versus Crop Class), and the application of this terminology is inconsistent throughout the Model
- In answering Question 9, users may find it easier to work in hectares (acres) rather than in percentages
- Many questions are overly complicated and time consuming (e.g. Questions 16 and 17) with inadequate explanation as to how to complete them
- There appear to be some coding errors in relation to building the Calendar of Operations. These errors can be overcome manually during data entry but they reinforce the belief that the Model was not completely finished and tested before release. Having said that, the fact that the underlying source code has not been locked means that the Model copy IQ reviewed may not be identical to that released at the conclusion of the CP2002 Project
- In some instances, the monthly cashflow worksheets do not accurately reflect the actual timing of cashflows – e.g. cane revenue is shown as all being received in the month of harvest rather than over a number of payments
- There is no reference to GST (whether GST should be included or excluded from the data) and the cashflow worksheet does not allow for the cashflow implications of GST payments
- The navigation buttons in the Model are imprecise and do not always deliver the cursor to the correct location. The navigation was found to be less confusing if one used key-board navigation aids rather than the buttons built into the Model
- Inconsistent formatting in the Model adds to the general usability issues. For example, the "Program Manual" stresses that only data shown in Blue should be altered, yet the Model contains areas where the variable data has not been shown in Blue even though this data can and should, in some cases, be altered
- The Model would benefit from having a button to delete all (or selected) previous data before starting a new analysis.

- This list is not meant to be exhaustive, and there may be other issues that have not been identified here.

5. CONCLUSIONS

- The review highlights that :
  - The Model has some underlying flaws that limit its value and practical application, and raise questions about the accuracy of the output. While the Model can be used to illustrate the relativity between various scenarios, the same end could be achieved using much simpler techniques

- While the Model has some useful features, and though the underlying concept is worthwhile, the Model is overly complex and difficult to use, for even a skilled spreadsheet operator
- There are a number of areas in which the Model could be improved to make it more `user friendly' either in Excel or by, if feasible, transferring the Model into another programme. It may also be possible to design a project to improve/adapt the Model so that it could be used in other enterprises or applications apart from sugar cane BMP
- Microsoft Excel may or may not be the best programme in which to have built the Model, but even using Excel, the Model could have been made easier to use with the application of very high level Excel skills to improve the navigation and data entry process
- Even ignoring its underlying flaws, it is extremely unlikely that the Model could be used in a practical extension setting due to the time required to gather and enter detailed farm specific data
- The "Program Manual" lacks sufficient detail for a `first time' user. The Manual needs to include a much more detailed, step-by-step explanation of how to use the Model.

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IQ Agribusiness

APPENDIX 8 – JACKSON CONSULTANCY REPORT, 2004

Consultancy report for BSES Limited

Project no. BSS257

Title. *GrubPlan 2: Developing improved risk assessment and decision-support systems for managing greyback canegrub*

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May 2004

Summary and Recommendations

- Greyback canegrub poses a very difficult problem for the Australian sugar cane industry, it can be highly damaging but it is difficult to predict where outbreaks will occur and control can be difficult and costly.

- *GrubPlan* provides an effective framework for developing integrated pest management options. New programmes and projects should be funded within the contextual framework of this programme.

- It is important to define easily monitored indicators of population growth and potential damage. The reliability of such indicators must be validated with field observations and analysis against data base information.

- Better prediction is required in areas of sporadic outbreaks. Emphasis should be placed on the role of abiotic factors (weather and soil type) in these areas. Matrix models could assist with analysis.

- In areas of persistent attack, biotic indicators may be of more value. Key areas for research include studies of female beetle behaviour, role of plant root vigour in susceptibility to damage and further research on diseases.

- Simple indicators of outbreaks are required. Remote sensing should be further evaluated.

- Better understanding of the benefits of prophylactic treatments will assist decision making. The availability of curative treatments will increase the benefit of short term predictions.

- Data should continue to be collected to build reliable data bases for the industry. Such data can be incorporated into Matrix models which will be useful in analysis of factors underpinning outbreaks and also for presenting to assist decision making protocols.

Purpose of consultancy

To take part in discussions on development and implementation of project BSS257, ***Grub Plan 2: Developing improved risk assessment and decision-support systems for managing greyback cane grub***, with particular reference to data gathering, analysis and model building for decision support.

The project visit took place from March 21 to March 26 2004 and was organised by Dr Peter Samson with visits to greyback sites in Mackay, Ingham and Tully as well as discussions on the programme at Ingham and Tully.

Comments on the programme

An excellent overview of greyback canegrub (*Dermolepida albohirtum*) biology and management was given to me by the research staff. As I was only in the field for a few days, my comments on the programme will be based on a general understanding gained from working with a range of scarab species with reference to common characteristics between species.

Objective 3 of the programme for prediction of greyback canegrub (and incorporation of predictive indicators into decision making) is ambitious, but poses a number of problems. Greyback numbers causing damage are thought to be influenced by factors including previous populations, area of local damage, flight behaviour and disease. The potential utility of prediction depends on how far in advance the prediction can be made and whether control actions can be implemented in time to prevent crop damage. Present "tools" for control include the insecticide chlorpyrifos (suSCon Blue and Plus) and *Metarhizium anisopliae* (BioCane) both of which must be applied prophylactically at planting of the crop. "De facto" management of greyback also comes about through cultivation of poor growing or damaged cane fields. The objective of effective greyback management is to maintain the yield of the ratoon crops by preventing extensive damage by the beetle larvae.

In order to predict greyback populations and damage it is important to understand factors influencing the biology at both a local and regional level. Evidence was presented of significant regional trends, possibly in response to drought and soil moisture effects (soil moisture/soil type interaction). Biotic factors are also recognised and flight behaviour and natural enemies (diseases) could be important indicators of population trends.

In order to understand factors influencing population change at both regional and local levels it is important to build a good data base of pest and crop information to develop models and test hypotheses. A good example of information gathering was presented by Gerard Puglisi for the Mulgrave area. It is important that key data are gained from such samplings are placed in accessible data bases to allow comparisons between sites and areas.

Prediction of greyback will only be useful to the growers if it is associated with "awareness indicators" that can be used by pest managers. It is important that measurement of such indicators is incorporated into the monitoring programmes so that the value of the indicators can be tested over time in relation to the database output. To obtain accurate figures for pest populations (larval densities) is very time consuming and cannot be used to drive predictive models. Indirect indicators such as crop gappiness should be further investigated especially if they can be evaluated by indirect methods such as satellite remote sensing.

Abiotic factors

Abiotic factors such as climate and soil type will provide common drivers of population change across a region or zone. They will set the potential for possible outbreaks as they provide the conditions within which populations can expand. Conversely when conditions are detrimental, populations will decline in a uniform fashion across a region. The effect of climatic factors can be determined by examining historical data sets or gathering data across climatically variable regions. Linear models and matrix models (see below) can be used to determine the importance of climatic trends.

Biotic factors – flight behaviour

Insect behaviour studies suggest that greyback females emerge from the ground, fly to feeding/breeding sites and return to the cane field for egg laying. Adult females can select oviposition sites as evidenced by egg laying in tall cane trap crops and the existence of oviposition preference sites (soil type). There is a suggestion that beetles return to the site area of emergence rather than random selection of oviposition sites.

If adult females move to the extent suggested, there are benefits to be gained from manipulation/disruption of this facet of behaviour which remains an important area for study. Further study should be made of trap crops and also the presence of aggregation pheromones (*Melolontha melolontha* aggregate towards damaged foliage). Traps can provide indicators of behaviour or be used in management if preoviposition females can be captured.

Biotic factors – gappiness and plant root vigour

Data suggest that greyback cane grub damage builds up from year to year in the ratoon crops. This may be due to flight behaviour (above) or to plant vigour. There are suggestions that root damage in one year will lead to lack of root vigour and increased susceptibility in the following season. If an objective measure can be developed, root vigour (previous root damage) could be a good indirect indicator of canegrubs and a predictor of susceptibility to damage.

Biotic factors – diseases

Insect diseases often act in a delayed-density-dependent manner. This means that level of disease in the population can be used as a predictor of population decline. The challenge is to find an indicator of disease that can be used as a predictor. While the protozoan *Adelina* is an important regulator in the Tully region (Robertson 1998, BSES Report SD98014) the effect of pathogens from other regions is less well understood.

The pathology assessment system may indicate the presence of other diseases. At present level of mortality in all samples from the field is high suggesting the influence of sampling damage or deterioration in lab conditions. It is recommended that a standard peat or soil mix be used for all larvae for rearing through the pathogen assessment. It is also probably better to reduce the amount of handling by examining the larvae at two-weekly intervals or less. Smears can be made of dead larvae for identification of spore forming pathogens. Further training of staff in insect pathology and identification of novel diseases is recommended.

A novel approach with potential for scarab management is symbiont disruption. Greyback larvae contain high numbers of microbial symbionts in the hindgut (fermentation sac). Characterisation of these bacteria and their ecology is underway at AgResearch and University of Queensland.

Predictive modelling

Key question – is population increase/damage predictable?

Modelling can have two objectives - analytical and predictive. Models for analysis of insect population dynamics and assessment of damage can be placed in several classes

- Continuous time
- Discrete time models
- Markov models

(See Barlow 1998, p60)

All have limitations in analysis of large data sets, such as are being established with the cane grub data. Greatest benefit may come out of using a combination of graphical, statistical and matrix methods. An example of matrix modelling using some simple data from the cane grub data base is attached at the end of this report (this is an illustration only, as a very small data set was used to illustrate the process of model building). Data are grouped into pre-assigned categories and placed into matrices based on the occurrence of historical combinations of events. In this example three parameters are included; Damaged blocks in the area in 2003 (year N), grub numbers 2003 (year N) and grub numbers 2004 (year N+1). In the simple two factor analysis, Damage in area year N vs grubs Year N+1, there appears to be a simple linear relationship between damage and subsequent grub numbers. Furthermore, matrix output provides a probability of the event. In this case, following a damage block indicator of >3 there will be 67% chance of high grubs (>2 per stool) in the following season.

Matrix output; Example 1. Two factor analysis. Probability of high or low grub numbers following defined levels of damage (indicators) in the surrounding crops in the previous season.

		Damage indicator (# damaged fields within 400 m)	
		<3	≥3
Grubs	High	40	67
	Low	60	33

In the second example 3 factors are compared; Damaged blocks in the area in 2003 (year N), grub numbers 2003 (year N) and grub numbers 2004 (year N+1). Numbers to provide model input in this example are obviously limited, but working through the same procedure as above we can see that in an area of low grub damage with low grub numbers there would be a 63% chance of low numbers in the subsequent year.

Matrix output; Example 2. Three factor analysis. Probability of high or low grub numbers following defined levels of damage (indicators) in the surrounding crops and high and low grub numbers in the field in the previous season.

Damage indicator	Low <3		High ≥3	
Grub nos Yr N	Low <0.25	High ≥0.25	Low <0.25	High ≥0.25
High grubs N+1	37	50	75	50
Low grubs N+1	63	50	25	50

Matrix models are only as good as the data that is used to prepare them and the probabilities of outcome reflect the historical inputs. The output, however, provides a different way of viewing the data which can be very useful in decision tool analysis.

While these results are illustrative only, they do show how the combination of models can be used to determine trends and also provide probabilities for incorporation into decision making assessments. Using these techniques for analysis of data base information it should be possible to define predictive parameters, incorporate probabilities into decision making models and provide appropriate data for econometric models.

Further information on matrix modelling can be obtained from Dr Shona Lamoureaux, AgResearch., Lincoln. (shona.lamoureuax@agresearch.co.nz). Further information on modelling of soil pest population dynamics can be obtained from Dr Frank Drummond, University of Maine, USA (frank.drummond@umit.maine.edu).

Modelling recommendations

- Use multifactorial and simple linear analyses to obtain indicators of interactions.
- Use simple probability matrix models for determining probabilities of outcome.
- Identify key indicators for incorporation of grub/damage parameters into econometric models.
- Develop use of satellite/remote sensing imagery for validation of predictions and model output

Acknowledgements

My thanks to Dr Peter Samson for the invitation to take part in this review and organisation of my visit. Thanks also to Keith Chandler, Mohamed Sallam, Warren Hunt, Ron Kerkwyk and Gerard Puglisi for useful discussion on the programme.

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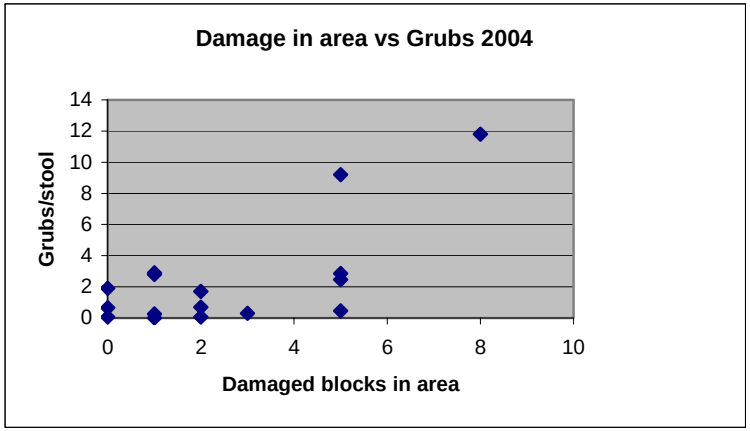
Matrix model development using a simple data set with up to three parameters

Parameters: Damaged blocks 2003, Grub nos 2003, Grub nos 2004

Simple 2-factor analysis
Does damage in area 2003 influence grub nos 2004?

Damage in area vs grub numbers

	Dam Block	Grubs 2004
3	8	11.79
5	5	9.2
15	5	2.85
9	5	2.45
9	5	0.45
1	3	0.3
9	1	2.9
5	1	2.8
1	0	1.9
3	2	1.7
10	2	0.7
10	0	0.65
27	1	0.25
10	2	0.05
9	0	0.05
24	1	0



		Dam <3	Dam>=3
Grubs	High >1	4	4
	Low	6	2

% Damage

		Dam <3	Dam>=3
Grubs	High	40	67
	Low	60	33

Linear relationship between damage 2003 and grub nos the following season
If damage has been high in area there is a 67% chance of high numbers the following season.

Damage blocks and grubs 2003 on grubs 2004

	Dam Block	Grubs 200	Grubs 2004
5	5	0.25	9.2
5	3	0.5	0.3
3	5	0.05	2.85
3	5	0	2.45
1	8	0.2	11.79
1	5	0	0.45
27	1	0.8	0.05
10	0	0.5	1.7
9	0	0.125	0.65
24	2	0.05	0.25
9	1	0.05	2.9
10	1	0.05	0.7
9	0	0.05	2.8
15	2	0	1.9
9	2	0	0
10	1	0	0.05

	Block damage (Number)				%			
Block damage	Low <=3		High >3		Low <=3		High >3	
Grub 2003	Low <=0.2	High >0.25	Low <=0.2	High >0.25	Low <=0.2	High >0.25	Low <=0.2	High >0.25
High grub 2004	3	1	3	1	37	50	75	50
Low Grub 2004	5	1	1	1	63	50	25	50

If damage has been low in area and grub numbers are low there is a 63% chance of low numbers the following season.

APPENDIX 9 – DRUMMOND CONSULTANCY REPORT, 2005

Consultancy report for BSES Limited, 2005

Project no. BSS257

Title. *GrubPlan 2: Developing improved risk-assessment and decision-support systems for managing greyback canegrub*

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Summary and Recommendations

- Greyback canegrub is a serious pest in Australian sugar cane production. It can be highly destructive and it is difficult to predict where and when outbreaks will occur. Control can be difficult and costly. Because greyback canegrub is aggregated across the sugarcane landscape and because management currently is performed at the field or block level, a predictive model to forecast the probability of a greyback canegrub outbreak from one year to the next should ultimately be designed for the field level of spatial scale.

- GrubPlan 2 provides an effective framework for developing integrated pest management options, especially when predictive models become available for farmers or extension professionals to better predict the risk of damage or not taking action against the greyback canegrub. New programs and projects should be funded within the contextual framework of this project, especially ones that provide a better understanding to predicting future outbreaks before they occur.

- Data should continue to be collected during 2006 to build and validate a reliable predictive model for greyback canegrub. It is suggested that additional data be collected, where possible, to supplement data that has already been collected from designated fields. These data might improve prediction of greyback canegrub populations by providing information about field characteristics relative to beetle behaviour/activity or farm-scale grub populations. Possible newly acquired data might be: distance from field to beetle feeding trees, distance from field to forest edge or creek bed, or an estimate of the number of fields with recent grub damage adjacent to a specific field.

- Such data can be incorporated into a matrix model (discrete time Markov chain model) in order to project the likelihood of greyback canegrub populations transitioning from low potential damage severity to moderate or high damage severity. Specifically, it is suggested that such a predictive model be parameterised with ordinal logistic regression using the data collected during 2003, 2004, and 2005 and partially validated using a jack-knife procedure. It is further recommended that data continue to be collected during 2006 to fully validate the predictive model with an independent data set. Dr. Drummond has offered his services to perform these analyses for this project.

- It may be useful to incorporate the mechanisms that regulate greyback canegrub populations into predicting population outbreaks. It is suggested that a preliminary population model be constructed. This computer-based simulation model would include parameters that have been identified in the literature as significant in regulating greyback canegrub populations. If there is not enough existing data to quantify the relationships that result in greyback grub population regulation, then this population model should prove useful in guiding future research objectives to more fully understand the population

dynamics of this serious insect pest. Dr. Drummond has offered his services to construct a preliminary model based upon a series of linked delay-differential equations representing a stage-structured population model for greyback canegrub.

Purpose of consultancy

To take part in discussions on development and implementation of the modelling component of project BSS257, *GrubPlan 2*: Developing improved risk-assessment and decision-support systems for managing greyback canegrub.

Dr. Drummond's consultancy visit took place between 8 August and 12 August 2005 and was organised by Dr Peter Samson with visits to greyback canegrub infested sites near the Meringa field station. In addition, several days of discussions took place reviewing the data collection process involved in the project, results from the past three years of data collection, and the statistical analyses and conclusions which will form the basis for the future development of models (both statistical and simulation) to make short-term predictions of greyback canegrub population trends.

Comments on the program

An excellent overview of greyback canegrub (*Dermolepida albohirtum*) behaviour, ecology and management was presented by the BSES research staff, Dr. Peter Samson and Dr. Keith Chandler. Since the project has been in progress for three years I felt it was my role to evaluate how the past and current data collection fit into the current project modelling objectives, i.e. developing a discrete difference equation Markov model for predicting future greyback canegrub population levels. I did NOT feel it was my role to suggest a new research project for developing another form of a greyback canegrub predictive model that would require new data collection methods. The research staff have a great investment in the current *GrubPlan2* project and I believe that they have collected much valuable data that can and should be incorporated into the currently proposed matrix model.

Objective 3 of the *GrubPlan2* project for prediction of greyback canegrub (and incorporation of predictive indicators into decision making) is fraught with a number of potential problems, as are all attempts at predicting future pest population levels. Greyback canegrub numbers causing damage in a particular field are hypothesized to be the result of previous field population levels, population levels in surrounding fields, adult flight behaviour and disease levels in the grub stage. The potential utility of prediction depends on how far in advance the prediction can be made and whether control actions can be implemented in time to prevent crop damage. Standard tactics for control include controlled-release formulations of the insecticides chlorpyrifos (suSCon Blue and Plus) and imidacloprid (suSCon Maxi/Confidor CR) as well as the fungal pathogen *Metarhizium anisopliae* (BioCane), all of which must be applied prophylactically at the time of or soon after planting the crop. "De facto" management of greyback also comes about through cultivation of poor growing or damaged cane fields. However, the newly developed control measure (Confidor Guard) for treating the ratoon crop after planting

may reduce the risk (but not the utility) of both making and relying upon greyback population level predictions and may change the way in which a predictive model could be used.

In order to predict greyback populations or damage potential it is important to understand factors influencing population growth at a field, farm and mill district level. Evidence from data collected during this project suggests that significant district effects, possibly in response to abiotic factors, can influence the population dynamics of the greyback canegrub. Biotic factors such as beetle flight and aggregation behaviour and grub natural enemies (diseases) are also hypothesized to regulate populations.

Modelling Approach

Modelling can have two objectives – *analytical or mechanistic*, where the purpose of the model is to gain more understanding of the population dynamics of a particular species or community; and *statistical or predictive*, where the purpose is to estimate future population levels or the probability of a future population attaining a certain population level given that it starts at a known population level at or before the time of prediction. Modelling crop loss or damage…is essentially modelling an index of insect pest population level, but with the added complication of plant physiological response to insect feeding. Modelling plant damage is more complex than modelling insect population dynamics alone (since it is an interaction between grub population dynamics and behavior and plant physiology as a response to grub feeding and abiotic stressors), but it is important in assessing the risk in managing greyback canegrub and therefore, any prediction of greyback canegrub populations should be cast in light of population levels that have potential to cause non-detectable amounts of damage, light damage, moderate damage, or serious damage. Only if this level of prediction can be made (by assigning probabilities to these damage levels), will economic decision-making aids be developed. Dr. Samson has been working on an economic decision-making algorithm that can incorporate probabilities of greyback canegrub population level projections (obtained from the proposed matrix model) and an economic cost/benefit model incorporating the costs of insecticide treatment and economic loss due to greyback canegrub. During my consultation, two modelling approaches were discussed with Drs Samson and Chandler. Most of our deliberations were focused on the data to be used for the construction of a discrete time difference equation model, referred to in this report as the "matrix model". Data collection has been developed and pursued by the BSES research staff for the past three years with the intent of model development. Therefore, it would seem the most logical step to continue with the intent of determining if a useful predictive model can be built. The use of a matrix model is a standard approach to predicting future states of a system, given knowledge of the state of the system (greyback canegrub population density) in the current or previous year(s).

A second modelling approach, an analytical or mechanistic approach, involves constructing a mathematical representation of the underlying processes of population growth, ie. birth, death, immigration, and emigration rates. These rates may be governed by temperature, soil moisture, populations in neighbouring fields, and disease levels. A further discussion of these approaches is presented below (see continuous-time population model).

Matrix model

The matrix model is one approach that the research staff involved in the *GrubPlan2* project has decided to employ. It is essentially a predictive model based upon statistical relationships between environmental and biological measures taken in sugarcane fields which relate greyback canegrub population levels in one year to grub population levels in the following year.

As described in a previous report (T. Jackson Consultancy Report, May 2004): "data are grouped into pre-assigned population categories that reflect damage potential to the crop and placed into matrices based on the occurrence of historical combinations of events. These occurrences can be a result of several factors; for example, damaged blocks in the area in 2003 (year N), grub numbers 2003 (year N) and grub numbers 2004 (year N+1). In a simple two-factor analysis, Damage in area year N vs. grubs Year N+1, there might to be a simple linear relationship between damage and subsequent grub numbers. Furthermore, matrix output provides a probability of the event".

The modelling problem becomes how best to quantify the transition probabilities in the matrix (i.e. the cell probabilities). The crudest means is to total up the number of occurrences of transitions from one state to the next and have these frequencies as a proportion of the marginal totals represent the transition probabilities. However, this does not allow significance testing of the various factors responsible for the transition probabilities and also does not necessarily represent an unbiased estimate of these probabilities. Therefore, I have recommended that the matrix model be constructed using a statistical procedure (ordinal non-linear logistic regression) in order to evaluate the significance of the environmental and biological factors measured during this project as predictors of the probability of change in population for the following year. It is recommended that an ordinal logistic model be used in order to model several greyback grub population levels. Each of the levels will represent different damage classes, i.e. none, slight, moderate, and severe. These damage classes will be defined by the BSES research staff and will be based upon the 2003-2005 sampling of greyback canegrub densities and associated damage. It is recommended that logistic regression be performed initially with all of the *GrubPlan2* sample data. These data will include the regional or district measures for each of the sample years (regional damage estimates, weather data, etc.) and the field-level data which include a time series of greyback canegrub densities and the associated field characteristics which have been measured (number of neighbouring damaged fields, distance from a forest edge or creek bed, distance from a beetle feeding tree, differential crop height, crop phenology stage, etc.). The initial logistic regression analyses will be used to assess significant predictors. Once these are established it is recommended that a jack-knife procedure be used to validate the model and provide a sensitivity analysis of the significant predictors. The jack-knife procedure involves sequentially modelling subsets of the data, building a model with a subset and then validating the model by predicting the classification of the data held out from the subset model. This is repeated n times (n being the number of subsets into which the original data set is randomly divided, a minimum of three subsets). Upon inspection of the jack-knife results, it should be able to be determined if a predictive model can be developed that is superior to simply predicting grub populations solely upon the population levels from the previous year. A predictive model would then provide the probabilities of population class change from one year to the next. This model would then

be used in the economic risk assessment algorithm developed by Dr. Samson. It is also recommended that data collected in 2006 be used to independently validate a model that might be developed from the 2003-2005 sample data. The validation will provide an estimate of whether extrapolation as a means of predicting population change is a reasonable modelling approach (see below…discussion of extrapolation). Following an independent validation, model parameter estimates will be improved (and may possibly be more precise) by using all four years data (2003-2006). Dr. Drummond has offered his services to conduct the statistical analysis for model construction, validation, and sensitivity analysis.

Matrix models are only as good as the data that are used to prepare them and the probabilities of outcome reflect the historical inputs. Thus, if the data used to build the model represents environmental conditions different from those characterizing the fields in which predictions are desired, inaccurate outcomes may result. This is commonly referred to as the fallacy of extrapolation and caution must always be exercised. It is hoped that the four years of data collection (by the end of this project) that have been used for model development will cover most of the year-to-year variation experienced in the near future. Given this dilemma, an additional prediction may provide useful, hence an investigation into the potential for the development of a mechanistic population model is recommended.

Continuous time population model

It is also recommended that a second approach to modelling greyback canegrub populations be investigated. The objective would be to determine if enough information exists in published and unpublished reports to construct a stage-structured phenology model. Either a discrete-time or continuous-time population model can be constructed. I have developed a simplified conceptual model below for the greyback canegrub that might form the basis of a preliminary population model. A model such as this could increase understanding of greyback canegrub population dynamics and thus add information to predictions derived from a matrix model and enhance overall predictions by increasing the confidence of a particular prediction. Thus, it is not expected that a mechanistic model as is proposed below would be a predictive model on its own, but a supporting decision-making tool which captures the ecological and behavioral processes that result in greyback canegrub population fluctuations. It is also not expected that a fully functional mechanistic model can be constructed under the current time horizon of the *GrubPlan2* project. However, it is expected that development of a preliminary model will help identify important research objectives for future projects aimed at refining the model for purposes of making it more realistic.

Envisioned as a series of delay-differential equations (the phenology component or insect development component is represented by a developmental delay, either in days or degree days depending on the data available), I have presented a conceptual model…meaning that each parameter may e a complex function of several variables representing several biological processes:

- Within-season models…immatures (at the block spatial scale). Therefore, each of the differential equations below represents a within-growing season or a single generation submodel.

- Between-season model - linking the growing seasons and grub generations…adults (possibly at the farm spatial scale) and the carry-over of any density dependent factors such as infective disease propagules.

Eggs – laid by recruiting adults (recruiting adults may be from the block of interest and in addition may represent adults from other blocks on the farm…this is an area that has to be a major focus of research in order to develop a realistic model).

$dE/dt = a_0A – [a_1 + b_1E]E – E(\dagger)$

where the change in egg density (dE/dt) is a function of the adults recruiting to the block (A) for oviposition (see adult model) and their fecundity (a_0) – this may be a function of temperature, soil moisture etc. – minus the density independent mortality of eggs (a_1) – this maybe a function of soil temperature or soil moisture etc. – and possible density dependent mortality factors (b_1) such as predation or cannibalism by early hatching grubs. The development time of eggs (†) determines the length of time that eggs are present before hatch occurs. E(†) is "representative" of the egg development time. Specifically, E(†) is the egg density that hatches and becomes the newly hatched grubs at a certain time t called † which might be in days, degree days or some other physiological or developmental unit.

Larvae (grubs) – all instars pooled as one stage…but we could model individual instars if a biological case is made to do it. Larvae are modeled as two streams: non-infected and infected grubs…this is because it is assumed that disease is the key factor regulating grub densities.

$dL/dt = E(\dagger) – [a_2 + b_2L]L – I – L(\dagger)$

$dI/dt = ZLI_{(g-1)} – a_3I – I(\dagger)$

where the change in non-infected grubs (dL/dt) is due to hatching eggs (E(†)) minus the density independent mortality of grubs (a_2), probably determined by abiotic soil conditions, and the density dependent mortality caused by factors other than disease (b_2), probably cannibalism, and diseased grubs (I). The length of time (†) that grubs are in the grub instars determines the severity of mortality, i.e. the virulence or time to death. The disease model states that disease in generation "g" is dependent upon the number of grubs that died of disease in generation "g-1" ($I_{(g-1)}$) and the number of susceptible non-infected grubs (L) and a transition coefficient (Z) which may be a simple constant or a complex function of grub density, grub age, spatial pattern of infected grubs, and/or abiotic soil conditions (Drummond et al. 1996). In addition, the density independent mortality of diseased grubs reduces the number of inoculative units ($I_{(g-1)}$) the following year. The assumption underlying the preliminary model is that if an infected individual dies before the internal inoculum is produced in sufficient quantity (in the case of a protozoan) or before the infected individual dies and sporulates then it will not produce inoculum for horizontal infection (same generation of grubs) or more reasonably with the canegrub, vertical infection (next generation of susceptible larvae).

The time to death of infected grubs is represented by (I(†)), it is actually the number of grubs dieing from disease and also the number of infective cadavers for the next

generation of disease. The longevity of disease inoculum is probably a complex function (b_3) of time, temperature, soil moisture, and other abiotic and biotic factors and is assumed to be represented as follows:

$dI_{(g-1)}/dt = -b_3\ I(\dagger)$

where b_3 represents the decay rate of inoculum from the time grubs die of disease until the following year when new susceptible grubs might be expected to encounter inoculum.

<u>Pupae</u> – a simple model which assumes that only density independent mortality occurs, but can be modified to include density dependent mortality.

$dP/dt = L(\dagger) - b_4P - P(\dagger)$

where the number of grubs surviving to pupation ($L(\dagger)$) is reduced by density independent mortality (b_4). The duration of the pupal stage is represented by †.

<u>Adults</u> – (at the block and farm level spatial scales) this could be a very behavior rich model…probably only modeling females (0.5 i.e. 50/50 sex ratio)

$dA/dt = 0.5[P(\dagger) + Af] - b_5 0.5[P(\dagger) + Af] - A(\dagger)$

where the female adult density in a block ($0.5(P(\dagger) + Af)$) is dependent upon the pupae producing adults within a block ($P(\dagger)$) and the other adults on the farm (Af) that might also recruit to the block for oviposition minus the adults emerging from the block ($P(\dagger)$) and other adults emerging from other blocks on the farm (Af) that do not make it to the block to oviposit, b_5 is a complex submodel that includes mean dispersal distance, distance to feeding trees from block, and abiotic mortality probably due to weather conditions. The longevity of adults is represented by $A(\dagger)$, ie., the number of adults dieing of old age. We may also want to incorporate a preoviposition maturity function and a density dependent mortality function if birds are a significant predator (hopefully not, as this would be difficult to model).

Drummond, F.A., N.D. Barlow, and T.A. Jackson. 1996. A sensitivity analysis of a within-season model for amber disease of grass grub , *Costelytra zealandica*, caused by the bacterial pathogen, *Serratia entomophila*. Proceedings of the Third International Workshop on Microbial Control of Soil Dwelling Pests (eds. T.A. Jackson and T.R. Glare). Lincoln, Canterbury, NZ. pp. 111-124.

It is suggested that a preliminary population model be constructed. This computer-based simulation model would include parameters that have been identified in the literature as significant in regulating greyback canegrub populations. If there are not enough existing data to quantify the relationships that result in greyback grub population regulation, then this population model should prove useful in guiding future research objectives to more fully understand the population dynamics of this serious insect pest.

I have extensive experience in modelling pest population dynamics and I can offer my services to the *GrubPlan*2 project for model development and validation as the principal investigators (BSES research staff) deem useful.

Further information on matrix modelling and derivation of parameter estimates and confidence limits for predictions, as discussed in this report, can be obtained from Dr. Frank Drummond. In addition, further information on modelling of soil pest population dynamics can also be obtained from Dr Frank Drummond, University of Maine, USA (frank.drummond@umit.maine.edu).

Modelling recommendations

- Use a matrix model (Markov chain) for determining probabilities of greyback canegrub population change from one year to the next.
- Select significant predictors and quantify transition probabilities of the matrix model using ordinal non-linear logistic regression.
- Initially validate the matrix model parameters and estimates using the jack-knife procedure.
- Use the 2006 data to validate the matrix model with an independent data set.
- After final validation, incorporate the 2006 data to provide more precise parameter estimates for estimating transition probabilities of the matrix model using ordinal non-linear logistic regression.
- Investigate the development of a mechanistic population model of the greyback canegrub.

Acknowledgements

My thanks are extended to Dr Peter Samson and BSES for the invitation to take part in this review and organization of my visit. Thank you also is in order to Dr Keith Chandler and Dr Peter Samson for useful and insightful discussion of the program and the biology of greyback canegrub.

APPENDIX 10 – DRUMMOND CONSULTANCY REPORT, 2007

Consultancy report for BSES Limited, 2007

Project no. BSS257

Title. *GrubPlan2: Developing improved risk-assessment and decision-support systems for managing greyback canegrub*

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SUMMARY

Two modeling components comprised the consultancy work on the project BSS257 entitled: *GrubPlan2: Developing improved risk assessment and decision-support systems for managing greyback canegrub.* The modeling objectives were initially formulated during the BSS257 project proposal. The specific objectives discussed in this report were formulated during a site visit to the Meringa field station by Dr. Drummond between 8-12 August 2005.

The first component involved development of statistical models for predicting greyback canegrub densities or population levels from data collected in sugarcane blocks over the four-year period 2003 – 2006. Several types of information were used in construction of these models including: sampled canegrub density estimates, sugarcane management practices such as fallowing and planting of legumes after harvest, various sampled estimates of damage severity, sugarcane canopy height, frequency of insecticide use, regional crop damage and insecticide treatment estimates, and many others (see Sections 1.0 and 2.0). Several modeling approaches were investigated. Predictions of the future (one year in advance) number of grubs / stool, grub population increase or trend (log (grubs/ stool in year (t) – grubs / stool in year (t+1)), and grub density classes (low, moderate, and high) were compared using various models such as linear multiple regression, nominal and ordinal logistic regression, and linear discriminant analysis. Models were developed and evaluated for specific years and regions, as well as independent of year and region. The summaries of the intermediate results are included in Section 2.0. The final derived models along with parameter estimates are presented and discussed in Section 1.0, "Final Statistical Models".

A preliminary greyback canegrub simulation model was also constructed. The goal of the work was two-fold. First, a continuous-time model formulated by parameterizing a series of linked differential equations, each equation representing the change in life-stage numbers relative to time of the growing season, was developed (see Section 3.0). The parameters for this stage-specific life history simulation model that governed development, survival, longevity, and fecundity rates were developed by reviewing the published literature, unpublished reports and unpublished field and laboratory data. In addition, discussions with BSES sugarcane entomologists (Drs. Samson, Sallam, and Chandler) provided critical understanding of greyback canegrub population dynamics. These data sources were used to develop quantitative relationships assumed to be important in regulating population densities of the greyback canegrub. Secondly, the model was developed using the STELLA® modeling platform so that BSES researchers could further modify the model for future research projects. Conclusions based upon the first drafts of the preliminary model and future modifications for the model are discussed in the "Simulation Model Results" section.

An independent validation and evaluation/re-parameterization of the statistical models discussed in this report will be carried out in 2007 under an extension to this project. In addition, modifications to the existing simulation model to incorporate additional aspects of greyback canegrub biology will also be addressed under this extension. These final analyses are covered in the 2008 report (Appendix 11)

1.0 FINAL STATISTICAL MODELS

Statistical models for prediction of greyback canegrub were derived from the four-year data set collected during the duration of the BSS257 project. This initial phase of the project resulted in the investigation of not only specific effects of sugarcane management practices on greyback canegrub densities, but also effects of disease incidence on subsequent grub densities and the surrounding outside environmental landscape on within-block grub densities (see section 2.0). During this phase of the project, three measures of greyback canegrub densities were used for predictive model development. These measures were: 1) logarithm (base 10) of grubs / stool in the subsequent year, 2) the population trend or intrinsic rate of growth from year (t) to year (t+1), and 3) the categorical grub density class of low, moderate, and high (these classes reflect grub density levels ranging from: low= 0 – 0.2 grubs/stool, moderate = >0.2 – 1.0 grubs/stool, and high = >1.0 grubs/stool.). Candidate models were developed for these three grub level measures (section 2.0). However, prior to accepting these models as final versions of a series of predictive models, several more analyses were conducted in order to evaluate their suitability and performance.

1.1 Spatial autocorrelation

A series of Mantel tests were conducted to test whether grub densities were correlated between districts along a distance continuum within a region. The reason for this analysis was to determine whether a spatial component based upon distance from neighboring farms was necessary or whether a regional spatial predictive factor is sufficient for predicting subsequent grub densities in a block.

Table 1. Spatial correlations (Mantel permutation test results, reps=5000). Pair-wise distance between districts (km) within a region vs. absolute difference in grub densities between district pairs

REGION	2003	2004	2005
Central			
r	-0.193	0.615	-0.084
P	0.071	0.033	0.393
Innisfail			
r	0.509	-0.578	0.209
P	0.199	0.187	0.502
Herbert			
r	0.081	-0.044	0.539
P	0.536	0.484	0.092
Mulgrave			
r	0.116	0.187	-0.101
P	0.302	0.222	0.372

The results of this test suggest that, apart from the Central region in 2004, there is no reason to expect that a strong spatial component exists between grub densities and the geographic separation in kilometers between blocks.

1.2 Insecticide use and frequency

During the consultation visit in February 2007 it was discovered that inaccuracies existed in the current model data set. Inaccuracies were corrected where possible and the new data set was used to re-evaluate many of the previously parameterized models. It was found that suSCon applied at time of planting, application of Confidor during the last year, and a suSCon/Confidor protection strategy where either insecticide was applied yielded the best predictors of log grub density in the subsequent year. The total amount of variation explained by these predictors on their own was quite low and ranged from 1.7 to 9%, with suSCon at planting explaining 9% of the variation in log grub densities. However, despite the low explanatory power, insecticides were often significant predictors in the overall models (see below).

1.3 Global models

Three models were developed for predicting: 1) log grubs/stool, 2) grub trend, and 3) grub density class. These models used all of the data collected during the four year duration of BSS257. These models are described by parameter estimates as follows:

1.3.1 Predicting Log grub densities:

Best model: $r^2 = 0.298$

factor	*coefficient*	*P value*
intercept	0.1022021	<0.0001
log grub (yr0)	0.3106069	0.0011
severity (yr0)	0.0398346	0.0008
all regions vs Herbert	-0.043244	<0.0001
gaps (yr0)	0.0142901	0.0221
suSCon at plant	-0.094271	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	3.1	-1.1
intercept	5.9	0.8
log grub (yr0)	9.8	-2.3
severity (yr0)	11.1	-0.1
all regions vs Herbert	2.0	0.3
gaps (yr0)	12.6	0.7
suSCon at plant	6.8	0.8

The model for predicting log grubs/stool has fairly low predictive potential with only 29.8% of the variation in future log grubs/stool being explained by the predictor variables. The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, coefficients derived from five iterations exhibit fairly low variation (%se/mean ca. 2-12.6%) and the average coefficient values derived from the five

jackknife runs depart from the whole model (all data points) by less than 2.3%. Therefore, the model coefficients appear to be very robust to 20% changes in the structure of the data with the resulting r^2 from the five jackknife runs only varying with a se to the mean of 3.1%. The main problem here is that while the model is quite robust to changes in data, an indication of the robustness of the model to new data in the future, the model in general has low predictive capability.

1.3.2 Predicting grub trend:

Best model: $r^2 = 0.245$

factor	*coefficient*	*P value*
intercept	0.0864432	<0.0001
log grub (yr0)	-0.632477	<0.0001
max severity (yr0)	0.029847	0.0064
replant vs fallow	0.0501921	0.0042
all regions vs Central	-0.064261	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	5.6	-1.8
intercept	3.2	<-0.01
log grub (yr0)	4.9	1.1
max severity (yr0)	7.6	1.1
replant vs fallow	5.8	0.3
all regions vs Central	4.8	0.2

The model for predicting grub trend also has fairly low predictive potential with only 24.5% of the variation in future log grub/stool being explained by the predictor variables. The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, coefficients derived from five iterations exhibit fairly low variation (%se/mean ca. 3.2-7.6%) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 1.8%. Therefore, the model coefficients appear to be very robust to 20% changes in the structure of the data with the resulting r^2 from the five jackknife runs only varying with a se to the mean of 5.6%. The main problem here is similar to that of the log grub predictive model…that while the model is quite robust to changes in data, an indication of the robustness of the model to new data in the future, the model in general has low predictive capability.

1.3.3 Predicting grub density class:

Best model: % correct :
Low: 71%, Moderate: 43%, High: 55%, Overall: 62%

factor		*coefficients*	
	low	*moderate*	*high*
intercept	-3.6334	-3.88098	-5.88572
Log grub (yr0)	4.866171	9.91104	17.5439
Severity (yr0)	0.661457	1.234218	0.831654
suSCon at plant	5.373762	4.530255	3.387462
Region(all vs Herbert)	-0.2765	0.46739	0.859198

Confidor (last year)	0.417346	-0.9946	-1.45016

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*		
	low	*moderate*	*high*
intercept	3.7	8.3	6.9
Log grub (yr0)	23.2	16.3	10.2
Severity (yr0)	20.9	19.6	39.5
suSCon at plant	4.4	8.1	1.8
Region(all vs Herbert)	33.6	12.4	3.9
Confidor (last year)	30.9	34.1	62.8

factor	*% difference*		
	low	*moderate*	*high*
intercept	1.8	2.1	-5.9
Log grub (yr0)	6.3	2.9	6.3
Severity (yr0)	-8.7	15.7	-8.9
SuSCon at plant	4.3	7.7	-4.3
Region(all vs Herbert)	–1.7	-77.2	-7.5
Confidor (last year)	-80.9	-18.4	55.7

%accuracy	*% se / mean*	*% diff*
low	8.0	13.8
moderate	4.6	25.6
high	2.9	14.5

The linear discriminant function predicts log grub density fairly well (overall 62% correct prediction) with an adequate rate of correct prediction of low density blocks (71%). The jackknife analysis shows that the linear discriminant model is only moderately sensitive to changes in the data structure (% se / mean of jackknifed coefficients ranging from 8 to 34%). The % difference in the model coefficients from the entire data set compared to the jackknifed data sets (20% less data), suggests that estimates for coefficients are for the most part only slightly affected (the exception being Confidor, but this is to be expected since dichotomous variables are notorious for bad behavior in discriminant functions). Overall, the model is quite stable and should be a good stable predictor, although the accuracy is not as high as desired.

1.4 Regional models

Another potential modeling strategy was development of a series of independent models for each region. This was investigated by constructing models for the Central, Herbert, and far North Queensland regions. In general, the results were quite variable depending upon region. Some of the models had quite high predictive power and some were mediocre to poor.

The regional predictive models derived to predict log grub density the subsequent year resulted in an adequate predictive model for the Central region, but while models with significant predictor variables were found for the Herbert and the FNQ regions, the degree

of predictive accuracy and the robustness of the models to changes in the data structure were lacking.

1.4.1 Predicting Log grub densities with regional models:

a. Best model for the Central region: $r^2 = 0.2991$

factor	*coefficient*	*P value*
intercept	-0.070766	0.5538
suSCon in plant crop	-0.17928	0.0385
Severity (yr0)	0.1086933	0.0240
Distance to neighbor (yr0)	0.0004161	0.0321
Maximum severity (yr0)	0.1335139	0.0071

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	13.3	3.7
intercept	12.5	-10.8
SuSCon in plant crop	7.3	-1.2
Severity (yr0)	11.3	1.9
Distance to neighbor (yr0)	9.2	-2.4
Maximum severity (yr0)	7.4	-2.6

The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, some coefficients derived from five iterations have moderate variation (%se/mean ca. 10-13%) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 5% (excepting the intercept that varies by 10.8%, but the intercept is not significantly different from zero). Therefore, the model coefficients appear to be moderately robust to 20% changes in the structure of the data with the resulting r^2 from the five jackknife runs only varying with a se to the mean of 13.3%.

b. Best model for the Herbert region: $r^2 = 0.1202$

factor	*coefficient*	*P value*
intercept	0.037275	0.0008
suSCon in plant crop	-0.023435	0.0488
Log grub (yr0)	0.3871915	0.0058

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	24.9	-0.9
intercept	14.6	0.8
SuSCon in plant crop	25.6	2.2
Log grub (yr0)	17.6	4.3

The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, coefficients derived from five iterations have considerable variation (%se/mean ca. 25.6% or less), although the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 4.4%.

Therefore, the model coefficients appear to be sensitive to 20% changes in the structure of the data and this regional model should be used with caution until a larger data set can be collected to re-parameterize the model.

c. Best model for the FNQ region: $r^2 = 0.1807$

factor	*coefficient*	*P value*
intercept	0.1305975	<0.0001
Log grub (yr0)	0.3060703	0.0061
Confidor last year	-0.099397	0.0017
Max relative canopy hgt	0.0000457	0.0478

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	7.9	1.4
intercept	3.4	0.2
Log grub (yr0)	5.1	-0.7
Confidor last year	8.2	-0.1
Max relative canopy hgt	11.0	-1.4

The jackknife analysis shows that even with deleting 20% of the data points to build a predictive model, coefficients derived from five iterations have a minimal variation (%se/mean ca. 11% or less) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 2% and the se/mean of the r^2 is only 7.9%. Therefore, the model coefficients appear to be very robust to 20% changes in the structure of the data.

1.4.2 Predicting grub trends with regional models:

a. Best model for the Central region: $r^2 = 0.1889$

factor	*coefficient*	*P value*
intercept	0.1536027	0.0910
Log grub (yr0)	-0.836436	0.0160
suSCon in plant crop	-0.178835	0.0515
Max severity (yr0)	0.0815773	0.0333

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	21.9	4.5
intercept	11.9	1.7
Log grub (yr0)	7.9	0.7
suSCon in plant crop	12.8	-0.9
Max severity (yr0)	13.3	-1.8

The jackknife analysis shows that coefficients derived from five iterations have a moderate variation (%se/mean ranging 7.9 – 13.3%). The average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 2.0%. In addition, se/mean of the r^2 varied by 21.9%. Therefore, the model coefficients appear to be moderately robust to 20% changes in the structure of the data.

b. Best model for the Herbert region: $r^2 = 0.218$

factor	*coefficient*	*P value*
intercept	0.037275	0.0008
suSCon in plant crop	-0.023435	0.0488
Log grub (yr0)	-0.612808	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	19.2	-6.8
intercept	14.6	0.7
SuSCon in plant crop	25.6	2.2
Log grub (yr0)	25.1	12.5

The jackknife analysis shows that coefficients derived from five iterations have a moderate to high variation (%se/mean ca. 14-25%) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by a range of 0.7 – 12.5%. But, the se/mean of the r^2 varied only 19.2%. Therefore, the model coefficients appear to be just adequately robust to 20% changes in the structure of the data. Caution might be advised with this model until tested with future field data.

c. Best model for the FNQ region: $r^2 = 0.399$

factor	*coefficient*	*P value*
intercept	0.1305975	<0.0001
Log grub (yr0)	-0.69393	<0.0001
Confidor last year	-0.0995336	0.0017
Max relative canopy hgt	0.0000457	0.0478

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	6.2	1.2
intercept	3.4	0.2
Log grub (yr0)	2.2	0.3
Confidor last year	8.2	-0.1
Max relative canopy hgt	10.9	-1.4

The jackknife analysis shows that even with deleting 20% of the data points to build a predictive model, coefficients derived from five iterations have a minimal variation (%se/mean ca. 11% or less) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 2% and the se/mean of the r^2 is only 6.2%. Therefore, the model coefficients appear to be very robust to 20% changes in the structure of the data.

1.4.3 Predicting grub density classes with regional models:

Best model for the Central region: % correct :
Low: 89%, Moderate: 44%, High: 69%, Overall: 63%

factor	*coefficients*		
	low	*moderate*	*high*

intercept	-2.10175	-2.31555	-3.52954
Log grub (yr0)	5.646569	8.244647	15.42485
suSCon at plant	3.039978	2.269117	1.939347
Severity (yr0)	0.506525	1.391377	1.789879

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*		
	low	*moderate*	*high*
intercept	19.5	13.9	18.6
Log grub (yr0)	24.6	33.0	15.1
suSCon at plant	24.8	28.0	34.1
Severity (yr0)	46.4	11.6	30.4

factor	*% difference*		
	low	*moderate*	*high*
intercept	-44.3	-42.7	-47.7
Log grub (yr0)	-33.9	-14.8	-20.8
suSCon at plant	-65.6	-29.8	-79.9
Severity (yr0)	-77.2	-79.56	-67.4

%accuracy	*% se / mean*	*% diff*
low	13.9	-24.9
moderate	12.5	10.9
high	9.1	-37.7

The Central linear discriminant function predicts log grub density fairly well (overall 63% correct prediction) with a high rate of correct prediction of low density blocks (89%). The jackknife analysis shows that the linear discriminant model for the Central region is very sensitive to changes in the data structure (% se/mean of jackknifed coefficients ranging from 11 to 46%). The % difference in the model coefficients from the entire data set compared to the jackknifed data sets (20% less data), suggests that estimates for coefficients are strongly affected. Because of this sensitivity, the models built with the reduced data sets resulted in reduced accuracy for low and high density classes (24.9 and 37.7%, respectively). Therefore, it appears that there is potential for the development for a Central Region model, but because of the small sample size, it would be risky to utilize the existing model coefficients for future predictions without also using an additional model to evaluate the results.

Best model for the Herbert region: % correct :
Low: 92%, Moderate: 57%, Overall: 89%

factor	*coefficients*		
	low	*moderate*	*high*
intercept	-2.74677	-3.54221	na
Log grub (yr0)	-4.91878	47.58489	na
Distance to tree	0.005608	0.004807	na
Max Severity (yr0)	1.10261	0.612567	na
Killing method	4.052418	2.013112	na
Legume planting	2.311118	2.731897	na

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*		
	low	*moderate*	*high*
intercept	4.2	16.0	na
Log grub (yr0)	92.2	21.6	na
Distance to tree	19.9	66.9	na
Max Severity (yr0)	34.3	40.2	na
Killing method	4.9	143.4	na
Legume planting	37.7	51.6	na

factor	*% difference*		
	low	*moderate*	*high*
intercept	-14.3	-41.3	na
Log grub (yr0)	-143.6	-55.9	na
Distance to tree	-1.4	1.6	na
Max Severity (yr0)	-27.6	316.4	na
Killing method	-22.1	48.2	na
Legume planting	17.6	-22.8	na

%accuracy	*% se / mean*	*% diff*
low	7.9	8.3
moderate	10.9	0
high	na	na

The Herbert linear discriminant function predicts log grub density fairly well (overall 89% correct prediction) with a high rate of correct prediction of low density blocks (92%). However, only low and moderate density classes were available for evaluation and construction of a model. The jackknife analysis shows that the linear discriminant model for the Herbert region is also very sensitive to changes in the data structure (% se/mean of jackknifed coefficients ranging from 4 to 143%). The % difference in the model coefficients from the entire data set compared to the jackknifed data sets (20% less data), suggests that estimates for coefficients are strongly affected. However, even with this sensitivity, the models built with the reduced data sets resulted in fairly high accuracy for low and moderate density classes (8 and 0% mean differences from the model built with all of the data, respectively). Therefore, it appears that there is potential for the development for a Herbert Region model, but because this model only can predict membership in low or moderate density categories, the utility of this model is minimal.

Best model for the FNQ region: % correct :
Low: 50%, Moderate: 50%, High: 31%, Overall: 51%

factor	*coefficients*		
	low	*moderate*	*high*
intercept	-4.41639	-4.7626	-4.97207
Distance to tree	0.00655	0.004014	0.003325
Log grub (yr0)	4.440108	7.452798	11.30879
Distance to Neigh.	0.006587	0.006207	0.006799
Severity (yr0)	3.65496	4.153477	3.702141

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*		
	low	*moderate*	*high*
intercept	4.5	4.8	10.1
Distance to tree	15.8	25.9	23.5
Log grub (yr0)	22.8	14.7	16.1
Distance to Neigh.	3.9	5.6	11.7
Severity (yr0)	7.9	8.3	12.1

factor	*% difference*		
	low	*moderate*	*high*
intercept	-7.6	-4.9	-8.2
Distance to tree	-33.2	-63.5	-57.1
Log grub (yr0)	-58.7	-28.7	-16.9
Distance to Neigh.	-9.1	-8.1	-10.5
Severity (yr0)	-4.7	-1.1	-3.1

%accuracy	*% se / mean*	*% diff*
low	7.9	8.3
moderate	10.9	0
high	na	na

The FNQ linear discriminant function predicts log grub density sub-optimally (overall 51% correct prediction) with a low rate of correct prediction of high density blocks (31%). The jackknife analysis shows that the linear discriminant model for the FNQ region is not sensitive to changes in the data structure (% se/mean of jackknifed coefficients ranging from 4 to 26%). The % difference in the model coefficients from the entire data set compared to the jackknifed data sets (20% less data), suggests that estimates for coefficients are moderately affected.

With this robust nature, the models built with the reduced data sets resulted in fairly similar accuracy for all density classes. The development for a Herbert Region model is minimal due to the overall low predictive nature of the model.

1.5 Predictions without using direct estimates of previous year grub density

I investigated the performance of models derived from suites of all possible predictors except those representing sampled estimates of grub density (log grubs/stool, and grub trend). The motivation behind this effort was the high cost of grub sampling. Three measures of grub population level were modeled for prediction: log grubs/stool, grub trend, and grub density class.

1.5.1 Predicting future Log grub densities with no grub density predictor

Best model: $r^2 = 0.209$

factor	*coefficient*	*P value*

intercept	0.0458835	0.0307
Maximum severity (yr0)	0.0714946	<0.0001
Maximum rel canopy hgt	0.0000483	0.0205
Gaps (yr0)	0.0230436	0.0139

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	12.3	0.7
intercept	16.4	-1.3
Maximum severity (yr0)	6.9	0.5
Maximum rel canopy hgt	11.2	-0.4
Gaps (yr0)	14.5	0.5

The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, some coefficients derived from five iterations have moderate variation (%se/mean ca. 6-16%) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 2%. Therefore, the model coefficients appear to be moderately robust to 20% changes in the structure of the data with the resulting r^2 from the five jackknife runs only varying with a se to the mean of 12.3%.

1.5.2 Predicting future grub trends with no grub density predictor

Best model: $r^2 = 0.082$

factor	*coefficient*	*P value*
intercept	0.1293061	<0.0001
SuSCon in plant crop	-0.08402	0.0007
Confidor in last year	-0.081842	0.0075
Replant fallow	-0.018899	0.0485

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	10.4	-3.6
intercept	10.7	0.3
SuSCon in plant crop	15.4	0.6
Confidor in last year	14.4	0.5
Replant fallow	10.9	1.2

Overall, the ability to predict grub trend without a measure of previous grub density was very poor. The jackknife analysis shows that with deleting 20% of the data points to build a predictive model, some coefficients derived from five iterations have moderate variation (%se/mean ca. 10-15%) and the average coefficient values derived from the five jackknife runs depart from the whole model (all data points) by less than 4%. Therefore, the model coefficients appear to be moderately robust to 20% changes in the structure of the data with the resulting r^2 from the five jackknife runs only varying with a se to the mean of 10.4%.However, as stated above the predictive ability of this model was poor.

1.5.3 Predicting future grub density classes with no grub density predictor

Best discriminant model: % correct:
Low: 69%, Moderate: 46%, High: 45%, Overall: 60%

factor	*coefficients*		
	low	*moderate*	*high*
intercept	-3.79929	-3.48044	-2.7758
Distance to tree	0.005171	0.002192	0.002821
SuSCon at plant	4.650871	4.353275	3.628333
Region (-Central)	0.796341	-0.04397	-0.84018
Severity (yr0)	0.708574	1.663446	1.629768

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*		
	low	*moderate*	*high*
intercept	4.3	6.6	7.5
Distance to tree	18.2	33.3	32.4
SuSCon at plant	8.3	7.3	14.3
Region (-Central)	17.4	194.6	55.7
Severity (yr0)	11.4	9.1	5.1

factor	*% difference*		
	low	*moderate*	*high*
intercept	-3.1	-0.4	-13.0
Distance to tree	-12.3	-63.9	-49.1
SuSCon at plant	-7.0	1.2	3.8
Region (-Central)	11.0	342.8	45.2
Severity (yr0)	-4.7	-1.1	-3.1

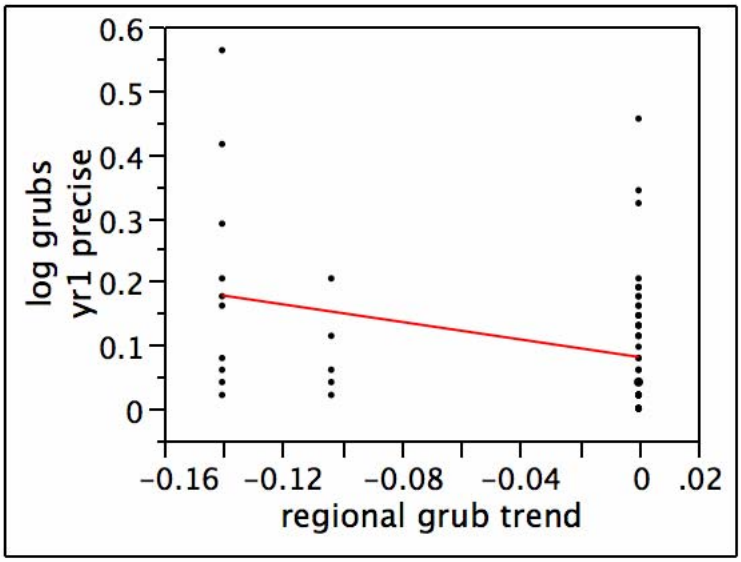
%accuracy	*% se / mean*	*% diff*
low	4.9	-3.8
moderate	26.5	34.3
high	4.4	-5.8

The ability to predict future grub density class is marginally adequate at a 60% overall correct classification rate. Evaluation of the model via jackknifing suggests that some of the parameter estimates are sensitive to the structure of the data (% se/mean = 33.3% for distance to nearest treeline, and 194.6% for region (central vs all other regions), but it must be recognized that these two sensitive parameters have very small values. Overall, the jackknife estimates of % accuracy suggest that the model is quite robust for predicting correct classification of low and high densities, but is more variable for predictions of moderate densities.

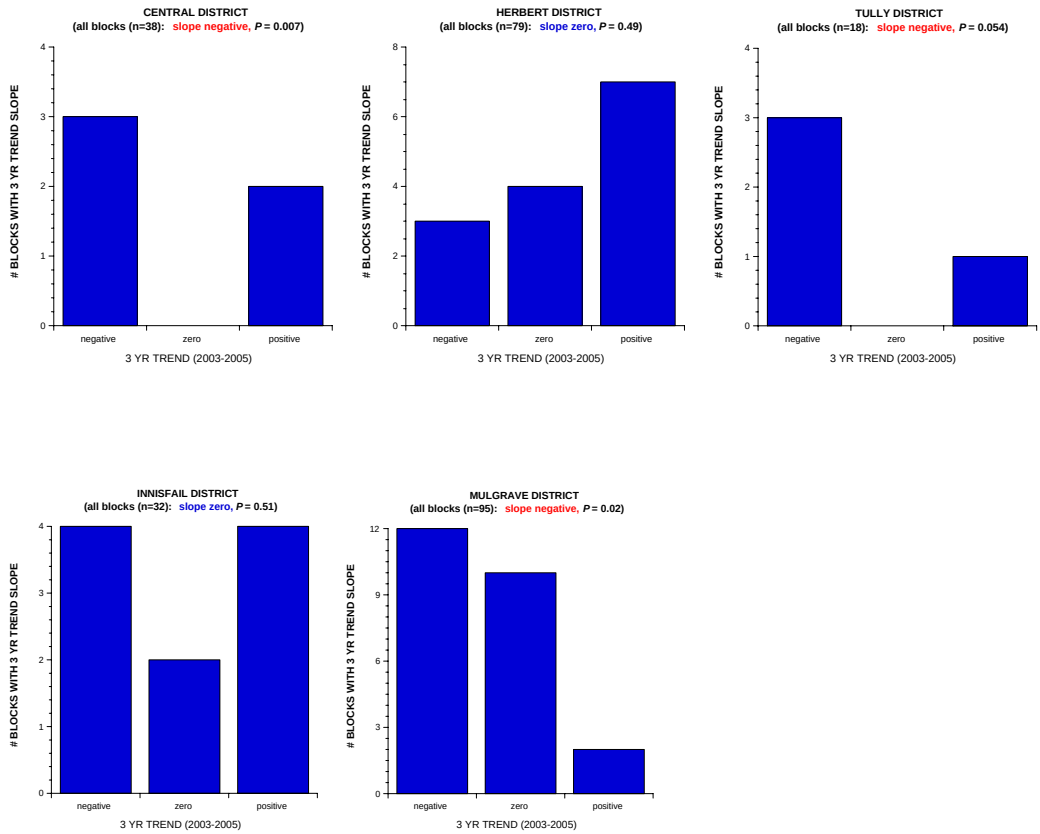
1.6 Use of regional indirect grub estimates

Another modeling strategy was development of a series of variables derived from Regional aggregated data. These data were then used in conjunction with the local block

variables for development of prediction models. Four variables of two types were used. The first three variables were based upon estimates of proportion total hectares in a region that were damaged or treated with insecticide the previous year, using data supplied by productivity services. Three variables were derived from these data: 1) the proportion of total hectares in a region damaged or lost, 2) the proportion of total hectares treated, and 3) the change in proportion damage of three years represented as the slope of a linear regression. Another variable was derived from the blocks sampled in the various regions during the duration of the BSS257 project. An estimate of grub trend over three years was calculated from all of the blocks within each region. Linear regression was then used to estimate a slope for the trend in population levels over a three-year period. Thus, the slope estimate essentially functioned as a quantified descriptor of region. Due to the lack of long-term data resulting from this project (only four years), slopes were estimated from 2003-2005 data and used to predict log grubs/stool in 2006. This was done solely as a means of evaluating the usefulness of a regional grub trend index for future predictions. An index of the linear change in grub trend (slope) was found to be a significant (0.0056) predictor of future (2006) log grubs/stool, explaining about 10% of the variation (see figure below). However, a small data set exists for 2006 and further analysis with more data will be needed to more thoroughly evaluate this index as a useful predictor.



Another look at this data by region (figure below) shows that there is much variation in the regional regression slope (noted in title of each figure) and the individual block grub trend over the same number of years, but in general, regions with a negative slope are characterized by blocks that had the mode represented by a negative slope, while those regions that had a zero slope (no trend over the three years) were not characterized by this type of distribution. Thus, the regional slope as an index of all farms within the region will not occur, but represents more of an average trend that may help in predicting the grub population levels of certain blocks within a region. In other words, it is not expected that these regional predictors will be useful by themselves, but only when used in conjunction with local block-specific data.



The other regional variables (proportion damaged ha, proportion insecticide-treated ha, and proportion damage trend over 3 yrs) were used in predictive modeling since there existed a time series of appropriate length for predicting the grub population levels for all years of this project.

1.6.1 Predicting log grub density with regional variables:

Best model of log grub (yr1) with regional variables: $r^2 = 0.446$

factor	*coefficient*	*P value*
intercept	0.1776393	<0.000 1
Log grub (yr0)	0.3667421	<0.0001
Severity (yr0)	0.0408249	0.0003
Gaps (yr0)	0.0135737	0.0175
suSCon at plant	-0.046734	0.0257
Regional prop damage	-6.817374	<0.0001
Regional prop treated	-1164653	<0.0001
Region (all vs Herbert)	0.1342099	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	3.1	-0.4
intercept	3.3	0.6
Log grub (yr0)	6.3	-1.4

Severity (yr0)	7.1	0.5
Gaps (yr0)	9.9	-0.01
suSCon at plant	9.3	0.8
Regional prop damage (yr0)	3.4	0.6
Regional prop treated (yr0)	3.1	0.4
Region (all vs Herbert)	2.4	0.3

The model that incorporates regional variables has a much higher predictive ability than a similar model previously described for predicting log grubs/stool (explains about twice the variation in log grubs/stool than without the regional predictive variables). The jackknife analysis suggests that the predictive variables are very robust (% se/mean all less than 10%) to changes in the data structure. In addition, the r^2 changes little when the data is changed by 20%. The conclusion here is that by adding regional predictor variables a more predictive and robust model results.

1.6.2 Predicting grub trend with regional variables:

Best model of log grub (yr1) with regional variables: $r^2 = 0.282$

factor	*coefficient*	*P value*
intercept	0.1588676	<0.0001
Regional prop damage (yr0)	-5.818442	<0.0001
Regional prop treated (yr0)	-0.732578	0.0004
Log grub (yr0)	-0.521265	<0.0001
Replant vs fallow	0.0617713	0.0009
Max severity (yr0)	0.0486154	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	7.4	0.6
intercept	2.2	0.2
Regional prop damage (yr0)	2.2	0.5
Regional prop treated (yr0)	2.1	0.6
Log grub (yr0)	7.1	-0.7
Replant vs fallow	3.9	-0.8
Max severity (yr0)	11.7	-0.2

The grub trend model that incorporates regional variables has only a slightly higher predictive ability than a similar model previously described for predicting grub trend. The jackknife analysis suggests that the predictive variables are very robust (% se/mean all less than 12%) to changes in the data structure. In addition, the r^2 changes moderately when the data is changed by 20%. The conclusion here is that by adding regional predictor variables, a slightly more predictive model results that is also fairly robust in coefficient estimates.

1.6.3 Predicting log grub with regional variables but no grub predictors

Best model of log grubs/stool with regional variables, but no grub predictors: $r^2 = 0.378$

factor	*coefficient*	*P value*

intercept	0.2370719	<0.0001
Max severity (yr0)	0.0487352	0.0003
Max rel canopy hgt	0.000048344	0.0135
Gaps yr (0)	0.0234671	0.0072
Regional damage (yr0)	-13.11742	<0.0001
Regional dam 3 yr slope	18.782551	<0.0001

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	7.4	0.6
intercept	2.1	0.2
Max severity (yr0)	11.7	-0.2
Max rel canopy hgt	7.1	-0.8
Gaps (yr0)	13.8	0.8
Regional damage (yr0)	2.2	0.5
Regional dam 3 yr slope	2.1	0.7

The log grub predictive model that does not use grub sample estimates for prediction is vastly improved with regional variables. An r^2 of 0.378 is much higher than a similar model with no regional variables (r^2 =0.209). The jackknife analysis suggests that the predictive variables are very robust (% se/mean all less than 12%) to changes in the data structure. In addition, the r^2 changes moderately when the data is changed by 20%. The conclusion here is that by adding regional predictor variables a much more predictive model results that is also fairly robust in coefficient estimates. However, this model is still not as good as a model with regional predictors and a measure of the grub density from the previous year (r^2 = 0.446, described previously).

1.6.4 Predicting grub trend with regional variables, but no grub predictors

Best model of log grub (yr1) with regional variables: r^2 = 0.174

factor	*coefficient*	*P value*
intercept	0.196524	<0.0001
Regional prop damage (yr0)	-6.861613	<0.0001
Regional prop treated (yr0)	-0.834437	0.0003
Replant vs fallow	0.0614218	0.0021
Confidor last yr	-0.074325	0.0177

Jackknife results (20% of data left out in each of 5 models)

factor	*% se / mean*	*% difference*
r^2	9.2	-1.2
intercept	13.4	0.9
Regional prop damage (yr0)	1.1	-0.2
Regional prop treated (yr0)	12.7	3.2
Replant vs fallow	3.3	0.2
Confidor last yr	15.0	-3.7

The grub trend model that incorporates regional variables but no grub predictor variables has less predictive ability than a similar model previously described for predicting grub

trend. The jackknife analysis suggests that the predictive variables are moderately robust (% se/mean all less than 15%) to changes in the data structure. In addition, the r^2 changes moderately (9.2%) when the data is changed by 20%. The conclusion here is that by adding regional predictor variables, but not sampling grubs, predictions can be made but with less confidence.

1.6.5 Predicting grub density class with regional variables

Best discriminant model: % correct:
Low: 72%, Moderate: 46%, High: 66%, Overall: 64%

factor		*coefficients*	
	low	*moderate*	*high*
intercept	-8.11269	-7.30803	-5.02173
regional prop damage	381.6209	335.489	182.4903
Confidor	-0.02802	-1.39241	-1.7004
Log grub (yr0)	-1.78002	4.263503	13.84803
Region (-Herbert)	-1.86922	-0.96065	0.10086
suSCon at plant	4.004073	3.247759	2.753151
Regional prop treat	60.26786	53.71257	28.72565
Severity (yr0)	0.68689	1.262584	0.937408

Jackknife results (20% of data left out in each of 5 models)

factor		*% se / mean*	
	low	*moderate*	*high*
intercept	10.4	10.3	5.5
regional prop damage	9.9	10.4	17.1
Confidor	94.2	23.0	57.4
Log grub (yr0)	22.6	7.8	21.3
Region (-Herbert)	16.0	22.1	77.9
suSCon at plant	21.8	21.1	8.6
Regional prop treat	4.8	7.0	22.0
Severity (yr0)	26.6	22.4	19.3

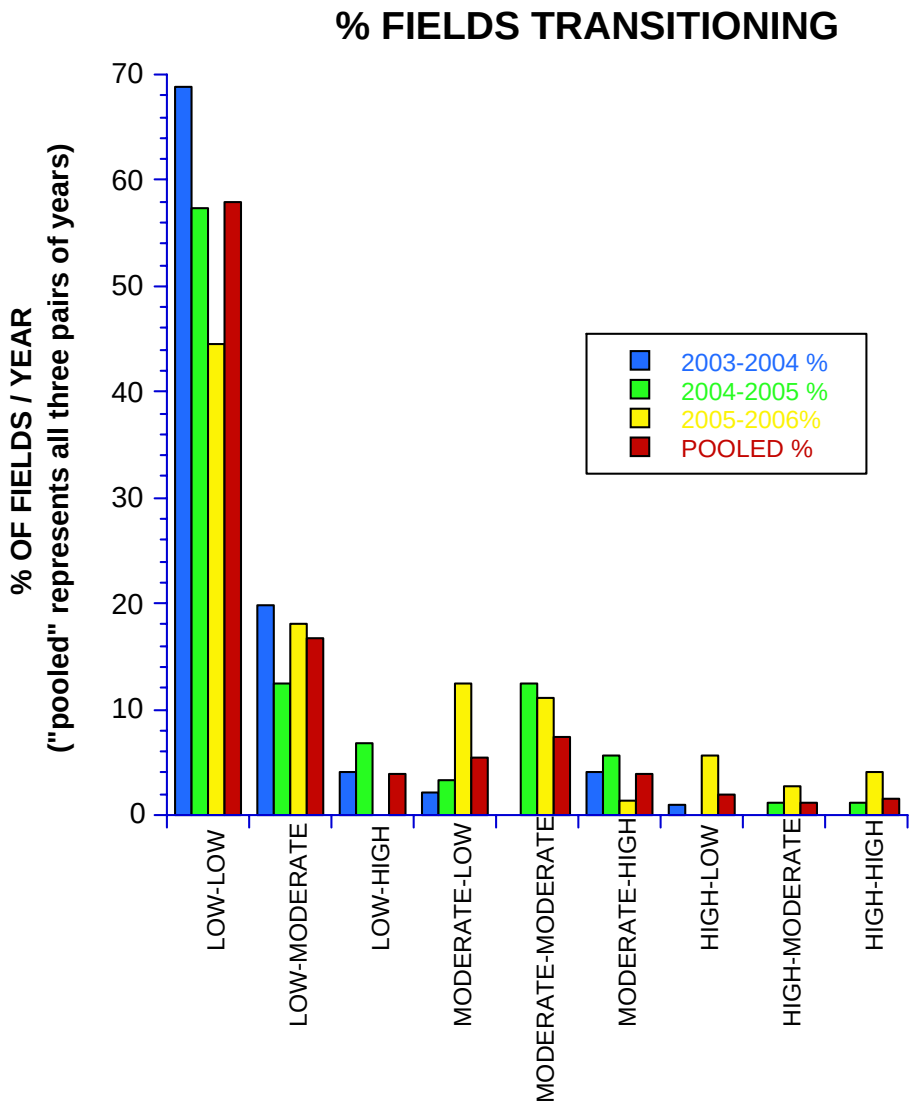
factor		*% difference*	
	low	*moderate*	*high*
intercept	-4.9	-6.0	7.7
regional prop damage	0.1	2.7	19.8
Confidor	125.0	5.5	32.3
Log grub (yr0)	-85.1	-5.6	41.3
Region (-Herbert)	11.7	-17.5	-169.7
suSCon at plant	-23.0	-30.3	-30.6
Regional prop treat	3.5	-0.1	21.9
Severity (yr0)	-10.6	-0.7	-34.5

%accuracy	*% se / mean*	*% diff*
low	4.7	11.2
moderate	3.2	19.6
high	6.4	29.3

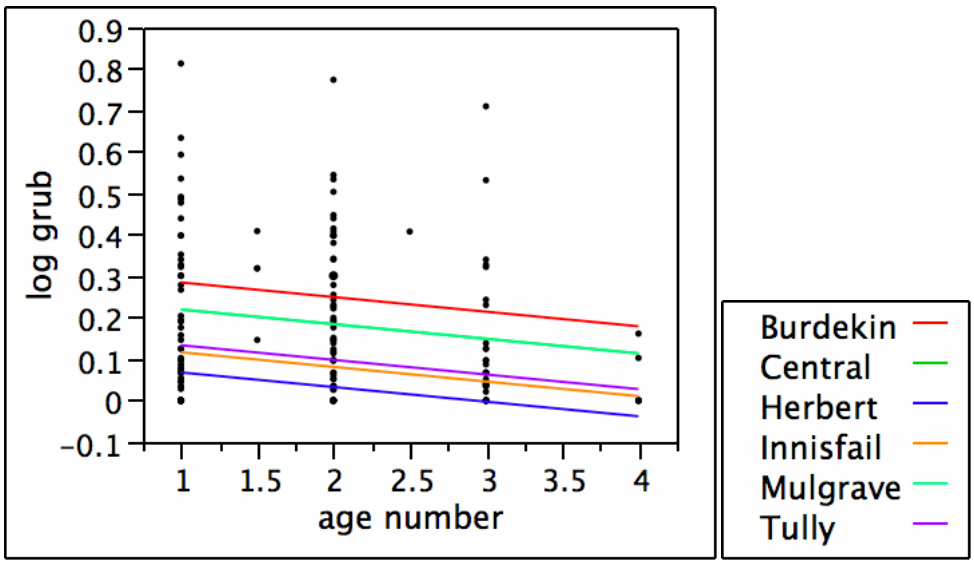
The ability to predict future grub density class is marginally adequate at a 64% overall correct classification rate. Evaluation of the model via jackknifing suggests that some of the parameter estimates are sensitive to the structure of the data (% se/mean = 94.2% for Confidor, and 77.9% for region [Herbert vs all other regions]), but it must be recognized that these two sensitive parameters have very small values. Overall, the jackknife estimates of % accuracy suggest that the model is quite robust for predicting correct classification of low and moderate densities, but is more variable for predictions of high densities.

1.7 Conclusion and Recommendations

Model development used several different statistical methods and data collected from sugarcane blocks during the four-year study as well as regional data reflecting damage and insecticide treatments. The population cycles observed during the conduct of this study made it extremely difficult to construct a predictive model. Data for the four years clearly shows that 60% of blocks with a low grub density in year (t) remained at a low density in year (t+1). Only about 17% transitioned from low density to moderate density the following year, and about 4% transitioned from low to high density over the four-year period. The result of these population dynamics is a very aggregated distribution, where most of the blocks sampled were at very low density with only a small number of moderate- or high-density blocks (see figure below).



Insecticide efficacy studies carried out by Keith Chandler over several years in several cane growing regions suggest that there is a natural tendency for grub densities in untreated control plots to decline over time (age number is age of trial after start). An analysis of covariance suggests that this dynamic is similar across all regions (see figure below).



Model	Independent variable	Goodness of fit
Region models		
Central	Log grub	$r^2 = 0.299$
	Grub Trend	$r^2 = 0.188$
	Grub Density Class	% correct = 63%
Herbert	Log grub	$r^2 = 0.12$
	Grub Trend	$r^2 = 0.218$
	Grub Density Class	% correct = 89% (2 classes)
FNQ	Log grub	$r^2 = 0.181$
	Grub Trend	$r^2 = 0.399$
	Grub Density Class	% correct = 51%
Global models	Log grub	$r^2 = 0.298$
	Grub Trend	$r^2 = 0.245$
	Grub Density Class	% correct = 62%
No Grub variables included	Log grub	$r^2 = 0.209$
	Grub Trend	$r^2 = 0.082$
	Grub Density Class	% correct = 60%
Region predictor models	Log grub	$r^2 = 0.446$
	Grub Trend	$r^2 = 0.282$
	Grub Density Class	% correct = 64%
Region predictor (no grub variables included)	Log grub	$r^2 = 0.378$
	Grub Trend	$r^2 = 0.174$
	Grub Density Class	% correct = 62%

Section 2 describes many other factors that affect grub density. The multitude of models described above did not all perform equally well. A summary of their predictive capability follows (see table above).

Region Models: in general the models developed for each region were the poorest performing models, with a few exceptions. The discriminant model for predicting grub density class was quite good, but the coefficients were very sensitive to small changes in the data. The Herbert discriminant function was very good at predicting grub density class, but the model can not be generalized to the three standard classes since there were not blocks representing the high grub density class in the region over the four-year study. The exception to the general poor performance of the region models was the model derived to predict grub trend in FNQ. This model resulted in the highest percent of variation explained (39.9%).

Global Models: these models were designed to predict grub density across all years and regions. The log grub and grub trend models were generally well behaved with respect to the sensitivity of parameter estimates to changes in the data structure, but they were marginal at best in terms of prediction. The discriminant model for predicting grub density class was a moderately good predictor, but because the model was using data pooled over years, much noise results in the prediction space. For instance, if just 2004 data is modeled a model can be derived that predicts 76% correctly overall, but a model for 2006 yields a correct prediction of 68%. These are both better than the global model of 62%.

Global Models with no grub predictors: these models were generally the worst of all the models, except for the linear discriminant model that resulted in a correct overall classification of 60%. However, the prediction for the high density class was quite a bit less than if a grub density predictor variable was used.

Region predictor models: Models that used variables that had incorporated regional proportion damage or insecticide treatment appeared to be the best models for predicting log grubs/stool and grub density class. The regional predictor variables did not appear to enhance prediction of grub trend to any large extent.

Region predictor models without grub predictors: These models suggest that regional predictor variables such as proportion damage and treatment make up partially for the absence of a grub predictor variable in the model. In general, models with regional predictors and no grub predictors are as good or better as models without regional predictor variables, but a grub predictor variable. The r^2 parameters for each of the types of models (region – grub vs – region + grub) are as follows: log grub predictor models, 0.378 vs 0.298; grub trend, 0.174 vs 0.245; grub density class, 62% vs 62%. However, caution should be used with models that do not have previous year local grub data, since these models tended to be a bit more sensitive to the structure of the data used to build the model.

In summary, the models with both Regional variables and previous year local grub density variables appear to be the best predictors at this point in time. The data collected in 2007 can be used to test all models, especially the models derived without grub predictor variables.

2.0 INTERMEDIATE STATISTICAL MODELING RESULTS

2.1 Outline of approaches for statistical model building

A. Predictions

1. Grub density – Multiple linear regression (both weighted and unweighted least squares)

2. Grub density classes – Nominal and ordinal logistic regression
   Linear discriminant functions

3. Rates of grub density change – Multiple linear regression
   Linear discriminant functions

B. Predictor variables

1. Previous year variables representing damage, grub density, district, insecticide use, etc.

2. 2003 variables representing damage, grub density, district, insecticide use, etc. for predicting grub density or rate of grub increase in 2005 and 2006.

3. Variables that were reorganized so that, independent of year, a predictive model could be assessed one year in the future based upon a single year in the past.

2.2 Analyses structured independent of year (e.g. Year 0 to Year 1)

A data set was constructed from years 2003, 2004, and 2005 (n=363) to allow model development for prediction of future grub densities or grub trend in year (1) given data from the previous year, year (0). Specific analyses were conducted to assess:

i) The effect of disease on grubs/stool, log grubs/stool, and grub trend [Log grubs/stool (yr1) / Log grubs/stool (yr0)].
ii) The best linear model for predicting Log grubs/stool (yr1)
iii) The best linear model for predicting grub trend
iv) The best linear discriminant model for predicting grub density class (low density=0-0.2, moderate density= >0.2 – 1.0, high = >1.0 grubs/stool) in yr1.

Variables considered for predictive models were many: year, cane growing region, region coded by increasing regional grub density, distance(m) from cane block to treeline, replant/fallow scenario, cultivation vs spray-out, whether a legume was used during break, log (grubs/stool in yr0), grub density category in yr0, sampled disease incidence (%) weighted by #grubs reared (diseases were *Adelina, Metarhizium, Bacillus popilliae*, unknown or undetermined pathogens, *Adelina* and *Metarhizium* combined, total of all diseases), % adults from reared grubs (yr0), ranked severity of damage (ranks=0-3, yr0), distance(m) to nearest neighbor damaged block (yr0), # damaged blocks within 400 m

(yr0), ranked (0-3) maximum severity of nearby damage (yr0), # gaps (>60cm)/10 m row (yr0), increase in gaps (yr0-yr(0-1)), crop class (yr1), cane variety (yr1), use of suSCon in plant crop, use of suSCon in previous year, suSCon within 2 years, use of Confidor in previous year, suSCon within past 2 yrs and/or Confidor in previous yr, harvest date (yr0), harvest in days since start of year, beetle activity (yr0), and % >1R <400m (yr0). Some factors of interest that were related to subsequent log grub densities were: harvest days since start of year (P=0.1234), method of killing (P=0.0064), suSCon in plant crop (P<0.0001), and variety (P<0.0001). Variety was not used as a predictor since there were year and region interactions. Since the canopy measures had inherent problems with the dates that the measures were taken, especially in 2003 in the Central region, analyses were conducted with and without 2003 Central region sites in order to evaluate the predictive capability of Ht to TVD (yr0), Canopy ht (yr0), Canopy ht relative to neighbor avg (yr0), and Canopy ht relative to neighbor max (yr0) (see section 2.2.2).

2.2.1 Disease as a predictor of grub density in yr1, or grub trend

The first analysis was to assess the relationship between disease measures (yr0) and the first year (yr0) grub density. The analyses were weighted according to the sample size used in the estimate of disease incidence (%) because the sample size of grubs reared was highly variable (n=121).

It was observed that, when all fields were pooled over years, *Adelina, Metarhizium,* and unknown incidence explained 6.9% of the variance in Log grub density in yr(0). All three of the coefficients for these variables were negative with *Metarhizium* having about twice the effect (-0.0078) compared to *Adelina* (-0.0030) and the unknown causal agents of disease (-0.0029). When total disease was used as a predictor, 7.6% of the variation in log grubs/stool (yr0) was explained by disease with the coefficient = -0.0037. It was found that the disease relationships are significantly affected by year. This is not surprising, since disease epizootics have been shown to be tempered by environmental effects. The model that included year explained a bit more of the variance in log grubs/stool, 8.1%. In this model, *Adelina* and *Metarhizium* were the only significant predictors and the %Adelina x year interaction was also significant. This interaction suggested that in 2003 there was a positive relationship between % *Adelina* (yr0) and log grubs/stool (yr0) (P=0.056, b=+0.0018), in 2004, a negative relationship (P=0.1, b=-0.006), and a positive relationship in 2005 (P=0.0001, b=0.0022). This complicates the use of disease as a predictor. One conclusion is that disease is significantly related to the current year's grub density and that this provides evidence for believing that disease might be a good predictor of the subsequent year's grub density. However, it might involve more complicated understanding of the year-to-year or environmental effects on pathogen/host dynamics.

The second analysis was conducted for the purposes of assessing the relationship between disease measures in yr(0) and the second year (yr1) Log grub density. Again this was a weighted general linear model (weighted least squares). Only % *Metarhizium* was a significant predictor of log grub density (yr1) and the amount of variance in grub density that could be attributed to this disease was 1.6%. The slope or effect of *Metarhizium* on Log grub density was b=-0.0026. When the effect of year was investigated on these dynamics it was found that year was a significant factor, but that in incorporating a year factor in the model, the *Metarhizium* factor was accounted for by year and thus was no

longer significant in itself. However, there was a marginal *Metarhizium* x year interaction (*P*=0.091). The total variance explained in Log grubs/stool in this model was 9.6%, but most of this variance is attributable to the year effect. The interaction of *Metarhizium* with year shows that in 2003 and 2004 there was no predictive relationship between *Metarhizium* and Log grub density (*P*=0.589 and *P*=0.718, for 2003 and 2004, respectively). In 2005 there was a significant relationship between *Metarhizium* and Log grub density (*P*=0.045), with the slope being *b*=-0.003 and about 6.06% of the variation in Log grub density (yr1=2005) being explained. The overall conclusion of this modeling suggests that *Metarhizium* is the only disease explaining future grub densities, but that this is highly dependent upon year, most likely due to environmental effects or possible past grub densities. In itself, disease was not a good predictor of year 1 log grub densities, but this might be expected since disease could be hypothesized to be more predominant in later years of greyback grub field colonization.

The third analysis was conducted for the purposes of assessing the relationship between disease measures in yr(0) and the grub trend or intrinsic rate of grub density increase between yr0 and yr1. When all disease causal agents were considered, *Adelina* was a significant predictor of grub trend (*P*=0.057) and to a lesser extent *Metarhizium* as well (*P*=0.078). Because of this, a model was constructed with the summed effect of both *Adelina* and *Metarhizium*. The sum of these two diseases resulted in a significant (*P*=0.0013) explanation of 7% of the variation in grub trend. The combined effect resulted in a slope of *b*=-0.0024. Incorporating year into the model resulted in year (*P*<0.0001) and the combined (*Adelina* and *Metarhizium*) (*P*=0.0309) being significant predictors with no evidence for an interaction between year and disease (*P*=0.303). The resulting variation in grub trend explained by this model is 18.8%, but the majority of this is explained by the year effect, as only about 7% is explained by disease. This model suggests that *Adelina* sp. and *Metarhizium anisopliae* can be useful factors in predicting the grub trend in years 0-1 of the early stage of greyback grub colonization of cane blocks. However, at this point it should be used cautiously, if at all, until more data are collected on the relationship between disease incidence and grub trend since much of this data is based upon very small sample sizes of disease incidence estimates and a weighted least squares procedure such as has been used here is basing MUCH of the relationships on only a few data points. When we did look at these relationships without weighting the samples, no measures of disease resulted in a significant predictor of either Log grub density (yr1) or grub trend.

2.2.2 Canopy effects

Canopy effects were assessed as to their usefulness in predicting greyback canegrub population densities and rates of increase (yr1). A series of covariance analyses were conducted to assess the relationship between grub trend and log grub density in yr (t+1) by various measures of the sugarcane canopy in yr(t). Because in 2003 in the Central region canopy measures were measured at a different time than in the other regions, these analyses were conducted without the data from the Central region (2003). Data were analysed by ANCOVAs, a form of ANCOVA performed by first extracting the residuals (of grub population measures) due to year and then modeling the residuals by the canopy measure, to see if, once year was factored out, one could ascribe a significant relationship between any of the canopy measures and the grub population measures.

Grub var	year	TVD (adjusted for year)	TVD x Year
Grub Trend	*P*=0.0153	*P* =0.1725 (0.1803)	*P* =0.5145
Log Grub(yr1)	*P* =0.0291	*P* =0.0533 (0.0622)	*P* =0.1202

Grub var	year	Canopy ht	Canopy htxYear
Grub Trend	*P* =0.0030	*P* =0.7225 (0.6825)	*P* =0.9365
Log Grub(yr1)	*P* =0.3152	*P* =0.6313 (0.7879)	*P* =0.5047

Grub var	year	Rel. Canopy ht	Rel. Canopy ht x Year
Grub Trend	*P* =0.7571	*P* =0.9937 (0.9290)	*P* =0.7101
Log Grub(yr1)	*P* =0.0997	P=0.6168 (0.4935)	*P* =0.4088

Grub var	year	Rel Max Canopy ht	Rel Max Can. ht x.Yr
Grub Trend	*P* =0.0152	*P* =0.1858 (0.2806)	*P* =0.2258
Log Grub(yr1)	*P* =0.8124	*P* =0.0793 (0.0642)	*P* =0.8284

Overall, there was a slight effect on Log grub (yr1) (P <0.06) for TVD and Rel Max Canopy ht when adjusted by year through ANCOVA. So this does confirm the hypothesis that canopy does have an effect on grub densities. If canopy is easy to measure relative to some of these other measures it might be something that should be considered…forcing this variable as a predictor in a multivariate model.

The various canopy measures were also assessed as to their inter-correlations. Maximum canopy height and relative canopy height were highly correlated (r=+0.917, P<0.0001). This suggests that it is not necessary to use both of these variables as predictors since they are essentially conveying similar information. Relative canopy height versus canopy height were less correlated at r=+0.442, P=0.0038; and canopy height versus maximum relative canopy height resulted in r=+0.408, P=0.0078. These correlations suggest a significant moderate correlation. These results suggest that any of the canopy measures may be viable predictors, but that it is not expected that more than one canopy predictor will end up in any one model.

2.2.3 Predicting greyback canegrub population densities and rates of increase (yr1)

All of the variables were used for predicting measures of grub population density (log grubs/stool or density class) or grub trend from yr0 to yr1, except disease because of the reduced sample size and because of the lack of precise (small sample size of reared grubs) estimates of disease incidence. In addition, variety was modeled to determine its effect on these population measures. The effects of variety were usually strong for grub trend (P<0.0001, r^2=0.224) and log grub density (P<0.0001, r^2=0.398), but it was not used as a predictor at this point, although it certainly can be entered into a model if it is known that the variety effects are consistent from year to year.

Grub trend analyses show that region needs to be considered for incorporation into a model for predicting grub trend. However, the effect of region is complicated by the interaction with year (P=0.0002). Region, year and their interaction explain 20.1% of the variation in grub trend. In 2003, Central has the highest grub trend (rate of increase in grub density from yr0 to yr1) compared to the other regions which are not significantly

different from one another. In 2004, Mulgrave has the highest grub trend and Herbert has the lowest and in 2005, Central has the highest and Tully the lowest. Therefore, region effects, while strong (explaining 13 – 37.8% of the grub trend variance for a given year), are not consistent, but for further modeling we did use a numerically coded region variable that separates Central from all other regions since Central was characterized by the highest grub trend in two of three years.

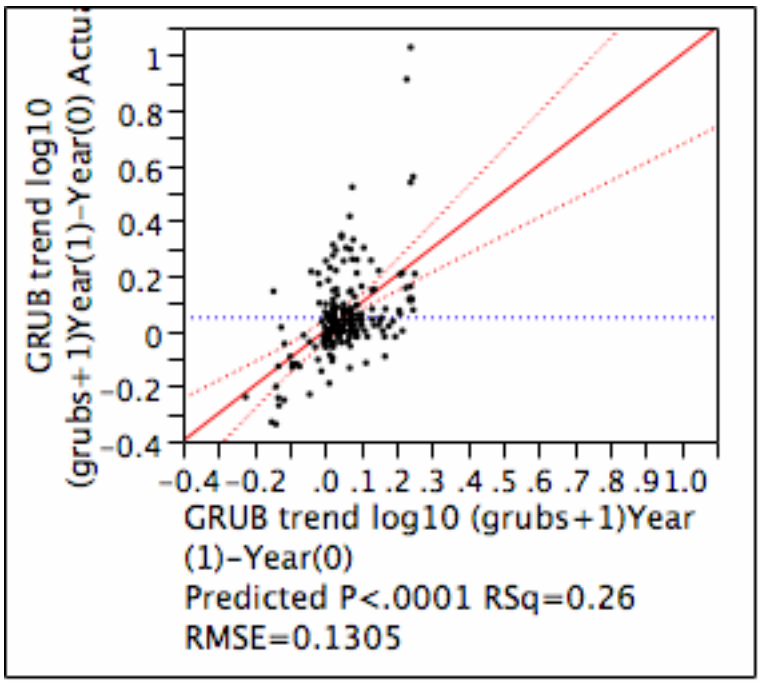
Other management-related factors such as harvest date, crop class, insecticide use, cultivation vs spray-out, legume during break, replant vs fallow, were assessed as to their effect on grub trend. Some of these factors did have effects on expected log grub density. suSCon in the plant crop affected grub trend (P=0.0010, r^2 = 0.037). Cultivation vs spray-out was also a significant factor affecting grub trend (P=0.025), but only explained 1.9% of the variation in grub trend. Harvest date was also a significant factor (P<0.0001) and accounted for 5.8% of the variation in grub trend. These factors were coded numerically and entered with all of the other continuous variables (i.e. severity of damage, canopy ht, etc.) and used to build an overall best predictor. Year and year interaction effects were seen to be strong effects, but since the overall objective in constructing a predictive model in this section was to build one that was independent of year we did not use year in any of the models that were considered. The best model for predicting grub trend explained 24.5% (adjusted r^2) of the total variance (n=242 sites).

The predictors were:

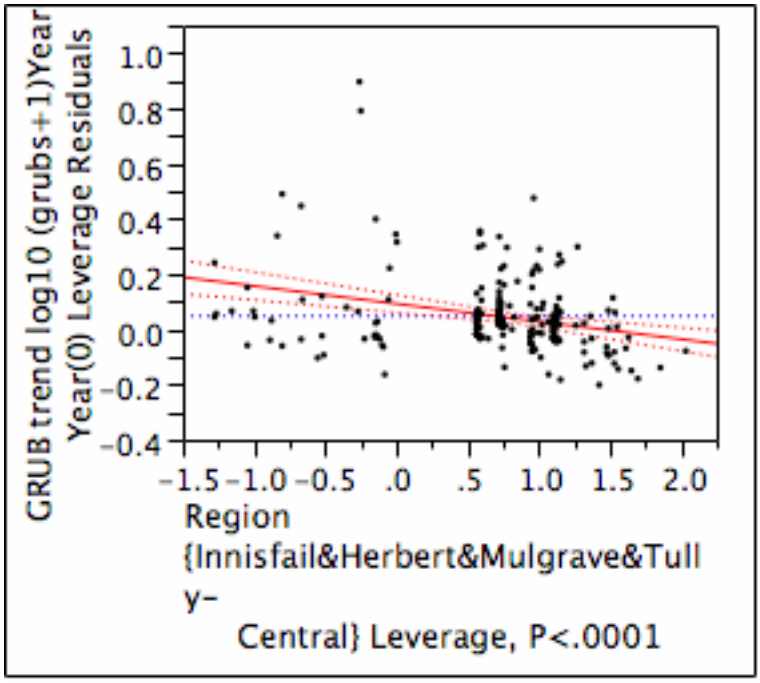
Factor	*P value*	*slope*
Log grubs (yr0)	<0.0001	-0.6325
Max severity (yr0)	0.0064	0.0298
Region (Central vs others)	<0.0001	-0.0642
Replant/fallow	0.0042	0.05019

Harvest date quantified as a Julian date was also a significant predictor (P=0.055), but it only explained an additional 0.1% of the variation and so it was not included in the best predictor model described above.

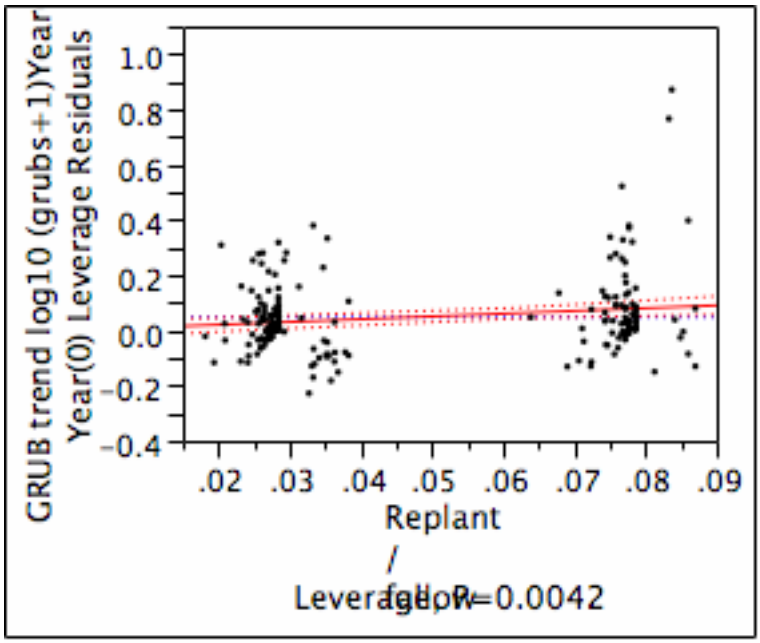
Response GRUB trend log10 (grubs+1) Year(1)-Year(0)
Whole Model
Actual by Predicted Plot



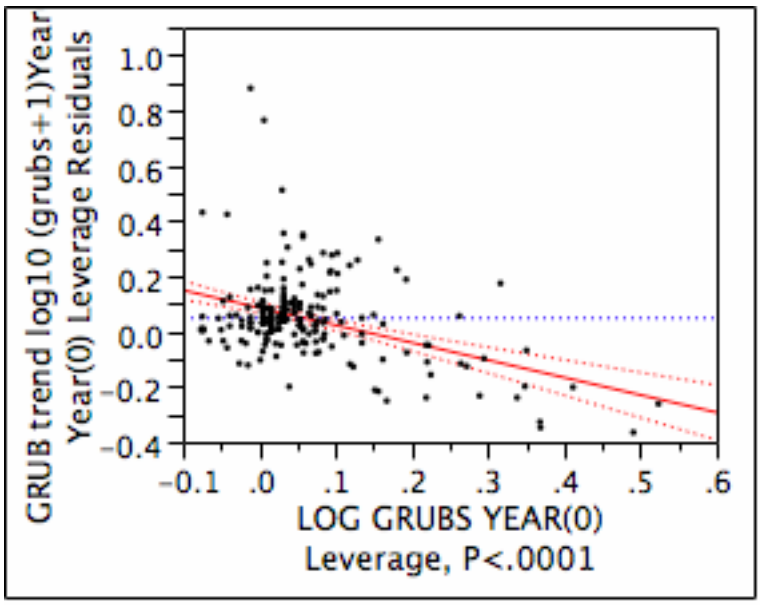
Region{Innisfail&Herbert&Mulgrave&Tully-Central}
Leverage Plot



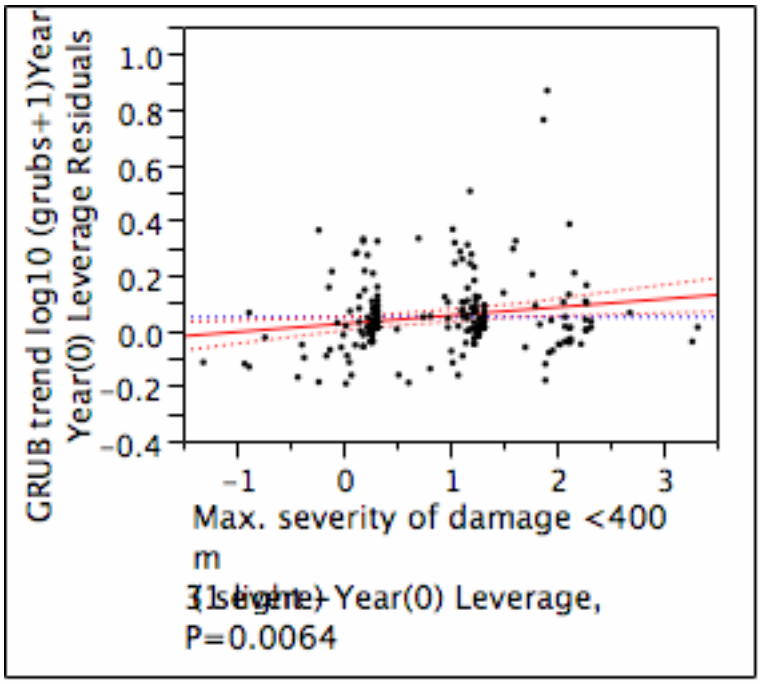
Replant/fallow
Leverage Plot



LOG GRUBS YEAR(0)
Leverage Plot



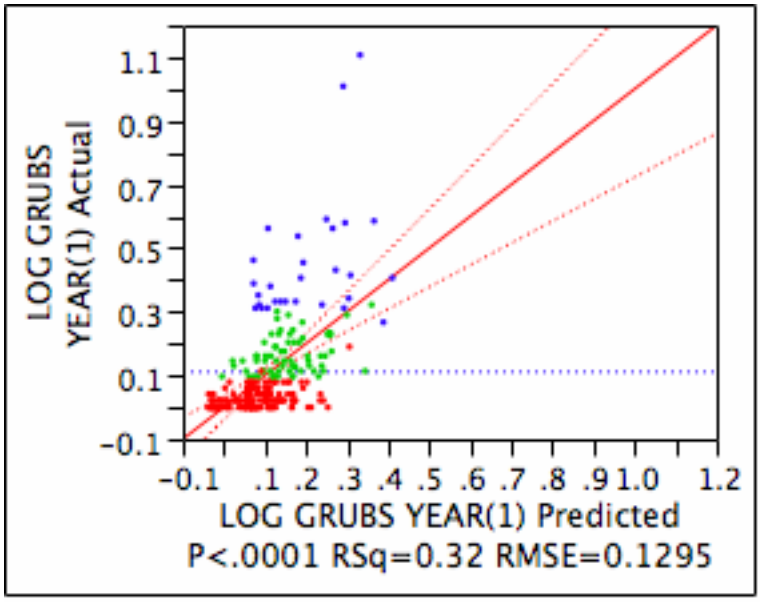
Max. severity of damage <400 m (1 light - 3 severe) Year(0) Leverage Plot



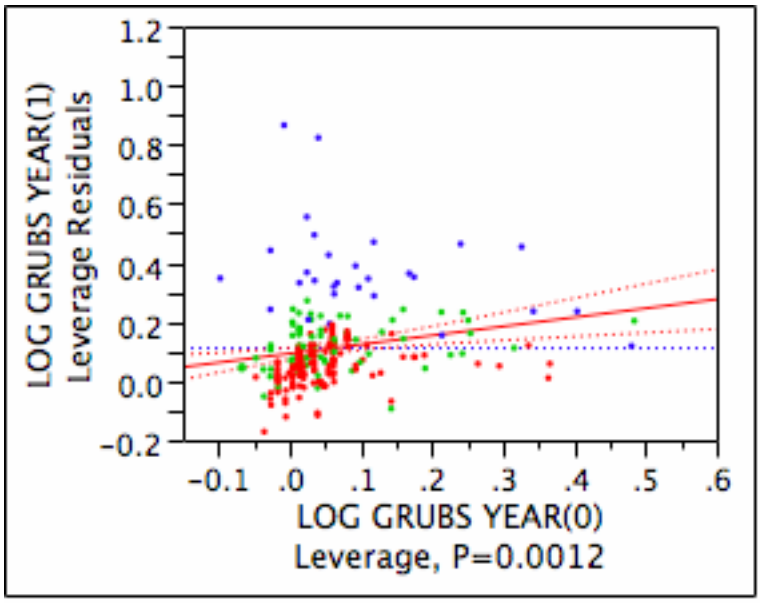
Log grub density models also show strong regional effects, explaining about 21% of the variation in density. Therefore, region coded in various ways to describe the lowest and highest regions, or all of the regions as continuous degrees of suitability for grubs were used. In addition to variety effects (described above), suSCon in the plant crop was highly significant (P<0.0001) and explained 8% of the variation in yr1 log grub densities. The only other cultural/production factor that affected log grub densities was cultivation vs spray-out (*P*=0.0064) explaining 4.4% of the variance. All of these variables and the entire suite of potential continuous predictor variables were used to determine the best model for predicting yr1 log grub densities independent of year. The best predictive model explained 31.2% (adjusted r^2) of the total variation in log grub densities (n=252 sites). The model factors are:

Factor	*P value*	*slope*
Intercept	0.0300	0.0589
Log grubs (yr0)	0.0011	0.3106
Severity (yr0)	0.0008	0.0398
Region (Herbert vs others)	<0.0001	0.0864
Gaps (>60 cm) per 10 m (yr0)	0.0221	0.0143
suSCon in plant crop	<0.0001	-0.0943

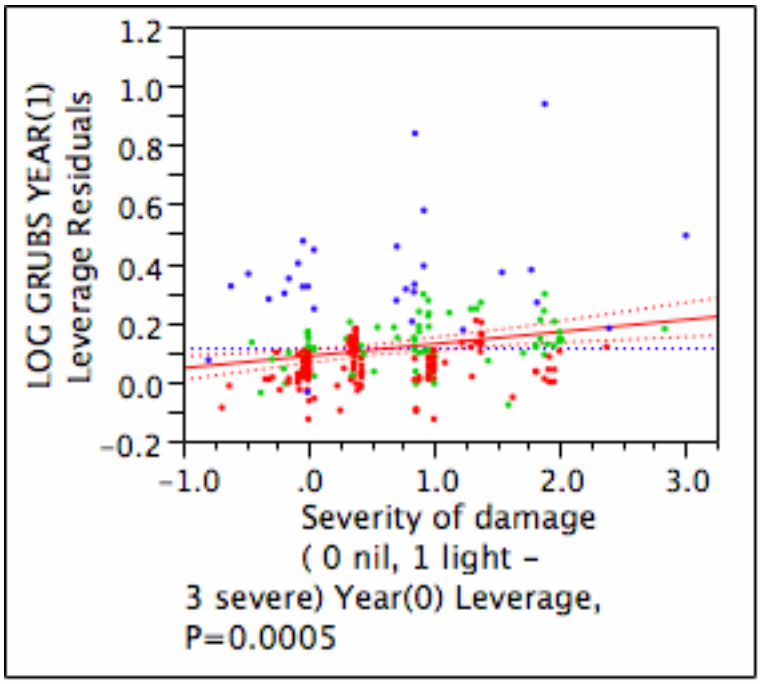
Response LOG GRUBS YEAR(1) (colors reflect density classes…see discussion and analysis below)
Whole Model
Actual by Predicted Plot



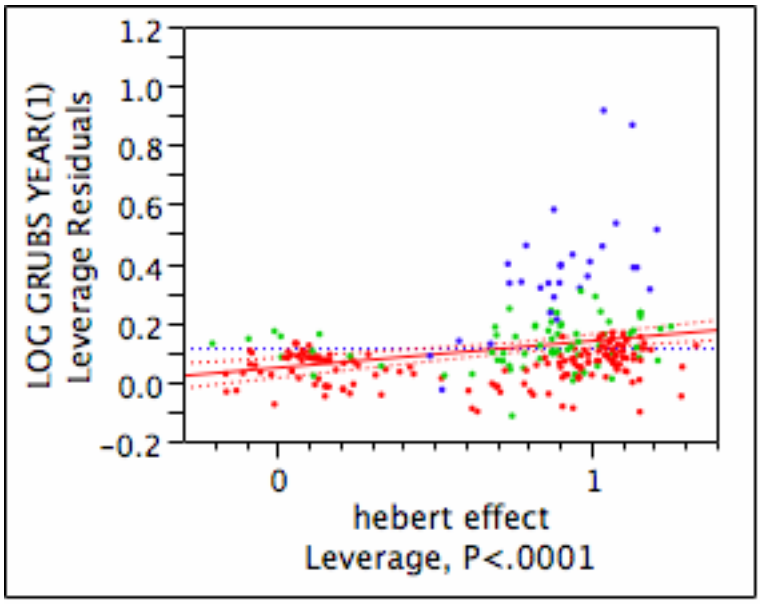
LOG GRUBS YEAR(0)
Leverage Plot



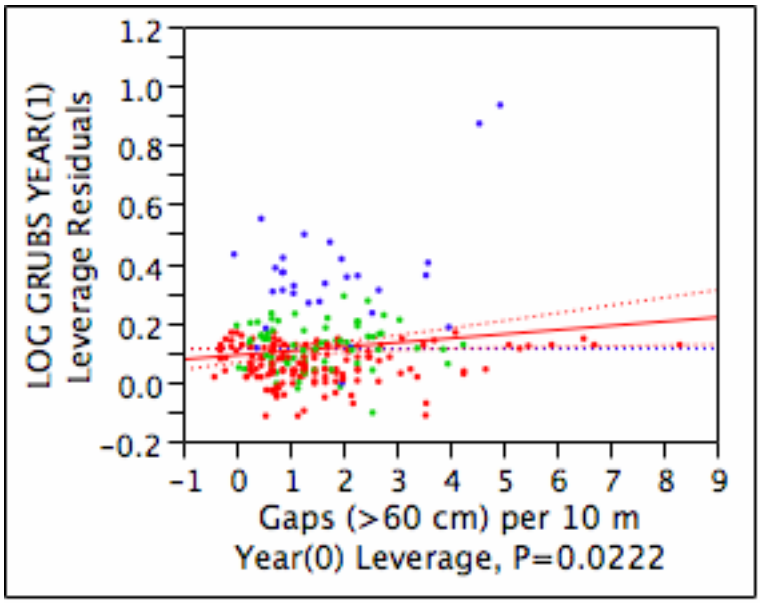
Severity of damage (0 nil, 1 light - 3 severe) Year(0)
Leverage Plot



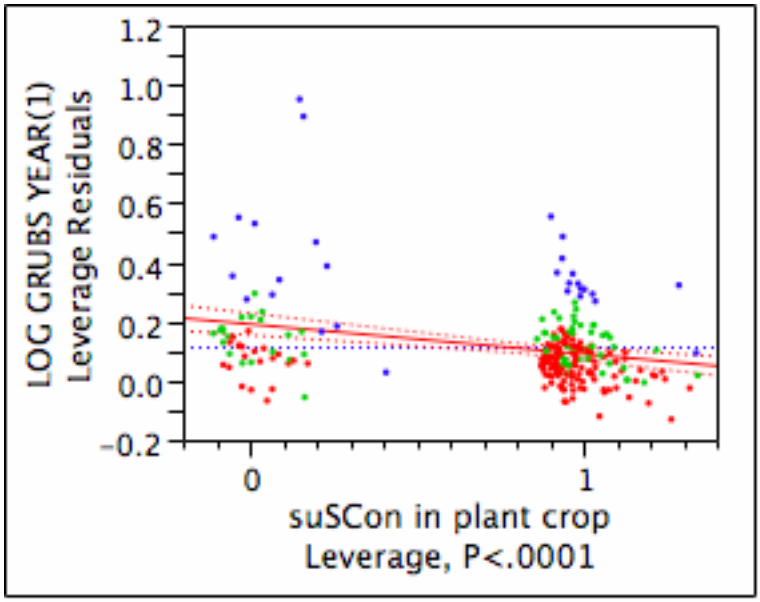
Herbert effect
Leverage Plot



Gaps (>60 cm) per 10 m Year(0)
Leverage Plot



suSCon in plant crop
Leverage Plot



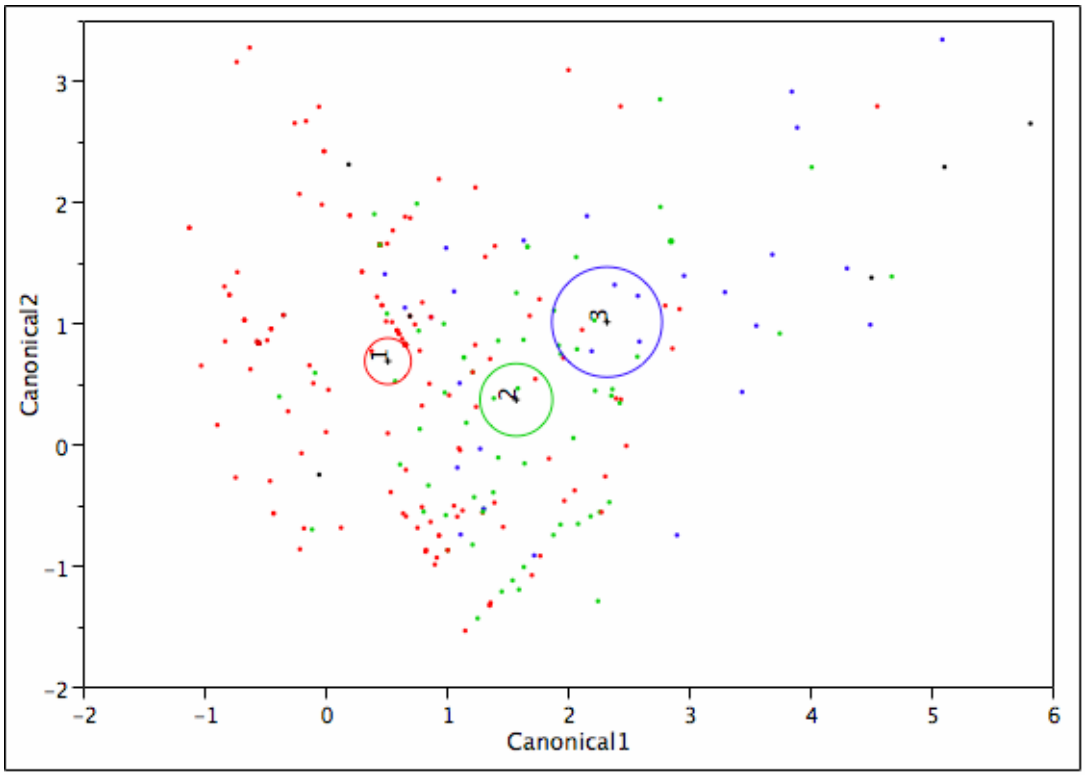
Categorical density models were first evaluated by using a mixed stepwise procedure to determine which variables would be suitable predictors in a multivariate linear discriminant model. The categories of density were: 1. low= 0 – 0.2 grubs/stool, 2. moderate = >0.2 – 1.0 grubs/stool, and 3. high = >1.0 grubs/stool.

The predictors which resulted in the best model were:

Distance to treeline m	P=0.0387
Region (Herbert vs others)	P<0.0001
Log grubs (yr 0)	P<0.0001
Severity of damage	P<0.0001
Distance to neighbor damage	P<0.0001
Max severity	P<0.0001
suSCon in plant crop	P<0.0001

There was little difference between using log grub densities or class densities as predictors and so a model was built with class predictors. The overall analysis did significantly separate all density class populations from each other (Wilke's lambda = 0.6739, 14,504 df, *P*<0.0001, see figure of class centroids plotted in a two-dimensional canonical variate space, below).

Canonical Plot
Discriminant Analysis



The false prediction rate was 38.7% overall. The tables below show the prediction when the rule for classification is solely that predicted membership is assigned to the density class with the highest probability of occurrence. The tables below show the classification, rows are the observed and columns are the predicted.

Number of fields classified

	L	M	H
L	**112**	38	15
M	15	**32**	20
H	6	7	**16**

Percent of fields classified into various density classes

	L	M	H
L	**67.9**	23.0	9.1
M	22.4	**47.8**	29.8
H	20.7	24.1	**55.2**

Therefore, this model is a bit disappointing in its ability to correctly predict density class. However, all things being equal a null model would suggest a 66.6% incorrect classification compared to this model of 38.7% incorrect classification. The discriminant model will also provide estimates for the probability of membership to each of the density classes, so for instance:

Field 1 (Central Region, Deguara site 1) was actually a high density field (grubs / stool = 2.85) and the predictions were that it was:

90.1% likely to be high density
9.5% likely to be moderate
0.4% likely to be a low density field

Field 9 (Central, Lay site 9) was also actually a high density field (2.80 grubs / stool) but it was misclassified by the model and the predictions were:

42.6% likely to be high density
52.5% likely to be moderate
4.9% likely to be a low density field

Field 97 (Mulgrave Region, J. Veronese site 11) was actually a moderate density field (grubs/stool = 0.3) and the predictions were that it was:

9.6% likely to be high density
63.3% likely to be moderate
27.1% likely to be a low density field

Field 124 (Central, Bourke site 3) was misclassified by the model; it was a moderate density field (0.35 grubs/stool) and predictions were:

84.6% likely to be high density
11.5% likely to be moderate
3.9% likely to be a low density field

2.2.4 Conclusion

It is not an easy task to predict log grub density or grub trend even one year into the future. There are other approaches that have not been attempted yet, such as quadratic discriminant functions, negative binomial generalized linear models, and ordinal

regression, but it may not be worth the effort to explore these techniques for what would probably be only modest gains in predictive ability. Bayesian methods might be productive, although a Bayesian statistician would have to be approached since these methods are highly specialized modeling techniques.

An example of another approach is logistic regression modeling. This technique is conceptually similar to discriminant function analysis except, instead of depending upon a Gaussian distribution, the error term is log likelihood of a binomial distribution. A model based upon the same data and same density classes does increase prediction a bit…to 69.4% correct classification of grub density class (n=245). The best predictors are:

Factors	*log likelihood ratio P values*
Log grubs (yr 0)	P<0.0001
Max severity (yr0)	P=0.0157
suSCon in plant crop	P=0.0094
Method of killing crop	P=0.0111

The prediction classification tables are as follows:

Number of fields classified

	L	M	H
L	**143**	12	1
M	39	**22**	2
H	11	10	**5**

Percent of fields classified into various density classes

	L	M	H
L	**91.7**	7.7	0.4
M	61.9	**34.9**	3.2
H	42.3	38.5	**19.2**

The 69.4% prediction rate initially seems better, but the model is not as well balanced. Prediction of the low density class is 91.7% correct, but for moderate and high density classes, the correct classification rates are only 34.9 and 19.2% correct, respectively. Therefore, the model excels in estimating low density fields, but is poor at predicting the densities classes that are of most concern for growers. The use of both models could be used in a hierarchical fashion to obtain a better or more robust prediction by using the likelihood of being a low density field (predicted from the logistic regression model) as a predictor in the linear discriminant function.

2.3 Analyses structured by year (e.g. 2003 to 2004, 2004 to 2005)

The first series of analyses showed that several management factors such as legume planting, fallowing and crop killing method had no consistent effect on the grub densities or intrinsic rates of growth for fields in 2003 or 2004. Fallowing vs replant did have an effect several years past, on intrinsic rate of growth for 2006/2005 and 2005/2004. However, the effects were opposite for the two year combinations. In 2005/2004 the

fallow fields had the lower intrinsic rate of increase relative to replant fields (P=0.032), whereas, in 2006/2005, the replant fields had the lower intrinsic rates of growth (P=0.043). Method of killing did have marginally significant effects on log grub densities in 2004 (P=0.057) and intrinsic rate of grub population growth for 2004/2003 (P=0.069).

Ratoon age did have some slight effects on grub density and intrinsic rates of growth for the years that they were jointly measured in 2002-2003 and 2003-2004. Seven percent of the variation in 2002 log grub densities was explained by ratoon age (2002-2003). In 2003-2004, 5 and 6% of the variation in intrinsic rate of grub population growth (2004-2003) and 2003 log grub density were explained by ratoon age (2003-2004). No significant effects on grub density or population increase were observed for ratoon ages recorded in 2004-2005 and 2005-2006.

Variety effects were not consistent across years. Only the varieties recorded in 2004 had significant effects. In this case, log grub density was significantly affected by variety (P<0.0001) as was grub population increase from 2003 to 2004 (P<0.0001), with Q121 and Q138 having the highest rate of increase and Q158 having the lowest rate of increase. There was also a significant effect on 2006 grub densities due to varieties recorded in 2006 (P=0.009).

Insecticides had an effect on grub densities. suSCon significantly lowered grub densities and this was observed in most years (except 2005). There was almost always an interaction between crop age and suSCon effect on grub densities with the 1, 2, and 3 crop years being those with significantly lower grub densities than the non treated fields or the 4-7 year old crops. Confidor on the other hand appeared to be a poor predictor of log grub densities. Neither the applications made one year prior to grub sampling nor applications made two years prior to grub sampling appeared to affect log grub densities. When all years were combined using year as a blocking factor and assessing the effects of a one year prior application, no significant effects of Confidor resulted (P=0.449). However, when the effects of Confidor were assessed on log grub population increase, significant effects were detected for 2006/2005 with a Confidor application in 2005 (P=0.017) and also for the rate of increase between 2004 and 2006 with a Confidor application in 2004 (P=0.025). When all three periods of increase (2004-2003, 2005-2004, 2006-2005) were modeled with an application of Confidor made during the previous year (t-1), no significant effects on increase due to Confidor were found (P=0.422).

Many of these management factors were not selected because of their poor explanatory ability or since other factors such as log grub density and damage estimates tended to be better predictors of the log grub densities or intrinsic rates of grub population growth.

The previous year's disease measures were in general not found to be good predictors of either log grub density or intrinsic rate of growth. *Bacillus popilliae* in 2004 was found to be a marginally significant predictor in both the rate of increase of 2005-2004 (P=0.08) and the 2005 log grub densities (P=0.10). *Metarhizium* infection rates in 2003 were a significant predictor of 2004 Log grub densities (P=0.061, r^2=0.119) and 2004-2003 rates of increase (P=0.041, r^2=0.132). However, disease measures were not pursued in any of the modeling because only a subset of the data could be used (n=30-40) since not all of the fields had disease sample data associated with them.

2.3.1 Predicting grub densities

Analyses of variance and stepwise regression was used to determine likely predictor variables. The first attempts were made at predicting grub densities. Log (grubs / stool) was chosen as it resulted in a better level of homoscedacity than sampled grub densities. A summary of the results is as follows.

2.3.1.1 Predicting grub densities with previous year's measures

I. Log grubs in 2003, $r^2 = 0.270$

Significant predictors were	*coefficients*
Ratoon, *P*=0.0012	-0.01448
District, *P*<0.0001	0.04451
Legume, *P*=0.0461	-0.01009

II. Log grubs in 2004, $r^2 = 0.674$

Significant predictors were	
District, *P*<0.0001	0.2567
% > 1R < 400m 2002, *P*=0.0295	0.0012
Severity of damage 2003, *P*=0.0012	0.0842
Distance to neighbor damage 2003, *P*=0.0048	0.0001
# Damaged blocks <400m 2003, *P*=0.049	0.0674

Alternative Log grubs 2004 model

IIa. Log grubs in 2004, $r^2 = 0.644$

Significant predictors were	
Log grub 2003, *P*=0.0436	0.7559
District, *P*<0.0001	0.2286
Severity of damage 2003, *P*=0.0175	0.0621
Distance to neighbor damage 2003, *P*=0.0006	0.0001
# Damaged blocks <400m 2003, *P*<0.0001	0.0628

III. Log grubs in 2005, $r^2 = 0.307$

Significant predictors were:	
Log grub 2004, *P*=0.0152	0.4017
Replant/fallow, *P*=0.0058	-0.0382
# Damaged blocks <400m 2003, *P*=0.0278	0.0295

Alternative Log grubs 2005 model

IIIa. Log grubs in 2005, $r^2 = 0.231$

Significant predictors were	
Log grub 2003, *P*=0.0671	0.8733
Log grub 2004, *P*=0.0009	0.5125

IV. Log grubs in 2006, $r^2 = 0.716$

Significant predictors were:

Log grub 2003, *P*=0.0507	-0.5656
Log grub 2004, *P*<0.0001	0.5986
Grub trend 2005-2004, P=0.002	0.2385
Variety (2006) contrast1, *P*<0.0001	-0.0736
Variety (2006) contrast2, *P*=0.0155	-0.0488

Alternative Log grubs 2006 models

IVa. Log grubs in 2006, $r^2 = 0.480$

Significant predictors were:

Log grub 2003, *P*=0.060	-0.7188
Log grub 2004, *P*<0.0001	0.6121
Log rub 2005, *P*=0.0012	0.3245

IVb. Log grubs in 2006, $r^2 = 0.491$

Log grub 2005, *P*<0.0001	0.3692
Increase in gaps 04-5, *P*=0.0082	0.0212
SuSCon in plant crop 4, *P*<0.0001	-0.1260

2.3.1.2 Predicting 2005 and 2006 grub densities with 2003 variables

I. Log grubs in 2005, $r^2 = 0.206$

Significant predictors were:

Log grubs 2003, *P*=0.0508	0.9481
# Damaged blocks <400m 2003, *P*=0.0037	0.0381

II. Log grubs in 2006, $r^2 = 0.384$

Significant predictors were:

Distance to treeline m, *P*<0.0001	0.1055
Log grubs 2003, *P*=0.0332	0.9528
# Damaged blocks <400m 2003, *P*<0.0001	0.0630
Severity of damage 2003, *P*=0.0003	-0.0902

Alternative Log grubs 2006 model

IIa. Log grubs in 2006, $r^2 = 0.334$

Significant predictors were:

District, *P*=0.0242	0.1182
# Damaged blocks <400m 2003, *P*=0.036	0.0465
Severity of damage 2003, *P*=0.0117	-0.0557

2.3.1.3 Predicting both 2005 and 2006 grub densities based upon 2003 measures:

I. Log grubs in 2005 and 2006, r^2=0.195.

Significant predictors were:

Log grubs 2003, *P*=0.0201	0.8682
# Damaged blocks <400m 2003, *P*<0.0001	0.0470
Severity of damage 2003, *P*=0.0798	-0.0315

2.3.1.4 Summary for grub densities

In general, grub densities can be predicted fairly well with the previous year's measures, except for 2003 and 2005 was only slightly better. Common variables that appear to be good predictors across years are previous year's grub density (log) and the district. A case in point to remember…many of the variables explain a significant amount of the variation in log grubs/stool, but they also co-vary with other predictors and so they may not be represented in the model since they lend no additional predictive capability.

The ability to predict several years in advance is represented by the models that use measures taken in 2003 to predict log grub densities in 2005 and 2006. Unfortunately, these models were not highly predictive (don't explain a high degree of the variation in log grub densities…ca. 20-40%). For both years, two common 2003 measures were significant predictors: log grub density in 2003 and the number of damaged blocks<400m in 2003. I used both of these variables along with the severity of damage rating in 2003 to model both the 2005 and 2006 log grub densities. In a repeated-measures ANOVA there was no year effect and all three predictors were significant. When treated as independent fields, 19.5% of the variation in log grub densities in the two years was explained by these three predictors (although severity was only significant at the P=0.07 level). Therefore, we can develop a predictive model that will predict both 2005 and 2006 log grub densities based upon the 2003 log grub densities, ranked damage severity in 2003 and # damaged blocks <400m 2003, but will only be able to explain 19.5% of the variation in these densities.

2.3.2 Predicting classes of grub densities

MANOVA and linear discriminant analysis (Fisherian) was used to estimate predictive models for grub density classes as defined by Samson "*(The infestation categories I used at the Project Review were less than or equal to 0.2 grubs/stool (light), 0.2 to 1.0 grubs per stool (moderate), and greater than 1 grub/stool (high))".* Stepwise backward selection was used to aid in variable selection. The estimated parameters explain linear additive multivariate models, one for each discriminant region or density class. A summary of the results is given below. All models presented have significant predictors (P<0.05) and as a multivariate vector separate at least one density class from the other two. The density classes described above are here referred to as L (low), M (medium), and H (high). Coefficients for the equations are not given since each density class has a model with coefficients of each of the significant variables.

2.3.2.1 Predicting grub density classes with previous year's measures

2004 density class predictive variables (Wilk's lambda = 0.3976, df=12,176, P<0.0001)

Log grubs 2003
Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage < 400m 2003
Ht to TVD (mm) 2003

76% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**65**	2	0
M	3	**15**	2
H	1	2	**6**

Percent of fields

	L	M	H
L	**97**	3	0
M	15	**75**	10
H	11.1	22.2	**66.7**

2005 density class predictive variables Wilk's lambda = 0.4732, df=18,134, $P<0.0001$

Log grubs 2003
Log grubs 2004
Log grub trend 2004-2003
Severity of damage 2004
Distance to neighbor damage 2004
Damaged blocks < 400m 2004
Max severity of damage 2004
Increase in gaps 2004

73% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**39**	4	2
M	4	**11**	5
H	3	3	**7**

Percent of fields

	L	M	H
L	**86.7**	8.9	4.4
M	20	**55**	25
H	23.1	23.1	**53.8**

2006 density class predictive variables (Wilk's lambda = 0.4819, df=10,102, $P<0.001$)

Log grubs 2004
Log grubs 2005
Log grub trend 2004-2003
Log grub trend 2005-2004
Max severity of damage 2005

68% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**24**	6	2
M	10	**9**	3
H	0	0	**4**

Percent of fields

	L	M	H
L	**75**	18.8	6.2
M	45.5	**41**	13.5
H	0	0	**100**

2.3.2.2 Predicting grub density classes with 2003 measures

2005 density class predictive variables (Wilk's lambda = 0.6198, df=12,154, *P*<0.0002)

Log grubs 2003
Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage 2003
Ht to TVD (mm) 2003

62% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**36**	9	6
M	5	**13**	2
H	6	4	**4**

Percent of fields

	L	M	H
L	**70.6**	17.6	11.7
M	25	**65**	10
H	42.9	28.6	**28.6**

2006 density class predictive variables (Wilk's lambda = 0.726, df=10,110, *P*=0.052)

Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage 2003

Ht to TVD (mm) 2003

63% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**28**	5	1
M	13	**7**	3
H	1	1	**2**

Percent of fields

	L	M	H
L	**82.9**	14.3	2.8
M	56.5	**30.4**	13.1
H	25	25	**50**

I also constructed discriminant models for a reduced classification. In this classification the prediction is an attempt to predict fields with low grub densities (less than or equal to 0.2 grubs / stool and those that are greater than 0.2 grubs / stool, resulting in just two density classes: low (L) or high (H).

2004 reduced density class predictive variables (F = 0.726, df=7.88, $P<0.0001$)

Distance to treeline
Log grubs 2003
Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage 2003
Ht to TVD (mm) 2003

86% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	H
L	**63**	4
H	9	**20**

Percent of fields

	L	H
L	**94**	6
H	31	**69**

2005 reduced density class predictive variables (F = 6.243, df=7.76, $P<0.0001$)

Log grubs 2003
Log grubs 2004

Log grub trend 2004-2003
Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage 2003

81% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	H
L	**45**	5
H	11	**23**

Percent of fields

	L	H
L	**90**	10
H	32.4	**67.6**

2006 reduced density class predictive variables (F = 3.171, df=7,49, *P*=0.0076)
Distance to treeline
Log grubs 2004
Log grub trend 2004-2003
Log grubs 2005
Distance to neighbor damage 2005
Max severity of damage 2005
Gaps 2005

77% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	H
L	**27**	5
H	8	**17**

Percent of fields

	L	H
L	**84.4**	15.6
H	32	**68**

I also categorized fields as to whether over a three or four year period they changed in their grub density class. Only fields that started out after planting as low densities were used. The categories were: 1 = Low to Low, 2=Low to Medium, 3=Low to High.

3 yr trend density class predictive variables (Wilk's lambda = 0.4540, df=16,142, *P*<0.0001)

Log grubs 2003
Log grubs 2004
Log grub trend 2004-2003
Severity of damage 2003
Distance to neighbor damage 2003
Damaged blocks < 400m 2003
Max severity of damage 2003
Ht to TVD (mm) 2003

72% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**39**	6	1
M	6	**14**	2
H	4	4	**5**

Percent of fields

	L	M	H
L	**84.8**	13	2.2
M	27.2	**63.6**	9.2
H	30.8	30.8	**38.5**

4 yr trend density class predictive variables (Wilk's lambda = 0.607, df=12,98, *P*=0.012)
Log grubs 2004
Log grub trend 2004-2003
Distance to neighbor damage 2003
Severity of damage 2004
Damaged blocks < 400m 2004
Max severity of damage 2004

64% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	L	M	H
L	**19**	4	0
M	7	**14**	5
H	3	2	**3**

Percent of fields

	L	M	H
L	**82.6**	17.4	0
M	26.9	**53.8**	19.3
H	37.5	25	**37.5**

2.3.2.3 Summary for grub density classes

In general, the discriminant functions were not the best predictors, ranging from 62-76% correct classification of the density classes. However, they were able to significantly distinguish between density classes and can be useful in that one can easily obtain the probability of density class membership for each of the three density classes for each field. This fits well with an original objective of developing a Markov-type model that would allow predicting the transition of a field from one density class to another. Model variables tended to be similar between years incorporating previous year's log grub density and various damage measures. The reduced density class models provided better prediction in some circumstances ranging from 77 to 86% correct classification, although the utility of being able to predict low density fields from all fields above 0.2 grubs / stool may be limited. The models developed to predict grub density class two and three years into the future were based upon the same set of variables, but only resulted in 62 & 63% correct classification. However, this is better than a random assignment resulting in a 33% correct classification. The three and four year trend models (predicting whether a field starting as a low density field at planting would remain low or increase to a moderate or high density over a 3 or 4 year period) faired no better than predicting density classes in a given year (only 72 & 64% correct classification, respectively for the 3 and 4 yr periods). A Bayesian approach was used to adjust prior probabilities, based upon observed frequency distributions of grub density classes, but this technique only improved the correct classification of the low density fields, up to 90-95%. However, the classification of the medium and high density classes was made worse by this technique and so it was not adopted since it is the medium and high density classes that are of most concern to growers.

2.3.3 Logistic regression approach

A similar modeling technique to discriminant functions was also used, ordinal logistic regression. A model using logistic regression to predict these same grub density classes is shown for predicting 2005 grub density classes from 2003 measures.

Logistic model…predicting 2005 grub density class with 2003 measures ($P<0.0001$)

Predictors

- Log grub density 2003
- Severity of damage 2003
- Distance to neighbor damage 2003
- # Damaged blocks < 400m 2003
- Max severity of damage 2003
- Ht to TVD (mm) 2003

The overall r^2 for this model is 0.24 and the correct classification was 69%. It can be seen that the selected variables were very similar to the discriminant function and the predictive capability of the model was also very similar. Therefore, it was decided not to continue using ordinal logistic regression for modeling density classes.

2.3.4 Predicting grub density rates of increase

Intrinsic rates of increase may be a useful population statistic to model. Again two approaches were used to develop and assess models for intrinsic rate of increase (log (grub densities in year (t+1) / grub densities in year (t))). Analyses of variance and backward and mixed stepwise regression were used to determine likely predictor variables for the calculated values of the intrinsic rates of growth. Discriminant functions were used to estimate models for classes of intrinsic rates of growth, where classes were defined as densities that: 1) increased from one year to the next, or 2) decreased from one year to the next. A summary of the results is as follows.

2.3.4.1 Predicting grub intrinsic rates of growth with previous year's measures

I. Log rate of increase 2004/2003, $r^2 = 0.575$

significant predictors were:	*coefficients*
Severity of damage 2003, *P*=0.0108	0.0595
Distance to neighbor damage 2003, *P*=0.0004	0.0002
# damaged blocks < 400m 2003, *P*<0.0001	0.0578
Ht to TVD 2003, *P*<0.0001	0.0002

II. Log rate of increase 2005/2004, $r^2 = 0.213$

significant predictors were	
Log grub density 2003, *P*=0.0524	0.8897
Log grub density 2004, *P*=0.0175	-0.3997
# damaged blocks < 400 m 2004, *P*=0.0091	0.0367
Ht to TVD 2003, *P*=0.0101	-0.0001

IIIa. Log rate of increase 2006/2005, $r^2 = 0.664$

significant predictors were	
District, *P*=0.0056	0.1183
Log grub density 2005, *P*<0.0001	-0.5995
Severity damage 2003, *P*=0.0014	-0.0586
# Damaged blocks 2003, *P*=0.0375	0.0287
Increase in gaps 04-05, *P*=0.0402	0.0174
Confidor 2005, *P*=0.0265	-0.0858

An alternative model for Log rate of increase 2006/2005

IIIb. Log rate of increase 2006/2005, $r^2 = 0.472$

significant predictors were	
Log grub density 2004, *P*=0.0001	0.5294
Log grub density 2005, *P*<0.0001	-0.7167

All three of these models had a few common predictors. These common predictors tended to be log grub densities from the previous year and the number of damaged blocks <400m. These can be the choice for development of a common global model, however, when these variables are used to predict each of the years the results are as follows. 1) 2004-2003, the model resulted in a $r^2 = 0.511$ and only two predictors were statistically significant (#damaged blocks 2003 and Ht to TVD 2003), 2) 2005-2004, the model

resulted in a r^2=0.092 and only one predictor was significant (2004 log grub density), and 3) 2006-2005, the model resulted in an r^2 = 0.326 and only one predictor was significant (2005 log grub density).

Some of the inability to develop a good global model is that these fields have a memory in terms of the population dynamics and so the trajectories of population increase are not the same from year to year. This is exemplified by the reversal in the sign of the log grub 2005 coefficient for predicting the 2006-2005 rate of increase. This dynamic might be a result of disease buildup or other density dependent factors. In addition, the rates of grub population increase from one year to the next tend to be negatively correlated suggesting density dependence mechanisms that might be responsible for the long-term population dynamics. There is a very weak relationship between the rates of increase in fields from 2004/2003 to 2005/2004 and 2006/2005 (P=0.0018, r^2=0.1166). However, the relationship between the rates of increase in fields from 2005/2004 (X) and 2006/2005 (Y) is strong, P<0.0001, r^2 = 0.453, slope = -0662. This suggests that fields that had high rates of increase over the years 2004 and 2005 had declines between 2005 and 2006 and vice versa. More separated in time, rates of increase from 2004/2003 are only modestly related to rates of increase two year later represented by the years 2006/2005 (P=0.071, r^2=0.056), suggesting that these density dependent mechanisms are of short time lags.

2.3.4.2 Predicting rates of increase for longer periods of time: 2-3 yrs

Log rate of increase 2005/2003 , r^2 = 0.114

significant predictors were	
# Damaged blocks 2003, P=0.0018	0.0376

Log rate of increase 2006/2003 , r^2 = 0.379

significant predictors were	
Severity of damage 2003, P<0.0001	-0.0915
Distance to treeline, P=0.040	-0.0002
# Damaged blocks 2003, P<0.0001	0.0630

The ability to predict several years in advance is represented by the models that use intrinsic rates of increase of 2005/2003 and 2006/2003. These models used a common predictor variable (number of damaged blocks in 2003) which is not surprising, since the log rate of increase between 2006/2003 and 2005/2003 are highly correlated (P<0.0001, r^2=0.228). In general, it appears that predicting rates of increase compared to log grub densities may be as profitable from the standpoint of explained variation, but possibly less relevant to making pest management decisions.

2.3.4.3 Rate of increase classification

An attempt was also made to predict classes of population increase or decline. Categories were constructed from the intrinsic rate of increase estimates. These categories were either as increasing (1), no change or decreasing (0). Two classes were used for 2006/2003 and 2005/2003 because there were not enough fields in each class to adequately estimate parameters. Models were constructed using MANOVA and linear discriminant functions.

2006/2003 rate of increase class predictive variables (*F* = 2.097, df=5,53, *P*=0.080)

Log grubs 2003
Distance to treeline
Severity of damage 2003
Distance to neighbor damage 2003
damaged blocks < 400m 2003

68% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	0	1
0	**7**	4
1	15	**33**

Percent of fields

	0	1
0	**63.6**	36.4
1	31.3	**68.7**

2005/2003 rate of increase class predictive variables (*F* = 2.332, df=5,76, *P*=0.050) no significant 2003 variables found so used 2004

Log grubs 2004
Severity of damage 2004
Distance to neighbor damage 2004
damaged blocks < 400m 2004
Max severity of damage 2004

70% correct classification as follows (rows are observed and columns are predictions, bold are correct classifications)

Number of fields classified

	0	1
0	**19**	4
1	20	**39**

Percent of fields

	0	1
0	**82.6**	17.4
1	33.9	**66.1**

2.3.4.4 Summary for rates of increase

In general, grub intrinsic rates of increase can be predicted with the previous year's measures, except there are fewer variables that appear to be good predictors compared to grub density prediction. However, the range of explanatory power (r^2) was similar for the

models based upon log grub densities compared to those based upon rates of increase. One common variable that is a good predictor across year combinations is previous year's log grub density (not surprising since there is a bit of autocorrelation expected based upon the derivation of the rates of increase). Another set of common variables that appeared to be significantly related to rates of increase were the previous year's measures of damage severity and the number of damaged blocks. However, when a global model was formulated for all three rates of increase based upon the previous year's log grub densities, severity of damage, and the number of damaged blocks, results were less than satisfying. The results showed no significant parameter estimates for the 2004-2003 model, The 2005-2004 model resulted in two predictive variables (Damage severity and Log grub density) and an $r^2 = 0.147$. The 2006-2005 model had an $r^2=0.32$.

Using a classification for rates of increase, the ability to consistently predict fields that from 2003 to 2005 or 2006 had positive rates of increase or rates that were zero or negative was fairly poor. In theory one could expect a 50:50 outcome if events were driven entirely by chance and these models only slightly exceeded this type of performance.

3.0 GREYBACK CANEGRUB SIMULATION MODEL

3.1 Introduction and Methods

A simulation model of the greyback canegrub, *Dermolepida albohirtum*, was constructed by reviewing the published literature, unpublished reports and unpublished field and laboratory data. These data sources were used to develop quantitative relationships assumed to be important in regulating population densities of the greyback canegrub. It was determined that a model should be general, but detailed enough that it could be adapted to specific sugarcane growing regions. It must be emphasized from the start that this simulation model represents a quantitative literature review. It is not a predictive population model. It is built more for exploring the effects of different environmental or biological factors on the population dynamics of the canegrub. Because the quantitative relationships that went into the model were dependent upon the availability of empirical data, important relationships such as the carrying capacity of a sugarcane stool in terms of grub numbers are not included in the model. This makes the model highly inaccurate as a predictive model, but hopefully still maintains a use for comparing potential factors that might affect canegrub population growth.

The specific modeling approach was based upon construction of a life-system model where all the major life stages were represented as state variables. The flow rate of individuals between state variables is regulated by adult longevity, oviposition, stage-specific development times and stage-specific mortality. State variables are modeled as differential equations, densities being the difference between rates of individuals coming into the life stage and rates of individuals leaving the life stage. The life stages that are included in the model are as follows:

1) <u>female adults</u> newly metamorphosed from pupae that are residing in the soil of sugarcane blocks prior to their emergence in October through January. Only females are kept track of in the model to simplify things. It is assumed that 50% of the pupae develop

into female adults. However, adult males would be easy to include in the model and would be important if a density-dependent response such as dispersal was shown to depend upon both male and female beetles. The emergence of adult female beetles has been designed so that precipitation can regulate emergence (ca. 40mm needed for emergence to commence). More sophisticated emergence functions can be added easily. There is no mortality that is currently taken out of the pre-emerged female beetles (set to zero).

2) emerged pre-oviposition adult female beetles. These individuals are assumed to all be mated and experience a development period (sexual maturity) of 14 days. It is assumed that all beetles have access to food. It is as pre-oviposition beetles that mortality as a result of stress from pan evaporation is applied. It could have been applied at any of the adult state variables (females in the soil, pre-oviposition females, ovipositing females) or in the egg and first instar stage, but the pre-oviposition stage was chosen at this point.

3) ovipositing female beetles. These individuals have a longevity of 50 days and lay 31 eggs over their life-time. Essentially longevity is a mortality factor and could be dynamic based upon further research. There is no dispersal, immigration, or emigration function in this model, but it is designed to incorporate it if need be. One could add a sugarcane submodel and incorporate sugarcane height, i.e. the "trap-crop" effect (Horsfield et al. 2002), but this is currently not in the model.

4) eggs. Egg development is 14 days and egg mortality is currently set to zero since little to nothing is known about egg desiccation, predation, or other forms of mortality. Life table estimates could be incorporated here to at least provide a static background level of egg mortality.

5) larvae or grubs. Larvae are represented as three different state variables (1st, 2nd, and 3rd instar stages). Other state variables could be added, such as diseased larvae etc., but it is probably not informative unless a more sophisticated submodel of larval disease, predation, or parasitism is constructed. Currently, the three larval instars have developmental durations of 28, 35, and 154 days, respectively. Mortality of neonate larvae (inflow to first instar state variable) represents losses due to cannibalism and is a function of total grub density (#/stool). Second instars currently have no mortality extracted (set to zero). Third instars are subjected to disease losses. Disease losses are a function of total grub densities (discussed in mortality section).

6) pupae. Pupae have a developmental duration of 31 days. There is currently no pupal mortality function. All pupae complete development, but only half metamorphose into adult females.

7) end of the season adult females in the soil. These females become the starting densities for the following year. There is no mortality of adult females prior to emergence.

All developmental rates and fecundity rates are a function of Julian days. If degree-day models are developed for all of the stages then the model could be translated to a temperature-dependent model. However, it is not practical to have temperature dependence for only some of the stages such as pupae. Development rates and oviposition rates were made stochastic by making the development parameter a Gaussian random

variable with SD being 10% of the mean. The model output consists of daily instantaneous density estimates, but it should be remembered that these are rates of individuals moving through particular stages. This is why it appears in graphs that third instars have a higher density than first and second instars. There is a higher likelihood to see more of the population as third instars than firsts or seconds because the developmental duration is so much longer than first or second instars. In order to get true density estimates the state variables have to be numerically integrated. This has been done but not graphed out, except for the year-end production of adult females.

There is currently no linkage to the sugarcane host plant, although this could be performed given specifics the insect/host plant relationships and some sort of simple plant model (see discussion). In addition, other factors such as soil type were also not incorporated into the model (Ward 2003), although this could be used as a regional variable that sets the overall background level of mortality.

A spatial version of the model was constructed implicitly. This was based upon the use of Taylor's power law to estimate a mean density-dependent k parameter for the negative binomial density function (k is a function of the mean for the greyback canegrub where k = mean^2 / (variance - mean)) (Fig. 1).

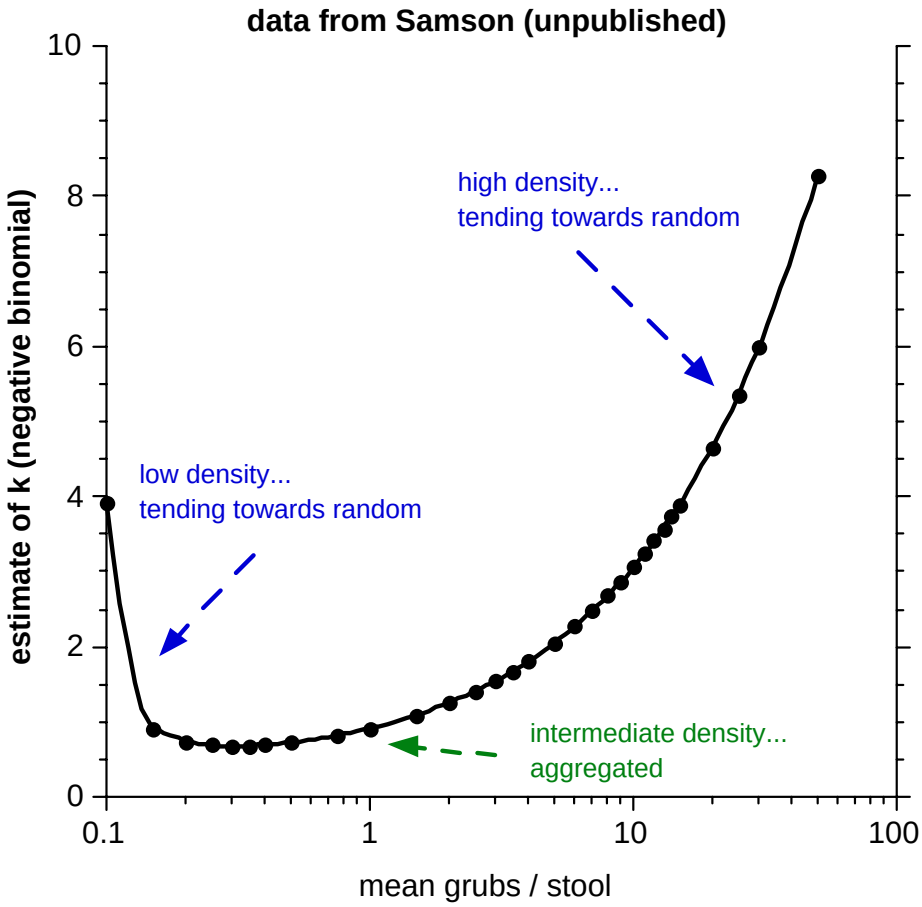


Figure 1 **Estimates of mean-dependent k for the negative binomial density function.**

The density-dependent negative binomial density function was then used to generate the expected proportions of grub density classes found throughout a sugarcane block (i.e. 0,1,2,3,4…etc. grubs/stool). Thus probability of having stools with no grubs = P(0), probability of having stools with 1 grub = P(1), probability of having stools with 2 grubs = P(2), … probability of having stools with n grubs = P(n), where $P(0) = (1 + (mean/k))^{-k}$ and P(n) = (k+(n-1)/k)*(mean/(mean + k))*(P(n-1))). These probabilities add up to 1 and so can be proxies for the proportion of stools with these density classes. This vector of density classes is then operated upon by the density-dependent mortality factors resulting in a new vector of densities (post-mortality).

The three mortality factors included in the current model are:

1) intra-specific competition mediated through cannibalism
2) disease
3) environmental stressors, using pan evaporation as a proxy

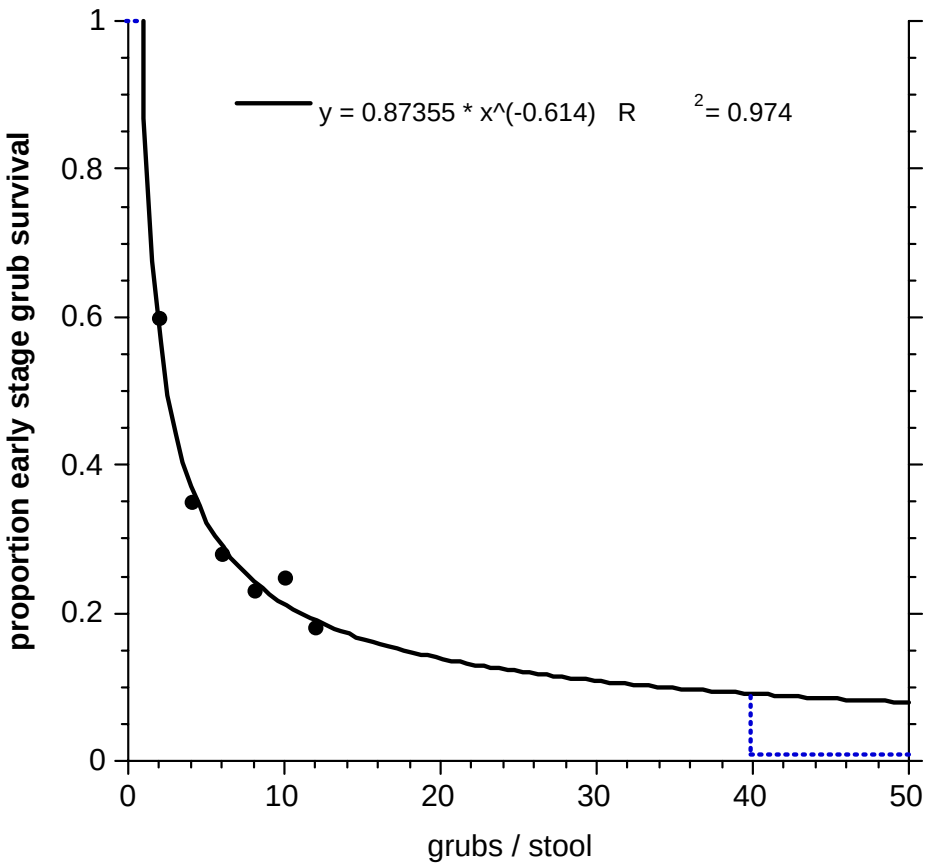


Figure 2 **Relationship between proportion survival and grub density (data from Ward and Robertson 1999). Dashed blue line indicates application of severe mortality at grub densities of 40/stool or greater.**

The three mortality factors are applied to neonate grubs, third instar grubs, and pre-oviposition adult females, respectively. Mortality was expressed as proportion mortality

and this was multiplied by the appropriate flow of individuals. Figures 2-6 depict the basic relationships that represent these mortality factors. Figure 2 shows the relationship used to assess proportion mortality to grubs from cannibalism. The data used for this relationship was taken from Ward and Robertson (1999). Inspection of this relationship shows that at, even at high grub densities, levels of survival that are still reasonably high (ca. 20%) relative to the fecundity of the greyback cane beetle. Therefore, in one simulation we set survival at 1% for densities of 40 neonate larvae or higher (blue dotted line). There was no indication of how many of these larvae might disperse to neighboring stools under high densities and thus the mortality relationship depicted in Figure 2 represents a very liberal estimate of mortality.

There are abundant suggestions that microbial pathogens are important in the population dynamics. Unfortunately, there is limited quantitative information available describing the epizootiology of the three main pathogens, *Adelina sp., Metarhizium anisopliae*, and *Bacillus popilliae*. Unpublished time series data (Robertson unpublished data) collected between 1994 and 1998 in the Burdekin, Herbert, Innisfail, and Tully areas allowed the development of a very crude disease model. Relationships between specific causal agents and the resulting disease did not show a discernable relationship between disease and grub density across all regions sampled. Therefore, the relationship between grub density and total disease (from all microbial pathogens) was investigated. All areas showed evidence of a potential disease threshold or population susceptibility of between 2 and 2.5 grubs/stool (Fig. 3).

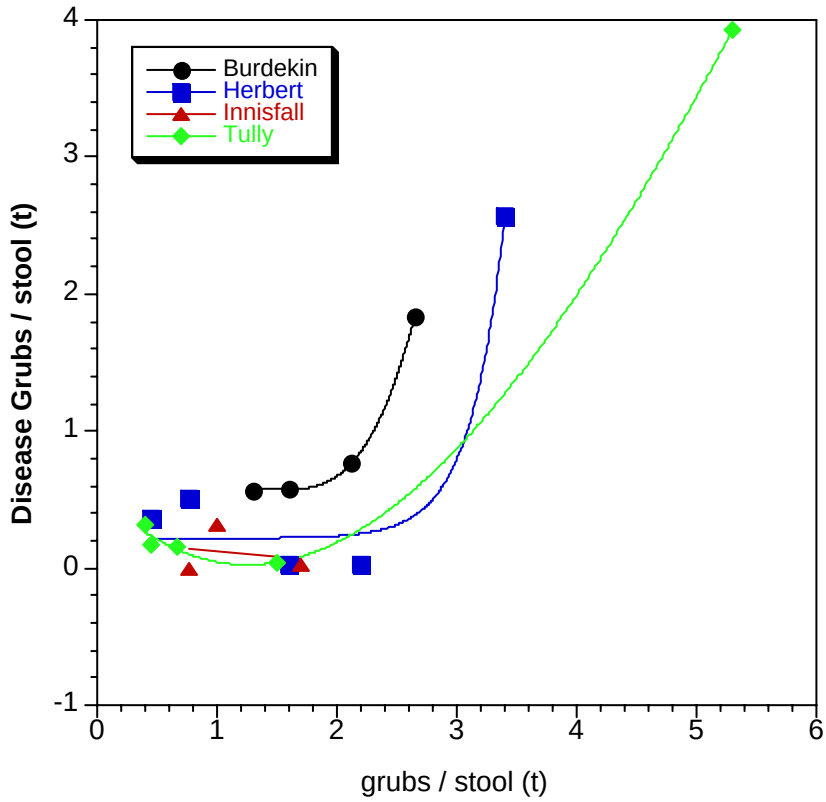


Figure 3 Data suggesting a disease threshold across all regions.

This time series also suggested that total disease might only be maintained at very low densities and epizootics quickly run their course, with high mortality at high densities, or possibly result in a stable cyclic equilibrium (Fig. 4).

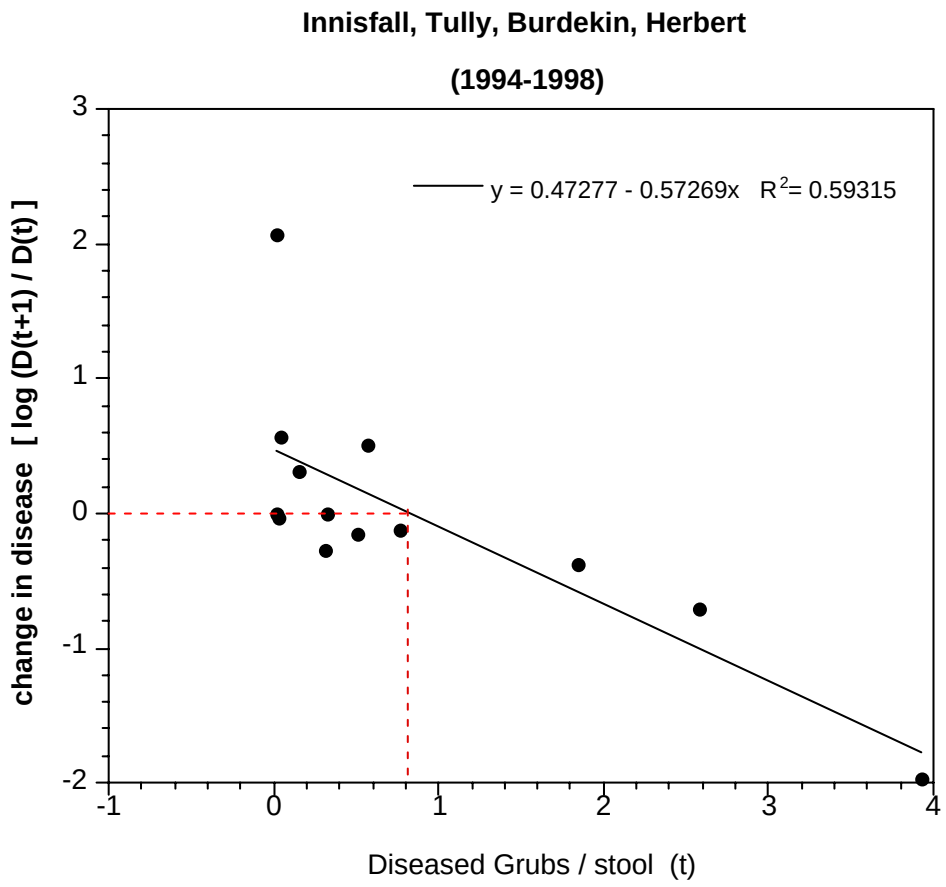


Figure 4 **Relationship between annual increase of total disease and the density of diseased grubs the previous year**

Because the mechanistic processes of diseases in greyback grub are not well defined, it was decided to construct a crude preliminary model that related total disease in the population at time t with the total grub density at time t (Fig. 5).

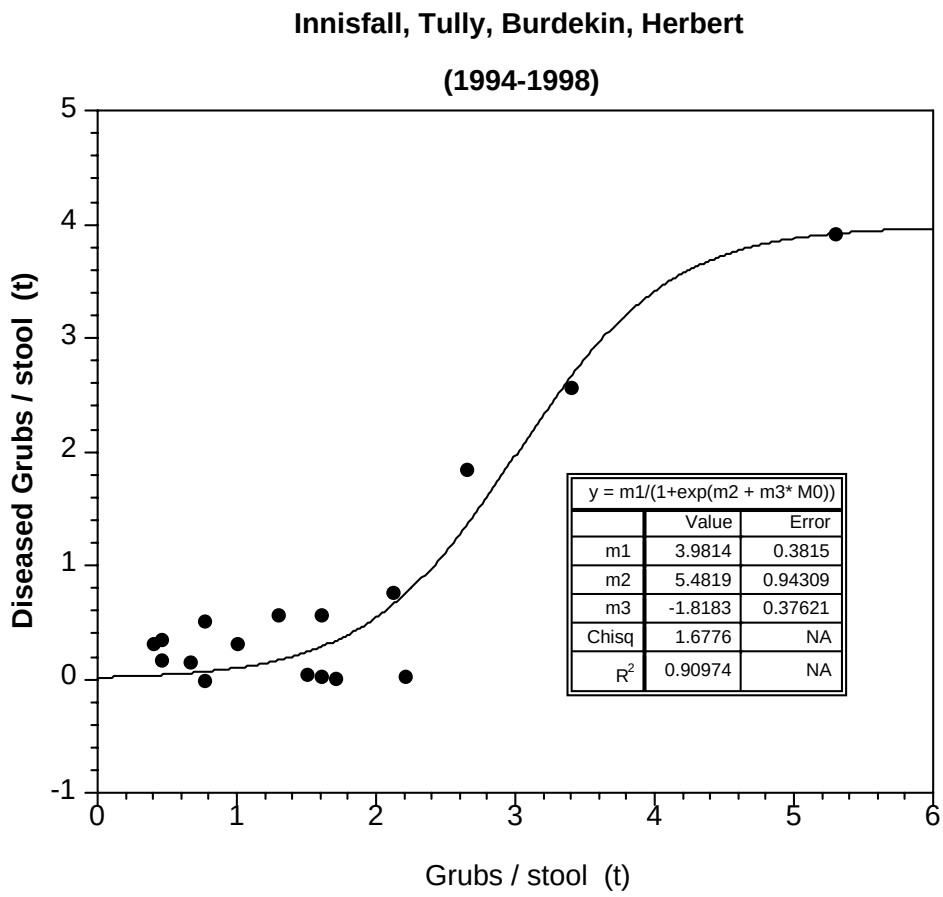


Figure 5 **The relationship between grub density and resulting diseased grubs through transmission of all diseases. This relationship was used in the model to generate grub mortality due to disease**

This relationship is well described when an asymptotic sigmoidal model is applied to all of the pooled data. In using this model it is assumed that inoculum (at least from one of the three disease organisms) is always in the soil and that any level of inoculum results in infection. In this model, infection is purely a function of the current year's grub density. While this model can be criticized in that it does not represent any mechanistic components, it does at least embrace the fundamental disease transmission relationship (disease prevalence being a function of inoculum and susceptible hosts). Because we modeled total disease, and time to death is probably too variable to model, it was determined that disease mortality should be imposed in the third larval instar stage.

The last mortality factor to be incorporated in the model was stress due to weather factors. Horsfield et al (2008) showed that a significant amount of the variation in crop damage to sugarcane across different blocks and years for different areas in the Burdekin district could be explained by several environmental variables. From their raw data, a composite model was constructed that related pan evaporation index to crop damage. Crop damage was assumed to be an inverse proxy of stress on beetles (i.e. when damage is high stress on beetles is low). The data were standardized as a percent of the greatest damage for each location and pooled so that an overall analysis could be conducted between pan evaporation between September and November during the adult emergence period and

canegrub severity (the inverse of the standardized crop damage) (Fig. 6). The proportion of the variance explained by pan evaporation (r^2) for the pooled data is 0.77. This relationship was used to determine a daily mortality rate (1-proportion severity) that could be applied against the pre-oviposition females.

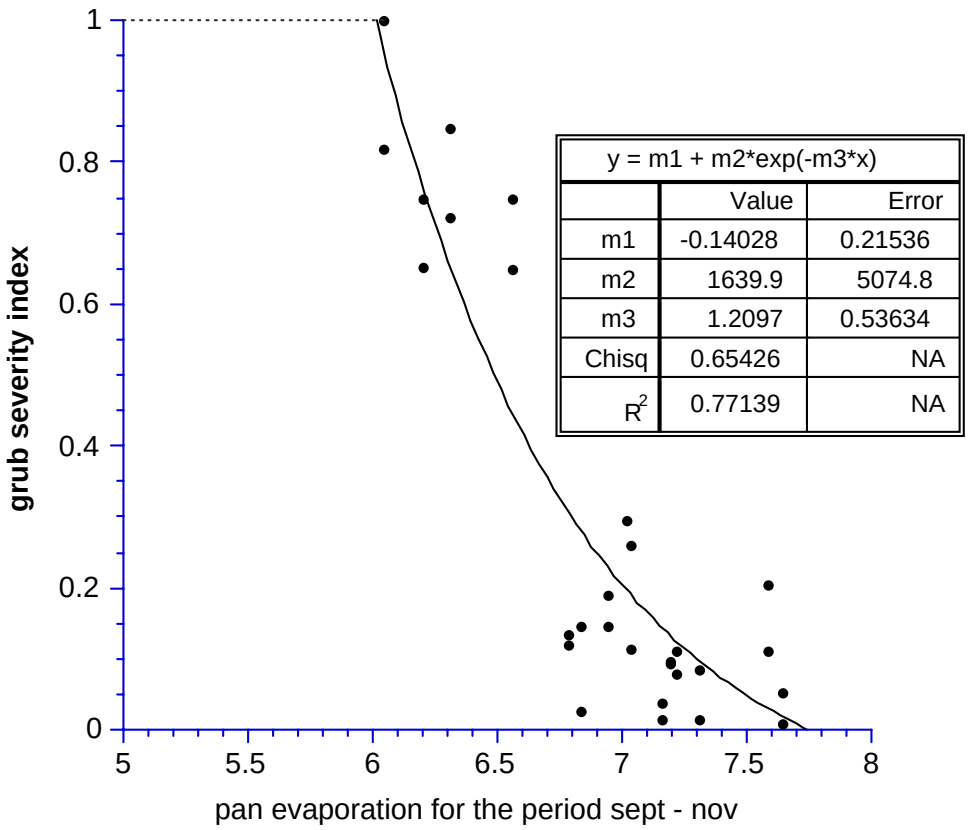


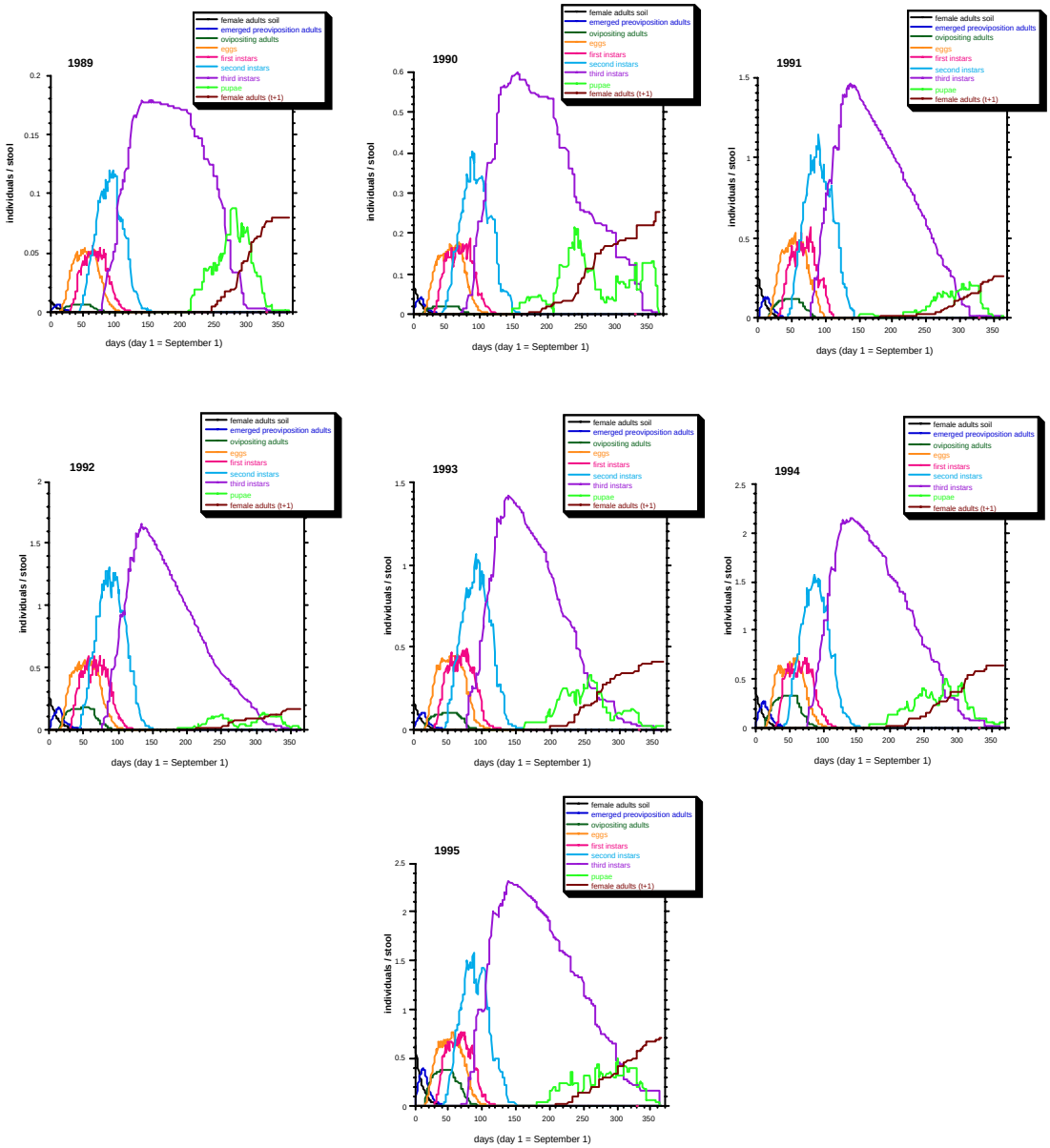
Figure 6 **Effect of pan evaporation on the index of grub severity, derived from a standardized crop damage index. This index subsequently was used as a reciprocal for grub mortality**

The completed preliminary model was used to conduct a series of inquiries regarding the response of greyback canegrub to possible density-independent and density-dependent mortality factors. The results are presented below. All runs were conducted for a 7 yr period and an initial starting female adult density emerging from the soil of 0.01 beetles/stool.

3.2 Results

An example of the model output from a 7 yr simulation run (these runs are a result of all three mortality factors being applied) is illustrated in Fig. 7a-g. The daily instantaneous number of individuals/day of the various stages is plotted over time. It should be remembered that the developmental duration affects the number of individuals within the stage at any one time and so it might appear that third instar densities are greater than first or second instar densities, but this is because of the longer residence time of third instars: a larger proportion of the population is present in that stage at any one point in time.

Integration of the area under the seasonal plot of individuals would yield the overall density. The subsequent plots of the results show the resulting integrated density of adult female beetles in the soil at the end of each year of the simulation run.



Figures 7a-g Greyback canegrub life stages simulated with mortality factors consisting of cannibalism, disease, and weather stress (pan evaporation)

A simulation run without any natural mortality or any resource limits (no ceiling on grubs/stool) suggests that the canegrub has the potential to increase geometrically (ca. 1.1 orders of magnitude/yr) over a seven-year period post-replant (Fig. 8). The resulting number of individuals is unrealistic because of the lack of any limits on the number of grubs that can be supported on a single stool. However, this parameterization of the model is interesting in suggesting the potential maximum that canegrub could reach barring any constraints.

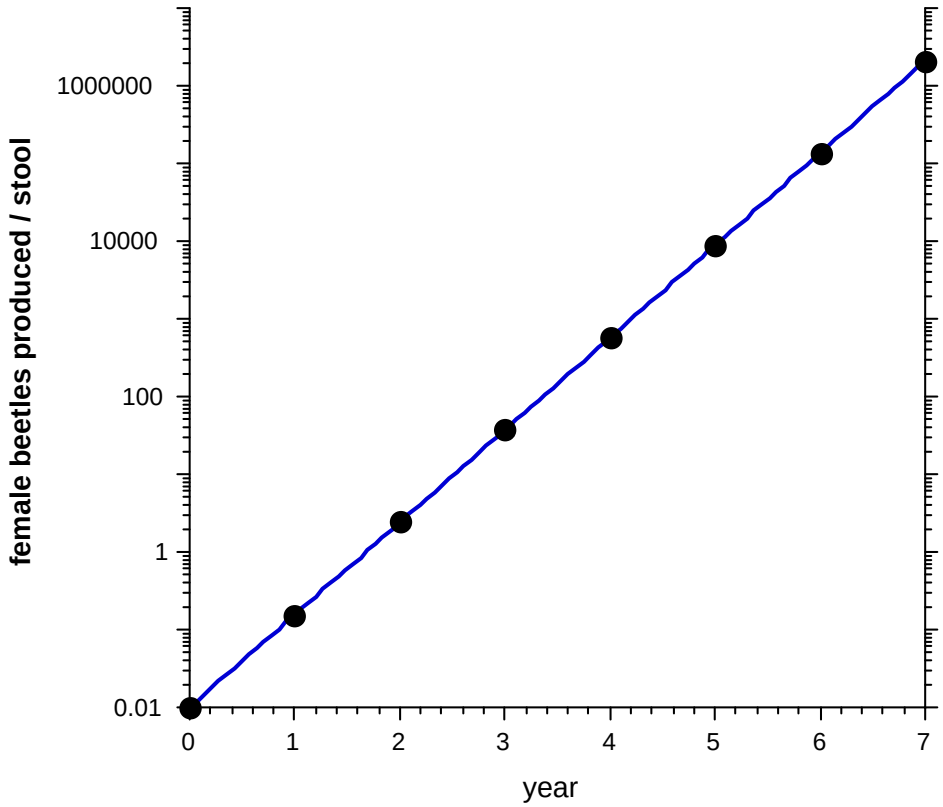


Figure 8 **The number of female beetles produced at the end of years 1-7 in a simulation run initiated with 0.01 females / stool. In this simulation there is no mortality operating, and thus this graph depicts the idealized maximum potential rate of increase that all other simulations can be compared with (note there is no limit to the number of grubs that can be supported by an individual stool)**

Abiotic mortality factors were modeled based upon the relationship between the environmental proxy, pan evaporation, and another derived proxy, beetle population quality as estimated by the annual proportion of crop damage. Pan evaporation does not appear to regulate canegrub populations, but decreased population increase to ca. 0.85 orders of magnitude over the seven-year period (Fig. 9).

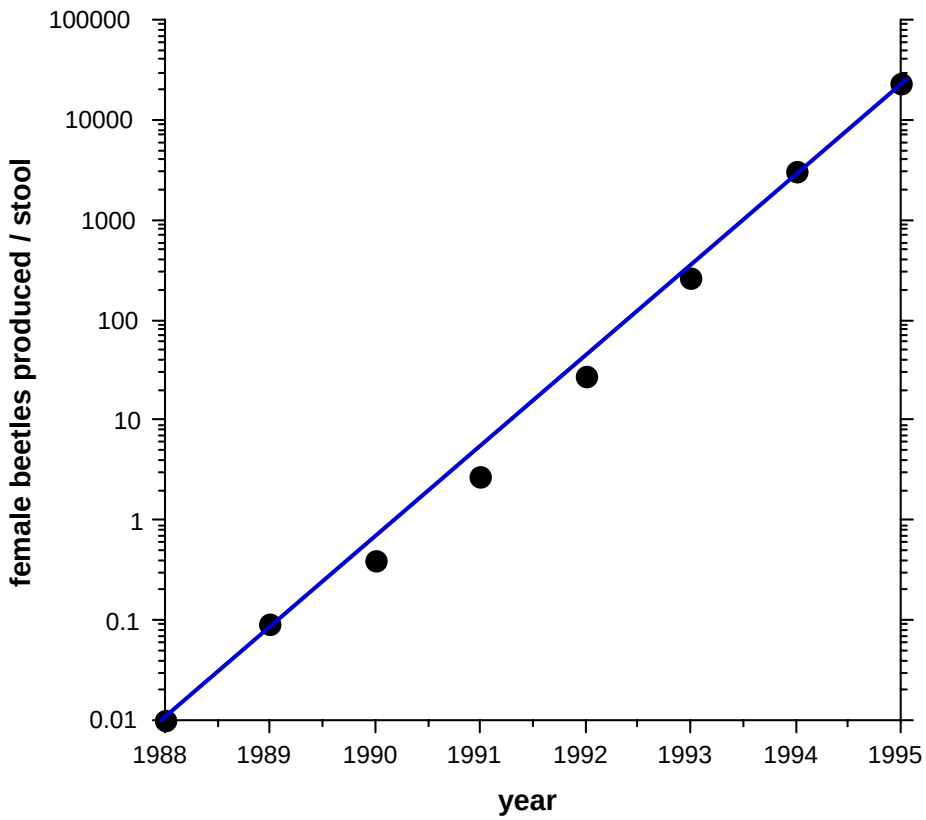


Figure 9 **The number of female beetles produced at the end of years 1-7 in a simulation run initiated with 0.01 females / stool. In this simulation only weather effects are incorporated as a form of mortality to the adults**

Two density-dependent sources of mortality were included in the model. The first was an intra-specific factor operating between neonate and early instar grubs, competition/cannibalism. Intra-specific mortality, when incorporated into the model, reduced population increase to 0.57 orders of magnitude increase per year, but there was no evidence of population regulation due to intra-specific interactions. A modification of the relationship between grub density and survival from cannibalism with an upper ceiling of 40 early instar grubs/stool resulted in only 1% survival. When this was included in the model, population regulation was exhibited between 0.5 to 2 grubs/stool (Fig. 10). This occurred under both a non-spatial and a spatial structure for the grubs. This is significant, and may suggest that only when intense mortality (ca. 99%) is operating would one expect to achieve population regulation. However, a stochastic analysis suggests that this might not be the case (see below).

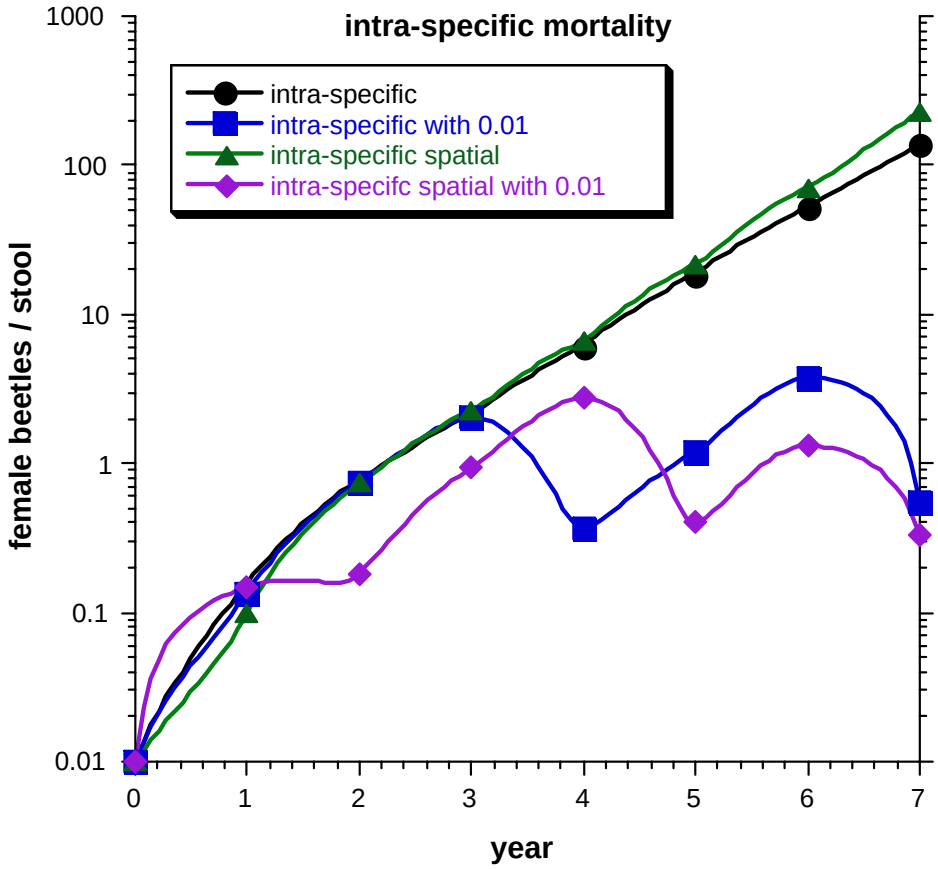


Figure 10 **The effect of intra-specific mortality, thought to be due to cannibalism. The four curves represent different 7 yr simulation runs: cannibalism with 18% survival at high densities; the same rate of cannibalism but with the spatial structure of the population taken into account; and cannibalism adjusted so that densities greater than 40 grubs/stool result in 99% mortality, with spatial structure either included or not included**

The second density-dependent factor incorporated into the model was disease. Due to a lack of specific quantitative relationships describing transmission and persistence of inoculum and host death rates for *Adelina, Metarhizium,* and *Bacillus* (milky disease), a disease submodel was formulated for total disease (all pathogen species) from field sampling data. This submodel quantified the relationship between total grub density and the associated diseased grub density resulting from disease transmission and persistence of inoculum under field conditions from which the data were collected. Incorporating disease into the model as a mortality factor applied to 3rd instar grubs did not produce any evidence of population regulation by itself (disease mortality in the absence of any other factors of mortality). A reduction of one order of magnitude in population increase of adult female beetles occurred over the seven-year period, compared to no mortality in the population (Fig. 11).

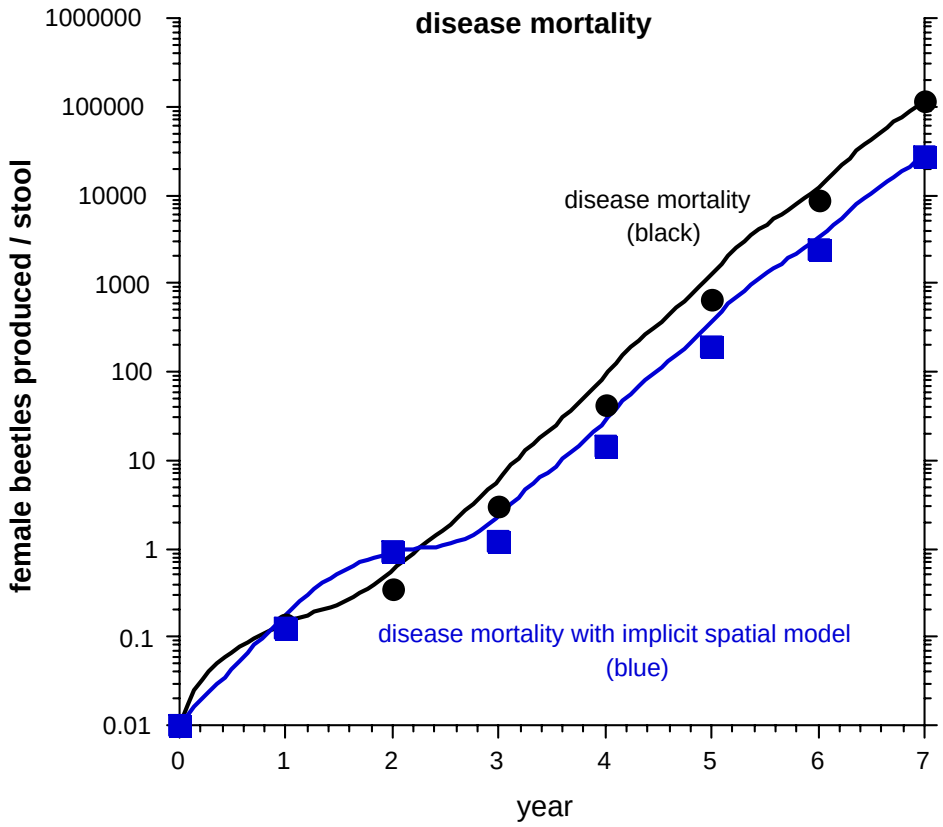


Figure 11 **Results of simulations with disease mortality extracted from the population. The two simulations represent disease without spatial structure and disease with a spatially structured population**

The spatial distribution of grubs within a sugarcane block was modeled using Taylor's power law (Samson, this report) to estimate parameters of the negative binomial density function. When spatial structure was incorporated into the model and the density-dependent effects of intra-specific cannibalism and disease were applied, there was little effect on population increase under mortality pressure from cannibalism…a bit lower in year 1 with spatial structure and a bit higher in years 6 and 7. This is most likely a result of the density-dependence being benefited only at very low densities of canegrub when the population is highly aggregated and less so at higher densities when the canegrub population is much more random (k increases such that the negative binomial produces a distribution close to a Poisson process). The results from the spatial structure interaction with disease was the reverse, indicating that disease will reduce the population further if allowed to act upon individual classes of stool densities instead of only being calculated on a pooled mean across the entire block. Overall, spatial structure may not be critical for incorporation into the present canegrub model unless a more sophisticated disease submodel is developed or more density-dependent mortality factors are included (Figs 10 & 11).

The interaction of the mortality factors represents a more realistic model for the canegrub and results in a very suppressed population growth trend. Fig. 12 shows that cannibalism

and disease incorporated together can lower the densities to those expected under field conditions. However, there is still no evidence of population regulation of canegrub populations.

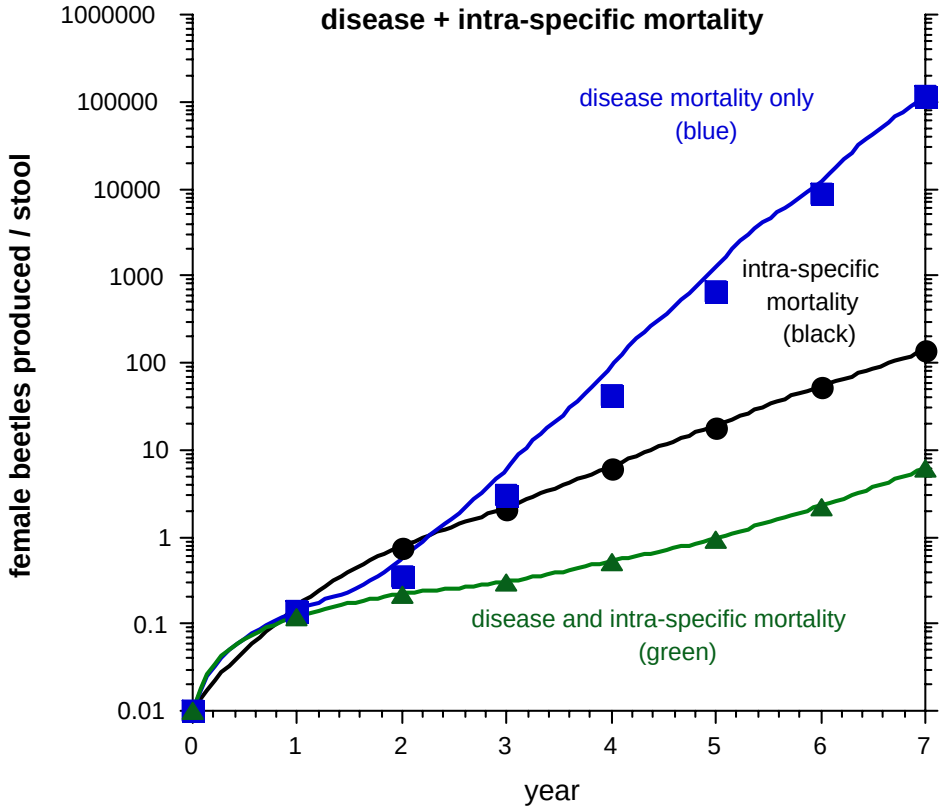


Figure 12 Simulation runs representing disease mortality only, cannibalism only, and the simultaneous operation of cannibalism and disease

The last set of deterministic simulation runs combined the abiotic density-independent mortality factor represented by pan evaporation from the Burdekin district of North Queensland with the two density-dependent mortality factors. Two runs were conducted (Fig. 13). One run used the daily pan evaporation data for the years 1989-1995 while the second simulation run used the daily pan evaporation data for the years 1996-2002. Results suggest that while pan evaporation alone has little effect on reducing the population increase of canegrub, its influence in determining the outcome of density dependent mortality factors such as cannibalism and disease is significant. The 1989-1995 run resulted in a final population density of 0.7 female beetles/stool, while the 1996–2002 run resulted in a final population level of 1.85 female beetles/- stool. Figure 14 shows the data used for these simulations expressed as beetle stress index as a function of pan evaporation for each year.

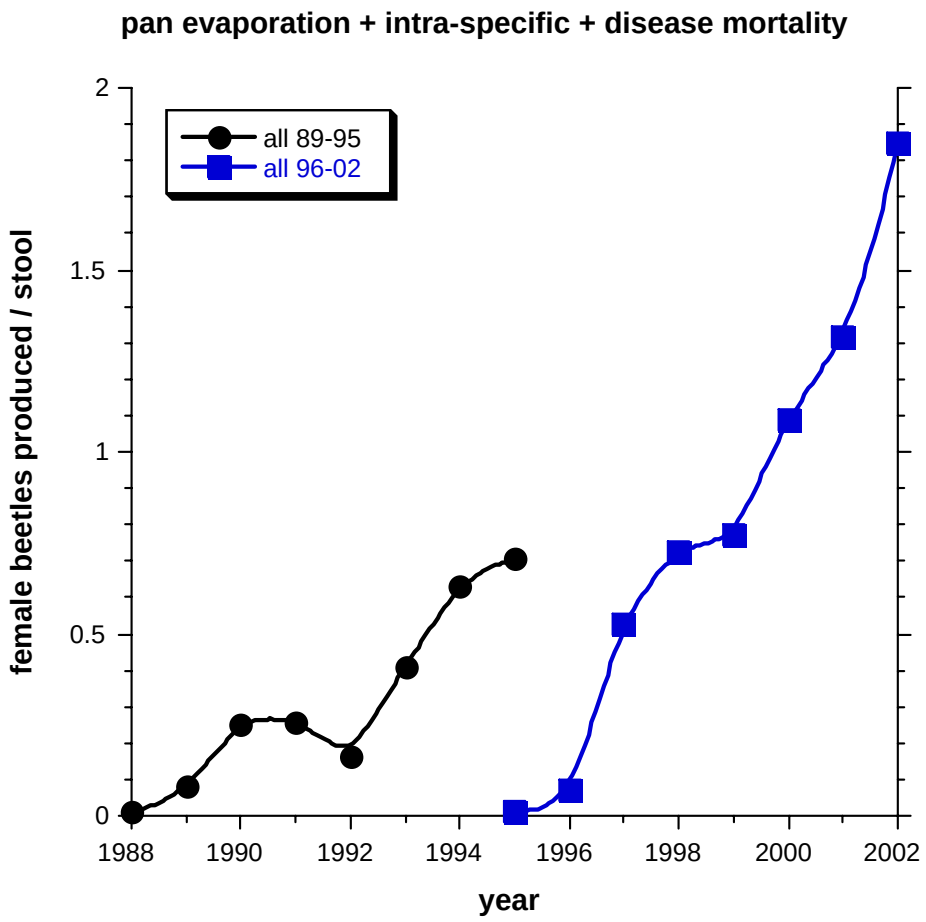


Figure 13 **The number of females produced during two specific 7 yr periods. Both simulations have intra-specific and disease related mortality incorporated. While the populations are suppressed under both scenarios, the earlier time period results in about 2.5x fewer adults by the seventh year**

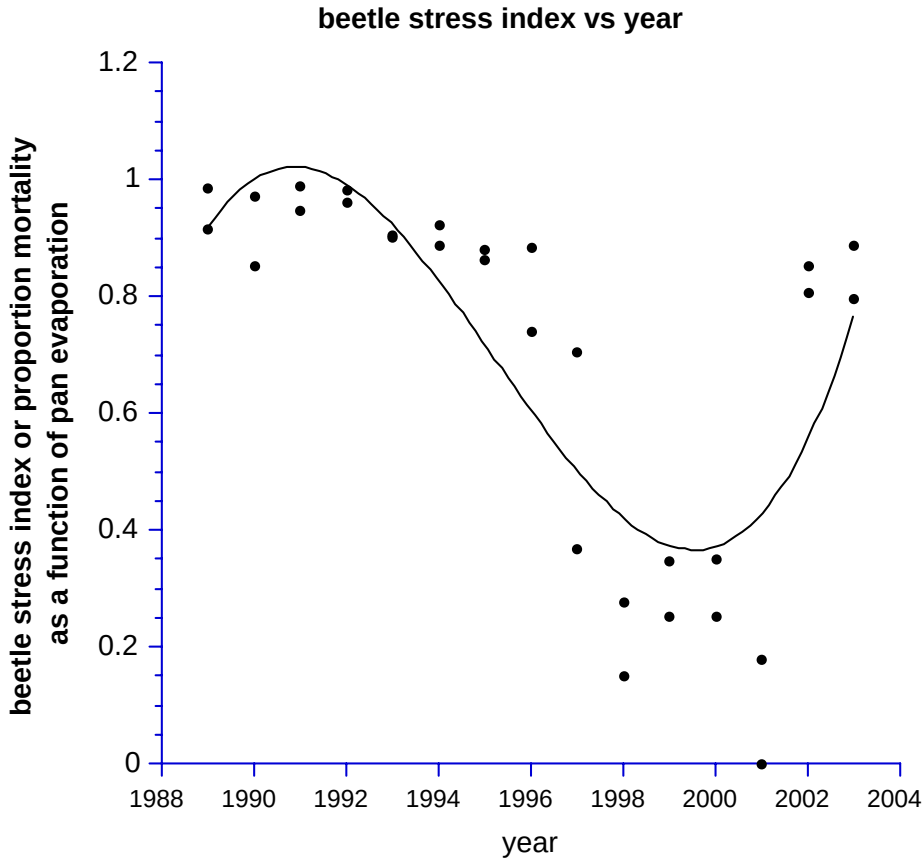


Figure 14 **An index of beetle stress (1 = high stress, 0=low stress) over the simulation years 1989-2002. The polynomial curve fit is only included to suggest a trend, it is not a model**

Thus one might conclude the following in the currently modeled canegrub system: abiotic influences appear to have an effect (at least in this model) of modifying the intensity of the density-dependent influences, cannibalism and disease, by reducing the grub density via adult beetle stress prior to the action of the density-dependent mortality factors that are acting on the early- and late-stage grubs, respectively.

To summarize the deterministic simulation runs, Fig. 15 compares the female production at year 3 after planting. It can be seen that only intra-specific mortality (cannibalism) and disease mortality suppress the population to any large extent by year 3. The weather simulations with intra-specific competition and disease suggest that this suppressive effect by the two density dependent factors may be greatly dependent upon the weather conditions during the periods of interest. However, Fig. 16 shows the same scenarios, but at the end of year seven.

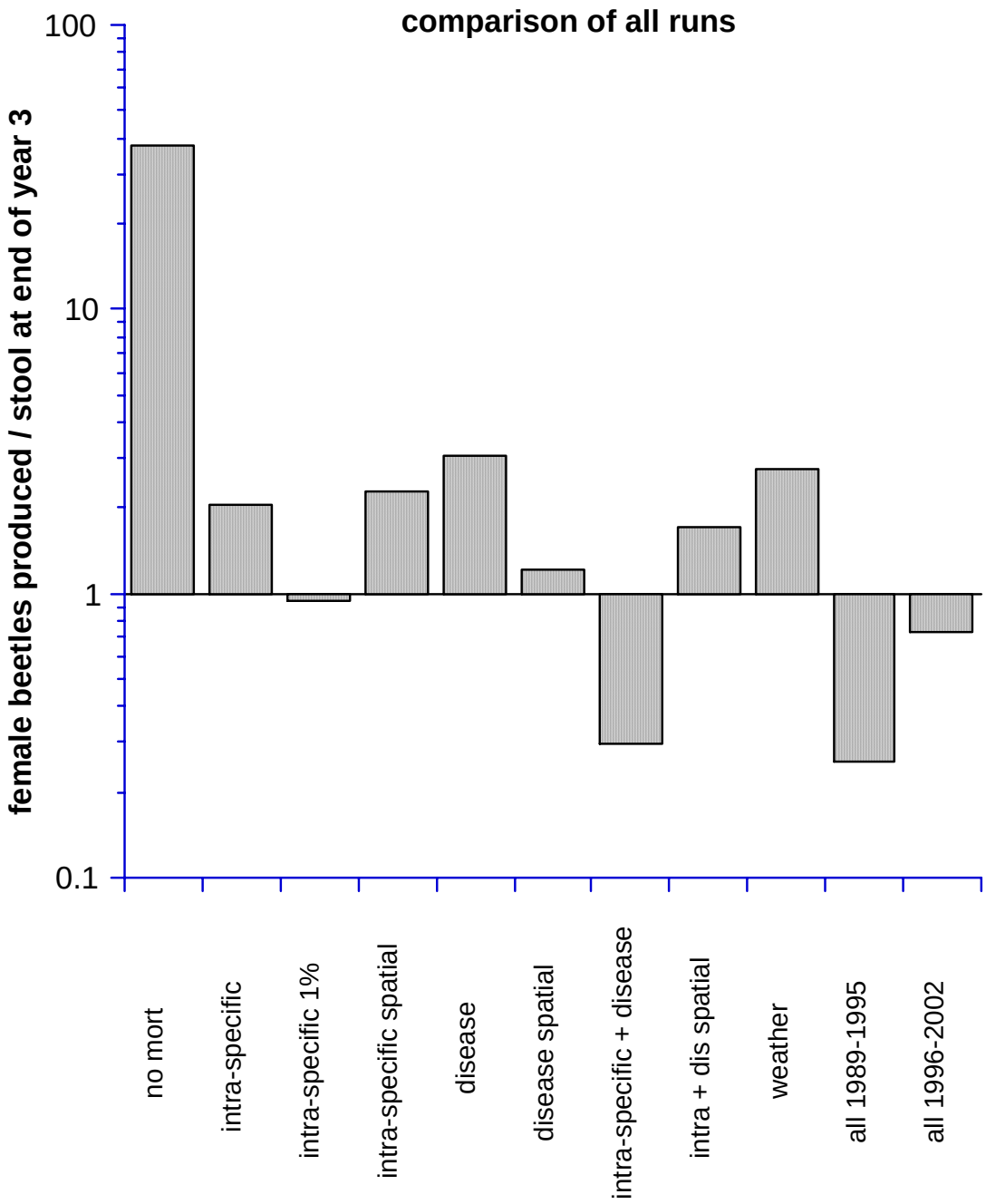


Figure 15 **A comparison of all of the deterministic runs plotted on a log scale. This graph depicts the numbers of female beetles produced by the end of year three**

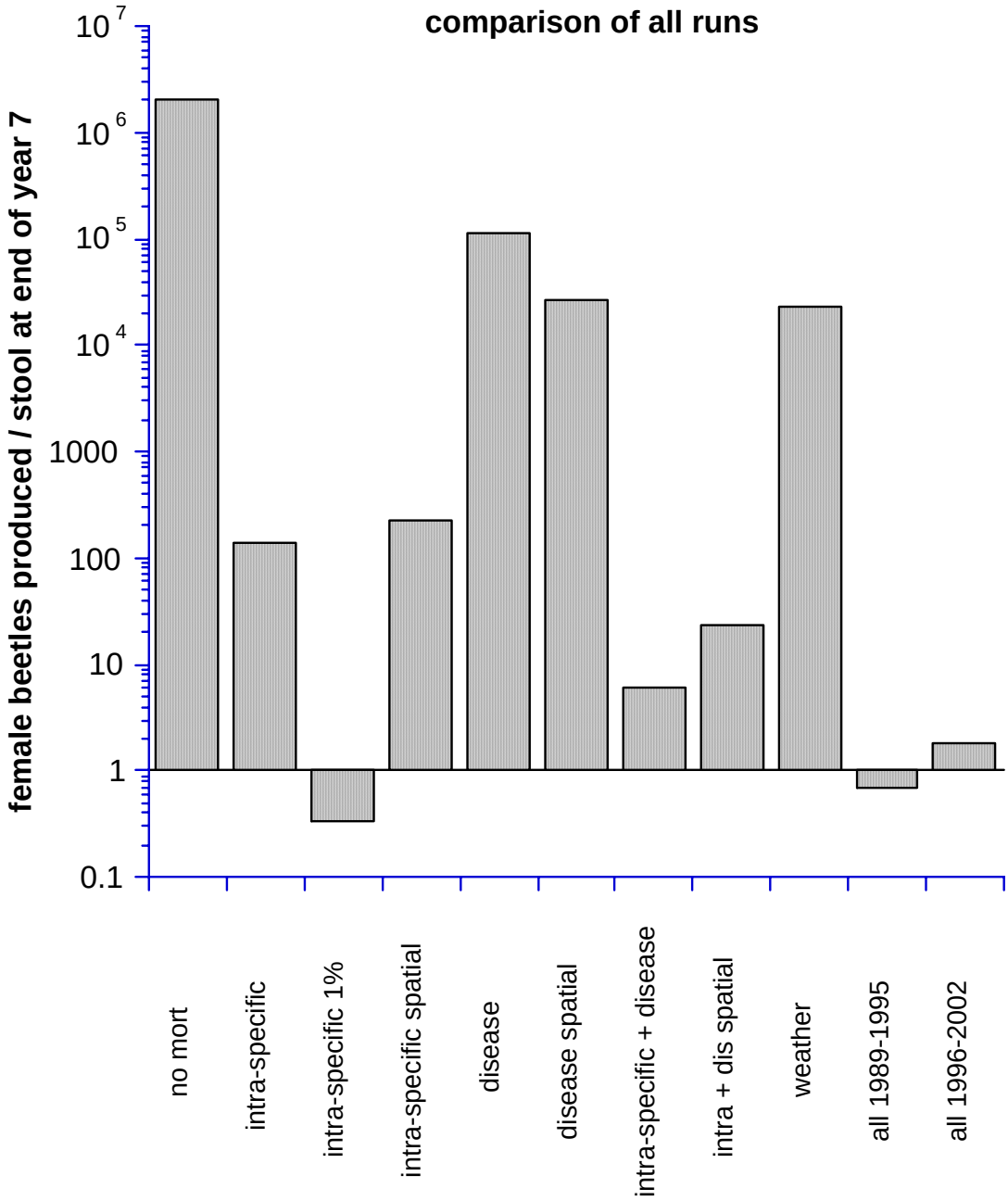


Figure 16 **A comparison of all of the deterministic runs plotted on a log scale. This graph depicts the numbers of female beetles produced by the end of year seven. Trends are similar to year three except that, over the longer time course, incorporation of weather appears to enhance the two density-mortality factor model in the absence of weather**

Stochasticity was incorporated into the model by modifying parameters that represented oviposition, development rates and mortality rates into probability distributions around a mean represented by the original parameter estimates. Simulation runs of the stochastic model suggested that when the density-dependent mortality factors of cannibalism and

disease were entered separately, the trends were the same. When disease was applied the final population increases over the seven-year period ranged from 37% less to 45% greater than the overall mean of 10 runs (se/mean = 0.088) (Fig. 17).

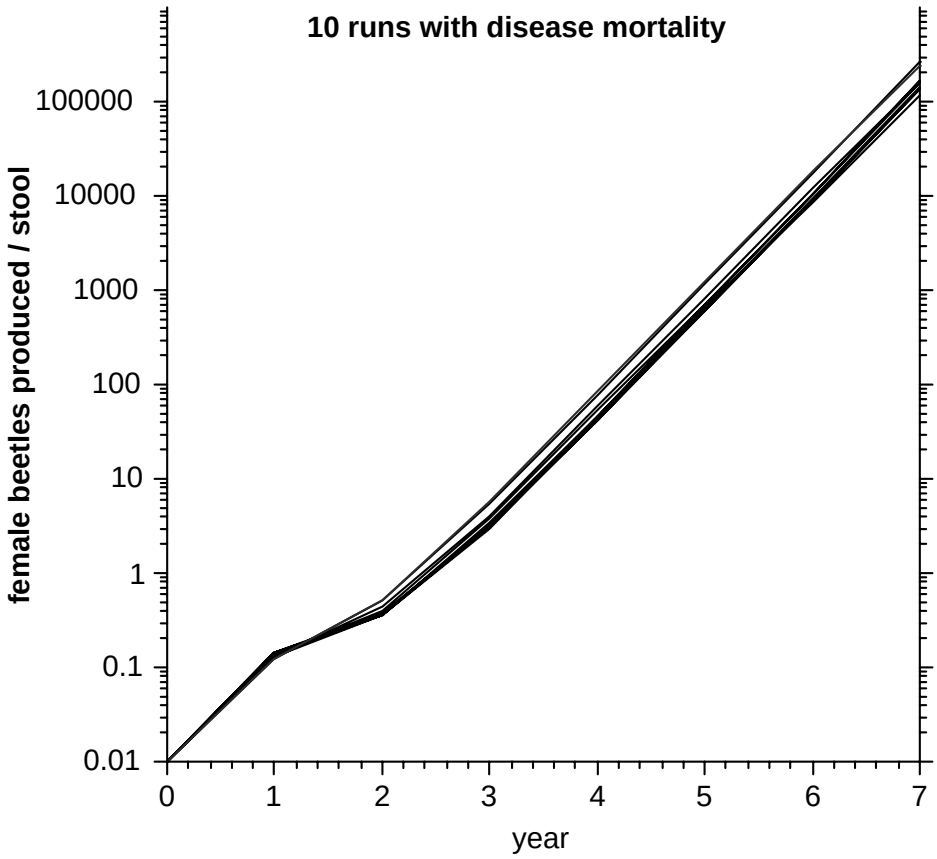


Figure 17 Results of 10 runs, all with same initial conditions for disease "only" simulations

Cannibalism resulted in a similar result, ranging from 29% less to 15% greater than the overall mean of 10 runs (se/mean = 0.048) (Fig. 18).

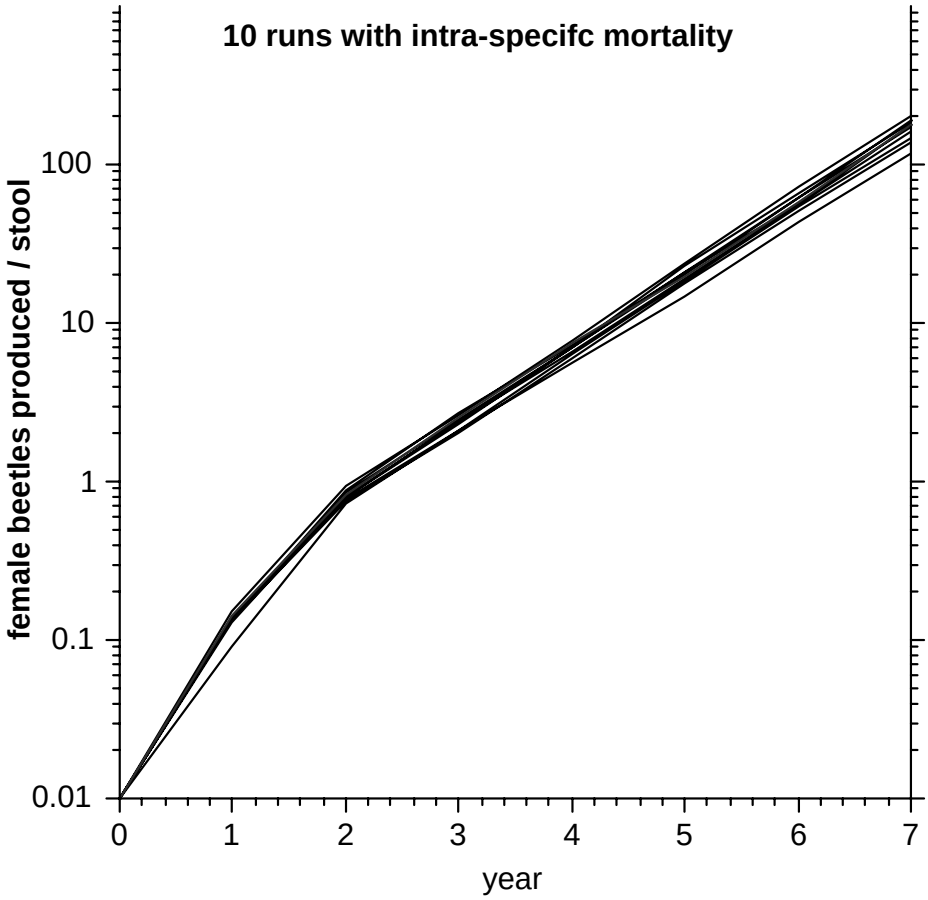


Figure 18 Results of 10 runs, all with same initial conditions for intra-specific (cannibalism) "only" simulations

However, the stochastic runs when both cannibalism and disease were incorporated suggested a very different outcome (Fig. 19). A series of 20 runs showed two patterns emerging. The majority of runs (75%) suggested that both disease and cannibalism greatly reduce population increase over a seven-year period, but no population regulation occurs. However, 25% of the runs resulted in population fluctuations characterized by no net increase over the seven-year period, a case for regulation. These results suggest that small changes in oviposition, population synchrony or mortality over the course of the growing season may result in a variety of dynamics. These runs might also suggest that is will be difficult to predict population densities several years in advance after planting. Densities by the end of year 1 for most of the simulation runs were similar, but by year 3 and 4 the densities were markedly different. The variability in population increase by the end of the seventh year in this simple stochastic system with two density-dependent mortality factors ranged 98% less to 400% greater than the overall mean of 20 runs (se/mean = 0.257).

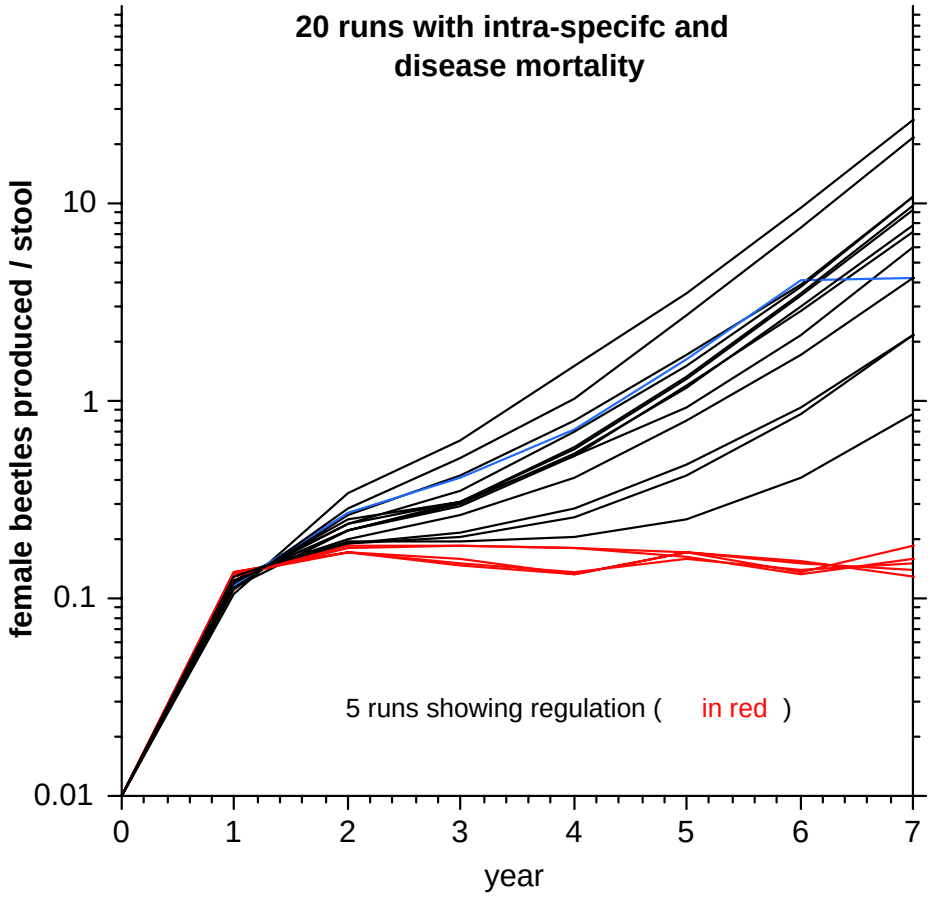


Figure 19 **Results of 20 runs, all with same initial conditions for intra-specific (cannibalism) and disease (operating simultaneously) simulations. The black runs suggest no population regulation and the red runs suggest regulation. The blue line indicates a leveling of population growth during the last year**

3.3 Conclusion

This model was not intended to be a predictive model of the population dynamics of the greyback canegrub. Instead, its formulation was intended to reflect the current understanding of the mechanisms of canegrub population dynamics…a quantitative literature review. Because of this, several assumptions were made in the formulation of the model, albeit some of them quite unrealistic. However, the model should be looked upon as a framework for thinking about canegrub population dynamics. Some of the aspects that were not included in the model that will affect the results of simulation runs are listed below. Many of these of course would involve prior research to parameterize hypothesized relationships.

- An upper limit to the number of grubs that a stool can support; this should be a function of the canegrub instar and plant size.
- Density-dependent movement of grubs to adjacent stools resulting in avoidance of cannibalism.

- Linkage of a sugarcane model, even if just a model of height and root mass over time. The interaction between plant stress and cannibalism might be represented in a link with a plant model, although the research has to be carried out first.
- Transmission of specific disease causal organisms, the relationship between density and transmission, and the persistence of inoculum as it relates to inter-year carryover of disease.
- Adult behavior – mating frequency of adult females…is it density-dependent? Dispersal and movement of adults at the landscape level…are adults presently produced in the model likely to return to the same block to lay eggs? Immigration? What is the likelihood of adults from outside the block coming into a block?

Some of these factors can be represented in a model and simulations can be conducted in order to assess the potential significance of the interactions, but it is always preferable if the range of likely values for parameters can be arrived at so that simulations are realistically grounded.

APPENDIX 11 – DRUMMOND CONSULTANCY REPORT, 2008

Consultancy report for BSES Limited, 2008 (Final)

Project no. BSS257

Title. *GrubPlan 2: Developing improved risk-assessment and decision-support systems for managing greyback canegrub*

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March 2008

Risk Prediction – There were two goals for the Risk Prediction component of the *GrubPlan* project. The first goal was to develop a predictive model(s) of greyback cane grub density from one year to the next in individual cane blocks throughout the cane regions sampled (Central, Herbert, Mulgrave, Tully, and Innisfail). The second goal was to construct a simulation model of greyback cane grub population dynamics that could be used to investigate the influence of abiotic and biotic environmental factors and control tactics on long-term grub fluctuation. The first goal of predicting grub density is discussed below.

1.0 Statistical Prediction of Canegrub Density

1.1 Summary of previous work (see Appendix 10)

Several approaches were evaluated for development of predictive models. All predictive model parameters in the preliminary analysis described in Appendix 10 were estimated from the sample data collected in this project between 2003 and 2006. The models evaluated were based upon simple density-dependent Markov chains, ordinary least-squares multiple regression, logistic regression, and multivariate discriminant analysis. Of these model structures, only multiple linear regression and discriminant analysis were pursued in the development of final models for prediction. A brief summary of the development of predictive models follows (more details in Appendix 10).

Initial modeling efforts suggested that linear multiple regression and discriminant analysis were modeling approaches that should be pursued. These two approaches were investigated due to the desire to develop models that could result in predictions of grub densities and more general grub density classes of low, medium, and high density.

It should be noted that the grub density classes were re-defined for the final statistical modeling, with boundaries of 0.5 and 2.0 grubs/stool, to better reflect the expected effect of the density classes on crop damage (compare with boundaries of 0.2 and 1.0 grubs/stool in Appendix 10).

Ordinal logistic regression did not appear to be better than discriminant analysis and so it was not pursued. Markov chain models were useful in showing general trends in cane blocks transitioning from low to moderate to high density grub population levels, but they lacked the ability to predict grub densities at the cane block level. They did show that in general (over five years) most cane blocks had a low (≤ 0.5 grubs/stool) density of grubs (Fig. 1) and that most low density blocks remained at low density the following year (85%) (Table 1). The transition of low density blocks to moderate (>0.5 – 2 grubs/stool) or to high (>2 grubs/stool) density cane blocks had likelihoods of 13% and 2%, respectively. Cane blocks with a moderate grub density were likely to remain as moderate (32%) or transition to low density (60%). Only eight fields were recorded as high density during the study; usually they were so badly damaged as to not be ratooned the following year, so transition to a new density class was not relevant.

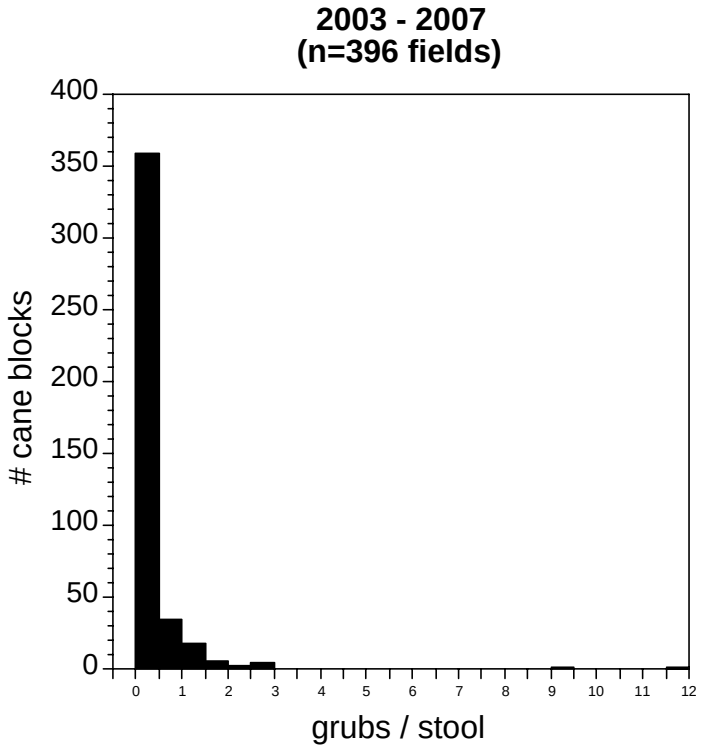


Figure 1 **Greyback cane grub density distribution in cane blocks over 5 years**

Table 1 **Greyback canegrub Markov chain transition matrix based upon all fields that were sampled in at least two successive years between 2003 and 2007 (n=298, numbers in each cell in parenthesis)**

Year(t) - row **Year (t+1) -column**	LOW (<=0.5 grubs/stool)	MODERATE (<0.5-2 grubs/stool)	HIGH (>2 grubs/stool)
LOW	0.849 (230)	0.600 (15)	0.000 (0)
MODERATE	0.129 (35)	0.320 (8)	1.000 (2)
HIGH	0.022 (6)	0.080 (2)	0.000 (0)

Several iterations of model building and discussion suggested that year to year variation in log grub density is high and so developing models independent of year (pooled over year) would result in models with compromised accuracy. However, the lack of a long time series of data prevented any attempt to model the mechanisms of the year-to-year variation as suggested by Horsfield et al. (2008). Regional variation in log grub density is about 1.5 times that of year-to-year annual variation. We evaluated whether it was reasonable to develop separate models for each region. In general, models developed for each region were poor predictors (Appendix 10). This was primarily due to the limited sample size available for these region-specific models. The exception to the general poor performance of the region-specific models was development of a Far North Queensland

(FNQ) model. This model resulted in explaining a high proportion of the variation in log grub density (r^2 = 0.399). The problem with developing a FNQ model is that a separate Central region model was a very poor predictor. Because of this we decided to develop a suite of "global" models (developed to be used in all regions with only farm-specific predictors such as block-level grub density estimates, block-level soil parameters, and block damage estimates) and "regional" models (developed with both farm-specific predictors AND regional predictors such as regional grub density and regional *Adelina* infection levels which were derived from cane block averages within a region).

Preliminary evaluation of the robustness of predictive models was assessed by using the jackknife technique. This technique builds a model with 20% of the data left out in each of five submodels. The five submodels yield an estimate of the variation in model coefficients as affected by a change in the data. For predicting log grub densities with multiple regression and density class using discriminant functions, fluctuations in coefficients were usually under 10% except for dichotomous predictors such as suSCon use where variation was as high as 55% for some models. In general, the models were quite robust to changes in the data, which suggests that they will perform well under new unknown data sets used for prediction. All variables were selected by a combination of stepwise procedures (mixed and backward elimination strategies), assessment of co-linearity by removing of variables individually from the models to assess changes that might occur in other predictor coefficients, assessment of predictor correlation matrices, and use of univariate analysis of variance for predictors considered in discriminant functions.

The variables ultimately selected for the models are listed below.

A. The predictors found to be significant explanatory variables of future grub density (log (grub +1) (yr1)) were:

1. log grubs (yr0)
2. rank severity of damage in a block (yr0)
3. suSCon at plant
4. damage gaps in a block (yr0)
5. Distance (m) to neighboring cane block with damage
6. coded variable for region (Herbert vs others)

B. The variables that were significant for predicting grub trend (log grubs (yr1)) – log grubs (yr0)) were:

1. log grubs (yr0)
2. rank maximum severity of damage in surrounding blocks
3. replant vs fallow
4. coded variable for region (Central vs others)

C. The variables that were significant explanatory variables of grub density class (low = 0-0.5 grubs / stool, moderate = >0.5 – 2.0 grubs / stool, high= >2.0 grubs / stool) were:

1. log grubs (yr0)
2. rank severity of damage in a block (yr0)
3. suSCon at plant
4. Confidor last year

5. coded variable for region (Herbert vs others)

In general, it can be seen that many of the same variables turn up in several models (Appendix 10). These preliminary models provided the guidance for development of the final models. Prior to final model development, other variables were reassessed.

1.2 Reassessment of variables for final model

1.2.1 Canopy height

Cane canopy height within a block is thought by BSES researchers to be an important determinant of grub infestation. Unfortunately, canopy heights were measured at very different times of the season in some years in some regions and so it was not possible to use this variable as a predictor. However, these confounded absolute and relative canopy heights (relative to neighboring blocks) were transformed to z-scores (standardized by subtraction from the regional mean and then divided by the regional standard deviation, for each block). A correlation analysis showed that Height to TVD (mm), and the relative height of the canopy relative to the neighboring cane block have a weak but significant positive correlation with each other (r=0.34, $P<0.0001$). As predictors using linear multiple regression, the canopy measures are both significant explanatory variables of the percent variation of log grubs/stool (yr1), but they only explain about 2.3% ($P=0.04$) and 2.2 % ($P=0.015$) of the variation, respectively, for TVD and relative Hgt. When both variables are used together in a model, only the relative canopy hgt is a significant predictor due to the positive correlation between the two measures.

1.2.2 Soil measures

New variables quantifying the soil characteristics of the cane blocks under investigation were collected in 2007. The soil variables – soil pH, % sand, % silt, % clay – were assessed as to their intercorrelations. Soil pH had relatively no correlation to the other variables (% sand: r=0.06; % silt: r=-0.03; % clay: r=-0.06). The % constituent variables had varying degrees of intercorrelation. Percent sand is highly negatively correlated with both % silt (r=-0.71) and % clay (r=-0.87). Percent silt and % clay were weakly positively correlated (r=0.27). When considering all of the soil characteristics, only pH appeared to be a significant predictor of log grub density (soil pH ($P=0.0004$), % sand ($P=0.146$), % silt ($P=0.151$), and % clay ($P=0.146$)). When a model to predict log grub density was fit for pH alone, about 4.4% of the variation in log grub density was explained ($P=0.0004$, slope = 0.0197, n=282). These variables were considered for the final models, but they did not surface as significant predictors in most models.

1.2.3 Modifications of other variables

Insecticides. Insecticide predictors were modified in 2007. The variable suSCon (2 yrs protection) was modified to reflect blocks that had 3 yrs of protection from the time of suSCon application (the time of sampling was related to the three year period after suSCon application). This modification was made to reflect the trends in grub numbers relative to suSCon protection in the model building data set. An additional modification was made in converting suSCon (2 yrs of protection) and the last year protected with Confidor to suSCon (3 yrs of protection) and the last year protected with Confidor. These

variables (2yr vs 3 yr protection) were highly correlated (r=+0.855 and r=+0.935, respectively) and so only the 3 yr protection variables were used in final model construction.

Ratoon. Another modification that was made involved a transformation of the ratoon variable describing the crop age in yr 1. The original variable was a rank variable that assigned an integer to each ratoon year (plant crop=0 through ratoon 7 = 7). A new transformed dichotomous variable was developed to describe crop age either as a plant crop (0) or as a ratoon crop of any age (1). Both these variables were used in the model variable selection stage, but both were not used in the same final model.

Interactions of variables. The last modification that was introduced into the modeling framework was incorporation of interaction terms. It was realized early on that several non-linear relationships exist with respect to predictors of grub density. Therefore, many interactions were included in the early stages of variable selection of the final regression models. Examples of these predictors are severity^2, ratoon^2, and insecticide x ratoon. An example of the relationship between log grubs and ratoon is shown in Fig. 2.

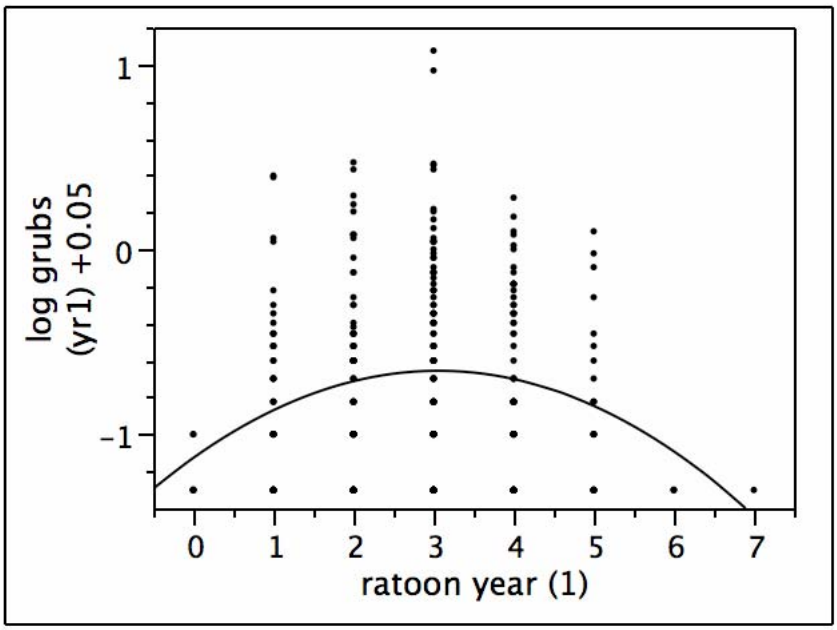


Figure 2 The relationship between ratoon and log grub density

2.0 Final model parameterization

2.1 Objectives for final model parameterization

The objectives for the final modeling phase of the project were to produce the best operational models for predicting canegrub density. Specifically the task was to:

a. Build global and regional models

In this objective GLOBAL refers to a model that relies only on predictors measured in the cane block or associated farm, whereas REGIONAL models refer to models that also utilize predictors that represent regional (Central, Tully, Herbert, Innisfail, Mulgrave) means of measured variables such as grub density or disease levels. A decision was made that coded variables of regions themselves would not be used as was done previously (Appendix 10) since the actual density rankings by region is highly likely to change over time, i.e. Central may not always be the region with the highest densities as shown below in Fig. 3.

b. Validate final models with a validation data set that is independent of the model building data sets

A modification of the validation procedure was adopted due to unique characteristics of the 2007 data (discussed below).

c. Provide model coefficients for future predictions of grub densities in cane blocks in 2008, 2009, and beyond

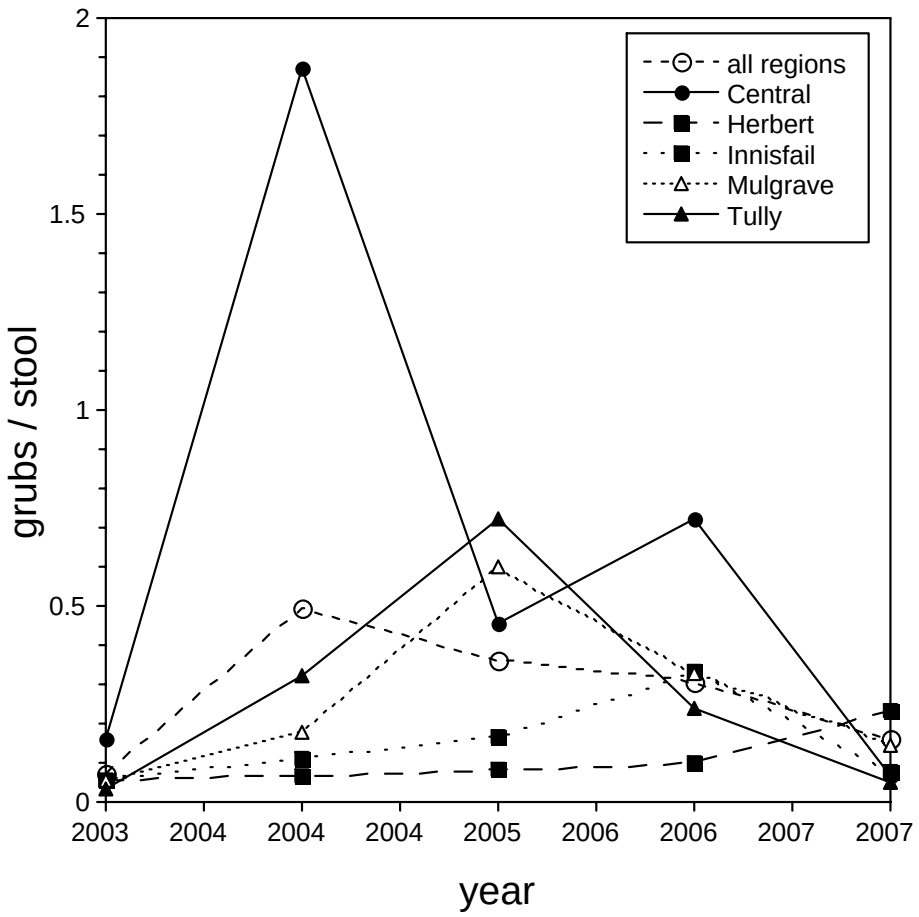


Figure 3 Average grub density over the five-year project period by region

2.2 Methods

Selection of new transformation. Bias in many of the candidate models suggested transformation of the dependent variable was required. Much of the previous modeling (Appendix 10) was conducted using the logarithm to base 10 of (grubs/stool + 1). Further inspection of the data suggested a less severe transformation was in order. Two candidate transformations were assessed:

- The power law transformation based upon a range of powers that bracketed b=0.35, which was derived from the log of the mean grub densities sampled in individual cane blocks vs. the log of the variance of the same associated grub densities, where $y = X^b$.
- The log (base 10) transformation assessed iteratively as log (grubs/stool + b), where b ranged from 0.001 to 1.

There was almost no difference in the power law transformation at b=0.35 and the logarithm transformation where b = 0.05, but both of these transforms did reduce bias that was characterized by the original logarithm (b=1) transformation (Table 2). However, none of these transformations resulted in a dependent variable that could be described by the normal distribution. A Box-Cox transformation was also attempted, but was unsuccessful. The logarithm (b=0.05) transform was chosen for the final models, to maintain some uniformity with the initial modeling investigations that were also based upon the logarithm transformation (b=1).

Table 2 Transforms for model: ratoon, ratoon^2, severity damage, protection 3 yr, grub transformed. Shown below is coefficient of transform (see above) and the slope of the error represented by a regression between the observed and predicted transformed grub density

Power coefficient	**Slope of error**
0.1	0.199
0.2	0.251
0.35	0.279
0.5	0.245
0.75	0.161
0.85	0.128
2.0	0.029
Log coefficient	
Log grubs + 0.01	0.262
Log grubs + 0.05	0.289
Log grubs + 0.1	0.284
Log grubs +1	0.212

Model scenarios

In addition to global and regional models, it was decided that several models be constructed to cover a range of scenarios that might be encountered when attempting to predict greyback canegrub densities in farmers' cane blocks. We did explore models that

only utilized non-protected (no-insecticide) data. The predictions were no better than global models that included all data and so we did not pursue this avenue further.

The scenarios were:

1) when only on-farm predictors are available (global model),
2) when only on-farm predictors are available, but an estimate of block grub density is not available (global model with no grub predictor),
3) when both on-farm and regional predictors are available (regional model),
4) when both on-farm and regional predictors are available, but an estimate of block grub density is not available (regional model with no grub predictor),
5) when both on-farm and regional predictors are available, but an estimate of regional *Adelina* infection levels is not available (regional model with no regional *Adelina* predictor).

2.3 Results

2.3.1 Regression models.

Linear multiple regression was used to construct final models for predicting log(grubs/stool + 0.05) one year in the future relative to the predictors. Five models were estimated. As described previously, all regressions utilized stepwise procedures as well as independently forcing variables of interest into the model prior to inspection of significance and likelihood of co-linearity. The coefficients are included below. Initially, we had planned on using the 2007 data as a validation data set, but the data was characterized by a unique structure in that there was no relationship between the previous year's log grub density (2006) and the log grub density in 2007. This appeared to represent a decline in greyback grub densities across all regions. In fact, all of the 2007 sites that were to be used for validation had extremely low grub densities (<0.35 grubs/stool), with more than 80% being characterized by densities ranging from 0 to 0.1 grubs/stool. The preliminary models that were built did not predict the 2007 validation data well (Fig. 4) and so the 2007 data were used to build the final model along with the previous four years of data and a new validation data set was derived. The new validation data set consisted of thirty pre-selected sites that were representative of the five regions and the four years (2003-2007). These sites were NOT used in the model construction and parameter estimation phase. Evaluations of the models were based upon the corrected coefficient of determination and inspection of predictions of the validation data set with their true or observed estimates of log grub density.

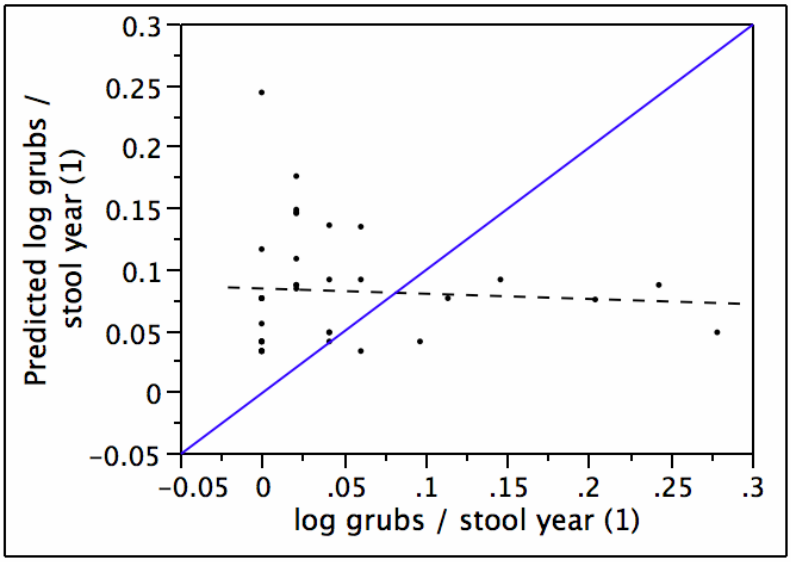


Figure 4 **The relationship between observed log grub density in 2007 (x-axis) and the predictions of log grub density for 2007 (solid line is perfect prediction, dashed line is least squares relationship between observed 2007 density and predicted 2007 density) (n=37). Model predictors are: log grubs (yr0) (*P*<0.0001), max severity damage <400m (yr0) (*P*<0.0001), suSCon plant crop (*P*<0.0001), r^2=0.256**

The final model coefficients are listed below along with their validation results.

1. Global model with an estimate of cane block grub density, r^2 = 0.324

Table 3 Parameter estimates for global model

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-0.759865	0.20333	-3.74	0.0002
replant/fallow #	-0.161643	0.054472	-2.97	0.0033
plant or ratoon	0.4173001	0.191445	2.18	0.0302
suSCon (3 yrs) Confidor (1 yr)	-0.117801	0.055407	-2.13	0.0345
log grubs (yr0) +0.05	0.3974251	0.065683	6.05	<0.0001
max. severity damage <400 m (yr0)	0.1405794	0.030424	4.62	<0.0001

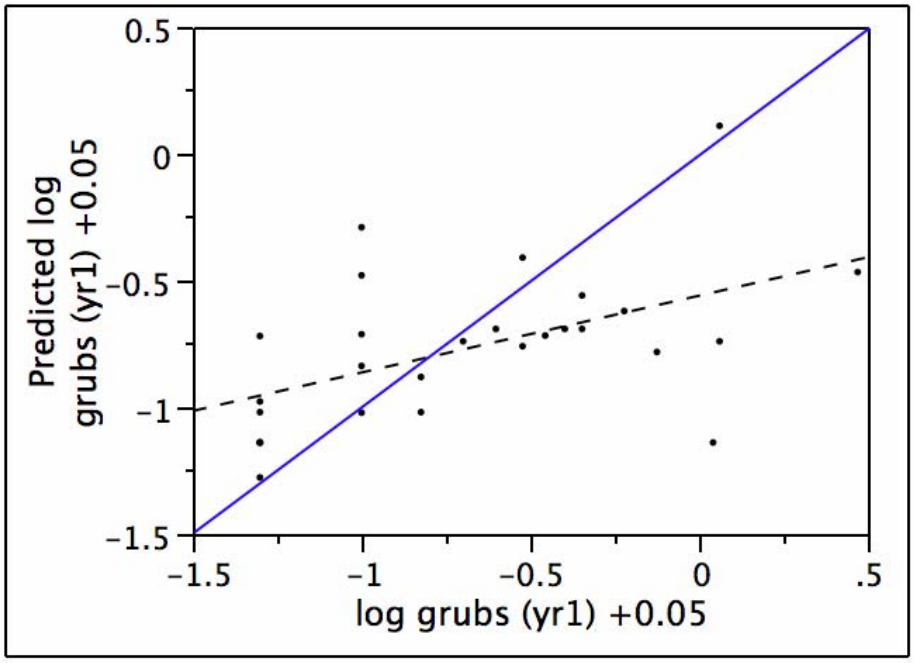


Figure 5 **Relationship between the observed and predicted of the independent validation data set (n=29) for global model with a grub density estimate. Dashed line is relationship between observed and predicted derived from model and solid line is line of perfect prediction (slope = 1)**

2. Global model without an estimate of cane block grub density, r^2 = 0.251

Table 4 Parameter estimates for global model with no grubs

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.178882	0.218125	-5.40	<0.0001
replant/fallow #	-0.154416	0.058075	-2.66	0.0083
plant or ratoon	0.4395422	0.207788	2.12	0.0354
suSCon (3 yrs) Confidor (1 yr)	-0.180092	0.057566	-3.13	0.0020
severity of damage year(0)	0.103807	0.046387	2.24	0.0261
max. severity damage <400 m (yr0)	0.14943	0.036254	4.12	<0.0001

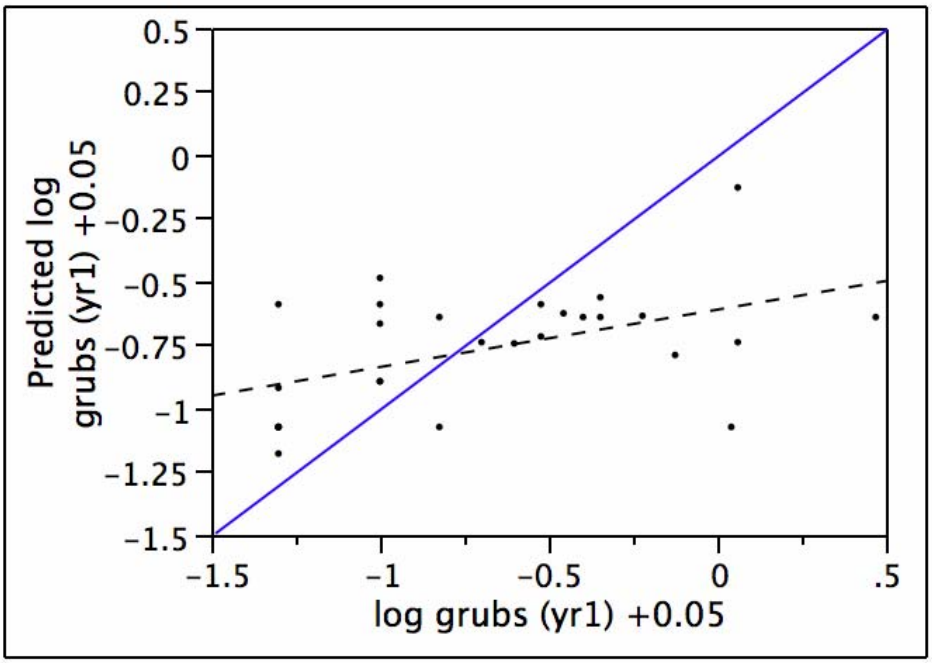


Figure 6 **Relationship between the observed and predicted of the independent validation data set (n=28) for the global model with no grub density estimates. Dashed line is relationship between observed and predicted derived from model and solid line is line of perfect prediction (slope = 1)**

3. Regional model with an estimate of cane block grub density, r^2 = 0.364

Table 5 Parameter estimates for regional model with grubs

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-0.803918	0.20914	-3.84	0.0002
replant/fallow #	-0.153186	0.054096	-2.83	0.0050
plant or ratoon	0.5806165	0.186943	3.11	0.0021
log grubs(yr0) +0.05	0.4023771	0.063264	6.36	<0.0001
severity of damage (yr0)	0.1462237	0.038018	3.85	0.0002
region % *Adelina*	-0.009927	0.002458	-4.04	<0.0001
(max. severity damage <400 m (yr0)-0.77255)*(region % *Adelina*-16.1451)	-0.007205	0.002283	-3.16	0.0018

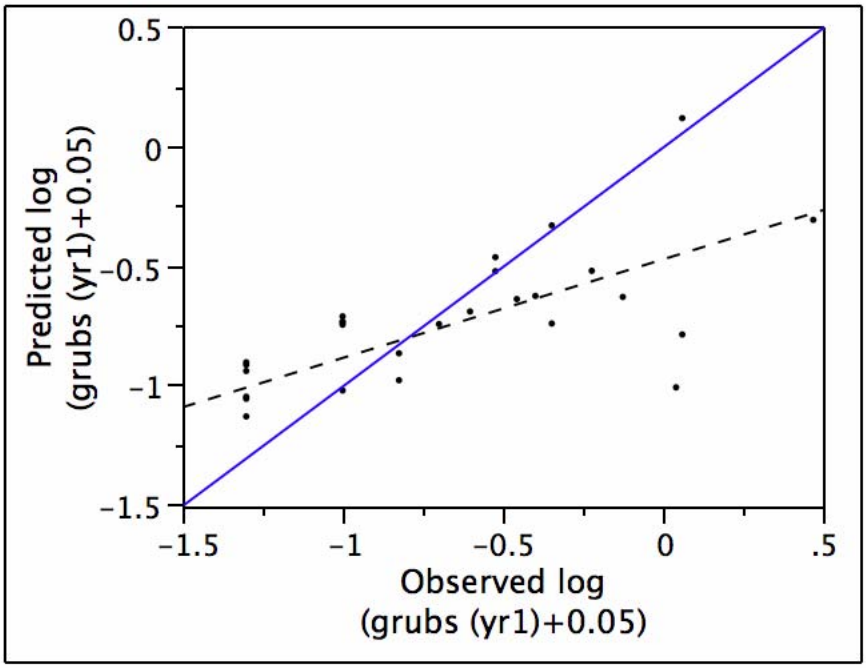


Figure 7 **Relationship between the observed and predicted of the independent validation data set (n=28) for the regional model with grub density estimates. Dashed line is relationship between observed and predicted derived from model and solid line is line of perfect prediction (slope = 1).**

4. Regional model with no estimate of cane block grub density, r^2 = 0.275

Table 6 Parameter estimates for regional model with no block grub estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.238698	0.214194	-5.78	<0.0001
replant/fallow #	-0.171745	0.056976	-3.01	0.0028
plant or ratoon	0.5834284	0.200277	2.91	0.0039
severity of damage (yr0)	0.2104231	0.038897	5.41	<0.0001
region grubs	0.1669365	0.080078	2.08	0.0381
region % *Adelina*	-0.009233	0.002576	-3.58	0.0004
(max. severity damage <400 m (yr0)-0.75191)*(region % *Adelina*-16.5153)	-0.008643	0.002519	-3.43	0.0007
(severity of damage (yr0)-0.56107)*(region grubs-0.2642)	-0.246551	0.09063	-2.72	0.0070

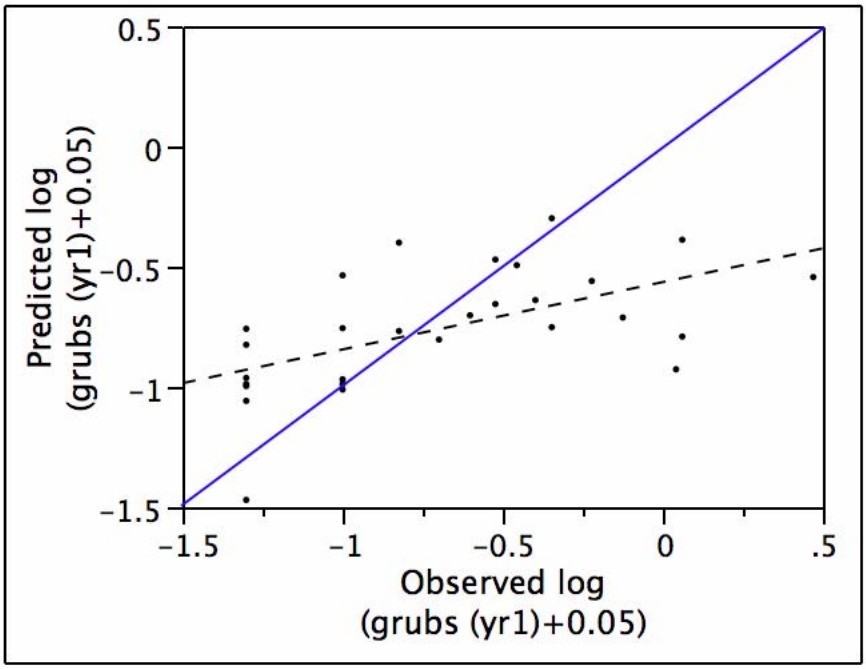


Figure 8 Relationship between the observed and predicted of the independent validation data set (n=28) for the regional model with no grub density estimates. Dashed line is relationship between observed and predicted derived from model and solid line is line of perfect prediction (slope = 1)

5. Regional model with no estimate of regional Adelina infection or grub density estimate, r^2 = 0.229

Table 7 **Parameter estimates for regional model with no estimates of block grub density or regional *Adelina***

Term	Estimate	Std Error	t Ratio	Prob>|t|
intercept	-1.369839	0.213518	-6.42	<0.0001
plant or ratoon	0.4678179	0.207181	2.26	0.0247
suSCon (3 yrs) Confidor (1 yr)	-0.165473	0.056437	-2.93	0.0037
severity of damage (yr0)	0.17737	0.037298	4.76	<0.0001
region grubs	0.2910185	0.102502	2.84	0.0049
(max. severity damage <400 m (yr0)-0.75273)^2	0.0949768	0.025025	3.80	0.0002
(max. severity damage <400 m (yr0)-0.75273)*(region grubs-0.2608)	-0.145422	0.069887	-2.08	0.0384

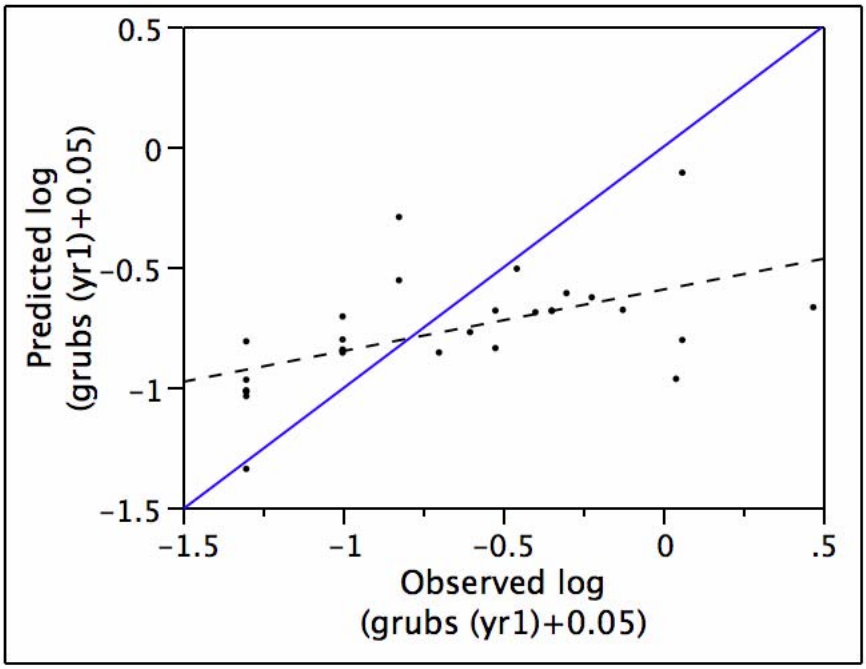


Figure 9 **Relationship between the observed and predicted of the independent validation data set (n=28) for the regional model with no grub density estimates nor any regional *Adelina* estimates. Dashed line is relationship between observed and predicted derived from model and solid line is line of perfect prediction (slope = 1)**

Summary of regression models: Five models have been developed for use in different prediction scenarios. In general, the ability to use block-level grub density estimates enhances prediction. Also the use of regional variables such as regional grub density and/or regional *Adelina* infection level improves prediction (as measured by the corrected coefficient of determination). One unfortunate aspect of all of the regression models is the bias in prediction. This bias is due in part to the inability to develop a transformation that corrects the problems with a left-truncated distribution (0 as a minimum and a high number of very low density sites). Correction of the bias was attempted by modeling the residuals, but while this did eliminate the bias, it produced a model with a very low explanatory power (coefficient of determination) (Fig. 10). It can be better to know the bias and have a more accurate predictor. In all of these models, low density sites are over-predicted and high density sites are under-predicted with a continuous linear trend in the bias as density increases. Therefore, it is believed that these models can be useful, but interpreted with caution and knowledge of bias. It is recommended that the discriminant models (described below) be used in conjunction with the regression models.

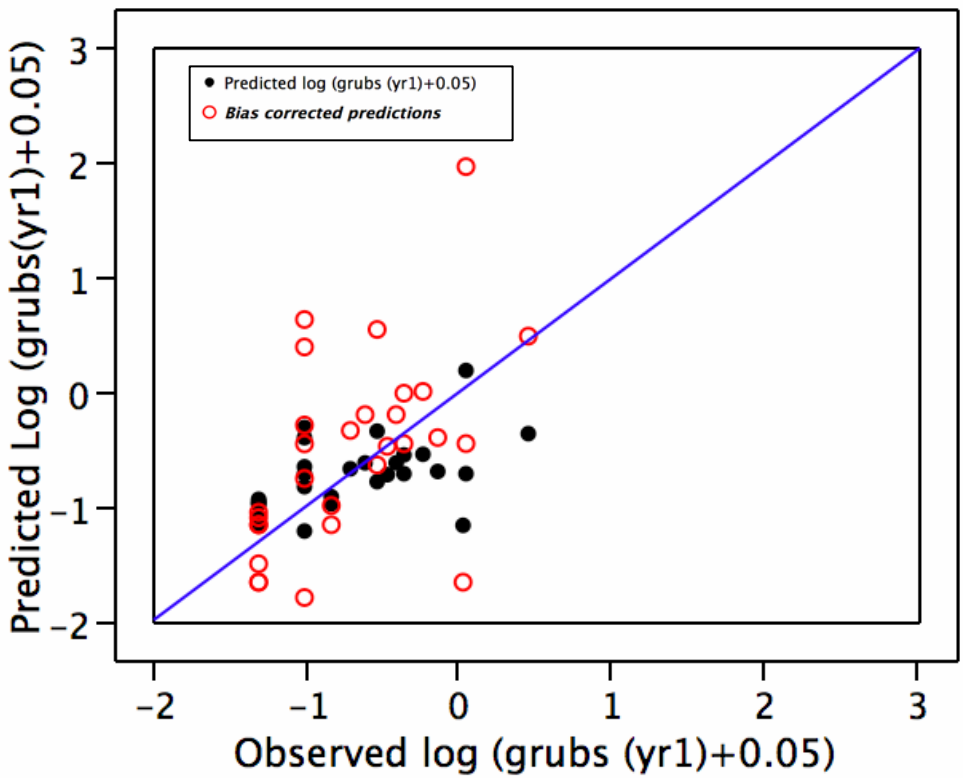


Figure 10 **The relationship between the bias-corrected and uncorrected predictions. Solid line is where observed equals the prediction. Uncorrected predictions show more bias (especially as observed grubs increases), but less variance**

2.3.2 Discriminant models

2.3.2.1 Methods and summary of results

Fisher-discriminant functions were used to develop a series of equations using a multivariate approach to predicting grub density classes. The density classes were three: low (≤0.5 grubs/stool), moderate (>0.5 to 2.0 grubs/stool) and high (>2.0 grubs/stool). These density classes were chosen to represent levels that would have economic importance to sugar cane production. Discriminant functions are additive linear functions of predictor variables that are parameterized to minimize the errors when predicting the density classes. Because the predictors are estimated in an n-dimensional (n = number of predictors) space and because the number of equations derived equals the number of classes, the model coefficients are difficult to interpret in a biological sense. The discriminant functions were parameterized based upon rules of thumb of good practice. Independent suites of predictors were selected since highly correlated sets of predictors tend to be less effective at predicting classes. We also limited the number of predictors so that there were no more predictors than the number of data points/30 (thus 1 predictor for every 30 data points). Thirty is a bit arbitrary, but it is generally considered a reasonable sample size for estimating mean responses. Manual backward stepwise selection was used to explore simultaneous fitting of variables and their co-linearity. In addition, univariate analysis of variance was used to test that each predictor independently was a significant predictor of at least one density class. Multiple analysis of variance (Wilks lambda) was used to assess the potential for the entire suite of predictors as a means of discerning at least one class from the two others. Validation was assessed by 3x3 contingency tables that were set up to determine the percentage of correct classification for each of the three density classes. A field was predicted as being either a low, moderate or high density field according to the class with the highest likelihood in the predictive model. These 3x3 tables were constructed for both the data used to build the model and the validation data set. As in the construction of the regression models, models for several scenarios were constructed and evaluated. Table 8 lists the % correct classification for both the model building data set and the validation data set. In addition, probability of class density membership for all three of the classes for all of the individual sites were output and used to evaluate the robustness and overall accuracy of the models. The results of canonical discriminant analysis (an ordination technique developed for inspecting multivariate models in 2-dimensional space) were also inspected on occasion to evaluate the overlap of class confidence intervals (Fig. 11).

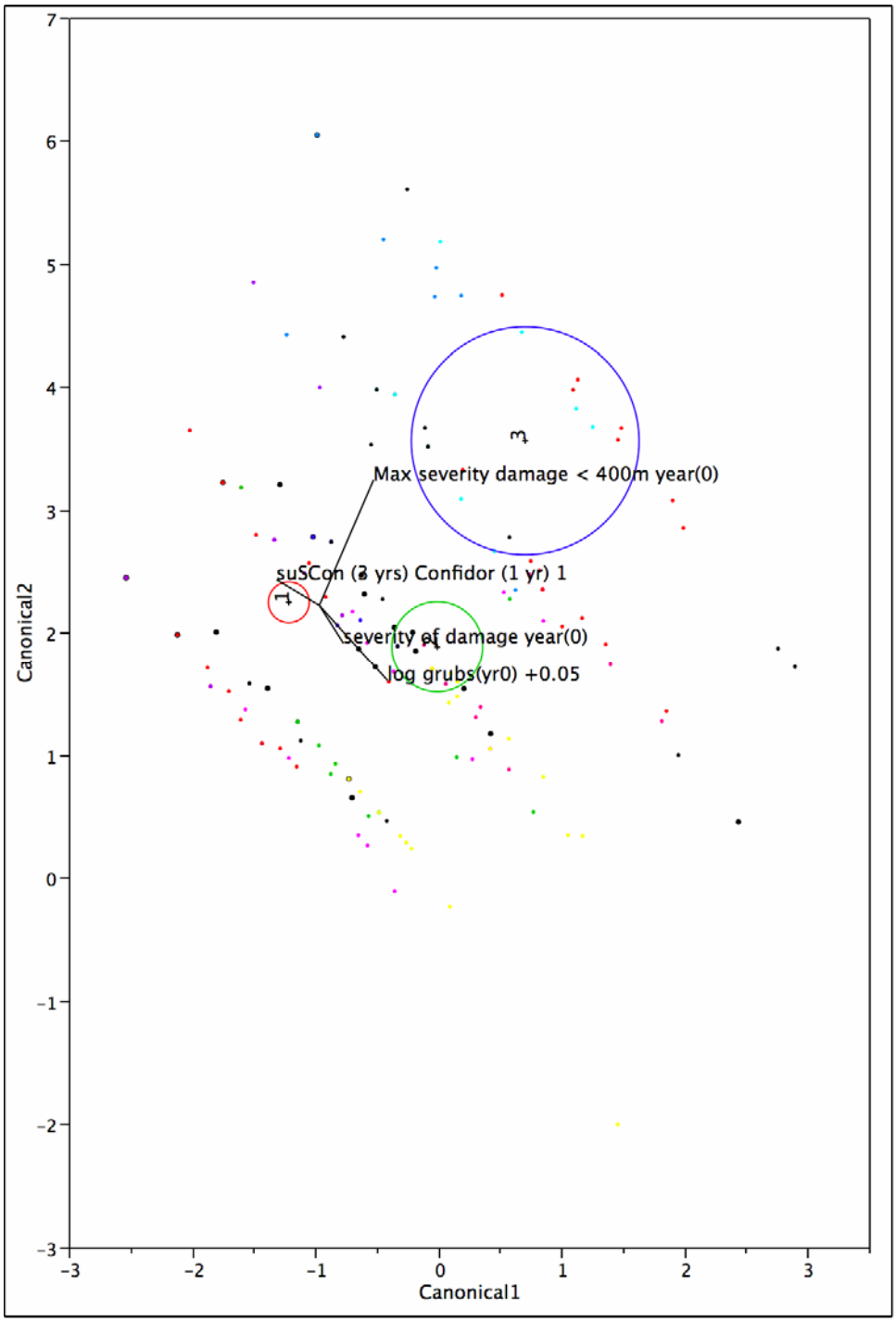


Figure 11 **Canonical plot of density class confidence elipses for the global model with grub density estimates. Vectors align with classes that they are strongest in separating. Numbers 1,2,3 are associated with low, moderate, and high density classes, respectively**

Table 8 **The percentage of fields predicted to fall into each of three infestation classes tabulated against their observed classes, using different types of predictive models (see text and section 2.3.2.2), for both the validation data set of 30 fields and (in parenthesis) for the data used to develop the models**

Model type (numbers in brackets refer to models in text)	Observed classes	Global models (include only variables measured for individual fields)			Regional models (include some variables averaged over region)		
		<0.5	**0.5-2**	**>2**	**<0.5**	**0.5-2**	**>2**
Grub density for field as #/stool, no pH (1,5)	**<0.5**	61 (70)	35 (19)	4 (11)	61 (73)	35 (20)	4 (7)
	0.5-2	40 (25)	60 (59)	0 (16)	40 (25)	60 (64)	0 (11)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density for field as #/stool with pH of soil (1a, 5a)	**<0.5**	65 (71)	30 (19)	5 (10)	61 (72)	35 (20)	4 (8)
	0.5-2	40 (25)	60 (59)	0 (16)	40 (25)	60 (66)	0 (9)
	>2	0 (14)	100 (0)	0 (86)	0 (14)	100 (0)	0 (86)
Grub density not estimated for field, no pH (2,6)	**<0.5**	74 (72)	22 (15)	4 (13)	65 (69)	31 (24)	4 (7)
	0.5-2	40 (39)	60 (41)	0 (20)	40 (33)	60 (57)	0 (10)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density not estimated for field, with pH (2a,6a)	**<0.5**	74 (70)	22 (19)	4 (11)	65 (69)	30 (24)	4 (7)
	0.5-2	40 (39)	40 (44)	20 (17)	40 (33)	60 (59)	0 (8)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
As above, *Adelina* not estimated for region, no pH (7)	**<0.5**				65(68)	31 (23)	4 (9)
	0.5-2				40 (33)	60 (59)	0 (8)
	>2				0 (14)	100 (14)	0 (72)
Grub density for field as <> 0.5/stool no pH (3, 8)	**<0.5**	70 (69)	26 (19)	4 (12)	70 (69)	26 (24)	4 (7)
	0.5-2	40 (30)	60 (50)	0 (20)	40 (30)	60 (57)	0 (13)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (14)	0 (72)
Grub density for field as <> 0.5/stool with pH (3a, 8a)	**<0.5**	70 (70)	26 (20)	4 (10)	70 (68)	26 (24)	4 (8)
	0.5-2	40 (30)	60 (52)	0 (18)	40 (30)	60 (57)	0 (13)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
As above, *Adelina* not estimated for region, no pH (9)	**<0.5**				70 (69)	26 (23)	4 (9)
	0.5-2				40 (30)	60 (57)	0 (13)
	>2				0 (14)	100 (14)	0 (72)
Grub density for field as Yes/No, no pH (4,10)	**<0.5**	48 (57)	48(31)	4 (12)	57 (68)	39 (25)	4 (7)
	0.5-2	20 (18)	80 (61)	0 (21)	40 (30)	60 (59)	0 (11)
	>2	0 (14)	100 (14)	0 (72)	0 (14)	100 (0)	0 (86)
Grub density for field as Yes/No, with pH (4a, 10a)	**<0.5**	48 (58)	48 (33)	4 (9)	57 (68)	39 (24)	4 (8)
	0.5-2	20 (18)	80 (64)	0 (18)	40 (30)	60 (59)	0 (11)
	>2	0 (14)	100 (0)	0 (86)	0 (14)	100 (0)	0 (86)

A summary of the discriminant function follows. In general, if one inspects the tables of model predictors (section 2.3.2.2) it can be seen that most of the predictors that are used in the regression models are also the best predictors in the discriminant functions with few exceptions. The common predictors for the various discriminant functions are: cane block density estimate, insecticide protection, severity of grub damage within the cane block,

and the maximum grub damage severity in neighboring blocks. The effect of an estimate of grub density, either as grubs/stool or a density class (< 0.5 or >0.5 grubs/stool) or presence and absence, can be seen to be important in the global models, although both damage severity in the block and a neighborhood estimate of damage tend to be surrogates for grub density. To a lesser extent, soil pH is also a significant predictor. Distance to treeline, # damaged blocks < 400m, distance (m) to nearest damaged block, ratoon age, and whether a block was fallowed are not significant at the $P \leq 0.05$ level when used in these multivariate models.

While it is difficult to make strong conclusions in the way the predictor variables work in concert by analysis of the coefficients (see tables below), some insight is possible. Inspection of these coefficients suggests the following:

Table 9 Effects of the different predictor variables in separating density classes in discriminant models

Predictor variables	Pattern in separating density classes*
Log grub	L vs M, L vs H, but not M vs H
Severity	L vs M only
Max Severity < 400m	L vs M, L vs H, M vs H
Insecticide protection	L vs M, L vs H, but not M vs H
Soil pH	L vs M, L vs H, M vs H, but to a small degree
% *Adelina* infection (a regional predictor)	L vs M, L vs H, M vs H
Regional grub density	L vs H, M vs H, only L vs M when in concert with grub estimate as <> 0.5 grubs/stool
<> 0.5 grubs/stool	L vs M, L vs H, only. When in regional model: L vs M, L vs H, and M vs H, but region density operates in inverse manner which allows for some prediction during population crash
Presence/absence of grubs	L vs M only

*L=low, M=moderate, and H=high density class sites

The regional models tend to be marginally better than the global models, although there are exceptions to this as seen in the models where presence/absence is used as the grub density estimate within the cane block. In this case, the global model is better at predicting moderate density sites, whereas the regional models are better at predicting the low density sites. When there is no block-level grub density estimate, global models are better at predicting low density sites whereas regional models are better at predicting moderate density sites. The role of a regional estimate of *Adelina* infection does improve prediction of high density sites in the model building data set when there is no block-level grub density estimate, but this is a fairly minor improvement and it is not seen when estimates of grub density are used.

The predictive significance of a presence/absence grub density estimator could be extremely important if sampling by using presence/absence sampling cuts labor costs dramatically. In this case, global models are less accurate in predicting low density and

high density sites and more accurate in predicting moderate density sites, compared with regional models.

In summary, discriminant functions have been developed to cover 10 different scenarios of possible use in predicting farmer grub densities. They vary in their accuracy, but only use of these models over the next several years will allow a better picture of how both of these types of predictive models can be used in preventing risk in pest management decision making.

2.3.2.2 Discriminant model coefficients in detail

1. Global model with an estimate of block grub density, without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
log grubs(yr0) +0.05	-7.176	-4.944	-6.540
severity of damage year(0)	1.116	1.595	1.076
Max severity damage <400 m year(0)	1.383	1.570	3.948
suSCon (3 yrs) Confidor (1 yr) 1	1.547	.504	.721
(Constant)	-5.632	-4.143	-8.957

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
log grubs(yr0) +0.05	.853	22.768	2	265	.000
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000

1a. Global model with an estimate of block grub density, with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
log grubs(yr0) +0.05	-6.783	-4.548	-6.127
severity of damage year(0)	1.635	2.116	1.620
Max severity damage < 400 m year(0)	-1.310	-1.135	1.121
suSCon (3 yrs) Confidor (1 yr) 1	.460	-.588	-.420
soil pH	28.028	28.149	29.415
(Constant)	-7.495E1	-7.406E1	-8.530E1

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
log grubs(yr0) +0.05	-6.783	-4.548	-6.127
severity of damage year(0)	1.635	2.116	1.620
Max severity damage < 400 m year(0)	-1.310	-1.135	1.121
suSCon (3 yrs) Confidor (1 yr) 1	.460	-.588	-.420
soil pH	28.028	28.149	29.415
(Constant)	-7.495E1	-7.406E1	-8.530E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
log grubs(yr0) +0.05	.853	22.768	2	265	.000
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
soil pH	.977	3.075	2	265	.048

2. Global model with no estimate of block grub density, without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.443	1.084	.435
Max severity damage < 400 m year(0)	.786	1.121	3.441
suSCon (3 yrs) Confidor (1 yr) 1	2.114	.851	1.210
(Constant)	-1.925	-2.279	-5.889

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.929	10.404	2	272	.000
Max severity damage < 400 m year(0)	.857	22.713	2	272	.000
suSCon (3 yrs) Confidor (1 yr) 1	.941	8.455	2	272	.000

2a. Global model with no estimate of block grub density, with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
soil pH	28.303	28.330	29.650
severity of damage year(0)	.970	1.611	.987
Max severity damage < 400 m year(0)	-2.087	-1.754	.432
suSCon (3 yrs) Confidor (1 yr) 1	.847	-.417	-.117
(Constant)	-7.197E1	-7.245E1	-8.276E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
soil pH	.978	3.106	2	272	.046
severity of damage year(0)	.929	10.404	2	272	.000
Max severity damage < 400 m year(0)	.857	22.713	2	272	.000
suSCon (3 yrs) Confidor (1 yr) 1	.941	8.455	2	272	.000

3. Global model with estimate of grub density class (<> 0.5/stool), without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.076	.727	.045
Max severity damage < 400 m year(0)	.471	.798	3.038
suSCon (3 yrs) Confidor (1 yr) 1	2.286	1.081	1.431
<0.5 density	12.934	14.292	14.714
(Constant)	-8.667	-1.060E1	-1.460E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
<0.5 density	.957	6.009	2	265	.003

3a. Global model with estimate of grub density class (<> 0.5/stool), with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
soil pH	28.344	28.463	29.755
severity of damage year(0)	.608	1.262	.604
Max severity damage < 400 m year(0)	-2.250	-1.934	.182
suSCon (3 yrs) Confidor (1 yr) 1	1.168	-.042	.258
<0.5 density	13.996	15.358	15.829
(Constant)	-7.952E1	-8.205E1	-9.268E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
soil pH	.977	3.075	2	265	.048
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
<0.5 density	.957	6.009	2	265	.003

4. Global model with estimate of grub presence (present/absent), without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.030	.510	.017
Max severity damage < 400 m year(0)	.676	.968	3.280
suSCon (3 yrs) Confidor (1 yr) 1	2.421	1.352	1.568
presence	2.522	3.815	2.726
(Constant)	-2.553	-3.788	-6.606

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
presence	.907	13.662	2	265	.000

4a. Global model with estimate of grub presence (present/absent), with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.841	1.321	.867
Max severity damage < 400 m year(0)	-1.901	-1.611	.576
suSCon (3 yrs) Confidor (1 yr) 1	1.116	.046	.199
presence	.953	2.246	1.081
soil pH	28.048	28.064	29.419
(Constant)	-7.174E1	-7.306E1	-8.273E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
presence	.907	13.662	2	265	.000
soil pH	.977	3.075	2	265	.048

5. Regional model with estimate of block grub density, without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	1.433	1.976	1.097
Max severity damage < 400 m year(0)	1.035	1.100	3.996
suSCon (3 yrs) Confidor (1 yr) 1	.778	-.211	.389
log grubs(yr0) +0.05	-8.907	-6.791	-6.961
region % *Adelina*	.200	.182	.090
region grubs	5.360	5.785	1.218
(Constant)	-8.549	-6.988	-9.381

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
log grubs(yr0) +0.05	.853	22.768	2	265	.000
region % *Adelina*	.942	8.158	2	265	.000
region grubs	.954	6.440	2	265	.002

5a. Regional model with estimate of block grub density, with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	1.463	2.006	1.128
Max severity damage < 400 m year(0)	-.743	-.678	2.145
suSCon (3 yrs) Confidor (1 yr) 1	-1.153	-2.143	-1.622
log grubs(yr0) +0.05	-7.883	-5.767	-5.895
region % *Adelina*	.429	.412	.329
region grubs	2.859	3.283	-1.386
soil pH	29.791	29.804	31.021
(Constant)	-8.363E1	-8.213E1	-9.078E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
log grubs(yr0) +0.05	.853	22.768	2	265	.000
region % *Adelina*	.942	8.158	2	265	.000
region grubs	.954	6.440	2	265	.002
soil pH	.977	3.075	2	265	.048

6. Regional model with no block-level estimate of grub density, without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.415	1.153	.249
Max severity damage < 400 m year(0)	.943	1.018	3.967
suSCon (3 yrs) Confidor (1 yr) 1	1.601	.375	.946
region % adelina	.172	.165	.078
region grubs	1.924	3.156	-1.462
(Constant)	-3.543	-4.052	-6.378

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.929	10.404	2	272	.000
Max severity damage < 400 m year(0)	.857	22.713	2	272	.000
suSCon (3 yrs) Confidor (1 yr) 1	.941	8.455	2	272	.000
region % *Adelina*	.946	7.696	2	272	.001
region grubs	.956	6.230	2	272	.002

6a. Regional model with no block-level estimate of grub density, with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.580	1.318	.421
Max severity damage < 400 m year(0)	-.971	-.891	1.979
suSCon (3 yrs) Confidor (1 yr) 1	-.518	-1.737	-1.254
region % *Adelina*	.407	.399	.322
region grubs	-.313	.925	-3.785
soil pH	30.278	30.186	31.448
(Constant)	-8.033E1	-8.037E1	-8.921E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.929	10.404	2	272	.000
Max severity damage < 400 m year(0)	.857	22.713	2	272	.000
suSCon (3 yrs) Confidor (1 yr) 1	.941	8.455	2	272	.000
region % *Adelina*	.946	7.696	2	272	.001
region grubs	.956	6.230	2	272	.002
soil pH	.978	3.106	2	272	.046

7. Regional model with no block-level estimate of grub density and no regional Adelina estimate

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.539	1.273	.306
Max severity damage < 400 m year(0)	.534	.625	3.781
suSCon (3 yrs) Confidor (1 yr) 1	2.130	.884	1.188
region grubs	1.297	2.553	-1.748
(Constant)	-2.020	-2.649	-6.062

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.929	10.404	2	272	.000
Max severity damage < 400 m year(0)	.857	22.713	2	272	.000
suSCon (3 yrs) Confidor (1 yr) 1	.941	8.455	2	272	.000
region grubs	.956	6.230	2	272	.002

8. Regional model with estimate of grub density class (<> 0.5/stool), without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	-.202	.547	-.456
Max severity damage < 400 m year(0)	1.123	1.230	4.160
suSCon (3 yrs) Confidor (1 yr) 1	1.781	.630	1.289
region grubs	-1.327	-.355	-5.581
region % *Adelina*	.142	.128	.030
<0.5 density	13.162	14.207	16.589
(Constant)	-9.863	-1.145E1	-1.638E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
region grubs	.954	6.440	2	265	.002
region % *Adelina*	.942	8.158	2	265	.000
<0.5 density	.957	6.009	2	265	.003

8a. Regional model with estimate of grub density class (<> 0.5/stool), with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	-.118	.631	-.369
Max severity damage < 400 m year(0)	-.650	-.542	2.313
suSCon (3 yrs) Confidor (1 yr) 1	-.245	-1.394	-.821
region grubs	-3.885	-2.911	-8.245
soil pH	30.340	30.323	31.600
region % *Adelina*	.375	.361	.272
<0.5 density	14.804	15.848	18.299
(Constant)	-8.770E1	-8.920E1	-1.008E2

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
region grubs	.954	6.440	2	265	.002
soil pH	.977	3.075	2	265	.048
region % *Adelina*	.942	8.158	2	265	.000
<0.5 density	.957	6.009	2	265	.003

9. Regional model with estimate of grub density class (<> 0.5/stool), but no regional Adelina estimate

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	-.094	.645	-.433
Max severity damage < 400 m year(0)	.847	.981	4.102
suSCon (3 yrs) Confidor (1 yr) 1	2.272	1.074	1.391
region grubs	-2.023	-.983	-5.726
<0.5 density	13.631	14.631	16.687
(Constant)	-8.885	-1.065E1	-1.634E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
region grubs	.954	6.440	2	265	.002
<0.5 density	.957	6.009	2	265	.003

10. Regional model with estimate of grub presence (present/absent), without soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	-.117	.470	-.344
Max severity damage < 400 m year(0)	.942	1.040	3.931
suSCon (3 yrs) Confidor (1 yr) 1	1.822	.773	1.338
region grubs	1.207	2.122	-2.381
region % *Adelina*	.181	.172	.078
presence	2.625	3.740	3.285
(Constant)	-4.152	-5.336	-7.292

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
region grubs	.954	6.440	2	265	.002
region % *Adelina*	.942	8.158	2	265	.000
presence	.907	13.662	2	265	.000

10a. Regional model with estimate of grub presence (present/absent), with soil pH

Classification Function Coefficients

	predict density class (3) 0.5,2		
	1	2	3
severity of damage year(0)	.210	.797	-.004
Max severity damage < 400 m year(0)	-.837	-.735	2.083
suSCon (3 yrs) Confidor (1 yr) 1	-.308	-1.352	-.874
region grubs	-.645	.274	-4.304
region % *Adelina*	.412	.403	.318
presence	1.687	2.805	2.311
soil pH	29.937	29.858	31.095
(Constant)	-7.996E1	-8.074E1	-8.907E1

Fisher's linear discriminant functions

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
severity of damage year(0)	.923	11.075	2	265	.000
Max severity damage < 400 m year(0)	.852	22.983	2	265	.000
suSCon (3 yrs) Confidor (1 yr) 1	.944	7.863	2	265	.000
region grubs	.954	6.440	2	265	.002
region % *Adelina*	.942	8.158	2	265	.000
presence	.907	13.662	2	265	.000
soil pH	.977	3.075	2	265	.048

2.3.3 Alternative models

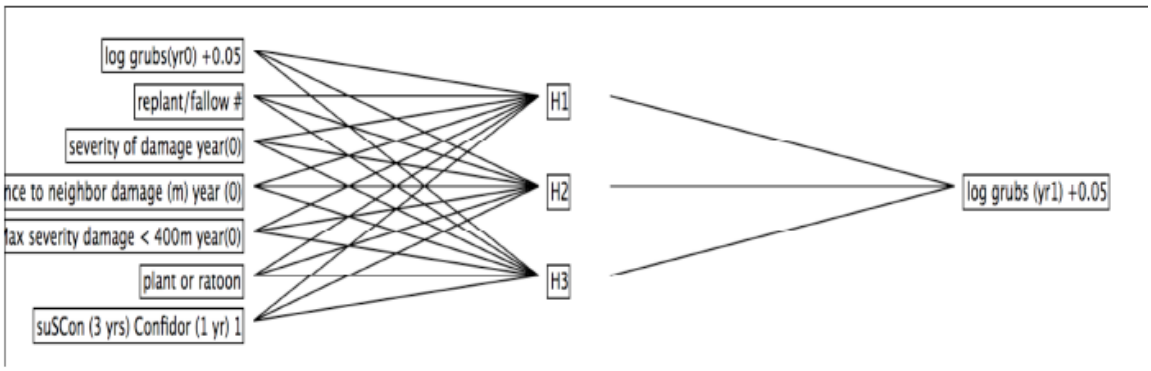
Several additional models were evaluated but not adopted. A brief summary of three modeling approaches follows.

2.3.3.1 Neural networks

A neural network is a set of nonlinear equations that predict output variables from input variables in a flexible, iterative manner using layers of linear regressions and S-shaped asymptotic functions. Unlike many modeling approaches, there is no apriori hypothesis that determines model structure. This approach also does not assume an underlying error or variance distribution. The advantage of a neural network is that it can efficiently and flexibly model different response surfaces. Any surface can be approximated to any accuracy given enough hidden nodes (submodels and predictors). Neural networks also have disadvantages: 1) the results are not as interpretable, since there is an intermediate layer (nodes or submodels) rather than a direct path from the predicted variables to the

predictors as in the case of regular regression; 2) it is easy to over-fit a set of data so that it no longer predicts future data well; and 3) the fit is not parametrically stable, so that in many fits the objective function converges long before the parameters settle-down. Despite these potential problems we decided to try this approach for modeling of the grub data. Non-linear regression algorithms were used to fit the neural network.

A global model was estimated to predict the future grub density (log (grubs + 0.05)). The resulting model has an $r^2 = 0.4885$. At first glance it would appear that this is a very good model. However, despite this high explanatory power (49% of the variation in future log grub density), the model is quite biased, as were the linear multiple regression models. The bias was 0.199, suggesting that predictions would on average be 20% less than the true (observed) future grub density. The model parameters and structure (three submodels or nodes) are presented below:



<u>prediction equations are:</u>

Log (grubs+0.05)= ((-0.94053102411363) + -1.50635676836814 * <u>Submodel1</u> (16.8778140274703 -14.2133381838109 * (log grubs(yr0) +0.05)+ 3.36179796528084 * replant/fallow -7.93875875239477 * severity of damage year(0) -0.00503324035141155 * Distance to neighbor damage (m) year (0) + 0.145112365657262 * Max severity damage < 400m year(0) -24.2154466670727 * plant or ratoon + 1.70205508613916 * suSCon (3 yrs) Confidor (1 yr) + 2.87313967096182 * <u>Submodel2</u> (2.97246235403712 + 1.15255135309039 * (log grubs(yr0) +0.05) -1.67547368483845 * replant/fallow # -2.21987452492832 * severity of damage year(0) + 0.00155303050851524 * Distance to neighbor damage (m) year (0) + 3.10107075235235 * Max severity damage < 400m year(0) -4.23627289475888 * plant or ratoon -1.27328429041242 * suSCon (3 yrs) Confidor (1 yr) + 1.6742052277006 * <u>Submodel3</u> ((-26.6984700240607) -13.6405029772748 * (log grubs(yr0) +0.05)) + 7.47602936021238 * replant/fallow) + 10.7366594567841 * severity of damage year(0) -0.0162914750033627 * Distance to neighbor damage (m) year (0) -20.9021908410342 * Max severity damage < 400m year(0) + 30.3554289988882 * plant or ratoon + 8.03971281443106 * suSCon (3 yrs) Confidor (1 yr) * 0.502489350762294 + (-0.739241106369051)

2.3.3.2 Generalized linear model with the Poisson error term

A nonlinear regression technique was used to model grubs/stool (count data) as a Poisson random variate (general linearized model). This approach is a maximum likelihood estimation approach where the loss function (or -log-likelihood) that is minimized is the

Poisson distribution, which is the log of the probability distribution function: -(N*model-Exp(model))-Log(Gamma(N+1)). A chi-square over-dispersion test was also used to assess the assumption that prediction of grubs / stool with a Poisson error term was appropriate. The resulting model had the predictors in Table 10.

Table 10 Poisson model: prediction of grubs/stool (year 1)

Source	DF	ChiSquare	Prob>Chisq
severity of damage year(0)	1	3.1029	0.0482
Max severity damage < 400m year(0)	1	29.4079	<.0001
suSCon (3 yrs) Confidor (1 yr) 1	1	5.5281	0.0187
log grubs(yr0) +0.05	1	6.5707	0.0104

The model fit was r^2=0.222 and was biased (0.300) suggesting that model predictions were under-estimated by roughly 1/3 as a function of future true (observed) grub density.

2.3.3.3 Modeling 4-5 year patterns of grub population fluctuations

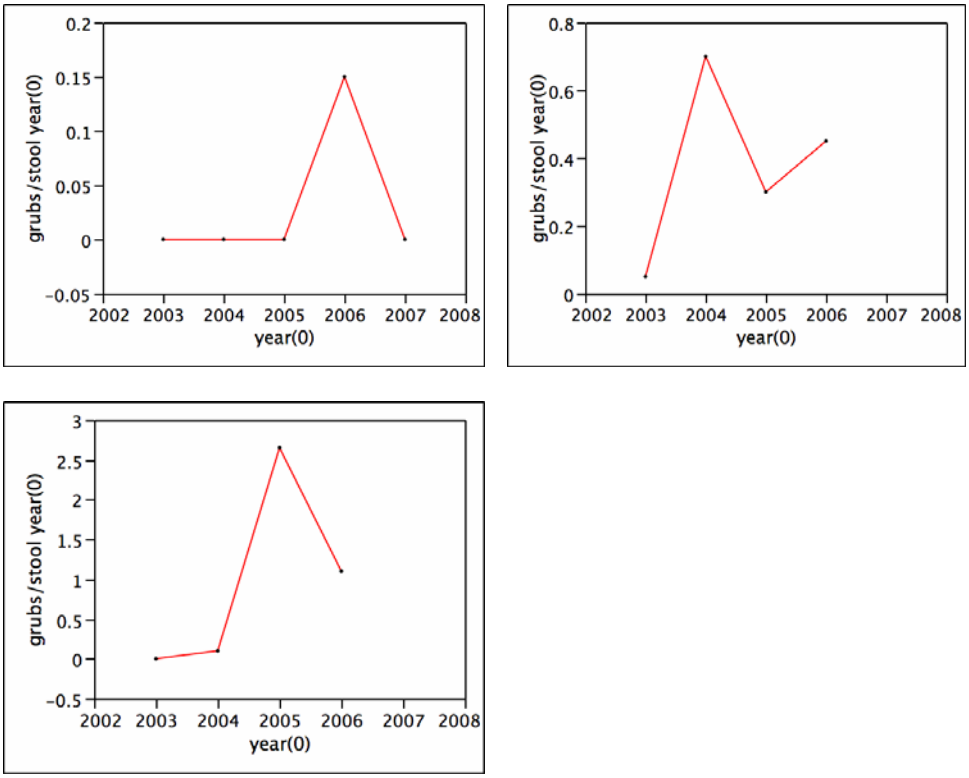


Figure 12 Time series of three different growth patterns of greyback cane grub in three cane blocks, clockwise from top left: Herbert site 9, low; Central site 6, moderate; Mulgrave site 20, high

Each of the cane blocks that was sampled for a 4-5 year period in which the sampling

began in the plant crop or first ratoon was categorized relative to the pattern of grub population change that occurred over the time period. Three response patterns were observed: 1) blocks that initially started with low grub densities (≤0.2 grubs/stool) and did not experience any significant change (grub density remained ≤0.2 grubs/stool); 2) blocks that experienced moderate population growth over the 4-5 year period (up to 1.0 grubs/stool); and 3) blocks that experienced a high rate of change in grub densities (≤0.2 grubs/stool to > 1.0 grubs/stool). Fig. 12 shows an example of each one of these types of population growth patterns.

There were a total of 58 blocks that had continuous sampling and were not ploughed-out over a four-five year period. Ordinal logistic regression was used to develop a predictive model of these three growth patterns. The only significant predictors were % silt content of the soil (P=0.049) and % regional disease (*Adelina* + *Metarhizium*+ *B. popillae*) (P=0.021). However, the prediction results were not adequate (Table 11). Only pattern type 2 (moderate population growth) could be predicted with any certainty (87% accuracy), while the low and high population growth patterns were predicted with very low accuracy (7% and 14% accuracy, respectively).

Table 11 True (observed) four-five year population pattern (three population patterns see above) (rows) by predicted population patterns (columns): count with % of sites in parenthesis

Predicted population growth	Observed population growth		
	Low	Moderate	High
Low	1 (7.1)	13 (92.9)	0 (0.00)
Moderate	3 (10.0)	26 (86.7)	1 (3.3)
High	0 (0.0)	12 (85.7)	2 (14.3)

2.3.3.4 Additional modeling approaches

As described in the previous section, many model structures and error terms have been evaluated for predicting future grub densities. Two different approaches that were not evaluated are Bayesian regression and log-linear variance models. Both of these methods are not familiar statistical methods to most scientists. Bayesian regression represents a very different paradigm in modeling. In contrast to a frequentist approach, where the model structure is determined by the structure of the data, the Bayesian approach relies upon modeling conditional probabilities where the prior probability density functions are derived from independent hypotheses or expert knowledge and used to condition the posterior or data-derived probabilities. This method is highly mathematical, which can make the method inaccessible to many scientists, but can be useful in developing hierarchical models of formidable complexity. Consultation with a statistician with expertise in Bayesian statistics might provide an initial indication of whether better models can be derived by this method. A semi-Bayesian approach to the development of discriminant functions by assessing prior classification frequencies was initially evaluated, but this proved to be ineffective as low-density class prediction was improved, but only by sacrificing prediction accuracy of moderate and high density class cane blocks. Log-linear variance modeling is a technique that incorporates both

the modeling of the mean effect (as in most predictive modeling approaches) with the simultaneous modeling of the variance with a set of different independent predictor variables. This modeling technique might be especially useful for the data collected in this project given the highly variable nature of grub outbreaks and population growth. The only caveat with this type of modeling is that generally larger sample sizes are needed to model variances than means. Therefore, a recommendation might be to evaluate this approach to prediction after collecting several more years of grub data.

2.3.3.5 Explicit incorporation of spatial structure

An early investigation of spatial autocorrelation suggested that limited spatial dependency existed between fields within regions for the years 2003-2005 (Appendix 10). However, an analysis on more accurately spatially referenced fields (cane block GPS locations) suggests a significant but somewhat weak spatial structure in the grub data for each of the years (2003-2005) (Fig. 13).

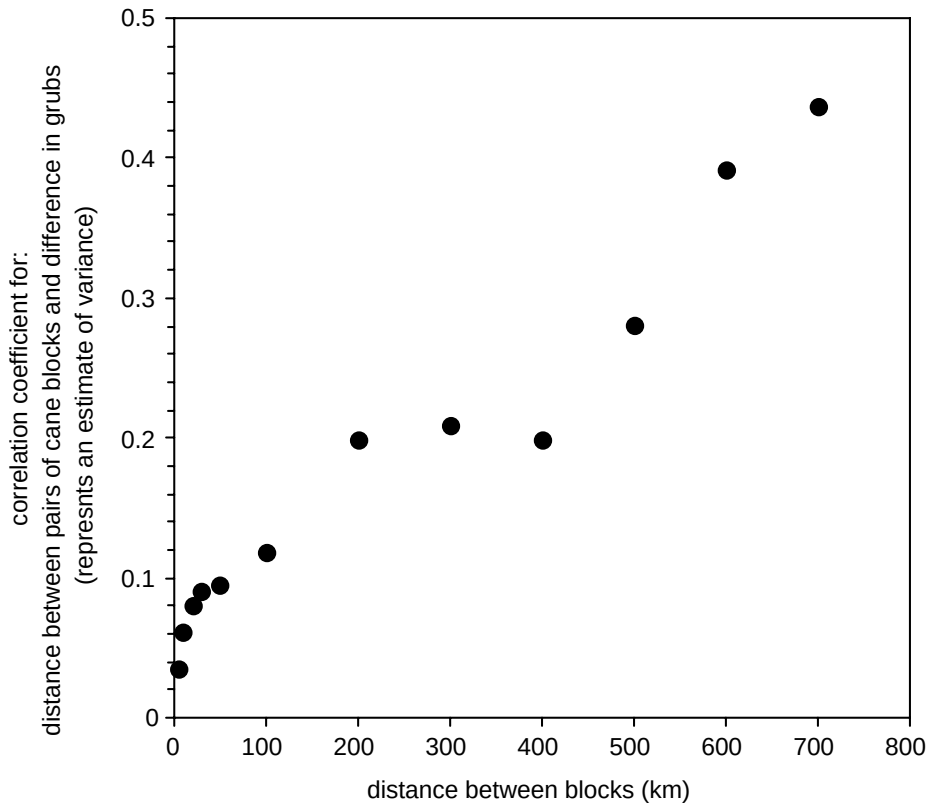


Figure 13 Relationship between pair-wise block distances and grub densities represented as a correlation coefficient.

This finding is in a sense corroborated by the demonstration that the variables: 1) maximum severity of damage in surrounding fields, 2) distance to neighboring fields that have damage, 3) regional grub density estimates, and 4) regional estimates of *Adelina* infection levels, are significant predictors of grub damage. The spatial autocorrelation in grub density between cane blocks could be modeled (with krieging or lagged variable models representing spatial coordinates) and explicitly incorporated into predictive

models to determine if this might increase the amount of variation in future grub densities. Development of a GIS database for the greyback canegrub data would facilitate this type of investigation.

2.3.3.6 Longer-time series approaches

Due to the length of the project, there were limited data for exploration of the use of grub population densities over several sequential years to predict a future grub density level in a specific cane block. The crux of the problem in predicting grub densities can be shown in Fig. 14. If a block is at "A", a prediction of the future grub density (Y) suggests an increase in density; whereas if a block is at "B" a prediction of the future grub density (Z) suggests a decrease in density. Knowing where the block is in terms of this time phenomenon can be modeled with such variables as "severity of damage" as has been done in our final models, but a more direct and potentially more accurate method is to model the time series directly with grub density estimates from previous years.

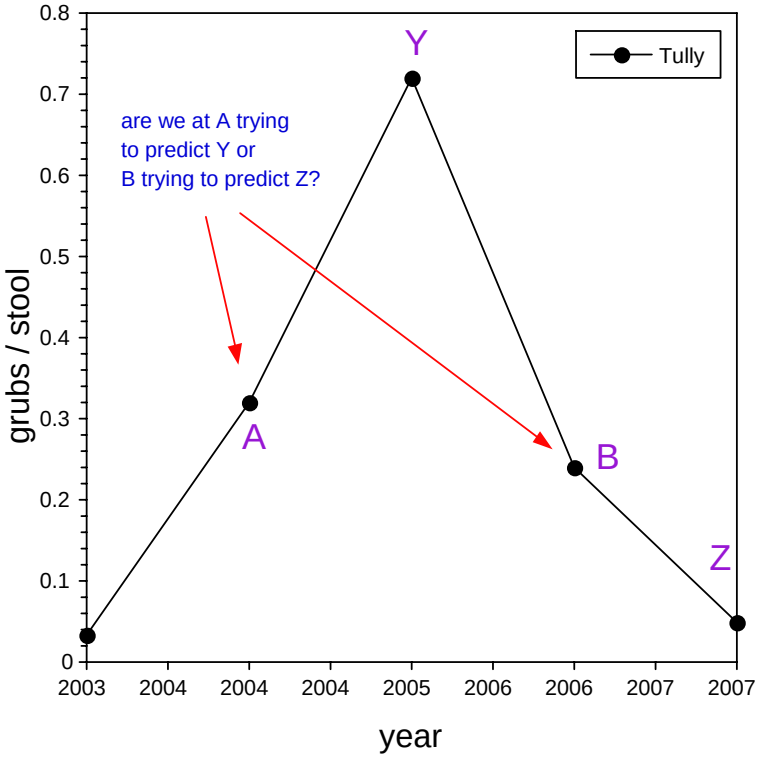


Figure 14 **Relationship between population density and time as it relates to predicting future grub density levels, at "A" predicting "Y" or "B" predicting "Z".**

Such a model where log grub densities in year(0)=2005 and 2006, year(-1)=2004 and 2005, and year(-2)=2003 and 2004 are used to predict log grub densities in year (1)=2006 and 2007 explains 22% of the variation in future log grub densities with no other predictors. This compares to explaining 15% of the variation with only log grubs (yr0). A fully parameterized model for all years was not possible to construct due to the lack of blocks that had three years of predictive grub estimates. However, the utility of this approach is limited if individual cane blocks are not sampled sequentially without a lapse

over time. This approach might be more amenable to predicting grub densities over an entire farm landscape where at least some of the blocks are sampled every year for a period of several years.

2.3.3.7 Re-evaluation of final models

A final recommendation is that the models developed during this project be used and evaluated over the next several years with at least 20-30 cane blocks/year, preferably independent blocks (on different farms) so that a more definitive validation can be arrived at. In addition, this test or validation data will give insight into the strengths and weaknesses of the models. The data can also be used to modify or re-parameterize the models as more data becomes available.

APPENDIX 12 – GREYBACK CANEGRUB SPATIAL SIMULATION MODEL USER GUIDE

BACKGROUND: The current simulation model has been constructed using Stella (version 9.03). The model was conceived as a means of providing a first step into the analysis of greyback canegrub populations using a computer simulation model. The model is essentially a life-system model of the greyback canegrub that incorporates an explicit spatial dynamics through dispersal of adults. The model can be used to model a local greyback population within a single cane block broken down into eight sections or a regional population distributed amongst eight separate cane blocks. Modifications of this model version could enable a researcher to add many more fields or sub-block sections (easily 12, 16, or 25) or allow the researcher to model more complex aggregations of fields each with a specific distance from the other fields (as represented by the likelihood of beetles dispersing over distance). Components of the greyback biology and management that were simulated and how they might be easily modified are as follows:

1. Life stages (none of the developmental durations are variable, all are constant…this can easily be changed to simulate a population that has a mean and variance with respect to development times, in addition, no temperature dependent development rates are used since the data to develop these relationships are lacking in the literature, but could easily be added when the data becomes available) –

    a. emerging female adults (male adults are not tracked by the model, although a PARALLEL flow of adult males could be added since both sexes of immatures are in the model). The period of emergence is set at an exponential decay with a mean rate of 20% / day (results in an emergence period of roughly 20-25 days depending upon the density of emerging adults, the emergence suggests a leptokurtic distribution with a long tail of very low density emerging later). This rate can easily be changed and it can also be made to vary by cane block. The timing of adult emergence from the soil is initiated with the start of the model run. This can be modified so that adults emerge after a threshold of soil moisture is reached, requiring soil moisture data and a description of the relationship between soil moisture levels and emergence.

    b. preoviposition dispersing or feeding adult females. This is the dispersing and tree-feeding stage. This pre-maturation stage lasts 14 days prior to becoming sexually mature with the ability to lay eggs. This rate can easily be changed and it can also be made to vary by cane block. Natural mortality of preoviposition adults can be set in the user interface, but the default value is 0 proportion natural mortality. Natural mortality can also be set in the user interface just prior to the simulation or during any given year.

    c. mature females (oviposition females). Longevity of these adults is 35 days. This is most likely on the short side (previous versions of the model used 54 days). However, longer longevity can result in individuals in the tail end of the population not completing development within the one-year period allowed for the life cycle. Longevity essentially reflects the rate of natural mortality. Fecundity has been set at 23 eggs over the life of the female, but this can be

easily changed, or changed just for selected cane blocks. The default is 0 proportion mortality.

d. eggs. The development time of eggs is 14 days and can easily be modified. Natural mortality can also be set in the user interface just prior to the simulation or during any given year. The default is 0 proportion mortality.

e. grubs. There are three instars simulated in the model. The development durations are fixed (28, 31, and 145 days, respectively for first, second, and third instar grubs; the third instar grub development was chosen to be a bit shorter than the literature value of 150 days so that 99% of the entire population would develop within a year's time frame) but these rates can be adjusted by the user changing the actual parameters in the model. Natural mortality cannot be applied to the larval stages without modifying the model structure. This is because of the already complicated incorporation of insecticide sources of grub mortality. Natural mortality in grubs can be simulated by taking this mortality out of the pupal stage (so at the end of the grub stage). The level of natural mortality can be set in the user interface just prior to the simulation or during any given year. The default is 0 proportion natural pupal mortality.

f. pupae. Pupae develop for 31 days prior to when they might be able to emerge as adults. Natural mortality can be applied as noted above. Insecticide mortality is not applied to the pupae, only the grubs.

2. Dynamics

a. Dispersal. The user interface allows one to design a dispersal matrix that is applied to all cane blocks. Adult movement between cane blocks is simulated as follows. Upon emergence of adults dispersal can occur such that:
   i. Adults leave cane block to feed and return to the original block from which they emerged. This is designated as dispersal pattern "d0".
   ii. Adults from one field disperse to the closest fields with which they share a linear border. This is designated as dispersal pattern "d1".
   iii. Adults from one field disperse to neighboring fields with which they share a point of adjacency (field 1 & field 6 in the layout diagram), designated as dispersal pattern "d1.5".
   iv. Adults move to a field one entire field away (field 1 & field 3), designated as dispersal pattern "d2.0".
   v. Adults move to a field that is one entire field away horizontally and then one field vertically (field 1 & field 7), designated as dispersal pattern "d2.5".
   vi. Adults move to a field two entire field widths away (field 1 & field 4), designated as dispersal pattern "d3.0".
   vii. Adults move to a field that is two entire field s away horizontally and then one field vertically (field 1 & field 8), designated as dispersal pattern "d3.5".

viii. Adults move from a given field and leave the cropping system of eight blocks or fields, designated as dispersal pattern "dem" for emigration out of system…these beetles are lost to the system.

ix. Adults immigrate in from outside the system. The number of beetles immigrating in is x proportion of the total regional density (sum of beetle density pooled across all eight blocks).

*NOTES**

1. *Dispersal coefficients for: i – viii have to add to 100*
2. *Dispersal coefficient for ix ranges from 0.0 to infinity (10000%)*
3. *There is no density dependent dispersal function in this model, BUT because the dispersal coefficients can be changed at the end of each year (model pauses after each year), the dispersal coefficients can be changed to reflect an increased or decreased proportion of beetles dispersing.*

b. Insecticide mortality. There is an option in the user interface for applying either suSCon insecticide, Confidor, or BOTH to individual fields. The insecticide mortality is applied to the three grub stages. suSCon can only be applied at the beginning of the simulation (at planting, see below to simulate other scenarios with suSCon). Prior to running the simulation, the user has to select what fields receive suSCon by typing a 1 in the suSCon list input after the desired field(s). There is no need to change the number back to 0 once the simulation starts. The efficacy of suSCon is set at 90% the first year, 60% the second year, and 40% the third year and 0% the fourth year. The percent efficacy is calculated and applied to the three instars so that by the time a cohort goes through all three instars the first year 90% will die, similar distribution of efficacy is made for year two and three. Confidor operates a bit differently. First of all the default efficacy for Confidor is 0.535. This is actually referred to as the leakage fraction which is the proportion of the grubs that don't make it through development of the instar. This level applied to each of the three instars results in 90% mortality at the end of a year. The user can adjust the leakage fraction in order to simulate different insecticides. IMPORTANT…UNLIKE suSCon application, the user MUST change the Confidor application from 1 back to 0 after the year of application (if you want only a single application). If one does not then a second application will result in the next year. One can apply both insecticides, so you can start out with suSCon and then at the beginning of the second or third year apply an application of Confidor.

c. Initial populations. The interface input allows the user to set initial grub densities in each field. At least one field has to have a density greater than 0. This can only be performed prior to the start of a simulation. Once the simulation starts population densities are only affected by dispersal, natural mortality, and insecticide-induced mortality. The smallest density is 1 beetle / 1 million stools or a density of 0.000001/ stool. The upper limit is 10 grubs / stool. This can easily be changed if necessary by clicking on the input list and resetting the max, min limits.

d. Carrying capacity. Carrying capacity can be adjusted by two parameters. The first parameter is the carrying capacity (in terms of adults / stool) where oviposition starts to be affected (can range from 0 to 500). The second parameter is the fecundity / female that occurs once the carrying capacity is reached (0 means that there will be no oviposition if the carrying capacity is reached, 1.0 means that each female will only lay 1 egg, range is 0 to 26). The carrying-capacity fecundity can be compared to the 23 eggs / female in a population below the carrying capacity. Both of the carrying capacity parameters can be changed each year.

e. Replant. There is no direct way in the simulation model to simulate a replant. If you want to do this, the following is a work around to this problem. Stop the simulation in any given year. Reset the model by selecting stop in the "run" menu. Initiate a new simulation…this time set the initial density to 0.0 or some low number in those fields that you want to replant and set the initial density in the fields that you do NOT want to replant with the densities that resulted when you stopped the simulation. Reset all other parameters – insecticides, dispersal, natural mortality, etc. – and then start the simulation, bearing in mind the number of years that make up the new simulation.

INSTALLING THE MODEL: After "down-loading" the model and the three picture files to your desktop, place them in a directory (model along with picture files). Then just double click on the model "grub spatial ver1" and it will be ready to run. *Make a copy of the original model so that if the model structure is accidentally changed and saved then you can always go back to the original model. In addition, do NOT change the dt. I have selected the Runge-Kutta integration technique which is quite accurate for the dt and time frame that the model operates over. If you change the "dt" interval there are some parameters that need to be corrected for by dividing by the "dt" as they are rate controllers and I did not take the time to do this.*

INFORMATION FOR RUNNING THE MODEL: There are four possible layers: interface, Map, Model, Equation. The interface and the Model layers will likely be the most useful. In fact you may not need to go to any layer other than the interface layer unless you want to modify the model structure to better suite your needs.

Information boxes: The interface layer has three information boxes. The first of these is the picture with the grub: click on the question mark and it provides a short description of the model. The next information box contains a picture of the cane block layout in the model: click on the question mark and a basic description of the cane block layout is contained. The third information block contains a picture of as adult greyback: click on the question mark and a brief description of the dispersal dynamics is provided.

Input devices. There are several input boxes for setting up and parameterizing the model. They are as follows:

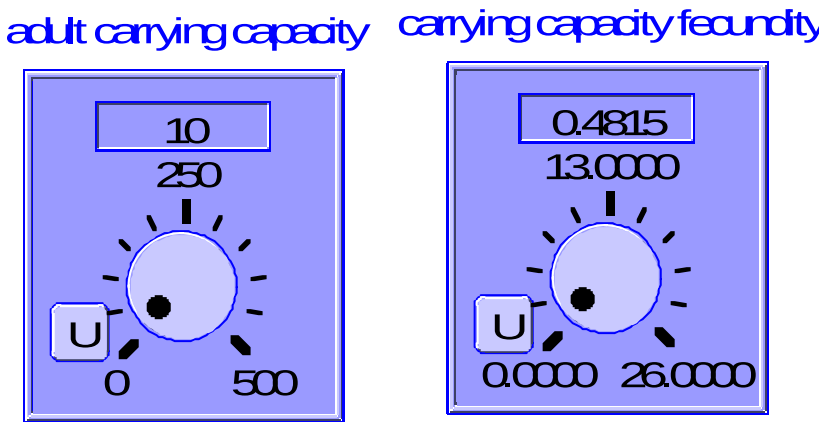
1. Initial population size (purple) – can only be set prior to simulation.

U	initial population size (female beetles / stool) AT START	
	female emerging adults F1	0.1
	female emerging adults F2	0.1
	female emerging adults F3	0.1
	female emerging adults F4	0.1
	female emerging adults F5	0
	female emerging adults F6	0
	female emerging adultsF7	0
	female emerging adults F8	0

2. suSCon list (red) – can only be set prior to simulation. This input dialog list allows one to determine which fields receive suSCon at planting (1=tmt). The application of suSCon can only be made prior to the start of the simulation. It imparts mortality to the grub population over a three year period (90%, 60%, and 40% for years 1, 2, and 3; respectively). There is no need to set the application trigger back to zero once the simulation has started as the initial conditions of suSCon application remain set once the simulation has started.

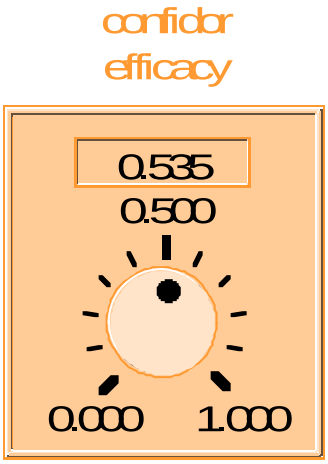
U	suSCon (0=NONE, 1=TMT) AT START	
	suSCon Application	0
	suSCon Application 2	0
	suSCon Application 3	0
	suSCon Application 4	0
	suSCon Application 5	0
	suSCon Application 6	0
	suSCon Application 7	0
	suSCon Application 8	0

3. Two carrying-capacity rheostats (blue) – can be set prior to simulation AND anytime at the end of each year prior to the following year. Definitions of "adult carrying capacity" and "carrying capacity fecundity" are delineated above. The carrying capacity parameters apply to ALL fields simultaneously. At present there is no way to apply individual field specific carrying capacities. It would be easy to change, however, by redefining each variable as eight individual field variables.

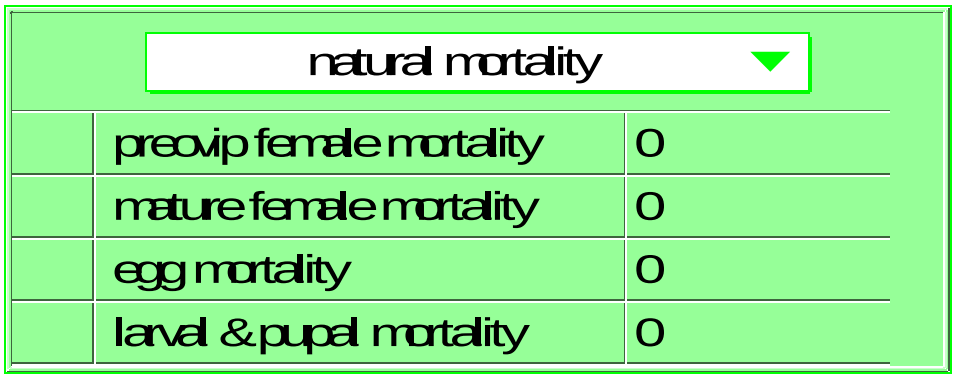


4. Two Confidor inputs (brown; list and efficacy rheostat) – can be set prior to simulation AND anytime at the end of each year. The efficacy rheostat results in 90% mortality when set at default = 0.535, 80% when set at 0.416, and 60% when set at 0.263. The efficacy is compounded over three grub instars and that is why 0.535 results in 0.9 proportion mortality by the end of the three grub instars.

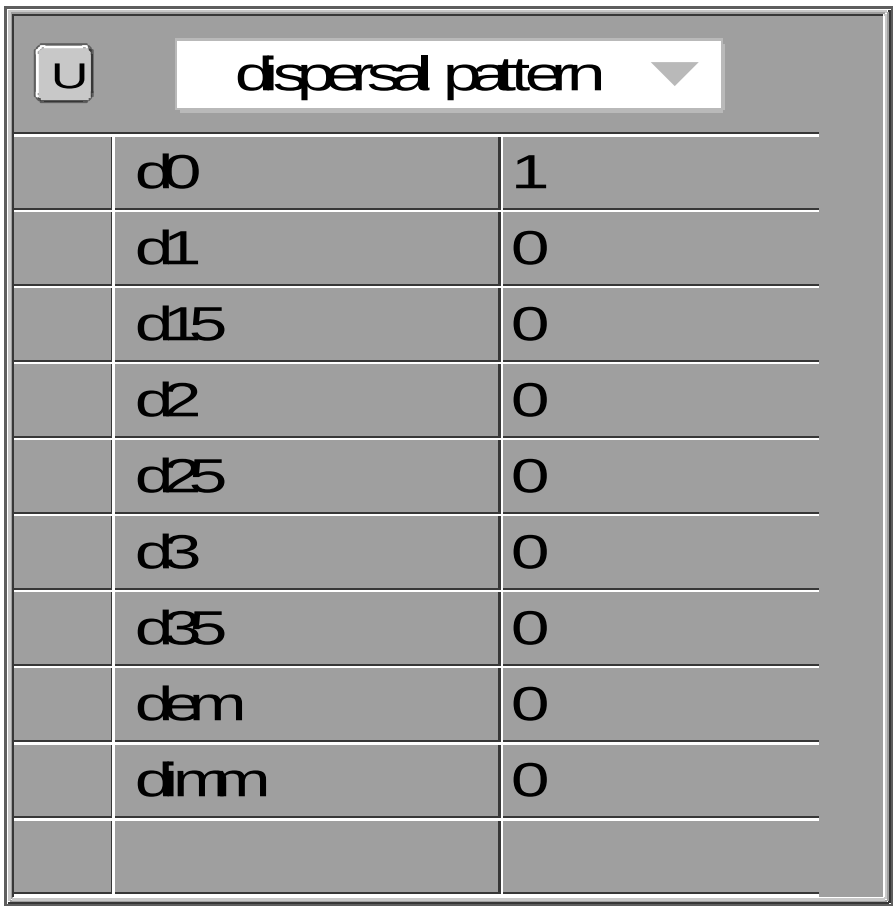
Confidor (0=NONE,1=TIMT) ANY YEAR		
	confidor application	0
	confidor application 2	0
	confidor application 3	0
	confidor application 4	0
	confidor application 5	0
	confidor application 6	0
	confidor application 7	0
	confidor application 8	0



5. Natural mortality rheostat (green). This list input device allows one to set background natural mortality to pre-oviposition female beetles, sexually mature females, and grubs/pupae. The actual value of the "leakage" parameter is the proportion mortality that will be extracted from EACH population in ALL fields. Since these parameters represent proportion mortality they all range from 0.0 to 1.0. The natural mortality can be set and reset throughout the simulation.



6. Dispersal pattern (grey). This list input device allows the user to set the proportion of pre-oviposition adults dispersing within the landscape (eight fields) and into and out of the landscape. The description of these parameters is given above. The dispersal pattern can be set and reset throughout the simulation.



U	dispersal pattern	
	d0	1
	d1	0
	d1.5	0
	d2	0
	d2.5	0
	d3	0
	d3.5	0
	dem	0
	dimm	0

Output devices:

1. Adult population monitoring (maroon): this output box allows you to see the annual population densities (adults / stool) at the end of each year. This allows you to make decision regarding treatments, replanting, etc. I could have just as easily made monitoring boxes for total grub densities and you can do it easily enough, but I thought that adult densities are good because this is the stage that the carrying capacity is operating on.

There is one box for each field. It is updated once at the end of the year.

Variables of importance: There are several variables that you might want to keep track of. I have given you a few EXAMPLE graphs and tables. Reporting can be every “dt” (in this case every day) or it can be every 364 days (second to last day of annual model run). It is difficult for me to set up not knowing which might be important and how you want to view the data. Adding an input device can be done in either the interface or the model layer. I suggest that you add output devices in the interface layer because it will be easier if you want to look at the output real-time as you run the simulation and change parameters during the simulation. I tend to like tables with output every 364 “dt” intervals

because this gives you the "initial" conditions at time 0 (really day 1) and at the end of each of the seven years. Graphs can be made to plot the data at these same intervals if desired.

Graphs can be copied (PICT files) and pasted into other applications and tables can be exported to EXCEL: this is straight forward and well explained in the STELLA manual. You can have graphs and/or tables for each field, or graphs and tables for each lifestage over all fields, or really large graphs and tables that include all of the fields and lifestages that you are interested in. In most cases you will be interested in just the "state variables", the dynamic states that change over time, these being the life stages. However, you might want also to have converters (circle symbols) written out such as year and insecticide application for descriptors in output data files. Any of the components of the model can be reported at any time interval.

I have two "types" of "state variables" in the model: 1) real-time "state variables" which have the potential to change daily, and 2) accumulators which measure the cumulative numbers of lifestages over time per year and which are then flushed to begin recording the number of lifestages that accumulate for the next year. They both have there uses as output. You may want to have a record of the change in numbers over time for each day (can be any time interval…so you could sample the lifestages by having the table record numbers every 5, 10, 20 days, etc.), and this output is what would one would expect to see from field sampling. However, it can be tricky to interpret because the peak for individuals on any one day will depend upon the recruitment rate into a stage AND the development rate through a particular stage. Therefore, one could have 100 individuals that go through a stage but, because they might be moving through one stage in 10 days and the next stage in 50 days, when the numbers are plotted over time the lifestage curve for the first stage will be shorter and have a lower peak whereas the subsequent stage will have a higher peak because individuals are stacking up in the stage as they are developing through it. One can estimate density from such curves by integrating them and dividing the resultant integral (area under the curve) by the development time. Since the same lifestages between fields have the same development time you can directly compare the curves. The accumulators give you the total number of individuals that go through the stage. Generally a plot of these "state variables" over time would be a sigmoidal curve that increases as more individuals go through the stage, reaching a plateau as the last individual enters the stage and then going to zero at the end of the year because they are flushed to start accumulating the next year's population. The nice thing about these variables is that you only need to write them to a field once at the end of the year and you will get the total density of the stage, so this means a data field that has eight lines of data for a 7-year simulation (initial conditions and then seven annual end-of-year densities).

The two "state variable" types are as follows (one for each field):

"Real-time"

1. female emerging adults
2. preoviposition adults
3. ovipositing adults
4. egg
5. instar 1
6. instar 2

7. instar 3
8. Pupae

"Accumulators"

1. Adult females (total female adults in a field)
2. Accum preovip adults
3. Accum ovipositing adults
4. Accum egg
5. Accum 1 (first instar grubs)
6. Accum 2 (second instar grubs)
7. Accum 3 (third instar grubs)
8. Accum female pupae

RUNNING THE MODEL:

1. Set up the output graphs or tables with the lifestages that you want reported and the reporting interval, and the precision of the output data to be displayed in a table

2. Set up the initial conditions in the input devices

3. Open up your table or graph so that you can see it during the simulation if you want

4. Type "Control + R" keys or go to the run menu and select RUN.

5. At the bottom left of the STELLA window there is a simulation clock that will tell you what the simulation time is. The model AUTOMATICALLY STOPS at the end of each year so that you can change parameter values (apply Confidor, etc.). To restart the model just type "Control + R" again and the model will run through the next year. Each year takes about 3-5 seconds to run. ***NOTE:*** *Watch the simulation clock because at the end of year 7, if you type "Control + R" again the model will respond by running a new simulation starting with year 1 and with the last parameter settings that were displayed at the end of year 7. This will wipe out your data in the output table for the subsequent seven years.* If you decide to **STOP** the simulation **before** the simulation has run for the full seven years, go into the RUN MENU and select STOP. Now you can export your data table or lock it, and set up new conditions for a new simulation run. You might want to do this if you made a mistake with the inputs, or you are just playing around to get an idea of the model response to different settings….OR you want to conduct a "REPLANT" as described earlier.