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RESEARCH ARTICLE

The nitrogen fertilizer conundrum: why is yield a poor determinant of crops' nitrogen fertilizer requirements?

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Abstract

The application of nitrogen (N) fertilizer both underpins high productivity of agricultural systems and contributes to multiple environmental harms. The search for ways that farmers can optimize the N fertilizer applications to their crops is of global significance. A common concept in developing recommendations for N fertilizer applications is the "mass balance paradigm" – that is, bigger crops need more N, and smaller less – despite several studies showing that the crop yield at the optimum N rate (N_{opt}) is poorly related to N_{opt}. In this study we simulated two contrasting field experiments where crops were grown for 5 and 16 consecutive years under uniform management, but in which yield at N_{opt} was poorly correlated to N_{opt}. We found that N lost to the environment relative to yields (i.e., kg N t^{-1}) varied +/- 124 and 164 % of the mean in the simulations of the experiments. Conversely, N exported in harvested produce (kg N t^{-1}) was +/- 11 and 48 % of the mean. Given the experiments were uniformly managed across time, the variations result from crop-to-crop climatic differences. These results provide, for the first time, a quantitative example of the importance of climatic causes of the poor correlation between yield at N_{opt} and N_{opt}. An implication of this result is that, even if yield of the coming crop could be accurately predicted it would be of little use in determining the amount of N fertilizer farmers need to apply because of the variability in environmental N losses and/or crop N uptake. These results, in addition to previous empirical evidence that yield at N_{opt} and N_{opt} are poorly correlated, may help industry and farmers move to more credible systems of N fertilizer management.

Keywords Nitrogen use efficiency · Environmental nitrogen losses · SIX EASY STEPS · APSIM · Sustainability · Water quality · Economic optimum nitrogen rate · MRTN

1 Introduction

Nitrogen (N) is an essential element for plant growth, and our ability to harness N in its reactive forms through the Haber–Bosch process has allowed farmers to increase crop and pasture production per unit of land, sustaining increasing human populations. The benefits of N fertilizer inputs to production have often led to applications in excess of plants' needs as farmers seek to maximize yields and/or profits, resulting in widespread N surpluses in agricultural lands (Zhang et al. 2015). Much of this surplus N is lost to the environment (Thorburn and Wilkinson 2013) where it causes multiple harms such as degradation of marine and aquatic ecosystems and groundwater, and stimulation of greenhouse gas emissions (Fowler et al. 2013; Martínez-Dalmau et al. 2021). As well as these environmental impacts, N fertilizer lost to the environment is an economic loss for farmers. These economic and environmental problems have led to widespread interest in ways to better match N fertilizer applications to crops' needs, i.e., applying "optimum" rates of N fertilizer. Where environmental problems occur, programs are implemented by governments to encourage (i.e., voluntary measures) or compel (i.e., regulations) farmers to apply "optimum" rates of N fertilizer (e.g., McLellan et al. 2018; Thorburn et al. 2022). In these situations, determining "optimum" N fertilizer rates (N_{opt}) is important, where

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"optimum" is commonly defined as the rate that maximizes economic returns to farmers, as commonly determined in field experiments (Fig. 1). The ease and accuracy with which optimum N rates can be translated from experiments to on-farm management is thus a critical factor in farmers' N fertilizer management.

The importance of good N fertilizer management in agriculture has resulted in numerous systems for recommending optimum N rates. N mass balance is a common concept in N fertilizer recommendations used by farmers in many industries. Examples include maize in USA (Ransom et al. 2020); sugarcane in various countries (Schroeder et al. 2014; Sanches and Otto 2022) and cereal crops in Australia (Cox 2018). This concept, which we call the "mass balance paradigm", essentially states the amount of N to be applied is the product of the yield of the coming crop and the amount of N fertilizer needed to achieve that yield. The approach is appealing because, to scientists it "balances mass" and to farmers the idea that "bigger crops need more N" is common sense (Morris et al. 2018).

Despite its appeal, the paradigm has a number of problems. One is that the yield of the coming crop is not known (Everingham et al. 2007; Raun et al. 2017), and that uncertainty motivates farmers to apply high rates of N fertilizer to maximize the likelihood of high yields. A more fundamental problem is the question: Do bigger crops actually need more N fertilizer? That question can be examined by looking at results from experiments on the response of crop yields to N fertilizer (Fig. 2a). If bigger crops do need more N, then as the yield at N_{opt} (Y_{Nopt}) increases, N_{opt} should also increase (e.g., comparing points i and ii in Fig. 2b). However, if crops with higher Y_{Nopt} have lower N_{opt} values (e.g., i and iii in Fig. 2b) the concept may be invalid.

There have been a number of studies examining how N_{opt} varies as a function of Y_{Nopt}. Extensive collations of data show little correlation between N_{opt} and Y_{Nopt} for maize crops in the USA (Fig. 2c; Sawyer et al. 2006) and sugarcane crops in Australia (Fig. 2d). Similar results have been found for cereal crop other than maize (e.g., wheat; Arnall et al. 2013) and sugarcane in other countries (e.g., Brazil; Sanches and Otto 2022) illustrating the broader occurrence of this phenomenon. This conclusion is supported by a related analysis of 25 long term wheat, barley and maize N response experiments from across the globe (van Grinsven et al. 2022).

There can be many reasons for the poor correlation between N_{opt} and Y_{Nopt} in extensive collations of data. One is that combining data from experiments conducted under different conditions (e.g., different locations or crop varieties) can produce a "cloud" of points even if N_{opt} and Y_{Nopt} are correlated in each experiment. There are also process-based reasons, such as physiological and varietal variations in the efficiency with which crops use N and variation coming from the influence of soil organic matter in N cycling, N loss and N availability to plants (Morris et al. 2018; van Grinsven et al. 2022). While these factors explain different relationship between N_{opt} and Y_{Nopt} for different crops and sites, they do not explain poor relationship between N_{opt} and Y_{Nopt} at sites where crops have been grown over multiple years with uniform management (dark points in Fig. 2c and d). These results suggest that there are multiple "optimum" rates of N for a given crop yield at a given location. If this conclusion is true, it means that even if the yield of the coming crop could be reasonably estimated the amount of N fertilizer needed to achieve that yield would still be unclear.

The year-to-year variability in the relationship between N_{opt} and Y_{Nopt} at these sites (dark points in Fig. 2c and d) suggests that the climate experienced by crops is exerting an important influence on N_{opt}. While this is intuitively sensible, it is not clear through which process climate is influencing N_{opt}, e.g., whether it limits crop N uptake or increases losses of N to the environment depriving the crop of N. Gaining insights into the way climate influences N_{opt} may improve the understanding of the limitations of the mass balance paradigm and help build better N recommendation systems.

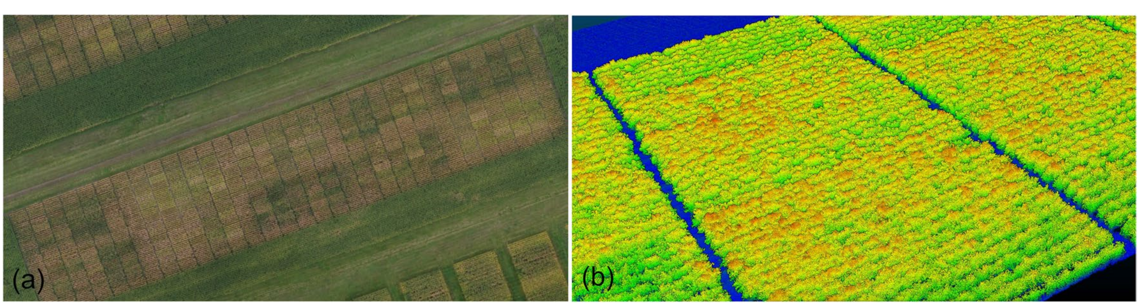

Fig. 1 Nitrogen fertilizer response experiments near (**a**) Ames, Iowa, USA and (**b**) Tully, Queensland, Australia. Image (**a**) was taken with an unmanned aerial vehicle. Image (**b**) is from LiDAR scans collected by Dr Yuri Shendryk using an Emesent Hovermap (Shendryk et al. 2020). Color indicates relative elevation, with green being low and red high.

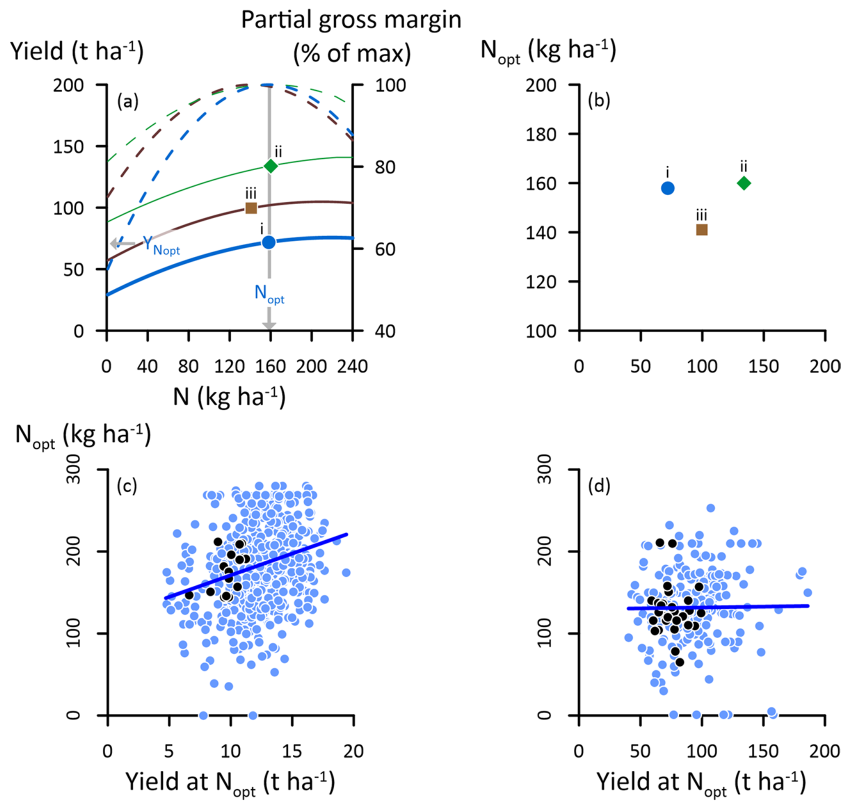

Fig. 2 (**a**) Three hypothetical relationships (shown as different colors) between yield and nitrogen (N) fertilizer applications (solid lines) and partial gross margin of production (dashed lines) for sugarcane in Australia. The symbols indicate the optimum N rate (N_{opt}, here defined as the N rate at maximum partial gross margin) and the yield at N_{opt} (Y_{Nopt}), with the arrows showing those values on the axes for one curve (i). The relationships between N_{opt} and Y_{Nopt} are shown for (**b**) the three hypothetical examples, and collations of data from N response experiment for (**c**) maize in mid-western USA (after Morris et al. 2018) and (**d**) sugarcane in Australia (after Thorburn et al. 2018). The correlation coefficients for the regression lines in (**c**) and (**d**) are 0.26 and 0.01, respectively. The dark points in (**c**) and (**d**) show data from multi-year experiments on maize (Puntel et al. 2016) and sugarcane (Thorburn et al. 2018), respectively, where management was constant across the years. Partial gross margin was calculated as the difference between the revenue from crop yield and the cost of applied N fertilizer.

In this study we aim to explain the cause of the poor correlation between yield at N_{opt} and N_{opt}, with a particular focus on the temporal variability in crop N uptake and losses of N to the environment and how these influence N_{opt}. This focus is justified because the temporal variability of these factors is less well studied than the other factors that affect N_{opt} (Morris et al. 2018). To guide our analyses, we develop a simple mass balance framework, consistent with the frameworks used in N fertilizer recommendation systems, that explicitly considers crop N uptake and losses of N to the environment. We then use output from simulations of the two multi-year experiments to estimate values of parameters in the framework. We focus on these two experiments because they were conducted on different crops, grown in contrasting environments and, in one case, with different crop residue managements. Thus, any consistency in the findings for these sites suggests broader applicability of the conclusions compared with results from a single site. Simulation data were used because relevant empirical data are generally not available for multi-year N response experiments. We conclude by discussing the implication of the results for improving management of N fertilizer applications to crops.

2 Methods

2.1 Mass balance framework

The mass balance concept behind many N fertilizer recommendations can be expressed as:

$$N_{opt} = n_t Y_{Nopt} - N_x \tag{1}$$

Where N_{opt} (kg ha^{-1}) is the optimum rate of N fertilizer, Y_{Nopt} (t ha^{-1}) is the crop yield at N_{opt}, n_t (kg t^{-1}) is a scalar of the relationship between Y_{Nopt} and N_{opt} equivalent to the quantity of N fertilizer that needs to be applied relative to the mass (t) of harvested produce, and N_x (kg ha^{-1}) is the N contributed from other material applied to the field (such as residues of legume fallow crops, manure, etc.) or coming from other sources (e.g., atmospheric deposition or biological N fixation). The value of n_t is crop- and/or variety-specific because of the physiological determinants of crop N requirements. Nevertheless, there are widely used values of n_t in N fertilizer recommendations for many crops; examples being the "Stanford 1.2 rule" for maize in USA (Morris et al. 2018) which equates to 21 kg t^{-1} and the "N multiplier" of 1.4 kg t^{-1} (Schroeder et al. 2014) in sugarcane N recommendations for Australia. Likewise, values of N_x can be estimated in many situations (e.g., Schroeder et al. 2014).

For this study we extend Eq. 1 by considering that N fertilizer applied to a crop may be removed from the field in harvested produce (n_c, kg t^{-1}), lost to the environment (n_e, kg t^{-1}) or immobilized in (or mineralized from) soil organic matter (n_i, kg t^{-1}), i.e.,

$$n_t = \left(n_c + n_e + n_i\right). \tag{2}$$

Thus, we can expand Eq. 1 to:

$$N_{opt} = \left(n_c + n_e + n_i\right) Y_{Nopt} - N_x \tag{3}$$

From Eq. 3 it is apparent that the lack of correlation between N_{opt} and Y_{Nopt} could arise from variation in n_c, n_e and/or n_i, as well as N_x. These latter processes (i.e., values of n_i and N_x) have been considered in different levels of detail in N fertilizer recommendation systems, from not being included in the Stanford 1.2 rule to more complete consideration in complex model-based N recommendations systems (Morris et al. 2018). However, the expansion of Eq. 1 to explicitly consider n_c and n_e is uncommon in N fertilizer recommendation systems. Interannual variability in losses of N to the environment is known to be high so explicitly decomposing n_t into n_c and n_e immediately leads us to thinking that variability in n_t and thus N_{opt} should be expected rather than being a surprise, and any concepts relying on n_t being (more-or-less) constant are flawed.

2.2 Experiments and simulations

We use data from two previously published long-term experiments that measured crop yields at multiple rates of N fertilizer over multiple years for sugarcane and maize crops. The sugarcane experiment was located near Tully (17.93° S, 145.92° E) on the north eastern coast of Australia, with an annual average rainfall of 3,480 mm and a mean annual temperature of 24°C. The maize experiment was located near Ames Iowa (42.03° N, 93.63° W) in mid-western USA with mean annual precipitation of 900 mm and a mean annual temperature of 9°C. The experiments were located in regions where N losses from cropping systems cause water quality concerns (Thorburn et al. 2003; Kroon et al. 2016; Jones et al. 2018). Crops at both sites were rainfed, and the experiments managed consistently across the years. This included consistent management of crop residues, timing of operations like fertilizer applications and harvesting, and weed control. However, the weather experienced by the crops varied between years.

The first experiment (Puntel et al. 2016) studied 16 consecutive maize crops (1999-2014). There were five N fertilizer treatments with application rates of 0, 67, 134, 201 and 268 kg ha^{-1}. The second experiment studied five consecutive sugarcane ratoon crops (2005-2009) grown with crop residue retained (R+) or removed (R-) (Hurney and Schroeder 2012). The residue treatments were established at the site in 1991 (Thorburn et al. 2012), with the N fertilizer rate experiment superimposed on the R+ and R- treatments in 2003. There were four rates of N; 0, 80, 160 and 240 kg ha^{-1}.

Crop growth and N cycling in both these experiments had been previously simulated (Puntel et al. 2016; Thorburn et al. 2018) with the APSIM (v7.7) farming systems model (Holzworth et al. 2014). Briefly, for the simulations in both studies, APSIM was configured with models for soil N, C and water dynamics (Probert et al. 1998), maize or sugarcane crop growth (http://www.apsim.info) and crop residue management (Probert et al. 1998; Thorburn et al. 2001). Details of crop management actions performed in the experiments (planting, harvesting, fertilizer applications, tillage, etc.) were specified in the APSIM MANAGER module. Parameter values in these models came from three sources: (1) either standard values within the model, or some variation of those developed in previous studies; (2) measured or derived values of state variables at the site (mainly parameters describing the soil in the experiments); or (3) in a small number of cases, calibration against measured values. The relative root mean square error of predictions of crop yields were 12.3 % for the maize crops and 13.9 % for the sugarcane crops, which we consider satisfactory agreement of predictions with the experimental data for the purposes of this study.

2.3 Derivation of terms in the mass balance framework

We used outputs from the simulations to determine N_{opt}, Y_{Nopt}, n_c and n_e. Values of N_{opt}, Y_{Nopt}, were derived from simulated N response curves. These N response curves were emulated by a second-degree polynomial equation fitted to the yields simulated at each N rate in the experiments. A range of other equations were tested as emulators (following Thorburn et al. 2017), but they had little effect on the conclusions of the study (data not shown). The polynomial also has the advantage of being able to represent situations where yields decline at high N rates (e.g., curve iii in Fig. 2a). The optimum N rate of the N response curves was defined as the economic optimum N rate (i.e., the N rate corresponding to the maximum partial gross margin, Fig. 2a) using long-term average economic data, following Puntel et al. (2016) for maize and Biggs et al. (2021) for sugarcane. For the calculation of partial gross margin, costs and revenues were assumed constant in the different years of each experiment. The value N_{opt} was derived from the emulated response curves and Y_{Nopt} calculated (as illustrated in Fig. 2a).

Values of n_c and n_e were determined for each crop in each year from the model output. Values of n_c were calculated from the N in the harvested produce (N_p, kg N ha^{-1}) expressed relative to the yield of the crop at N_{opt} (i.e., Y_{Nopt}):

$$n_c = N_p / Y_{Nopt} \tag{4}$$

Values of n_e were calculated from N lost from the soils each day through denitrification (N_d, kg ha^{-1} d^{-1}) and leaching (N_l, kg ha^{-1} d^{-1}). These daily values were summed over the life of the crop and expressed relative to Y_{Nopt}:

$$n_e = \sum \left(N_d + N_l\right) / Y_{Nopt} \tag{5}$$

3 Results and discussion

3.1 Optimum N fertilizer rates and yields at that optimum

There was considerable interannual variability in values of N_{opt} and Y_{Nopt} for each experiment simulated. Values of N_{opt} varied from 144 to 212 kg ha^{-1} over the 16 maize crops and from 27 to 207 kg ha^{-1} over the 10 sugarcane crops. Y_{Nopt} varied from 6.6 to 11.2 t ha^{-1} over the maize crops and 57 to 93 t ha^{-1} over the sugarcane crops (Table 1).

Values of N_{opt} and Y_{Nopt} were significantly, positively correlated for the simulated maize crops (Fig. 3). Despite the significance of the relationship, Y_{Nopt} explained only a small proportion (i.e., $R^2 = 0.26$) of the variation in N_{opt}. For the simulated sugarcane crops, N_{opt} and Y_{Nopt} were non-significantly and negatively correlated, explaining a smaller proportion (i.e., $R^2 = 0.11$) of the variability than in the maize crops. Correlations between N_{opt} and Y_{Nopt} for the two experiments simulated were higher than for the correlations of data collated from multiple experiments (Fig. 2c, d). This is to be expected because combining data sets, even if each is highly correlated, can reduce the overall correlation of the combined dataset. In both experiments studied, there could be a wide range of N_{opt} values for a given Y_{Nopt}. For example, in maize crops with Y_{Nopt} of ~10 t ha^{-1}, N_{opt} ranged from <150 kg ha^{-1} to >200 kg ha^{-1} and the 95 % confidence interval in N_{opt} was ~25 kg ha^{-1}. The variation was greater in sugarcane, with the 95 % confidence interval in N_{opt} being ~73 kg N ha^{-1} at Y_{Nopt} of ~75t ha^{-1}.

Table 1 Simulated optimum N fertilizer rate (N_{opt}) and the yield at N_{opt} for maize and sugarcane crops each grown in multi-year experiments where management was constant. The sugarcane crops were grown with crop residue either retained (R+) or removed (R-). In-crop rainfall is also shown.

Year of harvest	N_{opt} (kg ha^{-1})	Y_{Nopt} (t ha^{-1})	Rainfall (mm)
Maize			
1999	210	10.9	558
2000	182	9.4	327
2001	147	6.6	434
2002	175	9.8	506
2003	212	9.0	578
2004	209	10.7	524
2005	151	8.4	588
2006	144	9.5	312
2007	144	9.8	449
2008	192	11.1	761
2009	191	11.2	408
2010	190	10.7	892
2011	157	10.5	348
2012	146	9.6	261
2013	167	9.9	255
2014	196	10.0	749
Sugarcane R-			
2005	27	81	3129
2006	101	74	4136
2007	118	60	3769
2008	110	93	3955
2009	112	74	4421
Sugarcane R+			
2005	29	81	3129
2006	207	70	4136
2007	129	57	3769
2008	119	91	3955
2009	139	73	4421

Given that N_{opt} was defined as the economic optimum N rate, N_{opt} will vary through time if economic factors vary. However, revenues and prices were held constant in the calculation of N_{opt} across the years in the two experiments and so economic variation was not the cause of the variation in N_{opt}. N_{opt} may also change through time where soil N reserves increase or are depleted (van Grinsven et al. 2022). However, there were no significant trends ($p > 0.05$) in N_{opt} (or Y_{Nopt}) with time in either experiment suggesting changes in soil N was not a significant cause of variation in N_{opt} in these experiments.

Rainfall influences crop growth, crop N acquisition and soil N cycling, and there was substantial variation of in-crop rainfall during the experiments (255 to 892 mm across

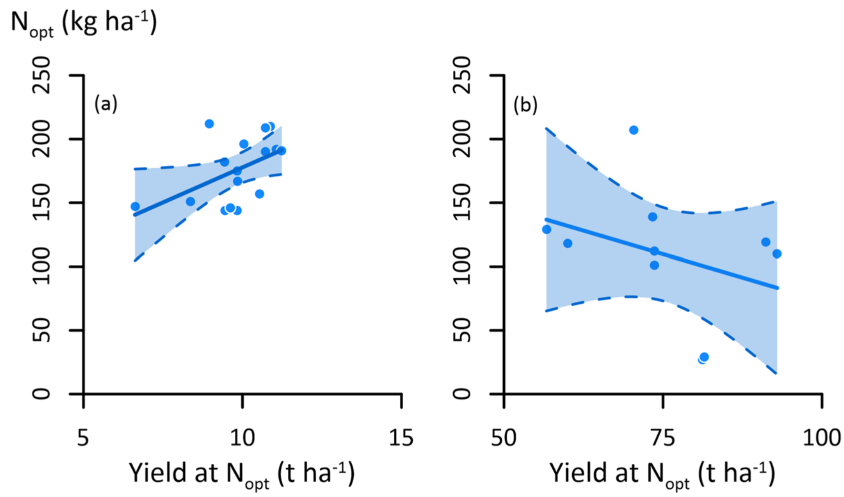

Fig. 3 The relationships between simulated optimum nitrogen fertilizer rate (N_{opt}) and the yield at N_{opt} for (**a**) maize (Puntel et al. 2016) and (**b**) sugarcane (Thorburn et al. 2018) crops each grown in multi-year experiments where management was constant. The correlation coefficients for the regression lines in (**a**) and (**b**) are 0.51 (p = 0.04) and -0.33 (p = 0.34), respectively. The data points in (**a**) and (**b**) are contained in Fig. 2b and c, respectively.

the successive maize crops and 3,129 to 4,421 mm across the sugarcane crops, Table 1). Thus, it is worth considering how well values of N_{opt} or Y_{Nopt} are related to in-crop rainfall. Values of N_{opt} and Y_{Nopt} were positively correlated with rainfall in both experiments (Table 2). The relationships for N_{opt} were significant (p >0.05), whereas the relationships for Y_{Nopt} were not. The lack of significance in the relationship between in-crop rainfall and Y_{Nopt} is likely because growth of the crops in these two experiments was not generally water limited. The sugarcane experiment was conducted in a region of high rainfall (Table 1), where crop yields are negatively correlated with rainfall because extensive cloud cover reduces solar radiation in years of higher rainfall (Thorburn et al. 2017). Shallow water tables are also common in the region, affecting crop growth (Biggs et al. 2021). While the maize experiment was located in an area with lower rainfall, the site was underlain by a shallow water table (1 to 1.8 m depth) that the crops could access (Puntel et al. 2016). Shallow water tables are common in mid-western USA and reduce the dependence of crop growth on rainfall (Archontoulis et al. 2020).

The poor correlation between values of N_{opt} and Y_{Nopt} supports previous criticisms of using yield as a predictor of N_{opt} (Sawyer et al. 2006; Arnall et al. 2013; Morris et al. 2018; Thorburn et al. 2018; Ransom et al. 2020). If yield is a poor predictor of N_{opt} in uniformly management experiments, it is likely to be even poorer in commercial cropping where management variability will add complexity to the relationship between N fertilizer supply and crop yields.

Table 2 Correlations (and p values) between rainfall and simulated optimum N fertilizer rate (N_{opt}) and the yield at N_{opt} (Y_{Nopt}) for maize and sugarcane crops each grown in multi-year experiments where management was constant.

Crop	N_{Opt}	Y_{Nopt}
Maize	0.53 (p = 0.034)	0.24 (p = 0.38)
Sugarcane	0.76 (p = 0.001)	0.14 (p = 0.63)

3.2 Crop-to-crop variability and the fate of N

Simulated values of n_t ranged from 15.2 to 26.7 (mean of 19.1) kg t^{-1} over the 16 maize crops (Fig. 4), compared with the values of n_t in "Stanford 1.2 rule" for maize in USA of 18 to 21 kg N t^{-1} (Morris et al. 2018). Likewise, for the sugarcane crops, values of n_t varied from 0.53 to 2.44 (mean of 1.3) kg t^{-1} compared with the value of n_t of 1.4 kg N t^{-1} in Australian sugarcane N recommendations (Schroeder et al. 2014). Some of the variation in n_t in the sugarcane crops was caused by the different residue management treatments, with mean values of n_t being 1.5 kg t^{-1} for the R+ and 1.1 kg t^{-1} for the R- treatments.

The variability in n_t (Fig. 4) explains why N_{opt} values may also display crop-to-crop variability (Fig. 3). The variability in n_t in the experiments also illustrates the shortcomings of using constant values of n_t in N fertilizer recommendation systems if the aim is to optimize N fertilizer management. It is, however, interesting to note that the mean values of n_t for both maize and sugarcane were close to the values of n_t in the relevant local mass-balance based N recommendations systems for both crops. It suggests that the values of n_t in N recommendations systems have been "fine-tuned" through experiments to reflect the average behavior of crop N response, as has been done for sugarcane in Australia (Schroeder et al. 2014). Using an average value of n_t in N management recommendations systems may be acceptable where be the aim is some broad, average management, and off-farm consequences of the management decisions are not of concern. However, the environmental impacts of N fertilizer applications increasingly drive the need for site- and time-specific optimum management, rather than average management.

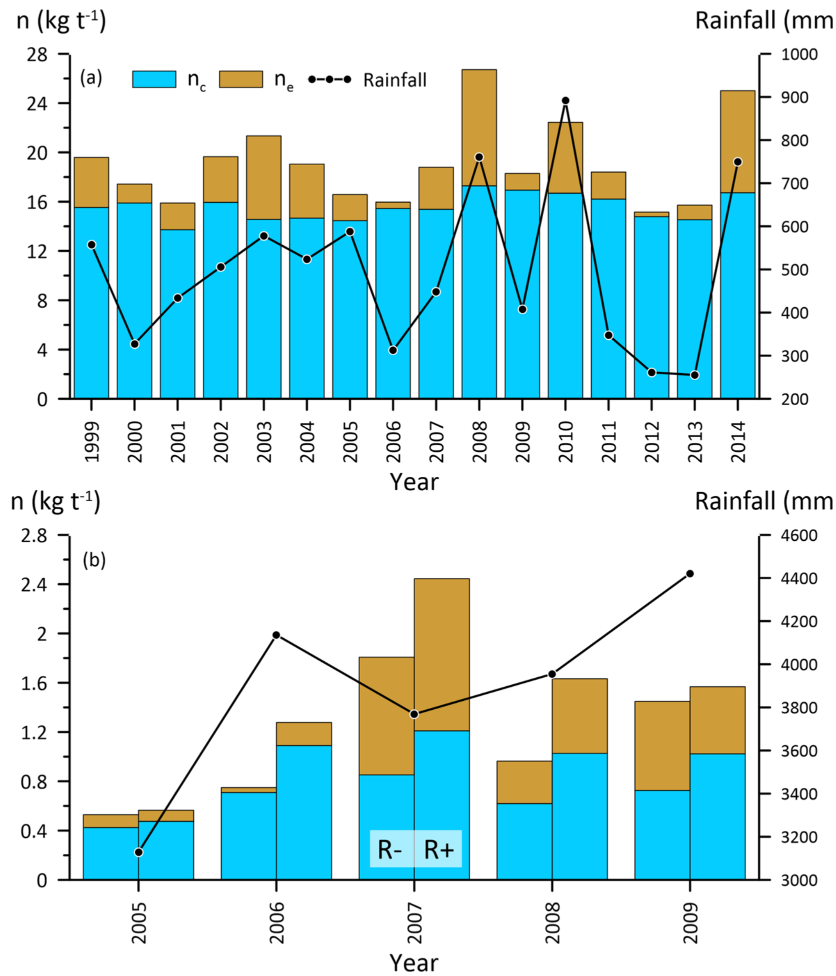

Fig. 4 Simulated values of nitrogen in harvested produce (n_c) and lost to the environment (n_e) for (**a**) maize and (**b**) sugarcane crops each grown in multi-year experiments where management was constant. Sugarcane crops were grown with crop residue retained (R+, right hand bars) or removed (R-, left hand bars). In-crop rainfall is also shown. The amount of nitrogen fertilizer applied relative to crop yield at N_{opt} (i.e., the value of n_t in Eq. 1) is approximated by the height of the stacked bars (i.e., $n_t \approx n_c + n_e$).

For the maize crops simulated, there was more year-to-year variability in n_e than n_c (Fig. 4a). Values of n_e varied by from 0.4 to 9.4 kg t^{-1} (+/- 164 %) whereas values of n_c varied from 13.7 to 17.3 kg t^{-1} (+/- 11 % of the mean). Values of n_e were significantly (p <0.01) and positively correlated with rainfall ($r = 0.85$). For n_c, correlations were positive, but not significant ($r = 0.44$, p =0.09). Given that variation in n_t is related to the variations in n_c and n_e (Eq. 2), the variation in n_t of the maize crops simulated was dominantly caused by the variation in n_e. Consistent with that conclusion, values of n_t had a similar correlation with rainfall ($r = 0.84$, p <0.01) as n_e.

As with the maize crops, n_e varied more than n_c in the sugarcane crops (Fig. 4b): n_e ranged from 0.04 to 0.96 (+/- 124 % of the mean) compared with 0.42 to 1.21 (+/- 48 %) for n_c. The variation in n_c was greater in the sugarcane crops than maize (+/- 48 % *c.f.* 11 % of the mean). The correlation with rainfall was stronger for n_c ($r = 0.55$) than n_e ($r = 0.25$), and closer to that for n_t ($r = 0.41$). Although these correlations were positive, none were significant (p = 0.10, 0.49 and 0.41 for n_c, n_e and n_t, respectively). The large variability in both n_e and n_c, together with the non-significant correlation of these variables with rainfall suggests that, unlike the maize crops, the crop-to-crop variation of n_t in the sugarcane crops was caused by the interplay between the crop-to-crop variability in both n_e and n_c.

The variability in crop N uptake and n_c is well known, and usually thought to make a small contribution to variability in optimum N rates (Morris et al. 2018) as we found for maize crops (Fig. 4a). However, this was not the case for the sugarcane crop simulated. The high variability in n_c of the sugarcane crops was caused by the luxury N uptake (i.e., taking up more N than is physiologically required by the crop at that time), a process that is represented in the APSIM-Sugar model used in this study (Keating et al. 1999). In practice this phenomenon manifests as considerable variation (e.g., up to 300 %) in N concentrations of sugarcane stems in crops grown with adequate applications of N fertilizer (Thorburn et al 2011a; Bell and Garside 2014). Luxury uptake also occurs in cereal crops; however, it impacts n_c differently than in biomass crops like sugarcane. Luxury uptake occurs early in the development of cereal crops, with the N stored in the biomass subsequently translocated to grain after flowering

(Bender et al. 2013). The storage and later translocation of N reduces the variation in crop N concentration and n_c at harvest. Conversely, sugarcane is a biomass crop that is harvested before N stored in the stem can be translocated to other parts of the crop, resulting in the highly variable N concentrations in the stem and crop which, in turn, increases variability in optimum N relative to the crop crops studied in this experiment. The N dynamics of other biomass crops may be similar to that of sugarcane so our results of this study, that n_c was highly variable in the sugarcane crops simulated, will be relevant to N fertilizer management in those crops.

The high variability in n_e in the maize and sugarcane crops simulated (Fig. 4) is consistent with the expectation that N losses to the environment are substantially climate driven, and so vary reflecting climate variability. The effect of N losses to the environment on optimum N rates is usually framed in terms of the effect of (lack of) N availability to the crop affecting (lowering) yields. This framing is consistent with the notion that greater additions of N fertilizer will overcome low N availability caused by losses to the environment. While high losses of N to the environment can constrain crop N availability and yields, our results show considerable variability in environmental N losses relative to yield at N_{opt}, the N fertilizer application rate giving the optimum yield. That is, applying more N fertilizer would not have increased yields in these experiements. The implication of this results is that the poor relationship between optimum N rates and yields at those rates (Fig. 3c, d) is primarily caused by intrinsic variability in N losses to the environment and, for the sugarcane crops luxury uptake of N, rather than availability of N to the crop constraining yields.

3.3 Implications of the study

There are three main implications that can be drawn from the results of this study. The first is that when there is a range of N_{opt} values associated with a given yield at N_{opt}, as was the case in the experiments analyzed in this study (Fig. 3a, b), even if yield could be accurately predicted for a coming crop it would be of little use in determining the amount of N fertilizer farmers need to apply. Crop uptake and, to a greater extent, N losses to the environment will usually be unknown at the time when fertilizer is applied because they are affected by climate. The effect of climate is illustrated by the significant influence of in-crop rainfall on N_{opt} in the two experiments simulated (Table 2). This correlation may lead to a conclusion that N_{opt} values, and thus farmers' N fertilizer applications should be higher in years with high rainfall. However, despite the significant correlation between in-crop rainfall on N_{opt}, rainfall-based recommendations are likely to be unreliable in practice. For example, 2006 was the second wettest year in the sugarcane experiment and had the highest N_{opt} in the R+ treatment, but the second lowest in the R- treatment (Table 1). Likewise, the highest N_{opt} value of the maize crops (212 kg ha^{-1}) occurred in 2003 when in-crop rainfall was only 16% above the average during the experiment. There is also the question of the accuracy of seasonal climate forecasts that underpin rainfall-based N fertilizer recommendations. The unreliability of climate forecast-based N fertilizer management has been shown in studies relevant to both the maize (Puntel et al. 2018) and sugarcane (Thorburn et al. 2011b) experiments. As well, it has been shown within cropping systems that, in contrast to the experiments we studied, are highly water-limited and thus rainfall exerts a greater influence on crop growth (Sadras et al. 2016).

A second implication is that by elucidating some of the biophysical mechanisms that cause N_{opt} and yields at N_{opt} to be poorly correlated this study adds new insights into the shortcomings on the paradigm. The poor correlation between N_{opt} and yield at N_{opt} has been known for nearly two decades (Sawyer et al. 2006; Arnall et al. 2013; Thorburn et al. 2018; van Grinsven et al. 2022). In addition, there is empirical evidence that the mass balance paradigm is an inaccurate way to predict N fertilizer applications needed to achieve a yield goal (e.g., Ransom et al. 2020). However, as described in the Introduction many recommendations are still made using this approach. The process-based explanation of the limitations of the paradigm provided by this study in addition to the previous evidence may help industry and farmers move to more accurate systems for N fertilizer recommendations.

The third implication of this study is that, while it focused on only two experiments, the conclusions may be more generally applicable. The basis of this generality comes from (1) the fact that we examined contrasting crops – an annual grain crop and semi-perennial biomass crop – in highly contrasting environments (annual average rainfall of 3,480 and 900 mm), and (2) that N_{opt} and yield at N_{opt} have been found poorly correlated in crops and locations (Arnall et al. 2013; Sanches and Otto 2022), and similar conclusions can be drawn from related studies (van Grinsven et al. 2022). Despite the potential generality of the conclusions, there will be value in better exploring the role of climatic variation in the poor correlation between N_{opt} and yield at N_{opt} in crops and locations outside those examined in this study. Examples include markedly drier location where environmental losses may be a smaller component of the N balance, or irrigated crops where effects of rainfall variation may be reduced by the timing of the application of irrigation water. The study has also used simulations, rather than empirical measurements to derive some of the parameters (n_c and n_e, Eq. 2) needed for understanding the factors determining the relationship between N_{opt} and yield at N_{opt}. Experimental confirmation of the results and conclusions from this study will be valuable.

4 Conclusions

Effective N fertilizer management systems are critical to minimizing environmental impacts of N fertilizer use (Thorburn and Wilkinson 2013; Zhang et al. 2015; Fowler et al. 2013; Martínez-Dalmau et al. 2021). The concept that optimum N fertilizer rates (N_{opt}) are well correlated with yields at that N rate (i.e., the mass balance paradigm) is the cornerstone of many N fertilizer management recommendation systems (e.g., Morris et al. 2018; Schroeder et al. 2014; Sanches and Otto 2022; Cox 2018), despite the empirical evidence that N_{opt} and yields at N_{opt} are poorly correlated (e.g., Fig. 2c, d). The mass balance paradigm encourages farmers to apply high rates of N fertilizer when they aim to produce high yielding crops, and these high rates will exacerbate environmental impacts of N. So it is important to better understand the limitations of the concept. While previous studies have discussed crop physiological, varietal and/or regional influences on the correlations (Morris et al. 2018), the role of climatic variations in causing the poor correlation has never been comprehensively explored. The contribution of this study is to show in two experiments the extent of climate-driven variability of both N in harvested produce (n_c) and losses of N to the environment (n_e), and how that variability reduces the correlation between crop yield at N_{opt} and N_{opt}. This is the first time the role of variations in n_e and n_c, and the contribution of year-to-year climate variability have been clearly identified as a cause of the poor correlation.

There are two main conclusions that can be drawn for these results. The first is that because there is a range of N_{opt} values associated with a given yield at N_{opt} (Fig. 3a, b), even if yield could be accurately predicted for a coming crop it would be of little use in determining N_{opt}. Thus, it is important for N fertilizer recommendations systems to move away from the mass balance paradigm. Secondly, by elucidating some of the mechanisms that cause optimum N rates and yields to be poorly correlated this study adds credibility to the empirical observations of the poor correlation. We speculate that the lack of process explanation for the poor correlation has contributed to the persistence of the mass balance paradigm and focus on yield predictions being critical for N fertilizer management (Morris et al. 2018; Schroeder et al. 2014) and, in some regions, regulation of N management (McLellan et al. 2018; Thorburn et al. 2022).

This study examined two different crops grown in contrasting environments suggesting some generality to the conclusions drawn. However, there would be value in applying the methodology and framework (Equations 1-3) developed in this study to a broader range of crops and environments to better understand the limitations of the mass balance paradigm for guiding N fertilizer management.

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Authors' contributions Peter J. Thorburn: Conceptualization, Formal analysis, Writing, Editing.

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Laila A. Puntel: Data analysis, Editing.

John E. Sawyer: Conceptualization, Research site management, Data curation, Editing.

Yvette L. Everingham: Conceptualization, Editing.

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Data availability The datasets generated during and/or analyzed during the current study are not publicly available but are available from the authors on reasonable request.

Code availability Simulations were undertaken with the APSIM (v7.7) farming systems available at https://www.apsim.info/download-apsim/.

Declarations

Conflicts of interest Peter Thorburn is an Associate Editor of Agronomy for Sustainable Development and was not involved in the evaluation of the manuscript at any stage. Other 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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