FINAL REPORT 2015/075

How much N will that crop need? Incorporating climate forecasting to improve Nitrogen management in the Wet Tropics

Final report prepared by:	2015/075 Project Team
Chief Investigator(s):	Yvette Everingham, Bernard Schroeder, Danielle Skocaj, Peter Thorburn.
Research organisation(s):	JCU, CSIRO, USQ
Co-funder(s):	DES
Date:	1 May 2018
Key Focus Area (KFA):	Soil health and nutrient management

Sugar Research Australia

JAMES COOK UNIVERSITY AUSTRALIA

UNIVERSITY OF SOUTHERN QUEENSLAND

CSIRO

Queensland Government

Department of Environment and Heritage Protection

Please cite as: Everingham Y, Biggs J, Schroeder B, Skocaj D, Thorburn P, Sexton J. 2018. How much N will that crop need?: Final Report 2015/075. Sugar Research Australia Limited, Brisbane.

ABSTRACT

Determining the optimum amount of Nitrogen that is required by the crop to maximise production, profitability and environmental outcomes is a challenging problem. The modelling approach taken in this project has balanced each of these complex elements to produce, and demonstrate, a novel and grower-friendly solution for the Tully canegrowing region.

Optim-N Gets a Thumbs Up

"How much Nitrogen does my crop need?" depends on many interacting factors such as soil type, harvest management, position in the landscape and climate variability!

This project took a unique and innovative approach to solving this problem and neatly embedded this process in a prototype tool called "Optim-N". Instead of applying the same rate of Nitrogen every year, Optim-N formulates Nitrogen guidelines based on climate forecasts, for eight important soils in two climate zones in the Tully region, and three harvest dates. The processes behind Optim-N were tested against all available data, both from experiments and, where these were not available, expert opinion.

When fully developed and operational, this tool will

- save farmers money by tailoring season- and site-specific recommendations for individual cane paddocks;
- improve water quality leaving farms and entering waterways to the Great Barrier Reef, and
- skill-up extension officers, allowing them to provide more targeted advice for farmers that factors in seasonal climate forecasts from the world's best climate models.

Two major activities are needed to take Optim-N from a prototype, to a widely used tool:

(i) Optim-N would need to be trialled with farmers in an action learning context so they could understand how it helps their decision making. This experience would also drive refinements of the Optim-N tool. It would also provide more empirical data for testing the science behind the tool, reducing the reliance on expert opinion and simultaneously increase trust and end-user confidence in the tool, which would accelerate adoption.

(ii) The Optim-N prototype also needs input from professional software experts to take it to commercial levels of robustness and usability.

When presented at a variety of forums, the Optim-N prototype receives a big "thumbs-up".

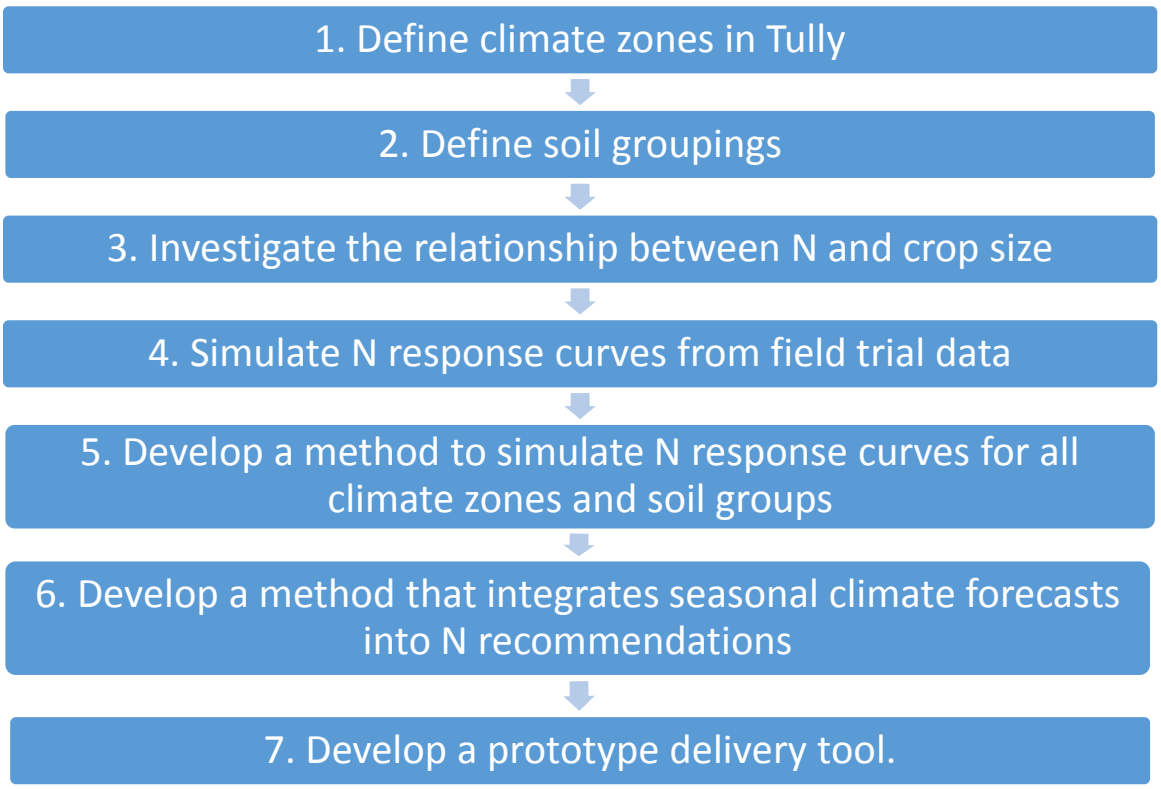
EXECUTIVE SUMMARY

ISSUE AND OBJECTIVES:

The Australian sugarcane industry and the Great Barrier Reef are important assets to the social, economic and environmental wellbeing of all Australians. The sustainability of both systems is vital, particularly in the Wet Tropics where the economic activity generated by the Great Barrier Reef is more than double that of any other region. In addition, improving the management of Nitrogen (N) in this region is a priority because loss of N poses the one of the highest risks to the health of the Great Barrier Reef and its lagoons.

Therefore, the objective of this project was to develop a methology for canefarmers in the Wet Tropics that answers the question: "How much N does that crop need?". Given, rainfall patterns vary enormously in the Wet Tropics, then so too might the optimal N (N_{opt}) required by the crop. If this is the case, then climate models commonly used for forecasting rainfall, should be adapted to forecast the crop's optimal N requirement for the coming season.

R&D METHODOLOGY:



These objectives were pursued using the methodological approach outlined in the steps above. In addition to using climate forecasts, this framework allowed for other factors such as soil type, climate zone and harvest date to interact to influence the optimum N requirements for the coming season. Since it was not possible to run field experiments for all combinations of these factors, the APSIM crop model was used to simulate crop and soil N dynamics for all these different scenarios using 60 years of historical climate records for Tully. Where possible these simulations were validated. The simulations were then linked with various climate models to estimate optimal N requirements for the coming season. Finally, this process was packaged into a conceptual prototype delivery tool in the form of a web application (App), called Optim-N. Optim-N allows farmers to

specify their soil type, climate zone, crop harvest date and a level of confidence to ensure their crop is not Nitrogen starved. The Optim-N App demonstrates how climate forecasts can inform N guidelines. It was discovered that crop size does not affect crop N requirement. Hence, Step 3 in the methodological framework became redundant.

THE PROJECT OUTPUTS:

Knowledge	• The Wet Tropics can be subdivided into two climate zones. The northern zone and southern zone approximately separated by the Tully River. Rainfall is typically higher in the North. • N management can be determined for more than 80% of the Tully region by understanding the interaction with the crop and the following soils - Tully, Coom, Thorpe, Bulgan, Hewitt, Warrami, Tyson and Liverpool soils. • Crop size and the amount of N needed to grow that crop are unassociated. Crop size was therefore eliminated as a way to inform N guidelines. • Relatively speaking, more N is needed on early cut blocks in wet years, particularly in the slightly drier, southern climate zone; for late cut blocks, less N is needed in wet years; seasonal climate forecasts have less impact on blocks cut mid-season (refer Fig. 1).
Skills, Processes & Practices	• Developed a new streamlined modelling process that can simulate optimum N for the season ahead using climate forecasts that works for different soils, climate zones, harvest dates and farmer confidence thresholds. • New data visualisation methods to present complex phenomenon, in simple ways that builds growers' intuition and knowledge. • A process that will make it easier for farmers to implement Steps 5 and 6 in the SIX EASY STEPS framework.
Products & Technologies	• The ABC framework: a simple framework that encapsulates complex social and technical processes to link climate forecasts and nutrient guidelines. • Optim-N: a simple and easy to use prototype App that helps farmers and their advisors estimate their crop's N requirement for the coming season.

OUTCOMES AND IMPLICATIONS:

For the first time ever, a robust and innovative process for connecting climate forecasts to the crop N requirements via the APSIM crop model exists for the Australian sugarcane industry. This allows farmers and their advisors to implement Steps 5 and 6 in the SIX EASY STEPS framework using a straightforward aproach. This process can be adapted for sugarcane and other cropping systems nationally and internationally. The process was made novel, by

- Developing and implementing the ABC framework to provide N management recommendations in a robust and risk tolerant way for farmers. The ABC framework encapsulates complex social and technical processes that surround end-user interaction with complex decision support systems such as APSIM and climate models.

- Developing Optim-N: a simple and easy to use prototype App that helps farmers and their advisors estimate their crop's N requirement for the coming season.
- Identifying, and demonstrating, that traditional thinking linking crop N requirements to crop size is flawed.
- Demonstrating that both the optimum N for a crop and the affect of climate on optimum N depend on harvest time.
- Establishing a vision for making this information easily accessible by a range of industry stakeholders.

The process will save farmers money by tailoring season- and site-specific recommendations for individual cane paddocks; improve water quality leaving farms and entering waterways to the Great Barrier Reef, and skill-up extension officers, more efficiently to provide better advice for the farmers they serve. Most importantly, this process, when operational, will demonstrate to broader society, that the Australian sugar industry is a world leader in sustainable Nitrogen management practices.

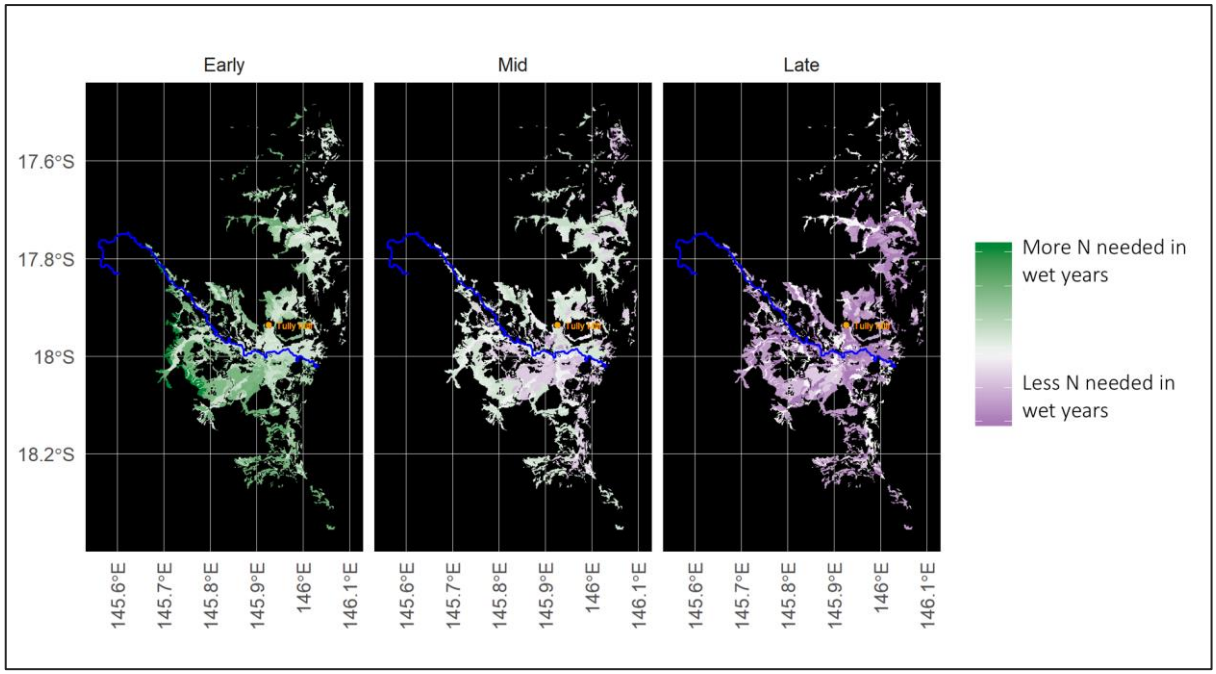


Figure 1. The difference in median N_{opt} (optimum N) for the wettest 33% of years and the driest 33% of years for crops harvested early, mid and late season. In wet years for early cut blocks, on most soils, the median N_{opt} is higher than the median N_{opt} for dry years. For late cut blocks, the situation is reversed and the median N_{opt} for wet years is less than the median N_{opt} for dry years. For some crops grown on soils such as Bulgan, Coom and Hewitt which are common in the south-eastern canegrowing region, the pattern is similar to a late harvest.

TABLE OF CONTENTS

TABLE OF TABLES

TABLE OF FIGURES

1. BACKGROUND

The Australian sugar industry is located on the coastal fringe of Queensland and Northern NSW. Much of the Queensland industry lies adjacent to the Great Barrier Reef (GBR), the world's largest coral reef ecosystem. Both of these contribute markedly to the Australian economy. The sugar industry is the third largest raw sugar supplier in the world and the seventh largest agricultural exporter in Australia (http://www.canegrower.com.au). It contributes $2 billion to the national economy, generates more than 40,000 jobs and supports many rural communities (http://www.sugaraustralia.com.au). The GBR contributes nearly $6 billion and almost 70,000 jobs to Australia's economy and people (Deloitte Access Economics, 2013).

Scientific evidence indicates the health of the GBR is under pressure from sediments, pesticides and dissolved nitrogen (N) discharged from nearby catchments (Waterhouse et al., 2017). Discharge of dissolved N is of particular concern as it stimulates outbreaks of the Crown of Thorn Starfish, a major predator of corals in the GBR (De'ath et al., 2012, Waterhouse et al., 2012). The amount of N fertiliser applied in a catchment is a primary determinant of dissolved N discharges from catchments (Thorburn et al., 2013). Increasing N use efficiency (NUE) and effectiveness in cropping systems is an important step in contributing to the sustainability and economic benefits of the sugar industry and the GBR.

The Wet Tropics has the highest level of the economic activity generated by the GBR, at least double that of any other region. The Wet Tropics also receives the highest annual rainfall in the country and few places around the world experience more extreme swings in year-to-year climate variability (Nicholls et al., 1997). These signature climate patterns contribute to N losses from catchments in the Wet Tropics (Brodie et al., 2012).

Nitrogen fertiliser management has continued to evolve from the early 1900s (Schroeder et al., 1998). In more recent times there has been recognition that N management should be aimed at sustainability - profitable sugarcane production in combination with environmental responsibility (Schroeder et al., 2010). Two strategies have emerged to improve NUE and reduce N losses in Australian sugarcane systems. These are the SIX EASY STEPS program and the Nitrogen Replacement strategy (Schroeder et al., 2006, Thorburn et al., 2011a). The SIX EASY STEPS program is the industry standard. Steps one to four of the SIX EASY STEPS program assumes the growing conditions, harvest management and climate patterns across a region are constant. In the Wet Tropics, some regions are wetter than other regions, and some years are drier than other years and, like most regions, harvesting is a continuous process. Steps 5 and 6 of the SIX EASY STEPS framework allow these factors to be worked into the nutrient recommendation. However, it is not a trivial exercise. There is a need to extend the SIX EASY STEPS Toolbox to help industry with steps 5 and 6 of the SIX EASY STEPS, and help farmers answer a question like …

> "If I am fertilising a late harvested paddock, with a Bulgun soil, in Tully's northern climate zone, how much N should I apply if the season is going to be wet?"

In recent years, the speed of computing and the ease at which we can collect, store, and analyse data has increased markedly. This means that we have more advanced climate monitoring systems and faster computers to run complex climate models. One type of complex climate model are General Circulation Models (GCMs). The gradual improvement in the skill of GCMs housed in Australia and around the world has also been documented (Zhao et al., 2014, Weisheimer et al., 2014). Today, these models are considered state of the art and are presently underutilised in agriculture, largely because they remain disconnected to industry decisions.

Crop models are another type of model that have the potential to help farmers make better management decisions, including those related to nutrient management (Keating and Thorburn, 2018). These models simulate the growth and development of sugarcane (and other crops) as it is influenced by climate (temperature, rainfall and radiation), soil (water, carbon and nitrogen cycling), plant physiology (photosynthesis, nitrogen and water needs and uptake), and management (nitrogen fertilizer applications, planting and harvest dates, trash management, tillage, etc.). They provide insight into complex interactions, which can sometimes be difficult or infeasible to assess through field experimentation. Apart from the studies of Skocaj (2015) and (Thorburn et al., 2011b, Thorburn et al., 2011a) there has been limited research on exploring the utility of crop models to improve nitrogen management for sugarcane crops grown in Tully.

An opportunity exists to harness the power of GCMs and crop models to fine-tune nutrient management guidelines in the Wet Tropics. This powerful combination of tools will address the multiple interacting factors that affect nutrient requirements. How to 'tune' these models to the Wet Tropics, and how to have these two models 'talk' to each other is the major challenge that must be addressed in pursuit of maintaining a sustainable sugarcane production system and the world heritage standing of Australia's natural wonder of the world – the Great Barrier Reef.

2. PROJECT OBJECTIVES

To improve Nitrogen (N) management in sugarcane, this project will:

1. Use GCM based seasonal climate forecasts and the APSIM crop model to produce early estimates of yield potential for zones within the Tully mill region;
2. Determine how N requirement and hence how the N fertiliser application rate varies according to seasonal climatic conditions and estimates of yield potential for major soil types occurring throughout the Tully region;
3. Identify the benefits of optimal tactical, in-season applications of N fertiliser;
4. Propose options for adoption pathways.

3. OUTPUTS, OUTCOMES AND IMPLICATIONS

3.1. Outputs

The project generated a number of outputs that appear in the form of knowledge, processes, algorithms and prototype delivery tools. These include

- A “thumbs-up” attitude toward the crop and climate models.
- A prototype delivery tool called Optim-N that provides nutrient management recommendation for the Wet Tropics.
- A better understanding of the impact of climate on crop responsiveness to applied N so growers and advisors can make more informed decisions about the amount of N their crop requires.
- A new framework that highlights the dangers of adopting N management practices that assume bigger crops need more N and smaller crops need less N.
- A methodology that transforms whole of region N recommendations to N recommendations that are robust against year-to-year climate variability but sensitive to soil type, paddock management and location.
- A process for improving nutrient management practices that is transportable to other regions.
- Recognition that climate forecasting is compatible with the SIX EASY STEPS nutrient management program.
- A new tool that will help industry and their advisors implement steps 5 and 6 of the SIX EASY STEPS program.
- Climate zones that inform N management guidelines and help mill management.
- A desktop, parameterized crop model that can mimic N response curves generated from field trials in the Wet Tropics.
- A desktop simulation that revealed splitting fertiliser on a Coarse soil in the Northern and Southern climate zones in Tully, reduced Optimum N, increased yield and reduced N loss in most years, with the greatest benefits (e.g. higher yields and reduced N loss) occurring in La Niña years. The simulation identified there was little to no benefits associated with splitting on fine soils.
- Two ASSCT papers and four ASSCT poster abstracts that share new knowledge developed from the project.
- A sense of confidence that models can generate useful knowledge and are worth exploring more as part of an action learning environment.

3.2. Outcomes and Implications

If adopted and applied in practice the outputs generated from this project will ensure the Australian sugar industry remains sustainable by improving Nitrogen management and the water quality that leaves farms in the Wet Tropics.

4. INDUSTRY COMMUNICATION AND ENGAGEMENT

4.1. Industry engagement during course of project

The project team established a consultative group and maintained regular contact with this group throughout the life of the project. At consultative group meetings, the project team would present work done to date and the consultative group would provide critical feedback about how the project outputs could be made more useful for science, industry and the environment. At multiple meetings, this group was able to identify tasks to be performed to help build users understanding, trust and confidence in the methodology. Thanks to the experience of this group coupled with the multidisciplinary expertise housed in the project team, with further funding the project team is now ready to take the next step and initiate action learning processes with industry and extension partners outside the consultative group.

4.2. Industry communication messages

- N management is very complex.
- N guidelines differ with soil type.
- N guidelines differ between regions in Tully (e.g. north versus south).
- N guidelines differ with crop harvest date (e.g. early, mid and late harvests).
- N guidelines differ between wet and dry years and climate models can provide knowledge if the year is likely to be wetter or drier
- It is advisable to triangulate between forecasts from multiple leading, international climate models.
- N guidelines vary with many different combinations of soil x region x climate x harvest date.
- The project team developed a new and innovative way to unravel this complexity and provide better N recommendations by linking climate models and crop models.
- A simple and easy to use tool is needed to seamlessly merge the knowledge embedded in climate and crop models. In pursuit of this goal, a prototype App called Optim-N was developed to provide year specific, and block specific nutrient guidelines – the only one of its type for any sugarcane Industry.
- Interrogating the data libraries that underpin Optim-N revealed that
    - For most soils in Tully, more N is needed in wet years for blocks cut early (e.g. July), and this is especially the case for blocks in the drier southern Tully climate zone where radiation tends to be higher and rainfall less than the northern wetter region.
    - For most soils in Tully, less N is needed in wet years for blocks cut late (e.g. November)
    - For Bulgun, Coom and Hewitt soils, less N is needed in wet years for blocks cut midseason (e.g. September).
- An action learning approach that partners industry, researchers, extension staff and consultants is vital for successfully operationalising and sharing ownership of the innovations developed in this project.

5. METHODOLOGY

Modelling philosophy and assumptions

- The modelling approach adopted aimed to maximise production, profitability and environmental outcomes.
- Our definition of optimum N (N_{opt}) is the amount of Nitrogen required to produce 95% of maximum yield (Y_{95}). We followed the definition adopted in SIX EASY STEPS that assumed production, profitability and environmental outcomes were maximised when the optimum amount of N is applied.
- Given the number of variables that can affect the agricultural system, a robust approach was developed to determine the optimum N. This robust approach is adaptive to (i) the uncertainty in year to year climate variability, ii) the variability in different forecasting methods and iii) varying risk profiles of farmers.
- There exist many different climate indices that are useful for predicting climate. This project assumed that the central equatorial Pacific ocean (Niño 3.4 region) is a reasonable index to guide climate, and therefore, nitrogen requirement in Tully (Skocaj, 2015). Previous studies demonstrate this is a reasonable assumption (Clarke et al., 2010).

The research methodology undertaken in this project that led to the prototype delivery tool of the Optim-N App consisted of the seven key steps (Fig. 2).

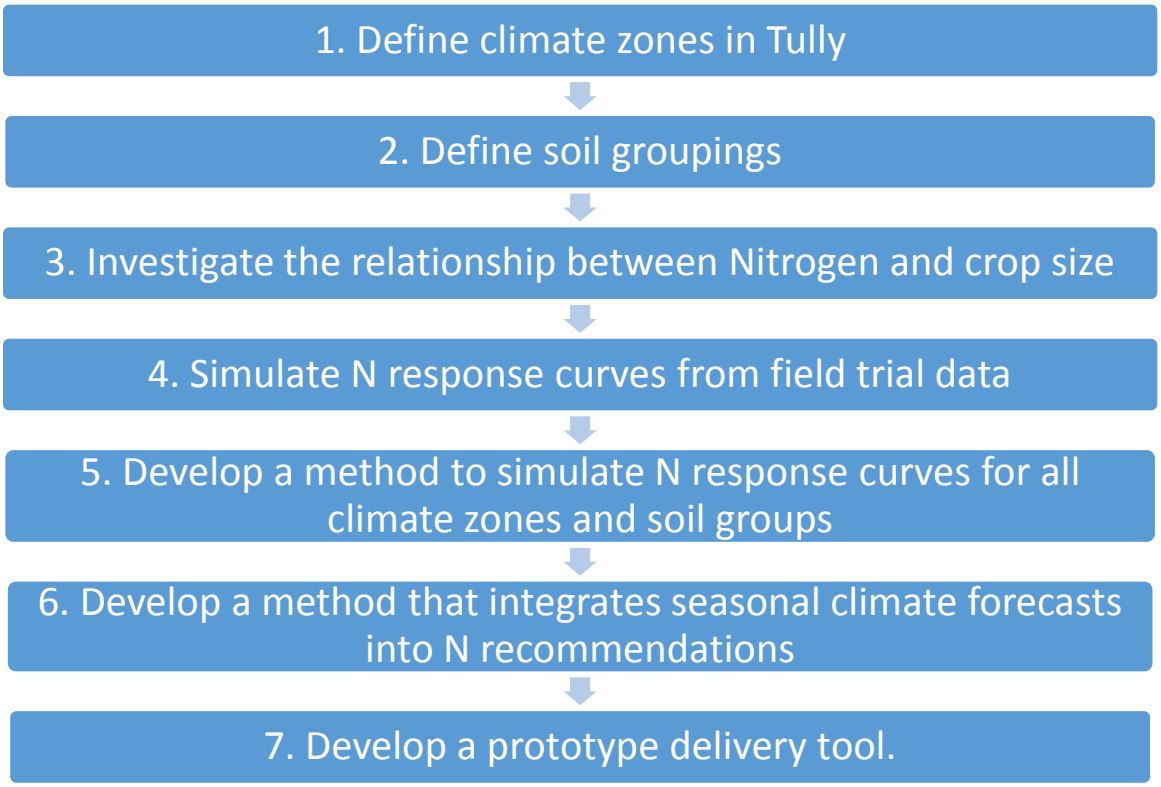


Figure 2. An outline of the methodological approach

Although the methodology is presented as a linear sequence of steps, a participatory action research approach was undertaken. At each step of the methodological framework, the project team sought feedback from consultative committee, reflected on their advice and revised the methodology

accordingly. Thus, the prototype delivery tool already incorporates several layers of action learning cycles of continuous improvement. We now describe the modelling components that formed part of each major step in Fig. 2.

5.1. Define climate zones in Tully

5.1.1. Data

The Tully mill region was identified as spanning from latitude 17.75˚ S to 18.30˚ S and from longitude 145.65˚ E to 146.10˚ E (Fig. 3a). Sugarcane-growing areas in the Tully mill region were identified on a 0.05 by 0.05˚ (approximately 5 x 5 km) grid (Fig. 3b). In total 52, sugarcane grid cells were identified.

Daily climate data for each 0.05 by 0.05˚ grid cell were obtained from the Scientific Information for Land Owners (SILO), Data drill data base (Jeffrey et al., 2001). This database contains daily climate data spatially interpolated from climate station records. Daily rainfall, temperature and solar radiation data were obtained for the 40 year period from 1975 to 2014.

For each sugarcane-growing grid cell, mean daily maximum temperature, mean daily minimum temperature and mean daily radiation as well as total rainfall were calculated for summer (Dec – Feb), autumn (Mar – May), winter (Jun – Aug), spring (Sep – Nov) and annual (Jan – Dec). For each sugarcane growing grid cell, the median of the 40 years of data was calculated for use in the spatial clustering analysis. This gave 20 climate based variables for use in the analysis (five 'seasons' (summer, autumn, winter, spring, annual), four climate variables (total rainfall, mean max temperature, mean minimum temperature, mean radiation)) each with 52 observations (0.05 by 0.05˚ sugarcane grid cells).

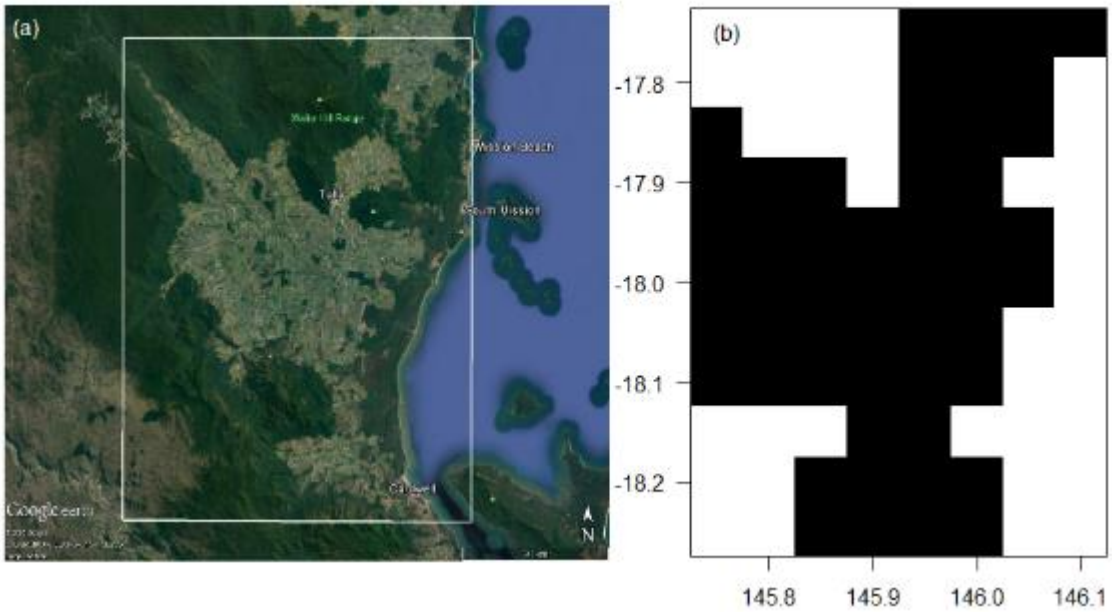


Figure 3. A map of the Tully mill area (a) and sugarcane-growing land in the Tully mill area identified on a 0.05° by 0.05° grid (b).

5.1.2. Statistical Analysis

K-means clustering (Hartigan and Wong, 1979) was used to cluster grid cells based on the 20 possible predictor variables. K-means clustering is method of finding K clusters of observations in a

set of unlabelled data (Hastie et al., 2013). The number of cluster centers (K; means) must be chosen by the user. The K-means algorithm then moves the cluster centers iteratively to minimize the within cluster variance, using the Euclidean distance, a least squares approach. The iterative procedure can be described in two steps (Hastie et al., 2013):

1. For each center identify the subset of points that are closer to that center than any other.
2. Compute the mean for each predictor variable in each cluster, with the new vector of means becoming the new cluster center.
3. Steps 1 and 2 are repeated until the cluster centers do not change.

While several K-means algorithms can be used, the Hartigan-Wong algorithm performs well and has the advantage of ensuring that no single observation switching clusters will decrease the variance further (Hastie et al., 2013). K-means has been used in defining rainfall zones in the East Asia monsoon region (Awan et al., 2015) as well as identifying in-field management zones for crops such as cotton in the United States of America (Boydell and McBratney, 2002) and sugarcane in Australia (Cupitt and Whelan, 2001).

The clustering algorithm “kmeans” in the R “stats” package (R Core Team, 2014), was applied to build 10 cluster models (Table 1). Models were built using all climate variables for each season (e.g. summer rainfall, summer radiation, summer maximum temperature, summer minimum temperature) and annually (e.g. annual total rainfall). Models were then built using only rainfall and radiation variables together as these are believed to have the most influence on yields in the Tully mill area.

Table 1. Design matrix of K-means algorithm analysed in this report. Numbers refer to the total number of predictor variables given to the K-means algorithm

Season	All climate variables	Rainfall and radiation variables
Summer	4	2
Autumn	4	2
Winter	4	2
Spring	4	2
Annual	4	2

There are many different indices that can be used to identify the “best” number of clusters. For each analysis of the design matrix (Table 1) the best number of clusters was found using the “NbClust” package (Charrad et al., 2014) in the R statistical analysis program. The NbClust package provides 30 indices for determining the ideal number of clusters. The final recommended number of clusters is the mode number of clusters recommended by all of the indices.

The NbClust analysis requires the specification of the distance measure (set to Euclidean by default), minimum and maximum number of clusters (set to two and 10 respectively), method of clustering (K-means) and indices to be calculated. The best number of clusters was recorded for each analysis. The “kmeans” function (R Core Team, 2014), in the R statistical package was then used to perform each cluster analysis from Table 1. For all analyses, predictor variables were standardized using the “scale” function in the R statistical analysis program. Scaling the data removed any effect of difference in scale between the climate variables. The resulting clusters were plotted spatially. Graphical analysis of the modelled clusters was used to check the sensibility of the modelled clusters and identify the most appropriate cluster model. The differences between the climatic variables for each sub-region identified by the final cluster model were then explored using boxplots. Significant

differences in climate variables between clusters were identified using a Kruskal-Wallis test. Significance was tested at the 0.05 level.

5.2. Soil groupings

Soils vary markedly throughout the Tully sugarcane-growing region and strongly influence many on-farm management decisions. Soil surveys have traditionally grouped soils according to their parent material. However, the agronomic behaviour of soils with the same parent material may be quite different. A system of grouping soils that better reflects their agronomic performance under different climatic conditions will greatly assist on-farm management decisions. This includes management of nitrogen fertiliser inputs.

Information was collected from soil surveys (Murtha, 1986, Cannon et al., 1992), soil reference booklets (Schroeder et al., 2007), agricultural land use suitability assessments (Murtha and Smith, 1994) and expert local opinion.

The major soils in the Tully mill area were identified using the 2015 Tully Sugar Limited block productivity and CSIRO soil type GIS layers. Major soils were defined as those occupying more than 1% of the Tully mill area.

The major Tully soils were then rated according to their water holding capacity, propensity to waterlogging, presence of a water table, N mineralization potential and position in the landscape for wet and dry years. In dry years, waterlogging and the presence of a water table do not impact crop growth to the same extent as moisture availability, and hence in dry years, it is more important to categorise soils based on the water holding capacity. As spring-summer rainfall is an important predictor of Tully cane yields, long-term spring-summer rainfall records for Tully were used to define wet and dry years. Wet years were defined as receiving more than 2200 mm of rainfall over spring-summer whereas dry years were defined as receiving less than 1500 mm of rainfall.

The categories used to describe the water holding capacity and propensity to waterlogging for the major soils were:

- Very Low (VL)
- Low (L)
- Moderate (M)
- High (H)
- Very High (VH)

The presence of a water table for wet years was described as being:

- n/a = no water table present
- Periodic = water table is quick to recede
- Prolonged = water table is slow to recede
- Persistent = water table is present most of the time

It was also important to consider if the major Tully soils differed between the two climate zones (northern and southern). This would ensure soils included in nitrogen response simulations well represented both climate zones. Traditionally the Tully mill area has divided into eight sub-districts: El Arish, Feluga, Lower Tully, Syndicate, Euramo, Riversdale, Murray and Kennedy. For simplicity, the El Arish, Feluga, Lower Tully and Syndicate sub-districts were included in the northern climate zone and the Euramo, Riversdale, Murray and Kennedy sub-districts were included in the southern climate zone. The northern climate zone (approximately 11,858 ha) is much smaller than the

southern (approximately 21,545 ha). The 2015 Tully Sugar Limited block productivity and CSIRO soil type GIS layers were used to identify the major soils in the northern and southern climate zones based on the partitioning of sub-districts. Major soils were defined as those occupying more than 1% of the climate zone.

5.3. Investigate the relationship between Nitrogen and crop size

5.3.1. Data

Data were collated from N response experiments (Allen et al., 2010, Anon, 2016, Catchpoole and Keating, 1995, Chapman, 1982, Chapman, 1994, Hurney and Schroeder, 2012, Schroeder et al., 2014, Skocaj, 2015, Thorburn et al., 2003, Vallis et al., 1994) conducted in all the major sugarcane regions in Queensland, from Rocky Point to the Wet Tropics. Experiments with less than four N rate treatments were discarded, as were experiments where there was relatively little difference (e.g. 20 kg N ha^{-1}) between N treatments. Plant crop responses were omitted because the conditions preceding planting have a large effect on the N response of plant crops, and there was no information on these conditions in most experiments. The collation resulted in 154 N responses for ratoon crops.

5.3.2. Statistical Analysis

For each experiment, the N response was emulated by a second degree polynomial equation fitted to N response data (Fig. 4). The value of Y_{95} was derived from the emulated response and then the value of N_{opt} calculated. Thus, each experimental N response curve was represented by a single value of Y_{95} and N_{opt}. Note: a range of other equations were tested as emulators (following Thorburn et al. (2017)), but they had little effect on the results (data not shown).

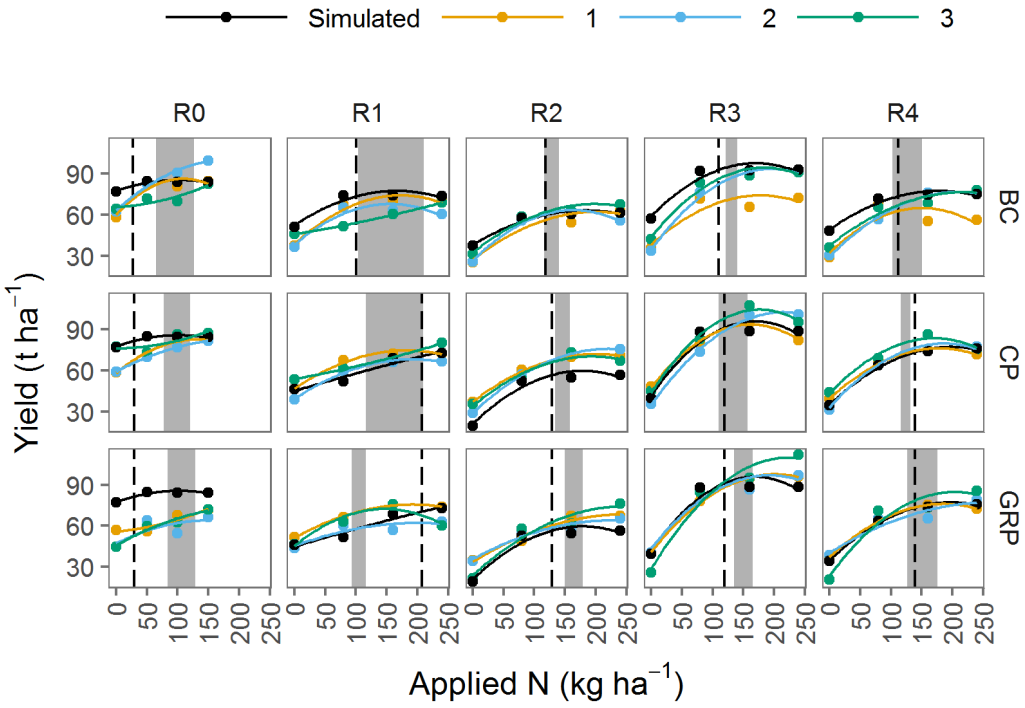


Figure 4. The variation in yield at different rates of N fertiliser in an experiment on a Coom soil in Tully (Hurney and Schroeder, 2012). The experiment included five sugarcane crops (plant = R0, 1st ratoon = R1, etc.) grown under three management systems (BC: burnt cane, conventional cultivation plant and ratoons. CP: GCTB, conventional cultivation plant crop, zero cultivation ratoons. GRP: GCTB, zonal or row tillage plant crop, zero cultivation ratoons). Coloured dots show the measured data for three replicates and the black dots are simulated values. The solid lines show the second degree polynomial equation fitted to the data. The grey shaded area shows the range of the optimum N (i.e. N rate at 95% of maximum yield) values for the three replicates and the dashed line is the optimum N value for the simulated data.

5.4. Simulate N response curves from field trial data

APSIM is a crop model that uses climate data, crop management information and soil specifics to simulate crop production and crop requirements. If the APSIM farming systems model is to provide nitrogen guidelines, then it should, as a minimum requirement, be able to simulate field experiments that have been conducted.

The performance of the APSIM farming systems model was assessed using measurements from two small plot trials conducted on sugarcane farms in the Tully region. One trial was conducted from 2003-2009 on a Coom soil where four Nitrogen (N) rates were applied to three different farming systems. The other trial was conducted from 2011 to 2014 on a Bulgun soil where twelve N rates were applied. These two trials covered 44 individual crops (excluding replicates) over a total of eight years. An important test for APSIM to pass was to accurately simulate measurements produced from these two small plot trials.

5.5. Develop a method to simulate N response curves for all climate zones and soil groups

5.5.1. A set of simulations were developed and run to provide data to enable the development of a method to automatically determine optimum N for a range of factors.

The test simulations were setup as follows:

- Two climates were simulated based on two representative stations representing the average conditions for the Northern and Southern climate zones
- Eight soils were simulated based on parameters developed using experiments conducted in the Tully region, industry consultation and the methods of Barboux et al. (2018) and Biggs et al. (2018).
- All simulations consisted of repeated 12 month long crops.
- Three different ratoon crops and harvest dates were simulated:
  - started on the 15-Jul (Early)
  - started on the 15-Sep (Middle)
  - started on the 15-Nov (Late)
- Soil mineral N, water content and surface residues were reset to initial values at the beginning of every crop to ensure that the climatic effects were not confounded by carry-over effects of previous seasons.
- Eleven different N rates were simulated in steps of 30 kg N ha^{-1} from 0 to 300 kg N ha^{-1}.

This provided 528 combinations of soil (8), climate zones (2), harvest dates (3) and fertiliser N rates, generating a daily output for 64 years. With over ten million numbers generated, this clearly meets the definition of “Big Data” and all the challenges associated with data processing, analysis and interpretation.

5.5.2. Determining optimum N

Optimum N was determined according to these steps:

1. A variety of mathematical functions (Weibull, Simple logistic, Gompertz, Four-parameter logistic, Asymptotic, Polynomial) were fitted to all N response curves
2. The function with the smallest residual standard error (RSE) was used to compute the optimum N (N_{opt})
3. Predict yields in 1 kg N ha^{-1} steps from 1 to 300 kg N ha^{-1} for each year, and then
4. Select the minimum N rate, to the nearest 1 kg N ha^{-1}, at which 95% of maximum yield (Y_{95}) is obtained.

In recognition of the variety of response curves possible (i.e. 'flat' responses, almost linear responses to a responses with a plateau), a variety of non-linear functions were included in the analysis with the best fitting function for each individual N response selected based on minimising the residual squared error (RSE).

The following non-linear functions were used to evaluate the relationship between sugarcane yield (*Yield*; t ha^{-1}) and fertiliser rate (*fert*, kg N ha^{-1}):

1. Weibull model for growth curve data and its gradient. It is a generalisation of the asymptotic model.
   - $Yield = Asym - Drop \times e^{-e^{lrc} fert^{pwr}}$
   - *Asym* is a numeric parameter representing the horizontal asymptote on the right side (large values of x).
   - *Drop* is a numeric parameter representing the change from *Asym* to the y intercept.
   - *lrc* is a numeric parameter representing the natural logarithm of the rate constant.
   - *pwr* is a numeric parameter representing the power to which x is raised.
2. Four-parameter logistic.
   - $Yield = A + (B - A)/(1 + e^{(xmid - fert)/scal})$
   - *A* is a numeric parameter representing the horizontal asymptote on the left side (very small values of input).
   - *B* is a numeric parameter representing the horizontal asymptote on the right side (very large values of input).
   - *xmid* is a numeric parameter representing the input value at the inflection point of the curve. The value of SSfpl will be midway between *A* and *B* at *xmid*.
   - *scal* is a numeric scale parameter on the input axis.
3. Loess (Local polynomial regression fitting)
   - Cleveland et al. (1992)

The following functions work best when there is no plateau at higher N rates:

4. Simple logistic model
   - $Yield = Asym/(1 + e^{(xmid - fert)/scal})$
   - *Asym* is a numeric parameter representing the asymptote.
   - *xmid* is a numeric parameter representing the x value at the inflection point of the curve. The value of SSlogis will be *Asym*/2 at *xmid*.
   - *scal* is a numeric scale parameter on the input axis.
5. Asymptotic regression model
   - $Yield = Asym + (R0 - Asym) \times e^{-e^{lrc} \times fert}$
   - *Asym* is a numeric parameter representing the horizontal asymptote on the right side (very large values of input).
   - *R0* is a numeric parameter representing the response when input is zero.
   - *lrc* is a numeric parameter representing the natural logarithm of the rate constant.
6. Gompertz growth model
   - $Asym * e^{(-b2 * b3^{x})}$
   - *Asym* is a numeric parameter representing the asymptote.
   - *b2* is a numeric parameter related to the value of the function at x = 0
   - *b3* is a numeric parameter related to the scale the x-axis.

These non-linear least-squares problems were solved by a modification of the Levenberg-Marquardt algorithm and conducted in the R statistics software environment (Elzhov et al., 2016).

Once the optimum N rate was identified, the simulated N lost at that rate was also estimated after fitting a polynomial surface determined by one or more numerical predictors, using local fitting (i.e. loess). This was also analysed with the R statistics software (R Core Team, 2016).

5.6. Develop a method that integrates seasonal climate forecasts into N recommendations

It is has been suggested that seasonal climate forecasts should be factored into N recommendations, especially in the Wet Tropics where rainfall is intense and cane land sits adjacent to the Great Barrier Reef. This idea has circumnavigated the Australian sugar industry for some time as a possible way to improve Nitrogen best management practices. Whilst Schroeder et al. (2018) acknowledges that climate forecasting is already compatible with STEPS 5 and 6 in the SIX EASY STEPS nutrient management program, there remains a lot of thinking to be done, before seasonal climate forecasts can become routinely operational in the SIX EASY STEPS toolbox.

Understanding how seasonal climate forecasting can be linked to N management, and thus be cemented in the SIX EASY STEPS nutrient management plan, requires us to understand many things. We need to know how the crop responds to different amounts of N, the timing, frequency and amount of application needed for different years, and the kind of fertiliser that should be applied. Efforts in this project concentrated on one application of urea applied at the time of harvest. This work follows from that done by Skocaj (2015), who showed that typically, less N is needed on a Bulgun soil in a La Niña year in the southern climate zone of Tully for a crop harvested mid-season. Whilst the work performed by Skocaj (2015) was a good start, it raises a number of questions that will inform the development of a new and innovative methodological framework that integrates seasonal climate forecasts with N management beyond one soil, one harvest date and one climate zone. Pertinent questions to address include:

- Would the findings in Skocaj (2015) be different for a Bulgun soil for an early-cut block?
- How about a late-cut block?
- Would the nutrient guideline be different for a Bulgun soil in the northern climate zone and how would this guideline change with early, mid and late cut blocks?
- What if the crop was grown on a completely different soil?
- When would nutrient management on this soil interact with climate zone and harvest date?

Few would argue, it would be a mistake to extrapolate the knowledge generated in Skocaj (2015) for all soils, harvest times and climate zones in Tully. Fortunately, Section 5.5 of this report reveals a new methodology that explains how the APSIM farming system model can be used to tackle this knowledge gap. A full factorial process for simulating crop N requirements for eight soils, two climate zones and three harvest dates is outlined. Unfortunately, this simulation process does not factor in climate forecasts. An approach that can capitalise on knowledge if the season ahead is likely to be wet or dry needs to be factored into the APSIM simulation process. This poses more pertinent questions, that when seeking the answer, can also be used to inform the methodological approach that links climate forecasts to the APSIM crop model. Questions include:

- How does one link complex climate models run by supercomputers in different countries around the world, with a desktop standalone APSIM farming system model?
- And, there are many climate models to choose from, which one is best?

Even, if the answer to these last two questions exists, other barriers that stem from economics and sociology come to the forefront:

- What if a farmer plans for a wet season and it turns out to be dry? What happens next?

The typical scientist will argue the farmer should implement a long-term strategy based on probability theory, and say something along the following lines of

> "if you plan for the climate forecast and act accordingly, then in the long run you will be better off".

Whilst, this represents a logical and often economically valid argument, human behaviour does not always obey mathematical logic. When dealing with uncertainty, the way people process information and make decisions is complex and ranges from displays of rational to completely irrational behaviours (Gigerenzer, 2002). Relevant to decisions influenced by climate forecasting, Stern and Easterling (1999) warn of the "once bitten, twice shy" phenomenon displayed by people toward climate forecasts. The reality of the situation is - people will abort climate forecasts when they act, and the forecast is 'wrong'. This is particularly the case when large economic losses occur as a result of the forecast being 'wrong' or they are put down by their peers. The story does not stop here. For each barrier to the adoption of seasonal climate forecasts, there exists a barrier to the adoption of decision support systems (DSSs). The literature is abound with explanations of why decision support systems (DSSs) such as crop models have failed in the past (McCown et al., 2009, Stone and Hochman, 2004, Hochman and Carberry, 2011, Thorburn et al., 2011b). Reasons include but are not limited to

- the DSS being too complex,
- the DSS not doing what the farmers need, or want it to do,
- the DSS not recognising some farmers are more risk averse than others,
- farmers not having ownership of the DSS,
- farmers not being able to use the DSS as a co-learning or educational tool
- lack of financial support
- and most commonly of all, a perception that the outputs from the DSS are not 'ACCURATE' enough to reflect reality.

Building on lessons learnt from the past, a new framework for linking climate models with DSSs is needed not only for the Australian sugarcane industry but for agricultural industries worldwide. A new and innovative framework that attempts to address some useful concepts for promoting wider use of seasonal climate forecasts and APSIM is presented as a key result in this report. Although APSIM is the base DSS, this framework is relevant to many other DSSs.

5.7. Develop a prototype delivery tool

Steps 5 and 6 of the Six Easy Steps framework requires advanced understanding of how N fertiliser requirement is impacted by many factors such different soils, management, climate zones, and climate forecasts. It is not possible to have field experiments to test all these scenarios, so we rely on a well-tuned crop model (Section 5.5) and multiple climate models (Section 5.6) to provide the answer. In pursuit of offering industry a way to embed Steps 5 and 6 of the Six Easy Steps framework into routine decision making, the project team developed an N estimation algorithm that integrates the complex interactions between soils, climate, and agro-climate models (see Section 5.5 and 5.6). For ease of communication, the N estimation algorithm has been embedded into an App. The App should be considered a conceptual or prototype delivery tool at the time of writing this report.

6. RESULTS AND DISCUSSION

The project team developed an innovative and robust modelling approach that is flexible enough to cope with uncertainty in climate forecasts, natural year-to-year variability and different farmer risk levels, but useful enough to guide management practices and maintain harmony between the environment, profit margins and production. This approach is the first of its kind anywhere. The components that led to the robust modelling procedure are now described.

6.1. Climate Zones

The final clusters were chosen based on the annual rainfall and radiation data model as shown in Fig. 5. Spatially, the Tully region was split into southern and northern climatic sub-regions (Fig. 5a). Geographically, these sub-regions split roughly along the Tully River.

The southern sub-region (red) was characterised by higher radiation and lower rainfall than the northern sub-region (blue) with an obvious difference in the distribution of annual rainfall, radiation and maximum temperature between the two sub-regions (Fig. 5). However, there was little graphical evidence for a difference in annual minimum temperature. Results from the Kruskal-Wallis test confirmed that differences in annual rainfall, radiation and maximum temperatures were significant at the 0.05 level, while there was no significant difference in annual minimum temperature. Therefore, the northern sub-region can be described as the area northeast of the Tully River consisting of higher rainfall, lower radiation and lower maximum temperatures. The southern sub-region can then be described as the area south of the Tully River consisting of lower rainfall and higher radiation and maximum temperatures. This agreed with local industry knowledge.

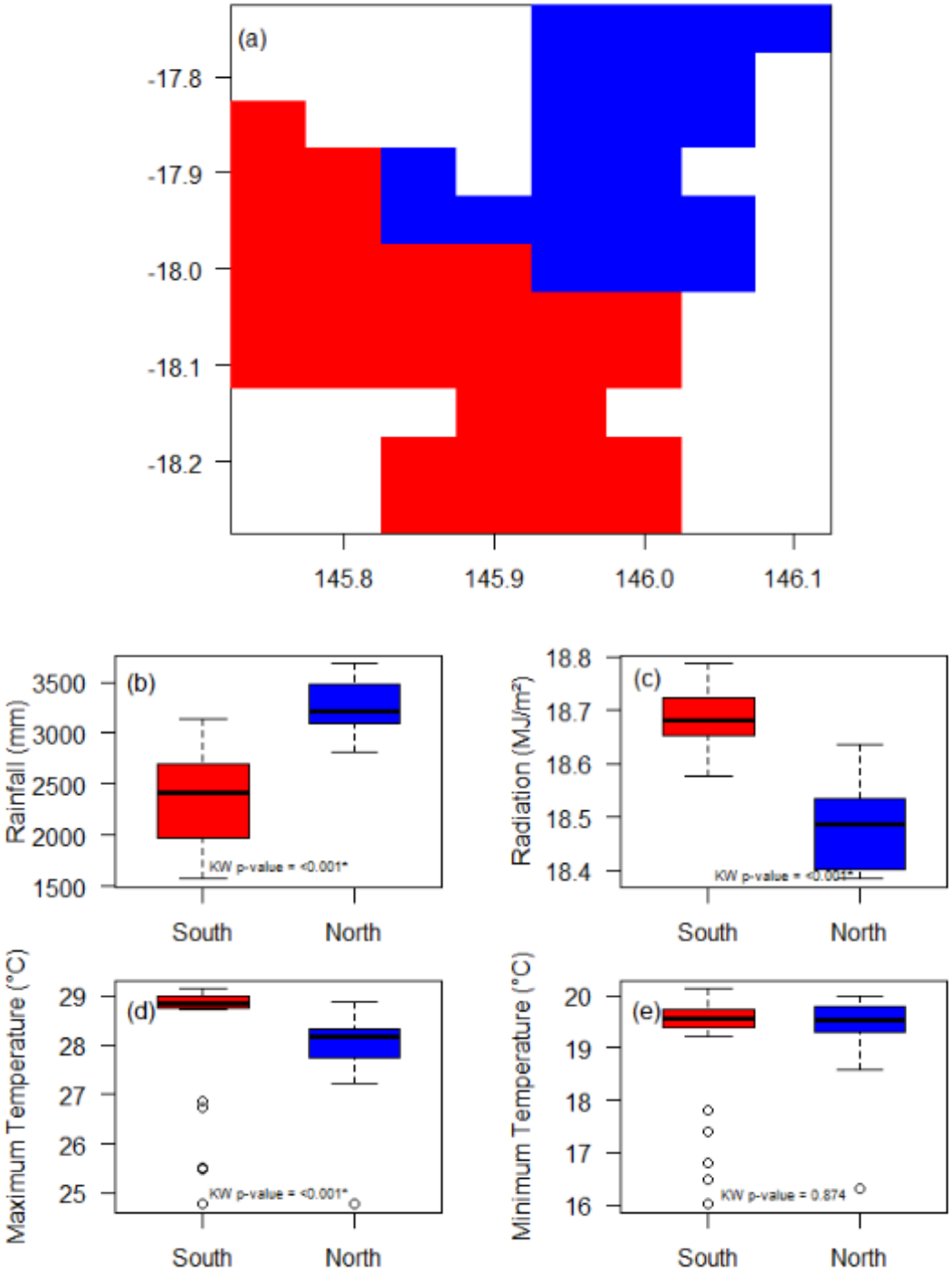


Figure 5. Climatic sub-regions in the Tully mill area using annual rainfall and radiation climate data. (a) Spatial plot showing the northern (blue) and southern (red) sub-regions. Figures (b) to (e) contain boxplots of median (1975:2015) annual climate variables for all 0.5 by 0.5˚ grid cells in the southern (red) and northern (blue) sub-regions. Boxplots show: (b) Total rainfall, (c) average daily radiation (d) average daily minimum temperature and (e) average daily minimum temperature. Differences in rainfall, radiation and maximum temperature were significant at the 0.05 level based on the KW test.

6.2. Soils

The impact of climatic conditions on the simulated N response curves for major soils in the Tully region has been investigated. Fifteen major soils of the Tully mill area were identified. Of these major soils, the Tully (28%), Coom (11%), Thorpe (11%), Bulgun (9%), Hewitt (6%), Warrami (4%), Tyson (1.5%) and Liverpool (1.5%) series soils were included in the investigation. The Tully, Coom and Thorpe series soils occupy the largest areas in both the northern and southern climate zones. The Warrami series soil only occurs in the southern climate zone. Due to the similarities between these eight soils and other soils in the region, with respect to the soil characteristics important to APSIM, 82% of the region is represented by these soils.

6.3. Investigate the relationship between Nitrogen and crop size

For the ratoon crop N response curves, the value of N_{opt} (the N rate corresponding to 95% of maximum yield, Y_{95}) varied from 0 to 253 kg N ha^{-1} and Y_{95} varied from 40 to 186 t ha^{-1} (Fig. 6). There was little correlation (r = 0.01, P = 0.91) between N_{opt} and Y_{95} in past N response experiments (Fig. 6). This result is likely due to variation in both yield potential and the amount of N needed to grow a tonne of cane. Further, this variation is likely to be caused by year-to-year variation in climate. An implication of this result is that focussing solely on yield potential is likely to be an ineffective means of improving N management recommendations, and further, doing so could result in sugarcane yield reductions. A more fruitful means of improving N management recommendations is to predict N_{opt} directly without reliance on assumptions of yield targets.

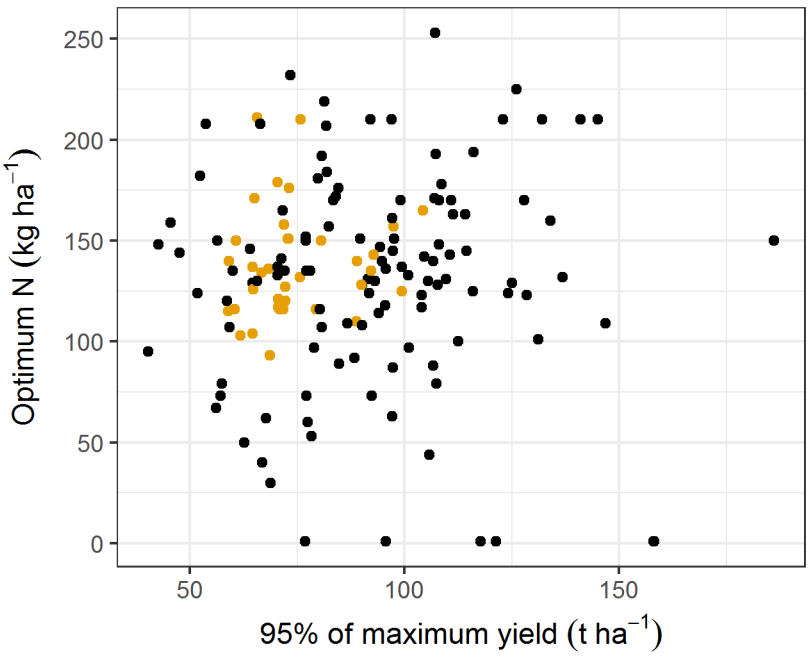


Figure 6. The relationship between 95% of maximum yield (Y_{95}) and the N rate corresponding to that yield (Optimum N: N_{opt}) derived from 154 ratoon crop N response experiments. The Tully-Coom experiment is identified in orange.

6.4. Simulate N response curves from field trial data

After including details of the climate, crop management and soil properties in the model, APSIM was able to represent quite well the relative cane yield response to applied N measured during two field trials in Tully (Fig. 7 and Fig. 8). The R-squared values were of 0.71 for the Coom trial and 0.66 for the Bulgun trial.

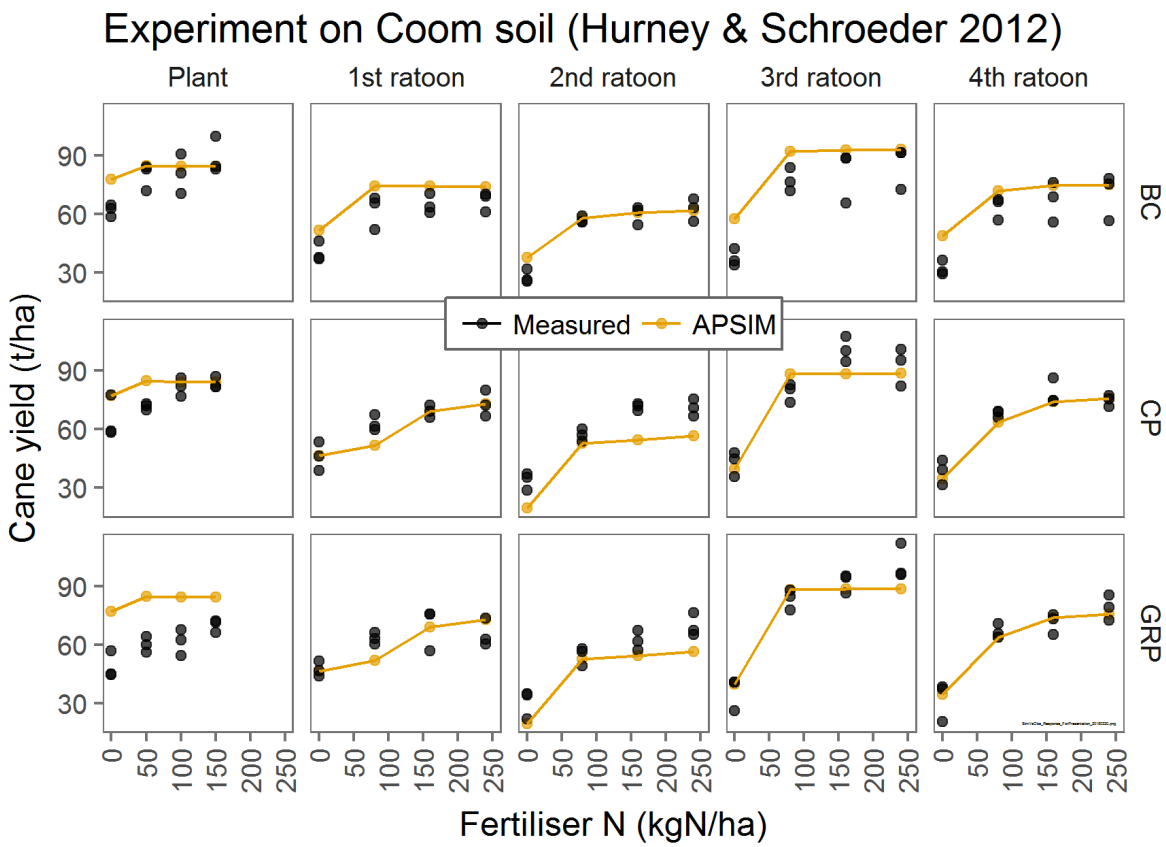


Figure 7. Coom trial (Hurney and Schroeder, 2012). Tested APSIM's ability to replicate behavior of N response experiment on a Coom series soil in Tully. Replicated cane yields are shown as solid black circles and APSIM yields as yellow lines. BC = Burnt Cane and conventional tillage, CP = Trashed retained and conventional tillage, GRP = Trashed retained & minimal tillage.

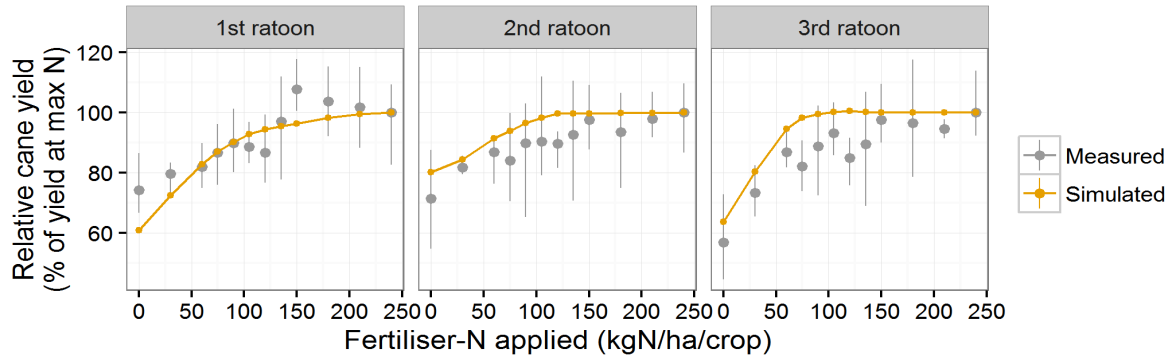


Figure 8. Bulgun trial. Simulated and measured relative yield response (percentage of yield at the maximum N rate) to different N rates. The maximum and minimum of measured yields (four replicates) are shown with vertical bars.

6.5 Develop a method to simulate N response curves for all climate zones and soil groups

When N response field trial data are available, it is possible to compare simulated N responses from the APSIM farming system model with the N responses observed from field trials. When field data are not available, the process is more challenging. The APSIM farming system model must be parameterised by applying specialist modelling know-how and mathematical modelling techniques (e.g. Barboux et al. (2018)), consulting with experts and the published literature. The simulations generated from the APSIM parameterisations can then be cross-checked with local experts and against a well-defined response (e.g. regional yields), that represents some fundamental part of the farming system. Failure to simulate a well-defined response would impart little confidence in the ability of APSIM to simulate crop N requirements. Strictly speaking the converse is not true, but it can be considered a necessary requirement to build confidence in the APSIM model.

The simulations conducted in this project is akin to running an experiment across 528 blocks for 64 years, noting that the number of blocks would need to be doubled for two replications and tripled for three replications. Clearly, such an experiment is not feasible. However, a "virtual" experiment can be conducted using APSIM. The model parameterisations used in this virtual experiment were used to simulate crop N requirements. The crop N requirements for the past 64 years for the 528 blocks is not known, but district yields are. Thus, the model was tested against historical district yields and demonstrated remarkable correspondence, imparting confidence in the ability of APSIM to simulate N response curves (Fig. 9).

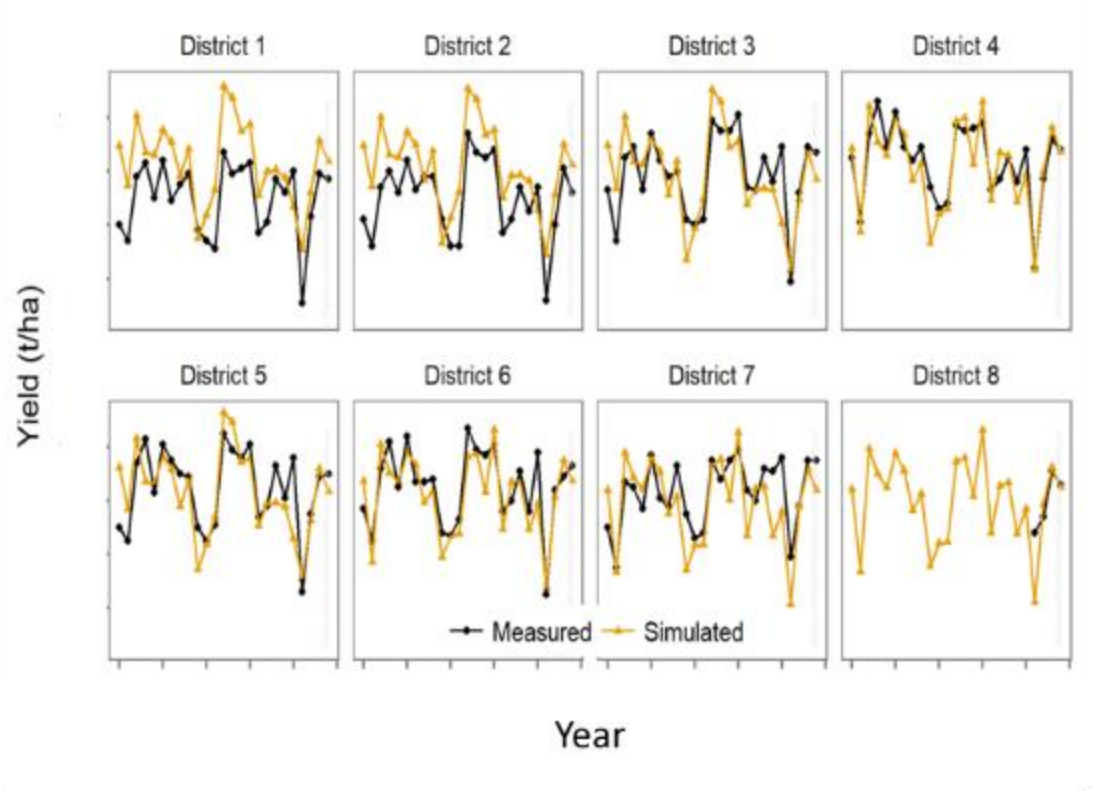


Figure 9. Ability of APSIM to simulate effect of year-to-year variability in district yields in Tully. District annual mean yield obtained from Tully district Comprehensive Area Productivity Analysis (CAPA) Tully sugar industry.

Based on this finding it is quite plausible to hypothesize that APSIM can provide useful insights about crop N requirements and levels of optimum N for different combinations of soils, climate zones and harvest times. One can then inspect how the simulations change from year to year based on natural inter-annual climate variability.

Fig. 10 and Fig. 11 demonstrate the large degree of inter-annual variability for a Tully soil in the southern climate zone for an early, mid and late harvest. Given the high degree of variability in the system, it will be important that any N guidelines are robust to the variability in this system.

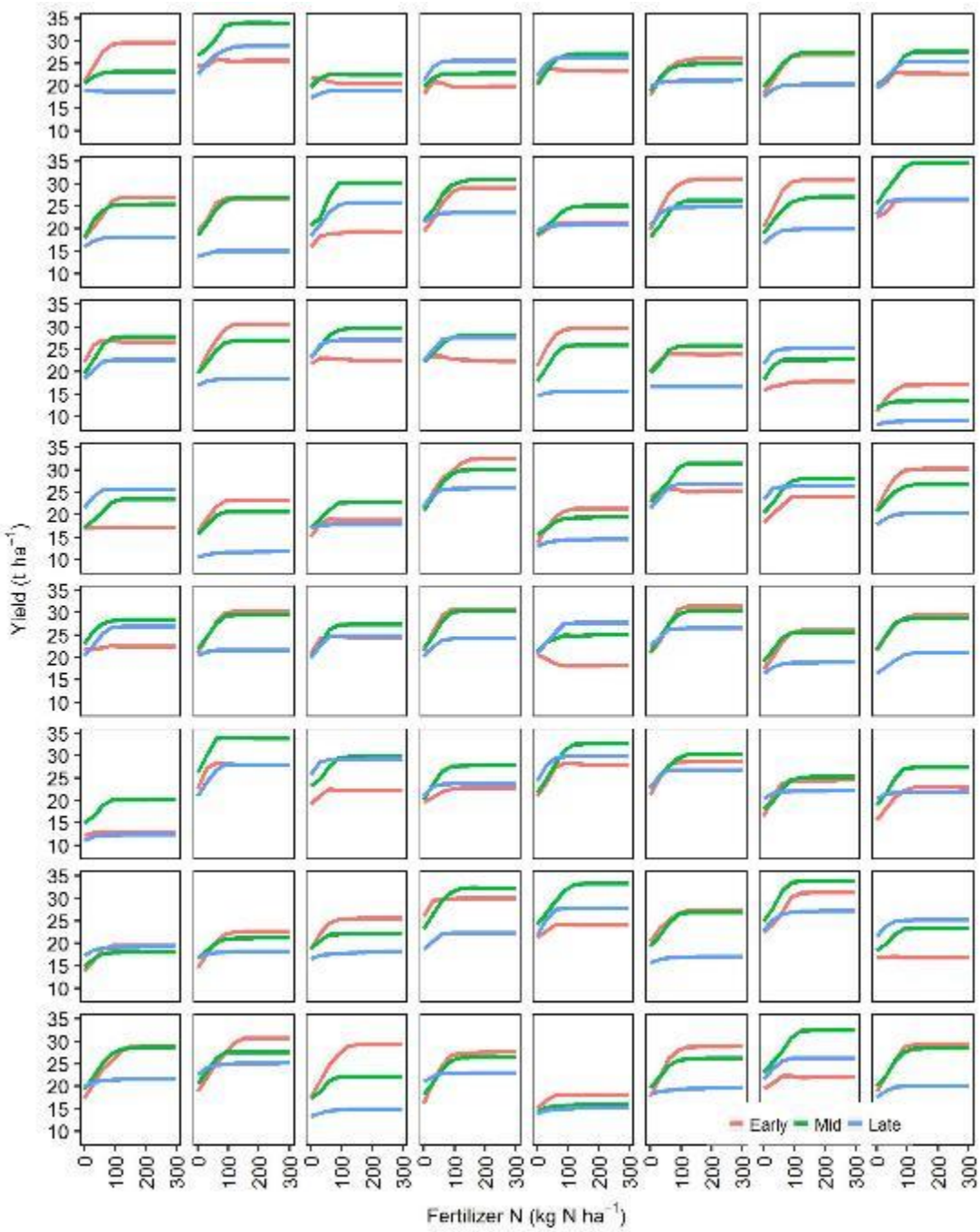


Figure 10. Nitrogen response curves for each of 64 years simulated using APSIM. Curves represent early (red), mid (green) and late (blue) harvested crops on grown in the Southern climate zone on a Tully soil.

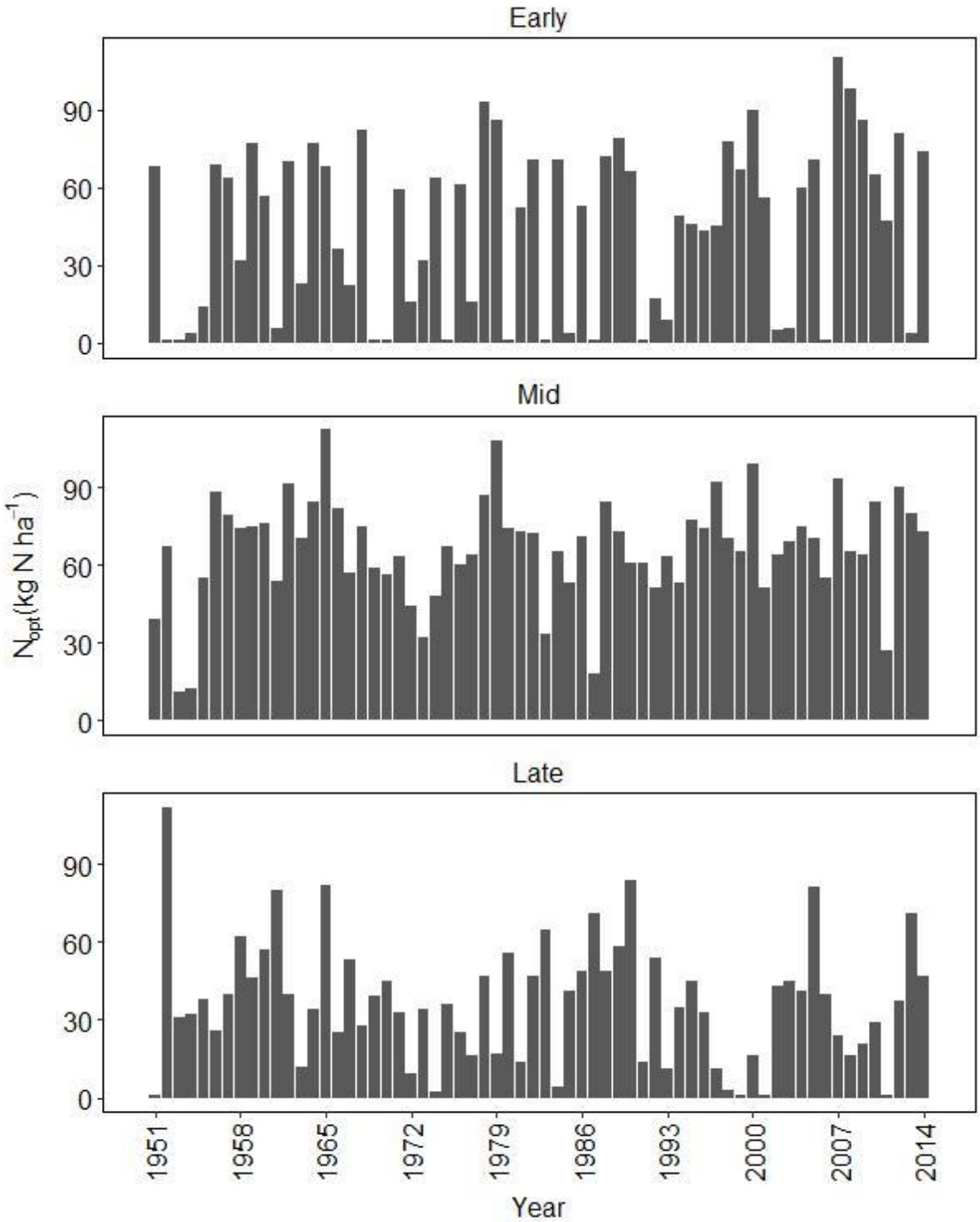


Figure 11. N_{opt} values for each year (1951 - 2014) for an early, mid or late harvested crop simulated in the Southern climate zone on a Tully soil.

6.6 Develop a method that integrates seasonal climate forecasts into N recommendations

6.6.1 Definition of La Niña, El Niño and Neutral

Climate agencies all around the world have slightly different definitions for El Niño and La Niña. For the purposes of this report, we define an El Niño (La Niña) event or year, to be one that occurs when the sea surface temperature in the Niño 3.4 region (Fig. 12) is higher (lower) than the long term average by 0.5°C (minus 0.5°C) for June to August in the year before harvest; a Neutral event as one where the deviation for July to August temperatures from the long term average in the Niño 3.4 region ranges from minus 0.5°C to plus 0.5°C, inclusively. Fig. 13 shows how the Niño 3.4 region has flipped between El Niño, Neutral and La Niña events for the 1951 and 2014 harvest seasons. In this report, an ENSO event can mean any one of the three events - El Niño, Neutral or La Niña.

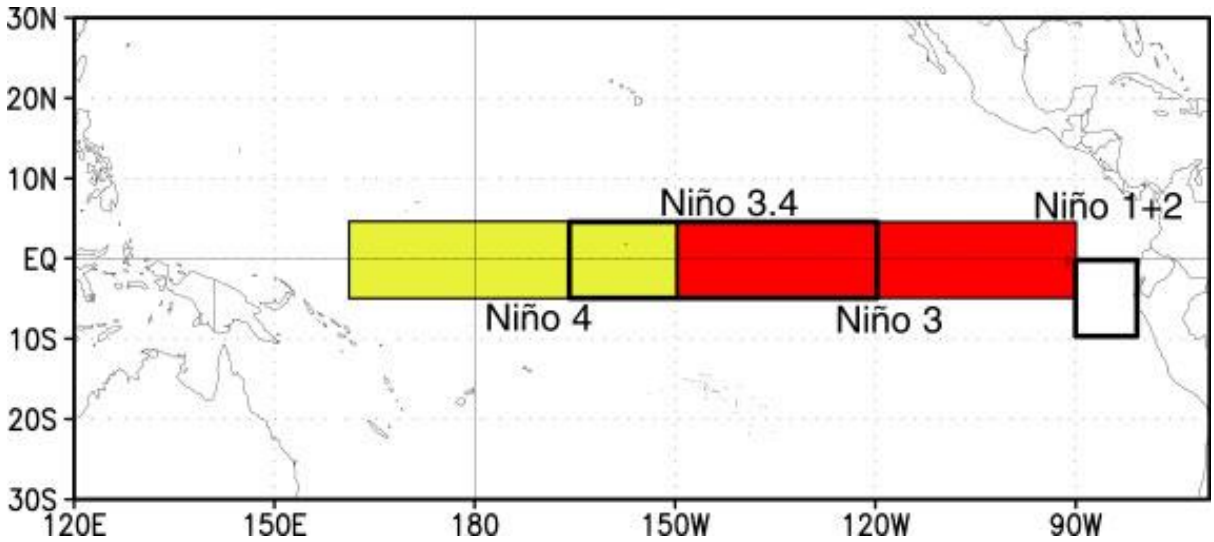


Figure 12. The Niño 3.4 region in the central equatorial Pacific Ocean. (Accessed April 2017 at http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/nino_regions.shtml)

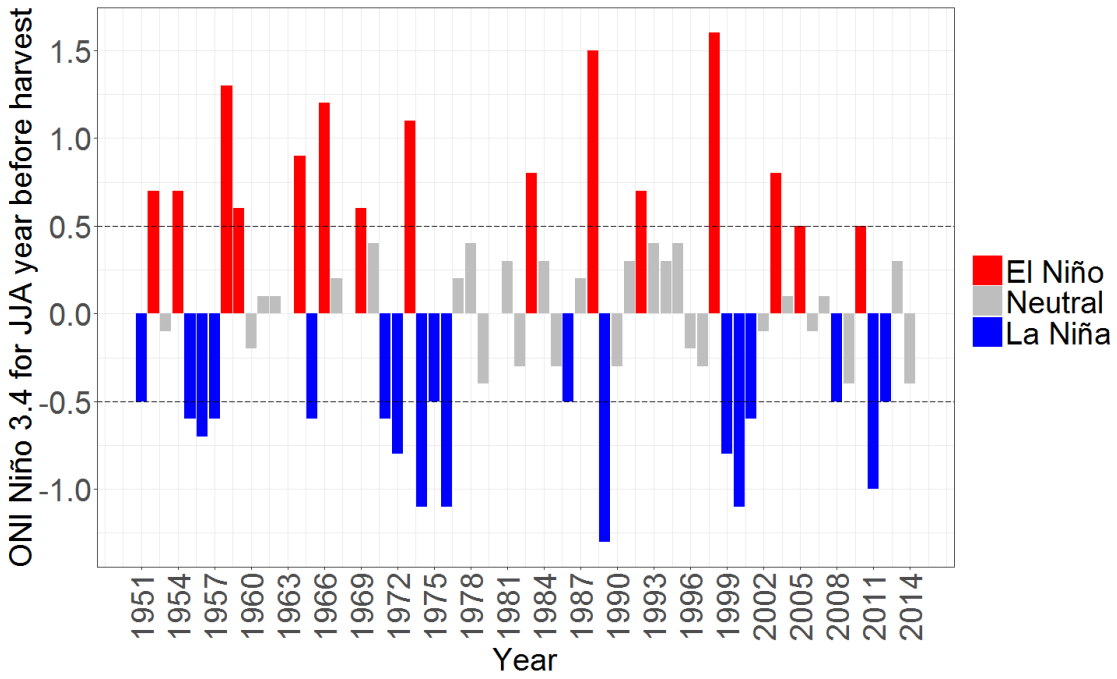


Figure 13. Time series plot of the June to August Oceanic Niño 3.4 Index for the 1951 to 2014 harvest seasons. Bars that reach or extend above 0.5°C are defined as El Niño events and are marked in red, bars that reach or extend below -0.5°C are defined as La Niña events and are marked in blue, and all other bars are for Neutral events and are marked in grey.

Anomalies in sea surface temperatures in the Niño 3.4 region (Fig. 12) have been found to influence climate in many parts of the world (Glantz, 2001). In Australia, El Niño can result in increased frost risk along the grain belt (Alexander and Hayman, 2008), reduced tropical cyclone numbers (Kuleshov et al., 2008) and increased fire danger (Cai et al., 2009). An overview of El Niño impacts in Australia including patterns of reduced rainfall and increased temperature can be found at http://www.bom.gov.au/climate/updates/articles/a008-el-nino-and-australia.shtml.

These climatic influences are especially important in the Wet Tropics of Australia and have been shown to influence cane yields (Everingham et al., 2003, Everingham et al., 2016, Skocaj and Everingham, 2014). It seems plausible that anomalies in Niño 3.4 sea surface temperature patterns could influence N management guidelines and is worthy of being explored in more detail.

6.6.2 How Optimum N and ENSO are related

Fig. 14 shows optimum N tends to be larger in La Niña years for an early harvest for a Tully soil in the southern climate zone and smaller in La Niña years for a late harvest. There is less of a difference between optimum N for ENSO events for a mid-season harvest. Although this pattern emerges, the spread in optimum N is quite large and ranges from 1 – 98 (La Niña), 1 – 78 (El Niño) and 1 – 110 (Neutral) for an early harvest crop. For a mid harvested crop optimum N ranges from 27 – 112 (La Niña), 12 – 84 (El Niño) and 11 – 108 (Neutral) while for a mid harvest crop and 1 – 82 (La Niña), 3 – 112 (El Niño) and 4 – 84 (Neutral) for a late harvest crop.

Fig. 15 extends upon Fig. 14, and compares the distribution of simulated optimum N for all eight soils (Tully, Coom, Thorpe, Bulgun, Hewitt, Warrami, Tyson, Liverpool), two climate zones (north and south) and three harvest dates (early, mid and late) by ENSO category (El Niño, Neutral, La Niña). Even with perfect knowledge of ENSO category, there is a large degree of variability in the system as previously observed for the Tully soil in Fig. 14.

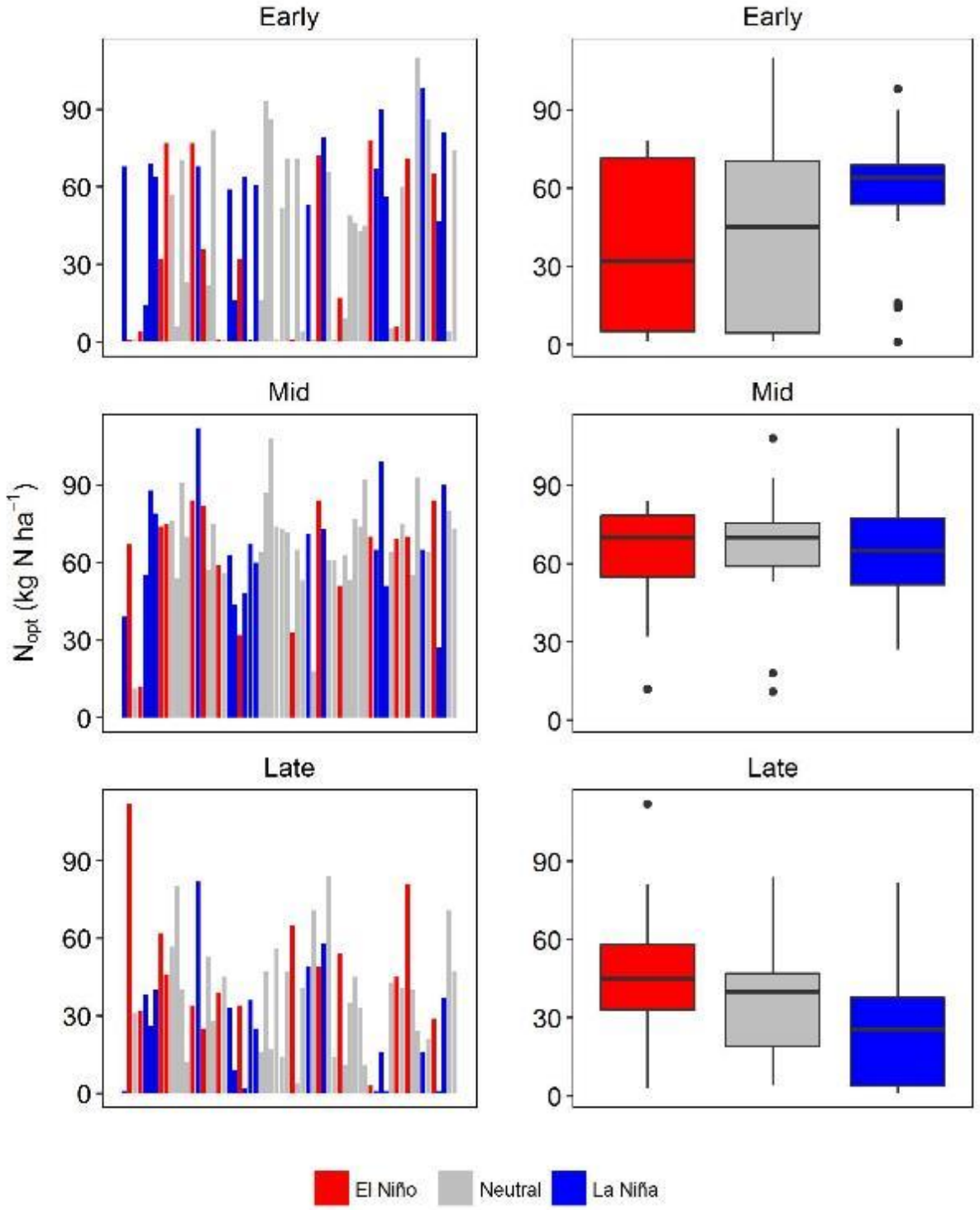


Figure 14. Optimum N from 1951 to 2014 and how it varies with La Niña, El Niño and Neutral events for a Tully soil in the southern climate zone. The bar charts in the left column displays the temporal variability, while the boxplots in the right column show the same data, but with the temporal component removed. The line in the box shows the median. This is the point that half the years had higher Optimum N values, and half had a lower optimum N. The top (bottom) of the box shows the upper (lower) quartile, the point which cuts off the top (bottom) 25% of optimum N values. The ENSO phase is for the June to August period of the year before harvest and is defined as El Niño (red), Neutral (grey) or La Niña (blue).

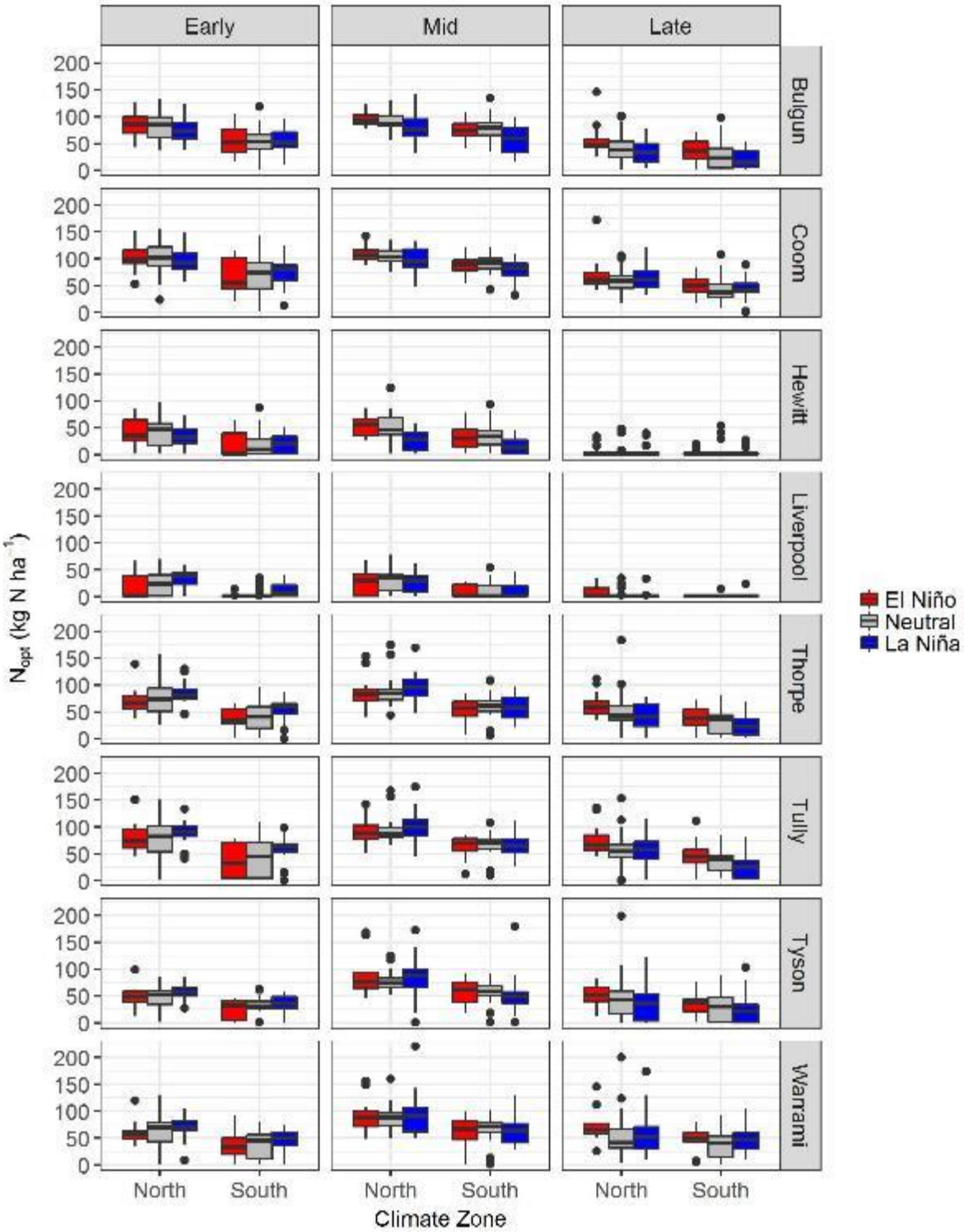


Figure 15. N_{opt} values by ENSO phase, simulated for eight soils, two climate zones and three harvest dates. Boxes represent the distribution of N_{opt} values for El Niño (red), Neutral (grey) and La Niña (blue) phases during the June – August period of the year before harvest.

6.6.3 Forecasting ENSO

Considerable effort by climate modelling groups around the world is spent on forecasting anomalies in sea surface temperatures in the Niño 3.4 region. An anomaly of just 0.5°C can signal the onset of an El Niño pattern while an anomaly of minus 0.5°C can signal the onset of a La Niña pattern. Fig. 16 shows the forecast of Niño 3.4 sea surface temperature anomalies that were made by different leading international authorities in mid-February 2017. This figure demonstrates a large degree of variability in predicting the Niño 3.4 index values by different leading international authorities. Models like the UKMO predicted the onset of an El Niño pattern later in 2017. Most statistical models predicted Neutral conditions. Interestingly, only the LDEO model correctly predicted the onset of a La Niña pattern, which was the actual outcome in 2017.

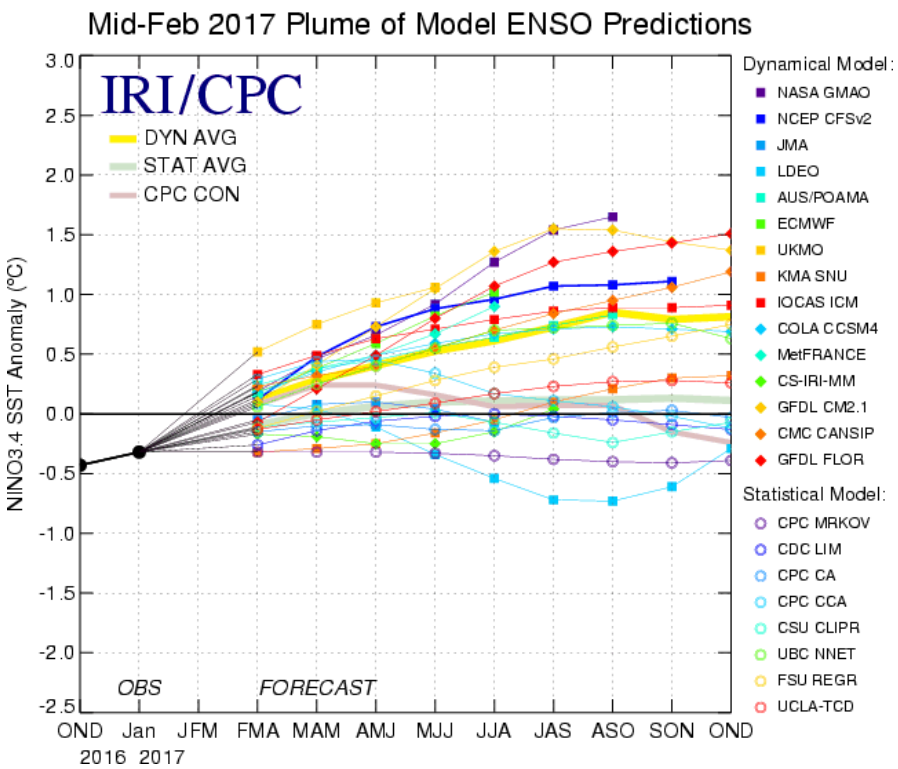


Figure 16. Forecasts of the Niño 3.4 sea surface temperature anomaly Index produced by a range of dynamical and statistical models (Accessed Feb 2017 at http://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/).

Fig. 17 shows the probability of an El Niño, Neutral and La Niña developing late in 2017. These probabilities were generated by equally weighting the forecast of each of the dynamical and statistical models in Fig. 16. Of interest to this report is the forecast for June to August Niño 3.4 conditions. The data in Fig. 17 show there is a 45% chance of an El Niño SST pattern, 47% chance of a Neutral SST pattern and only an 8% chance of a La Niña being established in June to August 2017.

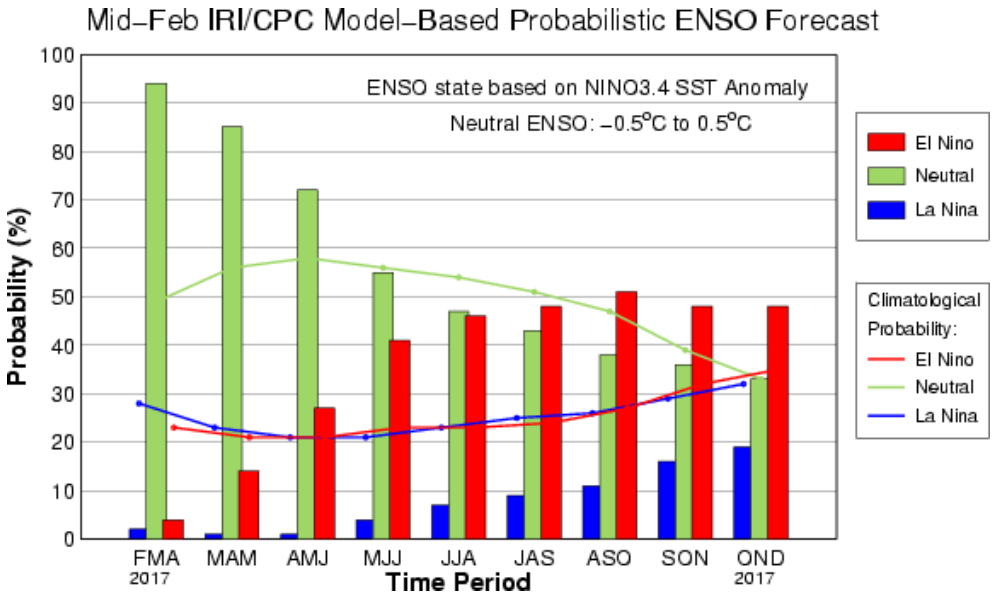


Figure 17. Probability of El Niño, Neutral and La Niña developing later in 2017. These probabilities are generated by a regression approach where the independent variables are the model predictions from the plume of dynamical and statistical forecasts shown in Fig. 16. Each model is weighted equally in the regression model (Accessed Feb 2017 at http://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/).

6.6.4 The ABC framework for forecasting optimum N

A framework that links seasonal climate forecasts to nutrient management via a decision support system (DSS) is needed. This framework should be informed by the social science literature that surrounds seasonal climate forecasting technologies and decision support systems. The framework is presented in Fig. 18 and it is "as easy as ABC".

A. Respect the widely varying risk profiles of farmers
B. Seamlessly connect climate forecast models with the APSIM farming systems model
C. Be robust to the variability in the agro-meteorological system.

Figure 18. Core elements in the ABC framework for forecasting optimum N.

A. Respect the widely varying risk profiles of farmers

Firstly, the framework must respect not all farmers have the same level of risk aversion, and that the level of risk of aversion for one farmer may change from season to season or be influenced by other factors such as soil type, price of urea and crop age. Farmers should be able to choose their own risk threshold.

The prototype form of the DSS (Optim-N), currently allows farmers to select one of three levels of risk – nine in ten years, seven in ten years and five in ten years. The nine, seven and five refers to how many years in ten the farmer wants to be sure that enough N goes on the crop. So, if a farmer wanted to be sure 90% of the time, they would select the nine in ten years option.

B. Seamlessly connect climate forecast models with the APSIM farming systems

Secondly, although the mathematical procedures that underpin the climate models, APSIM and the integration of the two is complex, the basic approach should be understood by the farmer and/or their advisor, and the connection between the two sets of models should be seamless. The prototype DSS demonstrates how this can be done and is explained in more detail in item C-IV below.

C. Be robust to the variability in the agro-meteorological system.

Repeatedly, the social science literature echoes that farmers and advisors fail to adopt DSSs because they perceive the DSS is not accurate enough. It is time to forget about the accuracy of models, especially models of complex systems. Instead, we must make models robust to the obtuse sensitivities in the system. The framework must be robust to the variability in both the climate and cropping systems. Our prototype DSS caters for robustness in four ways.

I. Robust against sampling variability

The DSS should reflect the sampling variability in a point estimate like the optimum N value. The "New Statistics" (Cumming, 2012), advocates that we must turn more to interval estimation techniques. The "New Statistics" has become standard in psychology and medicine, and we can expect the sciences to follow suit eventually. The prototype DSS currently provides a 95% confidence interval for the value of optimum N that is needed to ensure the simulated crop has enough N, nine in ten years. A similar interval estimate is also produced for the optimum N value that ensures enough N is put on seven years in ten, and five years in ten. Thus, these interval estimates are for the 90th, 70th and 50th percentile of optimum N and align with the risk profile selected by the farmer.

II. Robust against natural inter-annual variability

The optimum N will vary from year to year for each combination of soil, climate zone x harvest date. The nutrient guidelines must be robust against this volatility. By working with an interval estimate, the prototype DSS extinguishes this volatility by allowing the farmer to select their own risk profile.

III. Robust against outliers

We should use statistics that have minimal impact by an outlier. Outliers have less impact on percentiles than other statistics such as the mean. The prototype DSS therefore uses statistics based on percentiles.

IV. Robust against choice of climate model

There are many climate models that predict the Oceanic Niño 3.4 Index, most of these models perform well most of the time, but none of the models perform well all the time, and sometimes, some of the models do not perform well at all. In an operational setting it is difficult to know which 'horse' you should back. Horse punters spread their risk by backing a few horses each way. The analogy is similar for choosing a climate model, and, if you will pardon the pun, the Europeans are off to a good start. Although it is considered that European organisations are less experienced at using seasonal climate forecasts relative to other organisations around the world, climate-savvy organisations in Europe have quickly

realised that an *enabler* to the use of seasonal climate forecasts is to triangulate between the advice of multiple climate models (Bruno Soares and Dessai, 2016). It will be to the advantage of Australian organisations and other organisations worldwide, to adopt a similar approach.

Our prototype DSS already does this, and uses forecasts of the Oceanic Niño 3.4 Index for June through to August from all climate models displayed in Fig. 16. From each model, a probability for an El Niño, La Niña and Neutral event is computed. In the case of Fig. 17, for June to August, there was a similar chance of an El Niño or Neutral event and a much smaller chance by comparison, of a La Niña event. More precisely, there was a 45% chance of an El Niño event, 47% chance of a Neutral event and an 8% chance of a La Niña event. If there were 100 years of climate data, this would mean injecting APSIM with 45 El Niño years, 47 Neutral years and 8 La Niña years to generate a distribution of optimum N values as illustrated in Fig. 19**Error! Reference source not found.**[1].

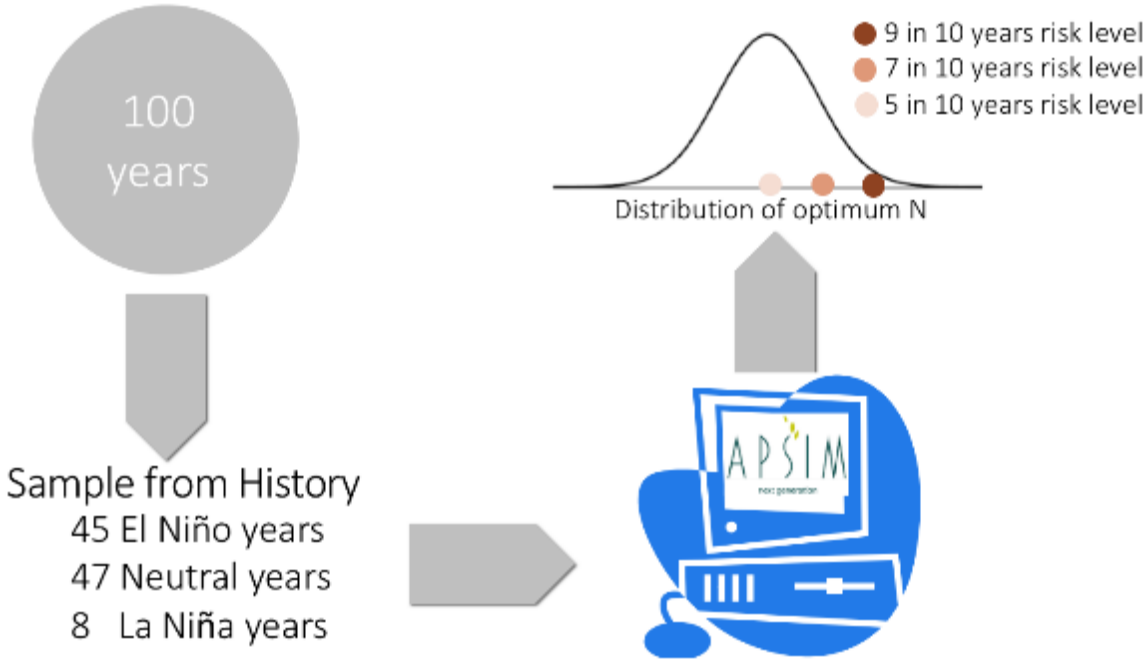


Figure 19. Modelling process of estimating N requirements based on the likelihood of an El Niño, Neutral or La Niña sea surface temperature pattern developing. Sea surface temperature predictions are determined from a broad spectrum of international dynamical and statistical models

6.6.5 Future work

Need to determine if the definition of an El Niño, La Niña and Neutral event is robust against early, mid and late cut blocks.

[1] To generate the interval estimate, this sampling procedure is repeated many times and this gives rise to the interval estimates for optimum N at the 9 in 10, 7 in 10 and 5 in 10 risk levels. Also, the distribution of optimum N shown above is for illustrative purposes only, the distribution may, or may not be bell-shaped.

6.7 Prototype delivery tool for the DSS

A method for transferring the knowledge embedded in the DSS is required. Optim-N, a prototype App has been developed to do this. Fig. 20 shows a draft design of the front-end of Optim-N and how it works. In this example, a block with a Tully soil is selected from the southern climate zone for an early harvest date. The forecasts produced from a host of internationally reputable forecasting systems have been consulted. Most of these models favour either an El Niño or Neutral event to develop during the harvest. Guidelines for the amount of N to apply can be interpreted as follows:

- If a farmer on a Tully soil in the southern climate zone who plans to harvest their block early, wanted to have a high level of confidence of applying at least the right amount of N fertiliser nine years in ten, then the App indicates there is a 95% chance that the true value for optimum N is between 74 – 86 kg N ha^{-1}.
- If a farmer on a Tully soil in the southern climate zone who plans to harvest their block early, wanted to have a high level of confidence of applying at least the right amount of N fertiliser seven years in ten, then the App indicates there is a 95% chance the that true value for optimum N is between 49 – 74 kg N ha^{-1}.
- If a farmer on a Tully soil in the southern climate zone who plans to harvest their block in June, wanted to have a high level of confidence of applying at least the right amount of N fertiliser five years in ten, then the App indicates there is a 95% chance that the true value for optimum N is between 17 – 57 kg N ha^{-1}.

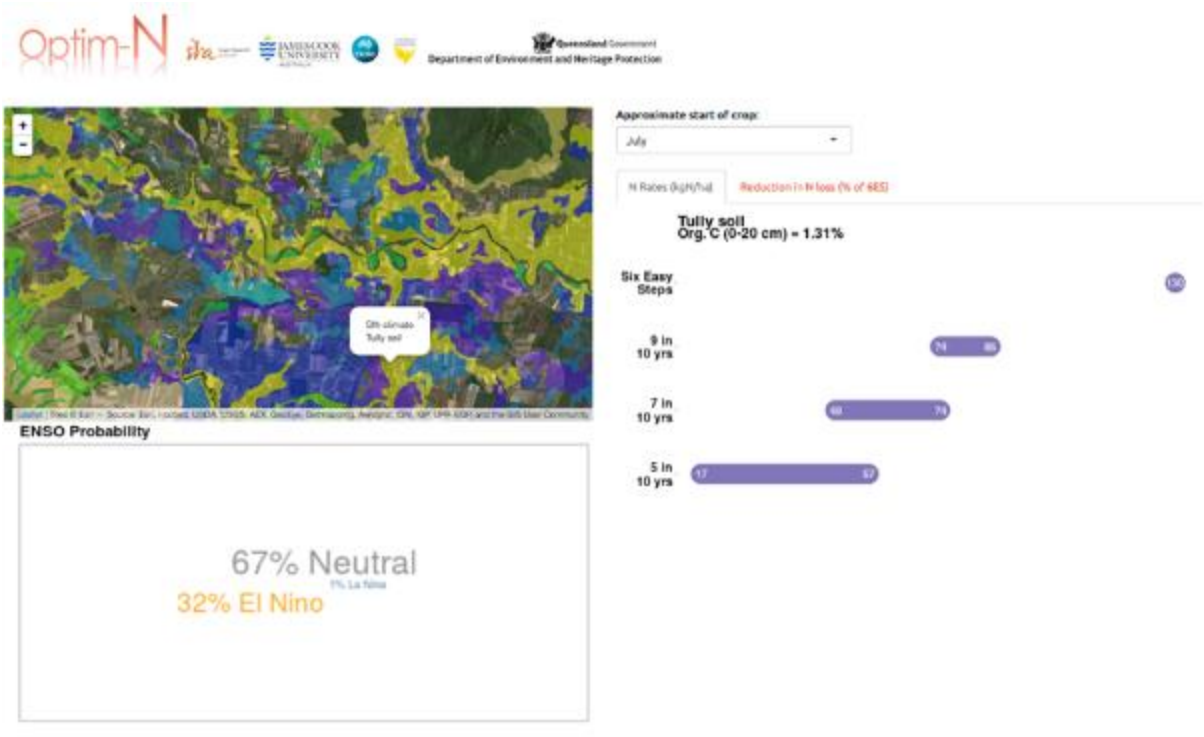


Figure 20. A screen-grab of the Optim-N prototype app. A geographic interface allows the user to choose a harvest time and select their block. Block selection identifies the soil type and climate zone. The chance of each ENSO event is captured. These chances are determined by surveying the forecasts from a range of international climate models. Optimum N intervals are produced for three risk levels are produced. Applying between 74 kg N ha^{-1} and 86 kg N ha^{-1} is a low risk option with a 9 in 10 chance that the true N_{opt} will be within the estimated range, and therefore the crop is unlikely to be under fertilized.

Two major activities are needed to take Optim-N from a prototype, to a widely used tool:

1. Optim-N would need to be trialled with farmers in an action learning context so they could understand how it helps their decision making. This experience would
    a. Drive refinements of the Optim-N App and the ABC framework that underpins it.
    b. Provide more empirical data for testing the science behind the tool reducing the reliance on expert opinion and
    c. Increase trust and end-user confidence in the tool, which would accelerate adoption.
2. Optim-N prototype also needs input from professional software experts to take it to commercial levels of robustness and usability.

7. CONCLUSIONS

For the first time ever, a robust and innovative process for connecting climate forecasts to crop Nitrogen requirements via the APSIM crop model exists for the Australian sugarcane industry. This allows farmers and their advisors to implement Steps 5 and 6 in the SIX EASY STEPS framework in a relatively straightforward manner. This process can be adapted for sugarcane and other cropping systems nationally and internationally. The process was made novel, by

- Developing and implementing the ABC framework to provide N management recommendations in a robust and risk tolerant way for farmers. The ABC framework encapsulates complex social and technical processes that surround end-user interaction with complex decision support systems such as APSIM and climate models.
- Developing Optim-N: a simple and easy to use prototype App that helps farmers and their advisors estimate their crop's N requirement for the coming season.
- Identifying, and demonstrating, that traditional thinking linking crop N requirements to crop size is flawed.
- Demonstrating that both the optimum N for a crop and the affect of climate on optimum N depend on harvest time.
- Creating a vision for making this information easily accessible to a range of stakeholders.

The process will save farmers money by tailoring season- and site-specific recommendations for individual cane paddocks; improve water quality leaving farms and entering waterways to the Great Barrier Reef, and skill-up extension officers, more efficiently to provide better advice for the farmers they serve. Most importantly, this process, when operational, will demonstrate to broader society, that the Australian sugar industry is a world leader in sustainable Nitrogen management practices.

Take home messages:

- Nitrogen management practices are complex, with optimum management varying in space and time.
- There is no silver bullet, only tools (e.g. Optim-N) that can guide management procedures and policies.
- APSIM is a simulation tool that if used properly, can reduce the effort associated with field trials and, in the absence of data from field experiments can help farmers make more informed decisions.
- The project consultative committee has developed a sense of confidence in the potential of the DSS. This sense of confidence was driven by:
    - The participatory, co-learning approach taken in the project.
    - The ability of APSIM to reproduce field trials on Bulgun and Coom soils.
    - The ability of APSIM to model subregional yields quite well.
    - Recognition and appreciation of the effort and data required to model complex agro-meteorological systems.
    - Taking a robust approach and producing interval estimates of optimum N stemming from multiple climate models.
    - Allowing farmers to choose their own risk confidence level.
    - Treating Tully as two separate climate zones within the DSS.
    - Enhancing farmer intuition by demonstrating

- less N is needed on late cut blocks in wet years
- more N is needed on early cut blocks in wet years, particularly in the drier, southern climate zone
- seasonal forecasts have less impact on mid season cut blocks.

- The project dispelled the myth, that N can be managed based on block yield production.
- Optim-N is a vehicle to bring climate to the front of farmer thinking.
- Optim-N will complement the effort needed to go beyond step 4 in SIX EASY STEPS.
- The project team has used innovative data visualisation techniques to maximise understanding of complex problems (e.g. the scatterplot of yield versus optimum N, and the heat map which shows different N requirements relative to wet and dry years). ·
- A communication plan is needed that exposes the effort, key findings and close industry engagement undertaken in this project.
- The project team together with the consultative committee have developed a method to identify and distinguish different soils in Tully.
- To maximise adoption of DSSs, it is important to understand and respect how people interact with DSSs, and it is equally important to understand why people in the past have failed to adopt DSSs.
- The Optim-N is a new tool for the SIX EASY STEPS Toolbox.
- Two major activities are needed to take Optim-N from a prototype, to a widely used tool:
    - 1) Optim-N would need to be trialled with farmers in an action learning context, so they could understand how it helps their decision making. This experience would also drive refinements of the Optim-N tool. It would also provide more empirical data for testing the science behind the tool, reducing the reliance on expert opinion and simultaneously increase trust and end-user confidence in the tool, which would accelerate adoption.
    - 2) Optim-N prototype also needs input from professional software experts to take it to commercial levels of robustness and usability.

8. PUBLICATIONS

BIGGS, J., SKOCAJ, D., HURNEY, A., SCHROEDER, B., THORBURN, P., BARBOUX, R. & EVERINGHAM, Y. L. 2018. Simulating 'How much N will that crop need?' for Tully soils and climates using APSIM *Proceedings of the Australian Society of Sugar Cane Technologists.* Mackay, Queensland, Australia.

SCHROEDER, B., SKOCAJ, D., THORBURN, P., BIGGS, J., SEXTON, J. & EVERINGHAM, Y. L. 2018. IS CLIMATE FORECASTING COMPATIBLE WITH THE 'SIX EASY STEPS' NUTRIENT MANAGEMENT PROGRAM? *Proceedings of the Australian Society of Sugar Cane Technologists.* Mackay, Queensland, Australia.

THORBURN, P., BIGGS, J., SKOCAJ, D., SCHROEDER, B., SEXTON, J. & EVERINGHAM, Y. L. 2018. CROP SIZE AND SUGARCANE NITROGEN FERTILISER REQUIREMENTS: IS THERE A LINK? *Proceedings of the Australian Society of Sugar Cane Technologists,* 40**,** 210-218.

THORBURN, P., BIGGS, J., SKOCAJ, D., SCHROEDER, B., SEXTON, J. & EVERINGHAM, Y. L. 2017b. Does crop size determine sugarcane Nitrogen fertiliser requirements? *Proceedings of the Australian Society of Sugar Cane Technologists.* Cairns, Queensland, Australia.

BARBOUX, R., BIGGS, J. & THORBURN, P. 2018. Producing APSIM soil parameters from soil survey data to underpin better nitrogen management. *Proceedings of the Australian Society of Sugar Cane Technologists.* Mackay, Queensland, Australia.

SEXTON, J., EVERINGHAM, Y. L., SKOCAJ, D., BIGGS, J., THORBURN, P. & SCHROEDER, B. 2017. IDENTIFICATION OF CLIMATOLOGICAL SUB-REGIONS WITHIN THE TULLY MILL AREA. *Proceedings of the Australian Society of Sugar Cane Technologists,* 35**,** 342-350.

SKOCAJ, D., SCHROEDER, B. & HURNEY, A. 2017. Categorising soils for improved Nitrogen management in the Tully Mill Area. *Proceedings of the Australian Society of Sugar Cane Technologists.* Cairns, Queensland, Australia.

9. ACKNOWLEDGEMENTS

The project team would like to acknowledge the "Tully *how much N will that crop need*? Consultative Group" for their time attending multiple project meetings, contributing ideas and providing valuable and honest feedback about the work conducted in this project. Their contribution to the project has allowed the project team to finish the project with a clear vision on how industry can benefit from the research conducted in this project.

10. REFERENCES

ALEXANDER, B. & HAYMAN, P. 2008. Can we use forecasts of El Niño and La Niña for frost management in the Eastern and Southern grains belt? Proceedings of the Australian Agronomy Conference.

ALLEN, D., KINGSTON, G., RENNENBERG, H., DALAL, R. & SCHMIDT, S. 2010. Effect of nitrogen fertilizer management and waterlogging on nitrous oxide emission from subtropical sugarcane soils. Agriculture Ecosystems and Environments, 136, 209-217.

ANON. 2016. Burdekin nitrogen trials, case studies and trial results [Online]. Available: http://www.sugarresearch.com.au/icms_docs/243579_Burdekin_Nitrogen_Trials_-_Case_studies_and_trial_results.pdf [Accessed 8/11/2016].

AWAN, J.A., BAE, D-H. & KIM, K-J. 2015. Identification and trend analysis of homogeneous rainfall zones over the East Asia monsoon region. International Journal of Climatology, 35, 1422-1433.

BARBOUX, R., BIGGS, J. & THORBURN, P. 2018. Producing APSIM soil parameters from soil survey data to underpin better nitrogen management. Proceedings of the Australian Society of Sugar Cane Technologists. Mackay, Queensland, Australia.

BIGGS, J., SKOCAJ, D., HURNEY, A., SCHROEDER, B., THORBURN, P., BARBOUX, R. & EVERINGHAM, Y. L. 2018. Simulating 'How much N will that crop need?' for Tully soils and climates using APSIM Proceedings of the Australian Society of Sugar Cane Technologists. Mackay, Queensland, Australia.

BOYDELL, B. & MCBRATNEY, A. B. 2002. Identifying potential within-field management zones from cotton-yield estimates. Precision Agriculture, 3, 9-23.

BRODIE, J., KROON, F., SCHAFFELKE, B., WOLANSKI, E., LEWIS, S., DEVLN, M., BOHNET, I., BAINBRIDGE, Z., WATERHOUSE, J. & DAVIS, A. 2012. Terrestrial pollutant runoff to the Great Barrier Reef: An update of issues, priorities and managemnet responses. Marine Pollution Bulletin, 65, 81-100.

BRUNO SOARES, M. & DESSAI, S. 2016. Barriers and enablers to the use of seasonal climate forecasts amongst organisations in Europe. Climatic Change, 137, 89-103.

CAI, W., T, C. & RAUPACH, M. 2009. Positive Indian Ocean Dipole events precondition southeast Australia bushfires. Geophysical Research Letters, 36, L19710.

CANNON, M., SMITH, C. & MURTHA, G. 1992. Soils of the Cardwell-Tully area, North Queensland. Division report No. 115. Division of Soils, CSIRO.

CATCHPOOLE, V. & KEATING, B. 1995. Sugarcane yield and nitrogen uptake in relation to profiles of mineral-nitrogen in the soil. Proceedings of the Australian Society of Sugar Cane Technologists, 17, 187-192.

CHAPMAN, L. 1982. Estimating sugar yield responses from N, P and K fertilisers in Queensland. Proceedings of the Australian Society of Sugar Cane Technologists, 4, 147-153.

CHAPMAN, L. 1994. Fertiliser N management in Australia. Proceedings of the Australian Society of Sugar Cane Technologists, 16, 83-92.

CHARRAD, M., GHAZZALI, N., BOITEAU, V. & NIKNAFS, A. 2014. NbClust: An R package for determining the relevant number of clusters in a data set. Journal of Statistical Software, 61, 36.

CLARKE, A. J., VAN GORDER, S. & EVERINGHAM, Y. 2010. Forecasting Long-Lead Rainfall Probability with Application to Australia's Northeastern Coast. Journal of Applied Meteorology and Climatology, 49, 1443-1453.

CLEVELAND, W. S., GROSSE, E. & SHYU, W. M. 1992. Local regression models. In: CHAMBERS, J. M. & HASTIE, T. J. (eds.) Statisitcal Models in S. Wadsworth & Brooks/Cole.

CUMMING, G. 2012. Understanding the new statistics, effect sizes, confidence intervals and meta-analysis, New York, Routledge Taylor & Francis Group.

CUPITT, J. & WHELAN, B. 2001. Determining potential within-field crop management zones. Proceedings of the 3rd European conference on precision agriculture.

DE'ATH, G., FABRICIUS, K., SWEATMAN, H. & PUOTINEN, M. 2012. The 27-year decline of coral cover on the Great Barrier Reef and its causes. PNAS, 44, 17995-17999.

DELOITTEACCESSECONOMICS 2013. Economic contribution of the Great Barrier Reef. Townsville: Great Barrier Reef Marine Park Authority.

ELZHOV, T. V., MULLEN, K. M., SPIESS, A.-N. & BOLKER, B. 2016. minpack.lm: R Interface to the Levenberg-Marquardt Nonlinear Least-Squares Algorithm Found in MINPACK, Plus Support for Bounds. 1.2-1 ed.

EVERINGHAM, Y. L., MUCHOW, R., R, S. & COOMANS, D. 2003. Using southern oscillation index phases to forecast sugarcane yields: a case study for northeastern Australia. International Journal of Climatology, 23.

EVERINGHAM, Y. L., SEXTON, J., SKOCAJ, D. & INMAN-BAMBER, G. 2016. Accurate prediction of sugarcane yield using a random forest algorithm. 36.

GIGERENZER, G. 2002. Reckoning with risk, learning to live with uncertainty, London, Penguin.

GLANTZ, M. 2001. Currents of Change: Impacts of El Niño and La Niña on Climate and Society, Cambridge, NY, Cambridge University Press.

HARTIGAN, J. A. & WONG, M. A. 1979. Algorithm AS 136: A k-means clustering algorithm. Journal of the Royal Statistical Society. Series C (Applied Statistics), 28, 100-108.

HASTIE, T., TIBSHIRANI, R. & FRIEDMAN, J. H. 2013. The elements of statistical learning, New York, Springer.

HOCHMAN, Z. & CARBERRY, P. 2011. Emerging consensus on desirable characteristics of tools to support farmers' management of climate risk in Australia. Agricultural Systems, 104, 441-450.

HURNEY, A. & SCHROEDER, B. 2012. Does prolonged GCTB influence N requirements of the sugarcane crop in the wet tropics. Proceedings of the Australian Society of Sugar Cane Technologists, 34, 1-9.

JEFFREY, S. J., CARTER, J. O., MOODIE, K. B. & BESWICK, A. R. 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environmental Modelling & Software, 16, 309-330.

KEATING, B.A. & THORBURN, P.J. (2018). Modelling crops and cropping systems – evolving purpose, practice and prospects. European Journal of Agronomy (in press).

KULESHOV, Y., QI, L., FAWCETT, R. & JONES, D. 2008. On tropical cyclone activity in the Southern Hemisphere: Trends and the ENSO connection. Geophysical Research Letters, 35, L14S08.

MCCOWN, R. L., CARBERRY, P. S., HOCHMAN, Z., DALGLIESH, N. P. & FOALE, M. A. 2009. Reinventing model-based decision support with Australian dryland farmers: 1. Changing intervention concepts during 15 years of action research. Crop and Soil Science, 60, 1017-1030.

MURTHA, G. 1986. Soils of the Tully-Innisfail Area, North Queensland, CSIRO Division of Soils.

MURTHA, G. & SMITH, C. D. 1994. Key to the soils and land suitability of the wet tropical coast, Cardwell – Cape Tribulation, CSIRO, Australia.

NICHOLLS, N., DROSDOWSKY, W. & LAVERY, B. 1997. Australian rainfall variability and change. Weather, 52, 66-72.

R CORE TEAM 2014. R: A language and environment for statistical computing. 3.1.0 ed. Vienna, Austria: R Foundation for Statistical Computing.

R CORE TEAM 2016. R: A language and environment for statistical computing. 3.3.0 ed. Vienna, Austria: R Foundation for Statistical Computing.

SCHROEDER, B., HURNEY, A., WOOD, A., MOODY, P. & ALLSOPP, P. 2010. Concepts and value of the nitrogen guidelines contained in the Australian sugar industry's 'SIX EASY STEPS' nutrient managment program. Proceedings of teh Australian Society of Sugar Cane Technologists, 27, CD:ROM.

SCHROEDER, B., SALTER, B., MOODY, P., SKOCAJ, D. & THORBURN, P. 2014. Evolving nature of nitrogen management in the Australian sugar industry. In: MJ, B. (ed.) A review of nitrogen use efficiency in sugarcane. SRA Research Report. Brisbane: Sugar Research Australia.

SCHROEDER, B., SKOCAJ, D., THORBURN, P., BIGGS, J., SEXTON, J. & EVERINGHAM, Y. L. 2018. IS CLIMATE FORECASTING COMPATIBLE WITH THE 'SIX EASY STEPS' NUTRIENT MANAGEMENT PROGRAM? Proceedings of the Australian Society of Sugar Cane Technologists. Mackay, Queensland, Australia.

SCHROEDER, B., WOOD, A. & KINGSTON, G. 1998. Re-Evaluation of the basis for fertiliser recommendations in the Australian sugar industry. Proceedings of teh Australian Society of Sugar Cane Technologists, 20, 239-247.

SCHROEDER, B., WOOD, A., MOODY, P. & PANITZ, J. 2006. Sustainable nutrient management - delivering the message to the Australian suage industry. Proceedings of teh Australian Society of Sugar Cane Technologists, 75, 14.

SCHROEDER, B., WOOD, A., MOODY, P., STEWART, B., PANITZ, J. & BENN, J. 2007. Soil-specific Nutrient Management Guidelines for Sugarcane Production in the Johnstone Catchment. BSES Technical Publication TE07001. BSES Limited.

SKOCAJ, D. 2015. Improving sugarcane nitrogen management in the Wet Tropics using seasonal climate forecasting. PhD PhD Thesis, James Cook University.

SKOCAJ, D. & EVERINGHAM, Y. L. 2014. Identifying climate variables having the greatest influence on sugarcane yields in the Tully mill area. Proceedings of the Australian Society of Sugar Cane Technologists. Gold Coast, Queensland Australia.

STERN, P. C. & EASTERLING, W. E. (eds.) 1999. Making Climate Forecasts Matter, Washington, DC: The National Academies Press.

STONE, P. J. & HOCHMAN, Z. 2004. If interactive decision support systems are the answer, have we been asking the right questions? Proceedings for the 4th International Crop Science Congress. Brisbane, Australia.

THORBURN, P., BIGGS, J., PALMER, J., MEIER, E., VERBURG, K. & SKOCAJ, D. 2017. Prioritizing crop management to increase nitrogen use efficiency in Australian sugarcane crops. Frontiers in Plant Science, 8.

THORBURN, P., BIGGS, J., WEBSTER, A. & BIGGS, I. 2011a. An improved way to determine nitrogen fertiliser requirements of sugarncane crops to meet global envirnomental challenges. PLant Soil, 339, 51-67.

THORBURN, P., DART, I., BIGGS, I., BAILLIE, C., SMITH, M. & KEATING, B. 2003. The fate of nitrogen applied to sugarcane by trickle irrigation. Irrigation Science, 22, 201-209.

THORBURN, P., JAKKU, E., WEBSTER, A. & EVERINGHAM, Y. 2011b. Agricultural decision support systems facilitating co-learning: a case study on environmental impacts of sugarcane production. International Journal of Agricultural Sustainability, 9, 322-333.

THORBURN, P., WILKINSON, S. & SILBURN, D. 2013. Water quality in agricultural landsdraining to the Great Barrier Reef: Review of causes, management and priorities. Agriculture Ecosystems and Environments, 180, 4-20.

THORBURN, P. J., JAKKU, E., WEBSTER, A. J. & EVERINGHAM, Y. L. 2011c. Agricultural decision support systems facilitating co-learning: a case study on environmental impacts of sugarcane production. International Journal of Agricultural Sustainability, 9, 322-333.

VALLIS, I., HUGHES, R., RIDGE, D. & NIELSEN, P. 1994. SRDC Final Report (CSC2S) - Improving nitrogen management in sugarcane in southern Queensland and northern New South Wales.

WATERHOUSE, J., BRODIE, J., LEWIS, S. & MITCHELL, A. 2012. Quantifying the sources of pollutants to the Great Barrier Reef. Marine Pollution Bulletin, 65, 394-406.

WATERHOUSE, J., SCHAFFELKE, B., BARTLEY, R., EBERHARD, R., BRODIE, J., STAR, M., PETER, T., ROLFE, J., RONAN, M., TAYLOR, B. & KROON, F. 2017. 2017 Scientific Consensus Statement: Land use impacts on great barrier reef water quality and ecosystem condition. In: SECRETARIAT, R. W. Q. P. P. (ed.). Brisbane: The State of Queensland.

WEISHEIMER, A., CORTI, S., PALMER, T. & VITART, F. 2014. Addressing model error through atmospheric stochastic physical parametrizations: impact on the coupled ECMWF seasonal forecasting system. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 372.

ZHAO, T., CHEN, L. & MA, Z. 2014. Simulation of historical and projected climate change in arid and semiarid areas by CMIP5 models. Chinese Science Bulletin, 59, 412-429.

11. APPENDIX

11.1. Appendix 1 METADATA DISCLOSURE

Table 2 Metadata disclosure 1

Data	The source of all data have been described in the projects' publications.
Stored Location	See project publications.
Access	See project publications. Some project data requires permission to access.
Contact	To be confirmed.