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Global insights into nitrogen losses and efficiency in rice, wheat, and maize cultivation

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ABSTRACT

Context: Nitrogen (N) use efficiency (NUE) and N losses in cereal systems are central to achieving the United Nations Sustainable Development Goals (SDGs) on food security and environmental sustainability. However, global variations in NUE across cereals, regions, and management conditions remain poorly quantified, especially in relation to the relative roles of synthetic and non-synthetic N inputs.

Objectives: This study aimed to (i) assess global differences in NUE and N losses among maize, rice, and wheat; (ii) compare efficiencies derived from synthetic versus total N inputs; (iii) evaluate regional and temporal patterns; and (iv) identify key drivers and management implications to enhance NUE and mitigate losses.

Methods: A global dataset was assembled to calculate NUE indicators including partial factor productivity of N (PFPN), agronomic efficiency of N (AEN), recovery efficiency of synthetic N (REN-S), recovery efficiency of total N (REN-T), and the fraction of N derived from non-synthetic sources (Ndfs). Synthetic and total N losses (Nloss-S and Nloss-T) were estimated. Trends were analyzed by crops, region, and time, and drivers of N loss were identified in relation to soil and management factors.

Results: Maize showed the highest NUE metrics (PFPN: 56.9 %; AEN: 21.0 %) and REN-S (45.6 %), while rice recorded the highest REN-T (63.6 %). On average, REN-S was 17 % lower than REN-T, indicating overestimation of N losses when only synthetic N is considered. Rice exhibited the largest non-synthetic N contribution (Ndfs: 57.1 %) and the strongest legacy effect of synthetic N. Africa achieved the highest PFPN and AEN, largely due to low synthetic N inputs, and also showed improvements in NUE over time. Non-synthetic N consistently contributed more to crop uptake than synthetic N across cereals. Key drivers of N loss included synthetic N application rates, soil texture, and pH, with distinct loss pathways evident across soil types.

Conclusions and Implications: Global differences in NUE and N losses highlight the importance of crop- and region-specific management. Accounting for both synthetic and non-synthetic N inputs provides a more accurate assessment of NUE and N losses, avoiding systematic overestimation. Strategies to improve NUE should focus on optimizing non-synthetic N use, leveraging legacy effects, and tailoring practices to soil and environmental conditions. Holistic approaches—including improved irrigation and precise N placement—are essential to enhance productivity while reducing environmental impacts. Future research should prioritize region-specific solutions and sustainable integration of non-synthetic N sources to support both food security and environmental goals.

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1. Introduction

Nitrogen (N) is indispensable for modern high-yield, intensive agricultural systems. As a vital component of plant proteins, it facilitates the conversion of solar radiation into carbohydrates, driving plant growth. Currently, the Haber-Bosch process supplies over 120 Tg of N per year as synthetic fertilizer, aiming to boost food production (IFA, 2016). Approximately 50 % of this is applied to three globally significant cereals—maize (16 %), rice (16 %), and wheat (18 %)—which provide most human food calories and proteins, either directly as grains or indirectly through livestock products (Poutanen et al., 2022).

Despite its critical role in global food production, many regions still suffer from N deficiencies, hindering efforts to achieve food and nutrition security (Alexandratos and Bruinsma, 2012; Ciceri and Allanore, 2019; Ladha et al., 2022). Rapid population growth is expected to increase the demand for cereals by at least 70 % by 2050. Coupled with shifting dietary preferences, this indicates a significant rise in synthetic N demand to feed a projected 10 billion population worldwide by mid-century (Rivas and Nonhebel, 2017; FAO, 2018). Meeting the anticipated global cereal demand of three billion tons by 2050, with only a 7 % increase in harvested area, would necessitate an approximately 65 % increase in synthetic fertilizer N application, assuming no improvement in crop N use efficiency (NUE). This would raise a global synthetic N use for these cereals from 51.8 Tg in 2010 to 85.4 Tg in 2050 (Ladha et al., 2020).

While synthetic N is pivotal for boosting food production, a significant portion escapes into the environment, causing air and water pollution and contributing to climate change (Phoenix et al., 2006; Galloway et al., 2008; Schlesinger, 2009; Vitousek et al., 2009). A 50-year (1961–2010) global N budgeting exercise for maize, rice, and wheat revealed that nearly 52 % of total N output (3190 Tg) was lost to the environment (Ladha et al., 2016). Of the 1594 Tg synthetic N applied over this period, 848 Tg entered the environment. Unlike non-reactive gaseous N_2, reactive forms of N, such as ammonia, nitrate, and nitrogen oxides, are released through volatilization, leaching, or emissions, causing numerous adverse effects on ecosystems and human health (Sutton et al., 2013; Battye et al., 2017). Experts warn that the sustainable planetary "boundary" for N has already been exceeded (Steffen et al., 2015), with anthropogenic N emissions rising faster than CO_2 emissions in recent decades (Battye et al., 2017).

Hence, N management has emerged as a critical challenge of the century, closely linked to several Sustainable Development Goals (SDGs) outlined by the UNDP in 2016 (Ladha et al., 2020). Urgent efforts are required on two key agroecological fronts: (a) reducing N losses per unit of crop yield in regions where excessive N use boosts no further productivity, and (b) improving N utilization where productivity can still be enhanced. Case studies have facilitated the geographical characterization of these contrasting scenarios (Ladha et al., 2020).

Research on synthetic N use and its efficacy in crop production has grown markedly in recent years. Two significant studies have published global datasets on NUE for major cereals cultivated across various agroclimatic regions (Ladha et al., 2005; Yu et al., 2022). The first compiled a dataset spanning 20 years (1980–2000), with 300–700 data points from 93 studies, focusing on agronomic efficiency (AEN), recovery efficiency (REN), and physiological efficiency (PEN) of N, reporting typical values of AEN ≈ 18–24 kg grain kg^{-1} N and REN ≈ 34–45 %, with 15 N tracer estimates ~7 % lower than difference-method recoveries. More recently, Yu et al. (2022) conducted a meta-analysis incorporating 3586 observations of REN from 261 studies worldwide, majority (60 %) of them from China. Yu et al. (2022) reported a global mean REN ≈ 39 %, with higher values for rice and wheat (~42 %) than maize (~36 %), and strong influences of fertilizer type/frequency, temperature, SOC, pH, and clay. Country-level analyses based on FAO data indicate stagnation or declines in NUE and rising N surplus, globally (Omara et al., 2019) and in India and China (Sapkota et al., 2023). However, as FAO aggregates, these are trend indicators rather than field-trial or plot-/system-level process measurements. The EU Nitrogen Expert Panel proposed a mass-balance NUE (output/input) to be interpreted jointly with N surplus and productivity, with a desirable 50–90 % range to avoid pollution at low values and soil N mining at very high values (EUNEP, 2015). Therefore, the indicator choice matters. Several other studies have since contributed new insights and introduced additional NUE indicators (Zhang et al., 2015; EUNEP, 2015; Quan et al., 2021). Recognizing the need for updating and expanding the global dataset, we aim to undertake a comprehensive analysis that co-reports agronomic (REN, AE, PEN, PFPN) and mass-balance (NUE, N surplus) indicators to generate deeper insights and relate plot-level responses to broader efficiency and surplus targets. In this study, we analyze various expressions of NUE, encompassing both synthetic and total N inputs, alongside grain and straw yields, including their N contents, as outputs. Leveraging close to five decades of published data, we analyze key NUE indicators to find broad patterns and connections at global, continental, and national scales. Furthermore, employing a nuanced approach, we scrutinize micro-level trends across specific crops, agroclimatic zones, and management practices, using two selected metrices to evaluate losses associated with synthetic N (Nloss-S) and total N (Nloss-T). Additionally, we employ machine learning techniques to identify complex, nonlinear relationships and interactions among environmental and management factors affecting N losses, patterns that traditional statistical methods may overlook.

2. Materials and methods

We analyzed ten NUE expressions, considering both synthetic and total N sources as inputs, and grain and straw yield (and their N contents) as outputs. A summary of these metrices is provided in Table 1. Broadly, there are (a) four N efficiency metrices: partial factor productivity of nitrogen (PFPN), calculated as the grain yield per unit of synthetic N applied; agronomic efficiency of nitrogen (AEN), defined as the yield increase due to synthetic N application per unit of N applied; recovery efficiency of synthetic nitrogen (REN-S), which measures the amount of synthetic N recovered in harvest (grain+straw) per unit of synthetic N applied; and recovery efficiency of total nitrogen (REN-T), expressing the N uptake in the harvest (grain+straw) per unit of total N input (synthetic plus non synthetic sources), (b) two metrices expressing fraction of crop N (i) derived from synthetic fertilizer (Ndff) representing the proportion of N in the harvest (grain+straw) originating from applied synthetic N, and (ii) fraction of crop N derived from non-synthetic (soil N) sources (Ndfs) as the remaining percentage of crop N uptake not attributed to synthetic N (i.e., 100-Ndff), (c) three N loss metrices (i) percentage of applied synthetic N not recovered in the harvested crop (Nloss-S), (ii) percentage of total N input that is not recovered in the harvested crop (Nloss-T), and (iii) Nsurplus - excess nitrogen remaining after accounting for crop uptake (N surplus), and (d) the legacy effect of synthetic N (Nleg) from previous seasons (the difference between REN-T and REN-S, representing the contribution of soil N to the N uptake by the crop). A conceptual framework for N losses and balances is presented in Fig. 1.

We employed the complete list of NUE expressions to compare global and continental averages of three cereal crops and to unveil trends and correlations. For micro trends, we employed two selected metrices to assess losses of synthetic (Nloss-S) and total N (Nloss-T) across crops, agroclimatic conditions, and management practices. To estimate REN-T and Nloss-T, we used crop N harvest in non-synthetic N plots as proxy of N inputs from sources other than synthetic N.

2.1. Mining and achieving primary data

Peer-reviewed publications from 1980 to 2019 focusing on maize, rice, and wheat crops were systematically identified through searches conducted on Google Scholar (https://scholar.google.com). The search utilized keywords such as 'maize,' 'rice,' 'wheat,' 'nitrogen use

Table 1
Crop N use efficiency and N loss metrices used in the present study.

Sl.	Indicator	Formula	Unit	Focus	Interpretation	Application	Limitations
1.	Partial factor productivity of synthetic N (PFPN)	$\frac{\text{Grain yield in plots with synthetic N input (GYs)}}{\text{Amount of synthetic N input (Ns)}} \times 100$	Per cent	Overall productivity of N	Borad assessment of NUE	Comparing productivity of N	Does not consider N recovery
2.	Agronomic efficiency of synthetic N (AEN)	$\frac{\text{Grain yield in plots with synthetic N input (GYs)} - \text{Grain yield in plots with non synthetic N input (GYns)}}{\text{Amount of synthetic N input (Ns)}} \times 100$	Per cent	Agronomic performance of N	Efficiency of synthetic N input for grain production	Optimizing N application	Does not account for N uptake
3.	Recovery efficiency of synthetic N (REN-S)	$\frac{\text{Crop N harvest (grain + straw) in plots with synthetic N input (HNs)} - \text{Crop N harvest (grain + straw) in plots with non synthetic N input (HNns)}}{\text{Amount of synthetic N input (Ns)}} \times 100$	Per cent	N uptake efficiency	Efficiency of synthetic N input for crop N production	Evaluating N management	Does not consider grain yield per se. Require crop N data
4.	Recovery efficiency of total N (REN-T)	$\frac{\text{Crop N harvest (grain + straw) in plots with synthetic N input (HNs)}}{\text{Amount of synthetic N input (Ns)} + \text{non synthetic N input (Nns)}} \times 100$	Per cent	N uptake efficiency	Efficiency of total N input (synthetic + non-synthetic) for crop N production	Evaluating N management	Does not consider yield per se Require crop N and non-synthetic N input data
5.	Fraction of crop N derived from synthetic N (Ndff)	$\frac{\text{Crop N harvest (grain + straw) in plots with synthetic N input (HNs)} - \text{Crop N harvest (grain + straw) in plots with non synthetic N input (HNns)}}{\text{Crop N harvest (grain + straw) in plots with synthetic N input (HNs)}} \times 100$	Per cent	Contribution of synthetic N in crop production	Proportion of N taken up by crop that originates from synthetic N	Optimizing synthetic N use and assessing soil N supply	Does not consider grain yield per se Require crop N data
6.	Fraction of crop N derived from non-synthetic (soil) N (Ndfs)	100 – (Ndff)	Per cent	Contribution of soil N in crop production	Proportion of N taken up by crop that originates from soil N pool	Assessing soil N supply	Does not consider grain yield per se Require crop N data
7.	N loss–Synthetic (Nloss-S)	100 – (REN-S)	Per cent	N loss	Synthetic N loss to the environment	Evaluating environmental impact and optimizing N use	Does not consider grain yield per se Require crop N data.
8.	N loss–Total (Nloss-T)	100 – (REN-T)	Per cent	N loss	Total N loss to the environment	Evaluating environmental impact and optimizing N use	Does not consider yield per se Require crop N and non-synthetic N input data
9.	N surplus (N_{sur})	[Amount of synthetic N input (Ns) + non-synthetic N input (Nns)] – [Crop N harvest (grain + straw) in plots with synthetic N input (HNns)]	kg ha^{-1}	N loss	Total N loss to the environment	Evaluating environmental impact and optimizing N use	Does not consider grain yield per se Require crop N and non-synthetic N input data.
10.	N legacy (Nleg)	(REN-T) – (REN-S)	Per cent	Legacy effect of synthetic N	Residual synthetic N in soil	Assessing effect of residual synthetic N	Does not differentiate synthetic and non-synthetic N

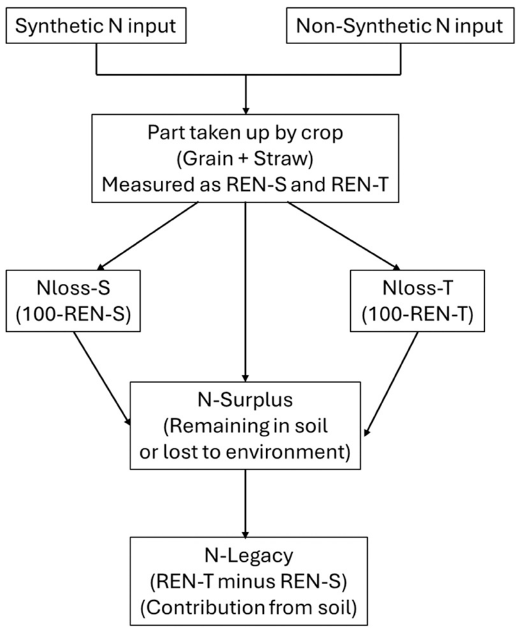

Fig. 1. Conceptual framework illustrating N flows and recovery efficiency metrices in cereals. Synthetic N and non-synthetic (soil) N inputs contribute to crop N uptake. The portion of synthetic N not recovered in harvested crop (grain + straw) is defined as synthetic N loss (Nloss-S = 100 – REN-S). The portion of total N inputs (synthetic + non-synthetic) not recovered is termed total N loss (Nloss-T = 100 – REN-T). The difference between total N input and crop N uptake reflects nitrogen surplus (N-surplus), representing potential environmental losses or soil retention. Nitrogen legacy (N-legacy) is defined as the difference between total N recovery (REN-T) and synthetic N recovery (REN-S), indicating the contribution of soil-N to crop uptake.

efficiency,' and ' N fertilizer' within the article abstracts. The selected nitrogen use efficiencies (NUEs) included: (a) partial factor productivity of N (PFPN), (b) agronomic efficiency of N (AEN), (c) recovery efficiency of N (REN). The N-difference method was employed throughout the search process for the archival and computation of NUEs. Conference proceedings and non-English language publications were excluded.

Studies were selected based on the following criteria:

1. Field experiments that included plots with or without synthetic N input and a synthetic fertilizer N rate treatment, with yields and crop N harvest or uptake by grain and straw measured at maturity.
2. Field experiments that incorporated at least one of the NUE expressions (see Table 1).
3. Papers that, despite not explicitly reporting any of the NUEs, provided data on grain and straw yields and their N uptake from plots with or without synthetic N input.
4. Short-term studies, spanning single or multiple seasons, were included, while long-term experimental data were excluded.

For each observation (biomass and N uptake by grain and straw), we recorded the source, amount, and frequency of synthetic N application. When studies reported NUE expressions, those were used. The location of each observation (region and country), site characteristics (soil texture, pH, organic C, available and total soil N, annual rainfall, and annual temperature), and relevant soil and crop management data were recorded. Missing data points were left blank and were not included in analyses requiring those specific variables. Geographical coordinates (latitude and longitude) of study locations were either obtained directly from the papers or extracted using Google Maps. These coordinates are visually represented on a global map (Fig. 2).

Data presented in the form of figures (not tables) in the published literature were retrieved using WebPlotDigitizer ver. 3.12 (Rohatgi, 2016). A comprehensive total of 210, 299, and 353 studies yielded 3068, 4409, and 6464 data points for maize, rice, and wheat crops, respectively.

2.2. Data compilation and processing

Climatic zones (tropical, arid, warm temperate, continental, and polar) were identified using the R package "kgc," which is based on the Köppen-Geiger climatic classification system (Rubel et al., 2017). The aridity index (the ratio of total precipitation to potential evapotranspiration) for each location was extracted from the "Global Aridity Index and Potential Evapotranspiration Database - Version 3" (Global-AI_PET_v3). This database provides high-resolution (30 arc-seconds) global hydro-climatic data, averaged monthly and yearly from 1970 to 2000, based on the FAO Penman-Monteith Reference Evapotranspiration (ET_0) equation (Zomer et al., 2022).

In cases where soil textural classes were not explicitly mentioned, they were determined using the texture triangle with the NRCS USDA Texture Calculator (www.nrcs.usda.gov). The textural classes were then grouped into three categories: clayey (including sandy clay, silty clay,

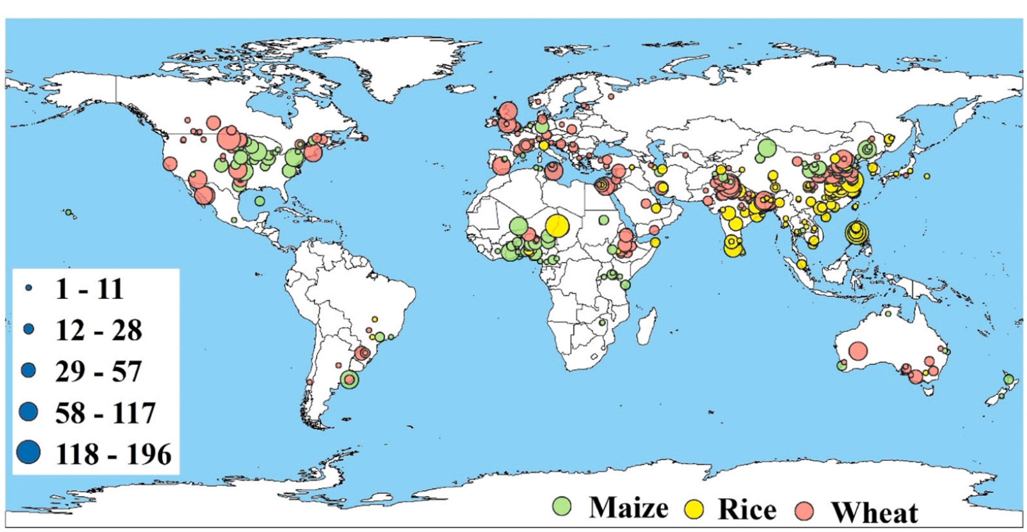

Fig. 2. Map showing locations of studies used in the analysis. Circle size represents number of observations in each location.

and clay), loamy (including silty clay loam, clay loam, silt, silty loam, and loam), and sandy (including sandy loam, sandy clay loam, loamy sand, and sand). Organic matter values were converted to organic C using a conversion factor of 1.724.

For rice crops, additional data were compiled for various parameters including season (dry and wet), crop establishment methods (transplanting and direct-seeding), ecosystem type (irrigated and rainfed), irrigation water management techniques (such as flooding and other water-saving methods), and fertilizer application methods (broadcast and other techniques such as band placement, soil incorporation, and broadcast with deep placement).

For maize and wheat crops, ecosystem type (irrigated and rainfed), fertilizer application methods (broadcast and localized application such as band and deep placement), tillage practices (conventional and reduced/zero tillage), and residue management (retained/incorporated or removed) were considered as categorical agronomy variables.

2.3. Machine learning model training and evaluation

In this study, various machine learning models were trained and evaluated to predict N loss (Nloss-S and Nloss-T) for maize, rice, and wheat crops (see Supplementary Information for details). The models used included elastic net (ELNET), support vector machine regression (SVMR), Gaussian process regression (GPR), multivariate adaptive regression spline (MARS), partial least square regression (PLSR), random forest regression (RFR), k-nearest neighbors (KNN), extreme gradient boosting (XGB), and Cubist. These models utilized independent variables such as soil texture (sand and clay), pH, soil organic C (SOC), total soil N, aridity index, synthetic N rate, and the number of N applications (splits). The dataset was split into training (70 %) and testing (30 %) sets using 'createDataPartition()' function from the caret package, with hyperparameters optimized using five-fold cross-validation and three repetitions (e.g., Gholamy et al., 2018; Sivakumar et al., 2024). Since the number of predictors was relatively small, and correlation analysis showed that no pair of variables exhibited an absolute correlation > 0.7 (a common threshold for multicollinearity; Dormann et al., 2013), all selected variables were retained for model development. We performed hyperparameter tuning using a grid search approach implemented through the caret package in R, with a 'tuneLength' of 10 (Supplementary Table S1). This setting explores a predefined range of values for each model's hyperparameters using the package's default search grid. The optimization was based on minimizing RMSE through repeated cross-validation (Supplementary Table S2).

The models were evaluated using several performance metrics, including the coefficient of determination (R^2), d-index, mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE), root mean square error (RMSE), and the ratio of performance to inter-quartile distance (RPIQ). Due to the complexity of selecting the best model based on multiple criteria, the standardized ranking performance index (sRPI) was employed (Aschonitis et al., 2019). This index simplifies comparison by translating various statistical criteria into a standardized range, with scores ranging from zero to one where "1" indicates the best-performing model.

Explainable Artificial Intelligence (XAI) techniques were also applied to interpret the models. Accumulated Local Effects (ALE) was used to assess the global impact of individual features on model predictions which is not impacted by feature intercorrelations (Molnar et al., 2020). SHAP (SHapley Additive exPlanations) was utilized to provide global explanations by analyzing the contributions of individual features based on cooperative game theory (Li et al., 2024). These tools helped in understanding the influence of different features on model predictions, enhancing the interpretability of complex machine learning models.

2.4. Data analysis

We selected four NUE metrices (PFPN, AEN, REN-S, and REN-T), on a global scale and across various continents, countries, soil textural classes, and agronomic management factors (categorical variables) for maize, rice, and wheat. The changes in crop-specific NUEs over time (1980–2019) were explored for different countries and continents using non-parametric Sen's slope as the data violates the assumptions of linear regressions (Sen, 1968). The temporal analysis was done to examine whether NUE metrices, which reflect N losses, have changed over the past four decades at global, continental, and national scales for these cereal crops. Additionally, crop-specific relationships were developed between crop N harvest in synthetic N plots versus non-synthetic N plots, as well as between N legacy and crop N harvest in non-synthetic N plots.

All our analyses were done in R software version 4.3.3 (R Core Team, 2024) and the figures were plotted by 'ggplot2' R package (Wickham, 2016).

3. Results

3.1. Global variances in crop NUE and N losses

In addition to the detailed summary provided in Table 2, Fig. 3a provides a visual comparison of NUE metrices across maize, rice, and wheat. Globally, the three cereals displayed notable differences in PFPN, ranging from 42.6 % to 56.9 %, and AEN, ranging from 15.1 % to 21.0 %, with maize exhibiting the highest values, followed by rice and wheat. Among these cereals, maize recorded the highest REN-S at 45.6 % (CI 44.5 %-46.8 %), while there was no statistical difference between rice and wheat, both standing at 43 %. However, REN-T was the highest in rice (63.6 %; CI 62.8 %-64.4 %), followed by maize, and lowest in wheat (57.4 %; CI 56.7 %-58.1 %).

It's noteworthy that, on average, REN-S was 17 % lower than that of REN-T. In other words, losses of synthetic N to the environment (Nloss-S) were 17 % higher than when calculated for total N (Nloss-T). The N surplus was highest in maize (90.2 kg ha^{-1} CI 85.6–94.9 kg ha^{-1}), which was 20 % and 14 % lower in rice and wheat, respectively (Table 2).

Continent-wise cereal averages revealed the highest PFPN (55.5 %; CI 53.5 %-57.4 %) and AEN (22.7 %; CI 21.7 %-23.7 %) in Africa followed by America + Europe (PFPN 49.8 %; CI 48.0 %- 51.6 %, AEN 17.3 % CI 16.6 %-18.0 %) and Asia (PFPN 45.7 %; CI 44.7 %-46.8 %, AEN 16.2 %; CI 15.8 %-16.6 %). However, REN-S, REN-T, Nloss-S, Nloss-T did not vary significantly (Fig. 4). A comparison between China and India illustrated similar PFPN but lower AEN in the former (13.7 %; CI 13.4 %-14.0 %) than the later (18.7 %; CI 18.3 %-19.2 %). Synthetic N losses consistently exceeded total N losses (54.4–56.0 % compared to 37.8–39.5 %), and although continental averages did not differ significantly, India exhibited lower losses than China for both synthetic and total N. Overall, a combination of environmental, technological, infrastructural, policy, and management factors likely explains the differences in cereal production in different continents, but much lower rates of synthetic N would also result in higher PFPN and AEN in Africa compared to America and Asia (Ladha et al., 2020; Zhang et al., 2015; Sapkota et al., 2023).

The fraction of crop N derived from non-synthetic N (Ndfs, referred to as soil N) consistently outweighed the fraction derived from synthetic N (Ndff), with Ndfs ranging from 50.5 % to 57.1 % across all three cereals, while Ndff ranged from 42.9 % to 49.5 % (Table 2, Fig. 3b). Rice had the highest Ndfs of 57.1 % and wheat the lowest of 50.5 %. Maize exhibited wide variations in Ndff and Ndfs and were similar to rice. Among the three continents, Africa had the highest Ndff but no difference between China and India. The Ndfs were similar in Africa and Asia but it was higher in China than India.

The legacy effect, which is the difference between REN-T and REN-S indicating carryover of synthetic N from previous seasons, rice displayed

Table 2
Global averages[1] of partial factor productivity (PFPN) and agronomic efficiency (AEN) of synthetic N, recovery efficiency of synthetic (REN-S) and total (REN-T) N, fraction of crop N derived from synthetic (Ndff) and non-synthetic (soil) N (Ndfs), loss of synthetic (Nloss-S) and total (Nloss-T) N, N surplus (Nsur) and N legacy (Nleg) in maize, rice, and wheat crops [all values in % except Nsur, which is in kg ha^{-1}; CI and N are confidence intervals and number of data points, respectively].

Crop	PFPN		AEN		REN-S		REN-T		Ndff	
	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Mean	CI
Maize	56.9 A	55.6–58.2	21.0 A	20.4–21.6	45.6 A	44.5–46.8	60.7 B	59.5–62.0	45.0 B	43.7–46.3
Rice	53.9 B	52.7–54.5	18.0 B	17.6–18.3	42.8 B	42.1–43.5	63.6 A	62.8–64.4	42.9 B	42.0–43.7
Wheat	42.6 C	41.9–43.2	15.1 C	14.8–15.3	43.0 B	42.2–43.8	57.4 C	56.7–58.1	49.5 A	48.5–50.4

Crop	Ndfs		Nloss-S		Nloss-T		Nsur		Nleg	
	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Mean	CI
Maize	54.9 A	53.7–56.4	54.4 B	53.3–55.6	39.3 B	38.1–40.5	90.2 A	85.6–94.9	18.5 B	17.8–19.2
Rice	57.1 A	56.3–57.9	57.1 A	56.5–57.9	36.4 C	35.6–37.2	72.3 C	69.8–74.6	21.2 A	20.6–21.7
Wheat	50.5 B	49.6–51.5	57.0 A	56.3–57.8	42.6 A	41.9–43.3	77.8 B	74.8–80.7	17.8 B	17.1–18.4

1 Refer to Table 1 for definition of metrices

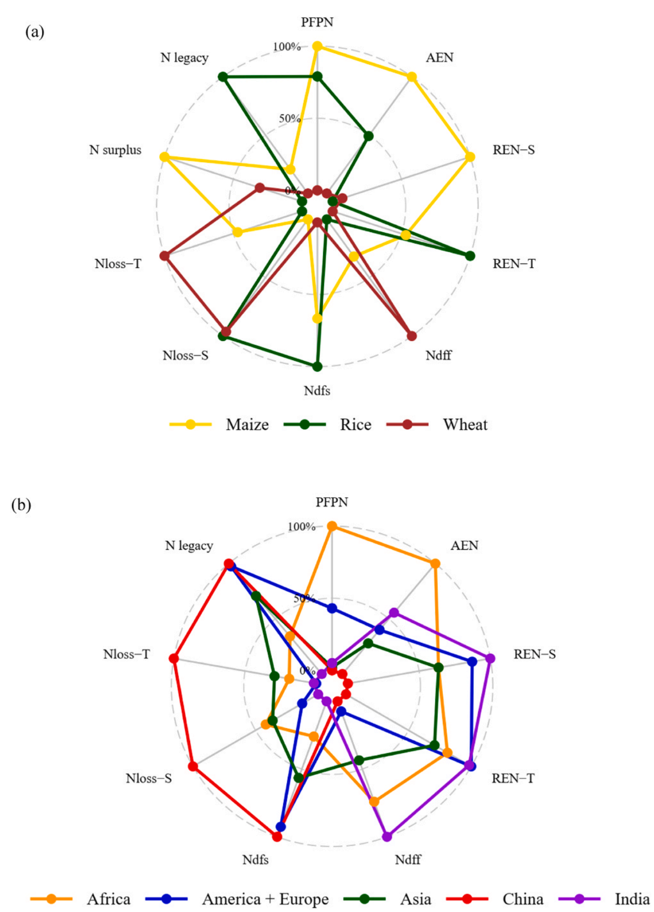

Fig. 3. Spider chart comparing N use efficiency and N loss metrics across (a) cereals and (b) regions. Each axis represents a metric, and lines represent the mean percentile values for maize, rice, and wheat.

the highest at 21.2 %, followed by maize at 18.5 %, and wheat at 17.8 % (Table 1). Among the continents, Africa had the lowest legacy effect at 14.9 %, while America+Europe had the highest at 17.5 % (Fig. 4).

3.2. Time trends and relationships among various NUE expressions

Although all the NUE metrices reported from 1980 to 2019 exhibited considerable variations, none of them showed strong trends over time (see Supplementary Table S3). The time trends of maize had negative trends in three NUE metrices except PFPN (no trend), rice showed positive trends in AEN and REN-T ($p < 0.01$) but negative trend in REN-S ($p = 0.02$), and wheat had a decreasing trend in PFPN and increasing trends in AEN and REN-T ($p < 0.01$) and no trend in REN-S. Likewise, across continents/countries, the trends remained stable except Africa where all the four NUE metrices had significant increase with time ($p < 0.01$) (data not shown).

The NUE values varied widely, ranging from negative to positive, and showed consistent patterns across the years for all three cereals. Notably, up to 6 % of the values surpassed 100 % efficiency for PFPN (6 %), AEN (negligible), REN-S (0.5 %), and REN-T (1.4 %). These four efficiency metrices displayed similar behaviors in their relationships with each other and other metrices, indicating that any one of them could effectively represent the overall efficiency of an agroecosystem. PFPN, AEN, REN-S, and REN-T were negatively correlated with N input and N loss metrices (Nloss-S and Nloss-T) (Supplementary Figs. S1 & S2). This suggests that, without judicious management of N, excessive N application reduces efficiency by increasing losses.

Crop N harvest in synthetic N plots exhibited a positive ($p < 0.001$) correlation with crop N harvest in plots with no synthetic N (Fig. 5), indicating the importance of soil N and possibly an added N interaction. Increased synthetic N stimulates soil N mineralization and likely replenishment from biological nitrogen fixation (Ladha et al., 2011, 2022).

The legacy effect of synthetic N was positively correlated ($p < 0.001$) with (a) crop N harvest in plots with no synthetic N, (b) Ndfs, and (c) synthetic N loss (Fig. 6). This suggests that the past application of synthetic N leaves a residual impact on subsequent crop N uptake, as reflected by soil N supply measured from plots where no additional synthetic N was applied. The positive relationship between synthetic N legacy and synthetic N loss implies that N losses are overestimated in REN-S calculations. There were negative values of N legacy (6 % in maize, 4 % in rice and 12 % in wheat) which typically indicates that there is either mining of soil N or the soil is not retaining N effectively.

3.3. Comparative performance of machine learning models for predicting N loss in maize, rice, and wheat

The optimum hyperparameters identified through cross validation are presented in Supplementary Table S2. The performance of different ML models for predicting Nloss-S and Nloss-T varied by crop and loss types (Supplementary Tables S4 & S5). Overall, tree-based and rule-based ensemble models, particularly RFR and Cubist consistently emerged as high-performance models, while linear models (PLSR and ELNET) showed poor prediction, reflecting the non-linear nature of the relationships in the dataset.

For maize, RFR showed the highest accuracy for predicting Nloss-S, achieving the best performance across metrices ($R^2 = 0.648$, RMSE = 12.35 %, RPQ = 2.21), closely followed by XGB and Cubist. In contrast, SVMR performed the best for Nloss-T in maize ($R^2 = 0.736$, d-index = 0.921, and NSE = 0.667), indicating that kernel-based methods may

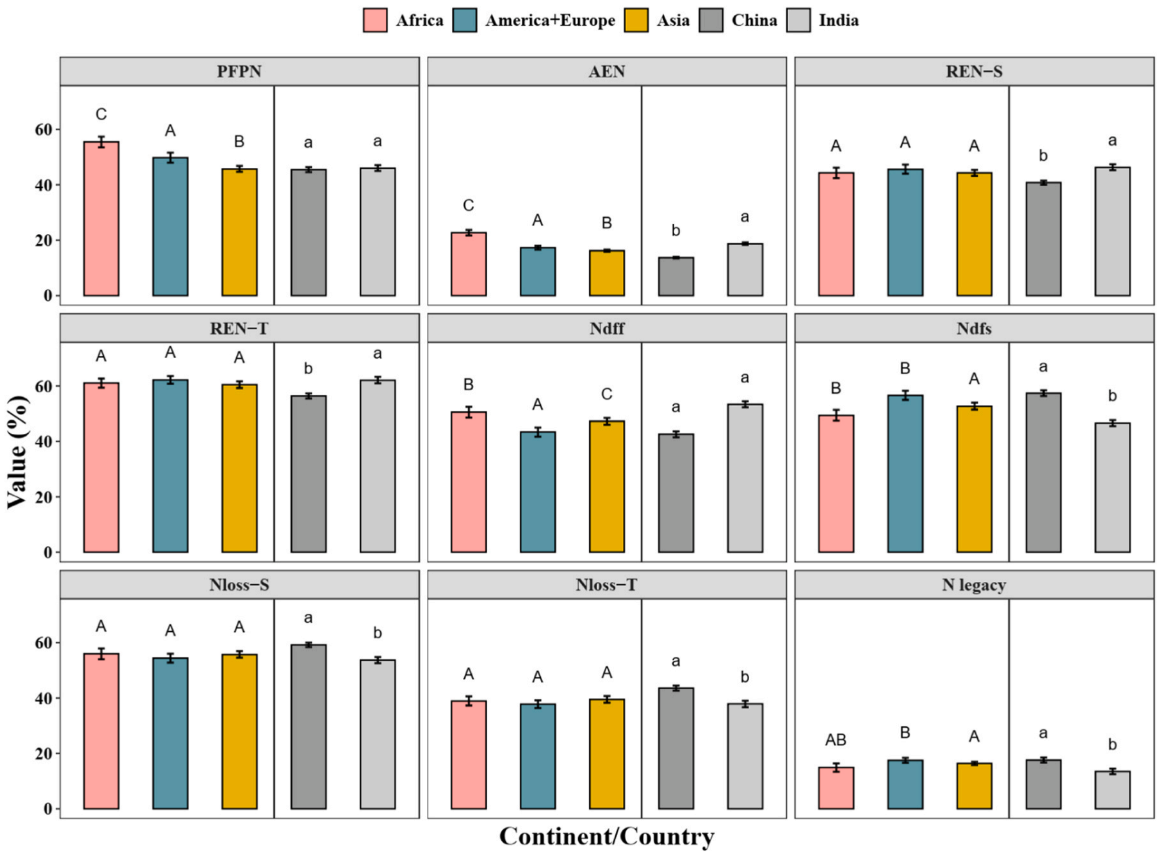

Fig. 4. Cereal averages of N use efficiency and N loss metrices across continents (Africa, America + Europe and Asia), and countries (China and India). Error bars are confidence intervals; Values are similar with similar letters.

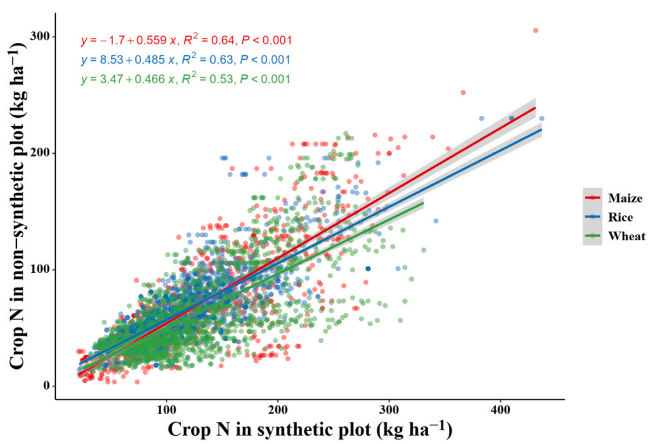

Fig. 5. Relationship between crop N harvest in synthetic N fertilizer plots vs crop N harvest in non-synthetic N plots in maize, rice and wheat.

better capture the broader N dynamics reflected in total loss.

In rice, RFR and Cubist delivered comparable and reliable results for Nloss-S with $R^2 = 0.611$, NSE ~ 0.61, RMSE ~ 11 %, and RPIQ ~ 1.94, while Cubist slightly outperformed other models for Noss-T ($R^2 = 0.716$, d-index = 0.916, NSE = 0.710). SVMR also demonstrated strong predictive performance suggesting complementarity between rule-based and kernel-based models.

In wheat, all models showed limited ability to predict Nloss-S (R^2 and NSE < 0.5, RMSE > 15 %), suggesting unexplained variability or unmeasured factors in the dataset. However, Nloss-T in wheat was predicted with greater accuracy, with Cubist achieving the best overall performance (sRPI = 1). RFR and other nonlinear models like XGB, GPR, SVMR, and MARS also performed well, highlighting their capacity for modeling more integrated N loss, taking account of sources other than synthetic N.

Across all crops, predictions of Nloss-T were more accurate than Nloss-S, possibly due to more cumulative and integrated nature of total loss. In contrast to the strong performance of ensemble-based and kernel models, linear models such as PLSR and ELNET underperformed consistently across all crops and N loss types, highlighting the inability of linear models to capture the complex, nonlinear interactions between soil, climate, crop, and management variables in the global dataset. These models yielded R^2 and NSE values below 0.5 in most cases, along with higher RMSE and lower RPIQ values.

Based on these results, models were ranked using standardized Ranking Performance Index (sRPI) values for both Nloss-S and Nloss-T. Observed vs predicted plots for the best performing models are presented in Fig. 7, and detailed performance metrices and optimal hyperparameters are presented in Supplementary Tables S3 to S5. Subsequently, the best performing models were used for explainable AI (XAI) analysis.

3.4. *Key determinants of N loss in maize, rice, and wheat: role of soil properties and application strategies*

Synthetic N loss (Nloss-S) in maize was primarily driven by N application rate, with minimal losses at around 150 kg N ha^{-1} and increasing losses beyond this threhshold (Fig. 8; Supplementary Figs. S3a). Soil N and sand content were also influential; N loss increased with soil N up to ~1 g kg^{-1} before plateauing. Sand content reduced losses up to ~37 % but increased thereafter. Lower organic C (<0.75 %) and increase in soil pH intensified N loss in maize, whereas increasing N

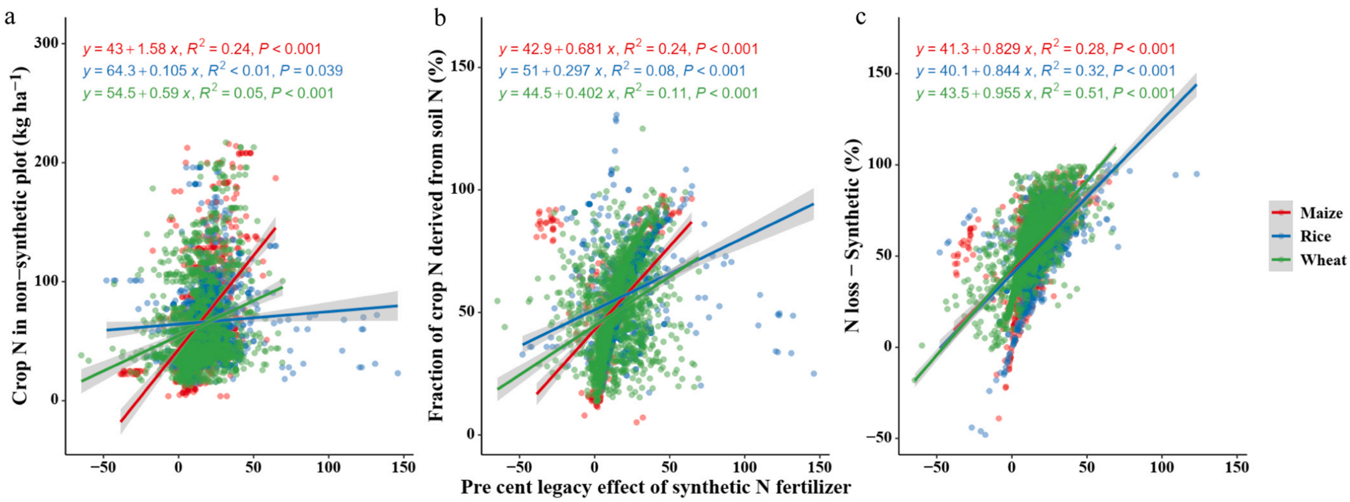

Fig. 6. Linear regression of the legacy effect as a function of (a) synthetic N fertilizer and crop N harvest from non-synthetic fertilizer N plots, (b) the fraction of crop N derived from soil N, and (c) synthetic N loss in maize, rice, and wheat.

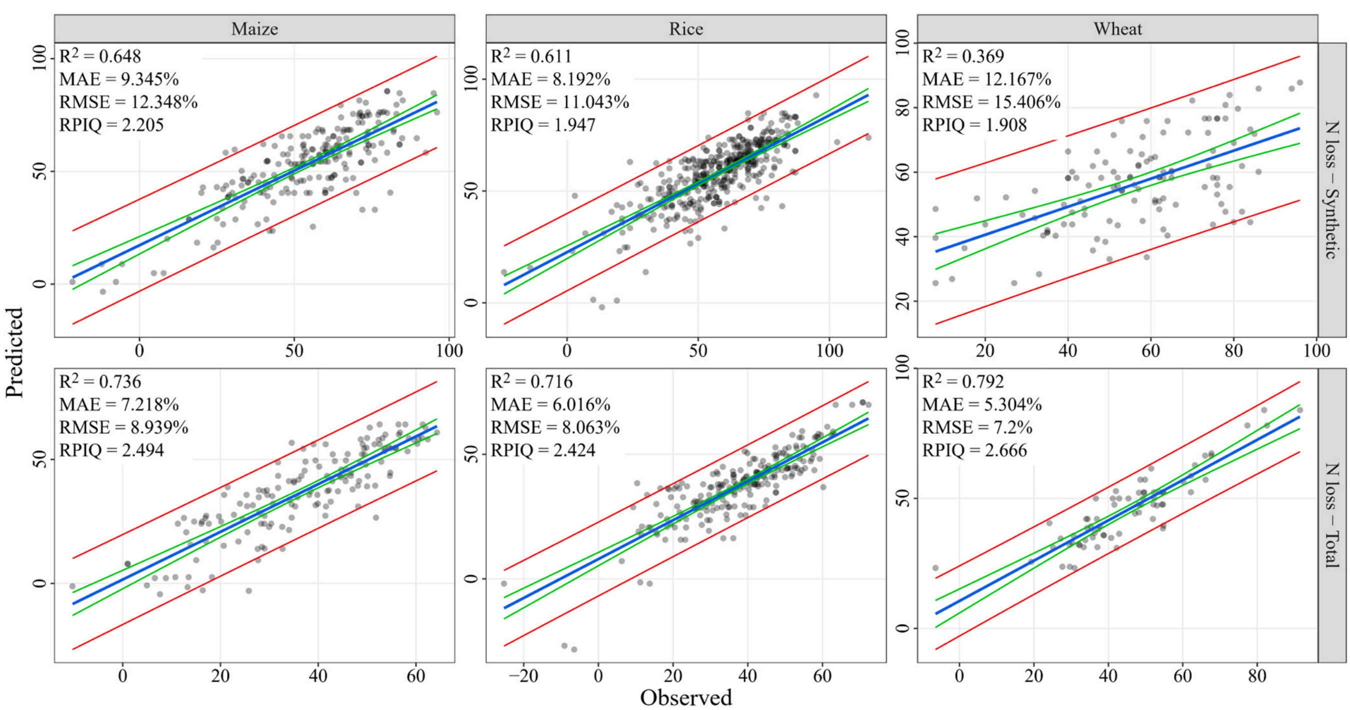

Fig. 7. Observed vs predicted plots of synthetic N loss (N loss-S) and total N loss (N loss-T) for the best performing models. R^2 = coefficient of determination, MAE = mean absolute error, RMSE = root mean square error, RPIQ = ratio of performance to inter-quartile distance.

applications (splits) and clay content (20–30 %) mitigated it. Nloss-S also increased with a higher aridity index in maize.

In rice, Nloss-S was most affected by sand content, N rate, and soil pH (Fig. 8). Losses were lowest, below 20 % sand and increased until stabilizing after 35 % (Supplementary Fig. S3b). Application rate near 100 kg N ha^{-1} minimized losses, which increased afterwards. Soil pH around pH 6.0 minimized Nloss-S, with higher losses at higher or lower pH levels. Clay, organic C, total soil N and aridity had smaller but consistent effects over their range of values, while three or more splits appeared to reduce Nloss-S.

For wheat, sand had the highest impact on Nloss-S, with sharp increases beyond 25 % (Fig. 8, Supplementary Fig. S3c). Higher clay (>25 %) also elevated losses. Aridity index below 0.4 reduced Nloss-S, while organic C showed mixed effects, reducing loss only at a higher (>2 %) level. Synthetic N rate, pH, and N splits had moderate effects. Losses enhanced above 150 kg ha^{-1} and in alkaline soils (pH > 8.0), while more frequent N applications decreased Nloss-S in wheat.

Regarding total N loss (Nloss-T), synthetic N rate dominated in rice, whereas sand was the most influential in maize and wheat (Fig. 8). In maize and wheat, Nloss-T decreased with sand up to 45 % and 35 %, respectively, but increased beyond these points (Supplementary Figs. S4a and S4c). Application rate showed minimal losses near 140–150 kg ha^{-1} (maize and wheat), and 110–120 kg ha^{-1} (rice), increasing at higher rates. Soil pH affected Nloss-T in rice non-linearly, highest loss at pH 5.0, decreasing near pH 7.8, and again rising beyond that (Supplementary Fig. S4b). Clay content showed mitigating impact, up to 25 %, in wheat.

Aridity was the third most important factor in maize and rice, fourth

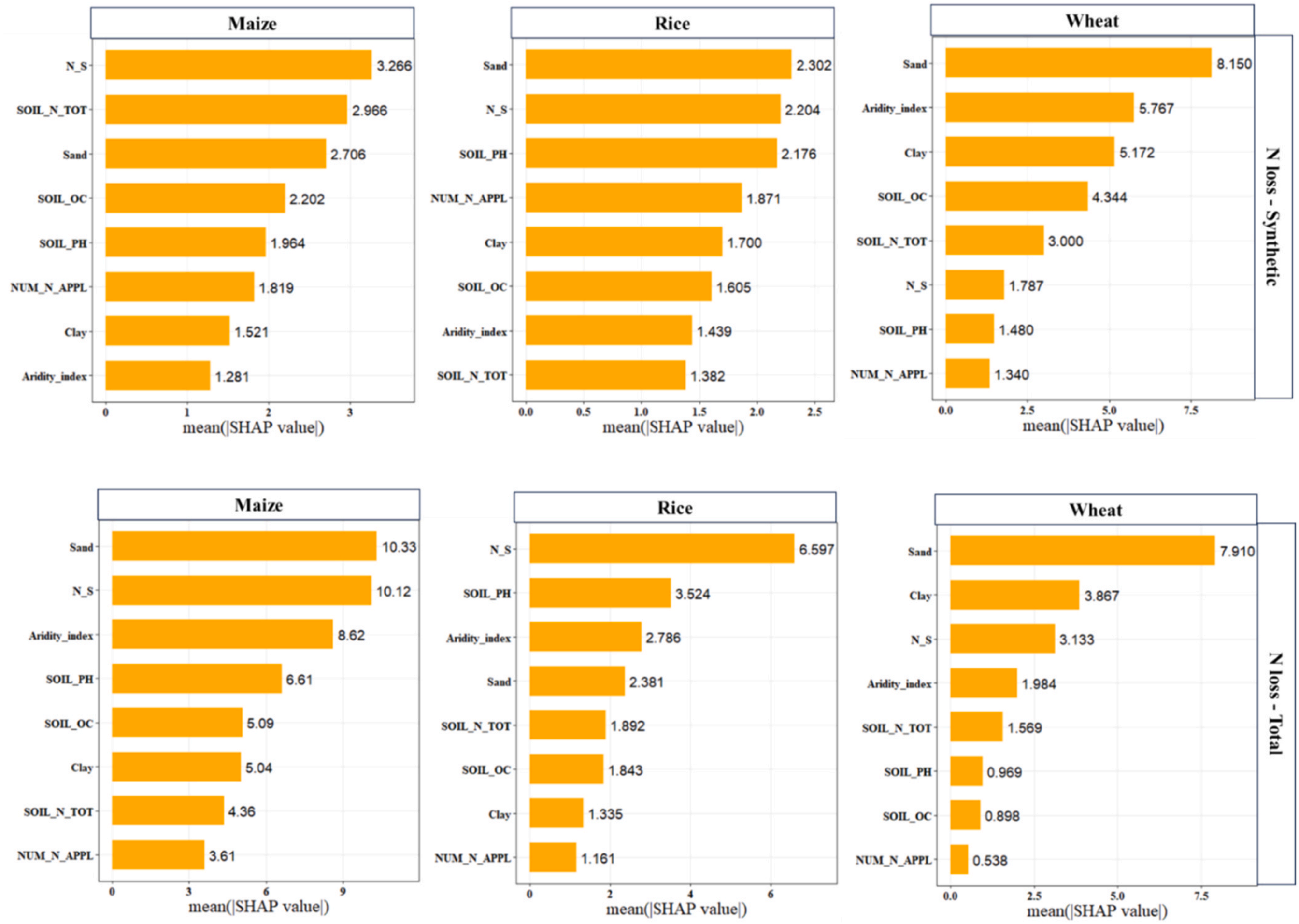

Fig. 8. Variable importance plots of SHAP values for synthetic N loss (N loss-S) and total N loss (N loss-T) using the best performing models in the three major cereals. Variables include: Sand, sand content in soil (%); N_S, synthetic fertilizer input (kg ha^{-1}); Aridity_index, ratio of precipitation to potential evapotranspiration; SOIL_PH, soil pH; SOIL_OC, soil organic carbon content (%); Clay, clay content in soil (%); SOIL_N_TOT, total soil nitrogen content (%); NUM_N_APPL, number of nitrogen application splits.

in wheat, generally promoting Nloss-T above certain threshold (0.45 in maize, 0.35 in wheat, 1.2 in rice). Soil organic C had mixed effects – negligible or positive in maize and rice up to 1.5–2.0 %, but consistently reduced Nloss-T in wheat. Soil N content limited Nloss-T until certain levels (~2 g kg^{-1} in maize and ~1 g kg^{-1} in rice and wheat). N application splits has the least impact on Nloss-T across all crops. Increasing splits lowered losses in maize (after two splits) and wheat (notably from one or two splits), while rice showed a complex pattern.

3.5. *Impact of management practices on N losses*

The impact of various management practices on Nloss-S and Nloss-T showed highly variable results across three cereals (Supplementary Table S6). Among the practices evaluated, improved irrigation consistently demonstrated a more significant reduction in N losses compared to other practices. Specifically, improved irrigation reduced both Nloss-S and Nloss-T by 1–6 % across all cases, except for Nloss-T in wheat, where the reduction was not statistically significant.

The strategic placement of synthetic fertilizer N also proved effective in reducing N losses, though the degree of effectiveness varied by crop. In rice, this practice led to the most substantial reductions, with Nloss-S and Nloss-T decreasing by 28 % and 38 %, respectively. For maize and wheat, the reduction was observed primarily in Nloss-T @16 %.

Interestingly, the number of synthetic N splits did not exhibit significant or consistent trends in either Nloss-S or Nloss-T across all three cereals, as shown in Supplementary Fig. S5. This outcome is contrary to expectations, possibly due to the lack of uniformly distributed data of N splits across varying N application rates. Tillage and residue management also showed inconsistent effects on N loss across sites, likely due to variability in management intensity and reporting. Therefore, it was excluded from reporting.

3.6. *Impact of soil texture on N losses*

Compared to clayey soil, sandy soil exhibited the highest N losses in maize and wheat. Specifically, in maize, N losses were 1.1–3.4 % higher in sandy soil, while in wheat, the losses were most pronounced in Nloss-T, reaching 4.4 % (Supplementary Table S7). Conversely, in rice, clayey soil experienced 5–7 % higher N losses than sandy soil.

4. Discussion

4.1. *Reframing nitrogen use efficiency*

Nitrogen use efficiency (NUE) serves as a comprehensive metric for assessing both N use and losses, integrating components of N budgeting, both inputs and outputs, and is often represented as a ratio (Ladha et al., 2005, 2022). While synthetic N fertilizers are a major input, other sources such as soil organic matter, atmospheric deposition, and biological nitrogen fixation, collectively referred to as the soil N pool, are equally significant (Ladha et al., 2016; Yan et al., 2020).

Nitrogen outputs include the harvested products (grain and straw, either as biomass or N content), environmental losses (via leaching, volatilization, denitrification), and a portion that remains in the soil. These components form the basis for various NUE metrices, often selected based on ease of measurement and data availability. Synthetic N, although expensive and with environmental consequences, is commonly used in calculating NUE due to its traceability. However, with growing recognition of the importance of soil N in crop nutrition, there is an increasing emphasis on integrating soil N dynamics into NUE metrics (Ladha et al., 2016; EUNEP, 2015; Yan et al., 2020; Congreves et al., 2021; Tamagno et al., 2024).

Although synthetic N input data are readily accessible, quantifying non-synthetic sources (like BNF, organics) remains a challenge (Ladha et al., 2022). Likewise, NUE output is often calculated using grain yield alone, assuming crop residues are uniformly returned to the soil. However, global assessments indicate that significant portions of crop residues are removed for animal feed, fuel, or burned (Smerald et al., 2023). We argue that a more comprehensive NUE should include total aboveground biomass to better capture true crop N recovery.

4.2. Comparing NUE metrices across crops and NUE time trends

Drawing from 40 years of global data on N usage in maize, rice, and wheat, we evaluated various NUE metrices. Our findings reveal that the four widely used NUE metrices (PFPN, AEN, REN-S, REN-T) are closely interrelated. This suggests that any one of them can reasonably represent short-term N responses in a crop and cropping system. This is significant given the high cost of measurements and often impractical data demands of many NUE metrices. Among non-synthetic N sources, inputs from biological N fixation and deposition at the plot or system level are not readily accessible. Often, estimates are used from published literature (Quan et al., 2021). We propose that for routine comparisons, PFPN serves the purpose well since the required data are readily available.

Globally, the average synthetic N recovery efficiency (REN-S) for the three cereals was 44.0 %, aligning closely with previously reported figures (Yu et al., 2022; Quan et al., 2021; Yan et al., 2020), except for a roughly 10 % higher value reported by Ladha et al. (2005). Ladha et al. (2005) used a smaller dataset primarily from the USA pre-2000, likely overestimated REN-S due to limited geographic scope. This reaffirms that REN-S and corresponding synthetic N loss (Nloss-S) have remained consistently around 50 % each. When considering metrics such as REN-T and Nloss-T, which incorporate total N inputs (both synthetic and non-synthetic), they demonstrate higher NUE (60.6 %) and lower losses (39.4 %). Given the significance of other N sources, REN-T and Nloss-T are more pertinent for assessing the environmental impact of N. Our global average REN-T closely aligns with the estimate of 62 % reported by Quan et al. (2021) based on FAO global data (Zhang et al., 2015).

Additionally, our long-term analysis (1980-present) indicates that global NUE (REN-S) trends in cereals have slow decline or remain relatively stable over time. In maize, three of four NUE metrices declined, except PFPN (no change). Rice and wheat showed improvements in AEN and REN-T ($p < 0.01$), with either stable or declining trends for PFPN and REN-S. Likewise, across continents/countries, NUE remained stable except Africa where all the four NUE indicators showed significant increases with time ($p < 0.01$). Earlier Yu et al. (2022) reported rising REN values in maize and rice but no change in wheat ($p = 0.9$, $n = 885$). In case of Yu et al. (2022) there were several lower values in rice between 1980 and 1990 which might have increased the REN. Importantly, earlier conclusions indicating a sharp global decline in NUE starting 1960s often relied on macro-scale FAO data rather than experimental data (Ladha et al., 2005; Sapkota et al., 2023; Tilman et al., 2002). However, even in these estimates (for example, in cases of China and India), although the NUE showed a sharp decline from 1960 to 1980, the trend appears to be stable thereafter (Sapkota et al., 2023). A possible reason for the sharp decline in 1960s could most likely be much lower doses of synthetic N application.

4.3. Understanding the legacy effect and unaccounted N sources

Our global calculations highlight a significant short-term legacy effect of N from previous seasons, averaging 19.2 % across cereals, peaking at 21.2 % in rice. This is slightly lower than the 21 % legacy N reported in China by Quan et al. (2021). Based on data from non-synthetic plots, this translates to ~66 kg N ha^{-1} (data not shown). A lower REN-S in rice indicates reduced immediate recovey of applied synthetic N under flooded conditions, consistent with higher gaseous losses via volatilization and temporary retention of N in reduced, NH_4^+-dominated soils (De Datta and Buresh, 1989). In contrast, the higher REN-T suggests that rice systems are more effective utilizing residual N over time and/or deriving N from non-synthetic sources. Paddy soils are known to favor BNF and improve N retention (Ladha et al., 1996) Together, these factors explain why rice systems tend to exhibit a higher N legacy compared to maize and wheat (Ladha et al., 2022). We also observed a positive correlation between legacy N and crop N harvest in plots receiving no synthetic N. This suggests that prior synthetic N applications leave a measurable residual impact on subsequent crop N recovery, as reflected in soil N supply where no synthetic N was applied. Since no synthetic N plots were established only short-term to estimate NUE, a carryover effect of N from the previous season cannot be discounted. This observation aligns well with ^{15}N tracer studies showing that 6.5 % of synthetic N can be recovered by subsequent crops over five growing seasons (Krupnik et al., 2004). By explicitly linking hydrology, N speciation, and recovery metrics, these results directly address why rice exhibits stronger N legacy than upland cereals, offering a mechanistic explanation grounded in prior evidence (De Datta and Buresh, 1989; Ladha et al., 1996, 2022).

Collectively, these findings suggest that the N loss and associated environmental impact might actually be lower when the legacy effect of N is considered. However, caution is warranted. Other unmeasured inputs such as BNF and deposition (Ladha et al., 2022), or a potential confounding effect of added N interaction or priming effects (Jenkinson et al., 1985), could also contribute to apparent N legacy. The added N interaction refers to the immediate effects of synthetic N addition on organic matter mineralization, resulting in greater short-term N availability. In contrast, N legacy effects reflect a relatively longer-term impact of past N management on soil fertility and ecosystem dynamics (Vonk et al., 2022; Zhao et al., 2024). Both processes complicate the attribution of current N uptake to specific sources, highlighting the need for more comprehensive tracking of N cycling in agricultural systems and guiding sustainable nutrient management practices.

The positive relationship between N legacy and synthetic N loss (Nloss-S) suggests a complex interplay of factors influencing N dynamics in the soil system. The calculation of synthetic N loss involves the assumption that all unaccounted N is lost and no or negligible N remains residual in the soil N pool. However, this assumption is not entirely accurate, as indicated by our calculations in this study and earlier research (Quan et al., 2021; Zhao et al., 2024).

4.4. Patterns of N loss across maize, rice and wheat

We used machine learning models to analyze complex, nonlinear relationships among variables influencing N loss, including explainable AI tools such as ALE and SHAP plots. These revealed crop-specific but interpretable relationships between N losses and soil, climate and management variables. Random Forest Regression (RFR) and Cubist models consistently outperformed others in predicting Nloss-S and Nloss-T across crops, while Support Vector Machine Regression (SVMR) was particularly superior for Nloss-T in maize. Linear models (PLSR and ELNET) performed poorly, highlighting the need for nonlinear models when dealing with complex data (Nayak et al., 2022; Zhou et al., 2022, 2019; Ransom et al., 2019). To our knowledge, this is among the first studies to apply machine learning models with explainable AI techniques to examine how environmental factors shape N losses across major cereal crops.

Although Nloss-S and Nloss-T were influenced by similar factors, the later was more reliably predicted, likely due to its integrative nature. Nloss-S predictions, on the contrary, were more variable and sensitive to specific soil properties and environmental conditions. The most important factors influencing nitrogen loss across all three crops were the synthetic N application rate, soil sand content, soil pH, and the aridity index. Nitrogen losses were generally lowest when the application rate was between 120 and 150 kg N ha^{-1}, while optimizing crop yields, and more frequent N applications generally reduced N loss. Sand content had a strong, crop-specific effect on N loss, generally increasing losses beyond crop-specific thresholds. Losses increase in more acidic or alkaline pH ranges, likely reflecting reduced REN, as suboptimal pH conditions can impair plant uptake and increase the risk of N loss. The aridity index has strong influence on losses in maize and wheat, but showed a weaker relationship in rice, likely due to the more uniform environments in which rice is typically grown.

The accuracy of ML models depends on high-quality covariates (Zhang and Ling, 2018; Wu et al., 2023). These factors interacted differently across crops, hence XAI must be interpreted carefully. Acquiring more accurate crop and management covariates would improve model precision in identifying dominant factors affecting N losses (Wadoux et al., 2023). For example, more frequent N applications generally reduced N losses, but the effect plateaued or reversed at high application frequencies. However, due to limited data on high-frequency application ($>$ 4 times), these effects should be interpreted cautiously.

4.5. Limitations

This study relied on a study-level observational dataset in which soil and climate conditions were consistent within invidual studies, while variations mainly restricted from differences in synthetic N applications. The machine learning models did not account for this hierarchical (nested) structure of the data, which may have led to pseudoreplication and biased estimates. Although stratified sampling was used, a grouped validation approach (e.g., leave-one-study-out) would have been appropriate to address within-study dependence. Additionally, the ML models are empirical in nature-they are effective to detect complex, nonlinear relationships but do not infer causality. Consequently, the explainable AI results should be interpreted within a sound agronomic context.

5. Conclusions

In exploring diverse N use efficiency (NUE) metrics, the integration of both synthetic and non-synthetic N inputs presents a holistic approach to assessing N efficiency and losses in agricultural systems. While traditional NUE metrics have predominantly focused on synthetic N due to its significant environmental impact and ease of measurement, there is an increasing recognition of the crucial role played by non-synthetic sources such as soil organic matter, biological nitrogen fixation, and atmospheric deposition. These non-synthetic inputs, though challenging to quantify, are integral to a comprehensive understanding of NUE. Our study underscores the importance of incorporating these factors into NUE metrics, as doing so provides a more accurate reflection of N dynamics within cropping systems. Moreover, given the prevalent practice of straw removal in many regions, we included straw as a constituent of harvested N.

Our analysis of global data over the past 40 years reveals that NUE, particularly synthetic N recovery efficiency (REN-S), has remained relatively stable across major cereal crops, with some regional variations. This stability suggests that the environmental impact of synthetic N, in terms of losses, has not worsened significantly, contrary to earlier projections. Additionally, our findings highlight the significant legacy effect of N from previous seasons, which plays a critical role in current crop N uptake. This legacy effect, coupled with the complex interactions of soil properties and environmental conditions, suggests that N losses and their environmental impacts might be lower than previous estimats when these factors are taken into account. The use of advanced machine learning models in our study further elucidated the non-linear relationships and interactions influencing N loss, pointing to the need for nuanced and data-driven approaches in predicting and managing N use in agriculture.

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CRediT authorship contribution statement

Debashis Chakraborty: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Timothy J Krupnik:** Writing – review & editing, Resources, Project administration, Conceptualization. **Mangi Lal Jat:** Writing – review & editing, Resources. **Dharamvir Singh Rana:** Methodology, Formal analysis, Data curation. **Mahesh Kumar Gathala:** Writing – review & editing. **Jagdish Kumar Ladha:** Writing – review & editing, Supervision, Conceptualization. **Bappa Das:** Writing – original draft, Visualization, Validation, Formal analysis.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT solely to enhance the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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.fcr.2025.110138.

Data availability

Data will be made available on request.

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