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Predicting nitrate leaching loss in temperate rainfed cereal crops: relative importance of management and environmental drivers

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Abstract

Nitrate (NO_3) leaching from agriculture represents the primary source of groundwater contamination and freshwater ecosystem degradation. At the field level, NO_3 leaching is highly variable due to interactions among soil, weather and crop management factors, but the relative effects of these drivers have not been quantified on a global scale. Using a global database of 82 field studies in temperate rainfed cereal crops with 961 observations, our objectives were to (a) quantify the relative importance of environmental and management variables to identify key leverage points for NO_3 mitigation and (b) determine associated changes in crop productivity and potential tradeoffs for high and low NO_3 loss scenarios. Machine learning algorithms (XGboost) and feature importance analysis showed that the amount and intensity of rainfall explained the most variability in NO_3 leaching (up to 24 kg N ha^{-1}), followed by nitrogen (N) fertilizer rate and crop N removal. In contrast, other soil and management variables such as soil texture, crop type, tillage and N source, timing and placement had less importance. To reduce N losses from global agriculture under changing weather and climatic conditions, these results highlight the need for better targeting and increased adoption of science-based, locally adapted management practices for improving N use efficiency. Future policy discussions should support this transition through different instruments while also promoting more advanced weather prediction analytics, especially in areas susceptible to extreme climatic variation.

1. Introduction

Nitrogen (N) fertilizer has fueled the intensification of agriculture worldwide, allowing humanity to sustain and increase food production for a growing population (Godfray *et al* 2010). Concurrently, agriculture has also become the major contributor to global N pollution, with gaseous emissions (i.e. nitrous oxide [N_2O] and ammonia [NH_3]), surface runoff and leaching being the major loss pathways from farming systems. Among these pathways, nitrate (NO_3) leaching represents the primary source of groundwater contamination and coastal hypoxia (Howarth *et al* 2021). Despite recent improvements in N use efficiency (NUE) in some regions (Zhang *et al* 2015), N leaching losses continue to pose a serious environmental and human health threat in many parts of the globe (Ward *et al* 2018, Uwizeye *et al* 2020).

Both natural and anthropogenic factors influence NO_3 leaching, including soil properties, climate and farming practices. Reports on N leaching are extensive (Padilla *et al* 2018), with previous work highlighting crop choice, N fertilizer management (rate, source, timing and placement), tillage, cover crops and soil texture and carbon as influential factors, among others (Zhou and Butterbach-Bahl 2014, Eagle *et al* 2017, Thapa *et al* 2018, Hess *et al* 2020, Ying *et al* 2020, Preza-Fontes *et al* 2021). Regardless of experimental conditions, N fertilizer rate is a particularly strong predictor of N losses (Lawlor *et al* 2008, Xia *et al* 2017, Wang *et al* 2019, Huddell *et al* 2020). However, emphasis on reducing N rate without considering impacts on yield may negatively influence crop productivity (Jeong and Bhattarai 2018, Martinez-Feria *et al* 2019), creating potential tradeoffs between environmental benefits, food security and farmer income. As an alternative approach, increases in crop productivity and associated N demand may represent a direct pathway for reducing N leaching, whereby efficient utilization of soil and fertilizer N supply contributes to high grain yields (and N removal) while simultaneously decreasing the risk for N losses (Cassman *et al* 2002, Gardner and Drinkwater 2009). Indeed, recent publications provide evidence that the combination of N fertilizer inputs and grain N removal are important predictors of N losses to the environment (McLellan *et al* 2018, Eagle *et al* 2020, Tamagno *et al* 2022). Yet, the relative impact of N management practices compared to other important drivers of N losses such as climatic conditions and soil texture, which are beyond the farmer's control, remain unclear.

Field and watershed hydrology strongly influence N leaching, especially the magnitude, frequency and distribution of rainfall (Austin *et al* 2004, Bowles *et al* 2018). Changes in hydrological cycles due to climate change are expected to negatively impact water quality. For instance, in the United States (U.S.) annual average precipitation has increased by 4% since 1901, yet the frequency and intensity of heavy precipitation events has increased more than 20% in the Midwest and Great Plains regions (Easterling *et al* 2017, Hayhoe *et al* 2018). In Europe and Canada, current and future N losses are linked to increased precipitation and temperature changes (Jabloun *et al* 2015, He *et al* 2018, Rozemeijer *et al* 2021). Moreover, years with low precipitation or drought enable the accumulation of NO_3 in soil that is 'flushed' in the subsequent year, potentially causing above-average NO_3 losses (Murphy *et al* 2014). Given increasing interannual variability in precipitation and extreme weather events, an integrated analysis accounting for the relative importance of climate, soil and management effects will help prioritize research programs and funding to find solutions for decreasing N pollution.

To overcome challenges in measuring NO_3 losses from individual fields, predictive models provide a quantification alternative proven to be reasonably accurate and an effective decision-support tool for crop management (Dayyani *et al* 2010, Moriasi *et al* 2013, Gallardo *et al* 2020). Some drawbacks to process-based simulation models include (a) labor-intensive field measurements for accurate site-specific calibrations of parameters, and (b) large data input requirements to account for pedoclimatic conditions, crop characteristics and other management practices (Basso and Liu 2019, Puntel *et al* 2019). In view of increasing data availability and computational power in agriculture, machine-learning methods can improve predictive power and elucidate soil, weather and management effects on biogeochemical N fluxes (Philibert *et al* 2013, Saha *et al* 2021, Spijker *et al* 2021). Likewise, new developments in model interpretation methods provide another layer of knowledge to understand the causes behind machine-learning predictions (Doshi-Velez and Kim 2017).

Environmental policies aiming to prevent externalities from agricultural activities generally target farmers, but the consequences of climatic events are sometimes overlooked or hard to prevent (Bagley *et al* 2015, Abendroth *et al* 2021). In this study, we used machine-learning models to (a) account for interactions among soil, weather and management contributing to large variation in N leaching across studies in rainfed temperate-region cereal crops, and (b) identify the major leverage points for N leaching mitigation and building resilience in the face of climate change. Our specific objectives were to (a) quantify the relative importance of environmental and management drivers of NO_3 leaching loss and (b) determine associated changes in crop productivity and potential tradeoffs for high and low NO_3 loss scenarios.

2. Materials and methods

2.1. Data collection

The database consisted of a global literature review previously used by Tamagno *et al* (2022). Briefly, we conducted a comprehensive literature search using Elsevier's Scopus database to retrieve peer-reviewed articles reporting NO_3 leaching losses (kg N ha^{-1}) from experimental fields in temperate climate regions for rainfed cereals. The search was restricted to studies meeting certain criteria: (a) experiments were published between 1990 and 2020, (b) measurements were collected from field trials, results reported (c) grain yield, (d) N fertilizer rate, and (e) NO_3 losses on an area-scaled basis. Due to differences in soil hydrology and the risk of N leaching, studies on rice were not included. A full description of data collection, specific search terms and screening details can be found in Tamagno *et al* (2022) together with the complete list of publications.

The database was built by extracting additional variables reported in the studies related to crop management, soil, weather, NO_3 leaching methodology and crop N removal (table 1). Management variables were grouped based on the number of observations for each category. Crop type was grouped in corn (*Zea mays* L.), wheat (*Triticum aestivum* L.) and other types of crops that were less frequently reported (i.e., barley, oats, rye, sorghum). In a similar fashion, fertilizer placement, timing and source were classified following criteria to create representative groups of

Table 1. Variables used in the analysis, their abbreviation, type, levels and units.

Category	Variable	Abbreviation	Type	Unit/Levels
Management	Crop type	Crop_Type	Categorical	Corn, Wheat, Other
	Fertilizer placement	Placement	Categorical	Broadcast, Incorporated, Other
	Fertilizer source	Source	Categorical	Ammonium nitrate, Anhydrous ammonia, Organic, UAN, Urea, Other
	Fertilizer timing	Timing	Categorical	Pre-Season, In-season, Pre-Sowing
	Nitrogen fertilizer rate	NRatekgNha	Quantitative	kg N ha^{-1}
	Previous crop	Previous_Crop	Categorical	Annual legumes, cereals, other
	Tillage system	Tillage	Categorical	Till, No-Till
Soil	Clay content	Clay	Quantitative	%
	Sand content	Sand	Quantitative	%
	Silt content	Silt	Quantitative	%
	Soil Carbon	SoilC	Quantitative	g kg^{-1}
	Soil pH	pH	Quantitative	—
Weather	Annual precipitation	AnnualPrecip	Quantitative	mm yr^{-1}
	Extreme precipitation events	EPE.current	Quantitative	Number of precipitation events higher than 25 mm d^{-1} in the year
	Annual mean temperature	Tmean.current	Quantitative	°C
	Precipitation from the previous year	PP_prev	Quantitative	mm yr^{-1}
Methodology	NO_3 methodology	Method	Categorical	Lysimeter, suction cups, tile drainage
N output	N removal	N_removal	Quantitative	kg N ha^{-1}

balanced observations. Fertilizer timing was grouped in three categories where 'In-season' applications included fertilizer applied after crop emergence during the season, 'Pre-sowing' are applications that were done before planting or before emergence and 'Pre-season' includes application done in fall of the previous year. Soil characteristics (i.e., clay, sand, silt content, soil carbon, soil pH), annual precipitation and annual mean temperature were retrieved from publications. When missing, soil data were retrieved from SSURGO (Survey Staff Soil 2020) for experimental sites in the U.S. and from ISRIC's Soil Grids (Hengl *et al* 2017) for other locations using the latitude and longitude of the experimental site. Missing annual precipitation and mean temperature were retrieved together with precipitation from previous year using the weather database from NASA-POWER (Sparks 2018) using the coordinates from each site (Correndo *et al* 2021a). Extreme precipitation events (EPE) were calculated as the number of days during the year where precipitation was greater than 25 mm d^{-1} (Puntel *et al* 2019, Correndo *et al* 2021b).

2.2. Data analysis

2.2.1. Model setup

We developed a NO_3 prediction model using eXtreme Gradient Boosting (XGBoost), a scalable machine learning system for gradient boosted decision tree characterized for its model performance, computational speed, flexibility and scalability (Chen and Guestrin 2016). XGBoost works as an ensemble of decision trees grown in an adaptive way because models are added sequentially to enhance the performance of existing models until no further improvement is possible. The algorithm introduces an additional regularization term to prevent over-fitting and implements parallel tree boosting, making the learning process even faster. As such, it has become an attractive alternative among gradient-boosting implementations and is an increasingly popular tool in the agronomic field by outperforming other machine learning alternatives. XGBoost has been used to predict biomass (Mansaray *et al* 2020, Bahrami *et al* 2021), soil properties (Andrade *et al* 2020), crop yield and NO_3 leaching losses (Shahhosseini *et al* 2019).

We implemented the '*caret*' package (Kuhn 2021) in R software (version 4.1.2; R Core Team 2021) for model training, tuning hyper-parameters and validation. The dataset was randomly divided into training and testing sets representing 80% ($n = 770$) and 20% ($n = 191$), respectively. A repeated 10-fold cross-validation scheme was used as a resampling method on the training set to tune the model using a grid-search approach with different parameter combinations. In this cross-validation method, the data are randomly divided into ten groups, and for each iteration out of 10, nine groups are selected to train the model whilst the remaining one is used for validation. This procedure was repeated three times but with different splits each time. In this way, the effect of tuning parameters was evaluated on all possible models and we selected the best one across these combinations using the lowest root mean square error (RMSE) as the performance metric. In addition, the coefficient of determination (R^2) and the mean absolute error (MAE) of the model are presented. The testing dataset was used to compute the prediction error of the final model by plotting the observed vs predicted values and calculating R^2 and RMSE.

2.2.2. Model interpretability

We used feature importance analysis and accumulated local effect (ALE) plots as interpretable machine learning methods to display model predictions and the magnitude of how different variables influence NO_3 leaching. We implemented the R package '*iml*' (Molnar *et al* 2018) to perform these analyses. The feature importance analysis ranks the variable input of the model according to the increase in the prediction error of the model after permuting the feature (Fisher *et al* 2019). Variables ranking among the top five in our analysis were then used to create the ALE plots which illustrate the effect of each variable compared to the predicted NO_3 leaching average (28.1 kg N ha^{-1}). Briefly, a feature is subdivided into intervals of similar number of observations. The ALE method calculates the average difference in predictions for each interval and aggregates the average effects across all intervals (see details in Apley and Zhu 2020).

Lastly, to explore potential tradeoffs between N leaching and yield across different crop categories, we first calculated relative grain yield by expressing each yield observation as a proportion of the maximum value in each study. We then subset observations for each of the five most influential variables determined above into 25% and 75% quantiles (bottom and top 25% of data), which corresponded with scenarios leading to the lowest and highest N leaching predictions. For these two scenarios, relative yields were analyzed using violin plots, while also depicting the average N leaching predictions from ALE values for each group.

3. Results

3.1. Model performance

The average NO_3 leaching from the dataset was 27.7 ± 22.9 kg N ha^{-1} and varied between 0.07 and 138.7 kg N ha^{-1} with a median of 22.0 kg N ha^{-1}. Model training using a repeated cross-validation scheme and grid-search approach resulted in 243 iterations using the training subset. Based on the lowest RMSE, the optimized model presented acceptable performance metrics (RMSE = 12.1 kg N ha^{-1}, $R^2 = 0.71$ and MAE = 8.1 kg N ha^{-1}). Likewise, when testing the model using a subset of unseen observations (20% of data), prediction accuracy was also high for the most frequent range of observations (leaching < 60 kg N ha^{-1}) (figure 1). While there was more variation in extreme values (>60 kg N ha^{-1}), this represented only 8% of testing data. This model validation step showed similarly satisfactory prediction metrics (RMSE = 12.9 kg N ha^{-1}, $R^2 = 0.76$ and MAE = 8.7 kg N ha^{-1}).

3.2. Feature importance and model predictions

The importance of a variable was quantified by the increase in prediction error (loss of MSE) following permutation. The feature importance analysis (figure 2(a)) reflected a higher relative importance of hydrologic factors *versus* crop management practices in predicting N leaching. Among the top five variables ranked in our analysis, annual precipitation was the most influential variable associated with an error increase of 4.6 (kg N ha^{-1})^2 after permutation, followed by EPE and precipitation in the previous year. After all these three measures of precipitation, fertilizer N rate and N removal were the fourth and fifth most important variables. In contrast, variables related to soil texture (sand, silt, clay), crop management (tillage, crop type and previous crop and N source, timing and placement) and experimental methodology (method) were less influential.

When comparing ALE plots (figures 2(b)–(f)), annual precipitation (figure 2(b)) showed the sharpest increase in predicted N leaching from dry years (below 600 mm yr^{-1}) to wet years (above 1000 mm yr^{-1}). The magnitude of impact was also the greatest for annual precipitation compared to other variables, with predictions varying up to ±12 kg N ha^{-1} from the average (this range represents more than 80% of the average model prediction of 28.1 kg N ha^{-1}). Likewise, more than three EPE resulted in a spike of NO_3 leaching up to 6 kg N ha^{-1} at 9 EPE (figure 2(c)). Precipitation from the previous year had an inverse impact (figure 2(d)), where a dry previous year increased predicted N leaching by up to 7 kg N ha^{-1} while the opposite occurred for a wet previous year. Overall, these three variables depict how intra-annual variability (current and previous year) and the magnitude of individual precipitation events drive NO_3 losses.

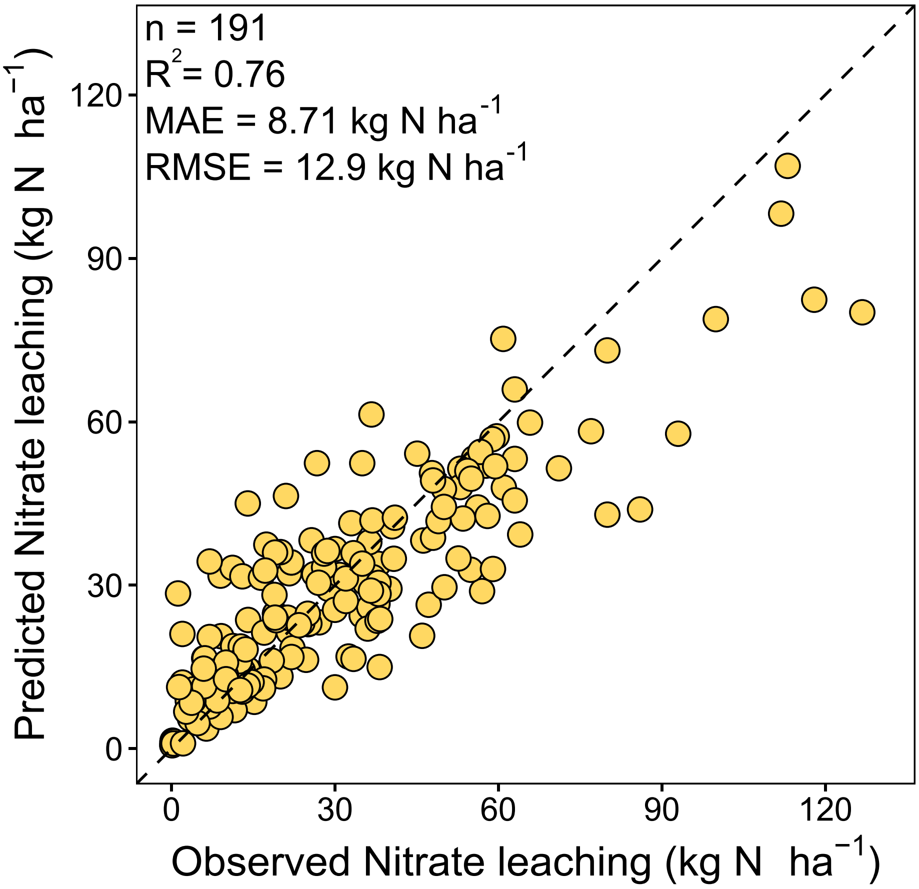

Figure 1. Model performance for testing data ($n = 191$, 20% of observations). Observed versus predicted values for NO_3 leaching, including coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RSME). Dashed line represents the 1:1 line.

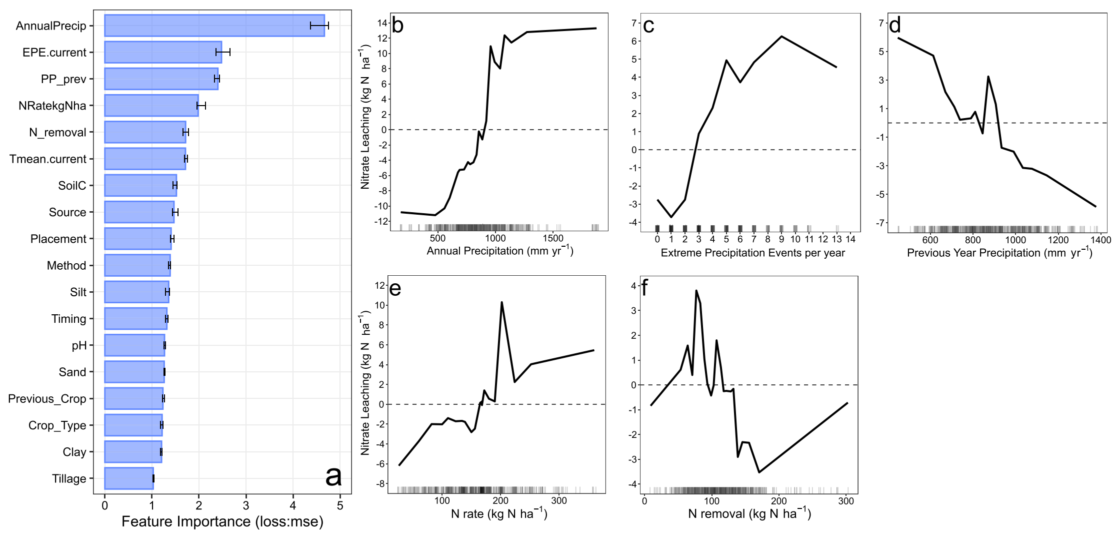

Figure 2. Feature importance analysis of the XGboost model (a) and ALE plots showing model predictions for the top five features (b)–(f). Bars in a represents the prediction loss of the model expressed in units of mean squared error (MSE) and horizontal bars are the 5% and 95% quantile importance distribution. Solid lines in ALE plots and short vertical lines (b)–(f) represent the predicted effect of that particular feature on NO_3 leaching (kg N ha^{-1}) centered to the average prediction of the model (28.1 kg N ha^{-1}) and each observation in the dataset, respectively. References for feature names are in table 1.

Predicted N losses increase with fertilizer N rates, reaching a maximum of 10 kg N ha^{-1} above the average prediction (figure 2(e)). Other aspects of fertilizer N management (source, timing and placement) influenced N leaching by a lower magnitude compared with N rate and precipitation-related

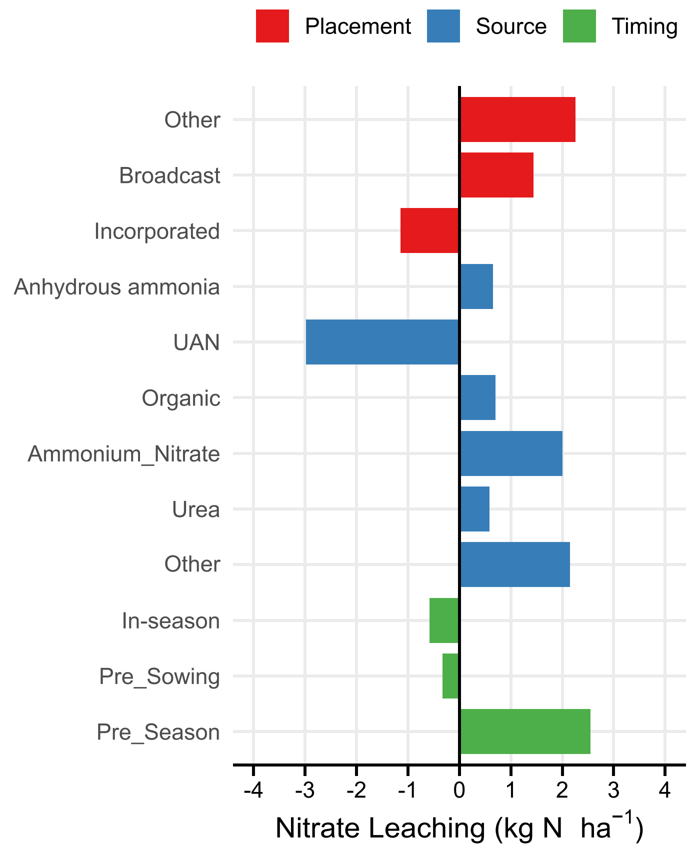

Figure 3. ALE plots showing model predictions for the N fertilizer placement, source and timing. Bars represents the predicted effect of that particular feature on NO_3 leaching (kg N ha^{-1}) centered to the average prediction of the model (28.1 kg N ha^{-1}).

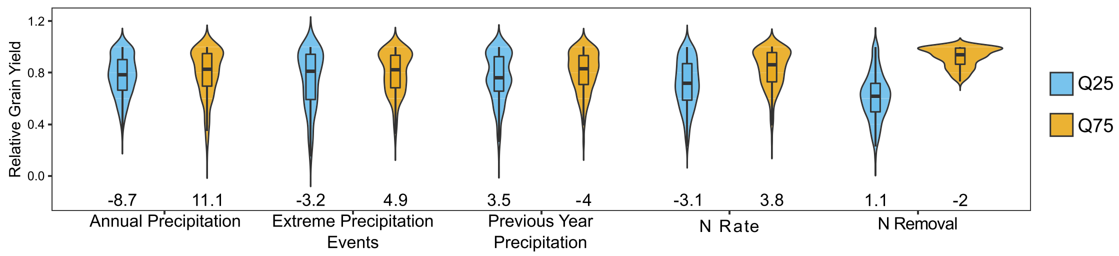

Figure 4. Relative grain yield for the 25% and 75% quantile (Q) observations of top five most important variables (figure 2(a)). Numbers below violin plots are the average of the predicted NO_3 leaching from the ALE plots for the 25% and 75% quantile of the observations (figures 2(b)–(f)).

variables (figure 3). Yet, several management practices showed potential for mitigation. For placement, only when fertilizer was incorporated NO_3 leaching losses were reduced in ∼1 kg N ha^{-1}. Timing practices that reduced N losses included in-season and pre-sowing applications, whereas pre-season applications increased NO_3 leaching. All N fertilizer sources except urea ammonium nitrate (UAN) increased N losses, however, this may be more related to the timing of N application than the source. In our study, a large proportion of UAN observations were in-season applications (figure S1 (available online at stacks.iop.org/ERL/17/064043/mmedia)), which is consistent with current farmer practice because of its easier manipulation, storage and equipment adaptation. For crop N removal (figure 2(f)), N leaching decreased ∼4 kg N ha^{-1} when crop N removal was higher than 130 kg N ha^{-1}, whereas N leaching generally remained neutral or increased below this threshold.

3.3. Yield response under low and high N loss scenarios

When comparing crop yields for scenarios of low and high N leaching predictions (corresponding with the bottom and top quantiles for each influential variable), effects differed depending on the variable (figure 4). For annual precipitation, EPE and previous year precipitation, we found no differences in relative crop yield but rather an overlap of mean values and observations. However, a large yield penalty was observed for the N rate variable, where relative yields for the 75% quantile category (high leaching observations) were 16% greater than the 25% quantile (low leaching observations). In contrast, a synergy was observed for the N removal variable, where a 1.5-fold relative difference was found when comparing the 75%–25% quantiles (this represented low and high leaching, respectively, due to the inverse relationship for N removal). Despite the larger difference in relative yields, the change in average N loss predictions between the 75% and 25% quantiles was greater for N rate than N removal variables (1.8- and 1.5-fold, respectively).

4. Discussion

Despite decades of research and policy initiative, the global challenge of N pollution continues to grow (Houlton *et al* 2019) requiring urgent action from the scientific community and policy makers (Sutton *et al* 2021). Here, we present an integrated assessment of N leaching in response to agronomic practices, soil properties and climate from a comprehensive global dataset of rainfed cereal crops. Despite the large amount of variability among studies (figure 1), the interpretable machine learning approach could predict NO_3 leaching at the field-level with an acceptable level of accuracy. Similar methods have been used to study N_2O emissions (Philibert *et al* 2013, Pan *et al* 2021, Saha *et al* 2021) where N rate and hydrological factors were also found to be influential. Yet for NO_3 leaching, machine learning studies have mostly been restricted to specific regions or countries (Shahhosseini *et al* 2019, Spijker *et al* 2021) or limited in the number of management variables evaluated (Ying *et al* 2020).

The analysis implemented here provides new insights because three of the five most influential variables were not included in previous syntheses (i.e., EPE, previous year precipitation and N removal). The main findings highlight precipitation as the key driver of N leaching in agricultural fields, illustrating how climate change and increasing severity of precipitation in some regions of the world (Masson-Delmonte *et al* 2021) will further magnify water quality problems. In addition, we found a lower relative impact of soil properties and management factors considered in this study (table 1) compared to those for precipitation and N inputs and outputs, suggesting well-documented crop management practices for N loss mitigation (discussed below) should be targeted to high-risk weather scenarios for greatest impact. Lastly, the observed tradeoffs between grain yield and N leaching under high N rates underscore the need for more efficient use of N inputs in order to meet growing cereal demand and combat the trend of increasing global N consumption in agriculture (Bodirsky *et al* 2014, Springmann *et al* 2018, Omara *et al* 2019).

Previous work has suggested that climate change, especially extreme precipitation events, will increase agricultural N losses and freshwater N pollution (Sinha *et al* 2017, Bowles *et al* 2018). Our study supports this prediction with field-level empirical data, and is consistent with long-term research at individual sites (Kladivko and Bowling 2021) and small watersheds (Bauwe *et al* 2020), where uncontrollable factors of weather and precipitation regulate N losses more than management practices or soil properties. Given the urgent need to decrease the environmental footprint of food production, local and national plans are being developed to reduce nutrient losses as a key pillar of agricultural sustainability, including in the European Union (EU Commission 1991, 2000), China (Ji *et al* 2020) and the U.S. (USDA 2021). Early adoption of policies in Europe has successfully reduced discharges of N loads in the coasts of the Netherlands (Fraters *et al* 2021) or the Baltic Sea (Iho *et al* 2015). However, our results indicate higher amounts of N leaching may occur with increased frequency of extreme weather events characteristic of climate change. The associated risks for nutrient pollution will present a key challenge, potentially decreasing the effect of mitigation practices, especially for intensive grain production regions with heavy reliance on external N inputs (Raymond *et al* 2012). For example, analysis of future precipitation patterns in the U.S. suggests that N inputs would need to decrease by more than 30% to offset the anticipated increase in riverine N loading due to extreme precipitation events (Sinha *et al* 2017).

While the factors in table 1 have been investigated in other studies, their interactions have not been accounted for using machine learning models with a field-level dataset covering a range of soil, climate and management conditions. This approach may explain some unexpected results. For example, soil texture and hydrology are often cited as a risk factor for N leaching, particularly sandy compared to fine-textured soils (Cameron *et al* 2013, Huddell *et al* 2020). Meanwhile, other studies have reported an effect of soil C and pH on N leaching (Ying *et al* 2020). The methodology to measure N leaching often constitutes a challenge for accurate observations and a source of variation (Zotarelli *et al* 2007), but was not evident in our results. The lower ranking of these variables in in our study may be due to the inclusion of three independent categories of precipitation (figure S2), each explaining a large amount of variation. For example, the magnitude of change for N leaching predictions spans 24 and 10 kg N ha^{-1} for annual precipitation and EPE (figure 2), respectively, but only around 5 kg N ha^{-1} for all N fertilizer sources, timing and placement variables combined (figure 3). Shahhosseini *et al* (2019) also reported that weather more strongly influenced N leaching compared to soil or management factors in their case study of the US Midwest.

Including crop productivity in our analysis helped address an important knowledge gap, as the two most important management-related factors were N rate and N removal. Fine-tuning fertilizer N inputs is often a management recommendation (Fageria and Baligar 2005, Cao *et al* 2018), especially to avoid high N rates exceeding crop demand which can trigger exponential N losses (Zhou and Butterbach-Bahl 2014, Zhao *et al* 2017, Wang *et al* 2019). The importance of N removal in this analysis provides further evidence that optimizing crop productivity is associated with efficient recovery of plant-available soil N and decreased risk of N leaching. In terms of management implications, N rate is an *a priori* decision, whereas N removal is a post hoc outcome resulting from a suite of management actions that include individual components tested in our model and others. Taken together, these results suggest the most effective management strategy for reducing N losses is to boost yields (N removal) while limiting N inputs, which also aligns with farmers' economic goals. Although, increasing yield potential could represent a challenge in some regions of the world where yield stagnation has been observed (Grassini *et al* 2013). Furthermore, farmers face a major challenge in precisely meeting crop N demand while controlling the fate of N to reduce potential losses, which is why they tend to apply excess N targeting crop physiological requirements to achieve profitable yields.

In this context, our results highlight the need to address the tradeoff between N leaching and yield through improvements in NUE. Relative yields were not different between high and low N leaching scenarios for precipitation-related variables. However, high N fertilizer inputs contributed to elevated N losses and a 16% increase in productivity compared to the low N leaching scenario (figure 4). To avoid limitations to crop growth without increasing N inputs (figure 2(e)), practices targeting the right rate, source, timing and placement of N fertilizer are the foundation of improved management (Fageria and Baligar 2005, Ladha *et al* 2020). Although variables other than N rate had less impact on N leaching in our study, they are undoubtedly important for improving yield and thereby crop N removal. Similarly, practices that improve internal N cycling (e.g., crop rotations, cover crops, improved genetics and others) have the potential to reduce the need for external N inputs and improve NUE in many parts of the world (Mueller *et al* 2019, Cassman and Dobermann 2021). We did not specifically include NUE as a variable in our analysis because limited experiments had control plots without fertilizer, which provide a measure of soil N supply. However, partial N balance (calculated as N fertilizer rate minus crop N removal) captures both of these components and is increasingly used as an indicator for N losses (McLellan *et al* 2018, Eagle *et al* 2020, Tamagno *et al* 2022). Our results support the use of these two variables, which can be easily tracked at the field-level, for N leaching predictions.

Here we present a retrospective analysis of seasonal climate trends, but the ability to translate precipitation-related results into actionable management strategies is currently limited by the predictive ability of long-term forecasts, which are not accurate enough to make seasonal management decisions *a priori*. Therefore, a key recommendation of this work is to prioritize the adoption of science-based, locally-adapted crop management practices for improving NUE and reducing N losses in regions with high-risk weather scenarios. This will become especially significant in light of climate change leading to higher variability and frequency of extreme weather events (e.g. El Niño events; Trenberth 2011, Buishand *et al* 2013), also recognized in the latest IPCC report (Masson-Delmonte *et al* 2021). Remote sensing tools that measure spectral properties from plants to detect crop N deficiencies at different scales (leaves or canopies) are useful for site-specific N recommendations and in-season N management (Dellinger *et al* 2008, Barker and Sawyer 2010). Likewise, given the increasing frequency of extreme weather and high inter-annual precipitation variability, our results strengthen the idea that wet years following dry years can substantially increase N leaching. Inclusion of pre-fertilization soil N testing after a dry season could help farmers adjust N rates and reduce uncertainty on the soil N supply potential in the following season (Andraski and Bundy 2002). In areas where precipitation and the number of EPE are expected to increase, enhanced efficiency fertilizers such as nitrification inhibitors or controlled/slow release fertilizers are alternatives to match crop demand with timing of N availability (Naz and Sulaiman 2016) reducing the risk of losses and thereby increasing NUE (Qiao *et al* 2015). Dynamic simulation models, such as Adapt-N (Melkonian *et al* 2008), are another alternative to estimate cropping system N dynamics and fertilizer needs. These models integrate real-time weather conditions with soil information and management which has potential to reduce N inputs (Sela and van Es 2018) and NO_3 leaching losses (van Es *et al* 2020).

We acknowledge there are several limitations of this study, such as not addressing the seasonality of precipitation or the timing of N leaching events across the year. Our dataset includes temperate regions where N leaching primarily occurs during winter and spring due to residual soil NO_3 remaining after harvest (Di and Cameron 2002), but this may differ in other environments with wetter conditions during the growing season. For example, a similar study focusing on tropical regions reported that the combination of soil texture and water and N inputs controlled N leaching (e.g., Huddell *et al* 2020), indicating that future work is necessary to understand if the variables studied here are likely to influence N leaching events elsewhere in the same manner. There are limitations in geographic coverage, crops and management practices employed in our dataset, thus more field experiments simultaneously investigating crop yield and N leaching losses are needed to address these imbalances (see Tamagno *et al* 2022). Finally, even though machine learning models account for multiple, interrelated factors to develop robust predictions, there are unexplored high-order interactions that need further attention (e.g., mitigation actions for high N rate, precipitation, or EPE environments). Accordingly, interpretable predictions of influential variables in this study can contribute to the development of robust hypotheses to test in future field experiments.

Ultimately, management practices for reducing N leaching and increasing NUE must be developed, adapted, and implemented by researchers and farmers at the local level to account for the biophysical, social, and political constraints of each farming system and agroecological context. While this is beyond the scope of the present study, a wide body of research outlining effective management practices exists including improved N management (Struffert *et al* 2016, Eagle *et al* 2017), adaptive N management based on soil testing and in-season crop N status (Shanahan *et al* 2008), cover crops (Rasse *et al* 2000, Malone *et al* 2014), or irrigation (Quemada *et al* 2013). However, reducing the pool of N susceptible to losses will also require a systemic approach beyond the crop growing season. Adoption of no-till or reduced-till, more diverse crop rotations (e.g. inclusion of perennial crops; Raymond *et al* 2012, Bowles *et al* 2018), and intensification of land to minimize fallow season (e.g. winter cover crops) will be among the beneficial practices to maximize N retention in fields (Grant *et al* 2002) and build resilience in agroecosystems to severe weather. Despite this knowledge, a main barrier is farmer adoption, which can have different causes such as socio-economic circumstances, access to information, operational, or political-economic structure (Rejesus *et al* 2013, Cavanagh *et al* 2017, Arslan *et al* 2020, Houser and Stuart 2020). Given challenges to adoption, economic policy incentives could focus on promoting these practices under certain climate conditions to support targeted, cost-effective N loss mitigation programs (e.g. reducing N rates or planting cover crops following dry years, or supporting enhanced efficiency fertilizers in areas with high EPE). The implementation of various incentives has proven to be a strong motivation for farmers to adopt sustainable practices for the benefit of either their farms, the environment, or both (Piñeiro *et al* 2020).

5. Conclusions

Reducing agricultural N losses in a changing climate will require better understanding of agronomic management, soil properties and weather interactions to develop effective mitigation strategies. Our results show that variation in predicted NO_3 is largely accounted for by hydrological factors, fertilizer N rate, and N removal, with several of these variables not previously considered in other synthesis studies. The magnitude of change in NO_3 leaching predictions for hydrological factors (up to 24 kg N ha^{-1}) relative to other management variables highlights the importance of intra- and inter-annual changes of precipitation regimes and brings further attention to current and future climate trends, particularly in areas susceptible to extreme weather variations. Under low and high N leaching scenarios, greater grain yields due to higher N rates translated into more predicted N leaching losses, whereas N removal due to higher yields showed a synergetic effect reducing losses. To minimize tradeoffs, our analysis emphasizes the need to increase crop yields while optimizing NUE and limiting the use of additional N fertilizer. Whilst implementation of known best N fertilizer management continues to be paramount, results from this study suggest the need for future policy discussions to develop economic incentives targeting practices that improve NUE in high-risk weather scenarios as the most effective opportunity for N leaching mitigation, while also supporting more advanced prediction analytics to enable proactive and adaptative measures from governments and the agricultural community in areas susceptible to extreme weather variation.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Conflict of interest

The authors declare no competing interests.

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