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Quantifying N leaching losses as a function of N balance: A path to sustainable food supply chains

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ABSTRACT

Growing public concern over agricultural nitrogen (N) pollution is now reflected in consumers' food choices and shareholders' resolutions, causing rapid changes in global food supply chains. Nitrate (NO_3) leaching represents the primary N source for groundwater contamination and freshwater ecosystem degradation. However, simplified science-based indicators are still lacking to facilitate improved N management practices at the farm-level. We conducted a global analysis of published field studies to evaluate N balance (N inputs minus N outputs) as a robust predictor for NO_3 losses. Using 82 studies (1110 observations) for rainfed cereal crops in temperate regions, we 1) quantified the response of NO_3 losses to changes in N balance for major rainfed cereal crops while accounting for environmental and management variables; and 2) assessed the feasibility of improving water quality through lower N balance under different scenarios using the case study of maize (*Zea mays* L.) data from the US Corn Belt. Observations were grouped in studies from the US and non-US regions. Results show that NO_3 losses increased exponentially as N balance increases for both the US and non-US regions, though they were 60% higher in the US at a given N balance. Scenario analysis revealed that reducing the N rate from the agronomic optimum to the lower point within the economic optimum N rate range decreased NO_3 losses by 13% without impacting economic returns. The case study for maize showed that improvements in N use efficiency that increase grain yield at a given fertilizer rate can substantially reduce N balance and mitigate NO_3 losses. This study provides an evidence-based foundation for food supply chain companies to mitigate global NO_3 pollution, specifically by using the generalized relationships presented here to track progress in NO_3 leaching mitigation. To further resolve uncertainties and improve region-specific estimates for NO_3 losses, we propose a tiered monitoring and assessment framework similar to the IPCC (Intergovernmental Panel on Climate Change) methodology for N_2O emissions, widely implemented in science and used for policy.

1. Introduction

Agricultural nitrogen (N) losses are a leading environmental sustainability challenge (Lassaletta et al., 2014; Sutton et al., 2021; Zhang et al., 2015). As current N mitigation approaches are fragmented and ineffective, bringing science and policy together under a coordinated global effort has never been more important (Houlton et al., 2019; Sutton et al., 2019). Growing public concern about N pollution is now reflected in consumers' food choices (Leach et al., 2016), which has important implications for food retailers and processors in global food supply chains. Multinational companies are keen to develop sustainable sourcing programs for agricultural commodities, to be able to track progress in mitigating N losses across their supply chains and to report quantitative environmental benefits to the consumer. In the agri-food sector, there are multiple outlets contributing to N pollution in different magnitudes, from the fertilizer industry to traders and processors, retailers, consumers, and wastewater (Kanter et al., 2020). However, the greatest contribution to the N footprint of food products is from N fertilizer use during crop cultivation (Goucher et al., 2017). This highlights the need to address N losses at the field level as the most critical leverage point for sustainability improvements.

Nitrogen use efficiency (broadly calculated as kg crop N harvested

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per kg fertilizer N applied) remains less than 50% for major crops (Ladha et al., 2005; Yan et al., 2020). Tracking N losses from agricultural fields is a challenge, particularly linking nitrate (NO_3) leaching from farm sources with the pollution of water bodies (Rivett et al., 2008). The magnitude of N losses is not only mediated by N inputs, but by various environmental, agronomic, and biological factors such as soil texture, precipitation, temperature, and tillage (Wang and Li, 2019). Many possible configurations of these factors contribute to the commonly reported variability observed in field measurements (Christianson and Harmel, 2015), adding a layer of complexity in separating the effect of management from environmental noise, especially in short-term studies (Cherry et al., 2008). In addition, hydrologic lag times pose difficulties in measuring and interpreting the impact of farm management on NO_3 loads in downstream waterbodies.

The N balance approach (also referred as N surplus or partial N balance; Kyllingsbæk and Hansen, 2007; Oenema et al., 2003) can be used to estimate environmental N losses in a shorter time-frame that is better suited providing feedback on the impacts of management changes (Cherry et al., 2012; Kim et al., 2020). Surplus or deficit N is calculated as the difference between N inputs and N outputs for a defined time period. Previous field studies have demonstrated N leaching increases exponentially with increasing N inputs (Bai et al., 2020; Huddell et al., 2020). While policy discussions and regulations revolve around reducing N input rates among other measures (Velthof et al., 2014), this approach has been criticized because it can compromise crop yield and farmers' profits. In contrast, N balance is an integrated metric that captures both the beneficial impacts of N fertilizer for crop productivity and the potential for N losses (Cherry et al., 2008; McLellan et al., 2018). An advantage of N balance relies on its simple calculation using readily available measurements at the farm level (e.g., grain N removal, N fertilizer rate). It has been used to explore variation in N use efficiency at the regional scale (Basso et al., 2019; Riccetto et al., 2020) as well as N losses at the field-level (Buczko and Kuchenbuch, 2010; Sela et al., 2019; Sieling et al., 2016).

A preliminary relationship between N balance and N leaching losses was previously reported for rainfed maize (*Zea mays* L.) fields in the United States (US) Corn Belt (McLellan et al., 2018). Although the study depicted an exponential trend, with N balance increasing rapidly after N inputs exceeded crop N demand, the influence of factors such as soil properties and precipitation was not investigated. In addition, the study by McLellan et al. (2018) used a smaller dataset with a limited variability in soil textures. Given recent commitments from food retailer and processing companies to reduce NO_3 leaching in global agri-food supply chains, a critical knowledge gap is whether this relationship can be expanded to other regions with different crops, agronomic management practices, and environmental conditions. For instance, half of the area harvested for cereals in Europe is planted with wheat (*Triticum aestivum* L.), whereas maize covers 62% of the area in the US (FAOSTAT, 2020). This contrast in crop types, N fertilizer requirements, and grain yield levels (N removal) contribute to different N use efficiencies for each region (Cassman and Dobermann, 2021). Furthermore, soil and weather variables such as precipitation and coarse-textured soils are usually associated with higher NO_3 leaching losses (Cameron et al., 2013; Huddell et al., 2020; Wang et al., 2019). Therefore, we hypothesized that the response of NO_3 losses to N balance will differ for other cereal crops and regions compared to rainfed maize in the US Corn Belt due to variation in these factors.

To our knowledge, no synthesis of current knowledge is available regarding the performance of N balance as a simple but robust indicator of NO_3 losses in rainfed cereal systems, which represent a considerable fraction of global cropland area and N fertilizer consumption. In this study, we conducted a systematic global literature review and analysis to address two specific objectives: 1) quantify the response of NO_3 losses to changes in N balance for major rainfed cereal crops while accounting for soil, management, and climate variables; and 2) assess the feasibility of improving water quality through changes in N balance under different scenarios without impacting grain yield. Given the large proportion of data for maize in the US Corn Belt (73%), the second objective was addressed using this region as a case study.

2. Materials and methods

2.1. Data collection

We conducted a systematic literature search using Elsevier's Scopus database to identify peer-reviewed publications reporting N fertilizer inputs, crop yields, and NO_3 leaching losses in experimental fields. The search was restricted to temperate climate regions and rainfed cereals (excluding rice). Data collection methods were an expansion of the literature search used by McLellan et al. (2018), who demonstrated a robust relationship between yield-scaled NO_3 losses and N balance for maize grown on silt loam soils in the North American Corn Belt. We used search terms associated with NO_3 leaching or N losses and wild characters to refer to all possible terms (e.g., "NO3 leach*", "nitrate* leach*") to capture the maximum number of publications. A subject for the group of crops was included (nine terms), as well as another subject for general terms associated with NO_3 leaching experiments (e.g., "drainage"). The exact search terms are provided in the Supporting Information.

Abstracts and titles for all publications flagged in the search were reviewed to identify those with potential data, with the full text to be examined further. Approximately 4000 publications were screened during this step. Selection criteria included i) studies published after 1990 and before July 2020, ii) experiments conducted under rainfed field conditions (modeled N losses were excluded), iii) measurements of NO_3 leaching losses for the study period reported on an area-scaled basis, iv) N fertilizer rate and source reported (e.g., organic, inorganic), and v) measured crop grain yield. This global search added 69 new studies (1005 observations) to the (McLellan et al., 2018) NO_3-loss dataset of 13 studies (105 observations), for a total of 1110 observations.

Specific variables were extracted from each study, including environmental (soil organic carbon, soil texture, soil type, annual precipitation), management (crop, tillage, previous crop, fertilizer source, rate, timing, and placement), and experimental design factors (year of experiment, number of replicates, methodology). Methodology procedures for measuring NO_3 leaching included tile drainage (64% of measurements), suction cups (18%), and lysimeters (16%). When not reported, soil organic carbon content data and soil texture were obtained from SSURGO (Survey Staff Soil, 2020) for sites in the US (7% and 55% of the observations, for soil C and texture, respectively) and from ISRIC's Soil Grids (Hengl et al., 2017) for other countries (7% and 11%), using the site's geographic coordinates. Missing annual precipitation data were extracted from weather stations closest to the study site and, when weather station data were not available, accessed through Google Earth Engine (27%; Gorelick et al., 2017).

Studies were geographically distributed across Europe, China, and North America, although heavily skewed towards the US and Europe. The crops included barley (*Hordeum vulgare* L.), maize, oats (*Avena sativa*), rye (*Secale cereale* L.), sorghum (*Sorghum bicolor* L. Moech), and wheat (Table S1). For each observation, N balance was calculated as:

$$N\ balance\left(kg\ N\ ha^{-1}\right) = N\ inputs\left(kg\ N\ ha^{-1}\right) - N\ outputs\left(kg\ N\ ha^{-1}\right) \quad (1)$$

where N inputs represents the amount of N applied as fertilizer (kg N ha^{-1}) and N outputs generally represent grain N removal from the field. This level of calculation does not include soil and other (e.g., deposition) processes that account for other N inputs or outputs, thus it is commonly referred to as N surplus or partial N balance. A similar approach using the same field-level data (ratio of N outputs to outputs) has been developed in Europe as an indicator of sustainable N management (UENEP, 2015). Inputs comprise organic and inorganic forms of fertilizer and outputs include grain N removal in most cases, except for several corn silage studies (Table S1) where whole-plant N was

Table 1

Coefficients estimates ± standard errors (SE) and p-values for the fixed effects of each model fitted in Fig. 1 for the entire database (n=1110; Fig. 1A and B) and subset including only studies with control treatments (n=361; Fig. 1C and D).

	Fixed effects	Full data		Subset with Control	
		Estimate ± SE	p-value	Estimate ± SE	p-value
$\ln(NO_3$ leaching)	(Intercept)	2.96±0.14	<0.001	3.41±0.33	<0.001
	Silt	-0.39±0.18	0.025	-0.86±0.42	0.050
	Precipitation	1.55±0.08	<0.001	0.82±0.11	<0.001
	N balance	0.49±0.07	<0.001	0.56±0.12	<0.001
	Region	-0.48±0.22	0.036	-1.01±0.47	0.045
NO_3 loss at 0	US	17		29	
(kg N ha^{-1})	non-US	11		11	
R^2_m		0.40		0.21	
R^2_c		0.79		0.68	
AIC		2351		1036	
BIC		2386		1063	

considered as N removal. All grain yields were converted to dry matter basis using the reported grain moisture from publications, and grain N removal (kg N ha^{-1}) was calculated as the product of grain yield as dry matter and grain N concentration in dry matter basis.

We used maize grain N concentration as reported in the publications, filling in missing values using published data by the International Plant Nutrition Institute (IPNI) for maize in dry matter basis (1.42 g 100 g^{-1}; IPNI, 2014). Previous work determined this value is adequate to calculate N removal (Tenorio et al., 2019). For other crops, we filled in missing values with grain N concentrations from global N trading estimations in food and feed as reported in Lassaletta et al. (2014): barley (1.62 g 100 g^{-1}), oats (2.08 g 100 g^{-1}), rye (1.76 g 100 g^{-1}), and sorghum (1.61 g 100 g^{-1}). For wheat we used grain N concentration from Ladha et al. (2016) in their estimates of global N budgets (1.84 g 100 g^{-1}). Overall, 33% of the total observations for grain N concentration were available in the original publications, whereas the rest were estimated as described above.

2.2. Data analysis

The relationship between NO_3 leaching and N balance was analyzed using linear mixed effects models in R software (*lmer* function, *lme4* package; Bates et al., 2015). Hierarchical statistical models were employed building on previous methods (Eagle et al., 2020; Huddell et al., 2020). This modeling approach helps address the lack of independence of observations retrieved from the same study and unbalanced data (i.e., reducing the influence of locations with large number of observations) (Pinheiro and Bates, 2000; Woltman et al., 2012). Given the geographical distribution of observations we evaluated NO_3 responses to N balance comparing the US and non-US regions. A binary variable was created to compare trends from observations in the US (Region = 0) with other regions (Region = 1). The N balance was included as a continuous numerical variable, region and its interaction with N balance were considered as fixed effects, whereas study ID was considered as a random effect using a unique identifier for each study.

To improve model fit and account for the potential effects of other study factors, different environmental and management covariates were tested as fixed effects through an iterative process including precipitation, crop type, previous crop, sand, silt, clay, soil C, tillage, fertilizer source, placement, and timing. The selection of covariates was based on model comparison using Akaike's Information Criterion (AIC; Aho et al., 2014). We calculated the *p*-values of the fixed effects using the *lmerTest* package in R (Kuznetsova et al., 2017). To achieve a parsimonious model with the greatest explanatory power, the final model included only the effects that decreased AIC and were statistically significant at $p < 0.05$ (Eagle et al., 2017). Residual plots were verified to meet normality assumptions and constant error variance. As a result of this process, silt content (representing soil texture) and annual precipitation were included in the model as numerical site-specific covariates (site-year-specific for precipitation). To increase interpretability, numerical covariates were standardized to unitless values by subtracting the mean and dividing it by two standard deviations (Huddell et al., 2020). Nitrate leaching was transformed into natural logarithmic scale for the analysis and backtransformed for plotting results (Eagle et al., 2020); coefficient estimates are presented in transformed units (Table 1). The fitted linear mixed model for NO_3 leaching is described in Eq. 2:

$$y_i = \beta_0 + \beta_1 \times Silt + \beta_2 \times Nbal + \beta_3 \times Region + \beta_4 \times P + b_i + \varepsilon \quad (2)$$

where y_i is the natural logarithm of NO_3 leaching, β_0 is the intercept, β_1 is the coefficient for silt, β_2 is the coefficient for N balance, β_3 is the coefficient for region (US = 0, non-US = 1), β_4 is the coefficient for precipitation (P), b_i is the random effect the ith study ID, and ε is the error term.

To explore the sensitivity of results, we were also interested in how this relationship might change when limited to experiments that explored a broader range of N balance. To do this, we filtered the database for studies where N rate treatments included a non-fertilized control, and implemented the same statistical analysis as described above. We calculated the 95% confidence intervals for plotted models in Fig. 1 with the population prediction intervals method (Bolker, 2008) using the *MASS* package in R (Venables and Ripley, 2002). Model variance was assessed by calculating the marginal (R^2_m) and conditional (R^2_c) R^2 values (Nakagawa and Schielzeth, 2013), where the former represents the variances explained by the fixed factors and the latter by the entire model (fixed and random effects).

2.3. Feasibility analysis for US maize data

The relationship between NO_3 leaching and N balance is agronomically relevant in the context of grain yield response to N fertilizer rate. That is, for a given N rate decreases in N balance must be achieved by lowering N rate or increasing grain yield, or some combination of both. However, efforts to track N balance and associated N pollution in supply chains are unlikely to be feasible if very large reductions in N rate (or increases in yield) are required to achieve a meaningful reduction in NO_3 leaching for a region. Therefore, given the large number of maize observations collected from the US Midwest, we explored the feasibility of using the N balance relationship developed here in supply chains by creating potential scenarios that integrate optimum agronomic and economic yield response and N balance to mitigate NO_3 leaching losses by at least 15%. In other words, we assessed what level of changes are required in N rate and yield outcomes to reach a certain magnitude of NO_3 reduction in our dataset (15%). This target reduction is in alignment with current environmental policy goals for some states in the region, aiming to reduce NO_3 loads by 15% in the coming years and 45%

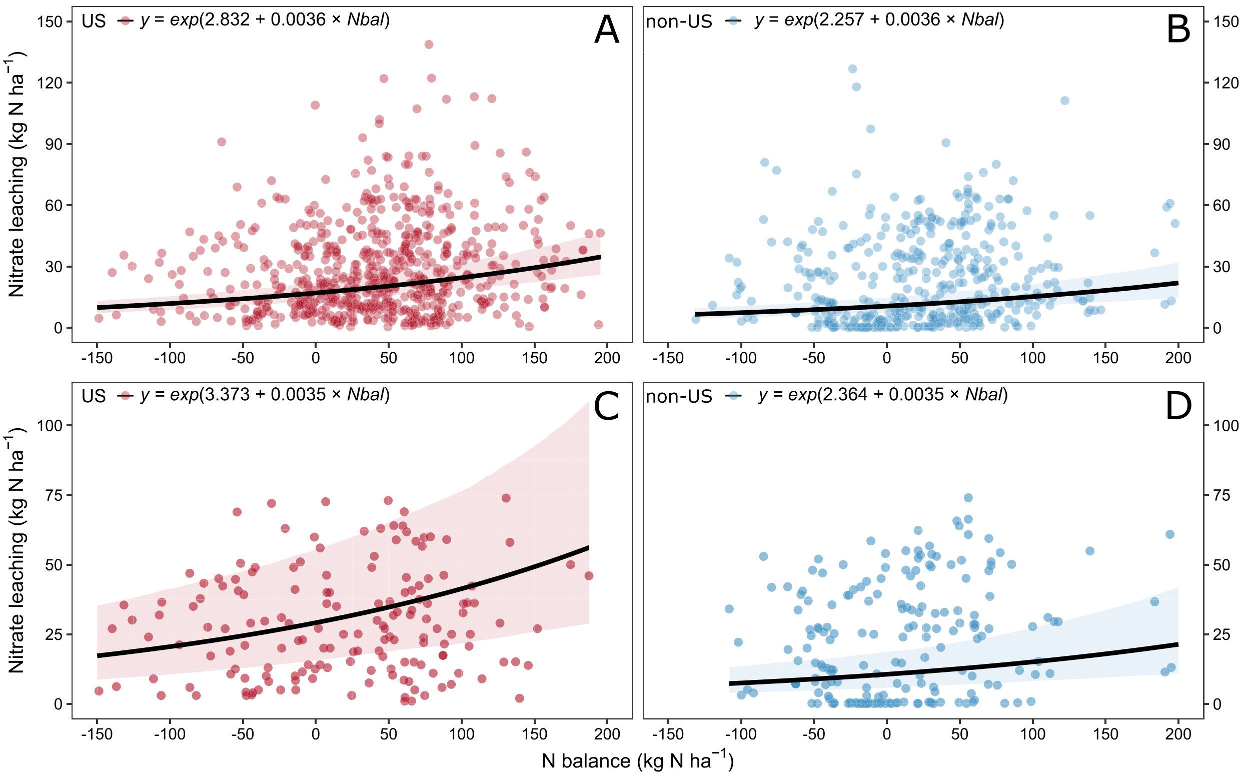

Fig. 1. Relationship between NO_3 leaching and N balance for studies in the US. (A), the rest of the regions (B), subset of studies that included a control treatment for the US (C), and studies with a control treatment for the rest of the regions (D). Solid lines are the model prediction represented by the equation in each panel, plotted at the mean silt percentage and annual precipitation. Shaded areas are the 95% confidence intervals. Each point represents an observation from the dataset.

ultimately (e.g., NLRS, 2019).

Given the interdependence of N inputs, yield, and N balance, we first selected all maize observations from the US and performed a response surface analysis using N balance as the response variable and grain yield and N rate as predictors. We used the *rsm* package in R (Lenth, 2009) to fit the model using a first-order response surface (i.e., linear function). Then, a quadratic-plateau model was fitted to the relationship between grain yield and N rate to estimate the agronomic optimum N rate, which is standard practice for this region. Additional details, parameters, and equations are given in the Supporting Information.

To determine the extent to which N losses can be reduced without influencing profits, we also constructed an economic scenario based on the maximum return to N (MRTN) approach. This methodology accounts for the price of corn grain and cost of N fertilizer, allowing farmers to identify the N rate with the greatest economic net return to N ($MRTN_{rate}$) based on yield response per unit of N input (Sawyer et al., 2006). Due to site-specific variability in yield response, a range of N rates is also commonly calculated within a profitable margin of ±\$2.47 ha^{-1} from MRTN, herein termed as $MRTN_{low}$ and $MRTN_{high}$, respectively (Sawyer et al., 2006). A fertilizer price of \$0.88 kg N and grain price of \$157.47 Mg^{-1} were used for economic calculations. These prices are used by default in the N rate calculator (Sawyer et al., 2006; http://cnrc.agron.iastate.edu/) and represent a ratio of 0.056 commonly used for maize economic analysis (Zhao et al., 2017).

Combining predictions from the surface response model and quadratic-plateau function, we created three potential scenarios for decreasing NO_3 losses and evaluated the corresponding combinations of grain yield, N rate, and N balance associated with each change. For all scenarios, NO_3 leaching was estimated using N balance as the input for the equation displayed in Fig. 1A. The assumed baseline N management for this dataset was the agronomic optimum N rate producing maximum yield (Scenario 1). The three strategies to reduce NO_3 leaching from this baseline were: i) reducing N fertilizer and N balance while maintaining yield level to achieve a 15% reduction in NO_3 losses (Scenario 2), ii) increasing grain yield while maintaining N fertilizer rate to attain a target N balance which decreased NO_3 losses by 15% (Scenario 3), and iii) reducing N balance while maintaining the profitability of grain production using the range of MRTN rates (Scenario 4).

3. Results

3.1. NO_3 leaching response to N balance

Relationship between NO_3 leaching and N balance are depicted for US and non-US regions using the full dataset (Fig. 1A and B) and for studies including a control treatment (Fig. 1C and D). Nitrate leaching increased exponentially in response to N balance in both the US and in non-US regions for the full dataset (Table 1; Fig. 1). Given the lack of significance for the interaction between N balance and region ($p > 0.05$), this factor was removed from the model. However, there was a significant effect of region, and the magnitude of NO_3 losses was 60% higher for the US at any given level of N balance. For example, NO_3 leaching at N balance values of 0 and 100 kg N ha^{-1} were 17 and 24 kg N ha^{-1}, respectively, for the US (Fig. 1A) and 11 and 15 kg N ha^{-1}, respectively for the other regions (Fig. 1B). When comparing the average N rates for observations close to neutral N balance (±10 kg N ha^{-1}) for the entire dataset, average N rates for the US region were greater by 48 kg N ha^{-1} (Fig. S2). For the subset of studies with zero N fertilizer control treatments, differences for the region factor were significant (Table 1).

The fixed effects included in our model explained 40% and 21% for the full dataset and the subset, respectively (Table 1). However, when the random effects are included, the conditional R^2 was 79% and 68% for each model. Comparing the coefficients, annual precipitation had a

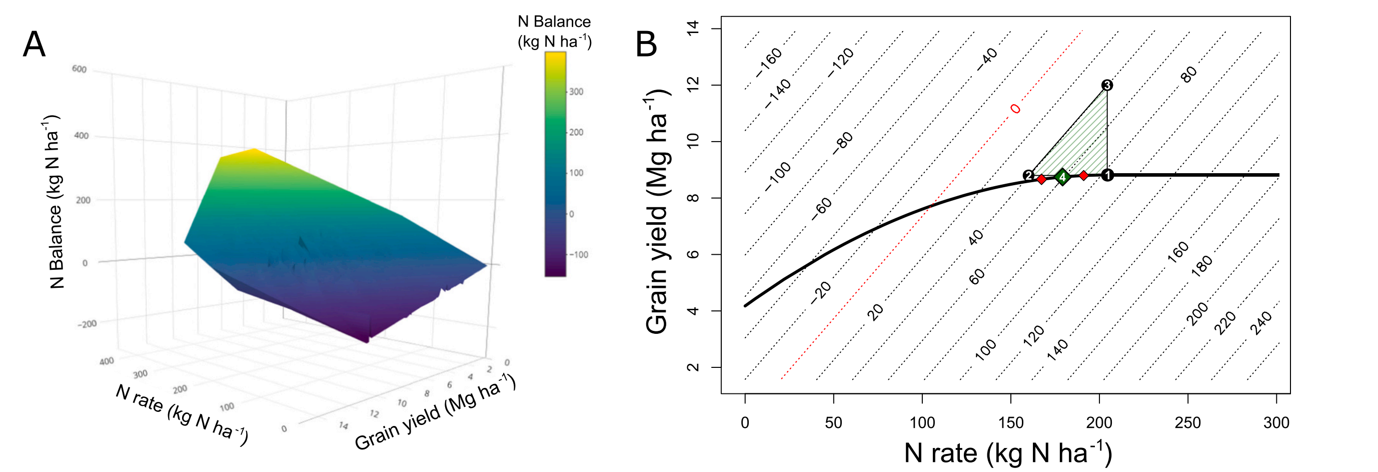

Fig. 2. 3D representation of N balance, grain yield, and N rate observations for maize in the US (A) and response surface plot for N balance, N rate, and grain yield (B) for observations from maize in the US. Color gradient in A represents changes in N balance. Isolines in B are the N balance (kg N ha^{-1}) range across different combinations of N rate and grain yield. Red dashed line represents the isoline when N balance is neutral (0 kg N ha^{-1}). Solid black line is the predicted quadratic-plateau model adjusted to the observations. Black points and green diamond are all possible scenarios described in Table 2. Green diamond is the $MRTN_{rate,}$ and red diamonds are the $MRTN_{high}$ and $MRTN_{low}$. The green area represents all possible optimum yield responses to reduce NO_3 leaching losses (Table 2).

positive effect on NO_3 leaching of about three-fold higher than N balance, whereas soil silt content had a negative effect, but in a lower magnitude.

3.2. Case study for maize in US: reducing NO_3 leaching losses integrating N rate, N balance, and grain yield

The continuous surface on the 3D representation (Fig. 2A) reflects the changes of N balance in response to the combination of grain yield and N rate observations of maize from the US. The peaks and valleys in the surface correspond with combinations of N rate and grain yield that produce higher and lower N balance, respectively. The surface analysis shows a smooth but strong linear increase in N balances in low grain yield situations (Fig. 2A) while decreasing at higher yields under low N rates (i.e., darker areas in the surface). For maize observations in the US, an optimum grain yield of 8.8 Mg ha^{-1} was achieved at 204.4 kg N ha^{-1} (Table 2, Fig. 2B). Similar trends were depicted in the 2D quadratic-plateau model, where an increase in N balance after the optimum N rate is evident (Fig. 2B).

Combining model predictions, we conducted an analysis of three different scenarios relative to a baseline amount of NO_3 leaching (calculated from the equation in Fig. 1A) using the N balance at the agronomic optimum N rate and grain yield (Table 2). For US maize observations, Scenario 1 represented N balance at the agronomic optimum N rate (83.1 kg N ha^{-1}), corresponding to a NO_3 leaching of 23 kg N ha^{-1} (Table 2). To target a 15% reduction in NO_3 losses, it would be necessary to achieve an average N balance of 35.5 kg N ha^{-1} as predicted by Fig. 1A and N balance isolines in Fig. 2B. Following the surface response representation and quadratic-plateau response, achieving such N balance would be possible through two extremes, either by reducing N rate or increasing yield, holding the other constant. Scenario 2 shows it would be necessary to reduce the amount of N fertilizer to 156 kg N ha^{-1} while maintaining grain yields levels (Fig. 2B), whereas Scenario 3 shows it would be necessary to increase grain yields to 12.3 Mg ha^{-1} without changing N rate to achieve an N balance of 35.5 kg N ha^{-1} (Table 2). Between these two extremes exist many potential combinations of reducing N fertilizer rates (between 156 and 204.4 kg N ha^{-1}) while simultaneously increasing grain yields (anywhere from 8.8 to 12.3 Mg ha^{-1}) (Scenario 3, Table 2). Importantly, all of these potential scenarios encompass an area of improvement in terms of decreasing N balance and therefore NO_3 losses (green area, Fig. 2B), relative to the agronomic optimal N rate identified in our dataset for maize in the US Midwest region.

Table 2
Potential scenarios where 15% reduction in NO_3 leaching is attainable based on different combinations of maize grain yield and N rate for the US Midwest region. Scenario 4 is based on the economic analysis shown in Fig. 3, representing the range of values corresponding to economic optimum range of N fertilizer rates ($MRTN_{low}$ to $MRTN_{high}$).

Variable	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Optimum yield	(−) N fert (=) Yield	(=) N fert (+) Yield	MRTN
N rate (kg N ha^{-1})	204.4	156	204.4	167–191
Grain yield (Mg ha^{-1})	8.8	8.8	12.3	8.6–8.7
N balance (kg N ha^{-1})[a]	83.1	35.5	35.5	49.2–71.5
N leaching (kg N ha^{-1})[b]	23	19.6	19.6	20–22
N leaching reduction (%)		15	15	13–4.3

[a] N balance obtained from the surface response model (Fig. 2B) based on grain yield and N rate combination.
[b] NO_3 leaching obtained using the equation from Fig. 1A

From an economic perspective, the N rate for $MRTN_{low}$ and $MRTN_{high}$ was 167 and 191 kg N ha^{-1}, respectively (Fig. 3). When considering this range of N rates relative to the agronomic optimum, a 13% reduction of NO_3 losses is attainable at the lower end of MRTN (Scenario 4, Table 2). The $MRTN_{rate}$ was 179.2 kg N ha^{-1} (green diamond in Fig. 2B), which represents a grain yield reduction of 0.8% from the agronomic optimum.

Overall, the use of MRTN to estimate profitable reductions in N rate corresponded with a reduced N balance (between 49.2 and 71.5 kg N ha^{-1}) (Fig. 2; Table 2), and reduced NO_3 leaching losses (between 20 and 22 kg N ha^{-1}).

4. Discussion

4.1. Implications for food supply chains

Our research provides a significant advance by establishing the relationship between NO_3 losses and N balance (Fig. 1) for rainfed cereals in temperate regions, while adjusting for influential soil and climate variables. Compared to the majority of previous research focused on N rate (Eagle et al., 2017; Pandey et al., 2018; Wang et al., 2019), this framework provides new opportunities for quantifying environmental benefits associated with any change in crop management that decreases N balance. In contrast to historical efforts to mitigate N

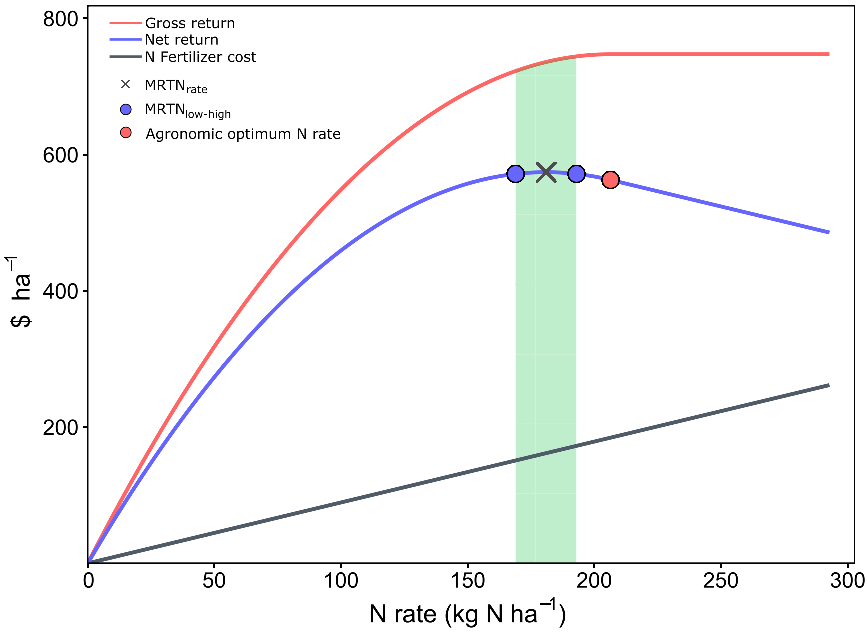

Fig. 3. Changes in gross return, net return, and N fertilizer cost across different N rates for US maize observations. The cross in the solid blue line represents the $MRTN_{rate}$ where net returns are greatest within the range of \$2.47 ha^{-1} (blue points and green area). The red point represents the agronomic optimum N rate at 204.4 kg N ha^{-1}.

pollution, the use of N balance as an indicator incentivizes increased crop productivity coupled with more efficient N fertilizer management, as this combination has the strongest impact on reducing N balance (Fig. 2). Understanding this relationship and how it differs between maize in the US and other cropping systems of the world is particularly timely with regard to new efforts in the private sector to reduce the N pollution of global food supply chains. While indicators are being developed to support sustainable sourcing of commodity crops in a variety of contexts (e.g., Gillum et al., 2016), such an indicator is not currently available for NO_3 losses.

One important consideration in our analysis is that NO_3 leaching showed substantial variation for a given N balance in both regions. Consistent with previous work, we observed that precipitation and soil texture strongly mediate N losses (Quemada et al., 2013). Hydrology is a key factor influencing NO_3 transport, with excessive precipitation causing downward movement of water, particularly in coarser textured soils (Di and Cameron, 2002; Li et al., 2009). Precipitation is directly associated with NO_3 discharge in agricultural catchments (Feng et al., 2013), and on a regional scale, the impact of hydrological variability controls fluxes of riverine N loss in the Mississippi River basin (McIsaac et al., 2001; Raymond et al., 2012). The negative effect from silt (Table 1) can be tracked to sites in our dataset with lower silt content (<30%), categorized as loamy sand and sandy loam soil textures (Fig. S1) that would be prone to facilitate NO_3 leaching compared with clay soils (Bergström and Johansson, 1991). Furthermore, higher permeability and greater potential for N mineralization are characteristics that contribute to NO_3 leaching susceptibility in sandy soils (Cai et al., 2016). In contrast, the other factors tested in our database were not significant covariates. Other studies that also evaluated management variables found that environmental controls (soil and climate) were stronger (Bauwe et al., 2020; Huddell et al., 2020).

Although the mechanistic response (slope) of NO_3 losses to N balance was the same in both regions, the overall magnitude of NO_3 losses was higher in the US (Table 1). As the model controls for soil texture and precipitation, the issue of higher NO_3 losses may be explained by a combination of higher N inputs at a given N balance and soil drainage characteristics. For observations within the range of 10 kg N ha^{-1} from the N balance of zero, N rates were on average 57% higher in the US compared with non-US regions, contributing to more frequent positive N balance observations (Fig. S2). In our dataset, a larger fraction of experiments also used subsurface drainage to measure NO_3 losses in the US compared to other regions (83 vs. 33%, respectively). It is well-documented that subsurface drainage is a major pathway for NO_3 transport, particularly under higher N rates (Christianson and Harmel, 2015). Even when only comparing observations that used the subsurface drainage methodology, average NO_3 leaching of 28.5 and 21.6 kg N ha^{-1} (Fig. S3) was observed for the US compared to non-US regions, respectively indicating the importance of higher N inputs. Accounting for such differences in the relationship between N balance and NO_3 losses is necessary to inform sustainable sourcing programs in different cropping systems and regions. The majority of observations in this study were maize in the US versus wheat and other small grain cereals in Europe, thus in reality results reflect the combination of crop productivity and N requirements (e.g., higher N inputs for higher-yielding crops like maize) that interact to determine N use efficiency and leaching outcomes. Given similar slopes between regions, actions to decrease N balance will have a similar relative impact on NO_3 losses (e.g., moving average N balance from 100 to 50 kg N ha^{-1} in a supply chain), whereas differences in the magnitude of losses in different regions allow for more accurate estimates of baseline conditions for a given N balance.

Regulatory policies governing the monitoring of NO_3 losses from agricultural lands may be a key aspect contributing to differences in N inputs between regions. For instance, the designation of nitrate vulnerable zones (NVZs) in European countries through the European Union Nitrates Directive (EU, 1991) has been implemented with moderate success (Kumar et al., 2020; Velthof et al., 2014). Whereas in the US there is no federal agricultural policy that requires mandatory adoption from farmers, leaving only voluntary strategies for N loss mitigation. Implicit to the lack of adoption is also the economic decision from farmers to avoid grain yield penalties. Here, we demonstrated that following the economic strategy for optimizing N rates in the aggregated response curve can have a significant impact on NO_3 losses by reducing N balance while securing net returns within profitable ranges. Such an approach also reduced yield-scaled N_2O emissions for maize production in the US, yet the economic risk of decreasing N rates was highly variable across fields (Zhao et al., 2017). Recognizing that farmers' voluntary adoption may be limited, N balance as an indicator could be concurrently useful for other actors in the agri-food chain or within policy that can influence on-farm N management in the long term to reduce N losses (Kanter et al., 2020).

The need for field-level indicators has also become critical in a commercial context, where there are increasing efforts to demonstrate responsible on-farm N fertilizer use to consumers. Multiple actors in food supply chains have made significant sustainability commitments without necessarily considering previous research or identifying appropriate indicators for tracking performance over time. Given the dominant role of the crop production phase in the N footprint of food products from a life cycle perspective, we stress that achieving sustainability commitments will depend on changes at the field-level, hence the management decisions of farmers. Thus, simple indicators are needed that are science-based and serve as a strong proxy for environmental outcomes, yet are also based on readily available information so that data collection and reporting is not a barrier.

We acknowledge different limitations in our study in regards to data collection and scalability. First, the unbalanced number of observations from regions and crops, with a large fraction from maize trials in the US. Despite the increasing interest in NO_3 leaching losses, research data is not available or limited in many regions. A recent bibliometric analysis showed that the number of scientific publications in NO_3 leaching has increased exponentially in the last decades, however, most of the research is conducted primarily in the US, followed by China with emphasis on corn and wheat crops (Padilla et al., 2018). Thus, it was not surprising that the studies fulfilling our selection criteria have followed a similar distribution. Further data collection from other regions is needed to expand the scope of analysis and generate new knowledge about NO_3 leaching. Second, although this study does not provide a detailed quantification of N losses along the food supply chain, the crop production stage can represent the biggest fraction of overall N losses. For instance, of the total N emissions from global livestock supply chains, 68% is associated with feed production (Uwizeye et al., 2020). Likewise, Goucher et al. (2017) showed that more than half of the environmental impact of producing bread is derived from the crop production phase. Our results suggest that N balance can fill the current gap for estimating N losses, at least in the short-term, until stronger data is available to support region-specific estimates or site-specific modeling (see discussion below). In this way, N balance could serve as a field-level indicator that food retailers and manufacturers could use in their aggregated supply chains to set goals, monitor progress, and incentivize improvements over time. For a complete description of what this process might look like, see McLellan et al. (2018) and Eagle et al. (2020). Importantly, in addition to the relationship with N leaching losses, the N balance indicator is sensitive to changes in farm management practices. Recent work has demonstrated the potential to decrease N balance in the US Midwest by agronomic practices such as including crop rotations instead of continuous maize (Tenorio et al., 2020a, 2020b) or split application of N fertilizer applications in maize (Sela et al., 2019), leading to sustainable reductions of N balance with little or null yield penalties.

4.2. Feasibility analysis

Our feasibility analysis targeting a 15% reduction in NO_3 leaching provided several important insights for maize production in the US Corn Belt. Across the different scenarios, improvements in water quality appeared to be more feasible through reductions in fertilizer N rate rather than increases in yield while maintaining the same N rate (Table 2). We found that reductions in N rate are possible without penalizing yields, which could represent an incentive for the adoption of better practices and highlight the importance of accurately estimating N rates. It should be pointed out that scenarios presented here consider aggregated data in a supply chain, not the yield response in individual farmer fields. Importantly, reducing N rates is not the only way to decrease N balance. Nutrient use efficiency improvements – such as improved 4R and other practices that keep more N within the field, combined with other cropping system modifications such as variety selection, planting date, crop rotation, pest management, and soil management practices – could shift the yield response curve upward at a given N rate, to enable results such as those in Scenario 3.

While the green area in Fig. 2B presents a range of possibilities for decreasing N balance, we caution that the level of yield increases required to reduce N losses by 15% without reducing N rates is high (39%). In theory, even under conditions where farmers could optimize management, the average gap in yields between average and top-yielding fields has been estimated around 20–26% by the Global Yield Gap Atlas and other studies in the US (http://www.yieldgap.org/united-states; Riccetto et al., 2020). As a result, the required yield increases under this scenario are unrealistic, indicating it is more feasible that a combination of modest yield increases with modest N rate reductions could lead to a similar outcome. This presents a key challenge for N balance to show a positive impact in supply chains, because farmers are generally more interested in increasing yield than reducing N rates, as discussed above. Yet, it is important to note that these calculations are constrained to available observations in the dataset for optimum agronomic yields. Our values for yield, N rate, and N balance were similar to the range of recent estimates at the sub-field level (Basso et al., 2019) and county-level (Riccetto et al., 2020) in the US Midwest region. However, grain yield response and N balance calculations will depend on the relationship between current yields achieved by farmers and the corresponding N rate to attain those yields. Accordingly, aggregated results across many individual fields in supply chains could lead to a lower N balance if higher yields are obtained with similar or lower N rates. To further investigate the feasibility of increasing yield without decreasing N rate, we urge for on-farm research to assess variability in N balance, similar to recent efforts carried out in Nebraska (Tenorio et al., 2020a, 2020b).

One distinction is that our framework relies on field-level inputs to determine N balance, but its future application in supply chains would be focused on estimating aggregate NO_3 losses. In other words, relationships presented here cannot be used to predict field-level water quality outcomes. While the precise estimate of NO_3 leaching for a specific field would require further site-specific variables (and arguably may not be useful at larger scales), we envision that the model reported here can be used across large areas and thousands of fields in the agri-food supply chain. There will always be a tradeoff in the accuracy of predictions in a specific field and being able to apply an indicator over a large scale. When viewed in this way, individual fields would represent the large amount of variability from Fig. 1 but, in the long term, will help address the variability introduced by management factors (Tenorio et al., 2020a, 2020b).

4.3. Future directions

As the magnitude and complexity of agricultural N pollution continues to increase, many experts are calling for new international partnerships and policy grounded in science-based frameworks for N management (Sutton et al., 2019, 2021; Houlton et al., 2019). As this involves social, economic, and environmental aspects, efforts to promote widespread mitigation of N losses are approached differently across countries and policy domains. For instance, the Agriculture Innovation Agenda released by USDA (https://www.usda.gov/aia) includes a goal to reduce nutrient loss by 30% by 2050. China's implementation of the "Action Plan for the Zero Increase of Fertilizer Use" in 2015 aims to reduce national N fertilizer use, with early signs it has proven to be effective (Ji et al., 2020). Likewise, the "International Nitrogen Initiative" (INI; https://initrogen.org/) and "International Nitrogen Management System" (INMS; https://www.inms.international/) are other examples of cross-sectoral collaborations to support policy development. Yet, a unique centralized program such as an intergovernmental organization that could boost the impact of such goals is still missing.

We recognize that the high variability in Fig. 1 is an important limitation in estimating N losses, particularly at the field scale. However, that does not prevent action from being taken to establish N balance as an environmental indicator, especially if it is situated within a framework explicitly designed for continuous improvement and more accurate prediction capacity over time across a range of cropping systems and regions (historical context for N balance adoption is described in the Supplementary Discussion). Following the same logic above, the use of a generalized N balance model would be suitable for estimating NO_3 losses in the short term, which is crucial for supporting programs and policies to improve water quality. In the long-term, one option is to follow the same path that has already been implemented by the IPCC for estimating N_2O emissions following a tiered methodology including national GHG inventories, food supply chain contexts, and research studies (IPCC, 2019). Tier 1 represents the relationship between N inputs and N_2O emissions to describe a global emission factor. Similarly, our results provide a preliminary quantitative description of the relationship between NO_3 leaching and N balance. With sufficient empirical data, a Tier 2 approach can be applied to estimate N_2O emissions in specific contexts. Ultimately, Tier 3 relies on process-based models that account for climate, soil, and crop management factors, currently adopted in only three countries (Ogle et al., 2020). While the Tier 1 global emission factor is imperfect and does not support accurate field-level predictions, it was developed based on available science to enable action around a growing environmental concern. Indeed, the IPCC framework has supported an explosion of research on mitigating N_2O emissions at different scales (Dorich et al., 2020), and equally important, it is designed to allow for continuous improvement through advances in science and technology for N_2O measurement and modeling.

It has been stated that N is the new carbon (Battye et al., 2017). Given the powerful impact of the IPCC framework on science and policy related to climate change, what is holding us back from developing a similar framework for NO_3 losses? One key aspect of IPCC success is that it provided clear opportunities for engaging researchers, governments, and the private sector in a stepwise, transparent process for estimating N_2O losses. We recognize that this process was a large effort combining the collective knowledge and expertise of many leading scientists, thus it is a long-term vision that requires significant commitment and funding. We propose that a similar internationally accepted framework would be useful for estimating NO_3 leaching losses. Furthermore, developing process-based models for NO_3 losses that also simulate N_2O emissions will help guarantee that reducing the former does not result in higher emissions of the latter.

5. Conclusions

This study provides evidence of a relationship between NO_3 leaching losses and N balance across an extensive global dataset of temperate-region cereal crops. We found that NO_3 leaching losses at a given N balance were significantly different when the US was compared to the rest of the data, although the rate of increase was similar in both regions. Combining US maize yield response data together with N fertilizer and N balance, we assessed different scenarios that highlighted the feasibility of reducing NO_3 leaching losses without incurring penalties in grain yield and profits. Reduction in N balance can be achieved both by reducing N rate and maintaining grain yields or increasing grain yield for a given N rate. However, both situations require practices that increase N use efficiency improvements. Moreover, the economic strategy of reducing the agronomic optimum N rate to the $MRTN_{low}$ can lead to reductions of 13% in NO_3 leaching losses. As a simple indicator, N balance can be used for estimating NO_3 losses and supporting improvements in water quality in the short term. The relationship between NO_3 losses and N balance reported here represents the first step before developing further methodologies that account for biophysical factors within production fields. With this information, companies and other actors from the agri-food supply chain can estimate the environmental impact of food production and support future improvement in agricultural sustainability to promote better N management for producers. In the long-term, we conclude that further refinements to estimating NO_3 losses for specific crops and regions would benefit from following an approach similar to the IPCC tiered methodology for estimating N_2O emissions.

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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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2021.107714.

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