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Use of 'virtual' trials to fill gaps in experimental evidence on enhanced efficiency fertilisers

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Abstract Enhanced-efficiency fertilisers (EEF) are of interest to the sugarcane industry because they have potential to increase N-use efficiency and reduce nitrogen (N) loss. However, it has been challenging to demonstrate the agronomic and/or environmental benefits of EEF experimentally. Using the APSIM-Sugar farming systems model we can run 'virtual' trials that mimic field trials but with many more treatments, N rates and locations, and over more seasons. For a selection of contrasting soil types from the Herbert mill area we simulated 273,360 virtual treatment-years to obtain complete yield N-response curves for urea and EEF under a variety of seasonal climate and management conditions. The virtual trial results explain that the mixed and often inconclusive results of field trials are due to the high seasonal variability of the yield response to both N rate and EEF. The responses to EEF can be classified into four types: A, increase in maximum yield; B, reduction in optimum N; C1, N responsive but no response to EEF; C2, no response to N rate or EEF. Daily output of variables from the model can explain these response types and provide interpretation of experimental results. The many virtual trials also allow specification of the likelihood of different response types under different conditions (e.g. soil and timing of ratooning/fertiliser application). While the virtual trials can be used to fill the large gaps in experimental evidence on EEF and enhance our understanding of the drivers, they do rely on the model to capture the system dynamics correctly. Ongoing experimental verification of the model's representation of different processes and, in particular, N responses is critical, especially when transitioning from using the model to understand the responses to using it for more quantitative decision support.

Key words Enhanced-efficiency fertilisers, controlled-release fertilisers, cropping systems modelling, nitrogen management, sugarcane, APSIM

INTRODUCTION

Enhanced-efficiency fertilisers have been proposed as one means of reducing nitrogen (N) losses from the sugarcane industry and, in combination with lower application rates, increasing N-use efficiency. The most commonly used products either slowly release the N (controlled-release fertilisers or CRFs) or keep the N in more stable forms (e.g. ammonium; using nitrification inhibitors or NI). This keeps the soil-nitrate concentration low, thereby reducing the risk of N loss through runoff, leaching or denitrification. The reduction in N loss can increase cane yield, but only if the sugarcane crop can use the 'saved' N. Alternatively, the N rate can be reduced while obtaining a similar yield.

Many field trials have attempted to test and demonstrate these benefits, only a few of which are published. Further trials are ongoing, including 180 on-farm trials of EEFs in a project funded by the Australian Department of Environment and Energy and the Queensland Government Great Barrier Reef Innovation Fund (EEF60 project). The field trials assess the benefits by monitoring ammonium and/or nitrate concentrations in soil (e.g. Wang *et al.* 2016a,b; Masters *et al.* 2017), by measuring and comparing N loss (e.g. Wang *et al.* 2016a,b; Masters *et al.* 2017), or by assessing the effects on sugarcane yield and/or sugar yield (e.g. Di Bella *et al.* 2013, 2014; Thompson *et al.* 2016; Schroeder *et al.* 2018a). Usually only a few N rates are chosen, e.g. a SIX EASY STEPS (6ES) rate (Schroeder *et al.* 2018b) and one or two lower rates, although a few of the more recent studies are including an assessment of the N response through use of five or more rates (e.g. Schroeder *et al.* (2018a)

and current work within the Tropical Water Quality Hub of the National Environmental Science Programme[1] (Tony Webster CSIRO pers.comm.)).

It has, however, proven challenging to demonstrate benefits of EEF in experimental trials. The changed dynamics of soil ammonium and nitrate is usually confirmed (e.g. Wang *et al.* 2016a,b). Nitrogen loss benefits are confirmed in some studies (e.g. positive effects shown by Wang *et al.* 2016b), but not others (e.g. Wang *et al.* 2016a). However, many field trials evaluating effects on cane yield have resulted in no or not statistically significant treatment differences (see e.g. in earlier review by Verburg *et al.* 2016). Many of these studies are unpublished. Demonstrating benefits is proving easiest for changed soil-N dynamics, followed by reductions in N loss and is hardest for increases in yield. This is because to get an N-loss difference, the N loss needs to happen during the period that the fertiliser N is protected. For EEF to be effective and result in a yield benefit, the crop also needs to be able to respond to the saved N. Other factors, including timing of rainfall and crop growth potential, affect this.

The APSIM-Sugar model simulates crop development as a function of climate input as well as its response to soil water and N dynamics (Thorburn *et al.* 2017). Using 'manager scripts', the model can be set-up to mimic different management strategies (e.g. timing of crop start and fertilisation, including type and amount). This provides the ability to run 'virtual' trials and test hypotheses just as one might with field trials, except that they can be run in a wide range of seasons and as a function of a wide variety of management options (Figure 1).

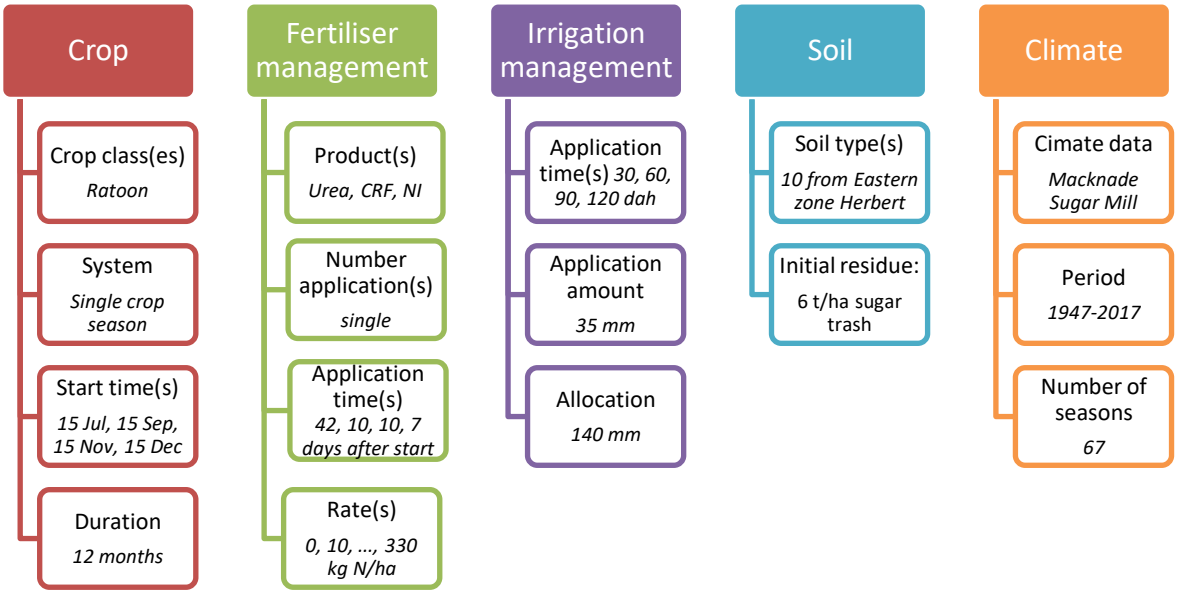

Figure 1. Example design of virtual trials for sugarcane using APSIM (in italics the options chosen here).

As part of work with Herbert Cane Productivity Services Ltd (HCPSL) to develop decision-support logic for EEFs for the Herbert mill area (Verburg *et al.* 2019), we have adopted a methodology of using 'virtual' trials to fill the gaps in experimental evidence on EEFs. Here we illustrate how we use the virtual trials to clarify, corroborate and extend beyond the experimental evidence. We also discuss implications for model verification.

MATERIALS AND METHODS

Model configuration and background

The simulation analysis was carried out using the APSIM-Sugar model (Keating *et al.* 1999; Thorburn *et al.* 2005, 2017; Holzworth *et al.* 2014). The model captures soil water and N dynamics, residue decomposition, crop

[1] http://nesptropical.edu.au/wp-content/uploads/2016/10/NESP-TWQ-Project-2.1.8-Factsheet.pdf

growth and N uptake, including responses to environmental conditions (solar radiation, temperature, water and N stress), and management actions such as planting, ratooning, irrigation and N fertilisation. In the case of water-logging, the proportion of the root system exposed to soil water conditions at saturation or near saturation was calculated and used to calculate a water-logging stress factor, based on work by Biggs *et al.* (2013). This factor reduced photosynthetic activity via a temporary effect on radiation use efficiency. Radiation-use efficiency reductions were also applied using a rule based on leaf number. Preliminary testing suggests this correctly simulated district yield.

Urea was applied in a single dose. The CRF product represented a 'linear release' product that exhibited linear release until 50% of the N was released and first-order declining release thereafter. The linear release product simulated had a release period similar to some of the products used in experimental trials in sugarcane. The release responded to temperature with a $Q_{10} = 2.5$ (rate increase of 2.5 times for a 10°C increase in temperature). We assumed that soil moisture did not affect the release rate, which is a common assumption for polymer-coated CRF that appears to hold provided there is some residual soil moisture to start the release process (Verburg *et al.* 2017).

The NI product was modelled as a urea product with NI. Its concentration was assumed to decline exponentially over time with a relatively long half-life of 28 days. Inhibition of nitrification increased linearly with increasing NI concentration up to a threshold of 0.5 kg/ha, above which there was full inhibition (Vilas *et al.* 2019b). Therefore, the longevity of nitrification inhibition was determined by the persistence of the NI and its bioactivity. There is uncertainty about the persistence of NI under different conditions and the resulting longevity of nitrification inhibition impacts on its effectiveness (Vilas *et al.* 2019a,b). For illustration purposes we used an optimally effective NI, but acknowledge that under field conditions the longevity of nitrification inhibition may be less.

The simulations presented here focussed on the eastern climate zone of the Herbert mill area and used historical climate data from Macknade Sugar Mill (station 032032, 67 seasons, 1949–2017; obtained from SILO Point Patch Data; Jeffrey *et al.* 2001). Average annual rainfall is 2156 mm (1949–2017) with 60% of rainfall in January to March.

Design of 'virtual trials'

The simulated scenarios represented rainfed 12-month ratoon crops started on 15 July, 15 September, 15 November or 15 December. To approximate local practice fertiliser (urea, CRF or NI) was applied 42, 10, and 10 or 7 days after these four crop start times, respectively. Fertiliser was applied at 34 different rates (0–330 kg N/ha) and the 'virtual' trial was carried out on 10 different soil types. This was equivalent to 4080 experimental plots and over the 67 seasons simulated 273,360 treatment years. The data analysis focussed on yield N response functions that were fitted using a local polynomial regression with automatic smoothing parameter selection to calculate the maximum yield and an agronomic 'optimum' fertiliser N rate, Nopt, achieving 98% of maximum yield.

The soil parameterisation method followed the approach described by Barboux *et al.* (2018) drawing on soil-survey data from Wilson and Baker (1990). The method involved the application of pedotransfer functions to estimate soil hydraulic properties from soil carbon, pH and particle size information. The soil-survey data was largely determined on undisturbed soils that have soil carbon concentrations much higher than soils that have been cropped for decades. Long-term simulations were used to 'run down' the organic carbon pools to levels matching those currently seen in agricultural soils. The subsequent step of verification against experimental N-response curves and expert opinion is ongoing, so the results presented here are preliminary. The preliminary tree analysis focused on the top nine soils (by area) in the eastern climate zone: Toobanna (clay loam over heavy clay), Hamleigh (clay), Ashton (sandy clay loam), Macknade (loam), Ingham (silty clay loam over medium clay), Yuruga (clay loam over heavy clay), Palm (structured clay loam), Trebonne (clay loam) and Leach (clay with high organic carbon). A coarser sandy loam soil more prominent in other parts of the Herbert mill area (Lugger) was added to provide a contrast. Specific examples shown focussed on three soils of contrasting texture: clay, loam, sandy loam.

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

Preliminary tree analysis

A conditional inference tree analysis was used to determine the important predictors of EEF response types. The analysis was performed using the R statistical language (v3.5.1; R Core Team, 2018) and the partykit package (Hothorn *et al.* 2006; Hothorn and Zeileis 2015). Predictors considered in the analysis were soil, timing of crop start, annual rainfall, annual radiation, average maximum and minimum temperature, and total growing degree-days.

RESULTS

Classifying EEF responses

The yield responses to N rate and EEF were highly variable. For example, for the simulations of urea on the sandy loam soil the maximum yield varied from 49 t/ha to 143 t/ha, the Nopt varied from 0 to 275 kg N/ha and the change in Nopt due to CRF use ranged from –148 to +73 kg N/ha (with those > 10 kg N/ha caused by higher maximum yield). Among these variable responses we can, however, distinguish four types of responses (Figure 2). Type A represents where EEF use leads to an increase in maximum (plateau) yield. Type B has no increase in maximum yield, but the yield plateau is reached at a lower N rate and Nopt is hence reduced (specified as a minimum of 15 kg N/ha). Type C1 and C2 have no yield response to EEF but the reasons differ. In the case of Type C1 it is due to lack of appreciable N loss during the period that the N is protected. In Type C2 situations the lack of an EEF effect on yield is due to lack of N responsiveness of the crop (specified as Nopt < 30 kg N/ha). This can occur when the soil can supply all N required by the crop, a situation often seen in plant crops, especially after legumes, or it can result from other factors reducing the crop yield potential (e.g. prolonged waterlogging).

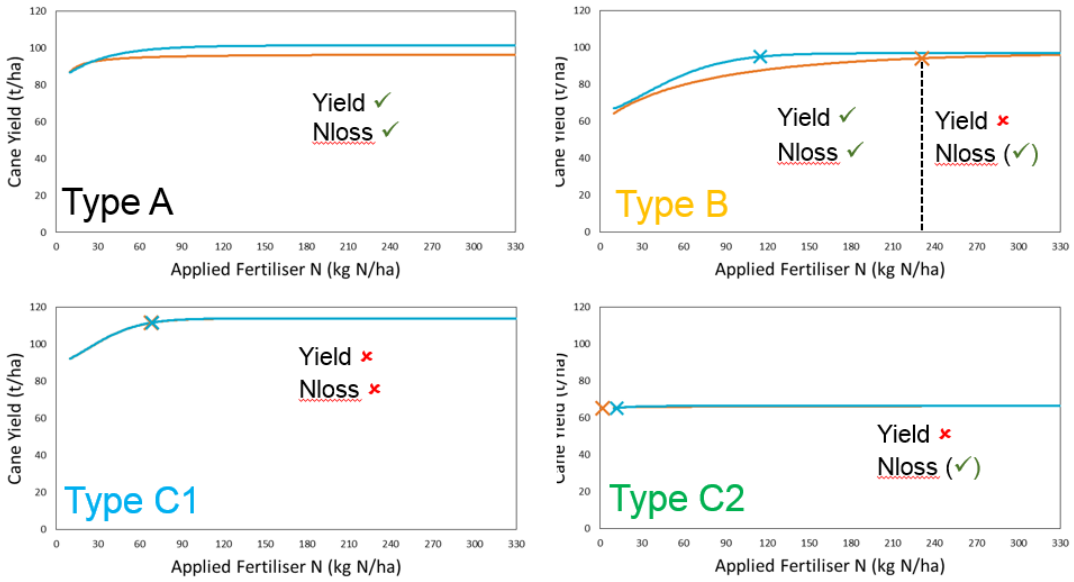

Figure 2. Classification of responses to EEF into four types (see text for details). Blue (CRF) and orange (urea) yield response curves fitted to the predicted yields for crops harvested in November 1981 (Type A), July 2011 (Type B), September 2016 (Type C1) and November 1991 (Type C2) on the sandy loam soil. Coloured crosses represent the Nopt. Presence or absence of benefits indicated by ✓and ×.

Given that the same virtual trials were run across 67 different seasons we can quantify the likelihood of obtaining the different response types and how this depends on e.g. soil type and timing of crop start (Figure 3). Earlier crops had a higher proportion of Type C1 responses. This is due to the lower likelihood of large rainfall events and, hence, N loss in the months after fertilisation. The reverse was true for the later crops which had an increased proportion of Type B responses. Type A responses only occurred in a small percentage of years (0.2% of trial years across the nine local soils and 1.3% of trial years on the sandy loam). Type C2 responses

were more common on the heavier soils (e.g. Figure 3) and for the later crops, which related to more prolonged incidences of waterlogging.

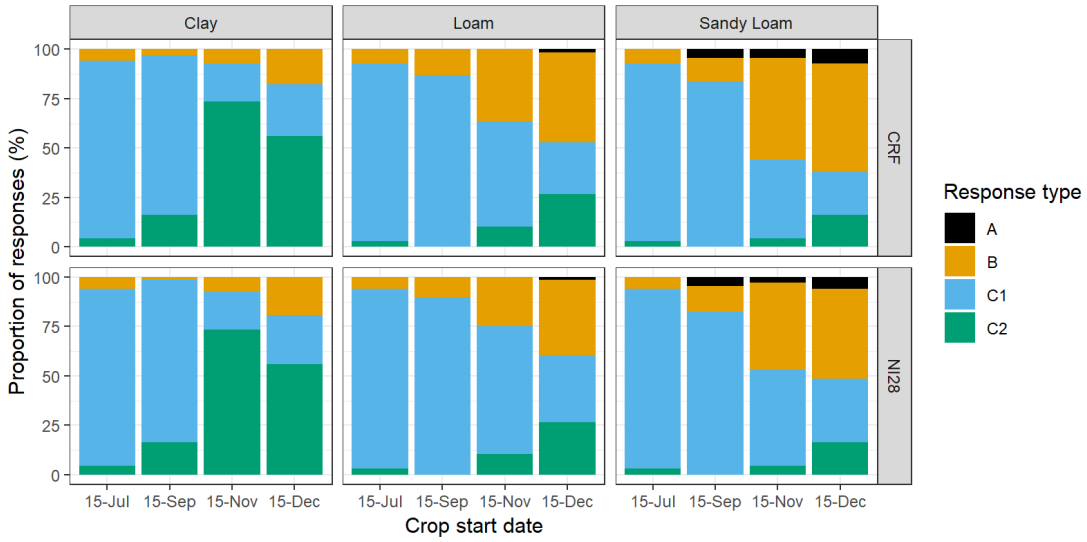

Figure 3. Likelihood of different EEF response types as a function of product, soil types and timing of crop start.

Explaining EEF response types

We can use output from the model on a daily time step to illustrate the system interactions that lead to different responses (see Figures 4 and 5). The July ratoon crop on the sandy loam soil harvested in 2011 had a Type B response to CRF. The CRF released the N more slowly (Figure 4a). In response the soil nitrate content increased more slowly (Figure 4b), which meant that less N was lost in deep drainage with the earlier rainfall events (Figure 4c). As this is a permeable soil, N loss through denitrification was limited, although still reduced too (Figure 4d). The reduced N losses meant that the crop could take up more N (Figure 4e) and experienced less N stress (Figure 4f).

As water stress and oxygen deficit stresses were similar or non-existent for the CRF and urea treatments, respectively (Figure 4g and Figure 4h), biomass increased more quickly in the CRF treatment (Figure 4i) with an increased cane yield as a consequence (Figure 4j). As the 100 kg N/ha rate used in this simulation was below the Nopt, there was still some N stress and yield was slightly below the maximum possible yield (cf. Figure 2).

In the November 1980–1981 cropping season with a Type A response an exceptionally large rainfall event caused all fertiliser to be lost, except for a small amount of CRF not yet released (Figure 5a,b). The crop responded to the resulting differential N stress (Figure 5c) with a higher cane yield for the CRF (Figure 5d). The September ratoon crop harvested in 2016 had a Type C1 lack of EEF response due to there being no N loss during the release period due to lack of significant rainfall (Figure 5e). This meant there was no difference in N loss (Figure 5f) and, hence, no difference in crop yield (not shown).

A wet start to the season (Figure 5g) for the November ratoon crop harvested in 1991 created a difference in N loss as in the Type A season (Figure 5h), but the wet conditions persisted for longer, resulting in prolonged waterlogging and issues with oxygen deficit stress (Figure 5i) limiting the crop's potential to make use of the saved N (Figure 5j).

The above dynamics also explains when we can expect to obtain yield and N loss benefits (ticks and crosses in Figure 2). Type A is characterised by both yield and N loss benefits at most rates. With a Type B response yield increases are only obtained below the Nopt of urea. Above it there may still be N loss benefits but that depends on the fate of the excess N – whether it is taken up by the crop as luxury uptake or lost with a late rainfall event. Benefits in a Type C1 season would be very small due to the lack of appreciable N loss. With Type C2 the lack of N response prevents a yield response to EEF, but it is possible that N loss benefits are obtained. This again depends on the fate of the excess N.

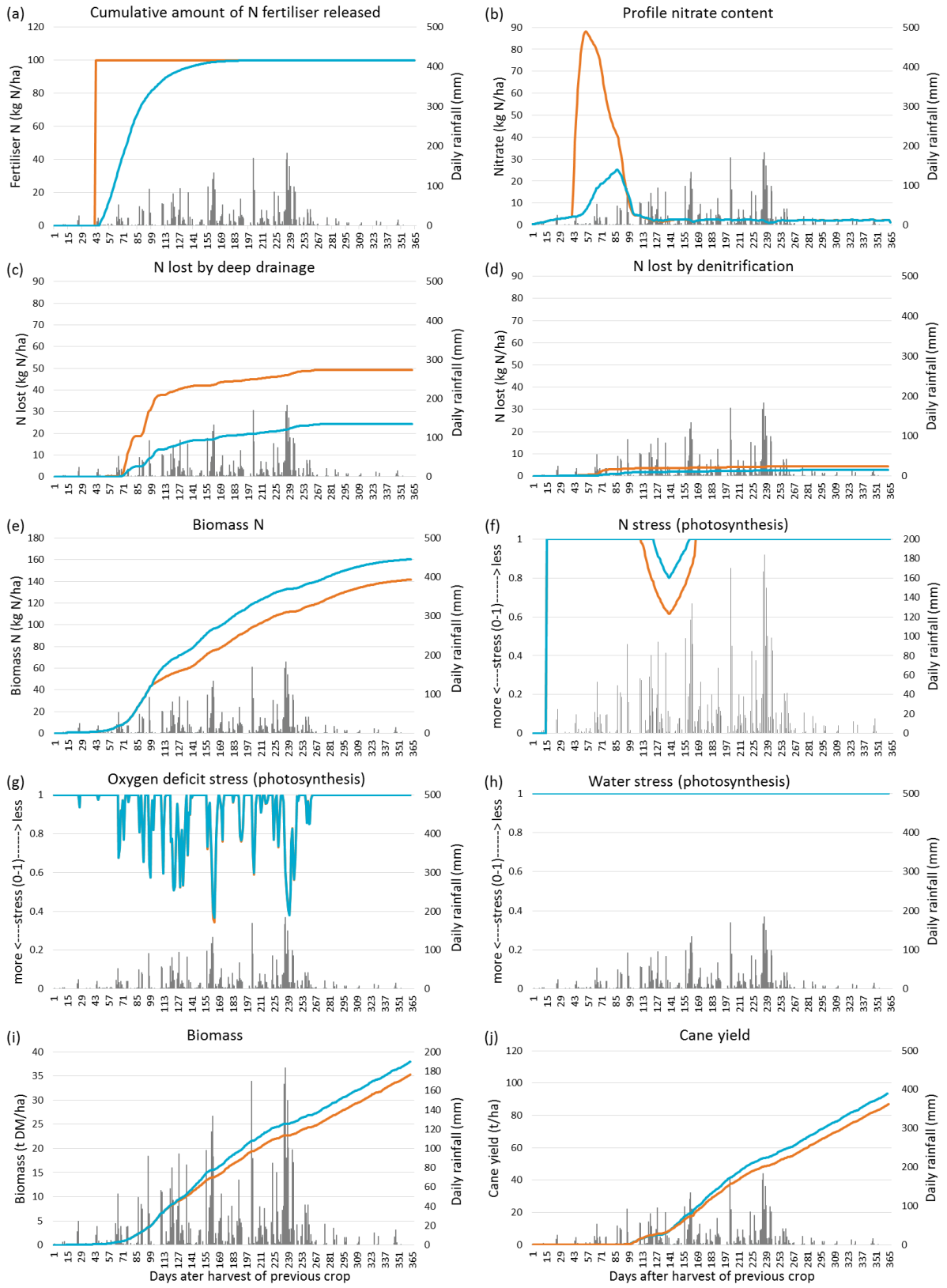

Figure 4. Time series of simulated system variables during the Type B season of a July ratoon crop harvested in 2011 on the sandy loam soil with a 100 kg N/ha application of urea (orange) or linear CRF (blue). Rainfall in grey.

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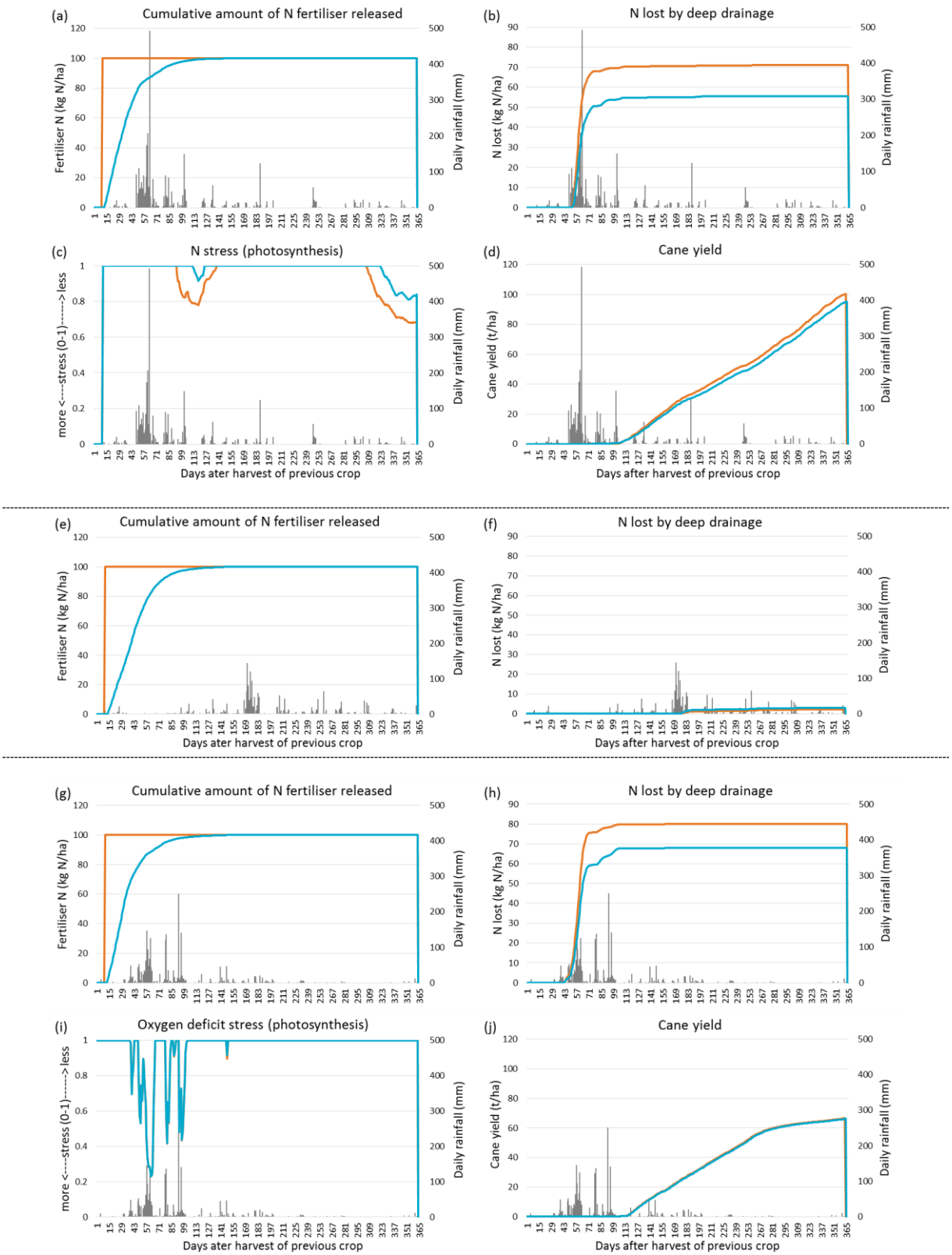

Figure 5. Select time series of simulated system variables for (a–d) the Type A, (e–f) the Type C1 and (g–j) the Type C2 seasons of crops harvested November 1981, September 2016, and November 1991, respectively on the sandy loam soil with a rate of 100 kg N/ha application of urea (orange) or linear CRF (blue). Rainfall in grey.

Clarifying the challenge of obtaining evidence from field trials

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

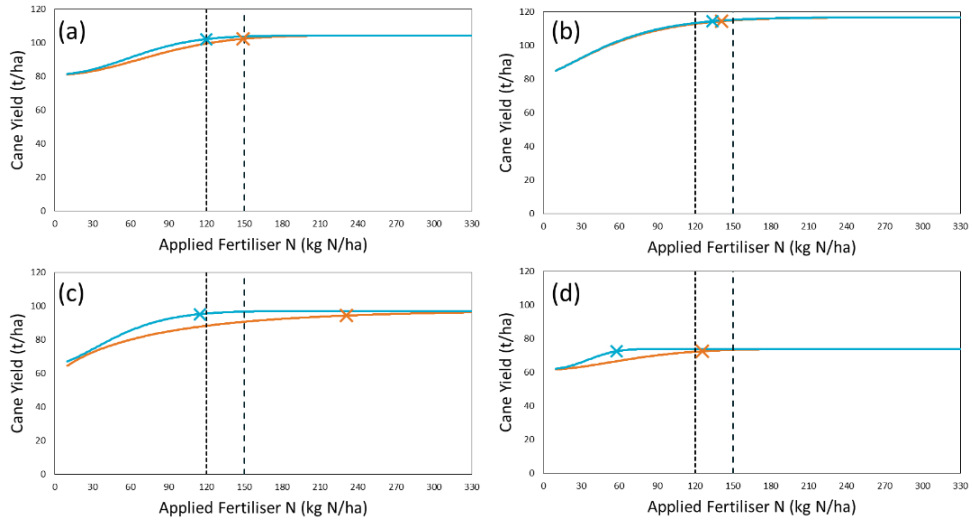

Figure 6. Illustration of the challenge of demonstrating yield or Nopt reduction benefits – the EEF effect may be (a, b) reflected correctly, (c) underestimated or (d) missed if only limited N rates are used in the experimental trial. Blue (CRF) and orange (urea) yield response curves fitted to the predicted yields for crops harvested in (a) November 1980, (b) September 1959, (c) July 2011 and (d) November 2001 on the sandy loam soil. Coloured crosses represent the Nopt. Vertical lines represent two fixed N rates.

The results in Figure 3 also demonstrate that there are many years in which even a complete N response curve would result in no response, not because the effect was missed, but because it was a season where the response was absent either due to lack of N loss during the period of N protection (Type C1 response) or due to lack of N response (Type C2 response).

Testing of hypotheses

Results of some trials have also suggested CRFs may be best suited to soils that experience N loss through leaching, whereas NIs could be more effective for conditions that cause N loss via denitrification (e.g. Di Bella *et al.* 2017). Virtual trials can be used to test such hypothesis and explore the processes responsible. The results in Figure 3 indicate that both products can achieve similar results for soils with contrasting properties and loss pathways. The proviso is that the CRF is well synchronised with crop-N uptake and that the persistence of the NI leads to sufficient longevity of nitrification inhibition.

Gaining insights into key drivers of EEF benefits

The vast number of results that can be generated with virtual trials allow us to apply data mining techniques to gain insights into the key drivers of the response types. Figure 7 shows preliminary results from our ongoing work. It indicates that the start time of the crop was a key driver with the early crops dominated by Type C1 responses. However, positive effects from EEF can still occur in these crops as evidenced by the example Type B response in Figure 2. Soil type provided the next split in the tree. Its effect is most noticeable for the late crops where the number of Type C2 responses are much higher, at the cost of Type B responses, in the heavier soil

types. The analysis in Figure 7 clearly indicates when the likelihood of benefits from EEF is low. To be useful for the development of decision support, further differentiation of the response types is required for the late crops. It is anticipated that this will come from further analysis of seasonal climate indicators (Verburg *et al.* 2019).

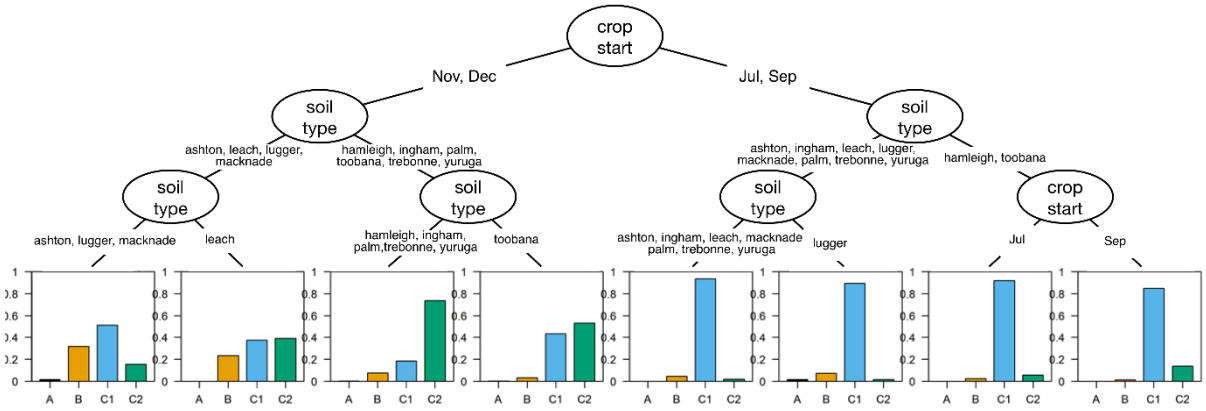

Figure 7. Example from preliminary tree analysis (see text for explanation).

DISCUSSION

Complementary roles for field and virtual trials in communicating benefits

The results in Figures 3 and 6 explain why it is challenging to demonstrate benefits of EEF experimentally, let alone deriving decision support from the experimental findings. Even the 3 years of 60 trials in the EEF60 project will likely, with the limited rates employed, not be enough to capture the variability of the system. However, the data can be combined with modelling. If the results of field trials are further explored and put in context using the results of virtual trials, we can build an understanding of what set of conditions led to the benefits or absence of benefits seen. Communicating that along with the results will build on and strengthen the demonstration power from the field trials. Model results are unlikely to be convincing on their own, so both field and virtual trials will be needed to develop decision support and communicate the benefits of EEF.

The classification into response types A, B, C1 and C2 provides a language for communication of EEF benefits. Experimental trial results could be compared with these response types. For example, Schroeder *et al.* (2018a) reported that there were no significant yield responses to applied N or use of EEF in the plant and first-ratoon crops of a trial in Bundaberg and in the plant crop of a trial in the Herbert, whereas there was N response but no response to EEF in the first-ratoon crop of the Herbert trial. Lack of marked N loss was noted as a possible reason, which would make the latter a Type C1 response, whereas the others corresponded to Type C2, possibly due to background soil N supply. The result of a yield increase from EEF in the presence of no N response to urea reported by Di Bella *et al.* (2013) could represent a Type A response, but with only three N rates this would need to be further explored using simulation.

The 'stories' behind the response types explain how EEF benefits are obtained. This can facilitate extension messages to industry about the likelihood of obtaining benefits from EEF in different situations and support decision making. Given the higher cost of EEF it is important to have guidance on circumstances when EEF will provide benefits and when they will not. Further work on seasonal climate indicators is required to improve the response prediction for late crops. While the distinction of Types C1 and C2 is not strictly necessary if the focus is solely on agronomic benefits from EEF, it sends a clear message about the cause of the lack of EEF response and about the need to reduce the N application rate in a Type C2 situation. In addition, the two response types can differ in environmental benefits.

Model requirements and need for further experimental data

The virtual trials do rely on the model to correctly represent processes and feedback loops that affect the expression of benefits from EEF. Given that a model is based on our understanding of these processes, it relies

heavily on experimental data. In the case of APSIM-Sugar this drew on data from many trials (Sugarbag project team 1994) as well as detailed crop physiology investigations on canopy development, leaf area expansion, radiation interception, biomass partitioning and responses to water and N deficits (see references in Keating *et al.* 1999).

Ongoing verification is needed in relation to the response of sugarcane roots to soil properties, including depth of rooting and effects of subsoil constraints and waterlogging. We have found that these aspects influence the predicted yield levels as well as the shape of the N-response curve. In turn that can affect the proportion of the response types. Experimental trials measuring complete N-response curves on a variety of soils and under different seasonal climate conditions are currently being used to refine the preliminary results presented here. In this analysis for the eastern climate zone of the Herbert mill area it was assumed that relatively shallow water tables would contribute to prolonged waterlogging events under wet conditions and affect crop potential quite strongly. This results in a relatively high proportion of Type C2 responses for the later ratoon crops where the benefits of EEF in reducing denitrification N loss are lost due to the reduced crop yield potential. It is possible the effects of waterlogging have been overestimated and hence the proportion of Type C2 responses. Indeed, in situations where crops grown on clay soils with a higher yield potential more Type B responses have been predicted (Verburg *et al.* 2019).

CONCLUSIONS

The use of virtual trials has provided insights into the responses to EEF under different conditions and allowed systematic study of key drivers affecting the agronomic and environmental benefits. This has led to a classification of four response types that provides a language for communication of EEF benefits and how they are obtained. The classification can be used to explain results from field trials. Understanding of the frequency of the four response types in different situations, generated by the virtual trials, provides a good basis for developing decision support for EEF.

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