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Accounting for differences between crops and regions reduces estimates of nitrate leaching from nitrogen-fertilized soils

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Nitrate (NO_3^-) leaching from nitrogen (N) fertilized soils is a significant global concern, affecting both the environment and public health. However, substantial uncertainties and variabilities in NO_3^- leaching factors (LFs) among regions or crops impede accurate assessments of NO_3^- leaching. Here we synthesize 2500 field observations worldwide and show that LFs vary by an order of magnitude across regions and crops, primarily driven by hydroclimatic and edaphic conditions rather than N fertilizer management. Global cropland NO_3^- leaching from synthetic N fertilization, calculated through spatially explicit (15.4, 14.8–16.1 Tg N yr^{-1}) and crop-specific (12.9, 11.0–14.8 Tg N yr^{-1}) LFs, is 41% lower than the Intergovernmental Panel on Climate Change Tier 1 global inventory. Over 47% of this leaching is concentrated in China, India, and the United States, with maize, wheat, rice and vegetables accounting for nearly half of it. Improved regional and crop-specific LFs will provide a benchmark for NO_3^- leaching abatement by pinpointing potential global hotspots.

Nitrate (NO_3^-) leaching is the leading cause of nitrogen (N) depletion from agricultural ecosystems, accounting for up to 73% of the losses of the applied N[1,2]. This extensive NO_3^- leaching process adversely affects environmental and public health by deteriorating the quality of drinking water, contributing to aquatic nutrient enrichment (eutrophication) and elevating health risks like methemoglobinemia and cancer[3–5]. Additionally, it plays a role in the indirect release of nitrous oxide (N_2O), a potent greenhouse gas, into the atmosphere[6]. Given the expected increase in global agricultural NO_3^- leaching in the coming decades due to increased application of N fertilizers[2,7], it is imperative to comprehensively understand the patterns of N fertilizer-induced soil NO_3^- leaching and their driving factors at the global scale. Such efforts are essential for improving global NO_3^- leaching assessments and optimizing management strategies that effectively reduce environmental risks.

The bottom-up approach is the most commonly used method for estimating large-scale NO_3^- leaching inventories and relies on the NO_3^- leaching factors (LFs)–defined as the rate of NO_3^- leaching per unit of N inputs–in conjunction with the total N fertilizer used[1,8]. This method, i.e., Tier 1 methodology, considers the NO_3^- lost via leaching to be a constant percentage of the applied fertilizer N, a figure recently updated to 24% ($Frac_{LEACH-(H)}$; uncertainty range is from 1-73%) by the Intergovernmental Panel on Climate Change (IPCC)[1]. However, it is obvious that the IPCC constant LF overlooks the influence of regional differences in environmental and management factors such as geographic location and type of ecosystem, and thus could not reflect the heterogeneity of local conditions[2,9]. This complexity is compounded by the global disparity in N fertilizer usage, with regions like India and China generally experiencing overfertilization, while places such as sub-Saharan Africa face underfertilization[10]. Consequently, a uniform LF application across different nations or regions is unlikely to accurately represent specific leaching scenarios. Further complicating the issue, Wang et al.[2] analyzed global field data encompassing 324 observations and found that the proportional changes in LF responses to increased N

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inputs varied significantly across different ecosystems. This highlights the necessity of not only quantifying total NO_3^- leaching resulting from fertilization but also clarifying where and to what degree it may vary across agricultural soils on a global scale. Considering these knowledge gaps, it is imperative to develop a spatially explicit and crop-specific framework for assessing NO_3^- leaching patterns.

In the last years, several data syntheses on the basis of the published field measurements have shed light on the dynamics of N fertilizer-induced NO_3^- leaching from agricultural soils[2,9,11–15]. These endeavors have mostly focused on evaluating the efficacy of mitigation practices (e.g., no-tillage, return of crop residues, and biochar application) on NO_3^- leaching. However, the establishment of an extensive worldwide database for a robust bottom-up estimation of soil NO_3^- leaching from agricultural N fertilization and identifying potential global hotspots for mitigation remains undeveloped. Furthermore, it is evident that complex interconnections exist among hydroclimatic (e.g., precipitation, irrigation, mean annual temperature (MAT) and leachate volume (i.e., the volume of water percolating through the soil profile)), edaphic (e.g., soil texture, pH, bulk density (BD), soil organic C (SOC), total N (TN) and C/N ratio) and management-related (e.g., N fertilizer rate/type) controls over NO_3^- leaching[16]. Although many individual field studies have investigated and reported the overall effects of one or several typical factors, it remains unclear as to how hydroclimatic factors, soil properties and management practices as well as their interactions affect agricultural NO_3^- leaching at the global scale.

The increasing body of published field studies on NO_3^- leaching now enables the development of specific LFs for different regions and crops. This advancement facilitates the creation of a global inventory of NO_3^- leaching, offering detailed insights into mechanism underpinning NO_3^- leaching dynamics, as well as evaluating the effectiveness of various mitigation measures. Here, we analyzed 2500 field observations from 189 peer-reviewed publications through a global meta-analysis to (i) develop spatially explicit and crop-specific LFs for soil NO_3^- leaching; (ii) identify the main drivers behind the variability of LFs; (iii) evaluate the effectiveness of current NO_3^- leaching mitigation strategies; and (iv) estimate NO_3^- leaching from global croplands using the newly calculated LFs alongside data on cropland N fertilization rates. Addressing these issues not only advances our understanding of soil NO_3^- leaching mechanisms but also aids in pinpointing the specific drivers and effective practices for reducing environmental impacts, thereby contributing to more sustainable agricultural practices globally.

Results

Soil NO_3^- leaching across ecosystems

In examining NO_3^- leaching across various ecosystems, the analysis highlighted differences in N application rates between grasslands and croplands, with croplands receiving an average of 296 kg N ha^{-1}, significantly >277 kg N ha^{-1} for grasslands (Fig. 1a). Specifically, vegetables (467 kg N ha^{-1}) received 2.1-3.1 times more N in rice, wheat and other upland crops (e.g., rapeseed, barley, rye, etc.) (152-226 kg N ha^{-1}). The mean soil background NO_3^- leaching, i.e., from unfertilized soils, across all ecosystems was 18.6 kg N ha^{-1}. For croplands, this rate was significantly higher at 20.2 kg N ha^{-1}, compared to 7.86 kg N ha^{-1} for grasslands (Fig. 1b). Variability in background NO_3^- leaching among crops was also observed with vegetables experiencing the highest level at 31.7 kg N ha^{-1}, significantly surpassing maize (21.6 kg N ha^{-1}), wheat (14.6 kg N ha^{-1}), and rice (2.82 kg N ha^{-1}). With regard to NO_3^- leaching from fertilized soils, the mean NO_3^- leaching was estimated at 50.6 kg N ha^{-1}, with grasslands showing a significantly higher value of 55.9 kg N ha^{-1} compared to 49.9 kg N ha^{-1} for croplands (Fig. 1c). Amongst the different crops, vegetables had the highest fertilizer-induced NO_3^- leaching at 83.9 kg N ha^{-1}, followed by other upland crops at 42.8 kg N ha^{-1}, maize at 41.3 kg N ha^{-1}, wheat at 34.4 kg N ha^{-1}, and rice at 5.45 kg N ha^{-1} (Fig. 1c).

The NO_3^- leaching factor of applied N

Across the 2003 datasets on the global scale, the mean LF of applied N stood at 13.9% (13.1–14.7%, 95% confidence interval), 42% lower than the IPCC default LF of 24% (Fig. 2). Analysis across ecosystems showed croplands and grasslands with mean LFs of 14.0% (13.1–14.8%) and 13.4% (11.2–15.7%), respectively (Fig. 2). Among crop types, vegetables showed the highest LF at 17.0% (15.5–18.6%), followed by maize at 14.9% (13.5–16.3%), wheat at 11.9% (10.1-13.8%), while rice exhibited a significantly lower LF of 0.85% (0.44–1.27%) (Fig. 2). The NO_3^- LFs for croplands displayed significant geographic heterogeneity at both grid (Fig. 3a) and continent (Supplementary Fig. 1) scales. The highest mean LF was found in North Asia at 19.6% (19.2–20.0%), closely trailed by Europe at 19.3% (19.0–19.5%) and Southeast Asia at 19.1% (17.1–21.0%), while all the LFs ranged from 13.4–18.7% in other regions (Supplementary Fig. 1). The differences between our regional specific LFs and IPCC default LF also showed high geographic heterogeneity (Fig. 3b), with the top three largest differences appearing in North America (10.6%), Oceania (9.92%) and East Asia (9.11%) (Supplementary Fig. 1).

Although not statistically significant, LFs appeared to rise with increased N application rates (Fig. 2 and Supplementary Fig. 2a). Regarding N fertilizer types, the combination of organic and synthetic N fertilizers resulted in a lower ($P < 0.05$) LF (12.2%, 10.9-13.4%) than using synthetic N fertilizer alone (14.6%, 13.6-15.7%). Furthermore, higher LFs were found under water inputs (precipitation plus irrigation water) of ≥400 mm (13.1-13.6%), SOC ≥ 10 g C kg^{-1} (14.1-15.3%), and TN ≥ 1.0 g N kg^{-1} (13.4-15.7%) (Fig. 2 and Supplementary Fig. 3). On average, the LFs were significantly higher at sites with leachate volume of ≥150 mm (18.3%, 16.9-19.8%) compared with those of <150 mm (11.2%, 9.79-12.7%) (Fig. 2). Regarding soil pH and BD, the average LFs significantly rose with decreases in both soil pH and BD. The most significant increase was observed in soils with pH <6.5, where LFs reached 16.4% (14.9-18.0%), and in those with a BD < 1.25 g cm^{-3}, showing LFs of 20.5% (16.2-24.6%) (Fig. 2 and Supplementary Fig. 3). Additionally, the results across different soil textures revealed a higher tendency for NO_3^- leaching in medium- and coarse-textured soils, with LFs of 12.9% (11.6-14.1%) and 16.5% (15.4-17.6%), respectively, compared to a lower ($P < 0.05$) LF of 3.92% (2.02-6.30%) in fine-textured soils (Fig. 2). Regarding the sampling depth, significantly higher LF was observed at sampling depth <60 cm (18.6%, 16.2-21.1%) compared to 60-100 cm (13.2%, 12.1–14.4%) and >100 cm (13.7%, 12.5-14.9%) soil depth (Fig. 2).

To evaluate the effects of environmental (i.e., hydroclimatic conditions and soil properties) and management-related variables on LFs, we utilized a Random Forest model tailored for meta-analysis, capturing interactions between numerous variables (Fig. 4). The total relative contribution of hydroclimatic (i.e., leachate volume, precipitation, irrigation and MAT) and edaphic factors (i.e., soil texture, pH, SOC, TN, BD and C/N ratio) to LFs was 178% and 205%, respectively, overriding the 53.9% of N fertilizer managements (i.e., N fertilizer rate and N fertilizer type) (Fig. 4). Specifically, among the twelve variables analyzed, leachate volume emerged as the most critical factor, contributing to 60.0% of the variation in LFs (Fig. 4). Other significant variables affecting LFs, in descending order of impact (46.8-17.1%), included soil pH, precipitation, irrigation, sampling depth, N application rate, C/N ratio, SOC, MAT, TN, BD, soil texture, ecosystem type and N fertilizer type ($P < 0.05$). Structural Equation Modeling (SEM) further confirmed that leachate volume was the most important factor influencing LFs, showing a direct positive correlation with a standardized coefficient of 0.15 ($P < 0.001$) (Fig. 5).

The analysis of field management effect showed that amendments (including nitrification inhibitors (NI), urease inhibitors (UI), slow-release fertilizers, biochar and liming materials), crop residue incorporation, and drip irrigation significantly reduced LFs by 22.9% (−36.2% to −7.60%), 21.3% (−36.2% to −1.98%), and 62.8% (−73.3% to −47.8%), respectively, whereas no-tillage slightly increased LFs by 10.5% (−8.61% to 33.6%) (Fig. 6a). When pooling the data from different amendment categories, biochar had the largest significant mitigating effect on LFs, reducing them by 50.2% (−76.3% to −17.9%), followed by liming at 47.2% (−57.9% to −35.2%), and NI at 36.9% (−50.2% to −21.5%) ($P < 0.05$) (Fig. 6a). In addition, regarding yield effects, NI, UI + NI, deep placement, crop residue

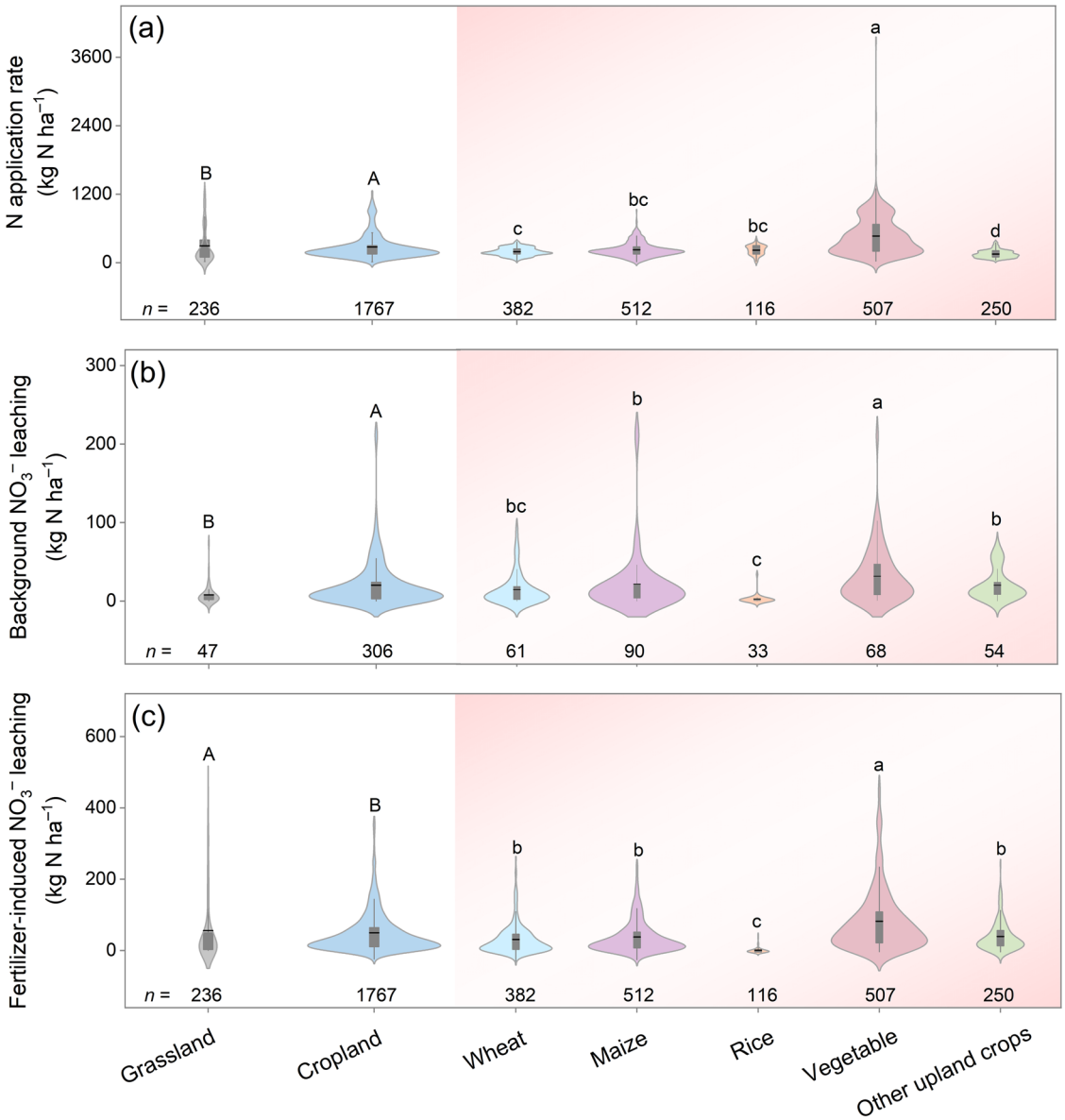

Fig. 1 | Total nitrogen (N) application rate and nitrate (NO_3^-) leaching across various ecosystem and crop types. a N application rate. **b** NO_3^- leaching from unfertilized (background) treatments. **c** NO_3^- leaching from fertilized treatments. The black lines inside the boxes represent the mean values. Box boundaries represent the 75th and 25th percentiles, and whisker caps represent the 95th and 5th percentiles. Significant variations in total NO_3^- leaching between different ecosystem types (denoted by capital letters) and among various crop types (indicated by lowercase letters), with significance level set at $P < 0.05$. The numbers next to the x-axis indicate sample sizes (n).

incorporation, and drip irrigation had positive influence on crop yields (Fig. 6b). The most notable yield increases were observed with deep fertilizer placement (22.3%, 17.8-29.8%), followed by gains from UI + NI (14.7%, 6.93-26.3%), NI (8.57%, 1.44-17.1%), drip irrigation (6.57%, 0.43-12.6%), and crop residue incorporation (3.51%, 0.83-6.55%) (Fig. 6b).

Global cropland NO_3^- leaching from synthetic N fertilization

At a global scale, NO_3^- leaching from synthetic N fertilization in croplands was estimated, using spatially explicit and crop-specific LFs, to be ~15.4 (14.8–16.1) and 12.9 (11.0–14.8) Tg N yr^{-1}, respectively (Fig. 7). These figures were lower than the 16.1 (14.8-17.3) Tg N yr^{-1} estimate derived from the constant LF of 14.9% (13.7-16.0%), but were substantially higher than the total NO_3^- leaching induced by manure N application (3.42, 2.72-4.16 Tg N yr^{-1}).

A closer analysis of NO_3^- leaching from synthetic N fertilization across different regions and countries highlighted the Northern Hemisphere, particularly Asia, as a significant hotspot (Fig. 7). In Asia alone, the estimated leaching rates in East and South Asia reached 3.96 and 2.49 Tg N yr^{-1}, contributing 25.7% and 16.1%, respectively, to the global total NO_3^- leaching. Europe (2.84 Tg N yr^{-1}) and North America (2.22 Tg N yr^{-1}) followed, accounting for 18.4% and 14.4 %, respectively (Fig. 7). The top three contributor for crops in terms of soil NO_3^- leaching–China (3.81 Tg N yr^{-1}), India (1.86 Tg N yr^{-1}) and the United States (1.59 Tg N yr^{-1})–were responsible for 47.1% of global NO_3^- leaching (Supplementary Fig. 4). In addition, the differences in the estimates of NO_3^- leaching between the methods using our regional specific LFs and IPCC default LF were striking at the grid cell (Fig. 7). More specifically, the estimates from the majority of regions based on regional specific LFs were lower than IPCC LF estimates (range of 0.02-2.21 Tg N yr^{-1}), with the largest difference appearing in East Asia (Fig. 7). From the perspective of crop-type, the three main staple crops (i.e., maize, wheat and rice) were responsible for leaching 5.08 Tg N yr^{-1} of NO_3^-, constituting 39.5% of the global total from croplands due to synthetic

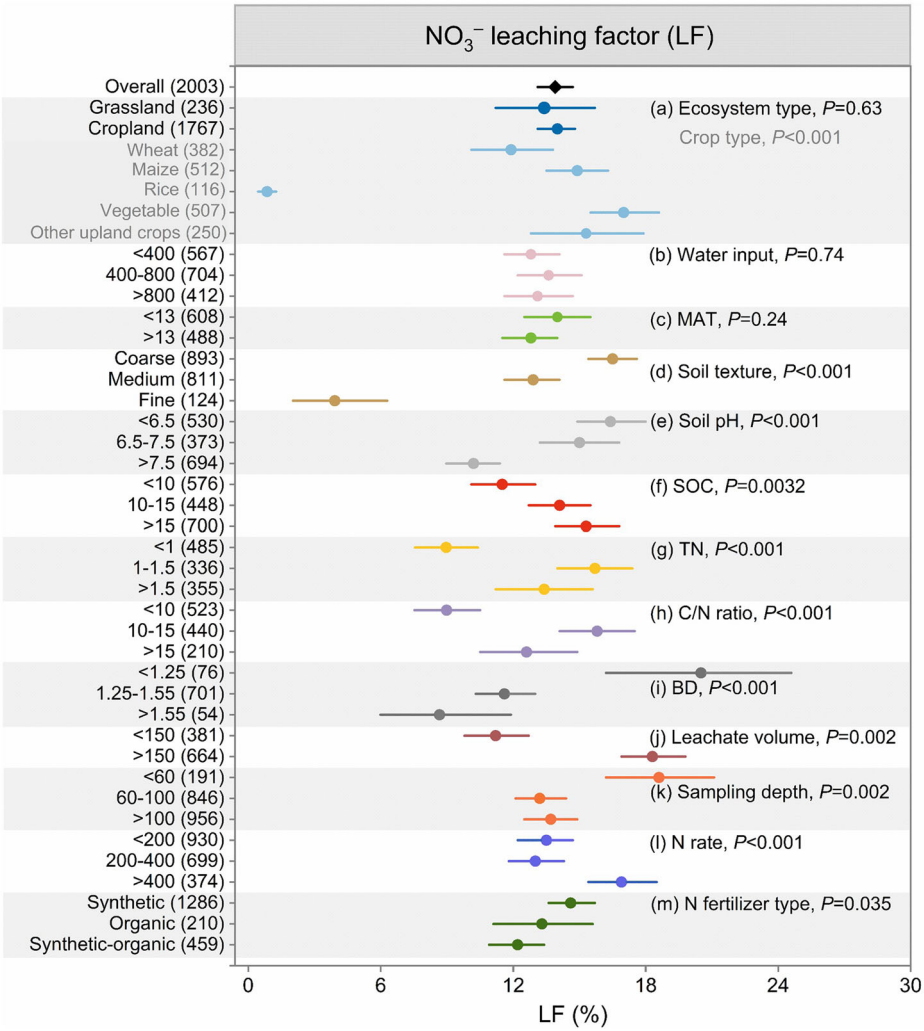

Fig. 2 | Effects of ecosystem/crop types, environmental and management-related variables on nitrate (NO_3^-) leaching factors (LFs). a ecosystem/crop type. **b** water input (precipitation plus irrigation water) (mm). **c** mean annual temperature (MAT) (°C). **d** soil texture. **e** soil pH. **f** soil organic C (SOC) (g C kg^{-1}). **g** total N (TN) (g N kg^{-1}). **h** C/N ratio. **i** bulk density (BD) (g C cm^{-1}). **j** leachate volume (mm). **k** sampling depth (cm). **l** N rate (kg N ha^{-1}). **m** N fertilizer type. Symbols represent means of effect size with 95% confidence intervals. A statistically significant difference in LF across different sub-group or levels is identified when their 95% confidence intervals do not overlap, with a significance threshold set at $\alpha = 0.05$. The significance of between-group heterogeneity indicates significant differences at $P < 0.05$. The numbers in parentheses indicate the count of observations within each sub-group or level that were analyzed statistically.

N fertilization (Fig. 7). Vegetables added another 1.29 Tg N yr^{-1}, accounting for 10.0% of the total global cropland NO_3^- leaching.

Discussion

Our study provides a comprehensive analysis of the role of hydroclimatic, edaphic and management-related factors in controlling NO_3^- leaching globally. Although N fertilizer managements (i.e., N fertilizer types and N application rates) are commonly seen as the major factor influencing NO_3^- leaching[2], these variables exerted a comparatively weaker contribution in shaping NO_3^- leaching at the global scale, compared to hydroclimatic and edaphic factors (Figs. 4 and 5). Similarly, a comprehensive study involving 453 site-years across 51 locations in China by Gao et al.[9] found that hydroclimatic conditions, rather than N management practices, predominantly influenced N leaching variation. In general, environmental variables (i.e., hydroclimatic conditions and soil properties) play a crucial role in NO_3^- leaching patterns at regional and global scales; however, one or more management practices may become more pertinent within a particular region[17,18]. Additionally, environmental factors may influence agricultural management to maintain crop yields[19], indirectly impacting local LFs. Yet, the adoption of climate-smart agricultural practices could potentially alter this dynamic in the future[20].

Our SEM showed that water input indirectly affected soil NO_3^- leaching by controlling the water percolation volume in the leachate, with leachate volume being positively correlated with soil NO_3^- leaching, in line with prior findings and highlighting leachate volume as a major predictor of soil NO_3^- leaching on a global scale[9,15]. Previous studies have shown that N accumulation in the soil appears under limited water conditions, and once the water supply exceeds the soil field capacity, NO_3^- can be washed out from the rhizosphere and leached into the groundwater[21]. The above interpretation can be partly supported by our finding that soil NO_3^- leaching significantly increased with increasing NO_3^- accumulation (Supplementary Fig. 2b). Furthermore, soil characteristics such as texture and BD played important roles in shaping LFs on a global scale. Coarse-textured soils, which have lower water retention and higher porosity, promote easier NO_3^- transport and leaching than fine-textured soils[13,21], as confirmed by the strong negative correlation between LFs and soil BD (Fig. 2 and Supplementary Fig. 3). Generally, soils with higher BD, indicating greater density and compaction, exhibit poor aeration, slower water drainage, and higher denitrification potential[14,22], reducing NO_3^- leaching for soils with BD > 1.55 g cm^{-3} (Fig. 2). However, in high-BD soils, surface runoff and potential erosion present concern due to decreased infiltration[23], indicating a need for future research to comprehensively explore the interactions between soil compaction, runoff dynamics, and nutrient cycling. Moreover, our analysis shows that LFs rose with increased concentrations of SOC and TN (Fig. 2 and Supplementary Fig. 3). High levels of soil organic matter associated with high TN enhance the soil N pool, thus accelerating mineralization and NO_3^- leaching processes[2,24].

Our findings suggest that co-application of synthetic and organic N fertilizers could significantly lower LFs, while yields remain unaffected (Supplementary Fig. 5), making it a more effective strategy than using synthetic N fertilizers alone (Fig. 2). Evidence from recent research supports the idea that the partial substitution of manure for synthetic N fertilizers can

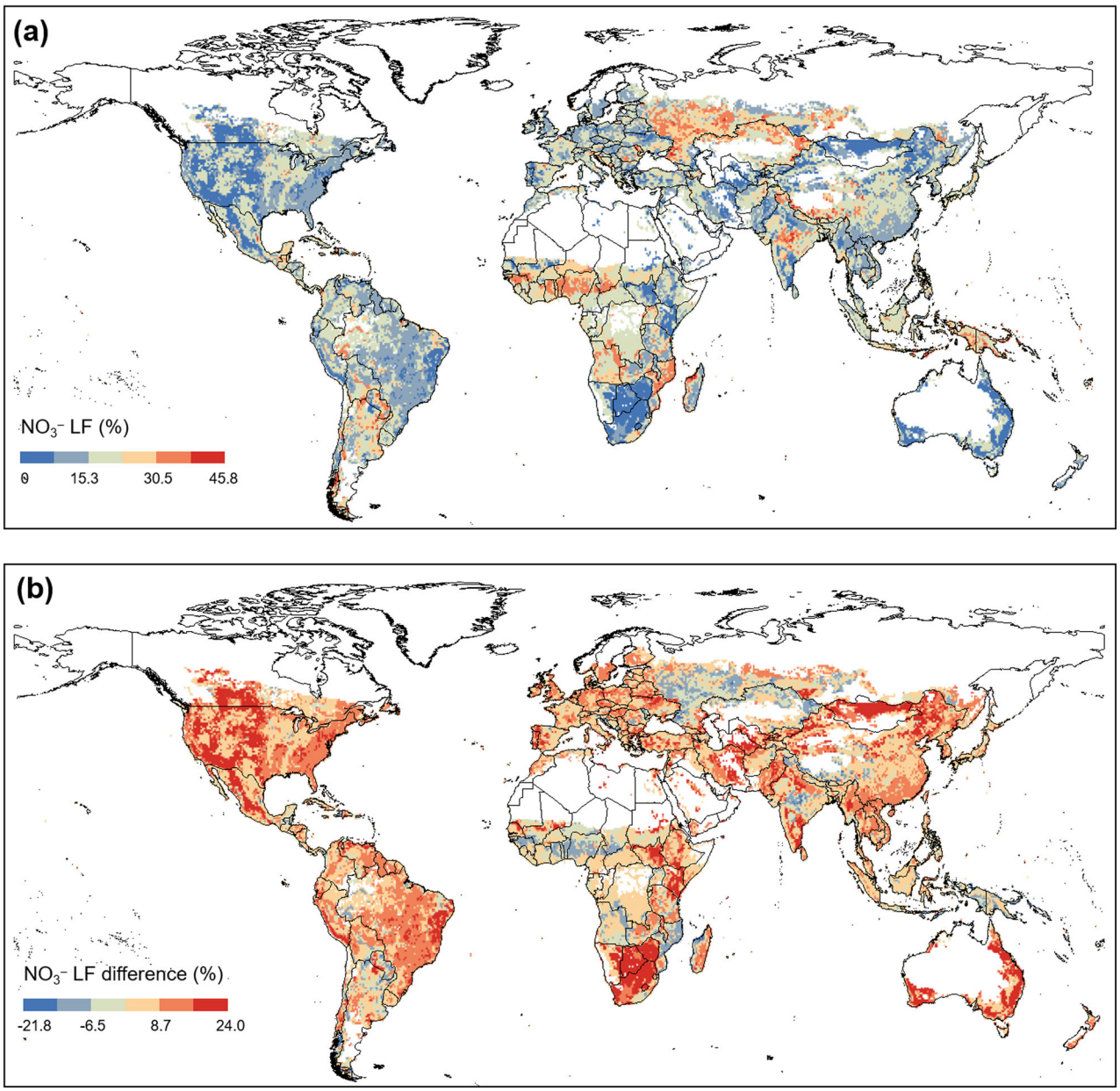

Fig. 3 | Spatial patterns of NO_3^- LFs and their differences with IPCC default LF for croplands. a The global maps of region-specific NO_3^- LFs for croplands. **b** The differences between region-specific LFs and IPCC default LF for croplands.

promote the microbial immobilization of NO_3^- by increasing the supply of orgainc C, leading to the reduction in the level of NO_3^- in soil profiles prone to leaching[13,25]. Contrary to some reports[2,26], the LFs in this study showed no obvious relationships with the rate of N fertilization. The absence of statistical significance between N fertilizer levels and LFs could be due to the studies in our dataset focusing on a single N application rate, with few investigating extremely low or high N input rates per site[27,28]. Therefore, we recommend that countries with detailed fertilizer application rates explore the possibility of a nonlinear (exponential) relationship between LFs and N inputs to better tailor the development of their own leaching factor response curves.

By focusing on regions and crops prone to high rates of NO_3^- leaching, the LFs developed here can help refine the global estimates of NO_3^- leaching. This will assist in crafting agricultural and environmental strategies that align with Sustainable Development Goals aimed at eradicating poverty, ending hunger, ensuring clean water, and combating climate change. Our analysis, tailored to specific regions and crops, estimated that NO_3^- leaching due to synthetic N fertilization on global croplands amounts to 15.4 and 12.9 Tg N yr^{-1}, respectively (Fig. 7). Both values are significantly below the estimate derived from our constant LF (16.1 Tg N yr^{-1}) and that provided by the IPCC Tier 1 methodology, which ranged from 1.08 to 78.8 Tg N yr^{-1} with a notable mean value of 25.9 Tg N yr^{-1}. This discrepancy suggests that the generalized LFs used by the IPCC might lead to an overestimation of global NO_3^- leaching by not accounting for regional and crop-specific variations.

Our analysis, employing region- and crop-specific LFs along with refined N input data, highlights the varied NO_3^- leaching across different regions and crop types worldwide. Notably, East Asia, Europe, South Asia, and North America as major contributors to global NO_3^- leaching, accounting for nearly 80% of the total despite possessing less than one half of the world's cropland area[29]. This discrepancy is largely attributed to the high N fertilizer input rates in these regions. As described above, one or more management practices may be the most important controlling factor for NO_3^- leaching within a particular region. At the country scale, China acted

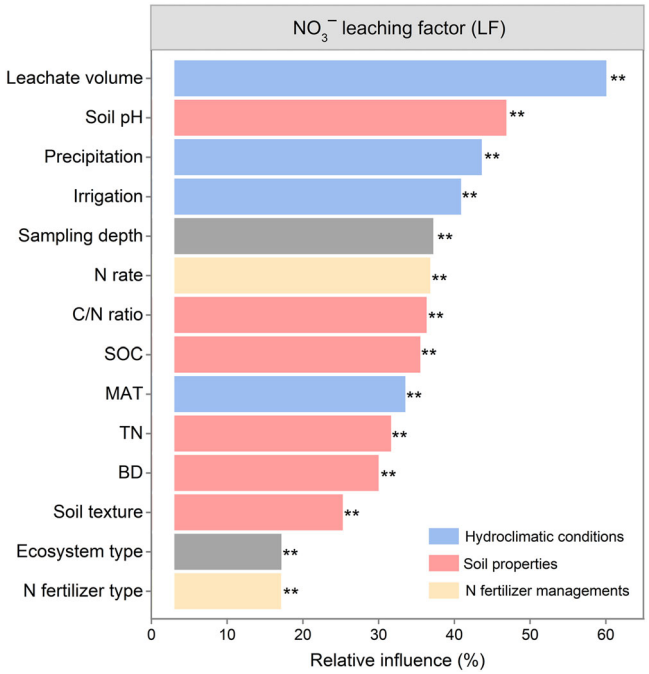

Fig. 4 | Random Forest model analysis for identifying the relative importance of ecosystem types, environmental and management-related variables that drive the variations of nitrate (NO_3^-) leaching factors (LFs). MAT, mean annual temperature. SOC, soil organic C. TN, total N. BD, bulk density. Significance levels are denoted with $^{**}P < 0.01$ for highly significant findings.

as the leading contributor of global NO_3^- leaching. Our findings indicate that NO_3^- leaching from synthetic N fertilizer use in China (3.81 Tg N yr^{-1}) surpasses the estimate of 0.64 Tg N yr^{-1} by Hu et al.[30], yet falls below the 4.57 Tg N yr^{-1} estimated by Qiu et al.[31]. This variance among estimates likely stems from differences in the underlying methods and scope of the datasets considered, such as the inclusion of various crop types and the reliance on diverse modeling approaches. For instance, Hu et al.[30] focused on upland cereal crops and rice, without considering cash crops such as vegetables, which could explain some discrepancies in leaching estimates. India followed closely, ranking second only to China in its contribution to global cropland NO_3^- leaching. This was driven by its intensive agricultural activities and a substantial fertilizer industry, positioning it as a key hotspot for reactive N loss[32,33]

Based on the crop-specific LFs established in this study, our estimates revealed that the primary staple crops (i.e., maize, wheat, and rice), which constitute 40% of the global harvest area and receive 51% of all synthetic N fertilizers[34], accounted for ~40% of the NO_3^- leaching from worldwide croplands. In contrast, vegetables, which occupy a mere 4% of the global cropland area yet receive about 7% of the total synthetic N fertilizers, contributed to roughly 10% of the world's cropland NO_3^- leaching. This is significant because vegetable farming involves high water use[35], which plays a crucial role in moving NO_3^- through the soil, and thus increases leaching losses[22]. These findings suggest that managing NO_3^- leaching from vegetable croplands should be a priority in efforts to mitigate climate change impacts within agriculture.

Moreover, we assessed indirect N_2O emissions resulting from NO_3^- leaching, applying the default emission factor (EF_5) of 0.011 kg N_2O-N kg^{-1} NO_3^--N leached as set by the IPCC (2019). Using this method, indirect N_2O emissions from synthetic N fertilization on global croplands were between 170 (162-177) Gg N yr^{-1} and 141 (121-162) Gg N yr^{-1}, for region- and crop-specific, respectively. These amounts correspond to 3.7-25.8% of the total direct cropland N_2O emissions, which range from 660 to 3800 Gg N yr^{-1} [35–38], highlighting the considerable contribution of indirect N_2O emissions through the NO_3^- leaching pathway to global N_2O emissions.

This underscores the critical need for effective management strategies to curtail NO_3^- leaching from N-fertilized soils. Our study identifies various potential pathways on how the mitigation of NO_3^- leaching may be achieved through various field management options, such as the use of amendments (e.g., biochar, liming materials and NI) (−36.9% to −50.2%), crop residue incorporation (−21.3%), or drip irrigation (−62.8%) (Fig. 6a). Beyond reducing NO_3^- leaching, these practices also have the potential to significantly increase crop yields (Fig. 6b). For example, the application of biochar or liming amendment can enhance soil capacity to bind NH_4^+, decreasing the associated availability and exchange rate of NH_4^+ with NO_3^-[39,40], thus mitigating NO_3^- leaching[12]. Moreover, drip irrigation can substantially decrease the loss of irrigation water, reducing soil water percolation and, consequently, the leaching of dissolved N[41,42]. Conversely, our findings indicate that no-tillage practices can increase NO_3^- leaching (Fig. 6a), which are consistent with a meta-analysis study[15]. This increase is primarily attributed to the higher soil water content in no-tillage soils, which reduces the soil capacity to absorb and retain additional water before it begins to drain[43], thus enabling greater NO_3^- leaching.

Despite the significant progress made in estimating NO_3^- leaching, uncertainties remain due to inherent limitations of the methodologies used and/or differences in data quality between different studies. First, we focused only on growing season LFs, as most of the field observations compiled in this study did not extend into the fallow periods. This omission is significant in systems with rotating annual crops, where leaving the soil bare for part of the year increases the risk of soil N being leached away in the absence of live plants to absorb it[5]. Further field research that measures NO_3^- leaching throughout the entire year is needed to better quantify LFs across different management practices and to explore the effects of growing days on NO_3^- leaching. Second, the uneven distribution of experimental sites may introduce biases, as not all aspects of the plant-soil-climate system are equally represented. There is a particular need for more field measurements in South America, Australia, and Africa to fill the existing data gaps. Finally, our study followed the IPCC methodology, which assumes that most leached N is in the form of NO_3^-. However, in certain agricultural systems, the leaching of organic N losses can also be significant[41], raising questions about its overall contribution to the global organic N leaching budget and its role in indirect N_2O emissions. Consequently, further research into organic N leaching is necessary to fully evaluate the environmental impact of current crop production systems.

Conclusions

In summary, our global synthesis clearly show significant variations in LFs across regions and crops, with hydroclimatic and edaphic conditions having a greater impact than the well-recognized N fertilizer management. Synthetic N fertilizer-induced NO_3^- leaching from global croplands, calculated using our spatially explicit and crop-specific LFs were substantially (41%) lower than that derived from the IPCC's default LF calculation. We conclude that our established specific NO_3^- LFs for different regions and crop types are more realistic than IPCC Tier 1 default value, being supported by a broad observation-based dataset across contrasting environmental conditions, so these should be included to ensure accurate NO_3^- leaching inventories. Overall, our findings would provide a new benchmark for constraining the IPCC Tier 1 default LF value. The mapping of NO_3^- leaching and the assessment on their drivers also facilitate identification of potential hotspots of increased leaching under varying levels of N inputs and guide targeted interventions to mitigate environmental risks.

Methods

Literature search and data extraction

To assemble a comprehensive dataset on soil NO_3^- leaching, we conducted an extensive literature review using the Web of Science (https://apps.webofknowledge.com/), Google Scholar (https://scholar.google.com/), and the China National Knowledge Infrastructure (https://kns.cnki.net/) up to

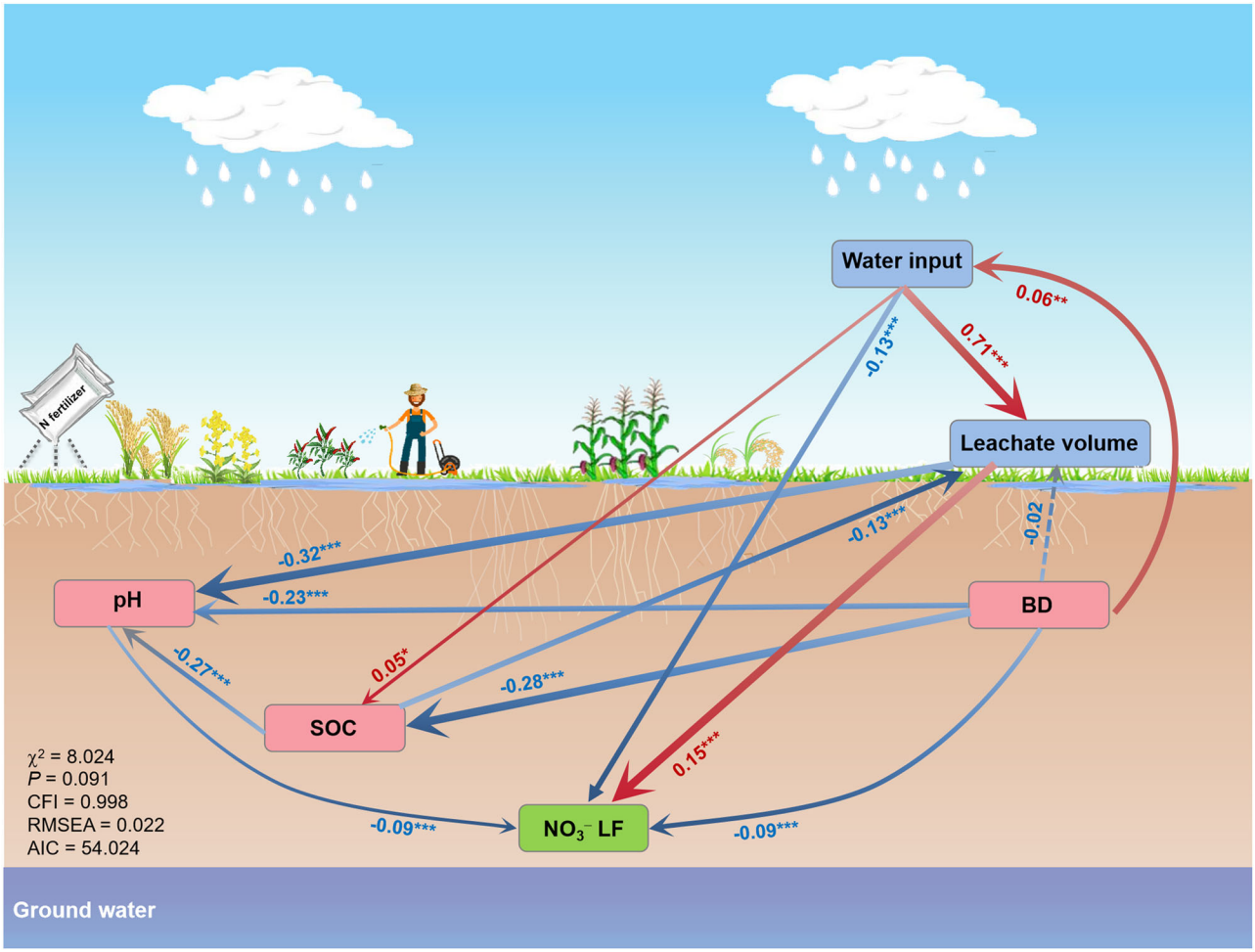

Fig. 5 | Structural equation modeling showing the effects of water input (precipitation plus irrigation water), soil pH, soil organic C (SOC), bulk density (BD) and leachate volume on nitrate (NO_3^-) leaching factors (LFs). The red and blue arrows indicate positive and negative relationships, respectively, with the thickness of these arrows proportional to the impact's strength, as shown by standardized coefficients. Statistical significance is marked with $^{**}P < 0.01$ and $^{***}P < 0.001$ next to the arrows. The dashed arrows represent no significant pathways. The model's fit is evaluated using several metrics: χ^2, chi-square. *P*, probability level. CFI, comparative fit index. RMSEA, root mean squared error of approximation. AIC Akaike's Information Criteria.

September 2023. Specific search terms were combined with regard to 'nitrate' OR 'NO_3^-' OR 'nitrogen' OR 'N', AND 'leaching', AND 'soil', AND 'fertilizer'. To avoid uncertainties associated with estimations, only experimental field data were included. Regarding data from cropland and managed natural ecosystems, occasional field NO_3^- leaching measurements that did not cover the entire experimental period (from planting to harvest) or non-representative consecutive measurements were excluded. Further, the prerequisite for the inclusion of a field study was that the application rates of synthetic and/or organic N fertilizers for each treatment were reported, and that measurements were available over the same experimental period for N fertilizer treatments and unfertilized control for sites with similar cultivation history. Studies evaluating the effects of soil amendments such as nitrification inhibitors, urease inhibitors, slow-release fertilizers, biochar and liming materials, were specifically identified to assess their potential in mitigating NO_3^- leaching. Nevertheless, data from these amendments were not used to estimate regional or global mean NO_3^- leaching and LFs. Notably, some studies measured NO_3^- leaching at various soil depths (e.g., 10, 20, 30, 60 and 90 cm was measured in Yang et al.[44]); in these cases, we only considered data from the deepest soil layer for our analysis[15]. In addition, NO_3^- leaching must be measured by suction cup, lysimeter, or soil sampling methods. The original data used in the present analysis was acquired directly from tables and texts or indirectly by digitizing graphs using GetData Graph Digitizer (http://www.getdata-graph-digitizer.com/). The detailed literature search was conducted based on the PRISMA procedure (Supplementary Fig. 6).

The resulting global database consisted of 2500 field measurements from 189 studies, including 298 measurements from grasslands and 2202 from croplands, spanning 23 different countries across six continents (Supplementary Fig. 7). This extensive collection also incorporates additional relevant data, such as geographical location (country, longitude and latitude), ecosystem/crop type, hydroclimatic conditions (e.g., precipitation over the growing season, irrigation, water input (precipitation plus irrigation), MAT and leachate volume), soil properties (e.g., soil texture, BD, soil pH, SOC, TN and C/N ratio), management practices (e.g., N fertilizer type/rate, tillage, crop residue incorporation, fertilization and irrigation mode), sampling depth, N accumulation at the deepest reported depth, and crop yields, to provide a comprehensive overview of global NO_3^- leaching dynamics. It should be noted here that most of the studies were from Asia, Europe and North America, with only 19 to 143 observations were from South America, Africa, and Oceania (Supplementary Fig. 7).

Data assembly and analyses

As suggested by preceding studies[34,45], we performed a pair-wise meta-analysis using NO_3^- LF as an effect size. When actual LF values were unavailable, we calculated them using the cumulative NO_3^- leaching data from both control and fertilized plots, alongside the total applied N

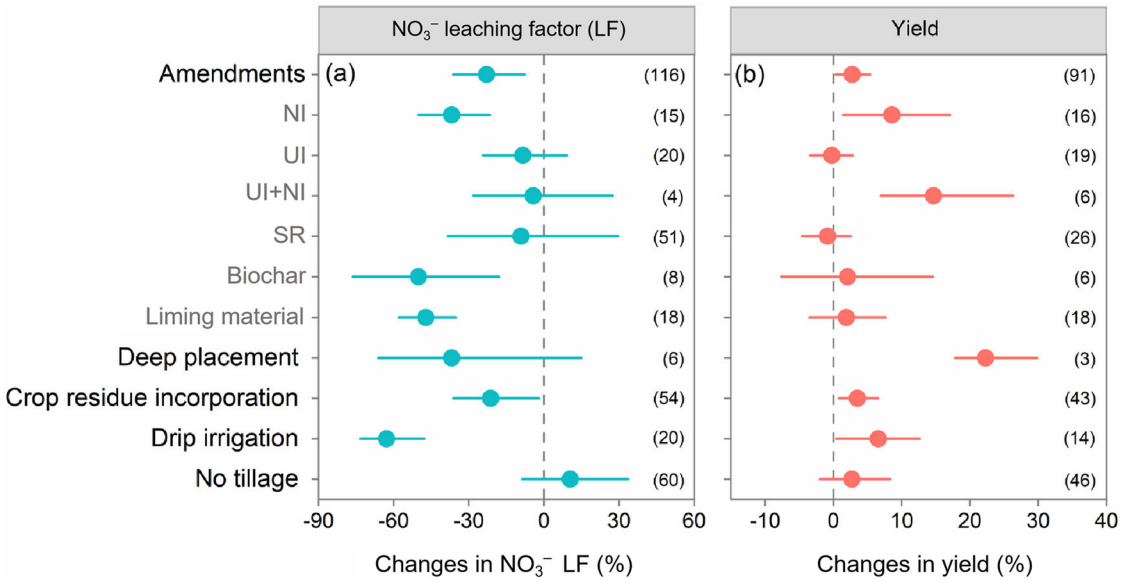

Fig. 6 | Effects of field management practices on nitrate (NO_3^-) leaching factors (LFs) and crop yields. a Changes in NO_3^- LF. **b** Changes in crop yields. Error bars represent 95% confidence intervals. The significance of variables is determined at the $P < 0.05$ level, indicated by error bars not intersecting with zero. Amendments studied include nitrification inhibitor (NI), urease inhibitor (UI), slow-release fertilizers (SR), biochar and liming materials. The number in brackets indicates the number of paired observations.

throughout the experimental period. The formula used was:

$$LF\,(\%) = (L_N - L_B)/N \times 100 \quad (1)$$

where, L_N is the total cumulative leaching of NO_3^- (kg N ha^{-1}) from N fertilized treatments, L_B is the cumulative leaching in control plots without N fertilizer (background NO_3^- leaching), and N is the total N applied (kg N ha^{-1}). For the 38 sites that lacked control treatment, we used the average background NO_3^- leaching value for the region, taking into account similar climate and soil conditions. This approach yielded 2003 NO_3^- LF datasets across various ecosystems including 236 for grasslands and 1767 for croplands. The croplands were further grouped into subsets for wheat (382 entries), maize (512 entries), rice (116 entries), vegetable (507 entries), and other upland crops (250 entries).

To clarify the factors influencing LF patterns, organized potential independent variables into specific categories (Supplementary Table 1). These categories included ecosystem types, such as grasslands and various croplands (e.g., wheat, maize, rice, vegetable, and other upland crops), which were identified based on the Whittaker Biome Diagram[46]. Soil types were classified into three textures (i.e., coarse (sandy loam, sandy clay loam, loamy sand), medium (clay loam, loam, silt clay loam, silt, silt loam), and fine (clay, silt clay, sandy clay)) following the USDA classification[47]. In terms of aiming for maximal in-group homogenization as outlined by Zhao et al.[48], MAT and volume of leachate were divided into two groups: <13 and ≥13°C for MAT, and <150 and ≥150 mm for leachate volume. Water input (precipitation plus irrigation), SOC, TN concentration, C/N ratio, BD, and sampling depth were segmented into three categories to facilitate analysis. These categories were defined for water input <400, between 400-800, and over 800 mm; for SOC as <10, between 10−15, and those above 15 g C kg^{-1}; for TN < 1, between 1–1.5, and over 1.5 g N kg^{-1}; for C/N ratio <10, between 10-15, and >15; for BD < 1.25, between 1.25–1.55, and >1.55 g cm^{-3}, and for sampling depth <60, between 60-100, and >100 cm. Soil pH was also classified into three ranges: <6.5, between 6.5–7.5, and >7.5, as described by Wang et al.[34]. Types of N fertilizers and application rates were segmented into three groups: synthetic, organic, and combined synthetic-organic, and for application rates at <200, and between 200–400 and >400 kg N ha^{-1}. To further assess the impacts of different management strategies on soil NO_3^- leaching, various reported treatments testing amendments (i.e., nitrification inhibitors, urease inhibitors, slow-release fertilizers, biochar, and liming materials) were analyzed, as were different modes of crop residue management, tillage, irrigation or fertilizer N placement (deep versus surface broadcasting) to assess their effectiveness for mitigating soil NO_3^- leaching. This was evaluated through pairwise comparison of LFs and yields across different management strategies using the following equation[49]:

$$RR = \ln\left(\frac{\overline{X_t}}{\overline{X_c}}\right) = \ln(\overline{X_t}) - \ln(\overline{X_c}) \quad (2)$$

where, RR refers to the response ratio, and $\overline{X_t}$ and $\overline{X_c}$ represent the mean values of LF or yield for the treatment and control, respectively (Supplementary Table 2). Due to the lack of standard deviations and error data in most studies, our analysis prioritized effect sizes weighted by the number of replication to minimize extreme weight issues[25], using the following equation:

$$w = \frac{N_t \times N_c}{N_t + N_c} \quad (3)$$

where, w is the weight given to each case, and N_t and N_c represent the number of replicates for the treatment and control, respectively.

MetaWin 2.1[50] was employed to calculate the means of effect sizes (i.e., NO_3^- LF) and RR, as well as their 95% bootstrapped (4999 iterations) confidence intervals for each category, following a fixed categorical model approach similar to that used in previous meta-analyses[51,52]. Significance in the mean LFs among different groups/levels was determined by non-overlapping 95% confidence intervals. Between-group heterogeneity tests were utilized to examine the significance of each subgrouping category. For RRs, significant was attributed when their 95% confidence intervals did not include zero. The mean RRs and their corresponding 95% confidence intervals were back-transformed and reported as percentage changes (i.e., % change = $(e^{lnRR}-1) \times 100\%$). A significant positive percentage change denoted an increase, while a negative value indicated a decrease in the target variable as an effect of the management strategy. Rosenthal fail-safe number was examined to test for the possibility of publication bias[53]. If the Rosenthal fail-safe number exceeded $5n + 10$ (where n is the number of studies)[54], we considered the results robust, regardless of any potential publication bias. In

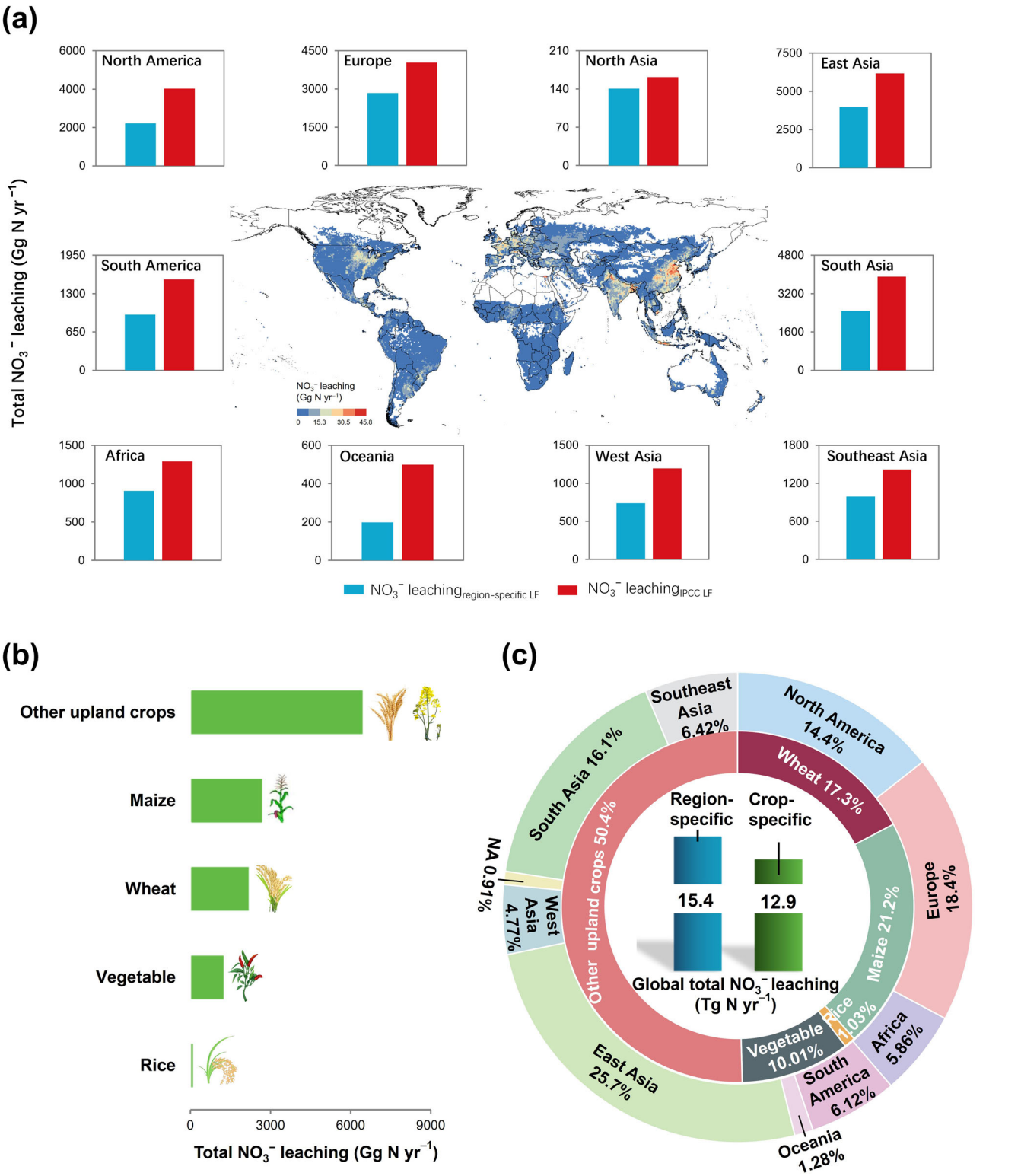

Fig. 7 | Synthetic N fertilizer-induced nitrate (NO_3^-) leaching from global croplands. a NO_3^- leaching across different regions. **b** NO_3^- leaching among different crop types. **c** Proportion of NO_3^- leaching attributable to each region (see the outer circle) and crop types (see the inner circle), and estimated region- and crop-specific total NO_3^- leaching from synthetic N fertilization globally. All estimated results are from croplands, excluding grasslands with N fertilizer application. NO_3^- $\text{leaching}_{\text{region-specific LF}}$ and NO_3^- $\text{leaching}_{\text{IPCC LF}}$ are the total NO_3^- leaching calculated using the spatially explicit LF of this study and IPCC default LF, respectively. Error bars in panel c represent 95% confidence intervals. The category "other upland crops" encompasses a variety of crops including orchards, rapeseed, barley, rye, oat, canola and tobacco. Abbreviations used are NA for North Asia.

our case, the Rosenthal fail-safe number was $>5n+10$ (Supplementary Table 3).

The normality of the data was assessed using the Kolmogorov-Smirnov test, and in cases where the data did not exhibit normal distribution, a natural logarithm (ln) transformation was employed to stabilize the distribution to approximate normality. In addition to the meta-analysis procedures, nonparametric (resampling) procedures were used for further analyses to test for differences in the N application rates and soil NO_3^- leaching between ecosystem types. Linear regression analysis was used to explore whether the LFs were affected by potential driving factors. To further clarify the factors that directly or indirectly influenced NO_3^- leaching, Structural Equation Modeling (SEM) was performed with AMOS 26.0 (Amos Development Corporation, Chicago, IL, USA) to determine the comprehensive effects between ecosystem types, environmental conditions (i.e., hydroclimatic conditions and soil properties), management practices, and LFs. Prior to SEM construction, the variance inflation factor was utilized to test for multicollinearity between impact factors, which were excluded when the variance inflation factor was >5. Subsequently, the SEM was constructed stepwise based on the selected impact factors until the SEM met the evaluation criteria (root-mean-square error of approximation <0.05, fit index (CFI) > 0.95, and P-value > 0.05)[55,56]. Moreover, Random Forest modeling, as an ensemble learning method, was applied to quantify the most important predictors of LFs, including continuous and discrete variables such as ecosystem types, hydroclimatic conditions (i.e., precipitation, irrigation, MAT and leachate volume), soil properties (i.e., soil texture, BD, soil pH, SOC, TN and C/N ratio), sampling depth, and management practices (i.e., N fertilizer rate/type). Further, Random Forest model training was used to structure a multiple regression model for the LFs based on the identified significantly important explanatory factors. To fit the multiple regression model, a tenfold cross-validation was conducted. Specifically, 80% of the derived dataset was employed to train the model, while the remaining 20% was used to validate the model[57]. Random Forest modeling was performed using the R package "*randomForest*", whereas the significance of the model and the importance of each factor were assessed by R of the "*A3*" and "*rfPermute*" packages. The performance of the model was assessed by the root mean squared error (RMSE) and the coefficient of determination (R^2)[58].

$$RMSE = \frac{1}{\bar{O}}\sqrt{\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}} \quad (4)$$

where, P_i and O_i represent the predicted and observed values of LFs, respectively; $\bar{o}$ is the average of all observed values, and n is the number of paired values. Model validation indicated that our developed models were robust, with high R^2 (0.76-0.89) and low RMSE values (0.55-0.81) (Supplementary Fig. 8), implying the developed models were appropriate for predicting grid-level LFs. Statistical significance was displayed as not significant for $P > 0.05$, and significant for $^{*}P < 0.05$, and $^{**}P < 0.01$. All statistical analyses were completed using SPSS version 23.0 (SPSS China, Beijing, China) and R[59]. The map was generated using ArcGIS 10.2 software.

Global mapping of NO_3^- LFs for cropland

Given the inherent challenges in quantifying the amount of N excretion during animal grazing and other stray N sources from managed grasslands, we limited our gridded NO_3^- LFs and leaching estimations to croplands. The global patterns of NO_3^- LFs at a spatial resolution of 0.5° × 0.5° were predicted using the Random Forest models mentioned above. Owing to the difficulty of obtaining high-resolution global data on sampling depth and leachate volume, we used root depth and groundwater rechange data as substitutes. The input data therefore included the global gridded dataset of climate, soil properties, root depth, fertilization, irrigation and groundwater recharge. Climate factors were obtained from the Climatic Research Unit Time Series (v. 4.03, 0.5° resolution). Precipitation over the growing season in each grid cell was identified as the period between the planting and harvesting dates. Soil properties and root depth were acquired from the Harmonized World Soil Dataset v. 2.0 (30 s). Global gridded cropland N input (5′), irrigation (0.25°) and groundwater recharge data (0.5°) were obtained from Cui et al.[17], Zhang et al.[60] and Wan et al.[61], respectively. All data were resampled at 0.5° resolution using the "*raster*" R package in R statistical software.

Scaling-up NO_3^- leaching

For estimating NO_3^- leaching induced by fertilization from global croplands, we used the constant (i.e., mean value) or crop- and region-specific (at grid scale) NO_3^- LFs derived in our study, as well as information on corresponding N input rates as reported by Cui et al.[17], FAO[62], and the statistical database of the International Fertilizer Industry Association (IFA, 2014 Crop-based Fertilizer Consumption Reports, https://www.ifastat.org/plant-nutrition). However, since data relating to the use of organic N fertilizers (i.e., manure) for different crops in various regions was not available, we focused our analysis on the effects of synthetic N fertilization on cropland NO_3^- leaching only. We used the following equations for our calculations:

$$F_{NO_3^- - N} = \text{constant } NO_3^- LF \times N \quad (5)$$

$$F_{NO_3^- - N} = \Sigma\,(\text{crop} - \text{specific } NO_3^- LF_i \times N_i) \quad (6)$$

$$F_{NO_3^- - N} = \Sigma\,(\text{region} - \text{specific } NO_3^- LF_j \times N_j) \quad (7)$$

where, $F_{NO_3^- - N}$ is the total NO_3^- leaching (Tg N yr^{-1}); Crop-specific NO_3^- LF_i and N_i represent the LF (%) and N fertilization rate (Tg N yr^{-1}) for different crop types (i.e., wheat, maize, rice, vegetable and other upland crops), respectively; Region-specific NO_3^- LF_j represents the LF (%) in each cropland grid predicted with Random Forest models, and N_j represents each grid's N fertilization rate (kg N yr^{-1}).

Data availability

The database that supports the findings of this study is available from https://doi.org/10.6084/m9.figshare.28079069.

Code availability

The computer code for global prediction is available at https://doi.org/10.6084/m9.figshare.28079069.

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Author contributions

Y.C. and Y.W. designed the study. Y.W. and Y.L. performed the research. Y.W. and Y.L. analyzed the data. Y.W. wrote the initial draft of the paper. Y.C., L.X., H.A., X.C., J.C., Y.F., T.V., Y.L., Y.Y., D.W., B.Y., and S.X.C. reviewed and revised the paper. All authors contributed to the discussion and interpretation of the results.

Competing interests

The authors declare no competing interests.

Additional information

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