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The potential for refining nitrogen fertiliser management through accounting for climate impacts: An exploratory study for the Tully region

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ABSTRACT

Increasing the precision of nitrogen (N) fertiliser management in cropping systems is integral to increasing the environmental and economic sustainability of cropping. In a simulation study, we found that natural variability in year-to-year climate had a major effect on optimum N fertiliser rates for sugarcane in the Tully region of north-eastern Australia, where N discharges pose high risks to Great Barrier Reef ecosystems. There were interactions between climate and other factors affecting crop growth that made optimum N rates field-specific. The regional average optimum N fertiliser rate was substantially lower than current industry guidelines. Likewise, simulated N losses to the environment at optimum N fertiliser rates were substantially lower than the simulated losses at current industry fertiliser guidelines. Dissolved N discharged from rivers is related to fertiliser applications. If the reductions in N applications identified in the study occurred in the Tully region, the reduction in dissolved N discharges from rivers in the region would almost meet current water quality improvement targets. Whilst there were many assumptions made in this exploratory study, and there are many steps between the study and a practically implemented dynamic N fertiliser recommendation system, the potential environmental benefits justify field validation and further development of the concepts identified in the study.

1. Introduction

The increasing use of nitrogen (N) fertiliser has underpinned dramatic improvements in agricultural productivity; however, this has also impacted marine ecosystems in some regions (Fowler et al., 2013; Howarth, 2008). Practices that increase the efficiency of N fertiliser use in agricultural systems are an important part of solving water-quality related issues (Mueller et al., 2017) and will also deliver benefits to farmers through reduced input costs. The cornerstone of increasing efficiency is often said to be applying fertiliser to crops at the “right rate, right time, right place, using the right type” (known as the ‘4R’ concept: (Snyder, 2017)). Numerous studies have been conducted that demonstrate the “right rate” of N fertiliser will vary from soil-to-soil and from region-to-region (e.g. Morris et al., 2018; Schroeder et al., 2014). The climatic conditions experienced during the crop growing season are also important because it affects crop growth, the demand of N by the crop and N losses to the environment. The growing season also influences soil water and nutrient cycling which contribute to the supply of N to the crop (Hochman and Waldner, 2020; Puntel et al., 2018; Palmer et al., 2017). Thus, incorporating forecasts of the coming seasonal climate should improve N fertiliser guidelines (Skocaj et al., 2013; Thornton and MacRobert, 1994). Yet systems for developing N fertiliser applications to crops usually lack an explicit consideration of climate. At best, applications are made implicitly by only assuming average climate (e.g. recommendations based on the average of long-term experience) or ideal climate (i.e. systems driven by yield goals). Given the annual variability of climate, explicitly accounting for climate in N fertiliser guidelines could better determine the “right rate” of N fertiliser for a crop in a specific year (i.e. at the “right time”) at a specific location.

A case in point is the Wet Tropics of north eastern Australia (Fig. 1). Discharges of dissolved inorganic N (DIN) from this region affect the Great Barrier Reef and reducing these discharges is a high priority for meeting government water quality improvement targets (State of Queensland, 2018). The Wet Tropics experiences both high annual rainfall and high spatial and temporal variability of rainfall (Nicholls et al., 1997). For example, average rainfall in the Wet Tropics region

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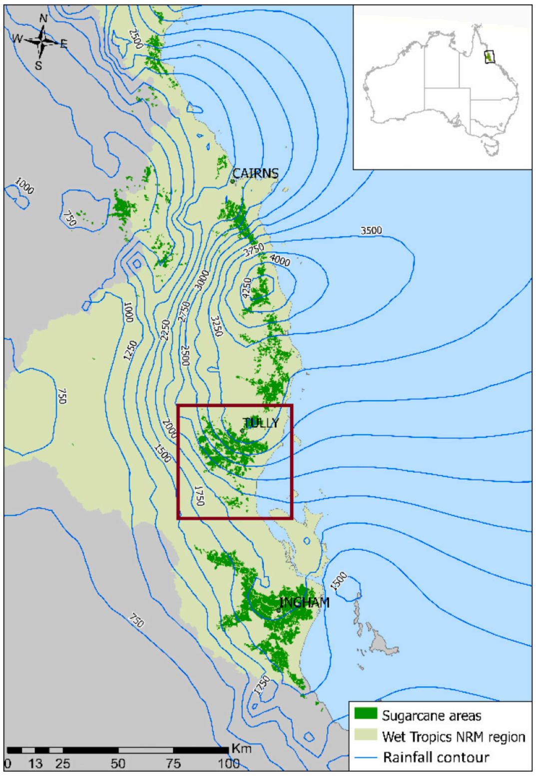

Fig. 1. Map of the Wet Tropics displaying average annual rainfall contours (250 mm intervals), sugarcane growing areas and the Wet Tropics NRM region. The Tully region, the focus of this work, is identified by the red box and receives 2500–3000 mm of average annual rainfall. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ranges from ~1000 to ~6200 mm yr^{-1}, with interannual variation of 1000 mm in the wettest region of the Wet Tropics. Sugarcane is a predominant crop grown in this region, making an important contribution to the regional economy (CANEGROWERS Australia, 2020). These crops are grown with substantial inputs of N fertiliser, a proportion of which is discharged into local rivers and impacts the health of nearby ecosystems of the Great Barrier Reef World Heritage Area (Kroon et al., 2016; Thorburn et al., 2013). Thus, farmers face the dilemma of how to best manage N fertiliser applications in the face of both the substantial climate variability and environmental imperatives whilst maintaining viability, productivity, and profitability. One of the other characteristics of the region's climate is that rainfall is well correlated with the El Nino-Southern Oscillation (ENSO) phenomenon, raising the prospect that climate forecasting could be incorporated into farmers' N fertiliser management decisions (Skocaj et al., 2013).

There have been studies in the Tully region, the wettest region of the Wet Tropics, on the possible effects of climate on farmers' N fertiliser management decisions. These have used cropping systems modelling, namely the Agricultural Production System sIMulator (APSIM; Holzworth et al., 2014), to capture the complex interactions of soils, climate and farm management to applied N rates that would otherwise be infeasible to do as part of a purely field based experimental approach (Keating and Thorburn, 2018). Thorburn et al. (2011c) predicted for two soils of contrasting texture that 'splitting' N fertiliser (i.e. applying half the N at two separate times) in seasons when above average rainfall was predicted using the ENSO phase system (Stone et al., 1996) increased yields and reduced N losses, and could also allow for N rates to be lowered. However, such split application strategies may not always be possible because of potentially excessive rainfall later in the growing season that could possibly prevent the second application. In addition, false positive ENSO predictions (i.e. above average rainfall predicted but not received) reduced the benefits of the climate-based management system compared with splitting N fertiliser applications in all years. Skocaj (2015) extended this work to show that the "optimum" rate of N (defined in their work as giving 95% of maximum yield) was predicted to be significantly lower in years forecast to be wetter than average based on a Clay soil (Bulgun series; (Cannon et al., 1992; Murtha, 1986)). If farmers lowered N fertiliser rates in these wetter years for this soil type, N discharged to Great Barrier Reef ecosystems may be reduced and farmers could reduce N fertiliser costs.

The Australian sugarcane industry has a well-developed nutrient management system known as SIX EASY STEPS® (Schroeder et al., 2014). For ratoon crops, (i.e. crops that regrow after harvest), the baseline N fertiliser guidelines (i.e. those coming from the first four steps) are based on both regional yield potential and soil organic carbon (C) concentrations as determined by the methodology of Walkley and Black (1934). Thus, for a given field, baseline N guidelines are static unless soil organic C changes or other aspects of improved N management are considered within Steps 5 and 6 of the SIX EASY STEPS program for individual blocks (Schroeder et al., 2018). The static nature of N recommendations is not unusual (Morris et al., 2018). Skocaj's (2015) results raise the prospect of a *dynamic* optimum N, which varies depending on seasonal climate. If that was true it would be a valuable enhancement of the SIX EASY STEPS system for the region and, possibly, other areas and other crops. What is currently uncertain is the extent to which Skocaj's (2015) results are applicable to other soil types in the study region. The applicability is hard to estimate from "first principles" because of two opposing effects of high rainfall on crop growth in this region (Palmer et al., 2017). On one hand, high rainfall increases N losses from soil through leaching, denitrification, and runoff, suggesting greater N applications would be needed to maintain crop yield under these conditions. Conversely, high rainfall also reduces the amount of solar radiation received by crops (because of increased cloud cover) and the likelihood of waterlogging, both of which possibly reduce crop growth and crop N requirements. Skocaj's (2015) results showed that the latter processes outweighed the former, on a clay soil, but do not inform the outcomes on soils of coarser textures or locations that experience lower rainfall.

Accordingly, this study builds on previous experience in the Tully region of the Wet Tropics to see whether simulated optimum N rates and cane yields vary depending on the seasonal climate for different soils encountered in the Tully region, and the extent to which these optimum N rates and yields differ from those simulated for the baseline SIX EASY STEPS N guidelines for the soils considered in the study. We also consider the potential effect of a dynamic optimum N rate on N losses in the region. Our analyses are conducted over the past 65 years, i.e. with "perfect knowledge" (Jones et al., 2000), to determine the maximum possible benefit that could be derived by incorporating climate into N fertiliser recommendations. If optimum N rates are predicted to be dependent on seasonal climate and this was subsequently validated in practice, there is an opportunity to couple the results from this study with seasonal climate forecasts for a fully dynamic N fertiliser advice system that delivers environmental and economic benefits.

2. Methods

2.1. Description of the region

The Tully sugarcane growing region is located within the Wet Tropics of Australia (Fig. 1) and is the focus of this study. Tully experiences large swings in rainfall with as much as 7898 mm in a wet year and as little as 1254 mm in a dry year. There are two climate zones in the Tully sugarcane growing region (Sexton et al., 2017), divided approximately by the Tully River and referred to as North and South. In general, the northern zone experiences more rainfall (average annual rainfall = 3271 mm) and lower radiation (average daily radiation = 18.4 MJ m^2

day^{-1}) than the southern zone (average annual rainfall = 2358 mm, average daily radiation = 18.7 MJ m^2 day^{-1}).

Sugarcane production averages 86 t ha^{-1} (standard deviation (sd) = 12 t ha^{-1}) across the whole region (1990 to 2018), with higher yields being associated with drier growing seasons and lower yields associated with wetter seasons (Everingham et al., 2003; Palmer et al., 2017). The harvest season runs from June to November and aims to be completed before the wet monsoon season arrives. In common with all sugarcane production areas, ratoon crops dominate the area as the crop is harvested and allowed to regrow multiple times (four being common) before it is destroyed and replanted.

The soils of the Tully region have been classified into 51 different soil types (Cannon et al., 1992; Murtha, 1986) and simplified into five groups according to agronomic performance (Skocaj et al., 2019).

Like all sugarcane growing regions between Cairns and Ingham (Fig. 1), reducing discharges of DIN is a high priority for Great Barrier Reef protection. Government water quality policy aims for a 310 t yr^{-1} (i.e. 50% of the total) reduction in DIN discharged from the two rivers draining the Tully basin (State of Queensland, 2018).

2.2. Overview of the research approach

Determining the relationship between seasonal climate and optimum N rate requires long-term information on yield response to N fertiliser applications for different soils in both climate zones. This information wasn't available from previous or current experiments in the region, which had only been conducted on a limited range of soil types and for a relatively small number of years. Thus, the response of yield to N fertiliser was simulated with the Agricultural Production Systems Simulator (APSIM Version 7.8) cropping systems model (Holzworth et al., 2014). The APSIM model was used in this study because of its proven capability for modelling yields and N cycling in sugarcane experiments in the region (Skocaj, 2015; Thorburn et al., 2018, 2017). Whilst these simulation studies provide general confidence of the model at the locations of these experiments, the experiments were not representative of broader soil types in the region (described below) and so parameters reflecting the broader soil types were developed. To provide confidence that the resultant yield responses to N fertiliser were consistent with local knowledge, we sought advice and feedback from local agronomists, farmers and sugar mill staff who formed an advisory panel for the research. This approach follows methodology previously used in the region (Thorburn et al., 2011c).

Soil parameters required by the APSIM model were developed from previously published soil profile information (Cannon et al., 1992; Murtha, 1986). Crop management was specified in the model based on local experience. Crops in the region suffer lodging and waterlogging and these processes were specified in the model based on the observations of local agronomists, together with comparison of the resultant simulated N responses with their (unpublished) experience in the region.

Yield responses to different rates of N fertiliser were then simulated for the different soils in each climate zone using historical climate data. The simulation output was analysed to determine an optimum N application rate, defined below, and assessed how this differed in wet and dry years (also defined below). The simulated cane yield and total N lost from the soil to the environment (i.e. sum of N lost via deep drainage, denitrification, and runoff) at the optimum N rate were also determined. These were compared with yields and total N losses simulated at the N fertiliser rates resulting from the SIX EASY STEPS N guidelines for these soils.

2.3. Overview of APSIM

APSIM has the capacity to represent important features of sugarcane production systems including residue decomposition algorithms to accurately capture the specific dynamics of crop residue management (Thorburn et al., 2001); nitrification and denitrification parameters validated for sugarcane farming systems (Meier et al., 2006; Thorburn et al., 2010); algorithms for predictions of nitrate N in run-off (Thorburn et al., 2011a) and deep drainage (Stewart et al., 2006). The APSIM model was configured with modules for soil N and carbon (C) (APSIM-SoilN; Probert et al., 1998), soil water (APSIM-SoilWat; Probert et al., 1998), sugarcane growth (APSIM-Sugarcane; Keating et al., 1999) and sugarcane residue dynamics (within APSIM-SurfaceOM; Probert et al., 1998). All modules are one-dimensional, use a daily time-step and are driven by daily climatic data.

Daily climate data were obtained (retrieved 2016-06-01) from the Scientific Information for Land Owners (SILO) climate stations and interpolated gridded data bases (Jeffrey et al., 2001). For the identified climate zones (Sexton et al., 2017) data from the Tully Sugar Mill (Station number: 032042) was used to represent the Northern zone and in the absence of a suitable climate station in the Southern zone, interpolated gridded data for the location closest to the zone's centroid was used (−18.05 S; 145.85 E).

Details of farm management, including crop harvest dates, fertiliser time and placement, are also specified in the model, based on previous simulation studies (Thorburn et al., 2017, 2011b) and experience of local agronomists.

2.4. APSIM parameter development

2.4.1. Soil parameters

Soil survey data (Cannon et al., 1992; Murtha, 1986) was used to develop APSIM parameters for eight soils (Table 1). The soil surveys had identified 51 soil types in the region. However, for N fertiliser management purposes many of these soil could be considered similar (Skocaj et al., 2019). The eight soils selected represented variation in soil chemical and physical properties, as well as landscape positions which affect processes such as the frequency and severity of waterlogging. Together they represented 82% of the sugarcane growing area in the Tully region.

Where possible bulk density (BD), water content at saturation (SAT), water content at drained upper limit (similar to field capacity; DUL), water content at lower limit (similar to wilting point; LL15), pH, total C and total N were extracted from soil survey reports. Soil survey data is often not available for all soils and/or at all depths in the soil profile. Also, some APSIM parameters (e.g. saturated hydraulic conductivity; Ks) may not be provided in the soil surveys. In the absence of these measured soil parameters, a complete set of APSIM soil parameters were developed using the following steps:

1. BD, SAT, DUL and LL15 were estimated from soil texture and C data using an ensemble of pedotransfer functions (Palmer et al., 2017).
2. Saturated hydraulic conductivity (Ks) was estimated using one of two pedotransfer functions (eq. 14 & 15 in Minasny and McBratney, 2000). If the soil had a sandy texture the Puckett function (eq. 15) was used otherwise the Cosby function (eq. 14). In the absence of data for deeper soil layers, parameters in these layers were extrapolated from parameter values in the shallower layers. For soil C we assumed an exponential decrease in C concentrations with depth (Minasny et al., 2006). For other parameters values were estimated via interpolation after fitting a polynomial surface using local fitting (i.e. loess; Cleveland, 1979) relating a specific parameter (e.g. DUL) to soil depth.
3. Soil survey data were generally measured on undisturbed soils under native vegetation (rainforests), rather than cultivated fields. In their native condition, soils had higher C than when cultivated (Wood, 1985), and the higher C concentrations would have resulted in lower BD and higher SAT (Palmer et al., 2017). To obtain parameter values relevant to cultivated soils we first simulated the reduction in C due to long-term cultivation by simulating 110 years of sugarcane production, with crop residues were burned in the first 85 years then

Table 1
Summary of important characteristics of soils used in the modelling. Organic C for the top 0.2 m, and the average clay, silt and sand percentages above the drainage restriction are also show. Texture classes were defined as Clay <0.002 mm, Silt 0.002–0.02 mm and Sand 0.02–2 mm.

Soil	Clay	Silty clay A	Silty clay B	Sandy loam A	Sandy loam B	Silty clay Loam	Sandy clay	Clay loam
Water table	Deep ~1.2 m	No	Shallow ~0.6 m	Deep ~1.2 m	No	Deep ~0.9 m	Deep ~0.9 m	Deep ~1.2 m
Flooding	Occas-ional	No	Occas-ional	Freq-uent	No	Occas-ional	Occas-ional	Occas-ional
Organic C (%)	1.48	1.15	5.11	0.97	0.81	1.31	1.25	0.90
SIX EASY STEPS guideline N rate (kg ha^{-1})	130	140	100	140	140	130	130	140
Clay (%)	45	43	47	16	17	39	33	29
Silt (%)	24	35	40	11	9	31	5	9
Sand (%)	31	22	13	73	74	29	62	62
Rooting depth (m)	1.2	1.2	1.2	1.2	1.2	1.1	0.9	1.2
Curve number (cn2_bare)	73	84	73	73	73	73	83	73
Coefficients defining diffusivity (diffus_const, diffus_slope)	88, 40	40, 35.4	40, 16	40, 16	88, 16	88, 35.4	88, 35.4	40, 16
C:N	15	14	15	10	15	12	12	10.3
Soil water conductivity (0-60 cm) (SWCON)	0.4	0.4	0.3	0.5–0.6	0.5	0.6	0.7	0.3–0.4
Soil water conductivity (60–120 cm) (SWCON)	0.4	0.4	0.3	0.01–0.5	0.5	0.05–0.6	0.2–0.7	0.4–0.5

retained in the final 25 years reflecting the major change in residue management in the region. The resulting soil C values compared favourably with locally available data (e.g. obtained when assessing soil fertility). This procedure provided new values of C more relevant to contemporary cultivated fields and defined the structure of the various C pools existing in the APSIM SoilN module.

4. The C concentrations estimated for cultivated soils were then used to estimate new values for BD, SAT, DUL, LL15 and Ks using the same pedo-transfer function approach described in points 1 and 2 above.
5. Texture class was used to estimate SWCON, curve number, and nitrous oxide gas diffusion coefficient.

Perched water tables were replicated in the model by restricting drainage through the profile (via the SWCON and Ks coefficients) at a specified soil depth (Table 1).

2.4.2. *Crop parameters*

Potential yields are generally not achieved on sugarcane farms in Australia (Larsen and Dougall, 2017) due to many reasons such as lodging, decline in leaf N concentration as crops age, disease and pest damage. To represent these processes collectively a simple "growth slowdown" process was implemented (Dias et al., 2019). Radiation use efficiency (RUE) was maintained at a specified rate up to the point when leaf #10 appears and then reduced proportionally to 80% of that value when leaf #24 appears, remaining at this rate thereafter. The value of 80% was obtained via calibration with average regional yields.

Soil profiles within the Tully region are often saturated due to the frequency and volume of rainfall in the region. This can lead to conditions where sugarcane growth can be restricted due to oxygen deficiency. This deficiency is represented in APSIM via a modified rate of photosynthesis based on the proportion of the root profile which is in saturated soil. Photosynthetic rate is reduced if a defined proportion of the root profile is saturated (oxdef_photo_rtfr in Table 2). When the whole root profile is saturated the photosynthetic rate is reduced by a defined amount (oxdef_photo in Table 2). In between these extremes the relationship is linear.

Flooding is also a frequent (sometimes annual) event (Table 1). Within the model the crops radiation use efficiency was reduced by 8% following a location-specific (i.e. soil-specific) volume of rainfall within the last three days (Sandy Loam A = 292 mm; Clay Loam = 600 mm; Sandy Clay = 700 mm; Silty Clay Loam = 900 mm; Clay and Silty Clay B = 1000 mm). The Sandy Loam B and Silty Clay A soils were not affected by flooding. These values were developed by calibrating maximum yields to the assessment panels expectations and the approximate frequency of flooding experienced by the soil's landscape position (e.g. Sandy Loam A is flooded annually).

Table 2
Non-default APSIM module parameters used to simulate N trial. Waterlogging parameters (oxdef_photo) were estimated using the Model-Independent Parameter Estimation & Uncertainty Analysis (Doherty, 2015). References for parameter values are provided.

APSIM module	Parameter name	Value	Reference/source
Soil	dnit_rate_coeff	0.001379	(Thorburn et al., 2010)
Soil	dnit_nitrf_coeff	0.002	(Thorburn et al., 2010)
Sugar	transp_eff_cf	0.0087	(Dias et al., 2019)
Sugar	oxdef_photo_rtfr	0.5, 1.0	(Doherty, 2015)
Sugar	oxdef_photo	1.0, 0.2	(Doherty, 2015)
Sugar	sen_detach_frac	0.004	(Thorburn et al., 2005)
Surface organic matter	crit_residue_wt	10,000	(Thorburn et al., 2001)
Surface organic matter	opt_temp	30	(Thorburn et al., 2001)
Surface organic matter	pot_decomp (sugar)	0.06	(Thorburn et al., 2001)

2.4.3. *Crop management*

In the simulations, crops were specified as 12-month long ratoon crops that were rainfed. For the APSIM-Sugar module, parameters for the sugarcane cultivar Q117 were used, with some modifications from the default parameters (values given in Table 2). Nitrogen fertiliser inputs in the simulations were as urea applied at 14 days after the start of the crop for the mid and late crops (the different crop starts are described below.) For the early crops, due to the other management activities occurring around July (e.g. planting), fertiliser would commonly be applied up to 70 days after the start of the crop. Zero tillage management was practiced and all crop residues after harvest returned to the soil surface.

2.4.4. *Model initialisation*

Within the simulation, the soil organic C, C partitioning into the different C pools in the model (BIOM, HUM, FOM), soil mineral N, water content and surface residues were reset to initial values at the beginning of every crop. The advantage of this approach is that it ensures climatic effects are not confounded by carry-over effects of previous crops on soil conditions (Lisson et al., 2000), whereas the disadvantage is that the possible effect of soil C rundown on yields at low N fertiliser applications is not shown. Although there is evidence of yields declining, relative to recommended N rates, across in field experiments run for long enough to exhibit soil C rundown (e.g. >4 years), the decline is often small and not significant even at N rates as low as half the recommended rate (e.g. Hurney and Schroeder, 2012; Skocaj, 2015; Skocaj et al., 2020; Palmer et al., 2017). A factor contributing to these results is likely to be the strong tendency of sugarcane to exhibit luxury uptake of N (Keating et al., 1999), which means sugarcane crops can adapt to lower N fertiliser application rates by reducing N concentrations in the plant (a phenomenon represented in the APSIM-Sugar model). We think the disadvantage of resetting parameters is acceptable for this exploratory study. The initial APSIM soil parameters were based on the average of the last three cropping cycles (~16 years) of the 110-year C rundown simulations described in Section 2.4.1.

2.5. Calibration and assessment

In the absence of empirical information for the eight soils, we used two processes to ensure simulated N responses matched local data and experience: (1) a modified Delphi approach where simulated N responses were assessed by the advisory panel and other local agronomists against relevant experiments and their general experience, and (2) comparison of the "scaled-up" yields simulated for individual soil-climate combinations against yields for eight "productivity districts" in the region. The first process underpinned calibration of model parameters. The second process provided an independent test of the plausibility of the simulated yields.

The local experts focused on yields at high rates of N fertiliser (i.e. yields at the yield plateaux) and the slope of the response to increasing N at lower N rates. They also looked at how these attributes differed between wet and dry years as yield and N responses are substantially affected by climate. Modifications were made to model parameterisations based on their feedback. Two examples of this process are described here:

1. A coarse soil with low soil C (Sandy Loam A) had very flat simulated N responses, which did not match the expert's expectations. During the interviews it became apparent that this soil occurred in landscape positions that are flooded almost annually and receive considerable soil deposition, improving their fertility. The soil parameters for the top layer in the model were modified to represent this deposition and the values used were parameter values for this layer derived from soils higher in the landscape. After this modification, simulated N responses better matched local experience.
2. Simulated N responses for some soils parameterised as reasonably well-drained based on soil survey data had a strong response to applied N and high yields at high N rates. This was the opposite of the panel's expectation which was more consistent with a poorly drained soil. During the interviews it became apparent that these soils occurred in a position in the landscape where they were susceptible to frequent flooding and can be submerged for up to a week after very heavy rainfall. The amount of rain needed to flood these soils and the effect of this flooding on crops was represented in the modelling resulting in N responses in line with those observed by panel members.

For comparison with productivity district yields, the simulated yields were "scaled up" to the district scale using the soil-area weighted average of the yields simulated with 150 kg ha^{-1} of N applied, a rate reflecting historical practice. The area of each of the eight soils within each district was obtained from soil surveys (Cannon et al., 1992; Murtha, 1986). As described above, the soils in the modelling represented 82% of the sugarcane growing area in the region. Yields in the remaining 18% of the area were represented by the average of those of the eight simulated soils. The district yield data were the average annual yields for each of eight productivity districts from 1990 to 2014 (25 years). Sugarcane growing only commenced in District 8 in 2011 and so data were available for only four years. The data were obtained from the annual Tully district Comprehensive Area Productivity Analysis (CAPA) reports produced by the Tully sugar industry using data collected by the local sugar mill, as part of the process of paying farmers for their crop. Performance of the model was assessed statistically using Root Mean Squared Error (RMSE), Nash-Sutcliffe Efficiency (NSE) and the coefficient of determination (R^2).

2.6. Simulations

The simulations included the eight soils and two climate zones (North and South). Also, there were three different growing seasons simulated, with ratoon crops starting (following harvest of the preceding crop) on the 15-Jul (early season crops), 15-Sep (mid-season crops) and 15-Nov (late season crops). Different growing seasons were simulated because preliminary analyses showed that N responses differed across these seasons. Combined in a factorial this provided 48 unique soil group (8) X climate zone (2) X growing season (3) combinations. For each of these unique combinations, 11 N rates (0 to 300 kg N ha^{-1} in 30 kg N ha^{-1} steps) were simulated for 65 years (1950 to 2014) using historical climate data, eventually producing 3120 separate N response curves. Using these curves allowed the identification of optimum N across the range of soils, climates, management options and years.

2.7. Derivation of optimum N

Empirical functions were fitted individually to the 3120 N response curves to interpolate between the 11 simulated N rates and allow calculation of the optimum N rate. Optimum N was defined as the N application rate resulting in 98% of the maximum yield, a yield that approximates the long-term maximum partial gross margin of sugarcane production (Fig. 2).

To allow for different shapes of N response curves, six different functions were fitted to each response curve and the function with the smallest residual standard error used to predict optimum N (following Palmer et al., 2017). The functions were the Weibull growth curve model, four-parameter logistic model, loess local polynomial regression, simple logistic model, asymptotic regression model and the Gompertz growth model. Parameters for each of these models were constructed using the *selfStart* and *nls* functions in R (R Core Team, 2020). Optimum N was then calculated (to the nearest 1 kg N ha^{-1}) for each yield response function. The yield and the N loss (sum of N denitrified, leached, and lost in runoff) at the optimum N rate were also calculated. The distributional shifts in N fertiliser, yields and N lost at optimum N were compared with those simulated based on the 'SIX EASY STEPS' fertiliser guideline using boxplots. Significance was quantified using a two-tailed Wilcoxon matched pairs test.

2.8. Rainfall terciles

To examine how optimum N is impacted by rainfall, each simulated N response curve was grouped by terciles according to rainfall received in the first six months of the simulated crop growing season. This was done to broadly compare crop performance in wet tercile years and dry tercile years (Table 3). Rainfall for the first six months was considered as this is the period when differences in rainfall are likely to impact the crop's ability to assimilate the applied fertiliser N.

Optimum N, yield at optimum N, and total N lost at optimum N were compared in wet and dry years using the method described in Fig. 3. Significance of the difference in the simulation results between wet and dry terciles was quantified using the two-tailed two-independent sample Wilcoxon-Mann-Whitney test.

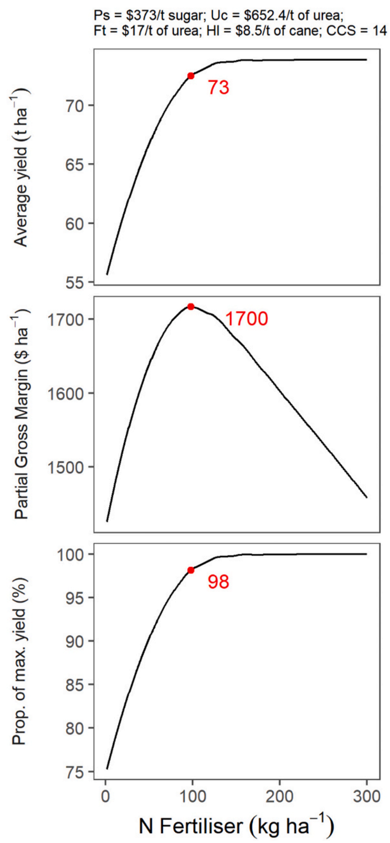

Fig. 2. Optimum N was defined as the amount of N applied to achieve 98% of maximum yield. This 98% of maximum yield corresponds to the maximum partial gross margin of the simulated average yield response and historical average prices for sugar (Ps), urea fertiliser (Uc), fertiliser transport costs (Ft), harvesting costs (Hl) and sugar concentration in the cane (CCS).

Table 3
Amount of rainfall during the first six months of the growing season (mm) at the 33 and 66% percentile used to define wet and dry years in the analysis of seasonal effects on yield, N loss and optimum N. The source of climate data used to determine the terciles are described in Section 2.3.

	North climate zone		South climate zone	
	Dry tercile	Wet tercile	Dry tercile	Wet tercile
Early (July) crops	< 697 mm	> 950 mm	< 434 mm	> 673 mm
Mid (Sept) crops	< 1512 mm	> 2236 mm	<1198 mm	>1905 mm
Late (Nov) crops	< 2754 mm	>3274 mm	<1916 mm	>2467 mm

3. Results

3.1. Simulation of district yields

The model was able to replicate the historic annual productivity district yields with an RMSE of 11.70 t ha^{-1}, NSE of 0.40 and R^2 of 0.51 (Fig. 4). The simulated yields had an average bias of 11–13 t ha^{-1} in Districts 1 and 2. However the relative impact of year-to-year variability was modelled well for these districts. Excluding these two districts, historic yields were simulated with RMSE of 9.87 t ha^{-1}, NSE of 0.50, and R^2 of 0.63. This result was considered appropriate by the advisory panel and local agronomists.

3.2. Optimum N

The effect of rainfall (i.e. wet and dry terciles) on optimum N differed across the crop growing seasons and, to a lesser extent soil type. The median simulated optimum N for crops that started to grow in July (early season) was greater in wet years than dry years, particularly in the slightly drier, southern climate zone (Fig. 5). For the late growing season, the trends were generally opposite. The median simulated optimum N was less in wet years compared to dry years, except for four soils (Silty Clay A, Silty Clay B, Sandy Loam A and Clay Loam) in the south zone.

The statistical significance for the difference in the median simulated optimum N between the wet and dry terciles was computed. Whilst multiple significance tests should be interpreted with care, *p*-values less than 0.001 as marked by the larger circle, indicate significance with the Bonferonni correction factor applied whilst maintaining a family-wise type I error rate of 0.05. Whilst statistical significance is less frequent for the mid-season growing crops, the difference in the medium simulated optimum N between the wet and dry terciles for the Clay, Sandy Clay A and Sandy Clay B soils were similar to the late growing crops, i.e. the median simulated optimum N was less in the wet tercile than the dry tercile but the remaining coarser (Sandy Loam to Clay Loam) soils behaved similarly for early growing crops and showed the median simulated optimum N was higher for the wet tercile than the dry tercile.

3.3. Yield at optimum N

Median yields simulated at optimum N in wet years were lower than that in dry years for the mid and late growing seasons (Fig. 6). Lower median yields in wet years are consistent with lower solar radiation in these years caused by more frequent cloud cover. Additionally, crops on soils prone to flooding and/or waterlogging had their growth in the simulations constrained more by those factors in wet years. Coarse soils are unlikely to be affected by flooding and/or waterlogging but will be impacted by the lower radiation. However, in dry years the coarse soils will experience higher levels of water stress that lead to a reduction in yield than on the finer soils (i.e. Clay, Silty Clay A and B).

For the early grown crops in the drier southern zone, median yields at optimum N on the five coarser soils (Sandy Loam A through to Clay Loam in Fig. 6) were higher in wet than in dry years and the difference was significant for the Sandy Loam A, Sandy Clay, and Clay Loam ($p <$ 0.001). These five coarser soils did not experience waterlogging conditions (Table 2), and so crop yields were not limited by oxygen deficiency in the simulations. However, crops on these coarser soils could experience water stress leading to yield reduction in dry years, as described in Section 3.5.1.

3.4. N losses to the environment at optimum N

Median N losses (i.e. sum of N lost via deep drainage, denitrification, and runoff) simulated at optimum N were typically higher for years in the wet tercile than in the dry tercile (Fig. 7). The higher N losses in the wet years for all soils in early season crops was partly due to the higher optimum N (Fig. 5) with the additional N fertiliser applied increasing N losses. Conversely, optimum N rates for late crops were most often lower in the wet years than in the dry years whilst N losses continued to be higher, or at least similar for wet years compared to dry years. However, in most soil-climate zone combinations in the late growing season crops, the difference in N losses were not significant ($p \geq 0.001$). In wet years, late growing season crops receive large amounts of rain ($>$ 2467 mm (South) and $>$ 3274 mm (North); Table 3) within the first six months of the growing season. Under these conditions yield potentials are severely impacted by low solar radiation and/or waterlogging (as described below) limiting crop N uptake and causing higher N losses even where optimum N was low. Thus, in these very wet situations there is unavoidable N loss even if N fertiliser applications (in the urea form) are optimised.

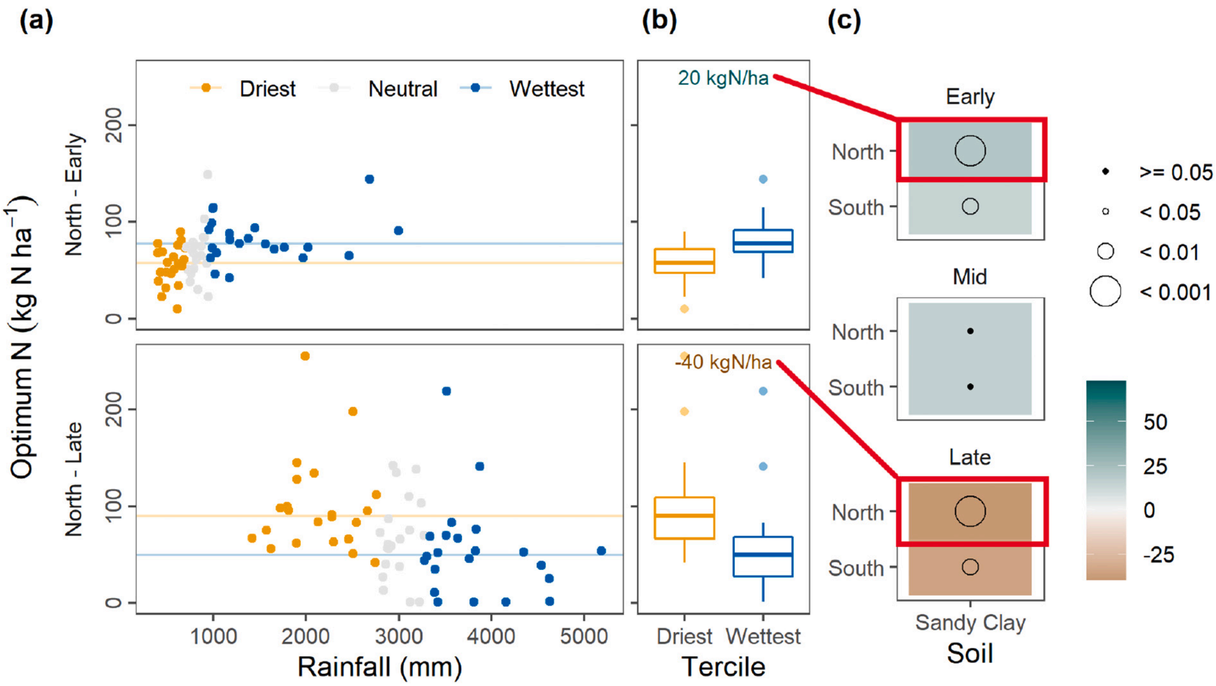

Fig. 3. An example of the methodology used to visualise the effect of rainfall during the first six months of sugarcane growth on simulated optimum N. Firstly, (a) the simulated optimum N for each year was classified according to the year type (i.e. dry tercile = orange, and neutral tercile = grey, and wet tercile = blue). Secondly (b) the difference between the wet and dry tercile medians (vertical distance between the blue and orange horizontal lines) was calculated (text at the top of each panel), and finally (c) heatmaps were used to visualise the tercile difference for all combinations of climate zone (North, South) and growing season (early, mid, late) for all soils (Sandy Clay is shown here as an example). Green hues (positive values) signify the median simulated optimum N is greater in wetter years when compared to drier years. Brown hues (negative values) signify the median simulated optimum N is less in wetter years when compared to drier years. The circles indicate the statistical significance of the difference calculated by a two-tailed two independent sample Wilcoxon-Mann-Whitney test *p*-value. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 4. 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. Note: District 8 is a new district and thus fewer data were available.

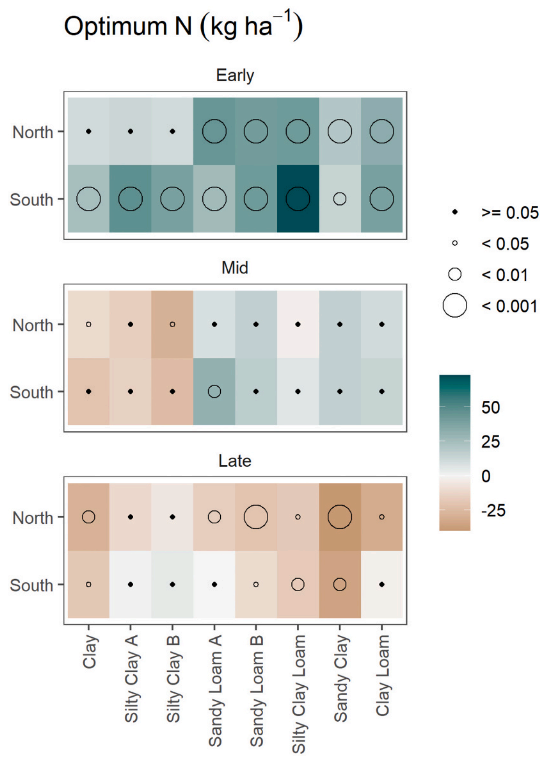

Fig. 5. Heatmap displaying the difference in median simulated optimum N between the wet and dry rainfall terciles. Green hues (positive values) signify the median simulated optimum N is greater in wetter years when compared to drier years. Brown hues (negative values) signify the median simulated optimum N is less in wettest years when compared to drier years. The circles indicate the statistical significance of the difference calculated using the methods described in Fig. 3. *p*-Values less than 0.001 indicate significance with the Bonferonni correction factor applied whilst maintaining a family-wise type I error rate of 0.05. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

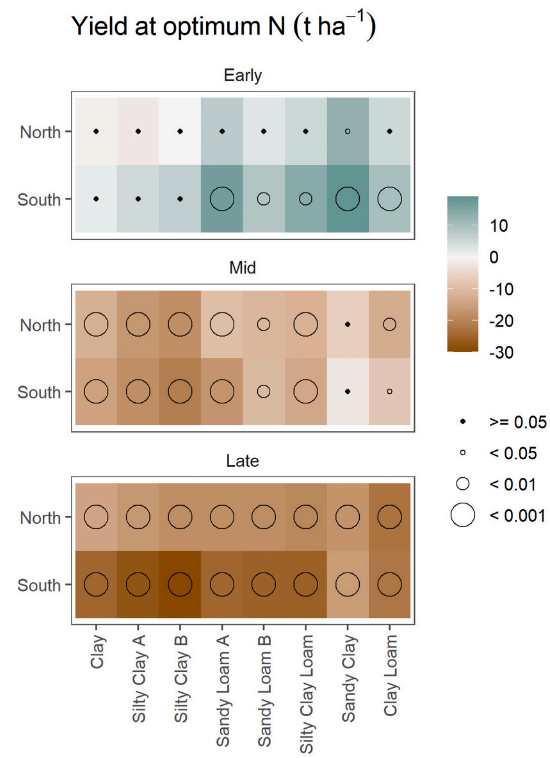

Fig. 6. Heatmap displaying the difference in median simulated yield at optimum N (t ha^{-1}) between the wettest and driest rainfall terciles. Green hues (positive values) signify that the median simulated yield is greater in wetter years when compared to drier years. Brown hues (negative values) signify that the median simulated yield is less in wetter years when compared to drier years. The circles indicate the statistical significance (*p*-value) of the difference calculated using the methods described in Fig. 3. *p*-Values less than 0.001 indicate significance with the Bonferonni correction factor applied whilst maintaining a family-wise type I error rate of 0.05. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.5. Factors driving interactions between simulated optimum N, yields and N loss

3.5.1. Soil water deficit

To understand the main factors driving the interactions between optimum N, wet/dry years and different climate zones we investigated in more detail the response of simulated yield, crop water stress and total N losses to increasing fertiliser N application using two contrasting soil textures; Clay and Sandy Loam B (Fig. 8). The main factor leading to higher optimum N rates for early season crops in the wet years relative to the dry years was crop yields being less impacted by higher soil water deficits and hence being more responsive to N applications. Yields at optimum N for late season crops in the wet years were much lower than in the dry years (Fig. 8) due to lower radiation, greater oxygen deficiency (via waterlogging) and increased chance of flooding (leading to reduced RUE) in the simulations. In combination with this lower yield potential, the crop's N demand is reduced leading to lower optimum N rates. However, the lower optimum N rates did not have a consistent or large effect on N lost at optimum N for the two soils shown in Fig. 8.

Interestingly, late season crops in the North climate zone experienced relatively similar and low levels of water stress (averaged across the whole life of the crop) for both the wet and dry years (Fig. 8). Thus, overall limited soil water supply was not a dominant cause of the lower yields in wetter years. In contrast, late season crops in the South climate zone had on average greater soil water deficits and lower yields in the wetter years than the North climate zone. The greater water deficits can be explained by a rapid accumulation of biomass during the first six months (wetter summer period – Nov to Apr, data not shown) which created crop water demand that was difficult to supply in the following drier six months. During the wetter summer period (Nov to Apr) in the South climate zone, growth will have been less affected by reduced radiation than during the same period in the North climate zone (compare rainfall terciles in Table 3).

Early season crops on the clay soil had similar yields at high N application rates in wet and dry years. However, in the dry years, they also had lower optimum N and greater soil water deficits at the optimum and higher N rates. This suggests that water stress may have been limiting yields of these crops at these N rates. N losses at optimum N were also consistently lower in early crops in dry years on clay soils. These patterns also occurred in the early season crops on the Sandy Loam B soil in the north climate zone. However, in the drier south climate zone, early season crop yields were lower at optimum N (and higher N rates) and soil water deficits were higher. These results suggest that water stress was an even greater limit to early season crop yields in the southern climate zone in this soil compared with the clay soil.

3.5.2. N supply and demand

As well as soil water deficits affecting optimum N in the simulations, supply of N from soil organic matter mineralisation or the ability of the crop to take up this N (i.e. crop demand) affected optimum N rates. The way that these factors interacted in the simulations to give the predicted optimum N rates is exemplified by examining the reasons for the low optimum N rates for the Silty Clay B and Sandy Loam A soils in late

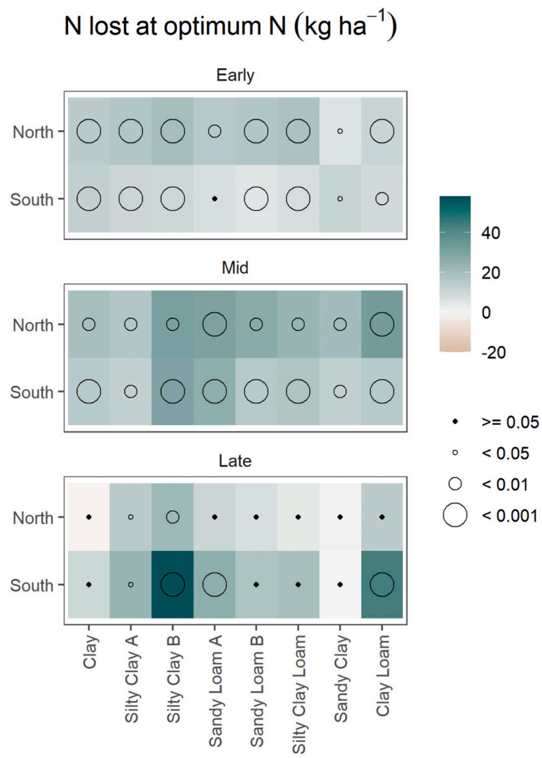

Fig. 7. Heatmap displaying the difference in median simulated N loss (kg N ha^{-1}) at optimum N between the wettest and driest rainfall terciles. Green hues (positive values) signify that the median simulated N loss at optimum N is greater in wetter years when compared to drier years. Brown hues (negative values) signify that the median simulated N loss at optimum N is less in wetter years when compared to drier years. The circles indicate the statistical significance (*p*-value of the difference was calculated using the methods described in Fig. 3. *p*-Values less than 0.001 indicate significance with the Bonferonni correction factor applied whilst maintaining a family-wise type I error rate of 0.05. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

growing season crops. These two soils, although very different, had median optimum N rates <6.0 kg ha^{-1} (Fig. 9) because there was very little or no response of yield to fertiliser N in the late growing season.

For the Silty Clay B soil the "flat" median responses were due to (1) very high soil C (Table 1) leading to high N mineralisation rates which met almost all of the crops N demand, and (2) shallow perched water tables that restricted N uptake and crop growth (through waterlogging) in the simulations. The high N mineralisation rates in this soil also contributed to the low median optimum N rates compared with other soils in other growing seasons (Fig. 9). The high N mineralisation rate and reduced N fertiliser requirements are already recognised in the SIX EASY STEPS N guideline for this soil type, and growers are already applying less N fertiliser to soils like this compared to other soils in this region (Skocaj, unpublished data).

For the Sandy Loam A soil, "flat" median responses, particularly in late growing season crops, were a result of the soil's position in the landscape leading to almost annual flooding (see Section 2.4.2 for more detail on how the model was parameterised) in the simulations. These annual flooding events could submerge the crop canopy for extended periods (see Section 2.5). So even though this soil would be described as a well-drained soil (Sand = 73%; Table 1), the radiation use efficiency during flooding events was reduced in the simulations preventing the crop from achieving potential growth. This in turn restricted N uptake of the crop in the simulations making it unresponsive to N fertiliser. This effect was greatest when the likelihood of flooding events occurred close to the time fertiliser was applied, which is the case in the late growing season crops.

3.6. *Optimum N relative to current guidelines*

As described above (Section 2.4.1), we have selected and parameterised eight soils to represent the variation in soil chemical and physical properties in the region. Based on the organic C data used to parameterise these soils we determined the amounts of N recommended by the SIX EASY STEPS baseline guidelines for each of the soils. These amounts would be constant through time in this study (Fig. 10a) because soil organic C remained relatively constant in our simulations (although this may not happen in practice). In comparison, the median optimum N rate varied from year-to-year. The simulated median optimum N rate was also consistently lower (between 13 and 140 kg N ha^{-1} less) than the simulated SIX EASY STEPS N rate for all soils. Overall, the median decrease in optimum N relative to the SIX EASY STEPS rate was 61 kg N ha^{-1} or 47% of the median SIX EASY STEPS rate. (The mean reduction was 54 kg N ha^{-1}). However, with many soils, optimum N in specific years could exceed the SIX EASY STEPS rate. Across all soils the highest

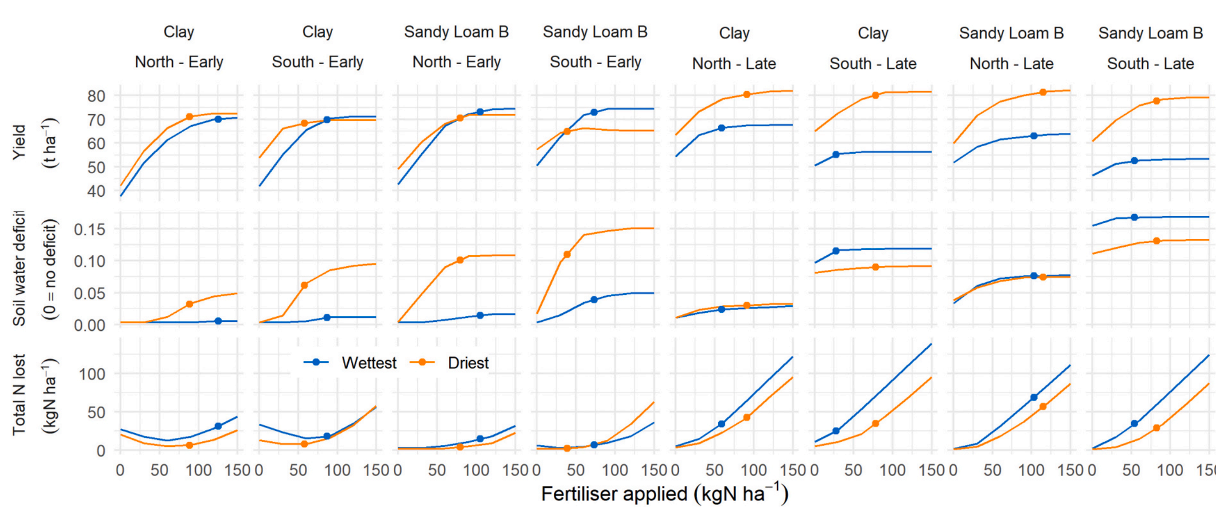

Fig. 8. Effect of wettest (blue) and driest (orange) years (as defined by the rainfall terciles for the first six month of the crop) on the median simulated response of yield (t ha^{-1}), soil water deficit and total N lost to increasing N fertiliser applications. Optimum N rates are shown as points. Two soils (Clay and Sandy Loam B) with contrasting texture are shown as examples of the general patterns found across all soils. Only simulated N rates up to 150 kg N ha^{-1} are shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

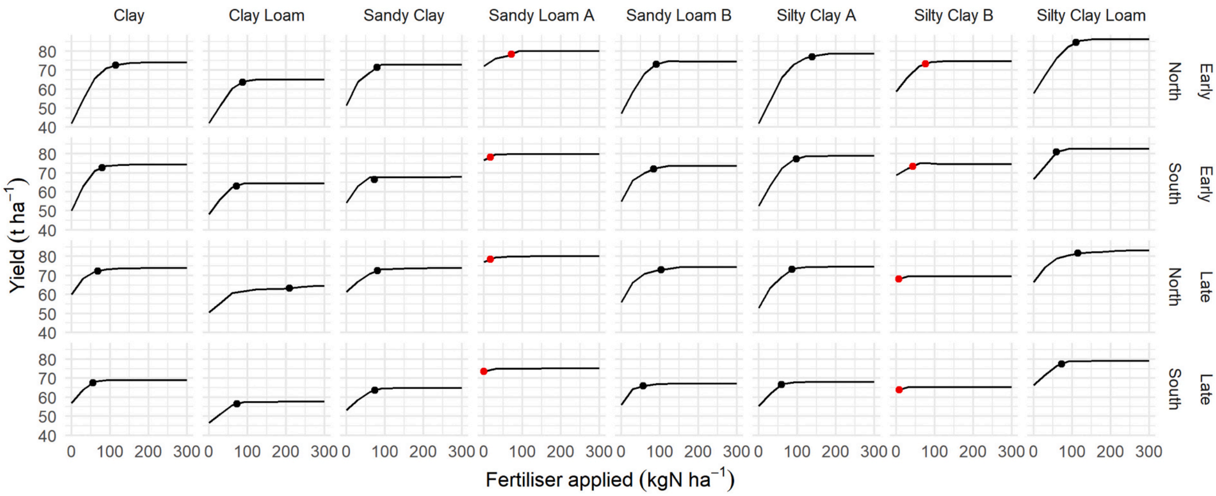

Fig. 9. Median yield responses for all eight simulated soils. Optimum N rates are shown as points. Red points identify the Sandy Loam A and Silty Clay B soils with the lowest optimum N rates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

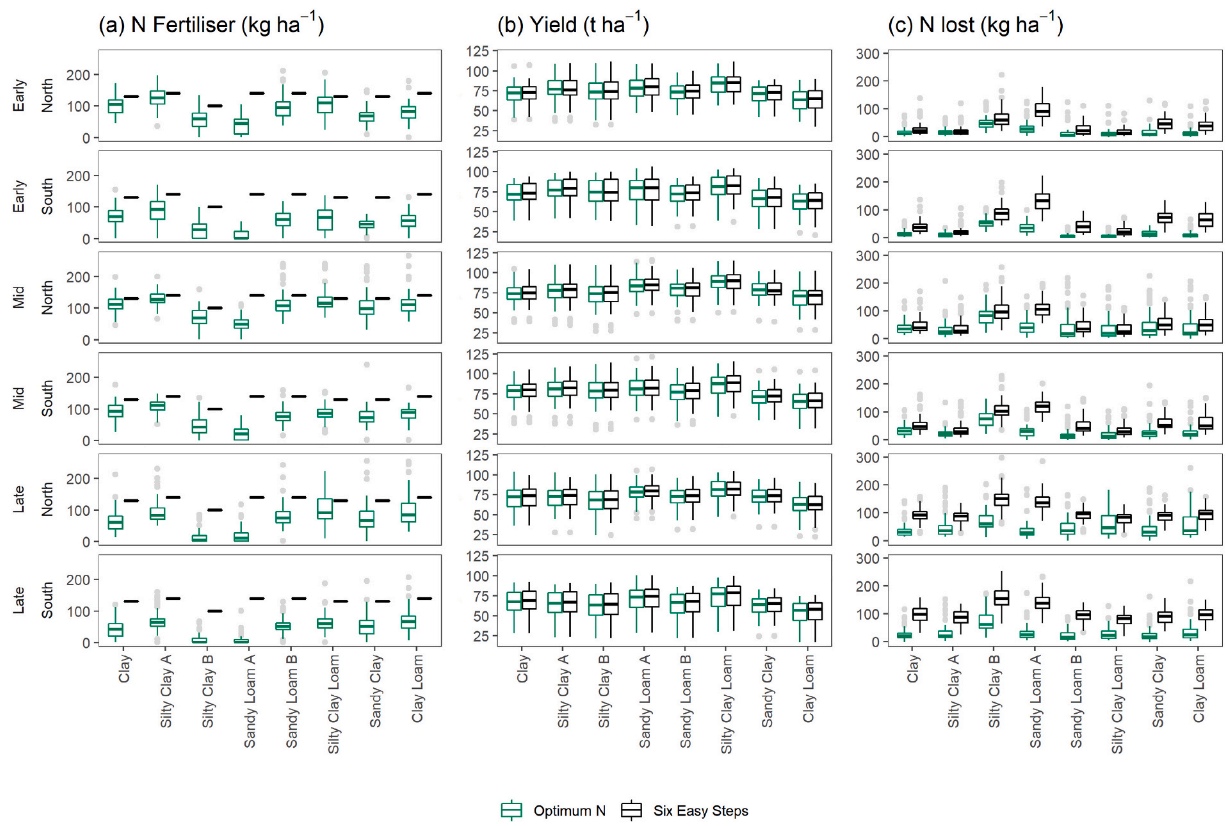

Fig. 10. Comparison of (a) fertiliser N, (b) yield and (c) total N loss variability for Optimum N (green) and the current guidelines (SIX EASY STEPS = black) across eight different soils (x-axis), two climates (North & South) and different growing seasons (Jul, Sep, Nov). The boxplot shows the year-to-year variability in outcomes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

optimum N rate in an individual year was 266 kg N ha^{-1} compared to the maximum SIX EASY STEPS rate of 140 kg N ha^{-1}. This high simulated optimum N rate was for a mid-growing season crop on a Clay Loam in the North in a wet year (i.e. 2377 mm of rain in the first six months and therefore classified in the wettest rainfall tercile).

There were small differences in the simulated median yield at the optimum and SIX EASY STEPS N rates across the different soils (Fig. 10b). Median yield at optimum N was between 0.6 and 1.5 t ha^{-1} (or 0.8% and 1.9%) lower than at SIX EASY STEPS rates, with a median of 1.2 t ha^{-1} or 1.8% across all soils-growing seasons-climate zones combinations. Although the decrease in yield was small, for 43 of these 48 combinations it was significant ($p < 0.001$). The five exceptions were Silty Clay A-North (Early and Mid), Silty Clay B-South-Early, Sandy Loam A-South-Early, and Silty Clay Loam-North-Mid. The yield decrease with optimum N for these exceptions was between 0.6 and 1.2 t ha^{-1}.

Median total N lost to the environment (the aggregate of N leaching, runoff and denitrification) in the simulations was lower at the optimum N rate than the SIX EASY STEPS rate for all soils-growing seasons-climate zones combinations except for two combinations (Silty Clay A-North-Early and Silty Clay Loam-North-Mid; Fig. 10c). Across all combinations the median reduction was 32 kg N ha^{-1} or 59%. The biggest reductions in N losses occurred in late growing season crops in the southern climate zone. A similar pattern occurred in the northern climate zone, but not as consistently. In many cases the between-year variability in total N losses was lower with optimum N than the SIX EASY STEPS rate, although there were still some years where optimum N resulted in greater losses in some soils-growing seasons-climate zones. For example, the largest N loss for Silty Clay Loam-North-Late season when applying an optimum N rate was 182 kg N ha^{-1} in a year (1952) when the optimum N rate was also very high 223 kg N ha^{-1}. In comparison, the SIX EASY STEPS rate for this soil is 130 kg N ha^{-1} and N losses in this year were 95 kg N ha^{-1}.

4. Discussion

More precisely matching fertiliser N inputs to crops' N requirements is important to increase the environmental and economic sustainability of cropping systems (Mueller et al., 2017). Our hypothesis was based on previous studies (Skocaj, 2015; Thorburn et al., 2011c) that year-to-year climate variability would result in year-to-year variation in optimum N fertiliser rates, something that is rarely considered in N management guidelines despite being identified long ago (Skocaj et al., 2013; Thornton and MacRobert, 1994). In our case study on sugarcane production in the Tully region of the Australian Wet Tropics, we found in the 65 years (1950 to 2014) simulated there was indeed substantial variability in optimum N fertiliser application rates between dry and wet years (defined by the highest and lowest rainfall terciles) (Fig. 5). In addition, we found variation across soils, crop growing seasons and climate zones within the region, with the effect of seasonal climate differing across these factors. Of these variables, soil type (based on soil organic C) is the main consideration in current N guidelines (SIX EASY STEPS) suggesting there is considerable scope for increasing precision of fertiliser N inputs to crops in the region by accounting for seasonal climate and the other factors. In fact, across the whole region for the years simulated, the median optimum N rates in the simulations were lower (−47% or 61 kg N ha^{-1}) than current N guidelines (SIX EASY STEPS). The lower optimum N rates were accompanied by a large (−59% or 32 kg ha^{-1}) reduction in N lost to the environment (the aggregate of N leaching, runoff and denitrification) and a small (−1.8% or − 1.2 t ha^{-1}) reduction in yield. Thus, there may be potential for substantial environmental benefits from a more precise approach to identifying optimum N compared with current baseline guidelines, and relatively small costs from lost production. Given the importance of reducing DIN discharges from rivers in the region, it is worth considering the potential impacts of a climate-based N recommendation scheme on DIN discharges. That is difficult to do with the simulated N losses because of the various transformations and attenuations of N as it moves from the field to the river mouth. Instead, we can use the empirical relationship between N fertiliser applications and DIN discharges in the region (Thorburn et al., 2013). Based on that relationship, the reductions in N fertiliser applications identified in this study would reduce DIN discharged from rivers in the region to such an extent it would nearly satisfy the government goal of a 50% DIN discharge reduction (State of Queensland, 2018). Whilst there are simplifications and uncertainties associated with the simulations undertaken and additional validation is needed before the concepts explored in this study could be implemented in practice (as discussed below), the substantial potential water quality benefits justify further efforts.

As well as the potential water quality benefits, there are also production and economic implications if the system to determine optimum N rates simulated in this study could be implemented in practice. At the field level, the lower median optimum N rate would save farmers (on average) approximately \$79 ha^{-1} in fertiliser N costs (based on data for Fig. 2) compared with the current N guidelines. That saving would be accompanied by an average reduction in income from lower sugarcane yield of \$38 ha^{-1}. So the potential field level economic benefits of the applying optimum N rates to the crop in the Tully region may be positive, albeit small. However, sugarcane production critically depends on there being a sugar mill in the local region to process the crop as the sucrose concentration of sugarcane deteriorates rapidly after harvest. The profitability of a sugarcane mill depends on the amount of sugarcane crushed, and consistent reductions in that amount can threaten mill viability (CANEGROWERS Australia, 2020; van Grieken et al., 2013). The average reduction in yield (1 t ha^{-1} y^{-1}) would result in a reduction of ~0.03 Mt. y^{-1} of cane across the region. This loss compares with total regional production of 2.6 Mt. y^{-1} (standard deviation 0.4 Mt. y^{-1}; (CANEGROWERS Australia, 2019, 2017; Schroeder et al., 2010). Whilst this is a relatively small loss, the loss of this production would still be of concern to growers and owners of the sugar mill in the region. However, there are activities that could be implemented cost-effectively in the field (e.g. improving efficiency of harvesting; Thompson et al., 2019) to overcome the reduction in production.

Whilst there were substantial potential advantages predicted for increasing precision of fertiliser N inputs to sugarcane crops in the region, this was a simulation study and thus exploratory in nature and it is important to consider some of the steps that would be needed to assess whether the concepts tested could be implemented in practice. These steps include (1) better validating and improving the simulations of sugarcane, and (2) linking the results with climate forecasting and assessing the impact of uncertainty in those forecast on the impacts of a climate-based N recommendation system. Regarding the simulations, these were based on substantial simplifications, such as: there being only eight soils in the region; soil organic C, N and water being reset for the simulation of each crop; and uniformity across many crop management factors. More realistic variability could be introduced into future simulations, including a greater number of soil types, allowing soil organic C, N and water to change through time (which would be reflected in SIX EASY STEPS N guideline) and a wider variety of crop management (e.g. timing of fertiliser applications, precise harvesting dates). The methods used in this study for developing soil parameters of the APSIM model could be applied more widely, e.g. to specific soils mapped in the soil surveys covering the region (e.g. Cannon et al., 1992; Murtha, 1986). Further, there is little empirical data against which to test the accuracy of simulated N responses. The data that are available (Hurney and Schroeder, 2012; Skocaj, 2015; Skocaj et al., 2020, 2012) do show the year-to-year variability in yield response to N but also suggest that the yield losses we simulated with reduced N fertiliser may be an underestimate. Thus, efforts would be needed to gather data to provide more extensive model testing. Finally, there are numerous other practical and contextual issues that would need to be addressed in a move from this exploratory study to implementation of climate-based N recommendation, as happens with the implementation and adoption of any agricultural innovation (Coggan et al., 2021).

As well as more empirical information to test the concepts arising from this study and improve simulations, farmers would need forecasts of seasonal climate to apply N at the optimal rates identified in this study. Because this study was retrospective, the seasonal climate was known for each year simulated. This is the equivalent of farmers having "perfect knowledge" (Jones et al., 2000). However, in reality, seasonal climate forecasts are not "perfect". Previous climate forecasting-based analyses proved unacceptable to farmers due to false positive ENSO predictions (Thorburn et al., 2011c). The N management strategy (splitting N fertiliser applications) analysed in that study was a limited management intervention compared with the comprehensive redefinition of optimum N rates developed in this study. Also, splitting increased the costs of fertilising, reducing, or negating the field level economic benefits. The previous negative response by farmers may have been specific to the concepts examined in that study which was limited in the climate forecasting indices explored. As well, climate forecasting has advanced considerably since that study was conducted (e.g. Johnson et al., 2019) and ENSO indices are becoming more widely adopted in agricultural industries (e.g. MacCarthy et al., 2017). Thus, further innovations may be possible using modern forecasting algorithms and indices compared to those used previously. Still, benefits of the future implementation of the concepts in this study will be reduced by uncertainty in climate forecasting. Qualification of that uncertainty will allow a more realistic assessment of the potential benefits of the redefinition of optimum N rates.

We have previously described how it is hard to estimate from "first principles" whether optimum N for sugarcane in Tully should be higher or lower in wet years because of two opposing effects of high rainfall on crop growth in this region (Palmer et al., 2017). This complexity is illustrated by the general trend for optimum N rate to be higher in wet years for early growing season crops but lower in late growing season crops (Fig. 5), with this difference being because the amount of rainfall in the first 6 months of a wet year is much lower for an early season crop in Tully than late (Table 3). The interaction between rainfall tercile and growing season on optimum N suggests that the general finding of this study will not be transferable to other sugarcane growing regions in the Australian Wet Tropics because most have lower annual rainfall than the Tully region (Fig. 1). The variability in optimum N across soil types (Fig. 5) also suggests that regionally-specific studies will be needed, as dominant soil types also differ across the different regions (Skocaj et al., 2019). Similar analyses to those in this study will need to be undertaken in the different regions and the results of this study cannot be assumed general to sugarcane production in Australia or elsewhere, nor to other cropping systems. Those analyses could be facilitated by the methods developed in this exploratory study.

5. Conclusions

Improving N fertiliser management in cropping systems is critical for reducing environmental impacts of N fertiliser use and improving farm profitability. An important path to improvement is the better specification of the optimum amount of N fertiliser for a crop growing in a specific location during a specific season. Whilst location is generally considered in N fertiliser management guidelines, climate usually isn't despite the vision for integrating climate being articulated many decades ago. In this study we showed that climate had a major effect on optimum N rates for sugarcane in a region of the Australian Wet Tropics. Optimum N rates also differed depending on the soil type and growing season of crops, and between climatic sub-regions. We further showed that there may be substantial environmental benefits of optimising N rates compared with current N guidelines (which do not quantify the effect of climate variability) and these benefits come at small yield reductions. There are many steps needed to capture these benefits in future, including testing and validating the approach developed in this study, and then coupling it with real time seasonal climate forecasts. These are not trivial steps. Whilst the results of this study cannot be assumed generally applicable because of the variation in climate, soil, management and thus N cycling in a different agroecosystem, it demonstrates that substantial benefits may be possible when optimising N fertiliser according to, not only climatic sub-region, soil type, and growing season, but also seasonal climate which may be at least partially achieved in combination with reliable real-time seasonal climate forecasting.

CRediT authorship contribution statement

J.S. Biggs: Methodology, Formal analysis, Data curation, Writing – original draft. **Y. Everingham:** Conceptualization, Formal analysis, Project administration, Writing – original draft. **D.M. Skocaj:** Conceptualization, Validation. **B.L. Schroeder:** Conceptualization, Validation. **J. Sexton:** Formal analysis, Visualization. **P.J. Thorburn:** Conceptualization, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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