FINAL REPORT 2017/015

Decision support for choice of enhanced efficiency fertilisers - Herbert catchment pilot study

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ABSTRACT

Enhanced Efficiency Fertilisers (EEF) are of interest to the sugarcane industry because they have the potential to increase N use efficiency and reduce nitrogen (N) loss. However, agronomic and environmental benefits are proving to be highly variable and condition specific. Therefore, tactical use of EEF will be a more economically sustainable strategy than use of EEF in every crop and season. This requires decision support for growers and advisors based on understanding of the conditions leading to benefits from EEF. This pilot project has tested and improved a decision support tree developed by HCPSL for use in the Herbert mill area. Because variable responses make it challenging to demonstrate the benefits of EEF experimentally, this project developed a method of running virtual EEF trials using the agricultural simulator APSIM. This allowed the generation of many thousands of virtual trial results which could then be systematically explored to identify the key factors influencing whether EEF provides a benefit or not. Early season rainfall, soil type and crop start date were factors that most affected the likelihood of getting benefits, with wet conditions for late ratoon crops on well drained soils providing the conditions where EEF delivered the most benefit. It was found that the virtual EEF trial results could be grouped into four types of responses reflecting different sets of conditions. This allowed the likelihood of obtaining benefits from EEF under different conditions to be quantified. This classification has also proven useful to explain the outcomes from field trials. Together with the decision support logic it provides a solid basis for the development of an industry-wide, evidence based EEF decision support tool.

EXECUTIVE SUMMARY

Enhanced efficiency fertilisers (EEF) have been proposed as a means for the sugarcane industry to reduce nitrogen (N) losses and, in combination with lower application rates, increase N use efficiency. However, results from field trials in sugarcane testing different EEF products have been mixed, with some studies showing benefits and others no effect. This has made it difficult to determine their fit in the system. The agronomic and environmental benefits are proving to be highly variable and condition specific. Growers and industry advisors are hence faced with questions around the choice of EEF products and when to use these. There is a need for decision support to underpin recommendations that identify situations in which EEF are more likely to deliver benefits in order to off-set their higher cost.

In this pilot project for the Herbert catchment (mill area) a collaboration between CSIRO, HCPSL and JCU set out to test and improve a draft decision support tree developed by HCPSL. A review of field trials indicated that their results would provide insufficient evidence to evaluate decision points in the decision support logic. The project therefore developed a method of running virtual EEF trials using the APSIM-Sugarcane model. The trials were designed to mimic field trials of 12-month ratoon crops started on a range of dates, grown on 31 different soil types, in three different climate zones and supplied with four different fertiliser products (urea, controlled release fertiliser and two nitrification inhibitors) at 34 different rates (0-330 kg N/ha). Over 67 seasons this represented 3,389,664 treatment years, which provided a wealth of data to systematically explore which key factors influenced whether EEF provided a benefit or not.

Variations on these trials were also run to test specific decision points in the decision support logic developed by HCPSL. Some of these were confirmed and others corrected. The combination of experimental evidence and virtual trials to test or build on these proved effective in filling knowledge gaps. One virtual trial also tested the effect of longevity of nitrification inhibition and found it to have a strong impact on the agronomic and environmental benefits that can be achieved with nitrification inhibitors. Hence recommending further research characterising these products and their persistence and bioactivity in soil.

In order to analyse the many virtual EEF trial results the project developed a classification of four EEF response types reflecting different sets of conditions. This allowed the likelihood of obtaining benefits from EEF under different conditions to be quantified and predictors to be identified using data-mining techniques. The EEF response classification has also proven useful to explain the outcomes from field trials.

The project delivered two successful workshops with industry advisors to discuss the development, testing and role of the decision support logic as well as the science behind it. The project also developed an improved understanding of the behaviour of nitrification inhibitors and ways to model their behaviour in order to assess the effectiveness of nitrification inhibitors within sugarcane systems. In addition to delivery of an improved and more evidence based draft EEF decision logic for the Herbert mill area, the project's development of a methodology for running and analysing virtual trials and of a classification of EEF responses provide a solid basis for the development of an industry-wide, evidence based EEF decision support tool.

Such a decision support tool would provide growers and their advisors with better guidance about circumstances when EEF will provide agronomic and environmental benefits and when they will not. The simulations performed in this project have shown that EEF can provide considerable reductions in N loss and N application (with no yield loss), but not in every situation or season. Defining the circumstances where EEF are more likely to increase fertiliser use efficiency can save a fertiliser price premium of at least 15% where EEF is not recommended and can reduce the N application by

between 25 and 70 kg N/ha in 50% of years where there is an EEF response. The environmental benefits of reduced N loss match these.

Work in this pilot has clearly established that early ratoon crops have a low likelihood of obtaining benefits from EEF. Agronomic benefits for later crops are more variable and linked more tightly to seasonal rainfall conditions. Further work on specification of climate indicators and their forecasting is needed and expected to improve specificity of decision support logic for these later crops.

The revised draft decision support logic was developed for the climate, soils and management practices of the Herbert mill area, with most attention given to the Eastern Herbert zone. The responses to EEF and hence the decision support logic may be different in other locations. Adapting the decision support logic for other regions will require further validation. Specifically, it will need analysis of the local likelihood, timing and drivers of N loss and of the crop yield potential and its response to N. The broad concepts of the decision support logic will, however, be directly transferable.

Unlike the decision support logic, the classification of EEF responses is not region-specific and can be readily adopted for communication purposes across the industry. This is also true for the approach of virtual trials to corroborate and/or fill gaps in experimental evidence, which could be applied not just to the evaluate decisions relating to EEF, but also other management questions.

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ABBREVIATIONS

APSIM	Agricultural Production Systems Simulator
ASSCT	Australian Society of Sugar Cane Technologists
CCS	Commercial cane sugar
CRF	Controlled release fertiliser(s)
CSIRO	Commonwealth Scientific and Industrial research Organisation
DCD	Dicyandiamide
DMPP	3,4-dimethylpyrazole phosphate
EEF	Enhanced efficiency fertiliser(s)
HCPSL	Herbert Cane Productivity Services Ltd.
ISSCT	Society of Sugar Cane Technologists
JCU	James Cook University
JJA ONI	June to August Oceanic Nino Index
N	Nitrogen
NESP	National Environmental Science Programme (specifically the Tropical Water Quality Hub)
NI	Nitrification inhibitor(s)
NI7	Nitrification inhibitor simulated with 7 day half-life persistence
NI28	Nitrification inhibitor simulated with 28 day half-life persistence
Nopt	Agronomic optimum N rate
PCU	Polymer coated urea
SILO	Scientific Information for Land Owners (a database of historical climate records for Australia)
SRA	Sugar Research Australia
TCH	Tons cane per hectare
TSH	Tons sugar per hectare
6ES	Six Easy Steps

1. BACKGROUND

Under pressure to reduce the amount of dissolved inorganic nitrogen lost to waterways draining into the Great Barrier Reef Lagoon, the Australian sugarcane industry is showing increasing interest in the use of enhanced efficiency fertilisers (EEF). The use of EEF has been proposed as one means of reducing nitrogen (N) losses and, in combination with lower N application rates, increasing N use efficiency (Brodie et al., 2013; Bell and Moody, 2014; State of Queensland 2016).

Several field trials have been carried out (see Verburg et al., 2014, 2016) or are underway (e.g. on-farm trials as part of Project Catalyst and GameChanger, as part of the National Environmental Science Programme (NESP) Tropical Water Quality Hub and within the Rural R&D for Profit program as well as other, formal and informal, trials across the industry). These aim to evaluate or demonstrate benefits from the use of both controlled release fertilisers (CRF), which release N more slowly than conventional fertilisers (e.g. Agrocote, ESN® and others), and nitrification inhibitors (NI), which temporarily stabilise the N in ammonium form (e.g. eNtrench® or ENTEC®).

Reviews of the available experimental evidence in Australian sugarcane systems (Verburg et al., 2014, 2016) have identified that while these trials have shown some positive results, it has often proven difficult to obtain statistically significant treatment effects in individual trials. In a number of trials the lack of response to EEF has been attributed to the dry conditions experienced (e.g. Thompson et al., 2016). In a meta-analysis across six experiments by Incitec Pivot Fertilisers it was noted that trials that experienced wet conditions, particularly in the two to three months after fertilisation, were more likely to show benefits than those performed in years with below average rainfall during this period (IPF, 2014). The experimental results in sugarcane to date have, however, been insufficient to characterise other factors of influence or quantify the likelihood or magnitude of benefits obtained from EEF use.

In relation to CRF, SRA Project 2014/011 confirmed that the benefits as well as the optimal management of CRF products are highly condition specific (Verburg et al., 2017a). It used modelling to carry out an analysis of the effects of seasonal climate variability, location (climate), crop class, soil and management (e.g. time of planting, ratooning and fertilisation). The agronomic and environmental benefits were found to vary considerably in response to these factors with experimentally quantifiable increases in yield or decreases in agronomic optimum N rate unlikely to be achieved every season. This suggested the need for development of region and condition specific advice to support decision making by growers; i.e. when to use CRF, another EEF or urea; the type of CRF to use; and the timing of its application.

A similar systematic analysis of factors affecting the benefits from NI use in sugarcane systems has not yet been carried out. In addition, there is uncertainty around the longevity of nitrification inhibition which is affected by temperature and likely by other factors as well (Verburg et al., 2014 and other references therein). The NI temporarily interrupt the N transformation from ammonium to nitrate. As this process is affected by soil microbial activity a number of soil and environmental factors may impact on it. While this calls for further research into NI, a first step would be to analyse the effect that longevity of the nitrification inhibition may have on the benefits from NI.

In the current situation of incomplete knowledge, growers are faced with choice of what EEF to use (CRF or NI and for CRF the choice of duration of release and usage as a blend with urea) as a function of circumstances (plant vs ratoon, time of ratooning/fertilisation, seasonal conditions, soil type and climate and management). Industry advisors currently have to base any advice they provide on limited experimental trial results. For the Herbert mill area Lawrence Di Bella of HCPSL structured that advice in a decision tree based on his local experience and interpretation of trial results (Figure 1). Presentation of this draft decision tree outlining EEF choices for different circumstances was well received at a combined sugarcane and fertiliser industry workshop organised by SRA project 2014/011 in May 2016. The workshop supported development of such a decision support tool for industry although it also noted that the decision support should be tested and underpinned by scientific evidence. This advice formed the basis for the current project.

As the draft decision logic was based on limited trial data collected under a variety of circumstances, it would be prudent to review and ground truth the conclusions drawn from experiments and field trials and their representation in the decision support logic. In SRA project 2014/011 modelling was effective in clarifying experimental findings and conceptual thinking on how and where the benefits from CRF use could be obtained (see e.g. Verburg et al., 2016, 2017a, b). The current project was, therefore, designed to use similar modelling to complement the experimental evidence.

While development of an electronic or web-based decision support *tool* would be the ultimate goal, this project focussed on the development of the EEF decision support *logic* and underpinning this with evidence. The project was designed as a pilot for the Herbert mill area to take advantage of early ideas for a locally relevant decision tree (Figure 1; Lawrence Di Bella, unpublished), the good understanding of soils within this catchment (Wood et al., 2003), and relatively high interest in EEF in the area (unpublished data from Di Bella suggested approximately 34% of growers were using or assessing EEF on their own individual farms in 2016). The project was designed to include workshop discussions with industry and project leaders of other EEF projects help to scope the shape and form of an industry wide decision support tool.

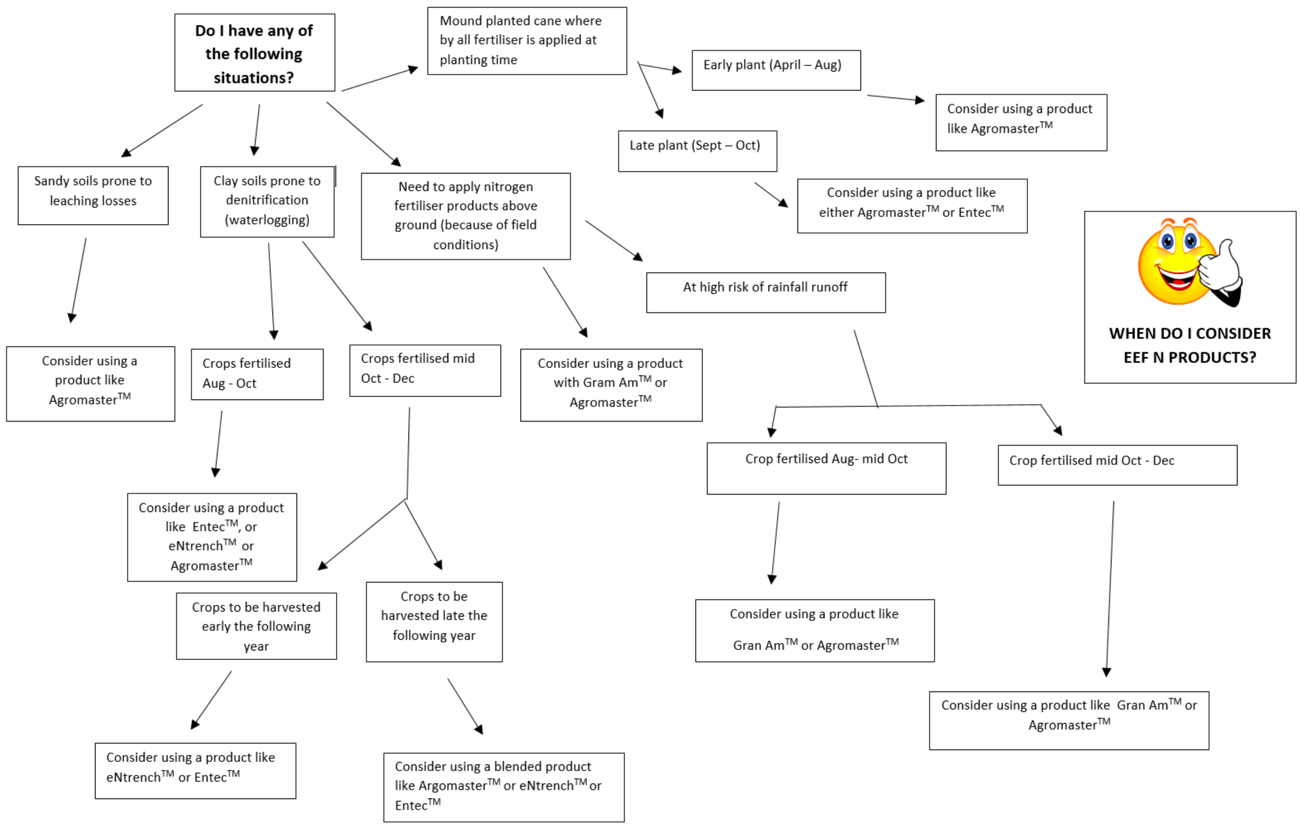

Figure 1. Draft decision logic for choice of EEF developed (pre-project) by HCPSL (Di Bella, unpublished, September 2015).

2. PROJECT OBJECTIVES

2.1. Overall project objective

Clarify, in a concise, logical and scientifically transparent way, the relative benefits of enhanced efficiency fertilisers (EEF) versus urea for different circumstances and translate this into a decision tree type decision support logic.

2.2. Specific project objectives

Specifically, the project objectives were as follows.

1. Update the review on experimental evidence of benefits from enhanced efficiency fertilisers (EEF) in sugarcane and communicate its findings.

2. Review the draft decision tree for the Herbert sugarcane growing region with industry

3. Quantify using simulation analysis the condition specific potential benefits from EEF (reduction N loss, increase yield and reduction of optimum N fertiliser rate) relative to urea for different soils in the Herbert catchment (mill area).

4. Test and underpin decisions relating to controlled release fertilisers using these simulation analyses to explain or refine draft decision support logic.

5. Discuss findings with sugarcane and fertiliser industry to define future directions for development of decision support for EEF.

3. OUTPUTS, OUTCOMES AND IMPLICATIONS

3.1. Outputs

The project set out to deliver:

1) Workshops to discuss with industry advisors the use of the decision support logic as well as the science behind it;
2) Updated review findings on the experimental evidence for benefits from EEF (presentations at project industry workshops);
3) Improved understanding of the potential benefits from controlled release fertilisers and nitrification inhibitors as a function of N release pattern, length/effectiveness of inhibition, timing of application and N loss pathways for different soils in the Herbert mill area;
4) Draft decision support logic for the Herbert mill area which outlines the different circumstances under which controlled release fertilisers would provide benefits over urea documented with supporting experimental evidence and simulation analyses.

The project held two workshops in Ingham targeting local advisors, researchers from the sugarcane industry and representatives from the fertiliser industry. Both workshops were well attended with productive discussions that helped shape the decision support logic. The first workshop (9 May 2018, 25 participants) reviewed the draft decision support tree developed by HCPSL (Figure 1) and the available experimental evidence. It also discussed a prototype interactive version of the decision tree, possible improvements and the use of so-called 'virtual trials' to corroborate the decision support logic using modelling. The second workshop (6 December 2018, 18 participants) built on this by discussing the results from the virtual trials and their implications for the decision support logic as well as ways to use and communicate the decision support logic.

The available experimental evidence and their interpretation relative to the decision support logic as well as results from the virtual trials are presented in Section 6. Various subsets and summaries of the results were also presented at the two project workshops, at the 2018 ASSCT conference in May, at the Innovative Nitrogen Use in Sugarcane Forum and at the 2018 National Soils Conference in November and at an International Workshop on Nutrient Stewardship and Next-Generation Fertilisers organised by the University of Queensland in December (see details below). In addition the project has produced a number of written papers:

- Verburg K, Biggs JS, Thorburn PJ (2018) Why benefits from controlled release fertilisers can be lower than expected on some soils. Proceedings of the Australian Society of Sugar Cane Technologists, 40, 237–249 (reprinted in International Sugar Journal 2018, 120 (1440), 936-945)
- Verburg K, Vilas MP, Biggs JS, Thorburn PJ, Bonnett GD (2019) Use of 'virtual' trials to fill gaps in experimental evidence on enhanced efficiency fertilisers. Australian Society of Sugar Cane Technologists, 41 (paper in press)
- Vilas MP, Verburg K, Biggs JS, Thorburn PJ (2019) How important is the longevity of nitrification inhibition in reducing nitrogen loss in sugarcane? Australian Society of Sugar Cane Technologists, 41 (extended abstract in press)
- Vilas MP, Verburg K, Biggs JS, Thorburn PJ (2019) Quantifying the effects of longevity of nitrification inhibition on nitrogen losses from sugarcane production. Proceedings of the International Society of Sugar Cane Technologists (paper submitted)
- Vilas MP, Verburg K, Thorburn PJ, Probert ME, Bonnett GD (2019) A framework for re-analysing nitrification inhibition: linking process with experiment. (paper submitted to Science of the Total Environment)

To analyse the complex and variable responses of sugarcane crops to EEF the project also developed a classification of EEF responses. This classification distinguishes four types of responses with different agronomic and environmental outcomes. It provides a language that more clearly communicates how EEF work and lead to benefits under different circumstances. This lends itself to grower communications to explain the conditions required to realise benefits and to clarify results from experimental trials. The classification was well received at the second project workshop and a meeting of the ReefTrust4 EEF60 project with a number of participants using it to reflect on some of their trial results and indicating it could be useful in their grower communications. The classification is described in more detail in Section 6.2 and in the 2019 ASSCT paper listed above.

The classification also allowed data-mining approaches to be employed on the large number of virtual trial results to generate statistically based decision trees that quantify the likelihood of each different outcome (Section 6.6). This is still work in progress but has informed revisions to the draft EEF decision support logic for the Herbert mill area (Section 6.7). The project also developed a prototype electronic version that allows the evidence that sits behind a decision point to be made transparent.

As this one-year project constituted phase 1 of what was originally proposed as a two-year project, further work is required to complete the validation of the EEF decision support logic for the Herbert mill area. This includes (as per original proposal) work on climate forecasting of early season rainfall indicators which was found to be an important factor in determining presence or absence of benefits for late ratoon crops (see Section 6.5 and 6.6) as well as a review of evidence on the effects of late N supply on Commercial Cane Sugar (CCS).

The revised draft decision support logic was developed for the climate, soils and management practices of the Herbert mill area. The responses to EEF and hence the decision support logic may be different in other locations. Adapting the decision support logic for other regions will require further validation. Specifically it requires analysis of the local likelihood, timing and drivers of N loss and of the crop yield potential and its response to N. The broad concepts of the decision support logic will, however, be directly transferable.

Unlike the decision support logic, the classification of EEF responses is not region-specific and can be readily adopted for communication purposes across the industry. This is also true for the approach of virtual trials to corroborate and/or fill gaps in experimental evidence, which could be applied not just to the evaluate decisions relating to EEF, but also other management questions. Indeed, the EEF response type classification and the virtual trials it is based on have been selected for a presentation at the Ingham grower research update in April 2019 and discussions have been held with the leaders of the ReefTrust4 EEF60 project to use it in their communications of trial results to growers.

3.2. Outcomes and Implications

Enhanced efficiency fertilisers have the potential to optimise the productivity achieved per unit of fertiliser input and lower environmental N loss through leaching, runoff and emissions. However, their successful integration in the sugarcane system does require an understanding of how, when and where they deliver benefits as they have a higher cost per unit of N compared with conventional fertilisers.

This project established that the available experimental evidence is too sparse for the development of a robust, evidence based decision support tool. The approach of 'virtual' modelled trials, developed within this project to verify and improve draft decision support logic, has improved the understanding of key drivers behind benefits. It provides a way to test the conclusions from experiments and fill gaps in experimental evidence.

The analysis by this project has clearly established when not to use EEF: the likelihood of obtaining benefits from EEF in early ratoon crops is small. Agronomic benefits for later crops are more variable and linked to rainfall conditions experienced during the early part of the season and subsequent crop growing conditions. Specification of climate indicators and their forecasting is expected to improve specificity of decision support logic for these later crops. Other recommendations for further RD&A are outlined in Section 8.

A tool based on the draft decision support logic developed by this project can assist advisors, agronomists and growers to understand when and why benefits from EEF are obtained and to make evidence based, informed decisions about the use of EEF. The technology will empower industry to seek opportunities to minimise N loss from within the farming system. A prototype electronic version developed by the project received positive feedback at the first workshop. Based on subsequent discussions with project leaders of SRA Project 2018/013 it was found to be consistent with ideas for the Six Easy Steps (6ES) Toolbox. This means the work in this Herbert mill area pilot provides a path to impact for an industry-wide, evidence-based EEF decision support tool.

The finding from this and the earlier SRA project 2014/011 that benefits from EEF are less likely to be obtained in plant and early ratoon crops has supported a shift in trial design with new field trials being focussed only on ratoon crops and a number of them specifically targeting late ratoon crops. The classification of EEF response types developed in this project has provided clarity around interpretation of lack of treatment effects in EEF trials and the benefit that can be expected in different situations, as evidenced by feedback received after presentations.

While the project has already provided useful learnings for local advisors, to fully achieve the intended project outcome, further work is required to complete the validation of the draft decision support logic in the Herbert mill area (as per original specification for a 2-year project). Specifically, exploring seasonal climate forecasting of early wet season rainfall which was found to be an important factor in determining presence or absence of benefits as well as reviewing the evidence around late N supply on CCS.

The immediate benefit of a decision support tool to growers accrues from having better guidance on circumstances when EEF will provide agronomic and environmental benefits and when they will not. The simulations performed in this project have shown that EEF can provide considerable reductions in N loss and N application (with no yield loss), but not in every situation or season. Defining the circumstances where EEF are more likely to increase fertiliser use efficiency can save a fertiliser price premium of at least 15% where EEF is not recommended and can reduce the N application by between 25 and 70 kg N/ha in 50% of years where there is an EEF response. This potential to reduce N rates is the result of a reduction in N loss (of similar magnitude), confirming the parallel environmental benefits.

4. INDUSTRY COMMUNICATION AND ENGAGEMENT

4.1. Industry engagement during course of project

The project team engaged with both the sugarcane and fertiliser industry over the course of the project. A draft EEF decision support tree developed by HCPSL (Figure 1) was the starting point for the project. It was developed further with the input received at the first project workshop from local advisors, researchers from the sugarcane industry and representatives from the fertiliser industry. This input helped shape the process of testing and improving the decision support logic. Other presentations, as well as papers for the 2018 and 2019 ASSCT conferences, not only helped communicate our findings to the sugarcane industry, but also sharpened our own thinking.

The early industry engagement focussed on presenting the rationale for the need for EEF decision support and the plans for its development and testing. The first project workshop in May 2018 established that there was limited experimental evidence on which to base the testing and further development of the draft EEF decision support logic. It hence explored the approach for 'virtual trials' using modelling. In addition it evaluated a prototype interactive version of the decision support logic and discussed the role of the EEF decision support logic within the broader context of other soil, crop management and economics decisions. Subsequent communications and the final workshop presented results from the virtual trials and the implications for the decision support logic. These communications also introduced a classification of EEF response types that allowed data mining techniques to identify key drivers behind the responses. This classification also lends itself to interpreting and communicating results from experimental trials.

Industry communications carried out during the course of the project and their main topics are listed below. The decision tree logic still requires the analysis of climate indicators earmarked for the second phase of the project. Therefore, the key communication messages that influenced the early adoption of project outputs related to the concept of virtual trials to fill gaps in experimental evidence and the classification of EEF response types and the understanding of EEF behaviour that went with that.

Project industry presentations, workshops, meetings and discussions:

- <u>SRA/EHP Nitrogen management in sugar cane research and co-investment programs meeting in Brisbane, October 2017</u>: Key findings of SRA project 2014/011; plans for SRA project 2017/015.
- <u>Sugar industry engagement meeting of Rural R&D for Profit 'Forewarned is forearmed' project in Townsville, October 2017</u>: Key findings of SRA project 2014/011; plans for SRA project 2017/015; climate forecasting requirements.
- <u>ASSCT 2018 Conference in Mackay, April 2018</u>: Simulations of CRF on two different soils illustrating soil effects and impact of broader system interactions on the realisation of benefits.
- <u>Project industry workshop 1 in Ingham, May 2018</u>: Review of experimental evidence; draft industry EEF decision support tree logic; prototype electronic interactive version; using modelling to run 'virtual' trials to test decision support logic; parameterisation of nitrification inhibition modelling capability and effect of longevity of inhibition; discussion on role of EEF decision support logic and possible improvements/additions.
- <u>Seminar at CSIRO Agriculture and Food in Canberra, August 2018</u>: Parameterisation of nitrification inhibition modelling capability and effect of inhibition longevity.
- <u>Meeting with SRA 6ES Toolbox team in Brisbane, October 2018</u>: Approach to decision support logic; identification of different types of EEF responses and quantification of likelihood of different decision outcomes.

- Innovative Nitrogen Use in Sugarcane Forum in Cairns, November 2018: Challenges capturing EEF response experimentally; seasonal variability in benefits; development of evidence based EEF decision support logic; classification of EEF response types and their use to quantify likelihood of different decision outcomes; future directions and opportunities to complement EEF60 project.
- National Soil Science Conference in Canberra, November 2018: Challenges capturing EEF response experimentally; lessons for experimental evaluation of EEF; impact of broader system interactions on the realisation of benefits.
- Project industry workshop 2 in Ingham, December 2018: Parameterisation of soil and climate and model verification; classification of EEF response types; and their use to quantify likelihood of different decision outcomes; results from using modelling to run ‘virtual’ trials to test decision support logic; process of identification of key drivers through data mining.
- Achieving impact from soil science – a mini-symposium at CSIRO Agriculture and Food in Canberra, December 2018: Impact of broader system interactions on the realisation of benefits; N management decision support for the sugarcane industry.
- International Workshop on Nutrient stewardship and next-generation fertilisers on Heron Island, December 2018: Challenges capturing EEF response experimentally; lessons for experimental evaluation of EEF; impact of broader system interactions on the realisation of benefits; using modelling to run ‘virtual’ trials or experiments to test concepts, interpret results and allow identification of key drivers through data mining.
- EEF60 project team meeting in Townsville, February 2019: Lawrence Di Bella and Shannon O’Brien explained the response curve types and use for interpreting experimental results with EEF60 project team

Further communications scheduled:

- CaneConnection, March 2019: Article by Brad Pfeffer (in collaboration with Kirsten Verburg and Lawrence Di Bella) ‘Answering the key questions on enhanced efficiency fertilisers’ about the virtual trials and the EEF response types in an article aimed at growers.
- SRA Ingham grower Updates, April 2019: Presentation entitled ‘Enhanced efficiency fertilisers – virtual trials help fill the knowledge gaps’ to trial use of the EEF response classification and virtual trials concept to explain to growers how and when EEF provide benefit.
- ASSCT 2019 Conference in Toowoomba, May 2019: Use of ‘virtual’ trials to fill gaps in experimental evidence on EEF; importance of longevity of nitrification inhibition in reduction N loss in sugarcane.
- XXX Congress ISSCT in Tucumán, Argentina, September 2019: Quantifying the effects of longevity of nitrification inhibition on N loss from sugarcane production.

4.2. Industry communication messages

The communication messages resulting from the project can be summarised into five overarching messages as follows.

1. Characterising the benefits from EEF experimentally is challenging, but modelled 'virtual' trials can fill the knowledge gap.
2. The agronomic and environmental benefits from NI depend strongly on the longevity of nitrification inhibition, which is currently not well understood.
3. The classification of EEF responses into four types provides a language to explain the likelihood of obtaining benefits under different conditions.
4. Using the classification of EEF responses to analyse the results of large numbers of virtual trials using data mining techniques allows robust development and verification of EEF decision support logic.
5. The variable benefits from EEF suggest tactical use which requires development of decision support that draws on modelling to complement the field trials.

Further detailed messages under each of these is included in Section 7. As the topic descriptions behind the various communications in Section 4.1 indicate, all of the overarching messages and almost all of the detailed messages have been shared with industry. There is, however, value in extending the messages to a broader audience as most of the communication to-date has been to advisors active in the Herbert mill area or researchers involved with other funded EEF trials. The exception was the Innovative Nitrogen Use in Sugarcane Forum in Cairns, which included a group of local farmers. A presentation for growers at the Ingham grower research update has already been scheduled.

While the full decision logic requires some further work incorporating the effects of seasonal climate, the virtual trials have already confirmed the following practical messages for growers.

- The main benefit of EEF is that they allow a reduction of the N rate; increases in maximum yield are not frequently obtained.
- EEF do not provide benefits every time and everywhere, their tactical use should be considered.
- Early (July-September) ratoon crops are less likely to benefit from EEF due to lower likelihood of N loss during the early part of the season (but if heavy rain follows fertilisation they can still make a difference).
- Late (October-December) ratoon crops are more likely to benefit from EEF, but this is dependent on early season rainfall.
- Late ratoon crops grown under wet conditions on heavy clay soils may not benefit from EEF as much as might be expected if these conditions result in yield limitations other than N (e.g. if prolonged waterlogging impacts negatively on the crop).
- Plant crops typically have a lower likelihood of getting benefit from EEF as they are less responsive to N.
- A wet outlook for in particular the first two to three months after the start of the crop increases the likelihood of getting benefits, or larger benefits, from EEF.
- To ensure agronomic and environmental benefits the use of EEF needs to be accompanied by best management practice, including the use of an N rate that meets, and is not in excess of, crop requirements. Under conditions where benefit from EEF is expected the EEF N rate should be reduced.

5. METHODOLOGY

The starting point for the project was the draft decision support tree developed by HCPSL (Figure 1). The project focussed on verification of this logic for the Herbert mill area. It discussed the draft decision tree and the available experimental evidence with industry in the first of two project workshops. Drawing on the experience in SRA Project 2014/011 the project team proposed to use modelling to verify, complement and fill gaps in the experimental evidence. This approach was referred to as running 'virtual' trials and was well received by the workshop participants. More details of the approach are provided in Verburg et al. (2019). The sections below summarise the methodology employed to run a variety of 'virtual' trials as well some aspects of model verification.

5.1. Model and parameterisation

APSIM model

The scenarios were simulated using the Agricultural Production Systems Simulator (APSIM; version 7.8)-Sugarcane model (Keating et al., 1999; Holzworth et al., 2014). APSIM has been tested extensively in sugarcane (e.g. Thorburn et al., 2005, 2014, 2017) and a variety of other crops (Keating et al., 2003).

Climate and soils

Climate data required by APSIM was sourced from the SILO patched point climate data set (Jeffrey et al., 2001) for representative stations within the three climate zones identified within the SRA project 2017/009 (Figure 2). The three stations were:

- Southern zone: Bambaroo (BoM station: 032001) (Date range: 1949-2017)
- Western zone: Upper Stone Exelby (BoM station: 032043) (Date range: 1949-2017)
- Eastern zone: Macknade Sugar Mill (BoM station: 032032) (Date range: 1949-2017)

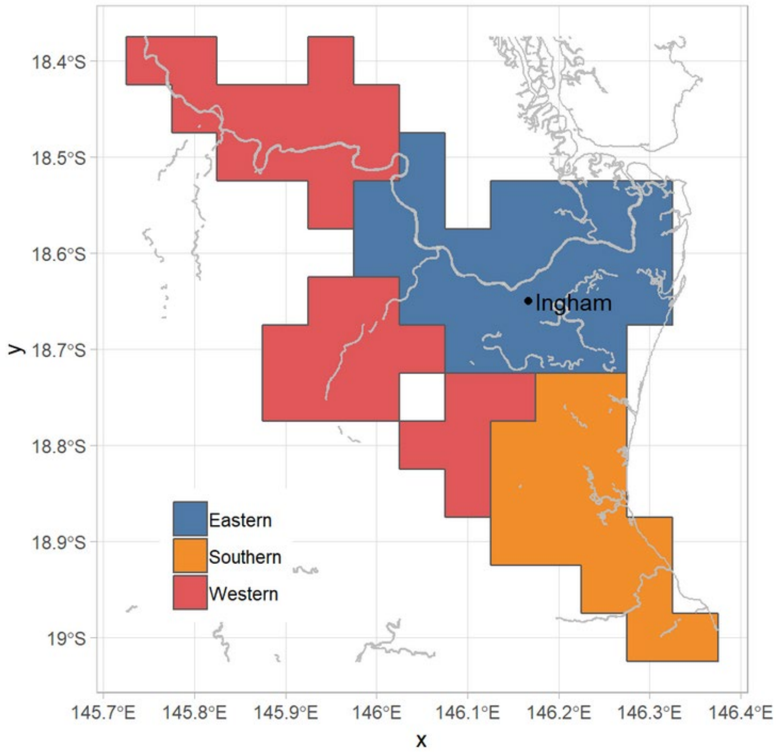

Figure 2. The three climate zones represented in the simulations (unpublished data, SRA project 2017/009).

According to Wilson and Baker (1990) there are 37 different soil types in the Herbert sugarcane growing region. Through work for SRA project 2017/09 in the Herbert area ("Unravelling the impact of climate and harvest time on nitrogen fertiliser requirements"), parameters required by APSIM, have been developed for 31 of the 37 soils (Figure 3).

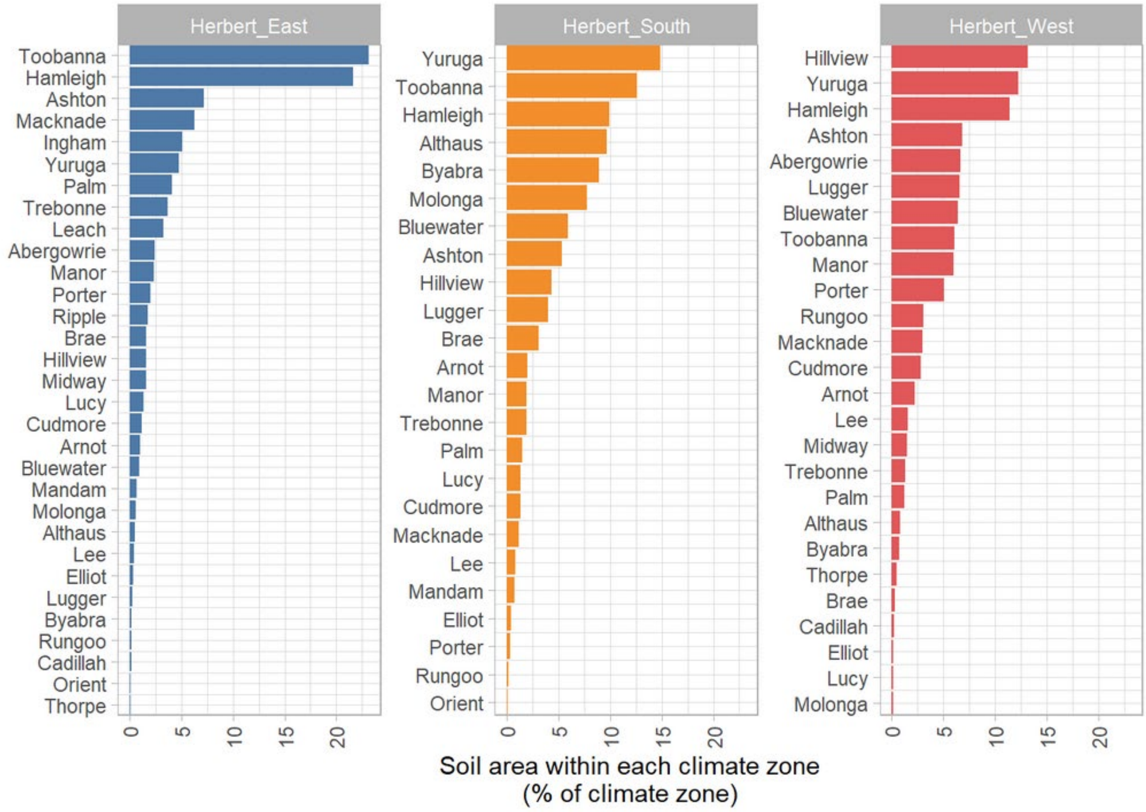

Figure 3. Soils simulated within each climate zone and ranked according to proportion of area. Soil naming follows convention used in Wilson and Baker (1990).

The method used to develop soil parameters is described in Barboux et al. (2018) and has been validated in the Tully region (Biggs et al., 2018). SRA project 2017/009 is collecting data on crop N response under different conditions and on different soils. Validation of the predicted N response curves is, therefore, ongoing in that project and will help fine tune some of the EEF results presented here.

Modelling of CRF behaviour

The CRF was simulated using a custom management script that described the controlled release of N using a three-stage conceptual model often associated with polymer-coated fertiliser granules in which release is only dependent on time and temperature (Shaviv, 2001): (1) a water absorption stage without release; (2) a linear release stage (to 50%); and (3) a (first order) declining release stage. The release product simulated had a release period similar to some of the products used in experimental trials in sugarcane. The release was parameterised to respond to temperature with a temperature coefficient Q_{10} of 2.5 (rate increase of 2.5 times for a 10°C increase in temperature). It was assumed that soil moisture did not affect the release rate, which is a common assumption for polymer coated CRF that appears to hold provided there is some residual soil moisture to start the release process (Verburg et al., 2017a).

Modelling of NI behaviour

We simulated the NI following the approach of Cichota et al. (2010) which assumes that the behaviour of NI and their effect on nitrification can be described by two processes. The first follows changes in the concentration of NI over time and the second describes the inhibitory effect on nitrification as a function of the NI concentration. For simplicity we refer to the concentration of NI over time as *persistence* and to their inhibitory effect as a function of the concentration of the NI as *bioactivity* (Keeney, 1980). Both persistence and bioactivity are determined by the activity of soil microbes and NI's availability to these (Di and Cameron, 2016). Thus, factors that enhance microbial activity in soils are likely to promote the degradation of NI and therefore decrease their persistence. Similarly, factors that reduce the availability of NI to soil microbes are likely to reduce their bioactivity. Thus, future investigations need to investigate how both persistence and effectiveness are influenced by soil and climate.

In this project we focused on 3,4-dimethylpyrazole phosphate (DMPP), which is the active component of ENTEC© and the most widely used NI in Australian agricultural systems (Duncan et al., 2017; Wang et al., 2016b). While the persistence and bioactivity of NI have been characterised for dicyandiamide (DCD) and nitrapyrin (Cichota et al., 2010; Di and Cameron, 2011; Keeney, 1980; Kelliher et al., 2008; Puttanna et al., 1999), studies examining the persistence and bioactivity of DMPP are scarce. The few studies available indicate that DMPP can persist in the soil for a few weeks (Barth et al., 2008; Doran et al., 2018) or up to one year (Guardia et al., 2018). Although the latter estimations were found to be based on a misinterpretation of the data (Vilas et al., 2019a). Similar uncertainty about longevity of the effect of DMPP has been noted in sugarcane. A study by Wang et al. (2016b) in sugarcane in Ingham suggested that their DMPP-based nitrification inhibitor was effective in reducing soil nitrate concentrations for over 12 weeks, whereas in another study in Mackay (Wang et al., 2016c) fast breakdown of the NI was suggested as a possible reason for the ineffectiveness of the NI in reducing N_2O emissions.

The limited available data makes it challenging to develop DMPP parameters to model its effect in APSIM, let alone to describe how the persistence and bioactivity may change with changing environmental conditions. Thus, in this project we assumed that: (a) DMPP concentration declines exponentially over time (Figure 4a) and (b) nitrification is inhibited linearly with increasing NI concentration, to a threshold concentration beyond which nitrification is fully inhibited (Figure 4B).

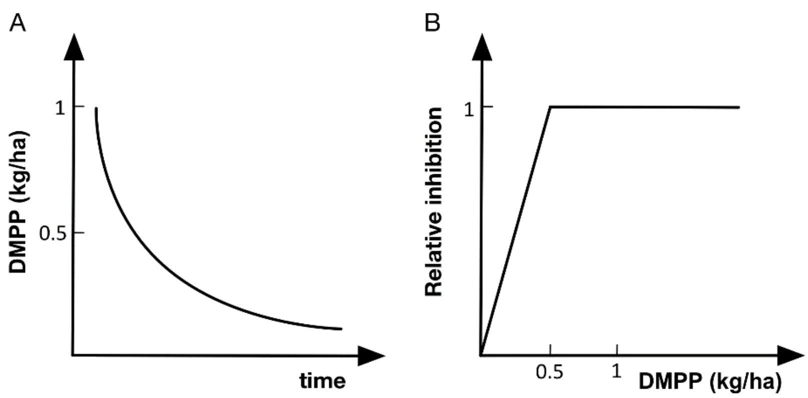

Figure 4. Conceptual diagram of the (A) persistence and (B) bioactivity of DMPP as implemented within the model APSIM (adapted from Vilas et al., 2019a).

Only a few studies have measured changes in concentrations of DMPP over time (Barth et al., 2008; Doran et al., 2018). These studies found that the DMPP concentrations decline exponentially over time with a half-life ranging between 7 (Barth et al., 2008) and 28 days (Doran et al., 2018). Thus, we performed simulations using a half-life of 7 and 28 days to account for these different estimations. We also performed simulations with longer half-lives to assess the effect to the persistence of DMPP on N loss reduction. We assumed that the initial concentration of the NI was 1% of the N rate (Duncan et al., 2017).

We characterised the bioactivity function as having a threshold concentration of 0.5 kg/ha beyond which nitrification was fully inhibited. This value was derived from NH_4 data measured by Zerulla et al. (2001) which showed that nitrification was fully inhibited at DMPP concentrations greater than 0.5 kg/ha. Please refer to Vilas et al. (2019a) for additional explanation on how this threshold was derived.

5.2. Model verification and sensibility testing

While the APSIM model has been verified in a number of past studies (see Section 5.1) additional verification or model sensibility testing was undertaken to strengthen the confidence in model performance relating to EEF simulation. This involved testing of the parameterisation of an N uptake model that could supply the crop with both ammonium and nitrate as well as simulation of two EEF field trials.

Uptake of N

Simulation of NI required testing of an alternative N uptake approach for both nitrate and ammonium uptake, because the standard version of the APSIM-Sugar model only allows the crop to take up nitrate. The alternative model and its parameterisation were successfully tested by comparing with experimental N uptake data and their simulation in the original APSIM-Sugarcane paper by Keating et al. (1999). Additional tests of hypothetical situations of low N supply, ammonium only, nitrate only and 50/50 ammonium/nitrate supply also confirmed the modelling of N uptake was not creating bias in the simulations. Details are provided in Appendix Section 12.2.

Simulation of EEF field trials

In order to verify the model against experimental evidence we modelled two EEF field trials undertaken in Ingham (Wang et al., 2016a,b). We based the modelling on previous work that had simulated the urea treatments only. The trials were performed on a first ratoon crop in a Hamleigh and a Toobanna soil (Wilson and Baker, 1990) for Wang et al. (2016a) and Wang et al. (2016b), respectively. Soil parameters were obtained through the methodology described in Section 5.1. To better represent the soil mineral N patterns we adjusted the nitrification rate following Meier et al. (2006). In addition, the soil surface pH was adjusted to match the measured data.

Simulations were undertaken with meteorological data obtained from Ingham Composite (station 032078, 1889-2018, https://silo.longpaddock.qld.gov.au). For Wang et al. (2016a) we simulated a ratoon crop started on 25 August 2013 and harvested on 13 October 2014. The crop received urea, CRF or NI on 9 October 2013. The following scenarios were simulated: (a) 0N, (b) 110N and 150N of urea, (c) 110N and 150N of CRF (a polymer coated urea; PCU), and (d) 110N and 150N of NI coated urea (DMPP). For Wang et al. (2016b) we simulated a ratoon crop started on 29 September 2012 and harvested on 6 August 2013. The crop received urea, CRF or NI on 4 October 2012. The following scenarios were simulated: (a) 0N, (b) 100N and 140N of urea, (c) 100N and 140N of CRF (PCU), and (d) 100N and 140N of NI coated urea (DMPP).

Simulation results for Wang et al. (2016a) are presented in Figure 5. The simulations represented the measured soil water dynamics well (Figure 5A). Simulations of mineral N were also able to capture the measured dynamics, except that the predicted decline in mineral N was slightly more rapid than observed (Figure 5B).

Although we were unable to fully confirm the N response due to the limited number of N rates in the experimental data (as this was not the aim of the trial), the cane yield levels were simulated well, apart from the 150N rate for urea and DMPP coated urea treatments (Figure 5C). For urea, we were unable to simulate the observed reduction in yield at the 150N rate compared with the 110N rate. However, as the authors found that yields for the 110N and 150N rates of urea were not significantly different, the reduction in the observed mean yield for urea at the 150N rate may be due to sample variability. For DMPP coated urea, the authors found a significant increase in yield for the 150N rate compared with the 110N rate. The model predicts that the maximum yield for all three fertiliser types is reached below the 110N rate, which matches with the fact that the yields of the 110N treatments showed no statistically significant differences between fertiliser types and that these were not statistically significantly different from the 150N rates with PCU and urea. It is not clear what caused the higher yield in the 150N DMPP treatment and whether that means the optimum N rate was not yet achieved at 110N. It is possible that variable levels of lodging affected the measured results of the 150N treatments (Weijin Wang, personal communication 19 Feb 2019).

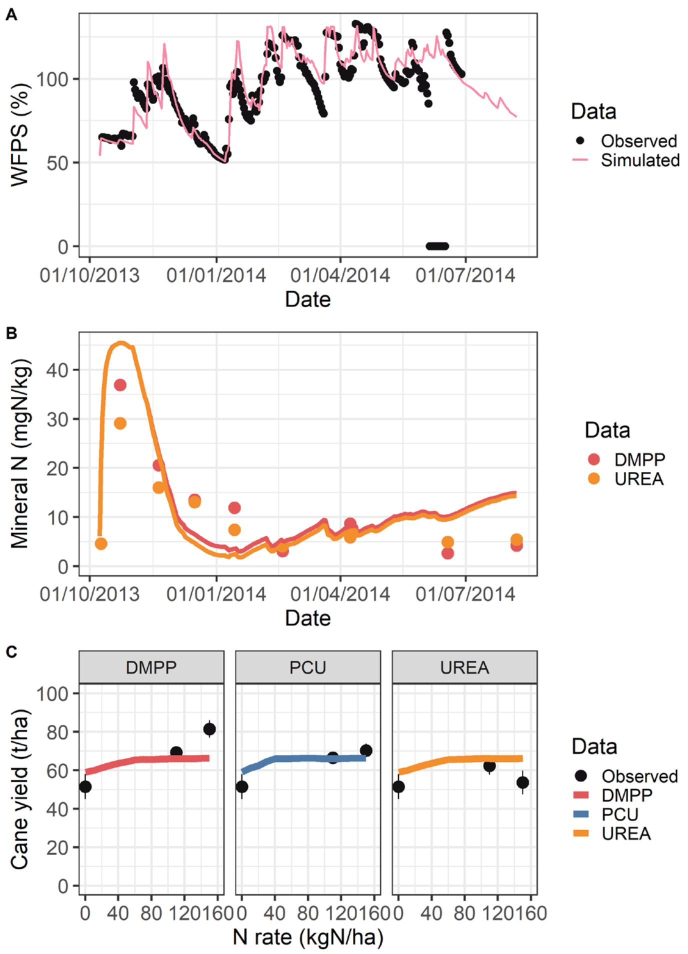

Figure 5. (A) Water filled porous space in the first 30 cm of the soil for the 150N rate of urea (WFPS, %), (B) mineral N for the 150N rate of urea (mg N/kg), and (C) cane yield (t/ha) for NI coated urea (DMPP), CRF (PCU) and urea. Cane yield data from Wang et al. (2016a) and unpublished WFPS and mineral N data provided by Weijin Wang, personal communication.

Simulation results of Wang et al. (2016b) are presented in Figure 6. The soil water dynamics were captured correctly (Figure 6A). Similarly, mineral N for the 140N treatments was simulated well, except for underestimating mineral N slightly in the mid-season (Figure 6B). The simulations also correctly captured the delayed release from the PCU. However, the simulated peak mineral N concentration in the PCU treatment was not as high as the measured value. It is not clear what caused the peak mineral N concentration measured in the PCU treatment to be higher than the initial increase in mineral N concentration in the urea treatment given its more instantaneous release. Normally CRF treatments are expected to keep the mineral N concentration lower due to the slow release, unless release precedes crop uptake. Rainfall and N loss were not experienced until 2 months after fertiliser application. The high mineral N measurement in the PCU treatment was mostly due to ammonium observed in the bed centre and had a relatively large error bar. Given the underestimation of mineral N during the mid-season in all treatments, it is possible that crop uptake of N was overestimated. Comparison with biomass N data would be required to confirm whether that was the case or whether the peak N concentration in the PCU treatment was affected by measurement uncertainty.

The simulations were also able to represent the achieved yields, apart from the 140N rate for the PCU treatment (Figure 6C). As in the previous experiment, the model predicted the optimum N to be below the 100N rate, corresponding with no significant differences between the 100N treatments of the different fertiliser types. Consequently, it underestimates the higher yield measured in the 140N PCU treatment. While the yield at 140N in the PCU treatment was significantly different from that in the 100N PCU treatment, it was not significantly different from the 100N and 140N DMPP treatments nor the 140N urea treatment. With a lack of strong treatment differences the data, unfortunately, do not provide a robust test of the model.

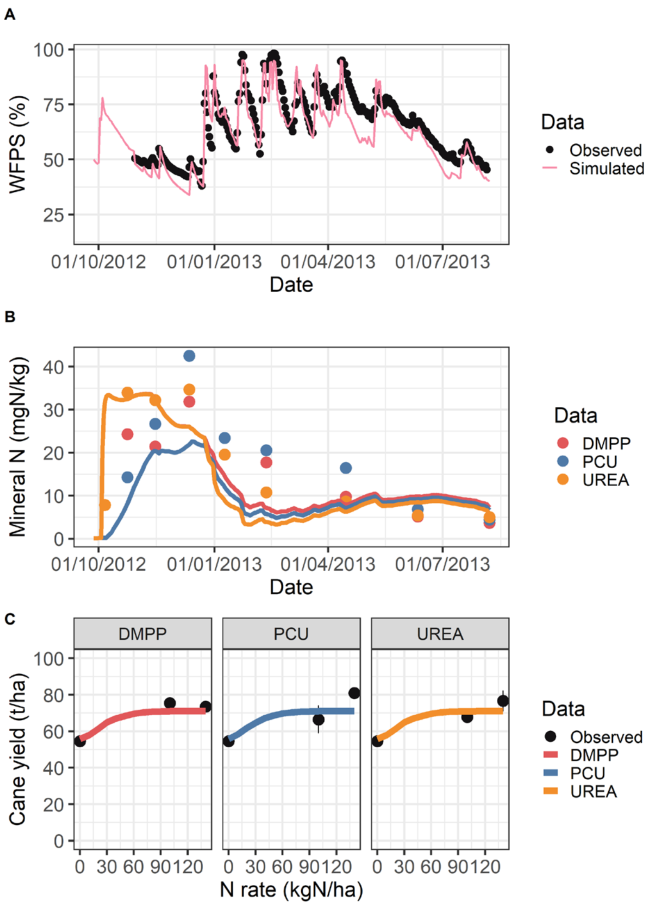

Figure 6. (A) Water filled porous space in the first 15 cm of the soil for the 140 N rate of urea (WFPS, %), (B) mineral N for the 140 N rate of urea (mg N/kg), and (C) cane yield (t/ha) for NI coated urea (DMPP), CRF (PCU) and urea. Cane yield data from Wang et al. (2016b), WFPS mean of bed and furrow position and mineral N data proportional average of bed centre (8%) and bed shoulder and furrow (92%) from Wang et al. (2016b).

5.3. Virtual trial designs

Modelling was used to set up a number of different virtual trials, which like field trials were designed to address different research questions or verify experimental results that the draft decision support tree of HCPSL was based on.

Virtual EEF trials for the Herbert mill area

A large factorial of virtual EEF trials was designed to investigate the impact of a range of factors on the effectiveness of EEF.

The simulated scenarios represented 12-month ratoon crops started on 15 July, 15 September, 15 November or 15 December. To approximate local practice fertiliser was applied 42, 10, 10, or 7 days after these four crop starts, respectively. Four types of fertiliser were simulated including urea, CRF and NI with a half-life of 7 or 28 days (NI7, NI28; see Section 5.1). Fertiliser was applied at 34 different rates (0-330 kg N/ha) and the 'virtual' trial was carried out on 31 different soil types. This represented 50,592 virtual experimental plots and was over the 67 historical climate seasons simulated equivalent to 3,389,664 treatment years.

Shallow water tables are prevalent in the eastern climate zone of the Herbert region (Chardon and Rudd, 1978; Mitchell et al., 2001). The model simulated temporary saturated conditions as a result of the soil parameterisation (e.g. saturated hydraulic conductivity) and water inputs (i.e. rainfall) as well as a restricted rooting depth of 1.2 m. Irrigation is practised in parts of the Herbert region, and after discussion with local experts (extension officers and farmers) and observing the level of simulated water stress, a simple irrigation rule was developed consisting of four applications of 35 mm at 30, 60, 90 and 120 days after crop start.

Virtual trial evaluating time of harvest time effect on EEF benefits

As a variation on the above virtual EEF trials, we simulated for two of the soils, a heavy textured Hamleigh and a light-textured Lugger, a trial to evaluate the time of harvest effects. We simulated a rainfed cropping system with a 12 month ratoon crop starting every year on 15 July to 30 December with a time interval of 15 days (12 starting dates). The crops received urea, NI28 or CRF 10 days after the crop was started. Fertiliser was applied at 34 different rates (0-330 kg N/ha).

Virtual trial evaluating effect of longevity on nitrification inhibition

Another variation of the above virtual EEF trials, also using a heavy-textured Hamleigh and a light-textured Lugger, focussed on evaluating the effect of longevity of nitrification inhibition. In this case we only simulated a 15 November start date. The crops received urea or urea+NI 10 days after the crop was started. The simulated half-lives were: 7, 14, 28, 60, and 120 days. We set up two simulations: (1) N rate of 130 kg/ha for the Hamleigh soil and 150 kg/ha for the Lugger soil with urea and urea+NI, and (2) N rates ranging from 0 to 330 kg/ha with a step of 10 kg/ha with only urea. The N rates applied in the first set of simulations were based on industry recommendations. The second set of simulations were used to calculate the optimum N rate by fitting a smoothing function to yield versus N rate data and estimating the optimum N rate (see below). All simulations were run over 67 years, starting in 1949, with a time step of 1 day.

Virtual experiment testing the effectiveness of CRF and NI for different N loss pathways

The draft decision support tree developed by HCPSL included an assumption that CRF would be more effective on light soils experiencing leaching loss and NI would be more effective on heavy soils experiencing denitrification N loss. This assumption was influenced by results from a glasshouse experiment by Di Bella et al. (2017). We simulated this experiment in order to explore the processes behind this assumption. We modelled a light-textured Macknade soil (Wilson and Baker, 1990) which is the equivalent of the terrace silty loam used by Di Bella et al. (2017) in their glasshouse experiment. The soil profile was assumed to be 22.5 cm deep to account for the depth of the pots.

Simulations were undertaken with meteorological data obtained from Macknade Sugar Mill (Ingham, Australia, station 032032, https://silo.longpaddock.qld.gov.au). We simulated a rainfed cropping system with a 12 month plant crop starting on 20 August 2015 and harvested after 1 year. The crop received urea, CRF or urea+NI on planting. As we lack of information on the half-life of the NI, we simulated NI with half-lives of 7 and 28 days (NI7 and NI28). The simulated N rate was 100 kg N/ha.

To mimic the experimental trials two scenarios were simulated: (a) leaching and (b) water logging. The leaching scenario was maintained at field capacity for the first 45 days of the experiment, then 20 mm of rainfall were added. Another 20 mm were added after 145 days. In the water logging scenario the bottom layer of the soil was made impermeable to prevent leaching from occurring. In this scenario, the soil was maintained at field capacity for the first 45 days, then 20 mm of rainfall were added. Another 20 mm were added after 145 days.

5.4. Analysis of virtual trial results and classification of EEF response types

The data analysis focussed on yield N response functions which were fitted using a local polynomial regression with automatic smoothing parameter selection to calculate the maximum yield and an agronomic ‘optimum’ fertiliser N rate (Nopt) achieving 98% of maximum yield. The total N lost via denitrification, runoff and leaching was calculated at the Nopt using the same regression method.

The maximum yield and the optimum N rate (N rate to achieve 98% of maximum yield) for the EEF (CRF and NI28) were compared with the urea treatment. Based on these comparisons the responses were classified into four response types (A, B, C1, C2):

- A is where the use of an EEF produced an increase in maximum yield of more than 3 t/ha when compared with urea;
- B is where the use of an EEF reduced the optimum N rate by more than 15 kg N/ha;
- C1 is where there was no difference in optimum N rate but there was a noticeable N response (i.e. optimum N was more than 30 kg N/ha);
- C2 is where there was no difference in optimum N rate and there was no noticeable N response (i.e. optimum N rate was less than 30 kg N/ha).

The threshold of 3 t/ha yield increase for Type A was considered the minimum measurable. Workshop discussions judged the threshold of 15 kg N/ha for Type B the minimum worth considering.

5.5. Data-mining virtual trial results

Using datamining techniques we carried out a preliminary analysis to determine important predictors of the simulated N response types (A, B, C1, C2) as a result of using EEF for a range of soils, crop management and years.

APSIM was used to simulate the response of cane yield to applied nitrogen (N) for nine soils in East Herbert and crops starting at four different times and three fertiliser types (Table 1). These simulations were performed across 63 years (1951-2014). The resulting database consisted of 4608 records with a majority falling within the Type C1 and C2 response types (Table 2). Note that this result is specific to the conditions of the simulated scenarios and soils. It should not be generalised.

Table 1: Table of simulated combinations considered in the preliminary data-mining analysis

Factor	Code	Levels
Soil	Soil	Ashton, Hamleigh, Ingham, Leach, Macknade, Palm, Toobanna, Trebonne, Yuruga
Crop start	CropStart	Dec, Jul, Nov, Sep
EEF type	FertiliserType	crf, ni28

Table 2: Frequency of each response types in the simulated dataset for the Eastern Herbert climate zone.

Response type	Proportion of records (%)
A	0.2
B	10.1
C1	63.8
C2	25.9

Classification tree analysis was used to determine the important predictors of response type. However, due to the highly unbalanced nature of the response types (i.e. Type A class < 1% of records) the tree analysis would only be useful for determining the predictors of Type C1 and C2. To overcome this and emphasise the importance of the Type A and B response types, up-sampling of the data was conducted. Up-sampling consisted of randomly sampling, with replacement, a data set so that all response type class distributions are equal.

The analysis was conducted in three stages at which different sets of predictors were included (Table 3). In each stage the response type (i.e. A, B, C1, C2) was the target variable. In the third stage the influence of a potential climate forecasting index was investigated to demonstrate the potential benefit of included rainfall outlook in the decision process. The June to August Oceanic Nino Index (JJA ONI) phase was chosen for this analysis and the data was sourced from http://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php on the 22 Jan 2019. The JJA ONI was associated with following year's harvest.

The analysis was performed using the R statistical language (v3.5.1; R Core Team, 2018). More specifically, up-sampling was conducting using the *caret* package (v6.0-80; Kuhn et al., 2018) and the classification tree analysis was conducted using the *rpart* package (v4.1-13; Therneau and Atkinson, 2018). The model was developed on a training set (70% of original data) and validated against the remaining 30% of the data. Over-fitting was avoided by pruning the full tree to within one standard error of the minimum cross-validation error.

Table 3: Predictor codes and descriptions used in each stage of the classification tree analysis.

Predictor code	Description	Stage 1	Stage 2	Stage 3
CropStart	Crop start time	yes	yes	yes
Soil	Soil name	yes	yes	yes
FertiliserType	Fertiliser type	yes	yes	yes
EarlyRain	Total rainfall within 75 days after fertilising	no	yes	no
JJA	June to August Oceanic Niño Index (JJA ONI) phase	no	no	yes

6. RESULTS AND DISCUSSION

6.1. Workshop evaluation of draft decision support logic and experimental evidence

The first of two workshops held by the project was used to review the latest results from field trials, to get industry feedback on the draft decision support tree developed by HCPSL (Figure 1), to assess the available evidence for testing of the decision logic and how to generate more 'evidence' using virtual trials.

Experimental trial results

Earlier reviews of the available experimental evidence on benefits from EEF were undertaken as part of SRA project 2014/011 (Verburg et al., 2016) and the SRA Nutrient Use Efficiency Review (Chapter 7, Verburg et al., 2014). These studies identified that while the results from these trials showed some positive EEF responses, many trials suffered from not obtaining statistically significant treatment effects. That made it difficult to quantify the benefits, let alone identify factors such as climate, soil, seasonal and management conditions that affect them. Although, in broad terms, it was clear that large rainfall events (causing considerable waterlogging or leaching with deep drainage) within the first two to three months would probably be a prerequisite for obtaining measurable benefits.

For this update of the review of experimental evidence HCPSL staff asked their contacts across the wet tropics part of the industry for recent trial results and compiled a list of 41 trials and their characteristics and outcomes. A summary of these trials is shown in Tables 4-7 below.

Demonstrating that the EEF change the N dynamics (slower increase in soil mineral N or keeping mineral N in ammonium form) is often successful when it is undertaken (e.g. Table 4). It is more difficult to show evidence that this can translate into a reduction of N loss (Table 5), increase in yield (Table 6) or reduction in agronomic optimum N (changed yield N response or achieving same yield with lower rate of N; Table 7). This was also an observation made by Verburg et al. (2014) following review of findings internationally.

In relation to measurement of N loss reductions there are a number of studies that have observed increased N loss from CRF, particularly later during the season (e.g. Wang et al., 2016c; Di Bella et al., 2017). This occurs when peak N release coincides with a wet period and is either not well synchronised with crop uptake or crop uptake is hampered by other factors (including waterlogging). However, it should also be noted that, at least in some cases, the increased loss along one pathway is due to reduced loss along another pathway which may not be measured. Simulations, which capture all loss pathways, have been useful to demonstrate these effects (e.g. Verburg et al., 2017b, 2018).

The small number of statistically significant treatment differences in the trials means that it is currently difficult to base a decision support tool on experimental evidence alone. The limited number of replicate measurements typically included in the field trials (most often three) is likely to be insufficient to overcome the low precision of yield assessments caused by spatial variability inherent in sugarcane fields and the error associated with assessment of plot based yield. This means that the yield difference required for statistical significance may be larger than the yield difference that can be achieved with EEF. Myers and Vallis (1994) reflected on this for their early trials with EEF and noted that yield differences of more than 12 t/ha were required for statistical significance. This could be improved by increasing the number of replicates or by exploring precision agriculture analysis techniques in conjunction with strip-based or spatially distributed approaches (Bramley et al., 2013).

However, even if experimental precision is improved, previous research using modelling (Verburg et al., 2017b, 2018) indicates that variable outcomes of experiments are still likely due to highly variable seasonal climate conditions as well as complex, interacting processes within the sugarcane system. Further field trials will hence continue to suffer from variable results. The proposed approach of using modelling to complement the experimental findings with virtual trials allows an analysis across many more trials and a chance to get insights despite the variability in EEF responses. It also provides an opportunity to cheaply test hypotheses that can then be verified with field trials designed based on the outcomes of modelling.

Table 4: New experimental results from trials testing for altered soil N dynamics.

Statistically significant positive effects	**Inconclusive/not statistically significant effects**
Wang et al., 2016b (Herbert) N release from CRF continued for at least 5-6 months, lower NO_3 in NI treatment for at least 3 months **Wang et al.** (RnD4Profit milestone, Herbert) NI effective for at least 2 months, PCU higher mineral N in surface 2-3 months after fertilisation **Wang et al.** (RnD4Profit milestone, Tully) Very low fertiliser N (except unreleased PCU) in 0-120 cm within 2.5 months, due to leaching/denitrification from high rainfall **Wang et al** (RnD4Profit milestone, Innisfail) NI reduced nitrification in 1st 1.5 months; very low fertiliser N (except unreleased PCU) in 0-120 cm within 2.5 months from fertilisation after high rainfall	None reviewed
Statistically significant negative effects	
None reviewed	

Table 5: New experimental results from trials testing for reduction in N loss.

Statistically significant positive effects	**Inconclusive/not statistically significant effects**
Wang et al., 2016a (Herbert Clay) NI reduced annual fertiliser-induced N_2O emissions by 83%	**Wang et al., 2016b** (Herbert Hydrosol) No significant differences N_2O from CRF or NI
Statistically significant negative effects	
Wang et al., 2016a (Herbert Clay, Oct 2013) higher N_2O emissions from PSCU (indicted as possibly being due to reduced leaching loss)	

Table 6: New experimental results from trials testing for increased yield (tons cane or sugar per hectare (TCH, TSH), N uptake at same N rates).

<table>
<tr><th>Statistically significant positive effects</th><th>Inconclusive/not statistically significant effects</th></tr>
<tr><td>Wang et al., 2016a (Herbert Clay): increase sugar yield and N uptake by CRF and NI; yield increase from EEF but only significant for NI at lower rate
Bell et al. (NESP project 2.1.8; 1st yr., pers. comm.) blend of NI and CRF has been effective in terms of improved crop recovery of N
Rixon and Shannon (innovation project Tully) Entec NI increase in TCH at higher N rate used (not lower N rate)</td><td rowspan="3">Wang et al., 2016b (Herbert Hydrosol) No significant differences from CRF or NI
Wang et al. (RnD4Profit milestone, Herbert) no significant differences TCH and TSH
Wang et al. (RnD4Profit milestone, Tully) no significant differences TCH and TSH
Wang et al. (RnD4Profit milestone, Innisfail) no significant differences TCH
Parker/Stone (innovation project, Mossman) no significant differences
Parker/Stone (Catalyst project report, Mossman) no significant differences x 4
Di Bella and Stacey CRF tends to have higher TCH and/or TSH but not significant x 8
Bell et al. (NESP project 2.1.8; 1st yr., pers. comm.) yield responses few and far between
Rixon (& Shannon) (innovation project Tully) no significant differences (product, rate) x 3
Royle (Gairloch) NI lower (no stats)
Royle (project NEMO*) no difference (no stats) x 6</td></tr>
<tr><td>Statistically significant negative effects</td></tr>
<tr><td>None reviewed</td></tr>
</table>

Table 7: New experimental results of trials testing for changed yield N response.

Trials which achieved same yield with EEF at lower N rate than the urea treatment, but due to not including a urea control at the lower rate not conclusive of benefit of EEF as it could also be due to lack of N response (demonstration rather than research trials)	No difference in N response between EEF and urea
Royle (Abergowrie) same TCH for urea/CRF blends at rates 30 kg N/ha less than the urea treatment, but reduced TCH for those at 70 kg N/ha less **Royle** (Abergowrie) same TCH for urea/CRF blends at 20 kg N/ha less than the urea treatment, but reduced TCH for those at 65 kg N/ha less that the urea treatment. **Royle** (Project NEMO*) same TCH for various products at different rates, incl. EEF at lowest rate	**Schroeder et al., 2018** (ASSCT/ISSCT presentation) no difference between yield N response curves for urea and EEF (full response curves that did show N response) **Royle** (project NEMO**) same TCH, TSH for 3 rates Urea and NI (lack of N response) **Royle** (project NEMO*) same TCH, TSH for different rates and products (incl. urea and EEF at lowest rate) (lack of N response)

*Project NEMO: Project Nemo: http://www.hcpsl.com/wp/project-nemo/

Draft decision logic

As a first step the original draft decision support tree developed by HCPSL (Figure 1) was simplified to remove some of the redundancies it contained. It was also decided to focus on ratoon crops as the likelihood of getting agronomic benefit from EEF use in plant crops is small due to the typically flat N response in these crops caused by the usually high soil N supply (SRA Project 2014011; Verburg et al., 2017a). The simplified tree was developed into a prototype electronic tree (Figure 7) that would allow users to view the evidence sitting behind different decisions by clicking on that question.

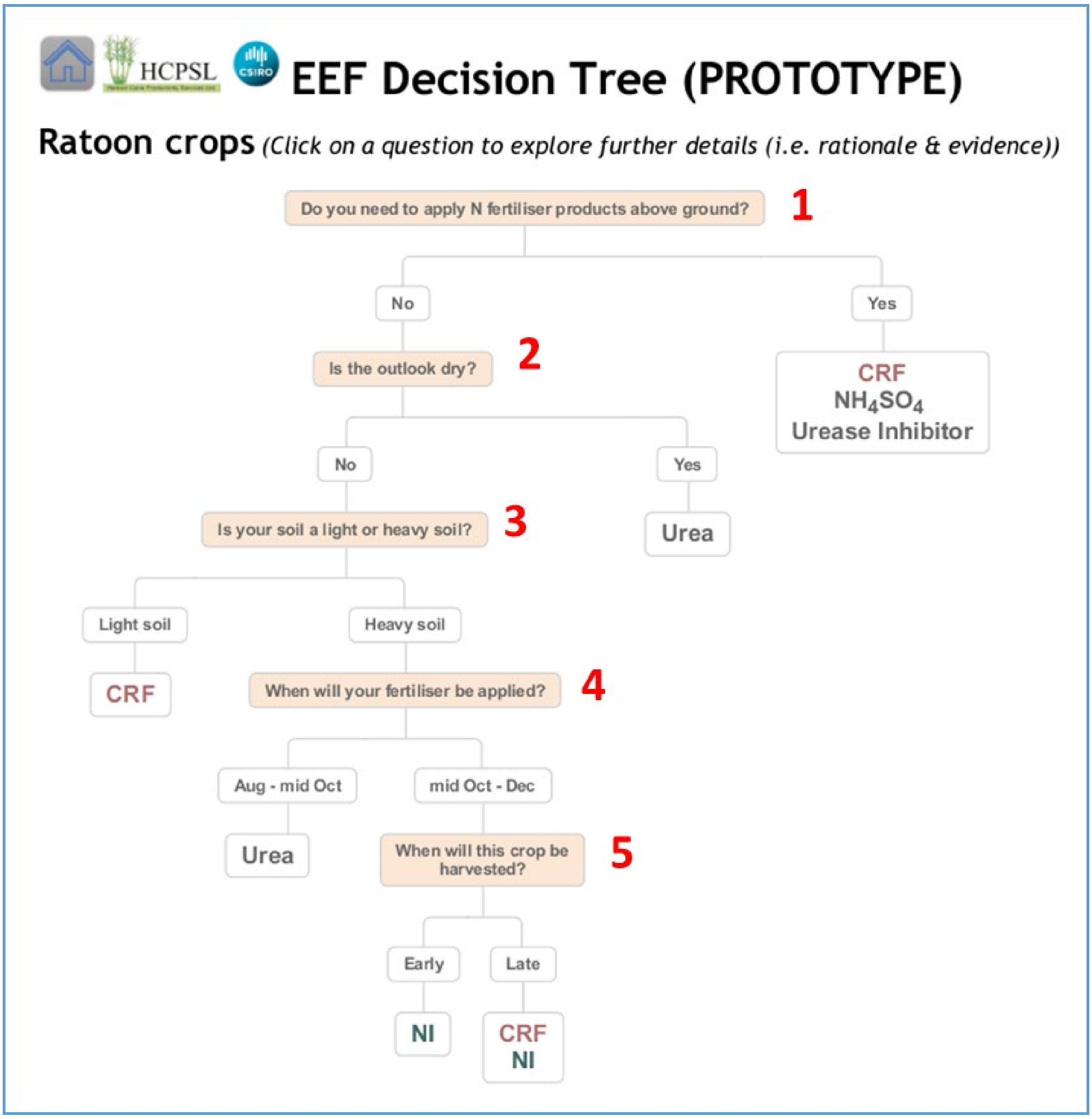

Figure 7. Prototype electronic version of a simplified version of the original EEF decision support tree developed by HCPSL. Numbers identify parts of the decision support logic to be tested (see text for details).

The following five decision points were identified for verification (see Figure 7):

1. Limiting EEF choice to CRF for above-ground application;
2. Using urea in case of a dry outlook;
3. Preferring CRF above NI for light soils subject to leaching;
4. Using urea for early timing of fertiliser application on heavy soils;
5. Using NI if ratoon crops are intended to be harvested early.

Decision 1 relates to the observation that above-ground application, while not usually recommended, could enhance ammonia volatilisation loss if NI was used, as the NI keeps the N for longer in the ammonium form. While this effect has not been observed in trials in Australian sugarcane, soil core experiments performed in Brazil (Soares et al., 2012) have confirmed increased volatilisation N loss when NI was added to a treatments of urea or of urea and a urease inhibitor. This would support this decision point and is also consistent with the advice from fertiliser companies producing NI to only use NI subsurface, as this reduces the risk of volatilisation.

Decision 2 stems from the observation that EEF can only provide benefits if there is N loss that the EEF can reduce. As the analysis of climate indicators and their forecasting was not part of the scheduled project activities (being intended for phase 2), the detail of how a dry outlook is quantified was not investigated in the current project. The virtual EEF trials and the subsequent analysis of their results were designed to provide some preliminary insights.

Decision 3 indicates that pathway of N loss would affect the relative effectiveness of NI and CRF. This decision point was based on results from a glasshouse experiment (Di Bella et al., 2017). It compared the relative effectiveness of CRF and NI in keeping soil N concentrations low and reducing N loss in leaching or in N_2O emissions. This involved growing sugarcane in pots that received urea, CRF or urea with NI and were at 45 and 145 days either exposed to a leaching event or a ponding event (free draining pot or close pot). The authors found that soil ammonium concentrations at day 50 where higher in the CRF treatment compared with the urea and NI treatments. Accordingly, leaching losses were significantly lower with CRF compared with urea and NI. These findings prompted the authors to suggest that CRF is better suited to reduce leaching losses than NI. The study also found that N_2O losses were lower with NI when compared with CRF and urea. However, the measurements had large error bars which makes it difficult to assess the significance of the difference. As this was an important decision point in the tree based on just one study, it was identified for further testing using virtual trials.

Decision 4 relates to the observation that due to the typical seasonal rainfall patterns experienced in the Herbert mill area the early fertiliser applications would less likely be followed by a large N loss event in the first 2-3 months. With a reduced risk of N loss it would also be less likely that EEF could provide benefit. It was decided this warranted further testing using virtual trials to better quantify what would constitute 'early' and what would be considered 'late'.

Decision 5 relates to a concern that slow release of N from CRF may impact on CCS, suggesting the use of NI would be preferred. This hypothesis needs verification through a literature review, but was not included in this phase 1 project.

Discussions at the first workshop also identified that the decision points would never provide a 100% guarantee of a certain outcome. If a decision point suggested "CRF", "Urea" or "NI" this would reflect a situation where in most cases these fertiliser types would perform better than the others. It prompted a wish to have the likelihood of different outcomes quantified, so that users could make their own assessment whether that likelihood was sufficiently high for their decision making.

6.2. Classification of EEF responses

Analysing and interpreting the outcomes of thousands of virtual EEF trials requires a means to summarise their results. This is difficult as the shapes of the resulting yield N response curves can appear to vary infinitely. Looking through the collection of response curves and using the daily model output to explore the reasons for the responses observed in different seasons (see e.g. Verburg et al., 2017b, 2018, 2019) we realised that there were some consistent 'stories' behind the different EEF responses. This enabled the development of a classification of EEF responses, distinguishing four types of responses (Figure 8). See Verburg et al. (2019) for further details.

Type A represents responses where EEF use leads to an increase in maximum (plateau) yield. This response occurs when an early season, large N loss event causes most of the applied fertiliser N to be lost, except that which is still 'protected' by the EEF. As a consequence a higher N rate cannot compensate for the N loss and the EEF can achieve a higher maximum yield.

Type B has no increase in maximum yield, but the yield plateau is reached at a lower N rate and Nopt is hence reduced (specified as a minimum reduction of 15 kg N/ha). In this case the EEF reduced the loss of N to which the crop responded with a yield increase below the Nopt for the urea treatment.

Type C1 and C2 have no yield response to EEF but the reasons differ. In the case of Type C1 it is due to lack of appreciable N loss during the period that the N is protected. Without N loss the EEF cannot provide a yield benefit.

In Type C2 situations the lack of an EEF effect on yield is due to lack of N responsiveness of the crop (specified as Nopt < 30 kg N/ha). This can occur when the soil can supply all N required by the crop, a situation often seen in plant crops, especially after legumes. Or it can result from other factors reducing the crop yield potential (e.g. prolonged waterlogging).

Most of the analyses of virtual trial results discussed below draw on this classification. It proved a useful way to quantify and explain outcomes. It also provided the means to add information on likelihood to the decision support logic.

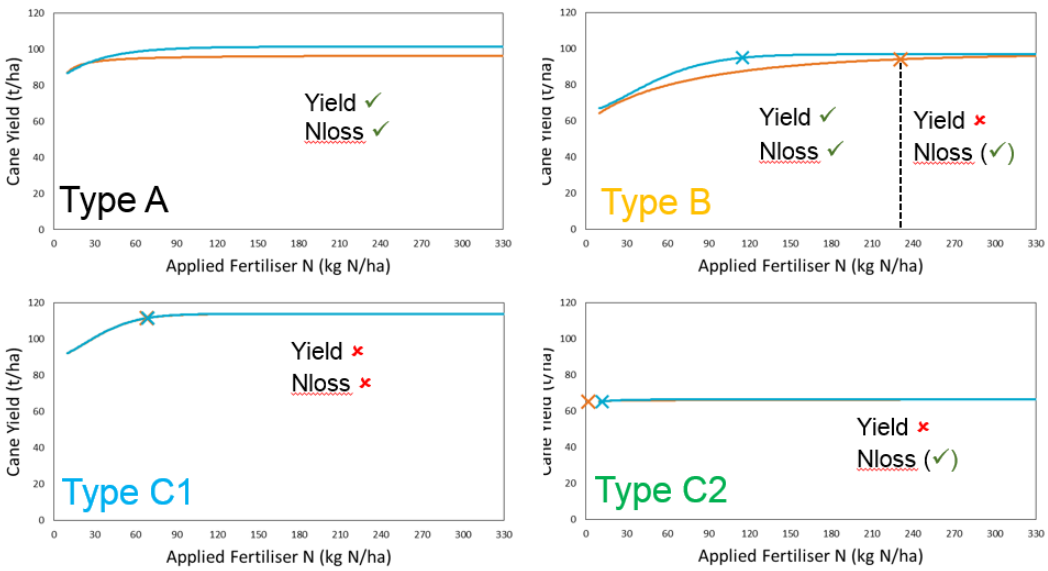

Figure 8. Classification of responses to EEF into four types (see text for details). Blue (CRF) and orange (urea) yield response curves fitted to the predicted yields for crops harvested in November 1981 (Type A), July 2011 (Type B), September 2016 (Type C1) and November 1991 (Type C2) on the Lugger soil. Coloured crosses represent the Nopt. Source: Verburg et al. (2019) with permission.

6.3. Effect of longevity of nitrification inhibition on N loss and yield

We virtually tested the effect of the persistence of NI on N loss and yield on two soils of contrasting properties. We found that increasing the half-life of the NI was correlated with a reduction in N loss in both soils (Figure 9A). In the heavy-textured Hamleigh soil, a half-life of 120 days had the largest effect on simulated N loss relative to the urea treatment (median reduction across the 68 years of 77 kg/ha). In contrast, a half-life of 7 days had a small effect on N loss (median of less than 5 kg/ha). Similarly, in the light-textured Lugger soil the reduction in N loss was greater with a half-life of 120 days (median = 62 kg/ha) than a half-life of 7 days (median < 2 kg/ha). In this soil, change in N loss were small as the half-life increased from 60 to 120 days. The results suggest that NI with half-lives lower than ~28 days are likely to provide only small benefits in terms of N loss compared with urea alone.

The reduction in N loss did, however, not always translate into yield benefits (Figure 9B). In the heavy-textured Hamleigh soil the median yield increase was <1 t/ha across all simulated half-lives. However, in the light-textured Lugger soil the yield increased with increasing half-life attaining a maximum improvement of ~7 t/ha.

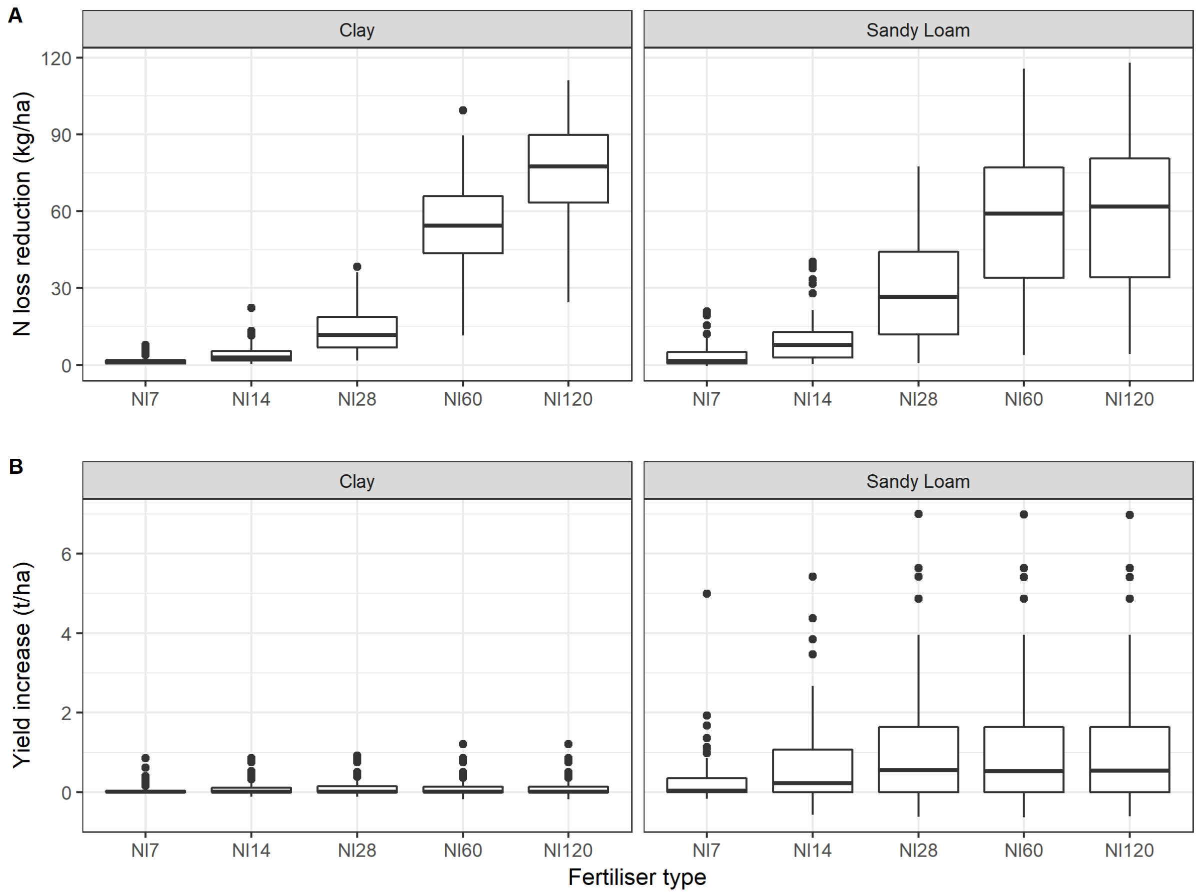

Figure 9. Simulated N loss reduction (A) and cane yield increase (B) relative to urea in a heavy-textured clay soil (Hamleigh) and a light-textured sandy loam soil (Lugger). Each box shows the median and the inter-quartile range (25–75 percentiles) based on 68 years of simulations. Source: Vilas et al. (2019c) with permission.

A paper describing this analysis in more detail, Vilas et al. (2019c), used daily model output of soil nitrate and ammonium contents, cumulative N loss by denitrification and leaching, N uptake and cane yield to explain that the small yield benefits related to the crops inability to use the 'saved' N in the chosen scenario. The virtual trials were run with a single rate for each soil, 130 kg N/ha for the Hamleigh soil and 150 kg N/ha for the Lugger soil. After assessing the N response to urea it was established these rates were below the optimum N rate of urea in only ~2% of years in the Hamleigh soil and in ~15% of years in the Lugger soil (Vilas et al., 2019b,c). Referring to Type B EEF response in Figure 8 explains that yield benefits will only be obtained below the Nopt of urea. The low percentage of years where the N rate was below the optimum N, therefore, explains the small yield benefits predicted in this virtual trial. At lower N rates than the ones simulated here the N loss reductions achieved by the NI are more likely to translate into yield benefits.

The virtual trial results indicate that half-life of the NI strongly affects its effectiveness in reducing N loss. This highlights the importance of improving our understanding how microbial, soil and environmental factors influence the persistence of NI as this will determine their potential to provide agronomic and environmental benefits in sugarcane systems.

These results suggest that for the soils, climate and crop management simulated, NI have the potential to reduce N loss provided they can persist in the soil for at least 28 days. The exact half-life threshold below which there is no benefit in terms of N loss likely depends on the combination of soil and climate and thus further investigations are needed to assess the influence of soil and climate on the optimum half-life.

6.4. Effectiveness of CRF and NI for different N loss pathways

To test the decision point in the draft decision logic that suggested only CRF should be used on light soils (Figure 7) we performed two types of virtual trials. The first mimicked the Di Bella et al. (2017) glasshouse experiment described in Section 6.1 and the second drew on the large factorial of virtual EEF trials to compare results obtained with NI and CRF.

Simulation Di Bella et al glasshouse experiment

This virtual experiment was used to evaluate the effect of NI with a half-life of 7 and 28 days (NI7 and NI28, respectively) and a CRF on the mineral N concentrations in the soil and N loss in the two types of scenarios used in the Di Bella et al. (2017) experiment: leaching or waterlogging (Figure 10). For the leaching scenario, NI7 and urea had similar nitrate concentrations in the soil on day 50 (when experimental measurements were taken; 5 days after start of leaching), which led to similar leaching losses. In contrast, CRF and NI28 had lower nitrate concentrations in the soil compared with urea, with NI28 having the lowest concentrations. This resulted in lower leaching losses and N_2O emissions with NI28 and CRF compared with urea. The lowest leaching losses and N_2O emissions were obtained with NI28.

For the water logging scenario, NI7 and urea had similar nitrate concentrations in the soil by day 50, which led to similar N_2O emissions. CRF and NI28, however, had lower nitrate concentrations in the soil compared with urea, with NI28 having the lowest concentrations. This resulted in lower N_2O emissions with NI28 and CRF compared with urea, with lowest losses obtained with NI28.

The results of the simulations suggest that CRF and NI can both be effective in reducing N loss through denitrification as well as leaching. The proviso is that the NI lasts for sufficiently long to keep the nitrate concentrations in the soil low relative to those in the urea treatment.

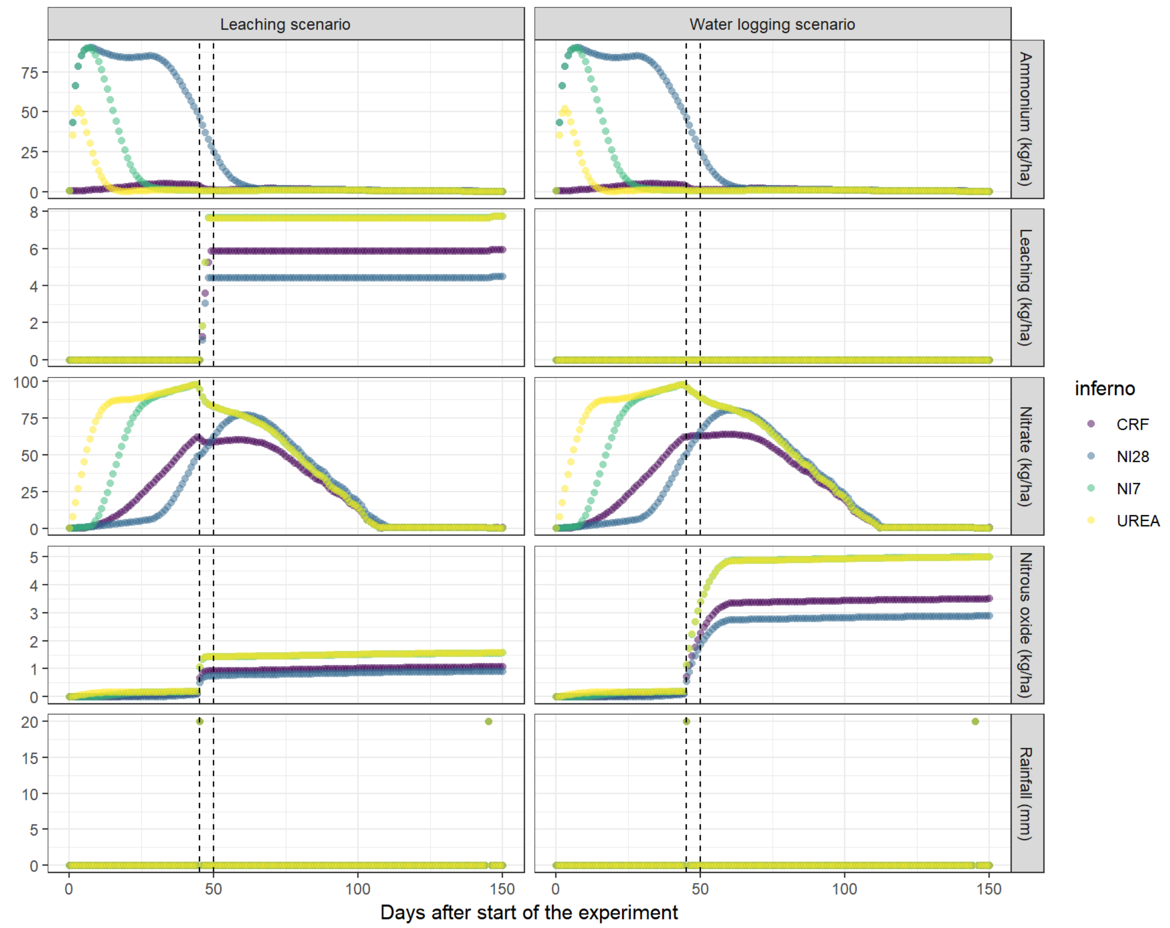

Figure 10. Ammonium (kg/ha), leaching (kg/ha), nitrate (kg/ha), nitrous oxide (kg/ha), and rainfall (mm) for the leaching and water logging scenario. The vertical dashed lines represent day 45 (rain water addition) and day 50 (when experimental measurements in Di Bella et al (2017) experiment were undertake). Rainfall graph shows the water additions on days 45 and 145. Light green reflects overlapping results of the Urea and NI7 treatments. Source: Vilas et al. (2019c) with permission.

The reduced effectiveness of NI in preventing soil N accumulation and N leaching loss in the actual glasshouse experiment could be explained if the persistence of the NI used was limited and hence the longevity of nitrification inhibition reduced. Elevated temperatures in the glasshouse could have contributed to reduced persistence of the NI. That would, however, not explain why the same NI would be more effective in limiting N_2O emissions. We have not been able to resolve this inconsistency between the experimental results of the two types of scenarios. As the N_2O measurements only represented a moment in time (measured over 24 hours on 5th day of waterlogging), the error bars were relatively high and the total N loss as N_2O was very small, it is difficult to determine exactly what happened. The fact that nitrate concentrations in soil measured on day 50 were below the detection limit may suggest that some of the gaseous losses may have occurred before the measurement period.

Virtual trials with CRF and NI

The virtual EEF trials with CRF and NI provide a second way to evaluate the relative effectiveness of CRF and NI on heavier and lighter soils. They have the added benefit of capturing a wider range of seasonal conditions. Here we present the predicted N loss as a function of fertiliser product (urea, CRF or urea with an NI with a half-life of 28 days (NI28) under sugarcane grown on three soils with contrasting soil properties (Figure 11). In the heavier Hamleigh soil, the CRF and NI28 treatments had slightly lower denitrifications losses than urea (median of 75, 70, and 65 kg/ha for urea, CRF and NI28, respectively). Similarly, both the CRF and NI decreased the leaching losses (median of 37, 33, and 30 kg/ha for urea, CRF and NI28, respectively). When compared with other soils, the Hamleigh had higher denitrification N loss but lower leaching losses. In both the Macknade and Lugger soils denitrification N loss was small. The proportion of N loss via denitrification and leaching pathways relates to the properties of these soils, with Hamleigh a heavy soil subject to waterlogging, Lugger a highly permeable soil and Macknade intermediate.

As in the virtual experiment mimicking the Di Bella et al. (2017) glasshouse trial, both CRF and NI reduced leaching losses in both soil types. The recommendation in the draft decision support logic to use only CRF on lighter soils does, therefore, not appear to be supported. Additional investigation using detailed experimental observations could, however, be warranted to further explore the experimental results of Di Bella et al. (2017).

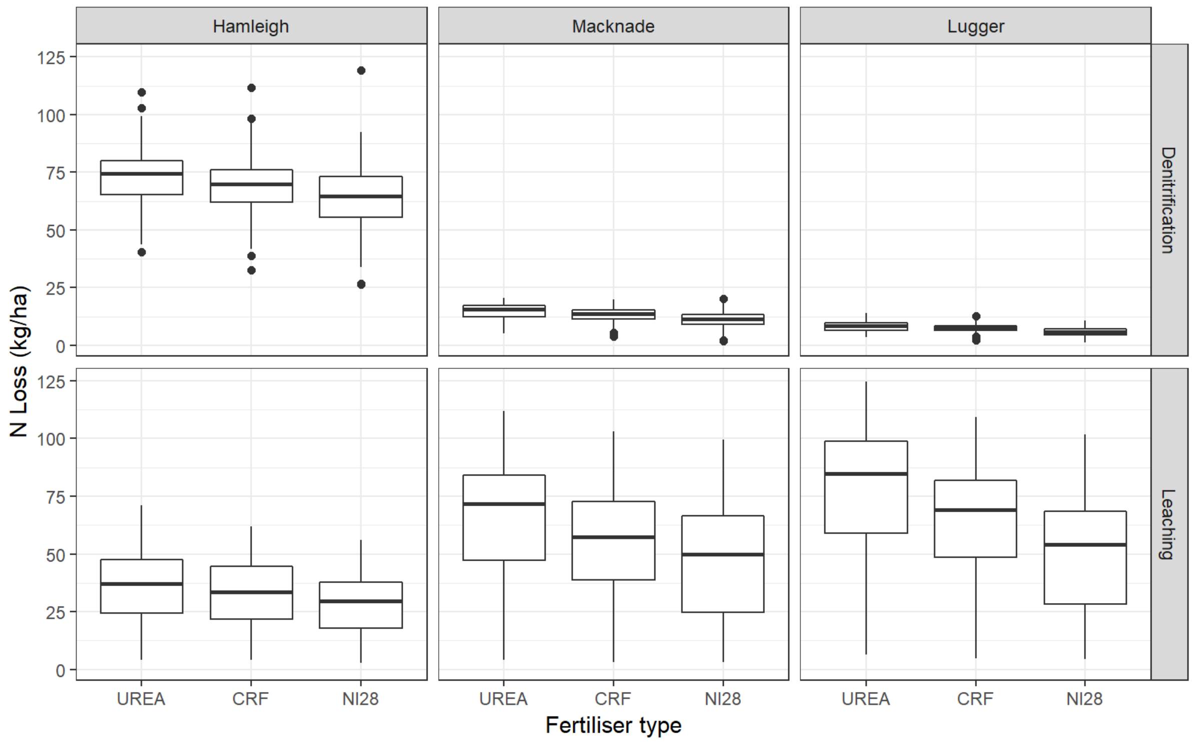

Figure 11. N loss (kg/ha) for the Hamleigh, Macknade and Lugger with urea, CRF and NI28. Each box shows the median and the inter-quartile range (25–75 percentiles) based on 68 years of simulations.

6.5. Quantification of likelihood of EEF responses and key drivers

When we classify the EEF responses that are obtained in the virtual EEF trials over 68 seasons according to the four types distinguished in Section 6.2 we can quantify the likelihood of the different EEF responses as a function of soil type, product and crop start date. Here we focus on the same three soils as above and consider three crop start dates as well as three EEF products: CRF, NI7 and NI28. The simulations were performed for the Eastern part of the Herbert mill area, which means the Hamleigh soil was affected by a water table limiting the rate of drainage. While the

Lugger soil only occupies a very small area in the Eastern Herbert mill area it was included to provide a contrasting highly permeable soil.

The use of EEF will be attractive in situations where the likelihood of Type A and B responses is high, but less so where either Type C1 or C2 dominate. The results in Figure 12 show that in all three soils Type C1 responses dominated for the 15 September crop start of ratoons.

The proportion of Type C1 responses decreased with later crop start dates, whereas that of Type B responses increased. These patterns were consistent for all three products. Type A responses occurred only in a small percentage of years, although its proportion generally increased with later crop starts too.

The proportion of Type C2 responses was more variable as a function of crop start date, but also strongly soil dependent. The Hamleigh soil as simulated in the context of climate and landscape position of the Eastern Herbert mill area has an increased propensity to experience prolonged waterlogging. This results in a relatively high proportion of Type C2 responses where the EEF response is lost due to lack of N response. This reduces the proportion of Type B responses compared with the better drained Macknade and Lugger soils. While in the Hamleigh soil the proportion of Type B responses was lower than 25% for all crop start dates, in the lighter soils the proportion of Type A and B responses were ~50% and >50% for the 15 December crops on Macknade and Lugger soils, respectively.

The proportion of Type A responses is highest on the Lugger soil. Its high permeability increases the chance that all applied fertiliser is lost during large events, but also ensures that crop growth is not hampered by the wet conditions and the crop can use the 'saved' N.

As already discussed in Section 6.3, a reduced half-life of the NI reduces its effectiveness. The proportion of Type C1 responses increases at the cost of Type B responses, because the likelihood of N loss events is reduced with the shorter duration of nitrification inhibition. This effect is most noticeable in the more permeable Macknade and Lugger soils.

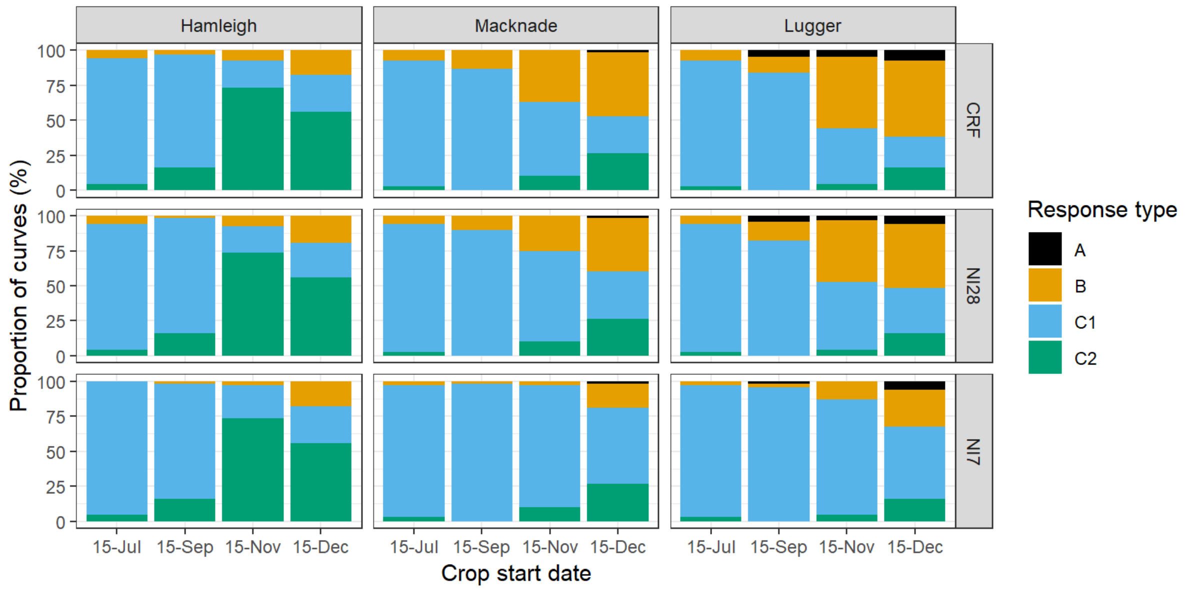

Figure 12. Proportion of response type curves for the clay (Hamleigh), loam (Macknade) and sandy loam (Lugger) soils with CRF and NI28. Adapted from Verburg et al. (2019).

These results confirm that CRF and NI are more likely to provide benefits in late crops than in early crops. This justifies the decision point in the decision support logic to provide separate advice for early and late crops.

To explore whether the virtual trials can help define the cut-off between early and late crops, Figure 13 shows how the proportion of response types changes as a function of crop start date for the Hamleigh and Macknade soils. The crop start date was increased in 14 day intervals. In both soils the C1 response was dominant in early crops with its proportion exceeding 85% of seasons for both EEF until mid-September for the Hamleigh soil and mid-October for the Macknade soil.

As the proportion of Type C1 responses decreases on the Hamleigh soil, the likelihood of Type C2 responses rapidly increases and becomes the dominant response from mid-October. The proportion of Type B responses increases more gradually and remains relatively small. On the Macknade soil the decrease in Type C1 responses is accompanied by an increase in type B responses and only later does the incidence of Type C2 responses increase as well.

The results suggest that both CRF and NI can reduce losses through both denitrification and leaching pathways, and so a soil type decision point based on loss pathway was no longer warranted. However, the heavy and light soils differed in their EEF response classification types and so a decision point on soil type would still be appropriate to capture the different response type dynamics. Even so, nominating a clear cut-off date for contrasting advice for early and late crops is not simple. Should it be based on the date where the dynamics changes most rapidly, where there is a change of dominant response type or where the proportion of Type B responses exceeds a certain level? And if the latter, what proportion would be appropriate – what constitutes an acceptable risk for not getting the intended Type B response from the EEF?

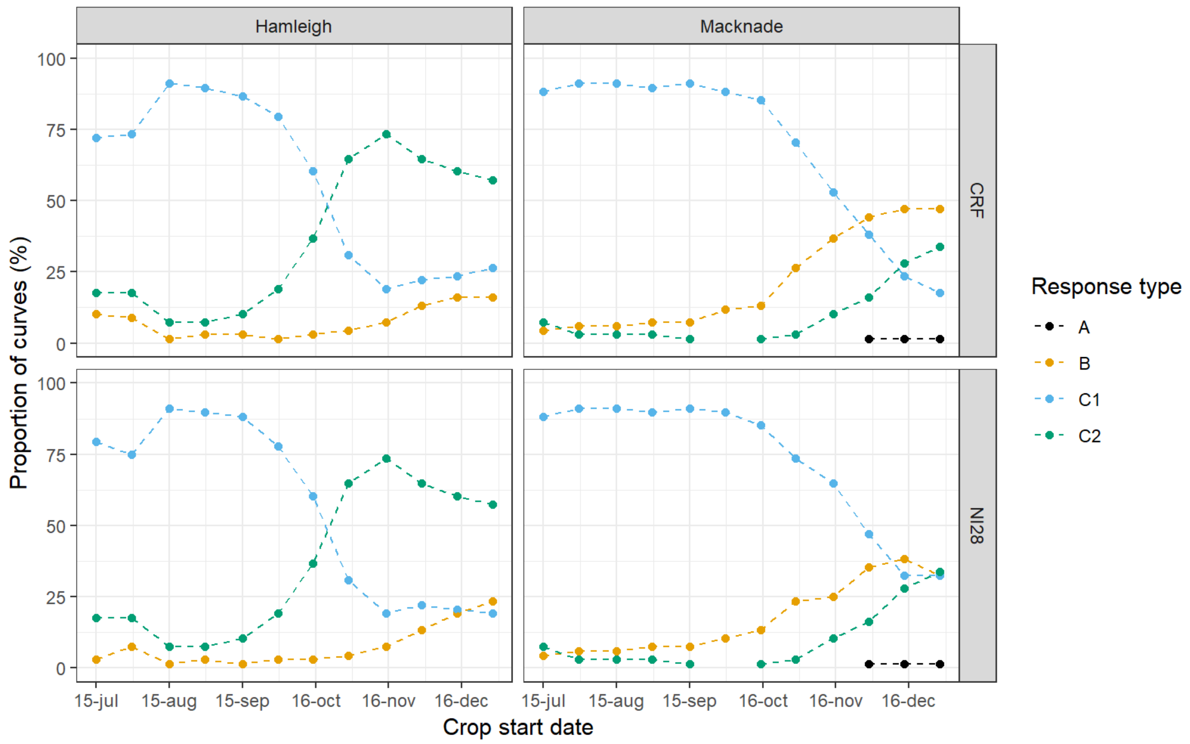

Figure 13. Proportion of response types (A, B, C1, and C2) for Hamleigh and Macknade soils with CRF and NI28.

This dilemma and the fact that even for late crops the proportion of Type B responses is by no means guaranteed, suggests there is a need to find better ways to distinguish between seasons in which late crops do achieve Type A or B responses and those in which Type C1 or C2 responses are obtained.

The draft decision support logic had identified a wet outlook as an earlier decision point. In addition, we know that Type B responses require an N loss event to occur during the period that the EEF provide protection. If not, a C1 response is obtained. Therefore, we examined the risk of N loss within the first 90 days after the application of urea for the different start dates (Figure 14). For the Hamleigh soil, the risk of N loss gradually increased in crops started between 15 July and 15 October. In addition, in crops started between 15 October and 30 November the risk of N loss rapidly increased, stabilising thereafter. For the Macknade soil, there were little losses in crops started between 15 July and 15 of October. However, the risk of N loss rapidly increased in crops started later than 15 October.

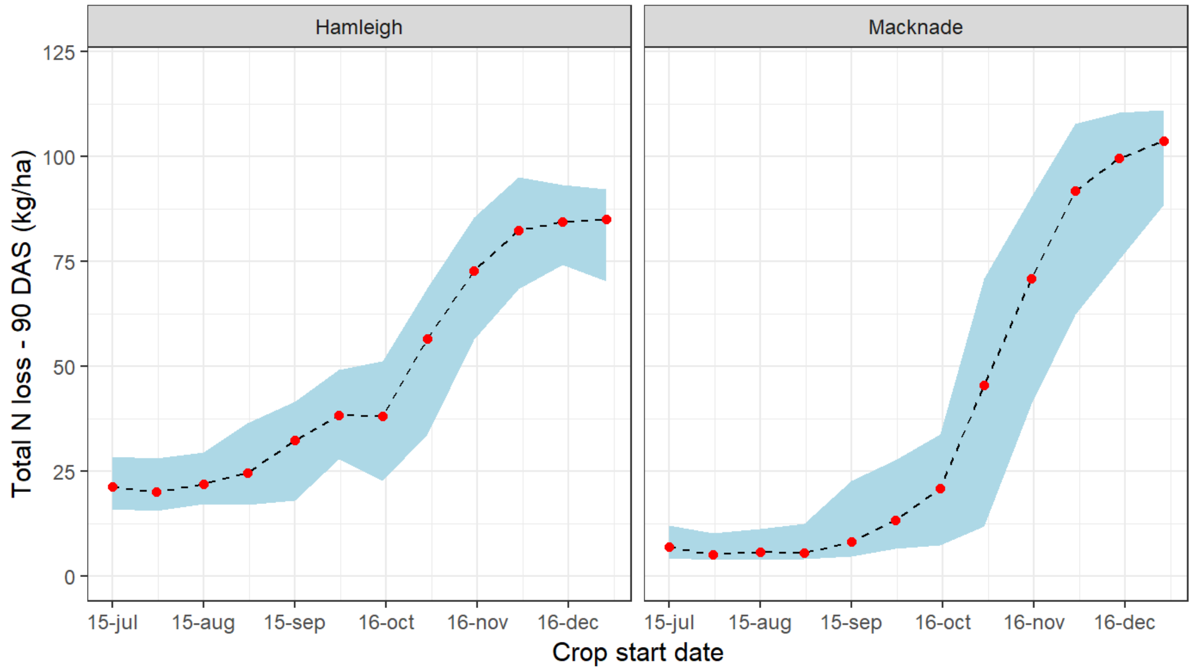

Figure 14. Median total N loss (kg/ha) (red dots) between 0 and 90 days after the crop was started (DAS) for urea; blue band indicates the interquartile range.

As the proportion of Type B response was higher in late crops and these were accompanied by higher N loss in the first 90 days after crop start, it is expected that early rainfall is an important predictor of the response type. To verify the relationship between early rainfall and response type we evaluated the total rainfall in the first 15, 25, 50 and 75 days after fertiliser application (Eastern Herbert climate zone) and compared the median rainfall by response type as achieved on a Hamleigh soil (Figure 15). We found that the rainfall amount within 15 and 25 days after fertilising was similar for the different response types, but that the rainfall amount within 50 and 75 days after fertilising was higher for the Type B response. This indicates that the rainfall amount within 50 and 75 days after fertilising would be a better predictor of response type than the rainfall amount within 15 or 25 days after fertilising. The importance of early rainfall in driving the benefits of EEF is further explored below in Section 6.6.

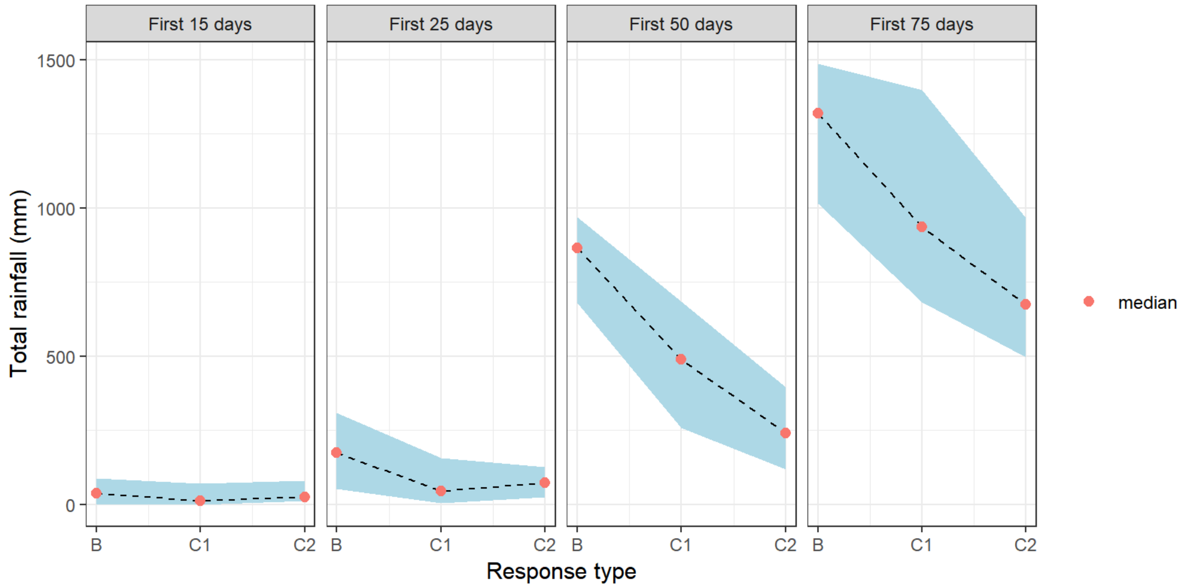

Figure 15. Median total rainfall (mm; red dots) in the first 15, 25, 50 and 75 days after fertiliser application relative to EEF response types as obtained in the Hamleigh soil. Blue band indicates the interquartile range.

6.6. Data-mining virtual trials

Classification tree analysis

A more formal approach to exploring predictors of EEF response types is to use classification tree analysis. It draws on the simulation results themselves to statistically derive the best predictors for benefit of EEF relative to urea. This results in trees that look like decision trees, but with the added advantage that they can provide the likelihood of different outcomes. To what extent the classification trees can be used as decision trees themselves depends on the predictors used. Many different predictors could be chosen and not every selection will work equally well (provide good accuracy of prediction) or be useful for practical purposes (e.g. if the predictor is something one only knows after the fact such as rainfall during the first 75 days after the crop start date).

The purpose of this preliminary analysis was to explore whether it provides a more robust approach to build or inform EEF decision support logic. It was also an early investigation into the role of climate indictors to improve the prediction of different responses for the late crops. Having a set of predictors of conditions that lead to an 80% or more likelihood of obtaining a Type B response would be a big step forwards.

The preliminary analysis was limited to the top 9 soils in the Eastern Herbert climate zone. This includes the Hamleigh and Macknade soils used in the analyses presented earlier in this section, but not the highly permeable Lugger soil. Outcomes are specific to the parameterisation of these soils relative to the climate and position in the landscape in the Eastern Herbert mill area. Results may differ in drier parts of the catchment and in other regions (see Discussion in Section 6.7).

The analysis consisted of three stages. The first did not consider rainfall or seasonal climate outlook. The second explored whether early rainfall could help separate the different responses. As rainfall is only known after the fact, a third stage replaced early rainfall by the June to August Oceanic Nino Index (JJA ONI) phase.

For each classification the methodology establishes the accuracy of the prediction. It tests the tree on 30% of the data not used to develop the classification tree. This helps establish how often the classification tree predicts an outcome correctly.

Stage 1

The accuracy for the final pruned classification tree based on the validation data set was 57%. The low accuracy likely indicates an over-looked predictor. All predictors supplied were used in the resulting tree (Figure 16). The primary predictor selected was the crop start time (CropStart) with the early starts (July and September) separated from the later starts (November and December). The resulting tree did not produce a terminal node dominated by Type A responses. Other observations were as follows.

- Type A responses were not clearly isolated.
- Type B responses were most dominant when the crop was on a Macknade soil and started in December (see far left in Figure 16).
- Type C1 responses were most dominant in the earlier crop start times (July and September).
- Type C2 responses were similarly dominant when the crop was started later (November and December) and was on an Ingham, Palm, Toobanna, Trebonne, or Yuruga soil. The tree continued to split according to EEF type and soil but there was little difference in the outcomes. The lack of clear distinction in the outcomes for these lower branches is likely related to the low accuracy of the fitted classification tree.

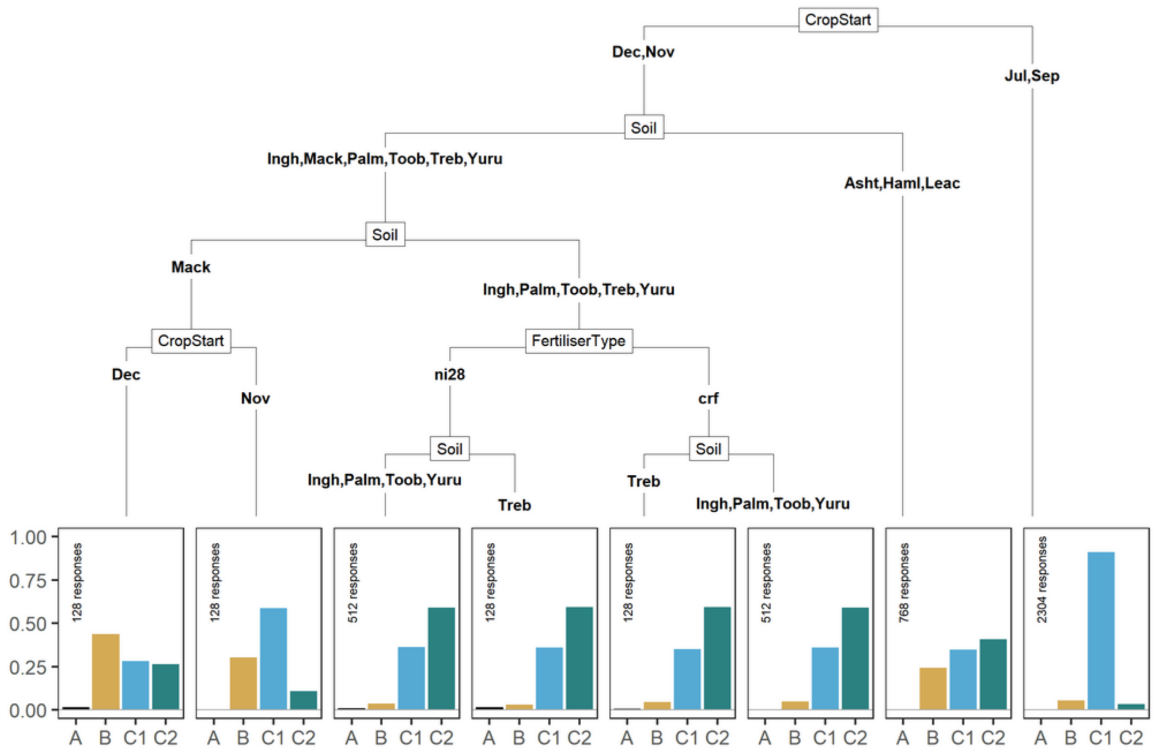

Figure 16. Classification tree fitted using rpart to predict response type according to list of predictors in Table 3. Number of responses in each terminal node are included.

Stage 2

Early rainfall after fertiliser is suspected to be important in the effectiveness of EEF. The analysis was performed using the rainfall within 75 days after fertiliser (EarlyRain) as an additional predictor. The accuracy for the pruned classification tree, tested using the validation data set, was 73%. This was a marked improvement in predictive accuracy over Stage 1. All predictors were used in the resulting tree except fertiliser type (Figure 17). The primary predictor selected was the total rain within 75 days of fertiliser (EarlyRain). The dataset was split at a value of 307.2 mm which was similar to the median rainfall for this period of 290 mm. This predictor was also used further down in the decision tree but the decision was based on larger volumes of rainfall. Other observations were as follows.

- Type A responses were most dominant when the total rainfall within 75 days after fertilising was between 893 and 893.4 mm (far left terminal node). As mentioned previously, this is a result of the very small frequency of Type A class responses (i.e. 9 responses). In fact, on the selected soils almost all instances of Type A responses occurred in a single year which explains the tight range of early rainfall totals (893 - 893.4 mm) identified in the classification tree.
- Type B responses were most dominant when the early rainfall was between 307.2 and 893 mm and the soil was Ashton or Macknade.
- Type C1 responses were most dominant when the early rainfall was < 307.2 mm and the crop was started early (July or September). It was also dominant in later crop starts for soils other than Hamleigh, Leach and Toobanna.
- Type C2 responses were most dominant when early rainfall was between 893.4 and 1037 mm on the Toobanna soil. There were a number of other scenarios for which Type C2 was the most dominant of the four response types.

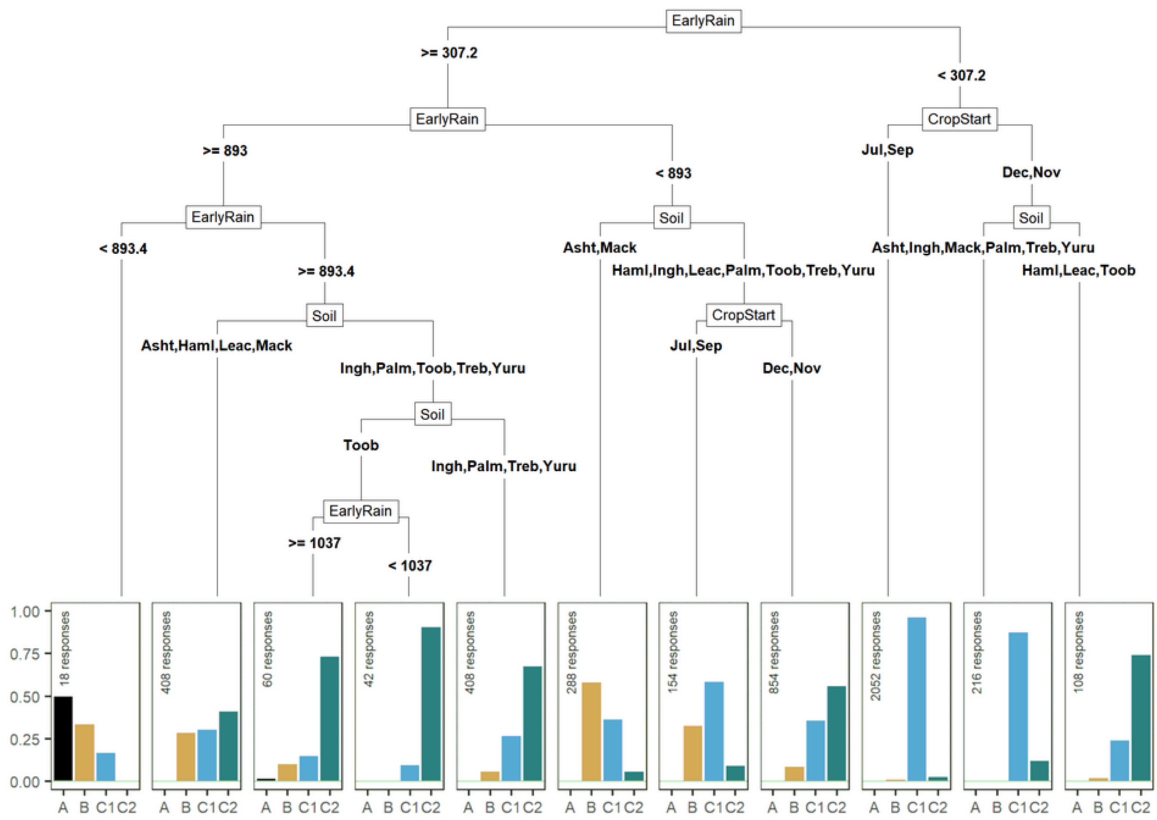

Figure 17. Classification tree fitted using rpart to predict response type according to list of predictors in Table 3. Number of responses in each terminal node are included. Median rainfall across all the crop start times was 290 mm.

Stage 3

In the absence of perfect knowledge of rainfall soon after fertilising, climate forecasting indices may be useful. In this demonstration, June to August Oceanic Nino Index (JJA ONI) was used.

The accuracy for the pruned classification tree, tested with the validation data set, was 66%. The accuracy was not as good as the tree based on perfect knowledge of the rainfall soon after fertilising (Stage 2) but was still better than relying solely on the crop start time (Stage 1). The primary predictor was the JJA ONI index with the split occurring at 0.65. Typically, an El Nino is forecast when the JJA ONI is above 0.5 (Figure 20).

- Type A responses were not dominant in any of the nodes but were all grouped together into a single node where the JJA ONI index was between 0.65 and 0.75 (El Nino conditions) and the crop was started late (November or December). This at first seems contradictory but the problem arises from the fact that all the Type A responses occurred in a single year where the forecast was for El Nino conditions but >1000 mm of rain fell in January which was within 75 days after fertiliser for these late crops.
- Type B responses were not the most dominant in any of the nodes but the node with the greatest proportion of Type B responses was when JJA ONI was < 0.65 and the crop was started late (November and December) and the soil was Ashton, Leach or Macknade.
- Type C1 responses were clearly dominant in a number of nodes but most dominant when JJA ONI was between -0.55 and 0.65 (similar to Neutral conditions) and the crop was started early (July or September).
- Type C2 responses were most dominant when JJA ONI was < 0.65 and the crop was started late (November or December) on soils other than Ashton, Leach and Macknade.

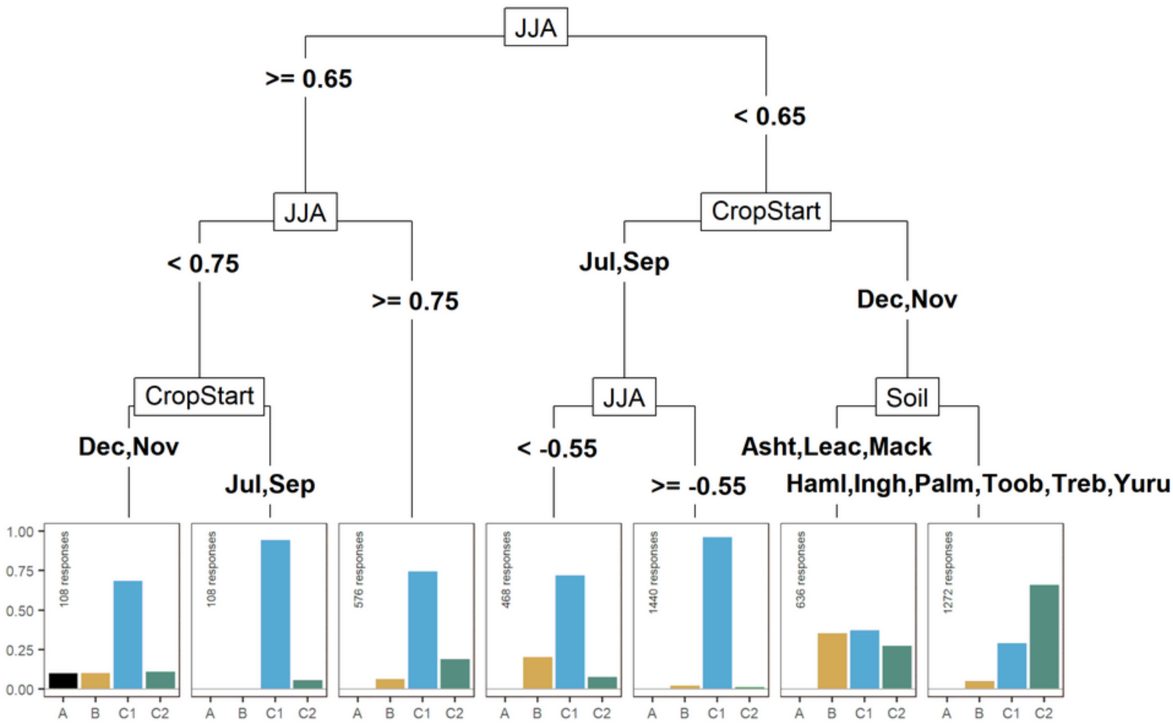

Figure 18. Classification tree fitted using rpart to predict response type according to list of predictors in Table 3. Number of responses in each terminal node are included. La Nina is predicted when JJA ONI < 0.5 and El Nino is predicted when JJA ONI is > 0.5. Between these thresholds conditions are forecasted to be Neutral.

Lessons

The above preliminary analysis provides a few early lessons.

- It highlights that climate predictors need to be included in the decision support logic to improve prediction accuracy.
- Early rainfall is an important predictor, but does not fully differentiate between the Type A or B responses and the Type C1 and C2 responses. Further work would need to explore other or complementary climate indicators. For example, early season conditions that would be suitable for Type A and Type B responses can turn into Type C2 responses if the season stays wet and causes crop growth limitations.
- Suitable forecasting of these climate indicators would also require further analysis. It will reduce the prediction accuracy relative to perfect knowledge of the climate indicators as forecasting error can cause misclassifications. These preliminary results indicate, however, that their inclusion is still better than not considering them at all (cf. stage 1 and 3). It will also be better than a qualitative “wet or dry season outlook”, which could be interpreted in many different ways and consider the wrong part of the season (e.g. a wet season could have a dry start).
- The results indicate that inclusion of soil type and start-date decision points in the draft decision logic was appropriate. However, as already seen in Figure 13, there is an interaction between soil type and start date, which relates to how the soil copes with different amounts of rainfall.
- The tree classification also indicates that the soil type decision would not be a simple differentiation between “light” and “heavy” soils, although it still needs to be explored whether instead of soil type names, actual soil permeability characteristics may be able to provide better groupings.
- The tree classification can lead to complex trees, which may not lend themselves as industry decision tool. Careful testing of different predictors may help obtain trees that strike a balance between simplicity and prediction accuracy.
- Alternatively the tree classification results could be used to inform rather than replace the decision support logic developed from conceptual understanding.

6.7. Discussion

Why it is challenging to capture EEF benefits in field trials

The high frequency of Type C1 and C2 responses predicted in the virtual EEF trials provide an insight into why so many experimental trials are unsuccessful in obtaining statistically significant treatment effects, even if the issue of measurement precision was resolved. But even when late ratoon crops are targeted and wet conditions do occur it may be difficult to capture the EEF benefits. The simulation results in Figure 19 show why.

Most field trials are run with a limited set of N rates, often only two – one at a standard practice or recommended (e.g. 6ES) rate and one at a reduced rate. The results obtained with such trials can (Figure 19a, b) correctly reflect the benefits, (Figure 19c) underestimate the benefits, or (Figure 19d) miss the benefits, depending on the values of Nopt for urea and EEF relative to the N rates in the trial. Similarly, lack of EEF and N response at two rates could represent a Type C2 response or be a Type B response that was missed (experimental N rates above the Nopt for urea). This reinforces the need to complement field trials with virtual trials.

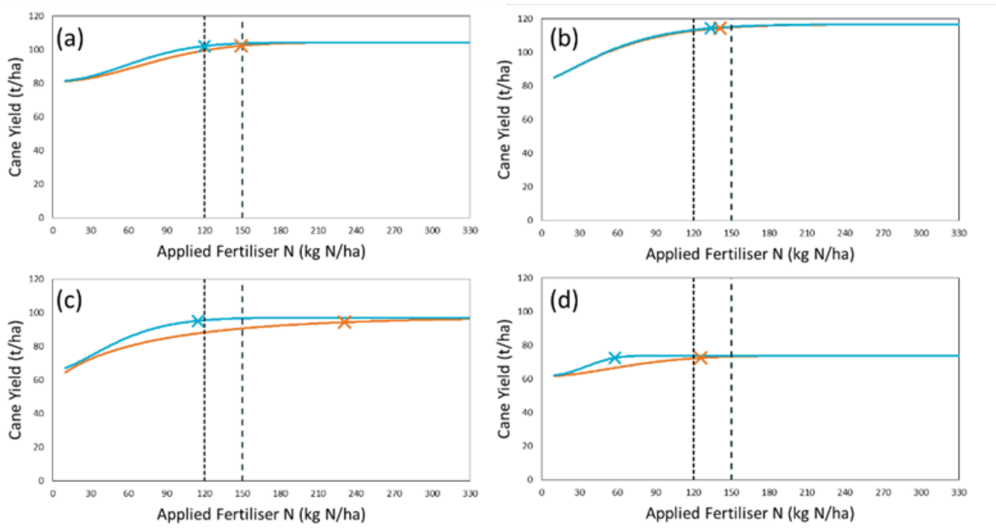

Figure 19. Illustration of the challenge of demonstrating yield or Nopt reduction benefits – the EEF effect may be (a, b) reflected correctly, (c) underestimated or (d) missed if only limited N rates are used in the experimental trial. Source: Verburg et al. (2019) with permission.

Changes to draft decision support logic

The work in this project has confirmed decision support logic is required to achieve more consistent benefits from EEF through allowing tactical use. The principles of the draft decision support logic developed by HCPSL that formed the starting point for the project were largely supported by the results from the virtual EEF trials. The results did suggest some fine tuning (Figure 20) as follows.

- There did not seem to be a case for limiting the EEF product choice to CRF for light soil. This means that much of the decision support logic then relates to not the choice of fertiliser product but whether use of EEF would be beneficial.
- EEF product distinction was confirmed for surface application.
- EEF product distinction in relation to intended early harvest of crops has not yet been tested.
- Soil type would still need to be considered as a decision point in the logic as this was found to impact on proportions of EEF response types and interacted with the start date factor.
- The seasonal climate outlook decision point which was not tested in this project has been shown to be important and will require further investigation to specify what climate indicators would give the best differentiation between EEF response types.

The discussions held at the two project workshops further clarified that the decision tree logic should be limited to the question whether EEF could provide agronomic or environmental benefit or not. It would assume best management practice is otherwise used to maximise the EEF benefits. This would include ensuring that the chosen N rate meets, and is not in excess of, crop requirements. It is acknowledged that this is a challenge in itself.

The decision support logic does not predict the economic benefits from EEF. These would need to be considered separately when the decision support logic indicates that agronomic and environmental benefits would be achievable.

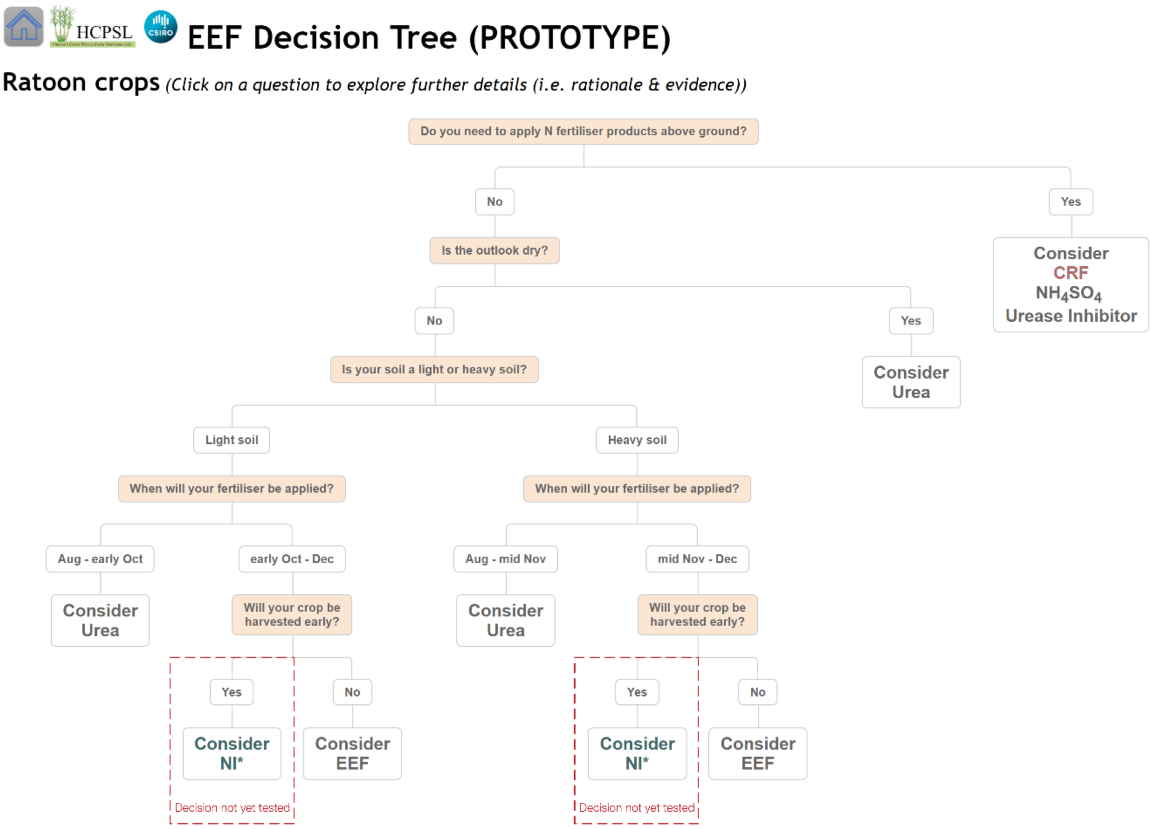

Figure 20. Revised decision tree. The * and dashed box indicate that this part of the decision has not yet been tested.

Extrapolation to other parts of the Herbert mill area and other regions

This project was a Herbert mill area pilot and in this first year most of the analyses focussed on the Eastern Climate zone. Given that the draft decision support logic is based on conceptual understanding of how EEF provide benefit and that this was corroborated by the various analyses carried out as part of this project, it is expected that the principal drivers will translate across to other parts of the Herbert mill area and to other regions within the Australian sugarcane industry.

The decision support tree logic will, however, require adaptations. Under different climate conditions and management practices the proportions of different EEF response types are likely to vary. SRA Project 2014/011 already noted different effectiveness of CRF in different regions (Verburg et al., 2017a). If we draw on their simulation results for four scenarios from the Burdekin and classify the EEF responses according to the scheme developed in this project (Figure 21) we obtain quite a different picture compared with that for soils in the Eastern Herbert mill area (Figure 12). The heavy (clay) soil in this case does not lead to Type C2 responses. This is due to the higher yield potential of these crops, which were limited less by waterlogging and received a higher radiation input. Crop start date (time of harvest of previous crop) was a key discriminator with more Type B responses for late crops. Type A and B responses were also obtained more frequently on the lighter soil compared with the heavier soil, especially for early ratoons.

The results in Figure 21 also enforce the message above that less well adapted EEF, in this case less well synchronised CRF products, will have reduced benefits (with Type B most affected) and change the proportions of different responses. It would need to be evaluated whether this would change the predictors in the classification trees.

Another lesson from the parallel validation of N responses for SRA Project 2017/09 was that soil type in itself was insufficient to capture soil water balance effects caused by the presence/absence of water tables. We learnt that relatively shallow water tables as experienced in the Eastern Herbert mill area could lead to waterlogging issues, with a negative impact on crop growth through oxygen deficit stress, as well as provide supplemental water for the crop, which could relieve water stress and hence improve crop growth during dry periods. The yield potential and shape of the yield N response curve are impacted by these processes and have in turn a large effect on the proportion of Type C2 versus Type A and B responses. It is possible the effects of waterlogging have been overestimated and hence the proportion of Type C2 responses. Therefore, it is critical that the predicted N responses are validated locally for people to be able to rely on the predicted outcomes.

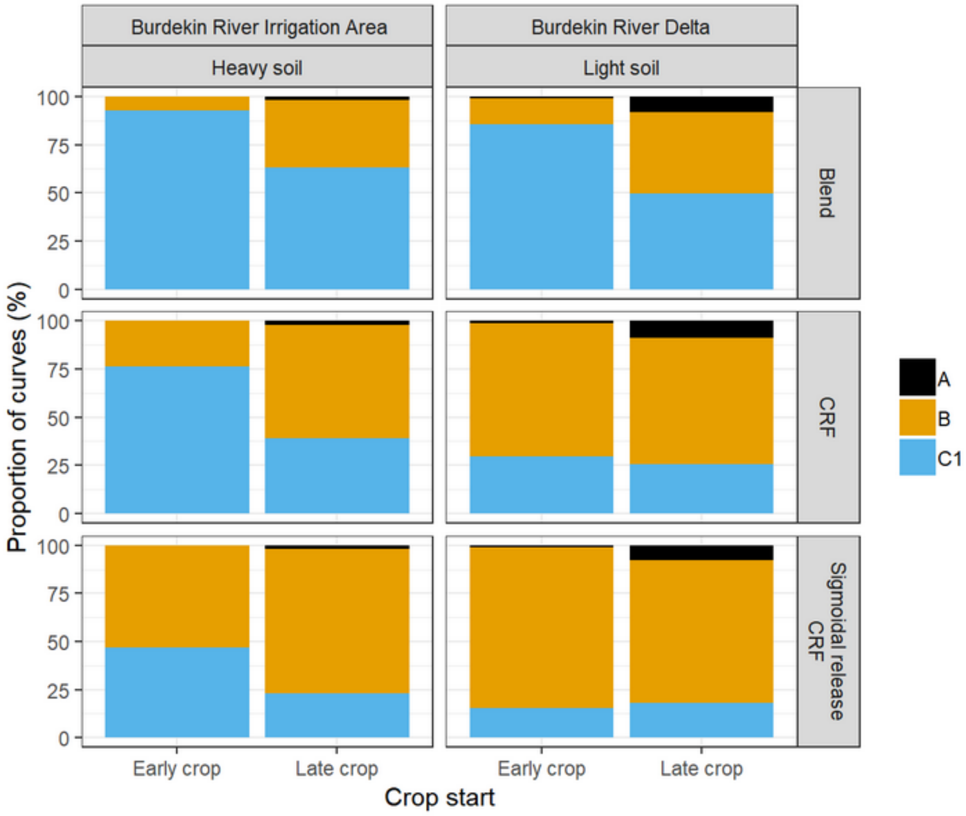

Figure 21. Proportion of different EEF response types obtained for three CRF products on heavy soil in the Burdekin River Irrigation data or a light soil in the Burdekin River Delta. Classification of responses seen in simulations performed as part of SRA Project 2014/011 (Verburg et al., 2017a). No C2 responses were simulated. Blend was a 50-50 Urea – CRF blend. Sigmoidal release was a hypothetical release product.

Adoption and potential benefits from tactical use

The idea behind the development of a decision support logic is to allow tactical use of EEF in situations where they will provide agronomic and environmental benefit. Knowing when EEF will not provide agronomic benefit can save the grower a price premium of at least 15% that these EEF products attract. Knowing when EEF will provide benefits can reduce the amount of N loss and allow N rate to be reduced while still achieving the same yield.

We get a feel for these potential N loss and N rate reductions by considering the seasons that produced Type B responses. This is shown in Figure 22 and Figure 23 for three of the soils studied in this report. Across the virtual EEF trials run with these soils the use of EEF can reduce the N loss and the agronomic optimum N rate by between 25 and 70 kg N/ha in 50% of years where there is a Type B EEF response. Summed across the industry it would be a step change in generating benefits from EEF if we can identify these years using decision support logic.

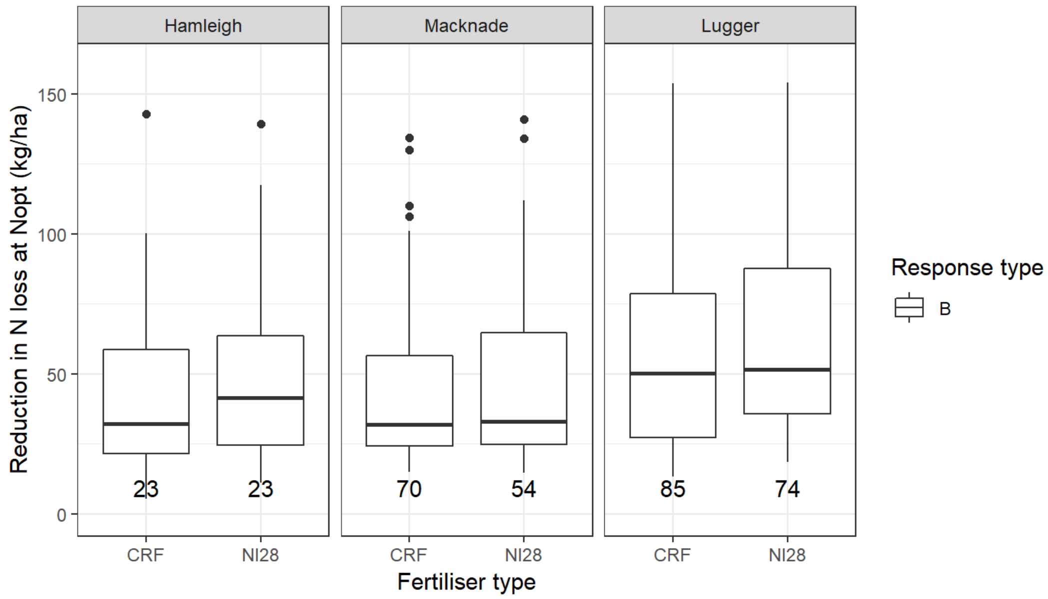

Figure 22. Reduction in N loss at optimum N (Nopt) for CRF and NI28 in a Hamleigh, Macknade and Lugger. Each box shows the median and the inter-quartile range (25–75 percentiles) based on 68 years of simulations. The vertical lines represent the whiskers. The numbers below each plot indicate the number of observations.

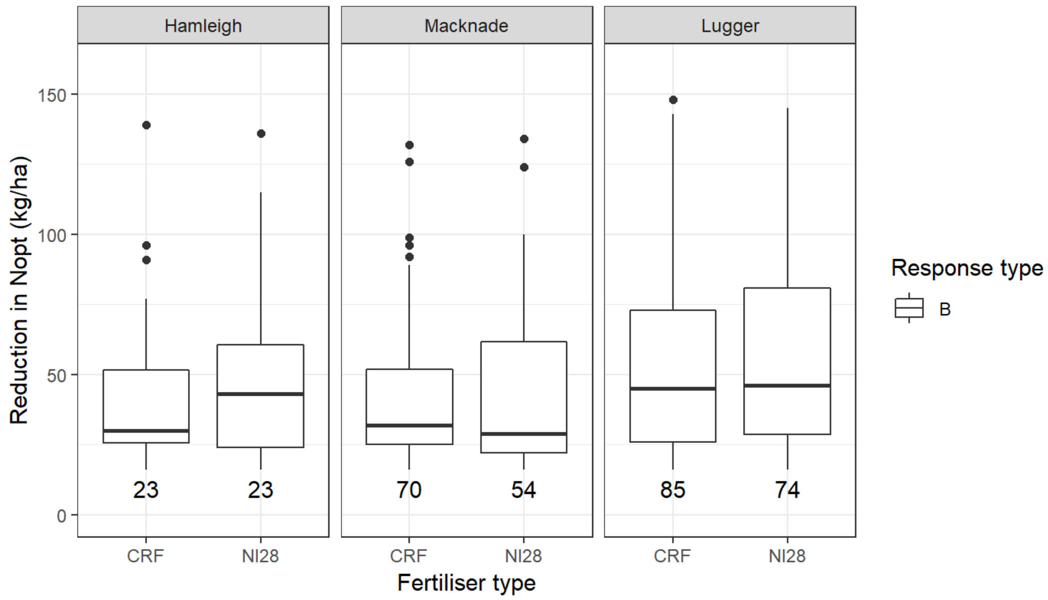

Figure 23. Reduction in optimum N (Nopt) for CRF and NI28 in a Hamleigh, Macknade and Lugger. Each box shows the median and the inter-quartile range (25–75 percentiles) based on 68 years of simulations. The vertical lines represent the whiskers. The numbers below each plot indicate the number of observations.

7. CONCLUSIONS

The discussions held as part of the project, modelling of virtual trials and their analysis resulted in many new insights and lessons. Below these are summarised under the five overarching project messages.

1. Characterising the benefits from EEF experimentally is challenging, but modelled 'virtual' trials can fill knowledge gaps.

Characterising benefits from EEF experimentally is challenging because of the following reasons.

- Responses to the use of EEF are highly variable from season to season. There are many situations in which measurable agronomic and environmental benefits may not be realised.
- The response of cane yield to N application and the resulting optimum N rate are seasonally variable. With agronomic benefits of EEF usually only obtained below the agronomic optimum N rate, this means that the benefits from EEF can be missed if the N rates used are higher than the optimum N rate for that cropping season.

To improve the likelihood of demonstrating benefits from EEF experimentally we provide the following recommendations.

- Conditions that increase the likelihood of N loss in the first three months after the start of the crop but that do not limit crop growth should be targeted; e.g. later ratoon crops for which yield is not limited by other factors such as waterlogging.
- Complete yield N response curves need to be determined in order to quantify the magnitude of the EEF benefits.
- For trials of CRF the release of N from the CRF product should ideally be assessed within the trial (e.g. using mesh bag method described in Final Report of SRA Project 2014/011) to provide confirmation of release under local conditions.
- In plot-based experiments, sufficient replicate measurements need to be taken to overcome both the low precision caused by spatial variability inherent in sugarcane fields, the error associated with assessment of plot-based yields, and the likely flatness, in many cane fields with a history of fertilizer use, of the N response curve; the use of just three replicates appears in many situations to require a yield difference for statistical significance that is larger than the yield differences achieved with EEF. Strip-based or spatially distributed approaches at scale may provide an alternative to plot-based experiments.

Modelling provides a means to carry out 'virtual trials' that can

- verify conclusions drawn based on limited experimental evidence;
- check internal consistency of experimental findings;
- 'repeat' experimental trials at different times, under different conditions and in different seasons;
- explore alternative scenarios and climate-soil-crop interactions;
- provide insights into the dynamics responsible for the presence or absence of benefits from EEF, e.g. through daily output of variables like soil N, N loss, crop growth and stresses.

2. The agronomic and environmental benefits from NI depend strongly on the longevity of nitrification inhibition, which is currently not well understood.

Modelling of NI in sugarcane systems has indicated that:

- Longevity of nitrification inhibition can be modelled by considering the persistence of NI in the soil and its bioactivity, but these parameters are not well defined, particularly for newer compounds like DMPP.
- The predicted longevity of nitrification inhibition has a strong effect on the magnitude of benefits derived from NI use.
- NI with half-lives lower than ~28 days are likely to provide only small benefits in terms of N loss or N rate reductions compared with urea.
- There is a lack of detailed data and understanding that allows prediction of the persistence and bioactivity of NI in different soils under conditions experienced in the Australian sugarcane industry.
- The longevity of nitrification inhibition is reduced at higher temperatures, which could be a concern for late ratoons especially; however, there is insufficient data to confidently predict this effect.

3. The classification of EEF responses into four types provides a language to explain the likelihood of obtaining benefits under different conditions.

'Virtual trials' of EEF use in sugarcane undertaken in this project have demonstrated that:

- The agronomic responses to EEF can be classified into four types: Type A – increase in maximum yield, Type B – reduction in optimum N, Type C1 – N responsive but no response to EEF, Type C2 – no response to N rate or EEF due to other growth limitations.
- Early ratoon crops have a high proportion of Type C1 responses due to lack of N loss during the first three months after the start of the crop and this limits the likelihood of agronomic and environmental benefits from EEF.
- Late ratoon crops have a higher likelihood of Type A or B responses to EEF due to the higher likelihood of N loss, which gives rise to agronomic and environmental benefits provided the N rate is matched with crop N demand.
- For late ratoon crops on soils where prolonged waterlogging limits yield and hence N response (e.g. heavy clay soils or determined by the position in the landscape) there is an increased likelihood of Type C2 responses with limited or no agronomic benefits from EEF and environmental benefits that may prove transient if the 'saved' N is lost during later loss events.
- Plant crops have a high incidence of Type C2 responses due to background N accumulated over the preceding fallow, reducing the agronomic benefits from EEF, although environmental benefits may still be obtained depending on the fate of the 'saved' N.

In relation to the original draft decision support logic developed by HCPSL the 'virtual trials' have shown that:

- There does not appear to be a basis for specifying a preference for the type of EEF (NI or CRF) based on N loss pathway. Both NI and CRF can reduce N loss via denitrification and leaching, provided the longevity of nitrification inhibition or the N release time is sufficiently matched with the time to N uptake by the crop.
- Including a distinction between early and late ratoon crops is 'correct', although for heavy clay soils this may requires a modification to accommodate the conditions leading to the Type C2 responses (very late ratoons in seasons).

- The cut-off between early and late crops will always be arbitrary, but for the Herbert mill area the modelling suggests the balance between Type C1, C2 and B responses changes rapidly between early-October and mid-December.

4. Using the classification of EEF responses to analyse the results of large numbers of virtual trials using data mining techniques allows robust development and verification of EEF decision support logic.

A preliminary data mining analysis of the results from virtual trials of EEF undertaken in this project indicates that:

- Early ratoon crops (July-September) have a low likelihood of achieving benefits from EEF.
- Late ratoon crops (October-December) have an increased likelihood of achieving benefits from EEF, but without considering seasonal climate or rainfall forecast the results remain variable.
- Data-mining techniques allow identification of combinations of factors that lead to different EEF responses.
- To improve the prediction of outcomes for late ratoon crops (October – December) climate indicators will need to be considered with rainfall in the first 60-75 days being the most important factor.
- While early season rainfall is a key driver, subsequent crop growing conditions also affect the EEF benefits due to their effect on N response and the ability of the crop to use the ‘saved’ N.

5. The variable benefits from EEF suggest tactical use which requires development of decision support that that draws on modelling to complement the field trials.

Development of EEF decision support logic:

- Cannot be based on experimental evidence from EEF trials alone. The variability in responses is too great to be captured through experimental trials and there will be too many situations where benefits are missed because the limited number of rates that are typically included or because conditions or system interactions meant benefits did not eventuate or would only be transient;
- Can be derived by using validated models and ‘virtual’ trials to test hypotheses derived from experimental findings and to extrapolate the field trials and systematically explore different factors of influence.

An industry wide decision support tool for EEF use:

- Will have predictive skills for tactical use of EEF once climate indicators have been considered;
- Would need be adapted for different regions to incorporate the effects of local climate and soil conditions and management practices as these may alter the likelihood of the different response types;
- Would need to assume best management practice is practiced, including that the chosen N rate meets, and is not in excess of, crop requirements.

8. RECOMMENDATIONS FOR FURTHER RD&A

The findings and learnings from this project lead to the following recommendations:

Development of decision support logic for Herbert mill area (phase 2 of project)

- Seasonal climate conditions, and in particular rainfall patterns, strongly affect the response to EEF. Further work is needed to evaluate early season rainfall indicators and their forecasting to better predict the outcomes for late ratoon crops.
- The quantification of likelihood of different EEF response types is sensitive to the prediction of cane yield N response on different soils and under different conditions. Further verification of N responses on different soils in the Herbert mill area is warranted and can build on the data currently being collected in SRA Project 2017-009 (Skocaj). Special attention should be given to the role of supplementary irrigation and the dynamics of shallow water tables that can both alleviate water stress under dry conditions and limit growth under wet conditions.
- It needs to be evaluated whether timing of N supply, as distinct from total amount of N supply, can affect CCS; and, if so, whether that should be taken into account in decisions on CRF N release patterns for crops designated for early harvest.

Industry wide decision support tool for EEF

- Due to the highly variable nature of the responses to EEF, results from experimental trials can only ever sample a small subset of outcomes. To develop decision support logic these results will need to be placed into context using modelling of 'virtual' replications and extrapolations of these experimental trials.
- The decision support logic for the Herbert can, once climate factors have been considered, form a starting point for similar decision support logic for other regions, but the specific climatic, soil and management conditions in each region will need to be considered and typical N responses verified.
- The prototype electronic interactive decision tree tool developed in this project allows the evidence that sits behind a decision to be made transparent. It is consistent with the idea of a 6ES Toolbox and should be explored as an industry wide decision support tool.
- The decision support logic developed in this project focusses on the question of whether to use EEF or urea given other management is best practice. This includes determining the appropriate level of N fertilisation. The decision support logic in the form of an electronic decision tree is not suitable to indicate the level of N rate reduction that the EEF may afford. It is best considered along with the prediction of N opt. Research in this area is currently under consideration.
- If best management practice is not employed the benefits from EEF will be reduced. The same is true if the EEF is not optimally adjusted to the system in terms of longevity of nitrification inhibition or synchrony of release with N uptake.

Further research needs

- Understanding and prediction of persistence and bioactivity of NI products in different soils as well as the effect of temperature is needed. If the half-life of the NI is different from 28 days this will change the proportions of Type A, B, C1 and C2 responses and the assessment of NI attractiveness.
- Quantification of early N demand by the roots of ratoon crops and improved understanding of root dynamics following harvest is required. This is still poorly understood and not captured well enough in the model to conclude with certainty that little N is required until the rapid growth stage. There are open questions around proportion of roots decaying and the timing thereof as well as possible translocation of N and N demand of new roots.

Adoption and implementation

- Experimental trials are powerful, on-the-ground demonstrations for industry. However, the results from modelling suggest that many EEF trials will not show treatment differences, due to conditions experienced or due to missing the effects. To avoid results that disappoint industry and discourage adoption it is important that the experimental results are put into context, e.g. using modelling.
- If EEF are adopted as standard practice, industry needs to be prepared for the fact that benefits will only be obtained in a subset of years and for the economic implications this will have.
- Enforced or subsidized use of EEF requires evidence to quantify the benefits, which cannot be based on experimental data alone.
- Tactical use of EEF will be a more economically sustainable strategy than use in every crop in every season, but needs to be informed by evidence based decision support logic that provides quantification of the likelihood of outcomes.
- The classification of EEF response types A, B, C1, and C2 provides a language to communicate results from EEF trials and to discuss with growers the likely EEF outcomes for the upcoming season. The 'stories' attached to each response type provide a simple explanation how different conditions lead to different outcomes. It is recommended that this classification is explored further with industry advisors as a communication tool to explain EEF to growers.

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- Verburg K, Biggs JS, Thorburn PJ (2018) Why benefits from controlled release fertilisers can be lower than expected on some soils. International Sugar Journal, 2018, 120 (1440), 936-945.
- Verburg K, Muster TH, Biggs JS, Thorburn PJ, Zhao Z, Vilas MP, Bonnett GD (2018) Evaluating benefits of controlled release fertilisers – Lessons from experimental characterisation and modelling in sugarcane. p.41 In: Book of Abstracts National Soil Science Conference, 18-23 November 2018, Canberra.
- Verburg K, Biggs J, Zhao Z, Vilas M, Thorburn P, Bonnett G (2018) Evaluation of fertiliser benefits – Lessons and opportunities from simulation analyses for controlled release fertilisers. International Workshop on Nutrient stewardship and next-generation fertilisers, 15019 December 2018, Heron Island, Qld.(abstract)
- Verburg K, Vilas MP, Biggs JS, Thorburn PJ, Bonnett GD (2019) Use of 'virtual' trials to fill gaps in experimental evidence on enhanced efficiency fertilisers. Australian Society of Sugar Cane Technologists, 41 (paper in press)
- Vilas MP, Verburg K, Biggs JS, Thorburn PJ (2019) How important is the longevity of nitrification inhibition in reducing nitrogen loss in sugarcane? Australian Society of Sugar Cane Technologists, 41 (extended abstract in press)
- Vilas MP, Verburg K, Biggs JS, Thorburn PJ (2019) Quantifying the effects of longevity of nitrification inhibition on nitrogen losses from sugarcane production. Proceedings of the International Society of Sugar Cane Technologists (paper submitted)
- Vilas MP, Verburg K, Thorburn PJ, Probert ME, Bonnett GD (2019) A framework for re-analysing nitrification inhibition: linking process with experiment. Paper submitted to Science of the Total Environment.

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12. APPENDIX

12.1. Appendix 1 METADATA DISCLOSURE

Table 8 Metadata disclosure 1

Data	'Datasets' resulting from APSIM simulations of 'virtual' trials as disclosed in Verburg et al. (2018), Verburg et al. (2019), Vilas et al. (2019a,b) and Section 6 of this Final Report.
Stored Location	CSIRO "\\nexus\projects\Agriculture\SRA Controlled Release Fertiliser\SRA Project 2017-015\Archive files"
Access	The stored location is not publically accessible. Data can be made available upon request.
Contact	Dr Kirsten Verburg, CSIRO Agriculture and Food, project leader

Table 9 Metadata disclosure 2

Data	(Description)
Stored Location	(I.e. organisation and server)
Access	(I.e. publically accessible or restricted? Please provide details.)
Contact	(I.e. Details of person/position with access)

12.2. Appendix 2: Testing of an alternative N uptake approach in the APSIM-Sugar model

Testing of an alternative N uptake approach was required, because the standard version of the APSIM-Sugar model only allows the crop to take up nitrate. In most situations that is an acceptable approximation as ammonium usually nitrifies (into nitrate) quite quickly. However, when we simulate the use of NI this approximation no longer holds. Sugarcane can take up ammonium (Brackin et al., 2015; Robinson et al., 2011), although the exact nature of its preference for ammonium versus nitrate is still subject of further investigation both in Australia and overseas (Robinson et al., 2011; Boschiero et al 2018)). The aim of this exercise was hence not to provide an accurate model description of ammonium versus nitrate uptake, but to ensure that modelling of N uptake by the sugarcane crop would not be negatively impacted by the higher ammonium concentrations that result from inhibiting nitrification.

APSIM-Sugar contains a second N uptake approach with the capacity to allow uptake of ammonium, but it has not previously been used. The standard N uptake approach is known as ‘Option 1’, and is used by all crops in APSIM 7.8 with the exception of wheat. It calculates potential N supply to the root system as the sum of (a) mass flow and (b) diffusion, where:

(a) Mass flow assumes that if 1/20th of soil water in the layer is extracted by the crop, then 1/20th of the nitrate-nitrogen in that layer is also available for uptake.
(b) When crop demand for N is greater than that available through mass flow additional N can be extracted through a term that has traditionally been labelled as ‘diffusion’, but is now understood to represent active N uptake. This ‘diffusion’ uptake can be as high as 50% of the remaining N (after mass flow uptake has been calculated) but decreases linearly as the proportion soil water available to the crop becomes smaller.

Despite not being previously used in conjunction with sugarcane, the alternative ‘Option 2’ N uptake approach has been used for nearly 20 years in the APSIM wheat model. As discussed above, unlike Option 1, Option 2 allows N uptake to occur in both ammonium and nitrate form. It is similar to the Michaelis-Menten N uptake approach used by many other crop models, in that it uses a second-order equation to ensure low N uptake at low N concentrations (Figure 24). The difference between the APSIM Option 2 (or kN) approach and the Michaelis-Menten approach is that the kN approach only has a single parameter to describe the N uptake response, whereas the Michaelis-Menten approach allows the modelling of a wider range of uptake responses. In addition, the kN approach assumes that the rate of N uptake increases with increasing N concentrations. In APSIM N uptake is simulated in response to N demand by the crop. This crop feedback provides the limit on N uptake that is not reflected in the second-order equation. The uptake is also moderated by the fraction of plant available water.

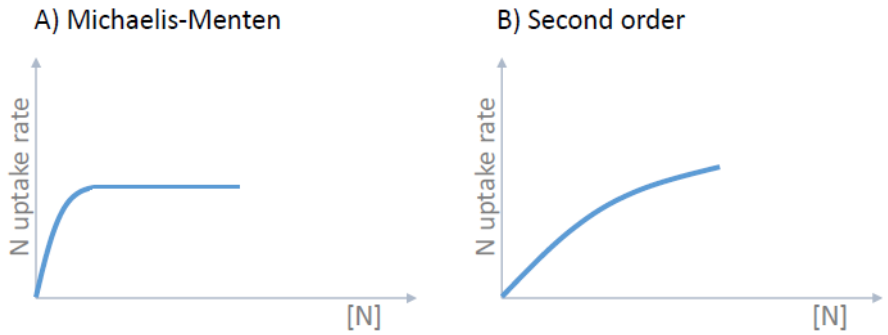

Figure 24. (A) Michaelis-Menten approach for N uptake; (B) second order approach for N uptake: N uptake rate as a function of soil N concentration.

Testing the 'Option 2' N uptake model for APSIM-Sugarcane

A variety of testing was conducted to assess the suitability of the Option 2 'kN' uptake model for use in simulating sugarcane production in a range of N uptake scenarios. Initially, simulations conducted by Keating et al. (1999) were re-examined to compare Option 1 uptake (e.g. Zhao et al., 2017; Zhao and Verburg, 2015) with Option 2 N uptake modelling. The Option 2 kN parameters for ammonium and nitrate uptake were tested at 0.05 (used in wheat) but was found to under-predict biomass N content (and to a lesser extent, biomass production) in several of the Keating et al. (1999) simulations (Figure 25 and Figure 26). This was unsurprising as irrigated, high biomass crops have been shown to have greater root system activity (Peake et al., 2008), whereas APSIM-wheat has largely been parameterised for low yielding, dryland environments. Setting kN at 1.0 for both ammonium and nitrate uptake most accurately reproduced the Option 1 results from Keating et al. (1999).

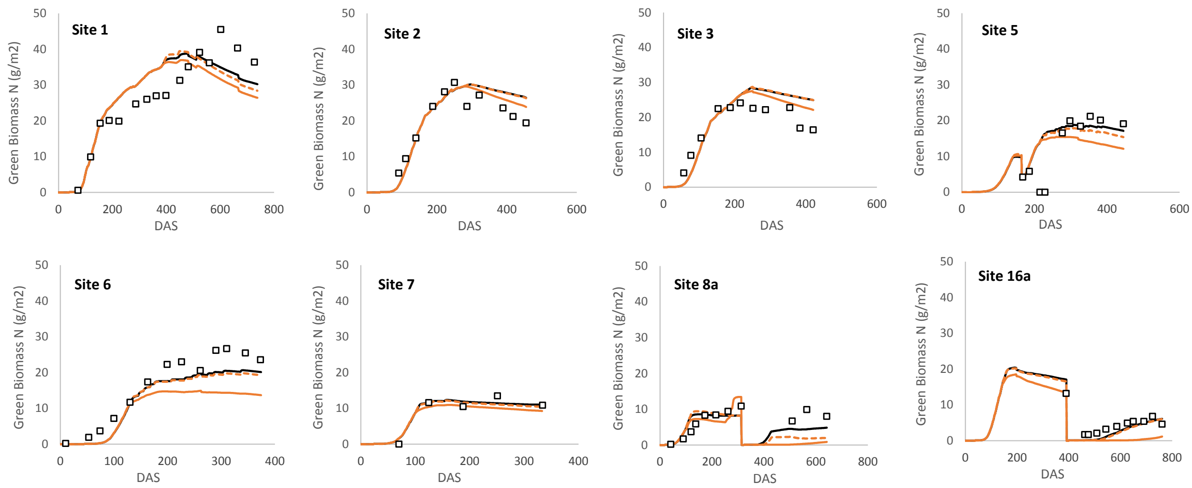

Figure 25: Observed data (squares) and modelled (lines) biomass N uptake for Site 1-7, 8a and 16a from the Keating et al. (1999) sugarcane simulations. Black line = Option 1 N uptake; Solid orange line = Option 2 N uptake where kN = 0.05; Dashed orange line = Option 2 N uptake where kN = 1.0.

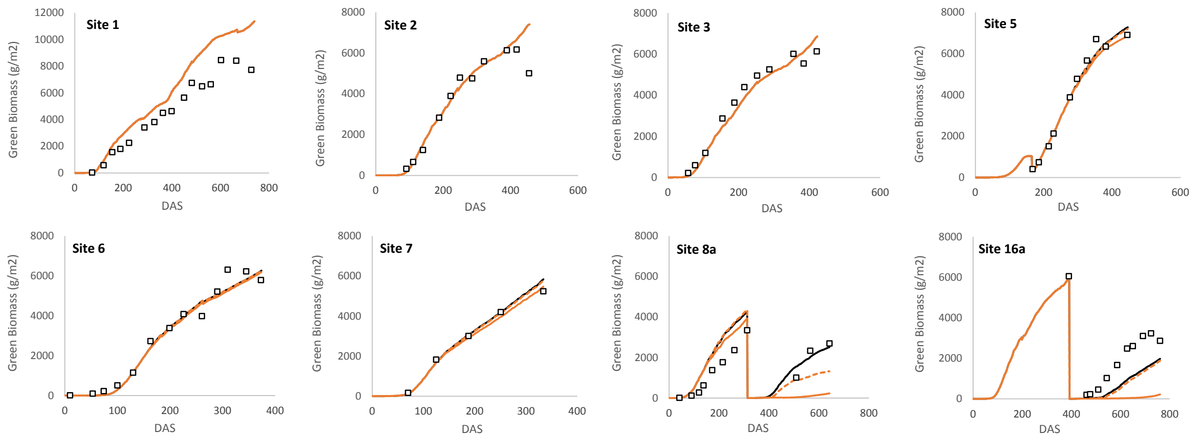

Figure 26: Observed data (squares) and modelled (lines) biomass for Site 1-7, 8a and 16a from the Keating et al. (1999) sugarcane simulations. Black line = Option 1 N uptake; Solid orange line = Option 2 N uptake where kN = 0.05; Dashed orange line = Option 2 N uptake where kN = 1.0

As many of the trials simulated by Keating et al. (1999) were performed under conditions of high N fertilisation, the parameterisation of kN = 1 was then tested to ensure that it would also operate successfully under N limiting conditions. The simulations conducted by Keating et al. (1999) were re-run to compare Option 1 uptake (e.g. Zhao et al. 2015, 2017) with Option 2 N uptake where the kN parameter was again set at 1, but this time with all N fertiliser applications removed from the simulations to mimic a low N environment. Figure 27 below shows the Option 2 N uptake when fertiliser was left in the simulations (black line) as a comparison, while the two orange lines show that when fertiliser was removed. The option 1 and 2 N uptake were similar under low N conditions, with occasional small differences over the course of the growing season in the order of 2-3 kg/ha N per hectare. These differences can be considered negligible in the context of our intended simulations.

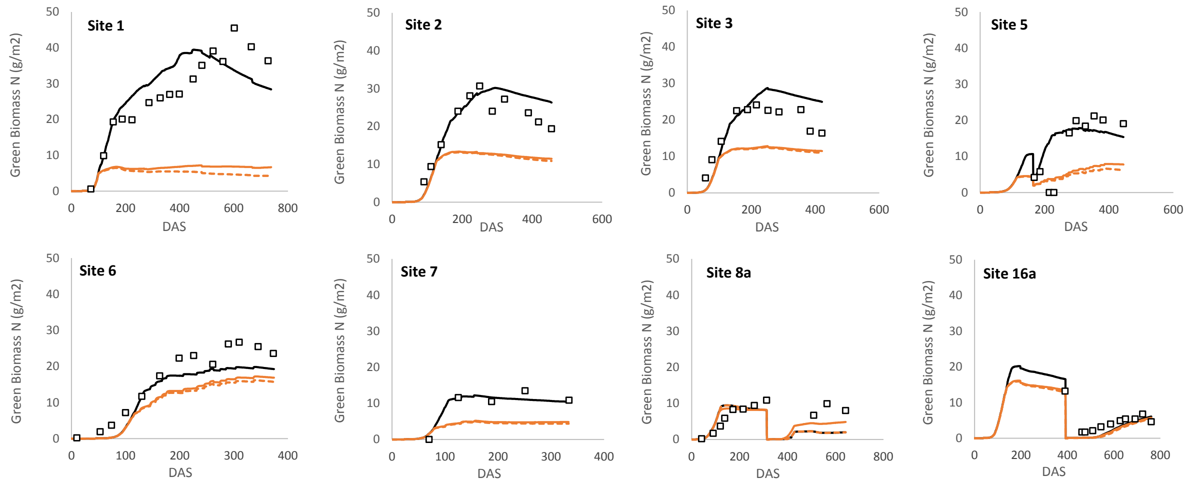

Figure 27: Simulated biomass N uptake for representative simulations from Keating et al. (1999) that were amended to remove fertiliser. Option 1 N uptake (solid orange line); Option 2 N uptake (dashed orange line) where kN = 1. Simulation output from the standard, fully fertilised simulations using option 2 N uptake (kN1) was also included for comparison (solid black line). Site 8a was already an N0 treatment.

Further testing was also conducted to ensure that Option 2 N uptake successfully accesses ammonium, and produces similar response curves regardless of whether N was available as ammonium, as nitrate, or a mixture of the two. This testing was carried out by using APSIM manager code and different fertiliser application strategies to compare three scenarios over a range of N fertiliser inputs:

- ‘Ammonium only’ – where N was kept in the form of ammonium by applying ammonium based fertiliser, and using APSIM manager logic to ‘turn off’ nitrification of ammonium to nitrate, such that only ammonium-N was available to the crop.
- ‘50/50’ where fertiliser was supplied to the crop as a 50/50 mixture of ammonium-N and nitrate-N, and the APSIM manager logic was again used to prevent nitrification, so that half of the fertiliser supplied to the crop was available as nitrate-N, while the remainder was only available for uptake as ammonium-N.
- ‘Nitrate only’ – where N fertiliser was applied only as nitrate N.

It was important for this testing to be done in a situation where N loss to leaching and denitrification was negligible, so that the results could be clearly attributed to differences in modelling of N uptake. This testing was therefore done in conjunction with one of the Keating et al. simulations that was identified as having negligible N loss to leaching and denitrification: Site 7 – Pongola (1986-1987). The response curves presented in Figure 28 below shows that in the absence of N loss due to leaching and denitrification, Option 2 N uptake gave very similar N response curves regardless of whether N was supplied as ammonium, nitrate, or a mixture of the two.

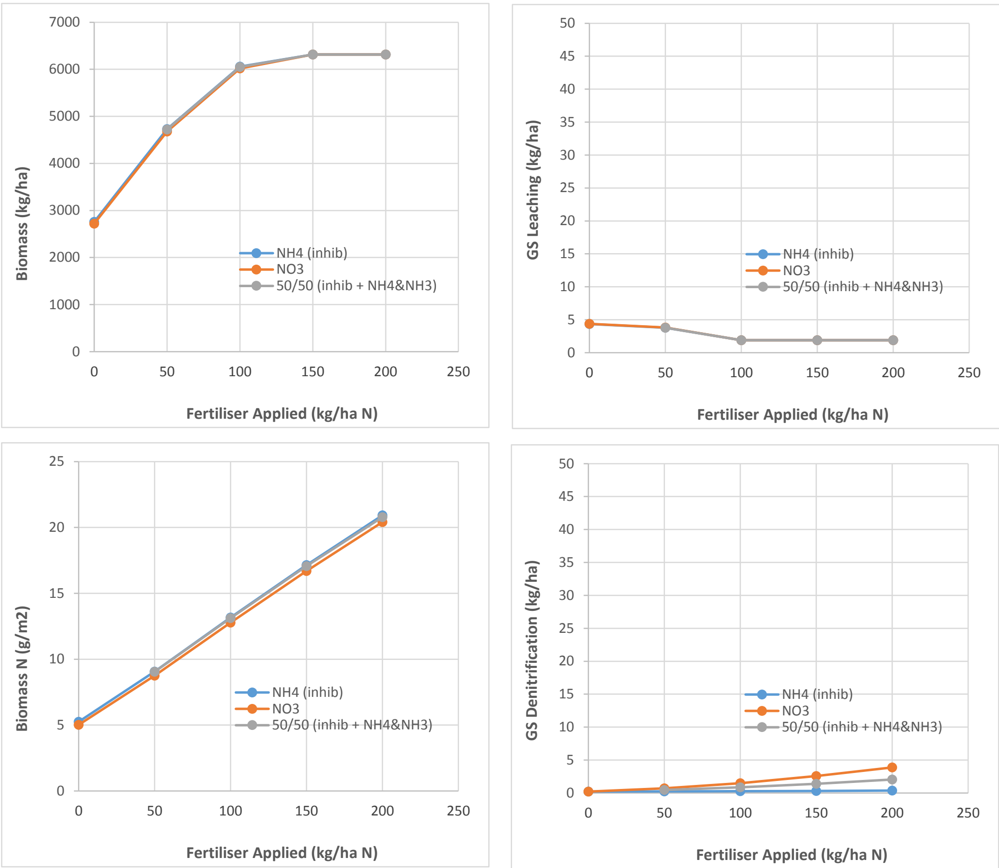

Figure 28: N response curves generated at Site 7 from Keating et al. (1999) for three different N fertiliser supply scenarios. Blue line = fertiliser supplied as ammonium N and prevented from nitrifying; grey line = fertiliser supplied as a 50/50 ration of ammonium-N and nitrate-N, with nitrification of ammonium to nitrate prevented; orange line = fertiliser supplied entirely as nitrate N