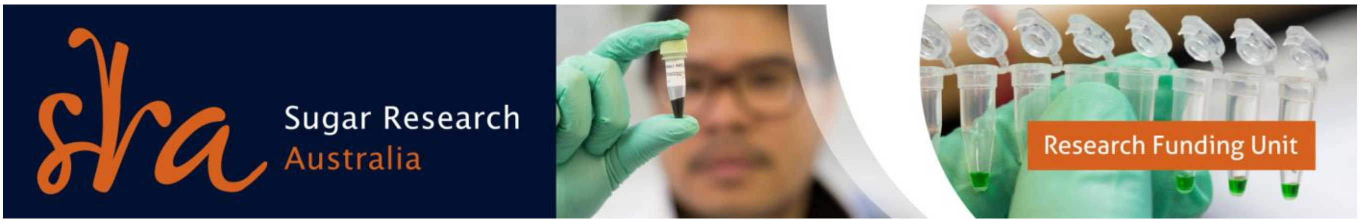


Modelling extreme yields in the wet tropics to improve nitrogen use efficiency

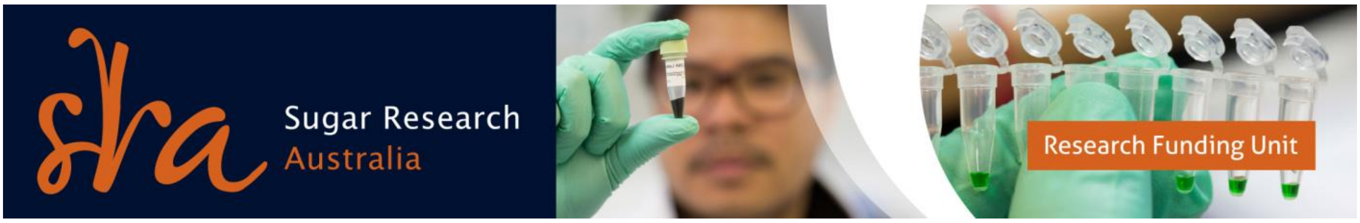
Final report submitted to Sugar Research Australia

Dr Yvette Everingham

Project 2014/024

Chief Investigator: Dr Yvette Everingham
Research Organisations: James Cook University

August 2015



How to cite: Everingham, Y, Modelling extreme yields in the Wet Tropics to improve nitrogen efficiency, Sugar Research Australia, 2015.

SRA Contact Details
Sugar Research Australia
50 Meiers Road
Indooroopilly Q 4068 Australia
PO Box 86
Phone: 07 33313333
Fax: 07 38710383
Web: sugarresearch.com.au

This report is an addition to SRA's diverse range of research publications and it forms part of our Soil health and nutrient management key focus area program, which aims to accurately model sugarcane yields in the Wet Tropics well before the exact size of the crop is known. The specific research questions that this project will answer are:

1. How early can we forecast yields in the Wet Tropics?
2. How accurate are the predictions?
3. Does this model have the capability to accurately predict extreme yields?

Most of SRA's publications are available for viewing and free downloading online at www.sugarresearch.com.au.

PART A

Section 1: Executive Summary

Background:
The Wet Tropics experiences one of the highest levels of climate variability in the world. These enormous swings in inter-annual climate patterns cause large fluctuations in crop size, and hence, how much nitrogen should be applied to the crop. Consequently, it is good to know the size of the crop before farmers apply fertiliser. Foreknowledge of the size of the crop can also help marketers and millers. Marketers armed with early and reliable information about crop size can better plan the sale and storage of the crop and millers can better plan mill labour requirements and mill maintenance scheduling activities. Given the close proximity of the Great Barrier Reef to sugarcane growing regions in the Wet Tropics, estimating yield potential accurately promises significant environmental benefits achieved by improved nitrogen management.

In pursuit of simultaneously increasing industry competitiveness and improving environmental outcomes, the objectives of this research were to determine how early and how accurate yields can be forecasted and if it is plausible to forecast extreme yields.

Methods:
Annual Tully mill sugarcane yields measured in tonnes of cane per hectare (TCPH) were obtained from industry partners. Mill yields were predicted using a range of predictor variables. These predictor variables included yields from previous years, simulated biomass indices from the Agricultural Productions Systems Simulator (APSIM), cumulative rainfall, temperature and radiation. Seasonal climate forecasting indices like the Southern Oscillation Index and departures from average Sea Surface Temperatures in the central equatorial Pacific Ocean were needed to improve the accuracy of forecasts produced before the main growing season. These predictor variables were supplied to stepwise linear and random forest regression and classification techniques. Regression models forecasted the magnitude and direction of crop size, and the classification models forecasted if the crop was more likely to be above or below the observed median yield. In addition to the regression and classification models, extreme probability models were deployed to calculate the probability of achieving an extremely high yield or an extremely low yield. An extremely high yield was defined to be a yield more than 20% above the observed mean yield, and an extremely low yield was defined to be a yield more than 20% below the observed mean yield.

Forecasts were initiated on the 1st May in the year before harvest and updated monthly until the 1st of November in the harvest year. The skill of each forecast was computed. The skill of forecasts provided on the 1st September, 1st January and 1st March were closely monitored. These forecasts can guide nitrogen applications (1st September), help marketers plan the forward sale of the crop (1st January) and assist millers plan labour requirements and mill maintenance schedules for the coming crop (1st March).

Results:
Regression models
Using an optimised random forest regression it was possible to produce a yield forecast model with moderate skill (cross-validated R-Squared = 0.689) as early as 1st September. The skill of the optimised random forest model increased for forecasts made on 1st January (cross-validated R-Squared = 0.746) and 1st March (cross-validated R-Squared = 0.833).

Classification models

Using an optimised random forest classification it was possible to produce models with excellent skill on the 1st September (cross-validated correct classification rate = 0.864), 1st January (cross-validated correct classification rate = 0.955) and 1st March (cross-validated correct classification rate = 0.955).

Extreme probability models

Extreme probability models demonstrated good skill at forecasting extremely low yields as early as 1st September (cross-validated relative operating characteristic score = 0.728) but was challenged to forecast extremely high yields. Forecast models for extremely low yields further improved for the 1st January forecast (cross-validated relative operating characteristic score = 0.746). Given that nitrogen is typically applied in early spring in the Wet Tropics it is very encouraging that skill exists for forecasting extremely low yields on the 1st September in the year prior to harvest.

<u>Outputs and Outcomes:</u>

Accurate and early forecasts of crop yield potential are needed for industry to improve existing nitrogen management guidelines. This project has at the regional level developed a skilful model for predicting yields. These predictions come early enough to influence fertiliser practices. We have identified that when La Niña conditions are present in the central equatorial Pacific Ocean in winter, in the year prior to harvest, there is a severe risk that the Wet Tropics regional yields will be extremely low. In these types of years it is critical that this information be used to better inform nitrogen management guidelines to improve nutrient management and minimise environmental impacts. The models developed in this project can also be used to increase industry competitiveness in the marketing and milling sectors of the industry value chain.

Section 2: Background

The Australian sugar industry is under pressure to improve nutrient management guidelines. Consequently, the industry is placing a greater emphasis on research that can deliver improved environmental outcomes whilst ensuring the industry maintains competitiveness. Two nitrogen management systems have been developed in the Australian Sugar Industry (Skocaj *et al*. 2013). These are the Six Easy Steps™ (Schroeder *et al*. 2005) and N Replacement (Thorburn *et al*. 2003) systems. Both systems do not factor in climatic conditions during the key growing season. Hence, neither system is geared to take into consideration seasonal climate conditions that can impact enormously on the size of the forthcoming crop. Predicting crop yields more accurately and factoring these forecasts into nitrogen management guidelines offers enormous opportunity to improve nitrogen management in the Wet Tropics and minimise environmental impacts.

It has been established that crop size is dependent on climate conditions during the key growing periods in spring and summer. Everingham *et al*. (2003) showed that a positive October-November SOI phase favoured lower regional yields while a negative October-November SOI phase was associated with higher yields in the Tully region. More recently Skocaj and Everingham (2014) developed a statistical model of Tully regional yields based purely on local climate attributes. The model proposed by Skocaj and Everingham (2014) was able to explain approximately 40% of the variance in Tully regional yields and found that excessive late winter/early spring rainfall negatively impacted regional yields. Skocaj (2015) also found that less Nitrogen was needed when Niño 3.4 sea surface temperatures in winter in the year before harvest were more than half a degree below the long term mean (La Niña).

Prior to this work, Everingham *et al*. (2009) applied a sophisticated ensemble modelling approach that utilised the APSIM sugarcane crop model to simulate yields in the Burdekin. Adapting this methodology for the Wet Tropics to improve existing yield forecasting capability was the focus of this project. Although the emphasis in this project was placed on estimating yields to improve nitrogen management in the Wet Tropics, better yield forecasting strategies provided added industry intelligence to enhance marketing and milling operations.

Section 3: Outputs and Achievement of Project Objectives

3.1 Project Objectives

The objective of this project was to accurately model sugarcane yields in the Wet Tropics well before the exact size of the crop is known. Specifically, this project aimed to answer the following research questions:

1. How early can we forecast yields in the Wet Tropics?
2. How accurate are the predictions?
3. Does this model have the capability to accurately predict extreme yields?

3.2 Methodology

For this project to produce useful and relevant outcomes, it was necessary to develop an industry calendar that flagged when important decisions were made by industry. Figure 1 identifies the crop cycle and three decision making periods representing fertilizer application, marketing and mill management. It was identified that forecasts to inform fertilizer applications, are required as early as 1st September the year before harvest (YBH). Accurate forecasts as early as 1st January in the harvest year (HY) would provide valuable insight for marketing decisions while forecasts as early as 1st March in the HY could assist mill planning activities.

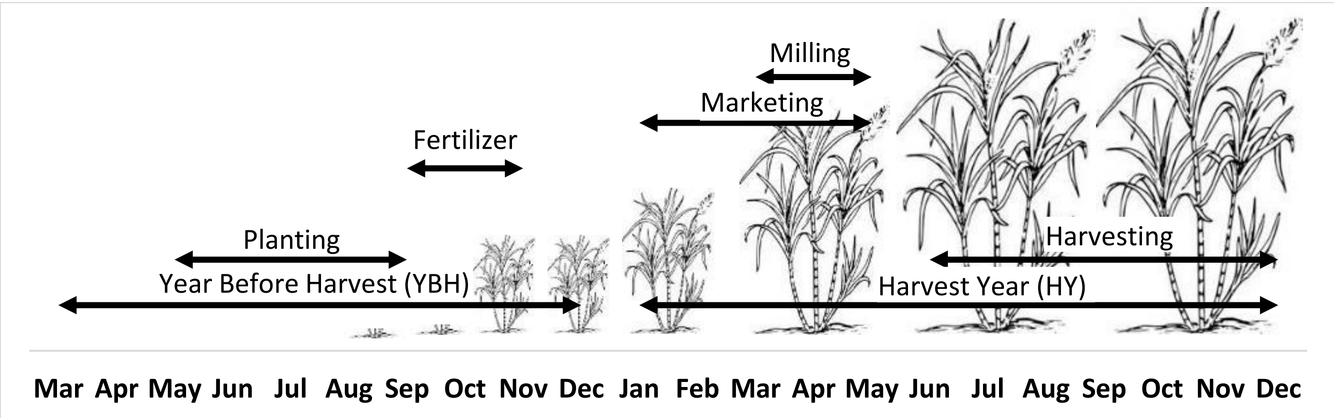


Figure 1. Crop growth and management cycle from March the year before harvest (YBH) to December in the harvest year (HY). Accurate forecasts before September were aimed at informing fertilizer management decisions. January forecasts can inform marketing decisions and March forecasts are helpful for millers.

Three classes of forecast models were investigated:

1. Regression models (used to forecast the size of the crop)
2. Classification models (used to forecast crop direction as above or below median)
3. Extreme probability models (used to forecast the probability of an extremely high or extremely low crop).

The three classes of models were used to develop forecasts issued on the first day of each month until the end of harvest. These models are now described in greater detail.

3.2.1 Regression and Classification

Regression and classification forecast models were built using climate data from 1991 to 2013 and productivity data from 1992 to 2013. Daily climate indices, seasonal climate indices and APSIM (Agricultural Production Systems Simulator) simulated biomass indices were used as predictor variables in the regression and classification models. Daily climate indices included cumulative daily rainfall, radiation and average temperature data. These data were obtained for the BOM weather station located at Tully Sugar Mill (Station number 32042). Seasonal climate indices included the monthly Southern Oscillation Index (SOI) obtained from the Longpaddock website (https://www.longpaddock.qld.gov.au/seasonalclimateoutlook/southernoscillationindex/soidatafiles/MonthlySOIPhase1887-1989Base.txt) and 3 month running average sea surface temperature anomalies in the Niño 3.4 region were obtained from the NOAA website (http://www.cpc.ncep.noaa.gov/data/indices/3mth.nino34.81-10.ascii.txt). A forward stagewise ensemble modelling approach (Everingham *et al*., 2009) was used to model regional yields from APSIM simulated biomass. The ensemble modelling approach was adapted to captured regional differences in climate, soils and management in the Wet Tropics. The skill of the APSIM biomass index was assessed using a leave-one-out cross-validated correlation between simulated biomass and observed yields (TCPH). Daily climate, seasonal climate and APSIM biomass predictor variables were calculated at the end of each month. Regression and classification models were built using only observed data prior to the forecast date.

For both the regression and classification classes of models, two modelling approaches were compared. For regression, random forest and stepwise linear regression models were compared. Regression model skill was assessed using the leave-one-out cross-validated R-Squared (CVR-Squared) and leave-one-out cross-validated prediction error (CVSPE). As CVR-Squared values range from 0 to 1 model performance was considered poor (CVR-Squared ≤ 0.5); moderate (0.5 < CVR-Squared ≤ 0.7); good (0.7 < CVR-Squared ≤ 0.85) or excellent (0.85 < CVR-Squared).

Random forest and linear discriminant analysis (LDA) approaches were compared for classification forecast models. Classification model skill was assessed using leave-one-out cross-validated correct classification rates (CVCCR). CVCCR values range from 0 (0% of years correctly classified) to 1 (100% of years correctly classified). Model performance was considered poor (CVCCR < 0.6); moderate (0.6 ≤ CVCCR ≤ 0.7); good (0.7 < CVCCR ≤ 0.85) or excellent (0.85 < CVCCR). Random forest regression and classification models were built using the "randomForest" package in the R statistics program (Liaw and Wiener, 2002). Stepwise regression and LDA models were built using the SPSS statistics program (IBM Corp., 2013). Regression and classification model methodologies are outlined in Figure 2.

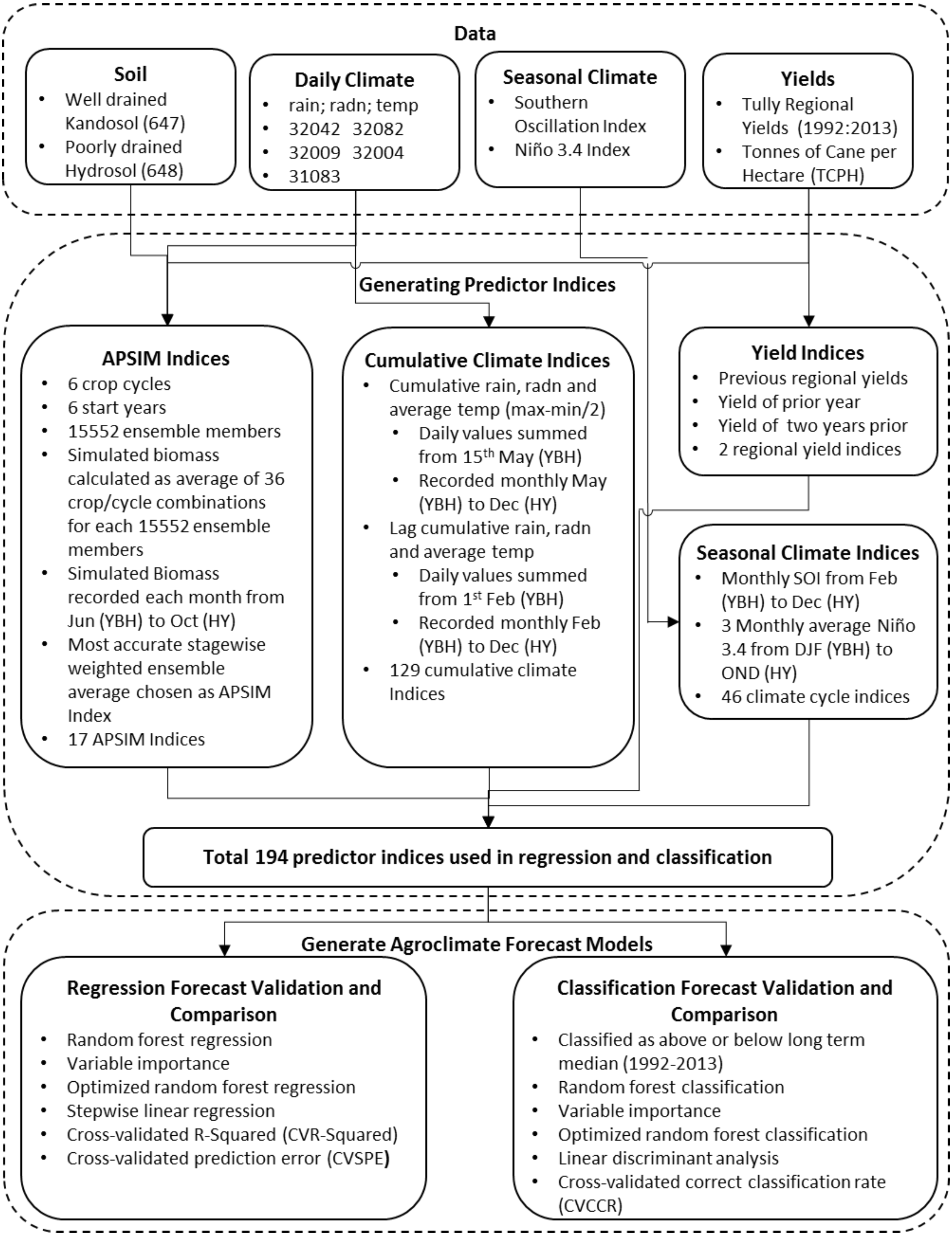


Figure 2. An overview of the materials and methods used to produce the regression and classification forecast models.

3.2.2 Extreme Probabilities

Extreme probability forecast models were built using data from 1970 to 2013. Regional yield data were obtained from the Tully Mill. A longer time series than that adopted in the regression and classification models was needed to better estimate the distribution of extreme events. Extreme probability models were used to forecast the probability of extremely low or extremely high crop yields based on El Niño Southern Oscillation (ENSO) phases. Extremely low(high) yields were defined to be more than 20% below(above) the mean average observed yield. ENSO phases were calculated based on the 3 month average Oceanic Niño Index (ONI). Three monthly ONI values were sourced from the NOAA NCEP Climate Prediction Centre (http://www.cpc.ncep.noaa.gov/data/indices/oni.ascii.txt). A three month period was classified as either El Niño (ONI > 0.5); La Niña (ONI < -0.5) or Neutral (0.5 ≤ ONI ≤ -0.5). Yield probability distributions for each phase were estimated using the "bkde" function in the KernSmooth package within the R statistics program (Wand, 2015). The probability of extreme events was calculated for each phase by integrating the estimated probability distributions using the "integrate" function in R (R Core Team, 2014). Extreme probability forecast models were assessed using a leave-one-out cross-validated Relative Operating Characteristic (ROC; Mason and Graham (1999)) score (CVROC). ROC scores ranged from 0 (worst) to 1 (best). A ROC score of greater than 0.5 is preferred (Everingham, 2007). Model performance was considered poor (CVROC ≤ 0.6); moderate (0.6 < CVROC ≤ 0.7); good (0.7 < CVROC ≤ 0.85) or excellent (0.85 < CVROC). Figure 3 outlines the data and methodology used to generate extreme probability models.

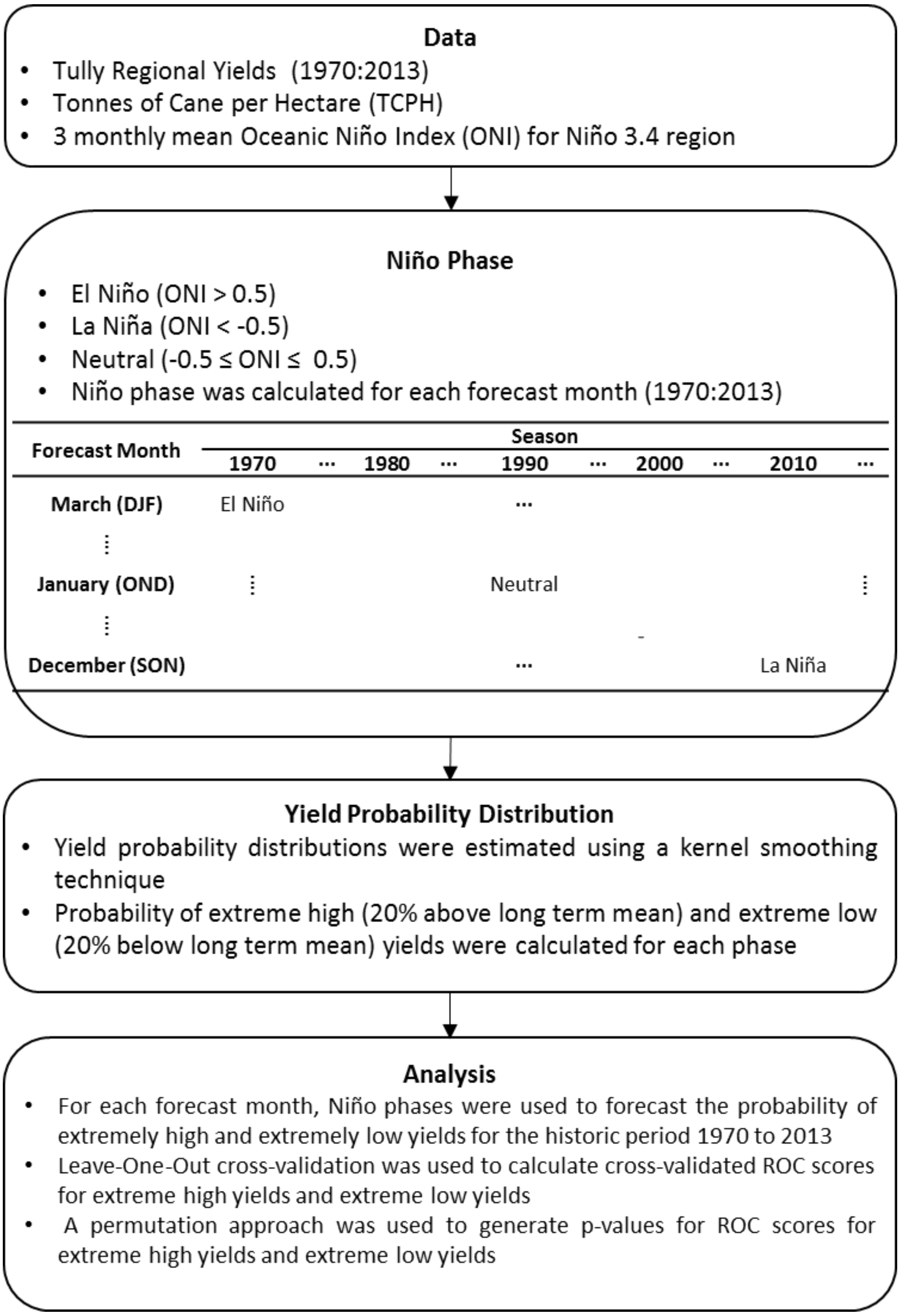


Figure 3. An overview of the materials and methods used to produce extreme probability forecast models.

3.3 Results and Discussion

3.3.1 Generating the Ensemble APSIM Simulations for inputs to the Regression and Classification Models

Ensemble models were generated using APSIM simulated biomass at the end of each month from July in the YBH to September in the HY. This was done to assess if the APSIM Ensemble model improved by using observed data closer to the end of harvest. The resulting 15 ensemble models were then used to forecast regional yields at lead times from 1st August in the YBH to 1st October in the HY. A cross-validated correlation (CVR) between ensemble model estimated yields and observed regional yields was calculated at each forecast date for each of the 15 ensemble models for the period 1992 to 2013 (Figure 4). CVR values ranged from -1 to 1. Negative CVR values represented a negative correlation between ensemble model forecast and observed yields and were considered inappropriate. CVR values closer to +1 were desirable. For example Ensemble model 3 (represented by the solid green line in Figure 4) was built using observed data (rainfall, radiation, temperature) up to and including 30th September in the YBH. When this ensemble model was used to forecast regional yields at 1st October in the YBH the CVR was 0.81 suggesting a good correlation between forecast and observed yields. However, if this model was used to forecast yields on 1st September in the YBH (i.e. using observed climate data up to and including 31st August in the YBH, that is, using less data than originally used to build the model) the CVR was reduced to 0.54. Ensemble model 12 (built using observed data up to and including 31st December in the YBH) consistently produced high CVR values. The APSIM simulated biomass from Ensemble model 12 was supplied to the regression and classification forecast models.

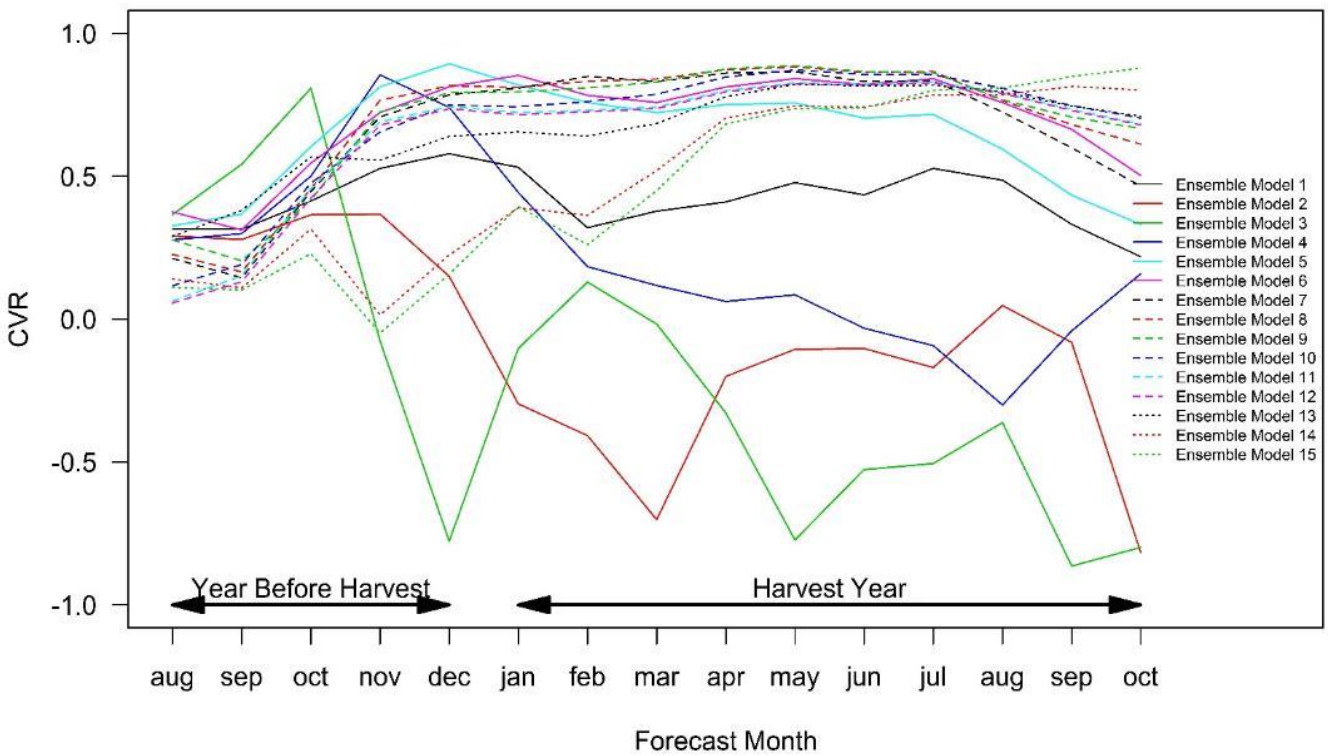


Figure 4. Ensemble APSIM simulation performance. Cross-validated correlations were computed for 15 ensemble models at lead times up to 16 months before harvest (1st August in the YBH). The 15 ensemble models were built using observed climate data at different lead times (e.g. Ensemble model 1 used observed data up to and including 31st July in the YBH while Ensemble model 15 used observed data up to and including 30th September in the HY).

3.3.2 Regression, Classification and Extreme Model Performance

Table 1 records the performance statistics for regression (CVR-Squared, CVSPE), classification (CVCCR) and the extreme probability (CVROC) forecast models. Statistics are reported for lead times ranging from 21 months before harvest (1st March in the YBH) to 1 month before harvest (1st November in the HY). Cells shaded in grey represent models that can guide nutrient requirements (1st September YBH), assist with the forward sale of the crop (1st January in the HY) and help plan scheduling and labour requirements (1st March in the HY).

Regression models
Using an optimised random forest regression it was possible to produce a yield forecast model with moderate skill (cross-validated R-Squared = 0.689) as early as 1st September. The skill of the optimised random forest model increased for forecasts made on 1st January (cross-validated R-Squared = 0.746) and 1st March (cross-validated R-Squared = 0.833).

Classification models
Using an optimised random forest classification it was possible to produce models with excellent skill (cross-validated correct classification rate = 0.864) on the 1st September, 1st January (cross-validated correct classification rate = 0.955) and 1st March (cross-validated correct classification rate = 0.955).

Extreme probability models
Extreme probability models was challenged to forecast extremely high yields, but demonstrated good skill at forecasting extremely low yields as early as 1st September (cross-validated relative operating characteristic score = 0.728). This model further improved for the 1st January forecast (cross-validated relative operating characteristic score = 0.746).

The ability of the model to forecast extremely low yields, was likely driven by a higher probability of extremely low yields under La Niña conditions. Extremely low yields occurred approximately 11% of the time between 1970 and 2013, inclusively. However, when the JJA ENSO phase was identified as La Niña the risk of an extremely low yield tripled to 35%. This agrees with results from Skocaj and Everingham (2014) who found that increased spring and summer rainfall had a negative impact on yields.

Table 1. Model performance statistics. Forecast dates are identified as the year before harvest (YBH) or the year of harvest HY. For regression, stepwise regression (Stepwise), random forest (RF), and an optimised random forest (ORF) methodologies were used to build models. Regression model skill was assessed using cross-validated R-Squared (CVR-Squared) and the cross-validated prediction error (CVSPE). Prediction error was reported as tonnes of cane per hectare (TCPH). For classification, stepwise linear discriminant analysis (LDA), random forest (RF) and an optimised random forest (ORF) methods were used to build models. Classification model skill was assessed using a cross-validated correct classification rate (CVCCR). CVCCR values close to 1 represent good skill. CVR-Squared values close to 1 represent good skill while lower CVSPE are desirable. Extreme probability models were built using ENSO phase classifications. Extreme model skill was assessed using cross-validated ROC scores (CVROC). CVROC values close to 1 are preferred. Cells shaded in grey represent models that can guide nutrient requirements (1st September YBH), assist with the forward sale of the crop (1st January HY) and help plan milling activities (1st March HY).

Forecast Date (Year)	Regression			Classification			Extreme Probability	
	Stepwise CVR-Squared (CVSPE; TCPH)	RF CVR-Squared (CVSPE; TCPH)	ORF CVR-Squared (CVSPE; TCPH)	LDA CVCCR	RF CVCCR	ORF CVCCR	Low yield CVROC	High yield CVROC
1st May YBH	0.138(13.92)	0.099(13.40)	0.403(10.79)	0.773	0.545	0.591	0.492	0.538
1st Jun YBH	0.012(16.54)	0.070(13.68)	0.472(10.18)	0.773	0.545	0.727	0.488	0.538
1st Jul YBH	0.023(15.56)	0.175(12.61)	0.559(9.68)	0.773	0.652	0.818	0.551	0.550
1st Aug YBH	0.364(11.35)	0.350(11.39)	0.599(9.36)	0.773	0.773	0.864	0.574	0.344
1st Sep YBH	0.187(13.86)	0.479(10.56)	0.689(8.09)	0.818	0.727	0.864	0.728	0.138
1st Oct YBH	0.268(13.41)	0.536(10.24)	0.714(8.58)	0.909	0.682	0.864	0.728	0.263
1st Nov YBH	0.299(12.41)	0.647(9.20)	0.736(7.90)	0.909	0.727	0.864	0.477	0.641
1st Dec YBH	0.549(9.96)	0.664(8.91)	0.726(7.78)	0.909	0.727	0.864	0.759	0.641
1st Jan HY	0.746(7.33)	0.663(8.80)	0.746(7.47)	0.955	0.727	0.955	0.746	0.584
1st Feb HY	0.731(7.65)	0.635(9.02)	0.776(7.12)	0.955	0.682	0.955	0.733	0.528
1st Mar HY	0.711(7.99)	0.670(8.57)	0.833(6.33)	1.000	0.682	0.955	0.656	0.509
1st Apr HY	0.711(7.99)	0.631(8.76)	0.771(6.95)	1.000	0.682	0.955	0.733	0.588
1st May HY	0.663(9.13)	0.664(8.38)	0.801(6.40)	1.000	0.727	0.909	0.625	0.525
1st Jun HY	0.623(9.43)	0.672(8.29)	0.767(6.87)	1.000	0.727	0.909	0.621	0.488
1st Jul HY	0.529(10.64)	0.687(8.08)	0.814(6.27)	1.000	0.727	0.909	0.336	0.150
1st Aug HY	0.517(10.74)	0.701(7.86)	0.785(6.55)	1.000	0.727	0.909	0.259	0.425
1st Sep HY	0.552(10.37)	0.707(7.72)	0.776(6.72)	1.000	0.727	0.954	0.226	0.475
1st Oct HY	0.576(10.02)	0.716(7.63)	0.760(6.93)	1.000	0.773	0.954	0.338	0.513
1st Nov HY	0.576(9.95)	0.702(7.77)	0.755(6.94)	1.000	0.818	0.954	0.331	0.675

Section 4: Outputs and Outcomes

Outputs:

- Regression models for forecasting the magnitude and direction (t/ha) of cane yields for the Tully region up to 15 months before harvest.
- Classification models for forecasting above or below median cane yields for the Tully region.
- Extreme probability models for forecasting the probability of an extremely low cane yield. Astonishingly this could be done up to 15 months before harvest and early enough to influence fertiliser practices.
- Models that can be consulted to inform industry decisions about nitrogen fertiliser applications, marketing decisions and mill planning.

Outcomes:

- Improved understanding of how climatic conditions impact regional cane yields.
- Improved nutrient management.
- Reduced environmental impacts.
- Improved forward selling strategies for marketers.
- Improved mill planning.

Section 5: Intellectual Property (IP) and Confidentiality

The background intellectual property used in this project which comprises of developed statistical algorithms is the property of James Cook University but they can be used in this project. If industry finds these models to be of value then negotiations can be conducted to discuss transfer costs of IP or delivery of ongoing information. New IP generated by this project includes advanced algorithms that predict sugarcane yields in the Wet Tropics.

Section 6: Industry Communication and Adoption of Outputs

Communications were maintained with industry representatives throughout the life of the project. Yield data was for the Tully region were obtained through connections between project members and representatives of the Tully Sugar Mill developed during this project. Communications with industry representatives also played a key role in defining extreme yields. Preliminary Outputs and Outcomes of this project were presented at an industry forum (Brisbane; 8th July 2015) and were well received by industry representatives.

Section 7: Environmental Impact

This project established that it is feasible to detect potentially low yields in September the year before harvest. This knowledge can be used to better inform N management systems and reduce the risk of negative environmental impacts associated with the runoff of excess nitrogen. Improved nitrogen management will also help to improve relationships between industry and environmental groups in line with the industry strategic plan KFA2 desired outcomes.

Section 8: Recommendations and Future Industry Needs

The work in this project will contribute to future projects on crop forecasting and nitrogen management especially in the Wet Tropics. The operational forecasting framework developed in this project and details of model skill at varying lead times will be used by the upcoming project 2015/075: "*How big will that crop be? Incorporating climate forecasting to improve Nitrogen management in the Wet Tropics*".

Section 9: Publications

The project team plans to submit publications of key findings from this project to suitable industry forums.

References

Everingham, Y. (2007). Comparing phase based seasonal climate forecasting methods for sugarcane growing regions. *Proceedings of the International Congress on Modelling and Simulation*. 10-13 December, Christchurch, New Zealand.

Everingham, Y., Muchow, R.C., Stone, C., Coomans, D.H. (2003). Using southern oscillation index phases to forecast sugarcane yields: a case study for northeastern Australia. *International Journal of Climatology*, 23(10), 1211-1218.

Everingham, Y., Smyth, C., Inman-Bamber. G. (2009). Ensemble data mining approaches to forecast regional sugarcane crop production. *Agricultural and Forest Meteorology*, 149, 689-696.

IBM Corp. Released 2013. IBM SPSS Statistics for Windows, Version 22.0. Armonk, NY: IBM Corp

Liaw, A., Wiener, M. (2002). Classification and Regression by randomForest. *R News*. 2(3), 18-22.

Mason, S., Graham, E. (1999). Conditional probabilities, relative operating characteristics, and relative operating levels. *Weather and Forecasting*, 14(5), 713-725.

R Core Team. (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria, http://www.R-project.org/.

Schroeder, B., Wood, A., Moody, P., Bell, M., Garside, A. (2005). Nitrogen fertiliser guidelines in perspective. *Proceedings of the Australian Society of Sugar Cane Technologists*, 27, 291–304.

Skocaj, D. (2015). Improve sugarcane nitrogen management in the Wet Tropics using seasonal climate forecasting. PhD Thesis (under review).

Skocaj, D., Everingham, Y. (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*, 32, pp. 12.

Skocaj, D., Everingham, Y., Schroeder, B. (2013). Nitrogen management guidelines for sugarcane production in Australia: Can these be modified for wet tropical conditions using seasonal climate forecasting? *Springer Science Reviews* 1.1-2, 51-71.

Thorburn, P., Park, S., Biggs, I. (2003). Nitrogen fertiliser management in the Australian sugar industry: strategic opportunities for improved efficiency. *Proceedings of the Australian Society of Sugar Cane Technologists*, 25, pp. 12.

Wand, M. (2015). KernSmooth: Functions for kernel smoothing supporting Wand & Jones (1995). R package version 2.23-14. http://CRAN.R-project.org/package=KernSmooth.