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Legacy effects cause systematic underestimation of N_2O emission factors

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Agricultural soils contribute ~52% of global anthropogenic nitrous oxide (N_2O) emissions, predominantly from nitrogen (N) fertilizer use. Global N_2O emission factors (EFs), estimated using IPCC Tier 1 methodologies, largely rely on short-term field measurements that ignore legacy effects of historic N fertilization. Here we show, through data synthesis and experiments, that EFs increase over time. Historic N addition increases soil N availability, lowers soil pH, and stimulates the abundance of N_2O producing microorganisms and N_2O emissions in control plots, causing underestimates of EFs in short-term experiments. Accounting for this legacy effect, we estimate that global EFs and annual fertilizer-induced N_2O emissions of cropland are 1.9% and 2.1 Tg N_2O-N yr^{-1}, respectively, both ~110% higher than IPCC estimates. Our findings highlight the significance of legacy effects on N_2O emissions, emphasize the importance of long-term experiments for accurate N_2O emission estimates, and underscore the need for mitigation practices to reduce N_2O emissions.

Nitrous oxide (N_2O) is the leading substance responsible for stratospheric ozone depletion and ranks as the third most important greenhouse gas (GHG)[1,2]. Its global warming potential is ~300 times greater than that of CO_2 over a 100-yr period[1,3]. Agricultural soils account for ~52% of global anthropogenic N_2O emissions, resulting from the addition of synthetic nitrogen (N) fertilizers and animal manure to soil[4,5]. Direct soil N_2O emissions from N input in the agricultural sector have increased from 1.5 Tg N yr^{-1} in the 1980s to 2.3 Tg N yr^{-1} during 2007–2016 (ref. 5). Furthermore, global use of chemical N fertilizer has increased from 81 Tg N yr^{-1} in 2000 to 113 Tg N yr^{-1} in 2020 (ref. 6) and is expected to continue rising[7], indicating that N_2O emissions from agricultural soils are likely to grow further.

Regional and global N_2O emissions are often estimated using N_2O emission factors (EFs), which represent the percentage of applied N

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emitted as N_2O-N. This approach is commonly used because N fertilizer rates are a reliable predictor of N_2O fluxes[8–10]. EFs are determined by comparing N_2O emissions from fertilized plots to emissions from control plots that receive no additional N, and then dividing the difference by the N rate in the fertilized plot. A recent global synthesis estimated EFs at 1.02% for maize, 0.58% for wheat, and 0.52% for rice[8]. In IPCC Tier 1 methodologies, default global EFs are 1% for upland crops and 0.4% for rice[9]. Emission factors can be estimated through several approaches. The EFs of IPCC Tier 1 methodologies[9] are calculated by statistical analysis of field measurements[11–14] and meta-analysis[15–17], both of which rely on measurement of in situ N_2O emissions. However, these in-situ EFs are usually derived from short-term experiments (e.g., 1–3 years) that involve setting both the control plots and the N-treated plots within working croplands[8]. Since the soils in these experiments have often been fertilized prior to the start of the study, there is the potential for legacy effects from previous fertilization[18]. However, the extent to which past fertilization affects current N_2O emissions remains uncertain.

N_2O emissions from agricultural soils are produced predominantly by the microbial processes of nitrification (the aerobic oxidation of NH_4^+ to NO_3^-) and denitrification (the anaerobic reduction of NO_3^- to N_2) [19,20]. Both processes are affected by soil N availability, soil pH, and especially soil microbial activity[19,21]. N fertilizer addition increases substrate availability for nitrifying and denitrifying microbial communities, which may change their composition and activity over time[22,23]. A global meta-analysis indicates that long-term N fertilization stimulates soil denitrification rates[21]. Also, long-term N fertilizer addition generally reduces soil pH[24,25], which may stimulate N_2O emissions[12]. Additionally, fertilizer N can stimulate N turnover process so that the microbes will use native soil N for N_2O production[26]. These results suggest that N_2O emissions from control plots in short-term experiments may be elevated due to legacy effects of prior fertilization, resulting in the underestimation of EFs. Similarly, modeling studies[27,28] suggest that legacy effects may affect EF estimates because of historical soil N accumulation. However, this hypothesis of legacy effect on N_2O emissions has seldom been tested experimentally. The contribution of legacy effects to N_2O emissions is still unquantified, both at field and global scales, largely because it is difficult to quantify in current model simulations[28].

To address these challenges, we employed a combination of experimental approaches and data synthesis to determine whether in-situ EF estimates change over time. First, we synthesized data from field experiments around the world to quantify differences in EFs between short-term (i.e., ≤3 years) and long-term experiments (i.e., >5 years) under similar experimental conditions (**see Methods**). In this approach, minor differences in soil properties, climate conditions, and agricultural management practices between short-term and long-term observations could still influence N_2O. To address these limitations and to determine the mechanisms underlying legacy effects, we conducted a series of long-term field experiments covering the three main crop cereals: maize, wheat, and rice. We compared N_2O fluxes across three treatments: long-term zero N input, short-term zero N input, and long-term fertilizer N input (**see Methods**). Because all three treatments were located at the same site, this approach eliminated artifacts related to differences in properties, climate conditions, and management practices on N_2O emissions. We also measured soil C and N availability, pH, and the abundances of functional genes associated with N_2O production to explore the underlying mechanisms. Finally, we scaled up our findings to estimate global fertilizer induced N_2O emissions from cropland. This study highlights the role of legacy effects on global N_2O emission estimates, particularly in the context of IPCC Tier 1 methodologies.

Results

EFs increase with experimental duration

Our data synthesis reveals that the average EF in short-term experiments is significantly lower compared to long-term experiments (Fig. 1a). This difference arises because N_2O emissions in the control treatments (i.e., background N_2O emissions, E0) were significantly higher in short-term experiments (Fig. 1b). Model selection analysis indicates that experimental duration is the strongest predictor of differences in both EFs and E0 between short-term and long-term experiments (Supplementary Fig. 1). Specifically, the differences in EFs between short-term and long-term experiments (ΔEF) increased with experimental duration (Fig. 1c), while differences in E0 were negatively correlated with experimental duration (Supplementary Fig. 2).

In our field experiments, high N_2O emissions were generally observed after N fertilization, rainfall, and drainage events (Supplementary Fig. 3). Current fertilizer N input and N input history both significantly affected N_2O emissions (Fig. 2a and Supplementary Fig. 3). Compared to plots without current N fertilizer input (i.e., +N − N and −N − N), N fertilizer input (+N + N) significantly increased the N_2O

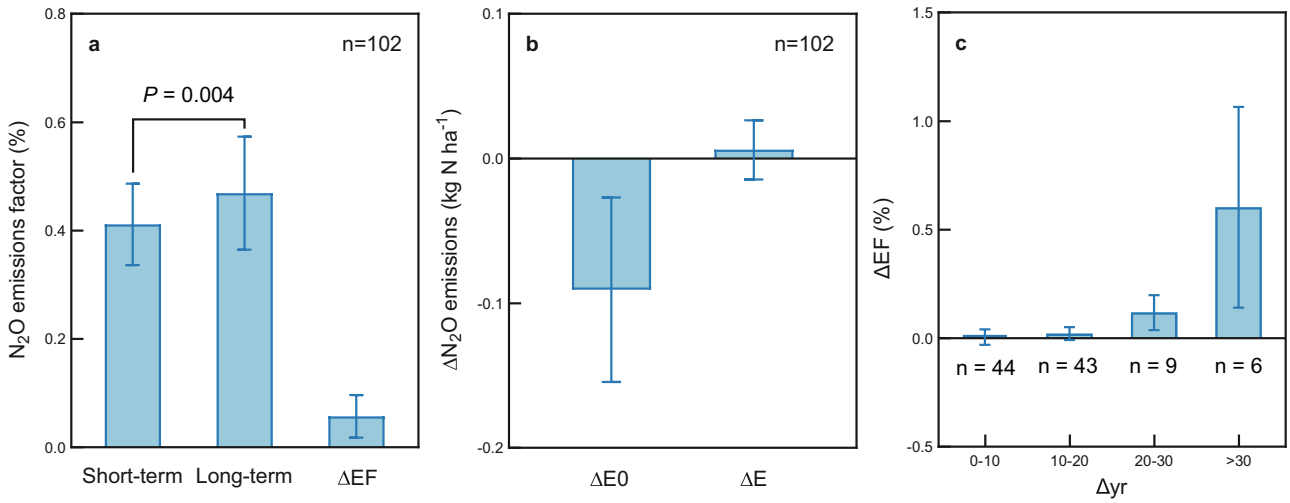

Fig. 1 | Results from a data synthesis on the effect of experimental duration on EFs. a the EFs of long-term and short-term N fertilization and their difference. **b** the difference in background N_2O emissions (ΔE0) and N_2O emissions under N fertilization (ΔE) between long-term and short-term N fertilization. **c** ΔEF under different durations (Δyr). EFs, N_2O emission factors; ΔEF, the difference in EFs between long-term and short-term N fertilization. The error bars represent 95% confidence intervals. Source data are provided as a Source Data file.

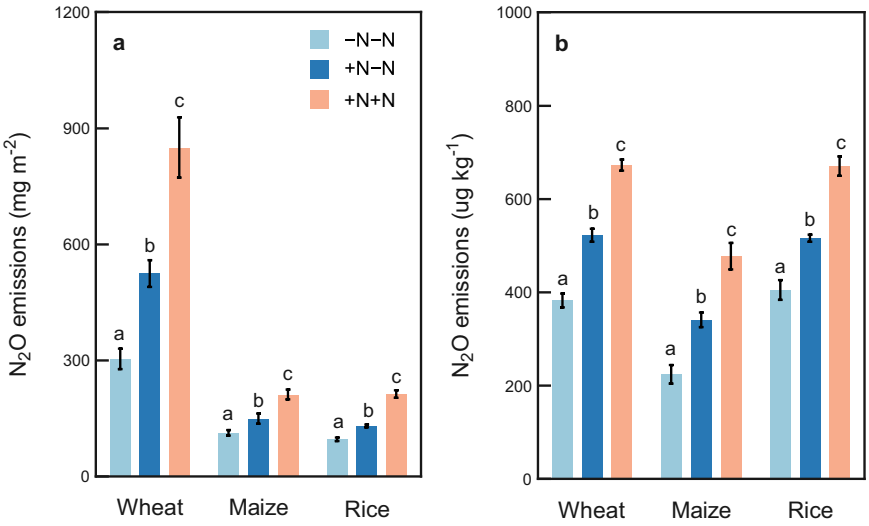

Fig. 2 | The effects of fertilizer N addition and soil fertilization history on N_2O emissions. a field experiment; **b** soil incubation experiment. −N − N, long-term zero N fertilizer input; +N − N, short-term zero N fertilizer input; +N + N, long-term N fertilizer input. Error bars indicate standard errors. Different letters represent significant differences ($p < 0.05$). Source data are provided as a Source Data file.

emissions in all three crops. The N_2O emissions were 33–73% higher in the short-term zero N fertilizer input (+N − N) treatment than in control plots that did not receive N fertilizer input for many years (−N − N). Consequently, the short-term EFs were 40%, 37%, and 30% lower than long-term EFs in wheat, maize, and rice, respectively (Supplementary Fig. 4a).

To study the effect of current and past N fertilization in the absence of plants, we conducted an incubation experiment using soils from the same sites. Consistent with the field measurements, N input and fertilization history significantly affected N_2O emissions in our incubation experiments (Fig. 2b, Supplementary Fig. 5). Compared to the treatments without current N fertilizer input, prolonged N input increased the N_2O emissions by 29–76% in wheat soils, 40–113% in maize soils, and 30–66% in rice soils. The N_2O emissions of +N − N were 36%, 52%, and 27% higher than that of −N − N in wheat, maize, and rice, respectively. As a result, short-term EFs were 42–48% lower than long-term EFs in the three experiments (Supplementary Fig. 4b). Together, these results indicate that short-term experiments underestimate EFs, mainly due to legacy effects of N fertilizer input on soil properties in zero N plots.

Soil properties change with experimental duration

Compared to the −N − N treatment, +N + N increased soil total N contents (Supplementary Table 1) and extractable N concentrations (i.e., NH_4^+ and NO_3^-) in all three field experiments (Supplementary Fig. 6a). Soil fertilization history also significantly affected the soil extractable N concentrations. Soil extractable N concentrations of +N − N treatments were 39–74% higher than for −N − N treatments (Supplementary Fig. 6a). Compared to the −N − N treatment, +N + N and +N − N reduced the soil pH by 0.2–0.7 units (Supplementary Fig. 6b), but they did not affect the soil organic carbon contents (Supplementary Table 1) and dissolved organic C concentrations (Supplementary Fig. 6c).

Current N fertilizer additions increased the abundances of functional genes associated with N_2O production (i.e., *nirK* and *nirS*) in all three field experiments (Fig. 3a, b). Compared to the −N − N treatment, +N − N significantly increased the abundance of *nirS*, but not the abundance of *nirK*. Current N fertilizer input also significantly increased the abundance of N_2O consuming microorganisms (i.e., *nosZ*) (Fig. 3c). Historic fertilizer N input did not affect the abundance of *nosZ* in wheat and maize, but significantly increased the abundance of *nosZ* in rice. Both current and historic N fertilizer additions increased the ratio of the abundances of *nirK* plus *nirS* to the abundance of *nosZ* (Fig. 3d). The relative importance analysis indicates that among a wide range of soil environmental factors, the abundance of *nirS* is the most important factor affecting N_2O emissions (Supplementary Fig. 7).

Global EFs and N_2O emissions from cropland

To quantify N legacy effects on global cropland N_2O emission inventories, we first developed a quadratic regression model for ΔEF, including duration of zero N fertilizer input in control plots and a wide range of environmental factors (i.e., soil organic carbon, soil clay, and pH), and then scaled up our results (**see Methods**). Because our data synthesis indicates that legacy effects wane over time and N fertilization is a long-term practice, we considered a long-term scenario (i.e., 40-year) without N fertilizer input in control plots (**see Methods**). In other words, ΔEF indicates the error made by assuming IPCC default values. The global average ΔEF value was estimated at 0.88% with a 95% CI from −0.07% to 1.37% (Fig. 4a). Most cropping areas around the globe show ΔEF values > 0.8%, but regions at high latitudes, such as northern Europe, parts of Central America, and the southern part of South America, exhibit relatively low ΔEF (< 0.5%). Soil organic carbon content was the most important driver of spatial variation in ΔEF in 75–77% of the total global harvest area (Supplementary Fig. 8).

We used our estimates of global ΔEF to adjust IPCC Tier 1 default EFs (**see Methods**). Our adjusted global cropland N_2O EF is 1.9% (Figs. 4b and 5a). To investigate global N legacy effect on hotspots of EFs, we used the global cropland EFs dataset by Cui et al.[8]. This dataset, which is derived from 1507 georeferenced in-situ field EFs observations around the world, accounts for variation in crop type, environmental conditions and management and served as a baseline to adjust the global cropland N_2O EFs. Consistent with IPCC defaults, we found that global cropland N_2O EFs increased by ~110% (Fig. 5a). Hotspots—defined as areas with EFs greater than 3%—were primarily located in high-latitude regions, Southeast Asia, and Middle America (Fig. 4c).

Based on the IPCC Tier 1 default and the global cropland EF dataset, the original global cropland fertilizer-induced N_2O emissions were estimated to be ~1.0 Tg N_2O-N yr^{-1} (Fig. 5b). However, our adjusted estimate indicates global N_2O emissions of 2.1 Tg N_2O-N yr^{-1}. This suggests that the IPCC Tier 1 default approach underestimates global cropland fertilizer-induced N_2O emissions by 1.1 Tg N_2O-N yr^{-1} when compared with our updated EFs.

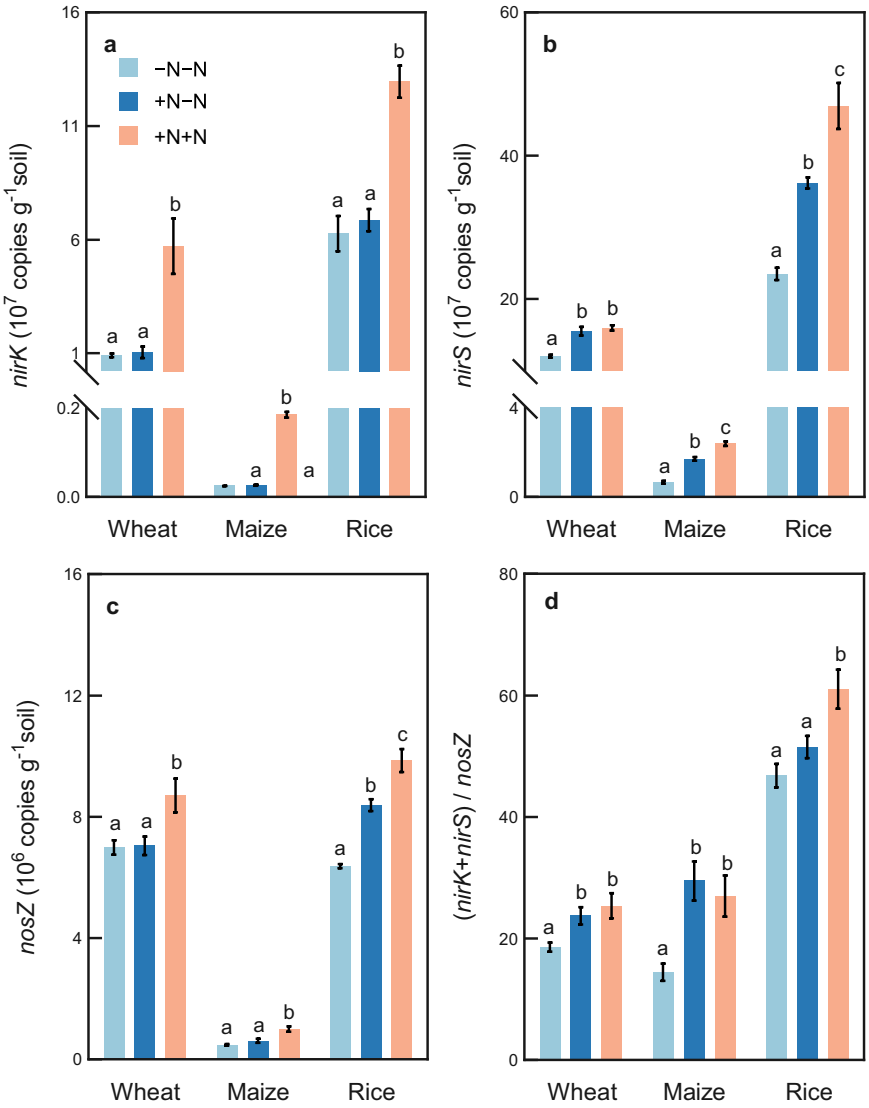

Fig. 3 | The effects of fertilizer N addition and soil fertilization history on the abundance of functional genes involved in N_2O emissions. a the abundance of *nirK* gene; **b** the abundance of *nirS* gene; **c** the abundance of *nosZ* gene; **d** the ratio of the abundances of *nirK* plus *nirS* to the abundance of *nosZ*. −N − N, long-term zero N fertilizer input; +N − N, short-term zero N fertilizer input; +N + N, long-term N fertilizer input. Error bars indicate standard errors. Different letters represent significant differences ($p < 0.05$). Source data are provided as a Source Data file.

Discussion

Our data synthesis revealed that historic fertilizer N input increases current N_2O emissions on a global scale. Additionally, our field and incubation experiments provide further evidence that EF increases over time with prolonged N application. Specifically, plots that recently stopped receiving fertilizer N input emit more N_2O than those where N input ceased longer ago (Fig. 2 and Supplementary Fig. 1). Several mechanisms may have contributed to these results. First, our experiments showed that historic fertilizer N input increased soil total N contents and extractable N concentrations, leading to higher N_2O emissions. These results are consistent with long-term experiments indicating that N fertilization increased soil N turnover rate and N availability over time[29–32]. Second, the soil pH was much lower in the short-term zero N fertilizer treatment, because historic N fertilization reduced soil pH over time[24,33]. Low soil pH often reduces the activity of N_2O reductase and increases the ratio of N_2O to N_2O and N_2, resulting in higher N_2O emissions[34].

Our experiments further indicate that the abundance of *nirS* was much lower in long-term zero N fertilizer treatment (−N − N) than in the short-term zero N fertilizer treatment (+N − N, Fig. 3b), which can result in lower N_2O production potential. These results corroborate several long-term experiments showing that prolonged N fertilization increased the abundances of *nirK* and *nirS*, and soil N_2O production potential[21,31,35]. Furthermore, the +N − N treatment increased the ratio of the abundances of *nirK* plus *nirS* to the abundance of *nosZ*, indicating a greater potential for N_2O production compared to N_2O consumption, relative to the −N − N treatment[36]. In addition, several studies indicate that long-term N input alters the structure of community structure of *nirK* and *nosZ*[37,38], and increases the complexity of microbial co-association networks[39–41]. These changes may further increase N_2O emissions in plots without current fertilizer N input. These results align with our observation that the abundance of *nirS* is the most important factor affecting N_2O emissions, and emphasize the role of soil microbes in driving the differences in N_2O emissions between the short- and long-term zero N fertilizer treatments. Taken together, our findings indicate that historic N addition increases N_2O emissions primarily through increased soil N availability, reduced soil pH, and the stimulation of N_2O-producing microorganisms.

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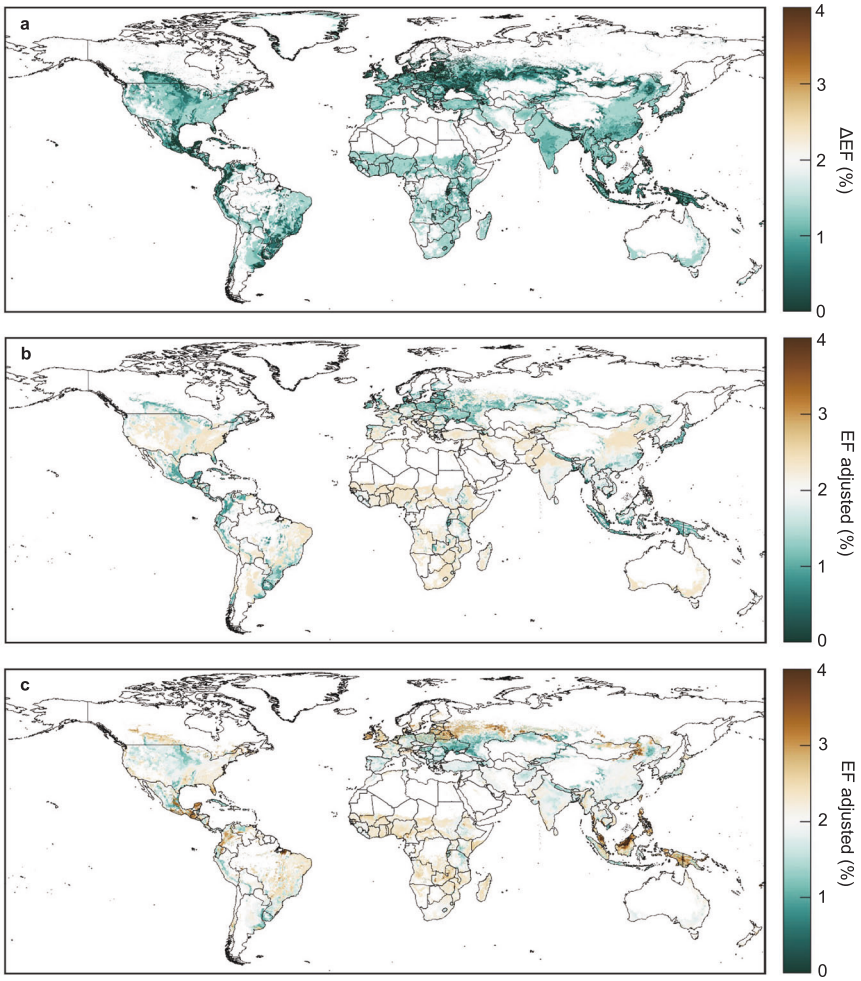

Fig. 4 | Spatial pattern of simulated ΔEF and adjusted global cropland N_2O EFs. **a** ΔEF is predicted with the quadratic model weighted by similarity. **b** adjusted global cropland N_2O EFs based on Tier 1 methodology. **c** adjusted global cropland N_2O EFs based on Cui et al. [8]. EFs, N_2O emission factors; ΔEF, the difference in EFs between long-term and short-term N fertilization. Values are shown only where the proportion of harvested area within the grid cell is greater than 1%. The map images were generated using MATLAB R2023a.

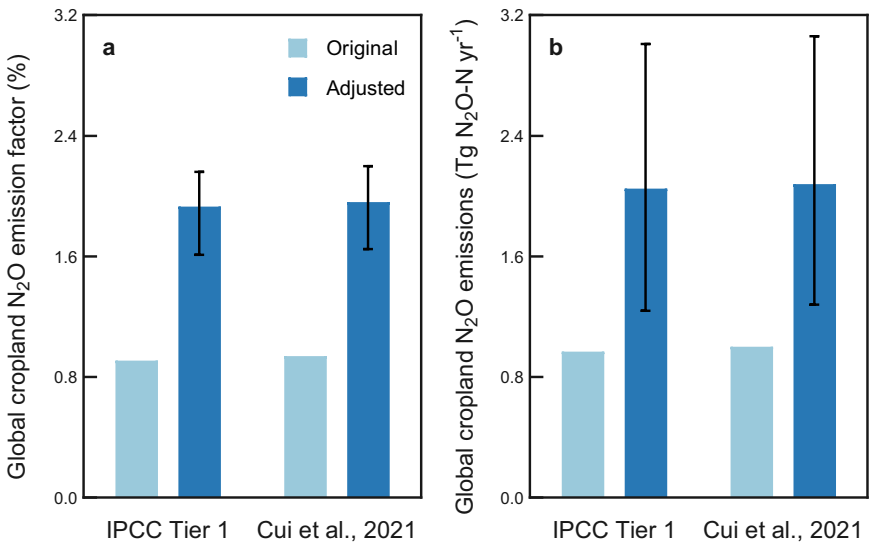

Fig. 5 | Comparison between our estimate of global cropland fertilizer-induced N_2O emissions and previous estimates. **a** global cropland N_2O emission factor. **b** global cropland fertilizer-induced N_2O emission. Error bars represent the 95% confidence interval. Source data are provided as a Source Data file.

N_2O emissions of short-term zero N fertilizer treatments are substantially higher than those from long-term zero N treatments in both our data synthesis and experimental results. This suggests that short-term experiments are influenced by legacy effects from historic N fertilization, which, in turn, lowers the estimated EFs. Consequently, our findings indicate that the IPCC Tier 1 methodology underestimates the global EFs for cropland, because it does not account for legacy effects of previous N fertilizer input. The IPCC Tier 1 default global EF of 1% is derived from empirical models based on in-situ N_2O emissions, factoring in variables such as climate, soil conditions, agricultural management, and measurement techniques[12,14,42]. However, these models assume the same soil conditions for both fertilized and zero-N treatments, overlooking the lingering impact of previous N fertilization.

Our estimated EF aligns with values from an ensemble of process-based models (1.7%, 1.2–2.3%)[5] and a recent top-down inversion model (2.3%)[10]. This consistency suggests that the legacy effect of fertilizer N is a key factor contributing to the discrepancies between field measurements and model-based approaches. Our EF estimates are likely conservative, because residual fertilizer N has accumulated over more than 40 years in major cropping regions with long histories of N fertilization, such as China, the USA, and Europe[43]. Furthermore, while this study focused on N_2O emissions during the crop season, recent research indicates that approximately 44% of global N_2O emissions occur during the fallow season[44], further supporting the likelihood that our estimates underestimate the true emissions.

Our experiments focused solely on the effects of chemical N fertilizer input, but other N sources, such as organic amendments and crop residues, also gradually stimulate soil C and N availability and the activities of soil microbes involved in N_2O emissions[45–47]. This suggests that EFs of these amendments are also time-dependent. Therefore, temporal changes in soil properties caused by management practices, along with climate variability, should be considered when estimating N_2O emissions from agricultural soils. Overall, our results emphasize the importance of long-term experiments in accurately assessing the impact of agricultural practices on N_2O emissions.

Our study introduces an approach for quantifying the contribution of legacy effects to N_2O emissions, offering new insights into the mechanisms driving these effects and helping to reconcile discrepancies between field measurements and model-based estimates of EFs. However, several uncertainties and limitations in our assessments should be acknowledged. First, although we took care to only include comparisons between short-term and long-term experiments that matched in N rate, crop type and spatial range (**see Methods**), there were inevitable differences in soil properties, agricultural management, and N_2O measurement technology, which introduce some uncertainty into the data analysis. Yet, relative importance analysis indicates that the impact of differences in climate conditions and soil properties between short-term and long-term experiments on ΔEF were minimal (Supplementary Fig. 9). Moreover, our statistical approach assigned greater weight to studies with high similarity between short- and long-term sites, further reducing the uncertainty in our ΔEF estimates. Additionally, although we have gathered as much information as possible regarding climatic conditions, soil properties, and management practices in our data synthesis, certain factors—such as climate extremes, soil tillage history, and soil acidification—were not included due to the lack of reported data in most studies, which may lead to uncertainty in our assessments. Second, the spatially explicit global dataset that we used to adjust global cropland N_2O EF includes ~5% of observations from long-term experiments. Since our approach assumes that all these observations are from short-term experiments, this may have slightly affected the accuracy of our estimates.

Thirdly, the number of observations in our data synthesis is relatively low, especially long-term observations. However, our field experiments demonstrate that the relationship between EFs and experimental duration occurs under a wide range of environmental and experimental conditions, suggesting that our approach is robust. Finally, our data synthesis may be subject to geographical bias, as the studies in our dataset are concentrated in China and the United States. This restricts the explanatory power of our empirical model at the global scale. To enhance model reliability and robustness given the limited observations, we employed repeated tenfold cross-validation for parameterization. Nonetheless, additional long-term fertilization studies with comprehensive information on climatic conditions, soil properties, and management practices would improve our estimates of legacy effects on EFs - specifically those incorporating both short-term and long-term zero-N input treatments to measure annual N_2O emissions. This is particularly important for understudied regions such as Southern Asia and Sub-Saharan Africa.

Our results indicate that due to legacy effects, N fertilization stimulates N_2O emissions from cropland more strongly than previously estimated, emphasizing the need for N_2O emission mitigation practices. Fortunately, several agricultural practices can reduce N_2O emissions from agricultural soils. For instance, modern high-yielding crop cultivars can reduce the N_2O emissions due to higher N uptake[48,49]. A recent study suggests that reducing global cropland N surplus can lower direct N_2O emissions from cropland by ~30% without yield loss[8]. Enhanced-efficiency N fertilizers (i.e., controlled-release fertilizer, urease inhibitors, and nitrification inhibitors) application can reduce N_2O emissions[50–52]. Finally, biochar can also reduce N_2O emissions substantially[53,54].

In summary, our findings indicate that short-term experiments tend to underestimate EFs due to legacy effects in the control treatments. Specifically, N_2O emissions from short-term zero N plots input are substantially higher compared to long-term zero N plots, due to increased soil N availability, greater *nirS* abundance, and lower soil pH. After accounting for these legacy effects, we estimate that the global EFs of cropland are ~110% higher than the estimates provided by the IPCC Tier 1 methodology. Likewise, we estimate that the IPCC Tier 1 methodology underestimates annual fertilizer-induced N_2O emissions from cropland by 1.1 Tg N_2O-N yr^{-1}. Given the substantial impact of N fertilization legacy effects on N_2O emissions, it is preferable to calculate to calculate EFs at both field and regional scale using data from long-term fertilization experiments. Our findings emphasize the importance of long-term studies, and underline the need for judicious agricultural management to curb N_2O emissions.

Methods

Data synthesis

To estimate the legacy effect of N fertilization on EF estimates, we updated the global N_2O EF observation dataset by Cui et al.[8] to May 2023, using Web of Science to search journal articles. Studies with N_2O emissions from field experiments with varying durations with at least two different N application rates were selected, including a zero N and a fertilizer N input treatments. Studies with the following measurements were excluded: (i) experiments conducted in laboratories or greenhouses, (ii) measurements conducted in organic (peaty) soils where N_2O emissions are much higher than those in mineral soils[9], and (iii) measurements with the use of controlled-release fertilizers, or nitrification or urease inhibitors.

The number of observations from long-term experiments (i.e., those lasting more than 5 years) in our dataset is an order of magnitude lower than those from short-term experiments (i.e., lasting 3 years or less). This imbalance could obscure the effects of fertilization duration in our analysis. To address this, we employed a pairing method to test the differences in EFs between short-term and long-term experiments[55]. Briefly, for each observation from a long-term experiment in our dataset, we identified nearby short-term experiments within a spatial range of no more than 1°. This range was selected to optimize the balance between data availability and accuracy, as

environmental and management conditions are generally homogenous within this distance (e.g., Global Land Data Assimilation System, https://ldas.gsfc.nasa.gov/gldas). Our approach was designed to reduce variation in N_2O emissions between short- and long-term experiments that might arise from differences in climate conditions between sites. Because N application rate and crop type (i.e., rice paddy versus upland crops) are key factors influencing EFs[56,57], we ensured that that paired comparisons involved the same crop type and a similar N application rate (within 20%) at both locations. Although the selected pairs had similar climate, N application rate, and crop types, minor variations remained, potentially affecting cropland N_2O emissions. To minimize the impact of these differences, we only included pairs where the variation in N_2O emissions of N addition treatments between long-term and corresponding short-term observations was within 20% and 0.3 kg N_2O-N ha^{-1}. If a long-term observation matched several paired short-term observations, we used the mean value of the short-term experiments. In total, we found 102 paired observations from China (96) and USA (6).

For each set of paired observations, we collected four categories of information: (i) N_2O emissions, (ii) climatic conditions, (iii) soil properties, and (iv) management practices. Paired observations of N_2O emissions with and without N fertilization in the same field experiment were used to calculate the N_2O EFs. Climatic conditions include annual mean air temperature (MAT, °C) and annual precipitation (MAP, mm). Soil properties include soil organic carbon content (SOC, g kg^{-1}), pH, bulk density (BD, g cm^{-3}), and clay content (g kg^{-1}). For each climatic and soil factor, averaged values of long-term and short-term sites were used in the data analysis. Management practices include crop type, N fertilizer application rate (kg N ha^{-1} $season^{-1}$), tillage, liming and experimental duration (yr). This information was obtained from the original papers, and the missing values were supplemented from climate (WorldClim v2.1, https://www.worldclim.org/data/worldclim21.html) and soil databases (HWSD v1.2, https://iiasa.ac.at/models-tools-data/hwsd).

The absolute differences in EFs between short-term and long-term experiments (ΔEFs), assumed to reflect the legacy effects of N fertilization, were analyzed using resampling methods. To determine whether our dataset followed a normal distribution, we conducted a Kolmogorov-Smirnov test, which indicated significant deviation from normality ($P < 0.001$). Given the non-normal distribution of the data, we used a bootstrapping resampling approach ($n = 100000$) to estimate the mean values of ΔEFs and calculate 95% confidence intervals (CIs) around these means, using the bootstrapping function in R.

To identify the key factors determining variation in ΔEF, we conducted a random forest (RF) analysis in R using the "randomForest" package. RF is an ensemble tree-based learning method, with its ability to quantify the relative importance based on the decrease in model accuracy of the absence of each variable. The difference in experiment duration between short- and long- term observations (i.e., Δyr) stood out as the most important predictor (Supplementary Figs. 1 and 9).

Field experiments

We compared long- *vs.* short-term effects of N fertilizer input on N_2O emissions in three long-term fertilization field experiments in Chinese cropping systems. One experiment was established in a rice-wheat system since 1980 at Suzhou Academy of Agricultural Sciences, Jiangsu Province, China (31°27′N, 120°25′E) and the other two experiments were established in a double maize system since 1986 and in a double rice system since 1981 at Jiangxi Institute of Red Soil and Germplasm Resources, Jiangxi Province, China (28°15′N, 116°20′E). Further details on the experimental design, climate, initial soil properties, and crop phenology can be found in Supplementary Table 2. The temperature and precipitation throughout the crop seasons when N_2O emissions were measured are shown in Supplementary Fig. 10.

In each experiment, we selected two treatments, i.e., long-term without N fertilizer input (−N plots) and long-term with N fertilizer input (+N plots), to conduct our field micro-plot experiments. Soil properties (0–20 cm) for −N plots and +N plots are shown in Supplementary Table 1. Both treatments received P and K fertilizers at the same rate. In each +N plot, we created four microplots by inserting plastic frames (length × width × height: 15 cm × 20 cm × 50 cm in the rice-wheat and double rice systems, 50 cm × 50 cm × 50 cm in the double maize system) into the soil with a depth of 45 cm (~5 cm of the frame remained above the soil surface). Two microplots received N fertilizer at the same rate as the rest of the plot, whereas the other two microplots received no N fertilizer. Also, in each −N plot, we inserted plastic frames to create two microplots that did not receive any N fertilizer. Thus, all field experiments included 3 treatments with 6 replicates: long-term without N fertilizer input (−N − N), short-term without N fertilizer input (+N − N), and long-term N fertilizer input (+N + N).

The N, P, and K fertilizer rates are shown in Supplementary Table 3. All other agricultural practices between the plots and microplots are the same. To avoid artifacts related to differences in climatic factors between short-term and long-term N fertilization treatments, we measured N_2O emissions from all plots simultaneously.

Incubation experiment

To eliminate the influence of crop plants on legacy effects, we conducted an incubation experiment to test the impact of fertilizer N history on N_2O emissions. We collected soils (0–15 cm) from the −N plots and +N plots in the above long-term field experiments using the 2 cm soil samplers. Soil samples were combined per plot, air-dried, and sieved. As with the field experiments, the incubation experiment consisted of 3 treatments for each site: −N − N, +N − N, and +N + N. We added 50 g soils into each bottle (10 cm in diameter, 16 cm in height). In the +N + N treatments, we also added 6 mg N as urea into each bottle. The moisture of the soil was adjusted to ~60% of the maximum water-holding capacity. The bottles were incubated at 26 °C in the dark for 25 days.

Sampling and measurement methods

In the field experiments, we used the static closed chamber technique to collect N_2O gas samples[58,59]. N_2O gas samples were collected at ~7-day intervals during the observation period, and additional gas samples were collected after N fertilization and rain events. Overall, gas samples were collected 16 times in wheat after thinning, 20 times in maize after thinning, and 15 times in rice after transplanting. On sampling days, chambers with a size of 50 cm/100 cm (depending on plant height) × 15 cm × 20 cm were placed over the plastic frames. We then collected four gas samples at 0, 10, 20, and 30 min after placement of the chamber. The N_2O concentrations were measured by a Gas-Monitor (1412 Photoacoustic, INNOVA, Denmark) in the rice-wheat system and by gas chromatograph (GC-2010 PLUSAF, SHIMADZU, Japan) in the double rice and maize systems. We used linear regression between gas concentrations and sampling time to calculate N_2O fluxes[60]. We only accepted measurements for which $R^2 > 0.90$ and discarded approximately 5% of the measurements. Cumulative N_2O emissions during the observation period were calculated from the emissions between every two adjacent intervals of measurements by the trapezoidal method[45].

In the soil incubation experiments, the gas samples were collected every day during the first week after N addition, and at 3-day intervals after that. Overall, gas samples were collected 11 times in the soil incubation experiments. On sampling days, we collected 50 ml gas sample from the bottle headspace at 0 and 2 h after sealing the bottle, using a gas-tight push button syringe. The N_2O concentrations were measured by a Gas-Monitor (1412 Photoacoustic, INNOVA, Denmark). The N_2O flux was calculated by the change in N_2O concentrations

between the two hours. Cumulative N_2O emissions were estimated using the trapezoidal method[45].

We collected fresh soils at the crop heading stage when N_2O emissions varied among treatments. Soil ammonium (NH_4^+) and nitrate (NO_3^-) concentrations were measured by flow autoanalyzer (Auto Analyzer 3, BRAN LUEBBE, Germany). A kit (Power Soil DNA Isolation, MoBio, USA) was used to extract soil DNA. We quantified the copies of *nosZ*, *nirK* and *nirS* genes to represent denitrifier abundances. We used the CFX96 (Bio-Rad, America) to perform the quantitative real-time PCR.

Statistical analysis

We analyzed the data on N_2O emissions and soil properties by one-way ANOVA. Differences between treatments were analyzed by using the least significant difference test. All analyses were performed with the statistical package SPSS 27. Differences between treatments were considered significant at $p < 0.05$.

ΔEF modelling

To evaluate global variations in ΔEF, we developed a quadratic regression model. The response of ΔEF in the model varies in response to environmental and management-related factors. Akaike Information Criterion-based stepwise regression was used to select key variables for the model using the 'MASS' package in R. The model was trained and tested on a tenfold cross-validation, repeated ten times[44,61,62]. Tenfold cross-validation divides observations into 10 equal parts, training the model on 9 parts and testing on 1, with this process repeated 10 times so each part serves as the test set once. To mitigate bias from random divisions, the tenfold cross-validation was repeated 10 times for possible subdivisions. The averaged coefficients of the models based on 100 trainings were stored for global spatial prediction.

Three types of weighting methods in the regression (i.e., unweighted, proximity- and similarity-based weighting)[63–65] were compared to identify the best model. The methods based on proximity and similarity utilize the shortest distances between paired long- and short-term sites, and the environmental and management (i.e., mean annual temperature and precipitation, soil bulk density, clay content, organic carbon content and N application rate) similarities, to weight the observations respectively. To avoid the influences of correlation between factors, principal component analysis was adopted to estimate the similarities between paired sites. The performance and robustness of the model was evaluated by comparing simulated and observed ΔEF, using R^2, slope and root mean square error (RMSE). The results showed that the similarity-weighted model performed best among all models both for calibration and validation (Supplementary Table 4), and was therefore selected to predict the global variations in ΔEF. The corresponding means and standard errors of the model coefficients for global prediction are listed in Supplementary Table 5.

Global prediction of ΔEF

The global patterns of ΔEF were predicted using the quadratic model at five-arcminute spatial resolution. The input data included the global gridded dataset of duration scenario, soil clay content, organic carbon content and pH, which were identified as variables for the model (Supplementary Table 5). Given that the differences in durations of short-term and long-term experiments range from 2 to 42 years in our dataset and ΔEF increases over time with prolonged N application, we considered a long-term scenario i.e., 40-year without N fertilizer input in control plots. This approach provides the most representative estimates, as N fertilization in main cropping regions has typically exceeded 40 years[43]. The soil data was acquired from the HWSD v.1.2, and all the input data was re-gridded at the resolution of 5′ × 5′.

Attribution of spatial variation in ΔEF

To identify the dominant driver of spatial variation in ΔEF, we performed a partial correlation analysis between ΔEF and environmental variables at the global scale[8,66,67]. This analysis was conducted using moving windows of 3.75°-by-3.75°. The data resolution was 5′ by 5′, meaning that the surrounding 2025 pixels were used for each 5′ pixel. We first calculated the coefficient and significance of partial correlation for each pixel, and then identified the dominant driver as the one with the largest absolute value of the correlation coefficient. To evaluate the robustness of our results, we performed similar analyses with moving windows at higher spatial resolutions, specifically 1.75° by 1.75°, and 2.75° by 2.75°.

Global prediction of adjhusted EF

To quantify the impact of legacy effect of N fertilization, we adjusted global cropland EFs. Grid-level adjusted EFs (AEF_{gy}) with spatial variation (spatial resolution: 5′ × 5′) and global-level EFs (AEF_y) were estimated by adding ΔEF to baseline EFs which did not consider the legacy effect. The baseline EFs were from IPCC Tier 1 EF defaults[9] and a recent crop-environment-management specific N_2O EF model[8]. We calculated the global variation of adjusted EF using unweighted, proximity- and similarity-weighted models to assess the robustness of the results.

Since cropland for each grid is cultivated with various crops, we firstly calculated the baseline EF (EF_{gi}, see Eq. 1) for each crop type at grid level, based on gridded global datasets of crop distribution, crop-specific N application amount, soil properties, climatic factors and related- management practices in 2000 (ref. 8).

$$EF_{gi} = \sum_j \alpha_{ij} \cdot x_{gij} + \theta_i \tag{1}$$

where g is grid index; i is crop type (IPCC Tier 1: upland crop and paddy rice; N_2O EF model: maize, wheat, rice and others); j is the variable index; x is the model independent variable; α and θ are the variable coefficient and intercept. For the IPCC Tier 1 method[9], x was crop type, and EF_{gi} for upland crop and paddy rice were 1% and 0.4%, respectively. For the crop-environment-management specific model[8], x includes soil properties (i.e., bulk density, clay content, organic carbon content, pH), climatic factors (i.e., temperature, precipitation and humidity index) and related-management practices (fertilization rate, type, frequency and placement, irrigation and tillage type). The values of variable coefficients and intercepts of the model can be found in Cui et al. [8]. Since ~95% of the EF observations in the dataset from Cui et al. [8] were from short-term experiments, we assume their results did not account for legacy effects.

The adjusted EFs for each crop within grid g (AEF_{giy}) were generated by adding EF_{gi} and the global prediction of ΔEF_{giy} (Eq. 2).

$$AEF_{giy} = EF_{gi} + \Delta EF_{giy} \tag{2}$$

The grid-level adjusted EFs (AEF_{gy}) were calculated by weighting AEF_{giy} based on N input of each crop (Eq. 3).

$$AEF_{gy} = \frac{\sum_i (N_{gi} \cdot AEF_{giy}/100)}{\sum_i (N_{gi})} \tag{3}$$

where N is the N input for each crop.

Finally, adjusted global-level EFs (AEF_y) were calculated as the sum of N fertilizer-induced N_2O emissions divided by the sum of N input from all grids (Eq. 4).

$$AEF_y = \frac{\sum_{gi} (N_{gi} \cdot AEF_{giy}/100)}{\sum_{gi} (N_{gi})} \tag{4}$$

Uncertainty estimation of adjusted EF

A Monte Carlo simulation was used to estimate the overall uncertainty for predicting the adjusted N_2O EF. Two uncertainty sources, the model coefficients and the global input dataset, were considered to generate a prediction interval. The uncertainties were obtained by randomly generating model coefficients from the fitted multivariate normal distributions and the soil variables following independent normal distributions with a standard deviation of 20% (ref. 8). Predicted ΔEF values were firstly calculated through 100 simulation iterations, and then used to adjust the N_2O EF of IPCC Tier 1 approach and Cui et al. [8]. This process constructed the 2.5% and 97.5% quantiles of the adjusted EF within a 95% prediction interval.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The dataset of differences in N_2O emission factors between short-term and long-term experiments for this study is available from Supplementary Dataset 1. Other data supporting the findings of this manuscript are available in the main text, and Supplementary Information. Source data are provided with this paper.

Code availability

The computer code for statistics, global prediction and uncertainty estimation used in this study has been deposited in the "Figshare" at https://doi.org/10.6084/m9.figshare.27247668 (ref. 68).

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Author contributions

Y.J. designed the study. H.Q. and Ziyin Shang performed data synthesis. Ziyin Shang conducted modelling and spatial simulation. H.Q., Z.Y., N.C., X.Z., S.H., C.L., and K.L. conducted the experiments. Y.J., Y.D., H.Q., and Ziyin Shang drafted the paper. F.Z., P.S., H.T., Q.X., J.Z., S.L.,

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Competing interests
The authors declare no competing interests.

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