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# An update of emission factors for nitric oxide emissions from croplands and grasslands

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ABSTRACT

Nitric Oxide (NO), an intermediate product in the soil nitrogen cycle, is also an air pollutant causing adverse health effects, including contribution towards the formation of fine particulate matter and tropospheric ozone. Accurate quantification of NO emissions is necessary to mitigate these impacts, but current emission factors used in national greenhouse gas and air pollutant inventories are associated with substantial uncertainty, necessitating an updated assessment based on recent field measurements. In this study, we compiled a comprehensive dataset of 692 field observations of NO measurements from 128 studies conducted globally. Using Bayesian generalised linear mixed-effects models, we derived new emission factors that account for synthetic and organic fertiliser inputs, climate zones and crop groups. The new global emission factor (expressed as mass fraction of nitrogen) for synthetic nitrogen inputs to common crops and grasslands was 0.0042 kg NO-N (kg N)$^{-1}$ (95 % credible interval: 0.0035–0.0049), while organic nitrogen inputs exhibited a negligible fertiliser induced emission factor of 0.0001 kg NO-N (kg N)$^{-1}$ (95 % CI: 0.0003 – 0.0005). The emission factors varied markedly upon stratification by climate zones and crop groups, with higher emission factors from synthetic fertilisers in the tropical rainforest regions, while paddy rice cultivation exhibited negligible fertiliser-induced NO emissions and tea plantations showed exceptionally high emissions with a factor of 0.0155 kg NO-N (kg N)$^{-1}$ (95 % CI: 0.0101–0.0225). The new emission factors are considerably lower than the Tier 1 value of 0.0133 (0.0015–0.0317) kg NO-N (kg N)$^{-1}$), currently recommended in the EMEP/EEA guidelines. Application to nitrogen fertiliser input data from EU member states' 2025 Informative Inventory Reports indicates that, adopting the new emission factors would result in reported emissions from synthetic fertilisers being lower by approximately 65 %. These findings highlight the need for refined inventory methodologies, replacing the default emission factor with climate and crop specific values, to better inform strategies for nitrogen management and air quality monitoring.

## 1. Introduction

Nitrogen Oxides ($NO_x$), a term which refers primarily to the reactive gases Nitric Oxide (NO) and Nitrogen Dioxide ($NO_2$), are air pollutants with many adverse effects on the environment and human health. They play a key role in formation of fine particles (Gu et al., 2021; Harrison, 2020) and other secondary air pollutants such as tropospheric or ground-level ozone ($O_3$) (Nguyen et al., 2022), which are health hazards (Fuller et al., 2022; Van Grinsven et al., 2013). $NO_x$ also contribute to atmospheric nitrogen deposition, which causes eutrophication of ecosystems (de Vries, 2021) and indirect emissions of the greenhouse gas nitrous oxide ($N_2O$) (Hergoualc'h et al., 2019).

$NO_x$ are released into the atmosphere primarily from fossil fuel combustion, biomass burning and through soil biogenic processes (Delmas et al., 1997). In the context of biogenic processes, $NO_x$ emissions originate as NO, an intermediate product during the processes of nitrification and denitrification in the nitrogen cycle (Butterbach-Bahl et al., 2013). NO rapidly reacts in ambient air to form other reactive nitrogen compounds such as nitrogen dioxide ($NO_2$) and Nitrous acid (HONO), both of which play important roles in atmospheric chemistry and contribute to air pollution. Agriculture contributes to $NO_x$ emissions significantly, accounting for about 14 % of the total $NO_x$ emissions in Europe (European Environment Agency, 2025). Moreover, NO is one of the major pathways for nitrogen (N) losses in agriculture and having a

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better quantification of such losses through NO emissions is essential towards improved N management (Delgado, 2002).

Despite agriculture's substantial contribution to NO emissions, there has not been enough focus specifically on the mitigation of NO emissions from agriculture. For instance, the Gothenburg protocol (UNECE, 2013) and the EU National Emission Ceilings directive (European Parliament, 2016), which set limits for emissions of air pollutants do not specify a limit for NO emissions from agriculture. To mitigate NO emissions and facilitate the setting of emission reduction targets, an accurate baseline of emissions is crucial. Presently, European countries follow guidelines laid out by the European Monitoring and Evaluation Programme (EMEP) for reporting $NO_x$ emissions in their national inventories (Hutchings et al., 2023), however, these estimates are usually based on general global methodologies and do not take into account crop production systems or climatic conditions. The methodology for estimating NO emissions from fertiliser application is based on an emission factor (EF) provided by Stehfest and Bouwman (2006) which is derived from data published until 2005 and this provides a scope for updating and refining the emission factor for NO emissions by including results of new primary studies. To maintain consistency and enable comparison across different reporting frameworks, emission factors in this study are expressed as mass fraction of nitrogen (NO-N) which represents only the nitrogen component regardless of the molecular form and chemical reactions in the atmosphere, i.e., NO-N represents all reactive nitrogen oxides.

Although there have been recent global meta-analyses accounting for the newer NO emission studies (Liu et al., 2017; Wang et al., 2022), they do not provide sufficient clarity on how to best estimate NO emissions for national emission inventories. For example, Liu et al. (2017) estimated the emission factor for NO emissions grouped by synthetic fertilisers to be 1.81 (1.23–2.39) % whereas Wang et al. (2022) reported an EF of 0.71 % for the same. There could be several reasons which explain such disparity between emission factors. For example, the EF of Wang et al. (2022) includes tea plantations, which exhibit exceptionally high emission factors and appear to have been influential on their results. The EF reported by Liu et al. (2017) includes forest soils and that does not seem advisable for estimation of emissions from synthetic fertiliser application in agricultural soils due to the much lower nitrogen load of forest ecosystems (Udawatta et al., 2011; Vuorenmaa et al., 2002), which can be expected to impact the fate of nitrogen.

In summary, while recent meta-analyses have refined our understanding of NO emissions, they do not yet offer clear inventory specific guidance for national reporting. This study therefore aims to consolidate new data and frame an inventory-focussed methodology to derive a new emission factor for NO emissions from agricultural soils.

## 2. Materials & methods

### 2.1. Data collection

The NO measurement studies used in the meta-analysis of Stehfest and Bouwman (2006) were used as the initial dataset of this study. Their dataset had 189 observations made on mineral soils from 58 studies after excluding data attributed to organic soils, nitrification inhibitors or coated fertilisers and grazing systems. An “observation” refers to the cumulative emissions of NO measurements, which is the average of replicates over a period of measurement. Further refinement was done to exclude observations that were not suitable to this study such as non-agricultural and unmanaged land use (abandoned pasture, forest etc.), nitrogen-fixing legumes and observations where location was unknown. To increase the spatial and temporal coverage of the dataset, a literature search was done to collect newer NO studies through the “Web of Science” and “Google Scholar” platforms. The keywords “NO”, “soil”, “emission”, “nitric oxide” were used to look for relevant literature. To keep the NO observations standardised, studies conducted in the laboratory or greenhouse were filtered out. Similarly, observations involving treatments with abatement practices such as biochar amendments, use of nitrification inhibitors and coated fertilisers were excluded as the aim of this study was to derive emission factors representative of standard agricultural practices. While certain mitigation measures may become state-of-the-art in the future, our analysis focuses on current baseline practices to ensure broad applicability and comparability of the derived emission factors.

The locations of observations were categorized according to their respective climate zones based on Gardner et al. (2020), which was constructed particularly based on variables relevant to plant physiology such as temperature, precipitation, soil moisture and their interactions with the growing season.

### 2.2. Data cleaning and organisation

The dataset was cleaned, organised and some variables were adjusted to ensure a robust modelling process. Including the duration of NO measurements in the modelling process is necessary to account for its effect on cumulative emissions. To facilitate the extraction of annual emission factors directly from regression models, the measurement period (in days) was expressed relative to 365 days (Mathivanan et al., 2021). Nitrogen (N) fertiliser inputs were separated into synthetic and organic fertiliser amounts, allowing the analysis of their individual effects on NO emissions. Three observations with known total N input, but unknown proportions of synthetic and organic fertilisers were excluded from the dataset.

Additional transformations and exclusions were done to improve the data quality and modelling process. For studies which reported soil carbon percentage as soil organic matter (SOM) rather than soil organic carbon (SOC), SOM values were converted to SOC using a factor of 2 ($SOC = SOM/2$), following Pribyl (2010). A small number of observations were excluded from the dataset if their duration was very short (33 observations with less than 14 days duration) or if no (emissions are zero) and negative cumulative NO emissions were observed (15 observations) during the measurement period. The latter could potentially introduce a small bias and subtly influence the model's expected values. However, excluding these values facilitated the use of standard statistical approaches for dealing with skewed conditional distributions. During the modelling process, the negative and zero cumulative emissions were included again and modified to a positive value closer to zero to test if their exclusion introduced underestimation of emission factors, but their inclusion did not affect the modelled values. The bias that could potentially be created by excluding these values did not exist in our dataset.

After the addition of newer NO studies and exclusion of some measurements based on the criteria discussed above, the final dataset had a total of 128 studies with 692 observations, forming the basis for the modelling process.

### 2.3. Modelling approach

#### 2.3.1. Exploratory data analysis

As the first step of the modelling process, the most-influential features affecting NO emissions were derived from the dataset using the ‘CatBoost’ machine learning approach (Dorogush et al., 2018). Predictors of interest such as Synthetic and Organic N inputs, Crop groups, Climate zones, Length of measurements, pH and SOC were analysed. The feature importances provided by the model were interpreted through a SHAP (SHapley Additive exPlanations) (Lundberg and Lee, 2017) summary plot, which visualises the magnitude of each feature's contribution towards the machine learning model's predictions.

#### 2.3.2. Parametric modelling

After analysing feature importance, parametric models were fit using an approach, where emissions are modelled as a linear function of the synthetic and organic fertiliser N application rates (Mathivanan et al., 2021). The intercept of the linear model represents the background emissions (i.e., emissions at zero fertiliser input) while the slope represents the fertiliser induced emission factor. This approach allows the explicit separation of background and fertiliser induced emissions. A generalised linear mixed model (GLMM) was used to model NO emissions, with a gamma distribution family and an identity link. Location clusters were used as random effects to account for correlations within them. To fit the models, a Bayesian approach was used which requires prior knowledge i.e., initial assumptions or estimates about the parameters in the form of a prior probability distribution which is then updated with new data resulting in a posterior probability distribution, from which the NO emission factors, and corresponding credible intervals are inferred. The Bayesian mixed effects models were run in the R statistical computing platform (v4.4.2; R Core Team, 2024) using the rstanarm package (v2.32.1; Goodrich et al., 2025).

Based on the exploratory data analysis, the dataset was split into three groups for parametric modelling: Common crops & grassland (611 observations, including all data except from paddy rice and tea plantations), paddy rice (50 observations, including one with a 10-day measurement period) and tea plantations (32 observations). The common crops group, apart from grassland (76 observations), consisted of wheat (177 observations), maize (201 observations), vegetable (122) and all *other crops* (35 observations).

### 2.3.3. Setting priors

The currently used emission factor for NO emissions from N applied in fertiliser, manure and other organic wastes of 0.01217 (0.0015–0.0316) kg NO-N (kg N)$^{-1}$ from the EMEP/EEA air pollutant emission inventory guidebook (Hutchings et al., 2023) was used as the prior for the emission factors in the models. This was specified in the model in the form of a normal distribution with mean 0.01217 and a standard deviation of 0.01. The background emissions for paddy rice, vegetables, other upland crops and grasslands from the meta-analysis by Liu et al. (2017) were averaged to get a mean estimate of 0.93 kg NO-N ha$^{-1}$ yr$^{-1}$, which was then used as the prior for emissions at zero fertilisation and specified with a standard deviation of 1.5 to accommodate a broader uncertainty range. The priors for both emission factors and background emissions were assumed to be constant across different crops and climate zones.

### 2.3.4. Model-analysis and cross-validation

Model performance was assessed using the root mean squared error (RMSE) to evaluate goodness of fit. To test the predictive performance on new data and compare different model specifications, a K-fold cross validation approach (K = 10) was used. Resulting RMSE values were used to select the best-performing models. Instead of random folds, a simple model (Model 1 in Table 1), was also cross-validated with countries as folds, to analyse how well data from other regions can predict NO emissions for the respective countries/regions.

## 3. Results

### 3.1. NO data

NO measurement locations were spread across six climate zones (Fig. 1), with a significant proportion located in the continental zone and the remainder spread among the temperate and tropical zones. The desert zone, however, was underrepresented, with only five measurements. Majority of NO studies were conducted in China, where 404 out of 692 measurements originated. The studies in the dataset spanned a temporal range from as early as 1976 to 2020, with a median measurement period of 154 days. The studies predominantly employed chamber-based measurements coupled with chemiluminescence analysers, which represents the standard approach for soil NO flux measurements. All measurements were taken from mineral soils (although measurements from organic soils were not actively excluded in the literature search), with soil organic carbon (SOC) values ranging from 0.12 % to 8 %, and a median value of 1.16 %. Reported soil pH values varied from 3.7 to 8.9, with a median of 7.7.

**Table 1**
Model specification and summary statistics of the Bayesian generalised linear mixed-effect models used to derive NO-N emission factors. Models are specified in Wilkinson-Rogers notation as extended by Bates et al. (2015), with all models having a Gamma distribution and identity link function. Fixed effects include synthetic N input, organic N input, total N (synthetic + organic), measurement duration, crop group, climate zone. Random intercepts are grouped by location groups. The number of observations (n) for each model is indicated. Model performance is evaluated using root mean squared error (RMSE) for goodness of fit and cross-validation RMSE (CV RMSE) for predictive accuracy.

| | Models | Number of observations (n) | RMSE (kg NO-N ha$^{-1}$ yr$^{-1}$) | CV RMSE (kg NO-N ha$^{-1}$ yr$^{-1}$) |
|---|---|---|---|---|
| | **Common crops & Grassland** | | | |
| **Model 1** | NO ~ Synthetic N + Organic N + Measurement duration + (1 \| Location) | 611 | 1.32 | 1.40 |
| **Model 2** | NO ~ Synthetic N + Organic N + Crop group + Climate zone + Synthetic N:Crop group + Synthetic N:Climate zone + Measurement duration + (1 \| Location) | 611 | 1.20 | 1.29 |
| | **Paddy Rice** | | | |
| **Model 3** | NO ~ Total N + Measurement duration + (1 \| Location) | 50 | 0.60 | 0.74 |
| | **Tea Plantations** | | | |
| **Model 4** | NO ~ Total N + Measurement duration + (1 \| Location) | 32 | 3.97 | 4.20 |

Of the total measurements, 376 (54 %) were conducted on plots fertilised with synthetic nitrogen (N) inputs, while 53 (8 %) were from plots fertilised with organic N inputs. Additionally, 85 measurements (12 %) involved plots receiving both synthetic and organic fertiliser N inputs. The remaining 178 measurements (26 %) were made on control plots with no N input. The median fertilisation rate for synthetic N inputs was 180 kg N/ha, with urea and urea-based combinations being the most common sources. For organic N inputs, the median rate was 175 kg N/ha, primarily derived from cattle, pig, and poultry manure/slurry. For mixed N inputs, the median fertilisation rate was 240 kg N/ha.

### 3.2. Exploratory data analysis

The feature importance analysis revealed that synthetic N inputs had the strongest influence on NO emissions, with higher inputs corresponding to increased emissions, while organic N input had the least impact on predicted NO emissions. The duration of measurements was the second most influential factor, where longer periods were associated with greater cumulative NO emissions (Fig. 2). Crop types and climate zones also had an impact on predictions with further stratification showing distinct effects (Fig. S3). Paddy rice was linked to lower NO emissions while tea plantations were associated with higher emissions compared to *other crops* such as vegetables, wheat and maize. Among climate zones, tropical regions (tropical rainforest, tropical savanna, and tropical wet) had a slightly greater influence on NO emissions than temperate and continental zones, though the differences were not pronounced. Soil properties, such as pH and SOC, showed moderate influence - however, no clear trend emerged linking higher or lower values to increased or decreased emissions, most likely due to potential interactions with other confounding factors.

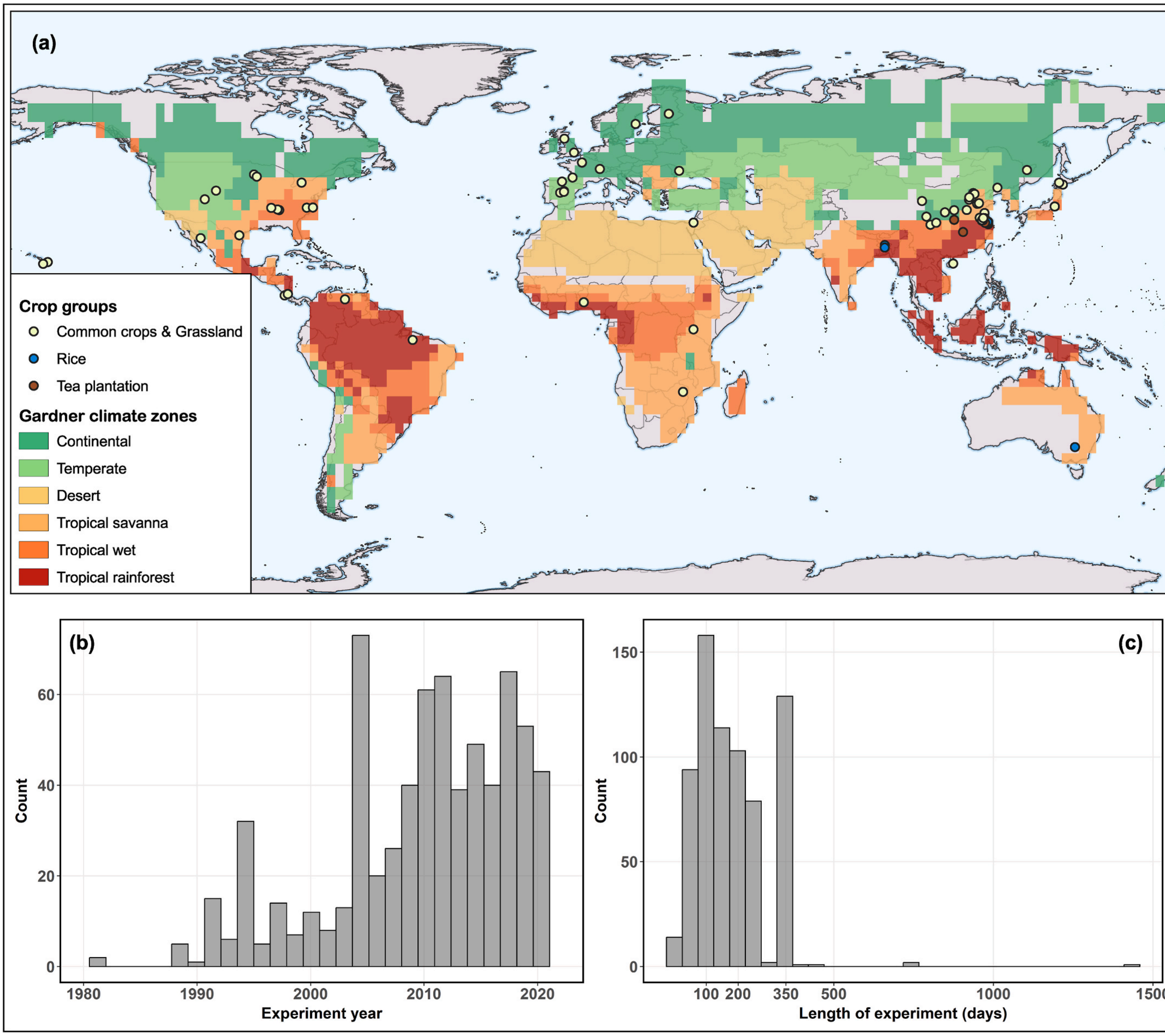


**Fig. 1.** **(a)** Location of NO measurement studies and climate zones according to Gardner et al. (2020). **(b)** Number of observations per year in the dataset. **(c)** Distribution of measurement period in the dataset.

### 3.3. Parametric emission models

Following the exploratory data analysis which highlighted the distinct impacts of paddy rice and tea plantations on NO emissions, the parametric models were fitted separately for common crops & grassland, paddy rice and tea plantations. Model specifications and summary statistics are shown in Table 1.

#### 3.3.1. Common crops & grassland

For common crops & grassland, a simple model (Model 1) yielded emission factors of 0.0042 (0.0035–0.0049) kg NO-N (kg N)$^{-1}$ and 0.0003 (−0.0003 – 0.0009) kg NO-N (kg N)$^{-1}$ for synthetic and organic N inputs respectively, while the emissions at zero fertilisation was estimated to be 0.52 (0.32–0.84) kg NO-N ha$^{-1}$ yr$^{-1}$. The effect of measurement duration was very low, with cumulative emissions increasing at a rate of 0.0002 kg NO-N ha$^{-1}$ per day (−0.0001 – 0.0006), suggesting that longer observation periods did not substantially increase cumulative emissions. Including year as random effect did not significantly improve the model fit. The coefficient of variation among the location groups was 75.35 %, indicating a high degree of variability in NO emissions across different regions and climate zones. The RMSE of a random 10-fold cross validation was 1.40 kg NO-N ha$^{-1}$ yr$^{-1}$. For the leave-one-country-out cross validation, it was 1.84 kg NO-N ha$^{-1}$ yr$^{-1}$ and ranged from 0.04 kg NO-N ha$^{-1}$ yr$^{-1}$ for Brazil to 4.81 kg NO-N ha$^{-1}$ yr$^{-1}$ for France, highlighting variability in predictive performance across countries (Table S1).

A more complex model (Model 2) provided stratified emission factors (Table 2), showing variability across climate zones and crop groups. Notably, the tropical rainforest zone had the highest emission factors for synthetic N inputs across crop groups (e.g., 0.0122 (0.0069–0.0189) kg NO-N (kg N)$^{-1}$ for wheat, 0.013 (0.0062–0.0211) kg NO-N (kg N)$^{-1}$ for maize, 0.0114 (0.0039–0.0215) kg NO-N (kg N)$^{-1}$ for grassland), consistently exceeding 1 % regardless of crop type. In contrast, temperate, continental, tropical savanna and tropical wet zones exhibited lower emission factors for synthetic N inputs, ranging from 0.0005 to 0.005 kg NO-N (kg N)$^{-1}$, e.g., 0.0029 (0.0014–0.0046) kg NO-

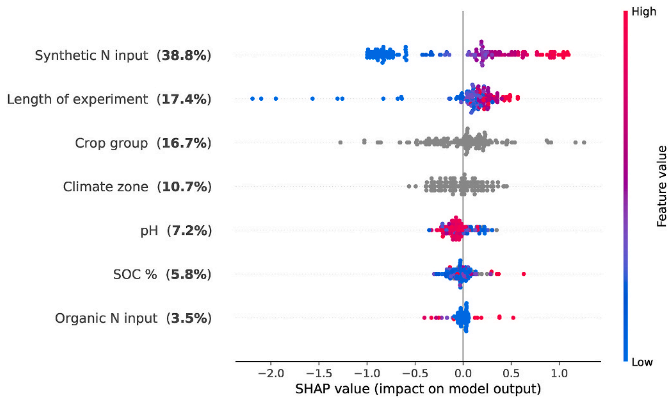


**Fig. 2.** Feature importances of potential factors influencing NO emissions. Features are ordered by their overall importance, from highest (top) to lowest (bottom). Values in brackets indicate mean SHAP contributions normalised to percentage of the total, with higher percentages reflecting greater overall importance for the model's predictions. Each dot represents a measurement, with the x-axis showing the SHAP value, where positive values indicate positive correlation with predicted NO emissions, and negative values indicate a negative correlation. The colour gradient represents the feature value: red denotes high values (e.g., high synthetic N input), and blue denotes low values (e.g., low synthetic N input).

**Table 2**
Emission factors (%) for synthetic N inputs derived from Model 2. 95 % credible intervals are given in parentheses.

| Climate Zone | Wheat | Maize | Grassland | Vegetable | Other Crops |
|---|---|---|---|---|---|
| Temperate | **0.29** (0.14, 0.46) | **0.37** (0.07, 0.68) | **0.21** (−0.16, 0.72) | **0.19** (−0.10, 0.51) | **0.41** (0.01, 0.91) |
| Continental | **0.38** (0.04, 0.72) | **0.46** (−0.03, 0.94) | **0.30** (−0.26, 0.98) | **0.28** (−0.20, 0.77) | **0.50** (−0.09, 1.17) |
| Desert (Irrigated) | *0.15* *(−0.41, 0.92)*[a] | *0.23* *(−0.48, 1.14)*[a] | *0.07* *(−0.71, 1.18)*[a] | **0.05** (−0.65, 0.97) | *0.27* *(−0.54, 1.37)*[a] |
| Tropical Rainforest | **1.22** (0.69, 1.89) | **1.30** (0.62, 2.11) | **1.14** (0.39, 2.15) | **1.12** (0.45, 1.94) | **1.34** (0.56, 2.34) |
| Tropical Savanna | **0.23** (−0.10, 0.54) | **0.31** (−0.17, 0.76) | **0.15** (−0.40, 0.80) | **0.13** (−0.34, 0.59) | **0.35** (−0.23, 0.99) |
| Tropical Wet | **0.32** (−0.02, 0.66) | **0.40** (−0.09, 0.88) | **0.24** (−0.32, 0.92) | **0.22** (−0.26, 0.71) | **0.44** (−0.15, 1.11) |

[a] Combinations which were not present in the dataset but were extrapolated by the model.

N (kg N)$^{-1}$ for wheat in temperate zone, 0.0046 (−0.0003 – 0.0094) kg NO-N (kg N)$^{-1}$ for maize in continental zone. Desert zones had the lowest emission factors but with wide uncertainty ranges. The differences in crop-specific emission factors were less pronounced compared to the differences in climate zones, apart from *Other crops* generally showing higher emission factors. The *Other crops* category included crops such as barley, cotton, oilseed rape, ryegrass, sorghum etc. Separate models for grassland and cropland were also tested but showed no improvement in combined predictive performance, supporting the inclusion of grassland and cropland in the same model. The stratification of emission factors for organic N inputs was not done as the differences across climate and crop groups were insignificant and because not many observations were available for different interaction groups. Consequently, there is only one emission factor of 0.0001 (−0.0003 – 0.0005) kg NO-N (kg N)$^{-1}$ generalised across all crops and climate zones, which is much lower than the emission factor for synthetic N inputs. The estimated emissions at zero fertilisation ranged from 0.25 to 0.92 kg NO-N ha$^{-1}$ yr$^{-1}$ (Table S2). The effect of measurement duration was very low, with cumulative emissions increasing at a rate of 0.0002 kg NO-N ha$^{-1}$ per day (0–0.0005), suggesting that longer observation periods did not substantially increase cumulative emissions. The RMSE of cross-validation of Model 2 was 1.29 kg N ha$^{-1}$ yr$^{-1}$ (Table 1). The leave-one-country-out cross validation was not done as the model is too complex to allow a successful fit if countries with many data points are taken out of the training set. Year as random effect did not have significant improvement in the model, while the variance due to the location effects was estimated to be 80.76 % indicating considerable heterogeneity in NO emissions across the location groups. Models incorporating soil parameters such as pH and SOC further improved fit, but their predictive accuracy remained quite similar, suggesting overfitting.

### 3.3.2. *Paddy rice*

For the rice group, a simple model with the total N inputs was used (Model 3). It was not possible to try and differentiate synthetic and organic N inputs as the dataset contained only 4 observations with organic N input. The emission factor for total N (Synthetic + Organic) inputs was 0.00 (−0.0002 – 0.0004) kg NO-N (kg N)$^{-1}$, indicating that the N inputs had no measurable impact on NO emissions. Thus, the emissions are estimated to be 0.47 (0.012–1.15) kg NO-N ha$^{-1}$ yr$^{-1}$, independent of fertilisation and effectively representing the baseline emission level at zero N input. The low emission factor for N inputs align with the feature importance analysis, which identified rice cropping to have a negative impact on NO emissions from fertilized fields. The effect of measurement duration was very low, with cumulative emissions increasing at a rate of 0.0006 kg NO-N ha$^{-1}$ per day (0–0.0024), suggesting that longer observation periods did not substantially increase cumulative emissions. Including year as random effect did not significantly improve the model fit, while the variance due to the location effects was estimated to be 115.76 % indicating high heterogeneity in NO emissions across the location groups.

### 3.3.3. *Tea plantations*

The emission factors for tea plantations were substantially higher than for the other crops, with an emission factor of 0.0155 (0.0101–0.0225) kg NO-N (kg N)$^{-1}$ for total N (Synthetic + Organic) inputs. The emission at zero fertilisation was also higher at 1.70 (0.96–2.92) kg NO-N ha$^{-1}$ yr$^{-1}$. Cumulative emissions increased with measurement duration at a rate of 0.0084 (−0.012 – 0.028) kg NO-N ha$^{-1}$ per day. A model with disaggregated N inputs was also specified but differences were not significant. Year as random effect did not have significant improvement in the model, while the variance due to the location effects was estimated to be 46.92 % indicating moderate heterogeneity in NO emissions across the location groups.

## 4. Discussion

The Convention on Long Range Transboundary Air Pollution (CLRTAP) mandates its 51 parties to report NO emissions and other air pollutants annually. The methodology used by these countries for NO emissions from fertiliser application, manure, excreta, and other organic wastes has thus far been based on a Tier 1 emission factor as laid out in the EMEP guidelines (Hutchings et al., 2023). The NO emission factor of 0.04 (0.005–0.104) kg $NO_2$ (kg N input)$^{-1}$ in the EMEP guidelines, more precisely 0.0133 (0.0015–0.0317) kg NO-N (kg N)$^{-1}$ (Skiba et al., 2021), is based on the global emission factor developed by Stehfest and Bouwman (2006) but only considers the data from Europe, former USSR and North America, broadly representing the temperate and continental regions in the Northern hemisphere. The recent study by Skiba et al. (2021) looked at improving the Tier 1 emission factor with additional data but found that the resulting emission factor of 0.60 % was associated with large uncertainties, leading to their recommendation to retain the older emission factor until more robust data is available.

The results from our study provide updated emission factors for NO-N emissions with smaller uncertainties associated with them: The new estimates are 0.0042 (0.0035–0.0049) kg NO-N (kg N)$^{-1}$ for synthetic N inputs (derived from Model 1) and 0.0001 (−0.0003 – 0.0005) kg NO-N (kg N)$^{-1}$ for organic N inputs (derived from Model 2). These are emission factors based on global datasets and applicable to general crops and grassland. Application of these new emission factors to the 2025 emission inventory reports of EU member states for the year 2023 would result in reported $NO_2$ emissions from synthetic fertilisers (335 kt NO2) being revised to 116 kt $NO_2$ (−65 %, cf. Supplement 3).

Further stratification provides emission factors for synthetic N inputs in the temperate and continental zones (Table 2) that are noticeably lower in magnitude than the value provided by the EMEP guidebook and have reduced uncertainty ranges. The new emission factor for organic N inputs is remarkably low. While empirical studies show that organic fertilisers cause lower emissions than synthetic fertilisers, they typically do not elucidate the underlying mechanisms responsible for such differences. Specific experimental setups or process studies are needed to do that. However, such a difference is plausible as organic fertilisers tend to release nitrogen more slowly. Hergoualc'h et al. (2021) found a similar effect for $N_2O$ emissions, which are also produced by processes of the N cycle in soil. They emphasize a "lack of quantitative data on how organic fertilisers influence $N_2O$ emissions" and a similar lack of data exists for NO emissions, which have been studied less than $N_2O$ emissions. Only one-fourth of observations with fertiliser input in the NO dataset received organic fertilisers and only 10 % received organic fertilisers exclusively. Thus, the new emission factor for organic fertilisers is less representative and has a higher probability of bias than the emission factor for synthetic fertilisers. It was also not possible to include manure properties (type of farm animals, slurries or solid manures, etc.) or types of synthetic fertilisers in the models. The lower emission factors for organic fertilisation strengthens arguments for substituting synthetic fertilisers with organic fertilisers (Menegat et al., 2022; Wu et al., 2024; Zhang et al., 2020). However, care needs to be taken to use correct nitrogen fertiliser replacement values (Hijbeek et al., 2018) and not exacerbate environmental issues (Svanbäck et al., 2019) when applying this mitigation strategy as organic fertilisers also usually contain significant amounts of phosphorous apart from nitrogen (Sharpley, 1995).

Climate zone is a major controlling factor of NO losses (Table 2). Notably, emission factors in the tropical zones were significantly higher than the temperate and continental zones. However, the tropical wet zone was an exception and the emission factors in this zone were closer to those of temperate and continental zones. Stratification according to climate zones highlights issues with representativeness. For example, emission factors for the desert zone have very large uncertainties because of the low number of observations in that zone. The effect of climate zone is a proxy of pedoclimatic and other environmental conditions as well as differing agricultural management practices and intensities.

The impact of crop type is less pronounced than the effect of climate zone. Estimated emission factors are in the order *Other Crops* > Maize > Wheat > Grassland > Vegetables. Since wheat is the most common crop in the dataset, its emission factor exhibits the smallest uncertainties. The crop classification is very coarse. It needed to be ensured that individual crop types were present in most climate zones and enough observations for a crop type were in the dataset. It should be emphasized that the interaction between climate zone and crop type was not included in the model because it led to overfitting as indicated by the cross-validation. This is due to limitations of the dataset and not because such interactions don't exist.

Some combinations of climate zone and crop type are not present in the data and the emission factors for these combinations are effectively extrapolations by the model (Table 2). Efforts should be made to replace such extrapolated emission factors with estimates based on actual measurements. However, some of these combinations are rare.

For paddy rice cultivation, the estimated NO emission factor is practically zero which aligns with the suppression of nitrification of fertiliser ammonium due to anoxic conditions in flooded rice soils (Islam et al., 2018). Studies with rice in the dataset predominantly followed a water management regime where the fields were flooded, drained mid-season and re-flooded or intermittently flooded (ca. 75 % of observations). For upland rice cultivation, which was not present in our dataset, it could be more appropriate to apply emission factors derived for general crops.

Similar to what has been reported for $N_2O$ emissions (J. Wang et al., 2022; Wang et al., 2020), tea plantations are a hotspot of NO emissions with an emission factor of 1.55 % (1.01–2.25 %) and also exceptionally high emissions at zero fertilisation. Such high emissions can be attributed to very high N fertilisation and corresponding low nitrogen use efficiency and environmental conditions such as soil acidity (Lin et al., 2023; Ruan et al., 2013; ZOU et al., 2021).

Studies have suggested that the relationship between N inputs and gaseous nitrogen emissions is non-linear (Jiang et al., 2017; Kim et al., 2013; Shcherbak et al., 2014; Wang et al., 2024; Zhao et al., 2015). In particular for tea plantations, J. Wang et al. (2022) have argued for the use of an exponential model. Following the arguments in Mathivanan et al. (2021), we decided to purely use linear models in order to be able to provide emission factors for emission inventory purposes. It must be acknowledged that doing so may introduce bias. On the other hand, combining a non-linear model with a non-Gaussian distribution family increases the demands on the quality of the dataset. Ignoring the skewness of the distribution and simply assuming a Gaussian distribution makes a non-linear model very sensitive to outliers and may increase bias.

Spatial representativeness of the dataset is quite poor: Large regions with a significant share of global crop production are not represented. There are no observations in India, Australia and West Africa. Central and Eastern Europe are underrepresented as is South America, while the majority of observations are in China, followed by Japan and Spain. This geographical imbalance of observations is also reflected in the leave-one-country-out cross-validation, where the predictive performance varied remarkably across countries. This variability in predictive performance also indicates that global emission factors may not fully capture country or region specific environmental and management conditions. Overall, there are less observations and a stronger geographic imbalance than for studies of $N_2O$ emissions (Hergoualc'h et al., 2021).

Investigating the correlation between NO and $N_2O$ emissions could provide useful context because both gases are produced by the same microbial processes (primarily, nitrification and denitrification). Although about 80 % of studies in the collated dataset report emissions of both gases, there was no significant correlation. This is probably because the relationship between NO and $N_2O$ production involves pronounced non-linearities resulting from interacting processes of the N cycle. The relative production of each gas is governed by confounding environmental conditions such as pH, temperature and, in particular, soil water filled pore space (WFPS), which determines the dominant pathway (Pilegaard, 2013). Unfortunately, WFPS was not reported across studies in our dataset, hindering further analysis.

Generally, many of the existing NO emission measurements are shorter than typical $N_2O$ measurement campaigns. Since NO analysers are comparatively cheap, future studies should aim to measure both $N_2O$ and NO emissions consistently. This would not only contribute to a larger global NO dataset but also allow to empirically investigate the relationship between NO and $N_2O$ emissions. Furthermore, for better interpretation, standard weather and site data such as WFPS, temperature, precipitation, SOC content and soil pH should always be reported in publications (Maier et al., 2022).

Results of this study are strictly limited to mineral soils. Studies of NO emissions from fertilized organic soils are needed to derive specific emission factors for organic soils where N transforming microbial activity is quite different due to availability of carbon and strong impact of hydrology. It has been shown that $N_2O$ emissions from organic soils are higher than from mineral soils (Mathivanan et al., 2021) and it seems plausible that results should be analogous for NO emissions. However, until such results can be derived, there is no alternative to applying emission factors from mineral soils also to organic soils.

## 5. Conclusion

Through this study, we have consolidated an expanded dataset of NO emission measurements from agricultural soils, incorporating newer studies to address gaps in spatial and temporal coverage. The derived climate and crop specific emission factors are substantially lower than the default emission factor currently applied in national inventories, indicating that existing methods may significantly overestimate emissions. The refined emission factors provide a more inventory-oriented methodology for estimating soil NO emissions. Adopting these updated emission factors in national GHG inventories could improve emission baselines, inform targeted mitigation strategies, and support policies like the EU National Emission Ceilings Directive. We recommend the use of emission factors from Model 2 which takes into account the effect of climate zones and different crop groups. However, doing so would require additional effort of distributing country-wide fertiliser amounts to individual crop groups. If such disaggregation is not feasible, the emission factors from Model 1 are applicable and still an improvement over previous emission factors.

Limitations remain due to scarcity of data from the global south, and limited representation of organic fertilisers that hinders deeper analyses. Future research should prioritize expanding datasets across diverse pedo-climatic conditions, and fertiliser types. Ultimately, adopting the updated emission factors in national inventories can enable more accurate monitoring of agricultural NO emissions, better align reported values with actual environmental impacts, and strengthen the scientific basis for improved nitrogen management and global air quality assessments.

## CRediT authorship contribution statement

**Gokul Prasad Mathivanan:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Andreas Gattinger:** Writing – review & editing, Supervision, Conceptualization. **Roland Fuß:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aeaoa.2025.100410.

## Data availability

Data and code are provided as supplements.

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