Agriculture sector:

Synthetic Fertilizer, Crop Residue, and Manure Application Emissions

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1. Introduction

Nitrous Oxide (N_2O) is a highly potent greenhouse gas (GHG), with a global warming potential (GWP) of 298 that of CO_2 on a 100-year timescale (EPA, 2018). The concentration of atmospheric N_2O has increased by more than 20%, from 270 parts per billion (ppb) in 1750 to 331 ppb in 2018 (Tian et al., 2020). This dramatic shift is primarily driven by increased anthropogenic sources that raise current total global emissions to ~17 teragram (Tg) nitrogen (N) (Syakila and Kroeze et al., 2011; Thompson et al., 2019; Tian et al., 2020). Approximately 52% of anthropogenic emissions come from the direct emissions from Nitrogen (N) application in the agricultural sector (Tian et al., 2020). Direct N_2O emissions from soils are primarily produced during two microbial-driven biological processes, nitrification and denitrification. Nitrification is the aerobic microbial oxidation, in which ammonium ion is oxidized into nitrate and N_2O is released as a byproduct.

On the other hand, denitrification is the anaerobic microbial (mainly bacterial) reduction of nitrate to nitrite and then to the gasses NO, N_2O, and N_2. N_2O production depends on the amount of mineral N substrates in the soil, i.e., ammonium and nitrate. Therefore, additions of mineral N fertilizers and other sources of N (manures, residue) to agricultural soil are considered the primary drivers of N_2O emissions and higher atmospheric concentrations. Lassaletta et al. (2014) estimated that only 47% of the reactive nitrogen added globally onto cropland is converted into harvested products, and the rest is lost into the environment. For sustainable agriculture, it is essential to quantify these emissions with more confidence and find ways to mitigate climate change by reducing them. Northup et al. (2021) have shown in their recently published work that there is a potential to reduce 71% (1,744 kg CO_2e/ha) of synthetic fertilizer's greenhouse gas emissions through a combination of innovations in digital agriculture, crop and microbial genetics, and electrification (using electrical farm equipment instead of fuel-based) in the next 15 years. According to this study, process-based models guided via high-resolution monitoring systems can be used to optimize the N fertilizer use for the crop, which can further reduce the N_2O emissions. Similarly, customizing crop genetics and root traits can help improve the plant's nitrogen use efficiency. The addition of N-fixing microbes (in addition to those that form root nodules) in the soil can reduce the need for chemical fertilizer, eventually leading to reduced emissions.

Various efforts have been made in the past to quantify N_2O emissions at the regional and global levels from the agricultural sector. The FAOSTAT emissions database of the Food and Agriculture Organization of the United Nations (FAO) covers emissions of N_2O from agriculture by country and globally from 1961 to 2018 (Tubiello et al., 2021). The United Nations Framework Convention on Climate Change (UNFCCC) provides N_2O emission data from agricultural managed soils reported by countries for a period 1990-2019. Another inventory, the Emission Database for Global Atmospheric Research version 4 (EDGAR v4.3.2), a product of the Joint Research Center and the PBL Netherlands Assessment Agency, contains global N_2O emission inventories (Janssens-Maenhout et al., 2019). EDGAR applies the Intergovernmental Panel on Climate Change (IPCC) guidelines mostly at Tier-1 (using emission factors and activity data). Still, EDGAR integrates higher tier information based on available country reporting, mostly from Annex I countries. EDGAR provides data from 1970 to 2012. The Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model (Winiwarter et al., 2018) is an extension of the Regional Air Pollution Information and Simulation (RAINS) model. This extended version (GAINS) estimates emissions of 10 air pollutants and 6 GHGs (including N_2O) for each country based on data from international energy and industrial statistics, emission inventories, and data supplied by countries. GAINS provides N_2O emissions data every five years (i.e., 1990, 1995, 2000, 2005, 2010, 2015) and uses the IPCC emission factor (EF) as a default option for estimation in the absence of more detailed information available for a country.

While there are databases that provide emissions information, each inventory reports N_2O emissions differently. For example, FAOSTAT and UNFCCC provide direct N_2O emissions for the category of synthetic N fertilizers applied to managed soils. In comparison, GAINS and EDGAR report the combined direct N_2O soil emissions from synthetic N fertilizers and manure as fertilizers and crop residues. This difference in emission reporting makes it difficult to compare the estimates of direct N_2O emissions (from synthetic N fertilizers) across different inventories. Additionally, all inventories described incorporate the IPCC Tier 1 guideline for calculating direct N_2O soil emissions, which mainly relies on the self-reported N fertilizer data. Reported data is prone to errors and might be purposely misreported leading to significant uncertainties in estimating N_2O direct emissions in the current approach (Seto et al., 2000). To reduce these uncertainties and provide greater temporal and country coverage, a new approach is needed that considers measurements that are more reflective of synthetic fertilizer usage.

This study introduces a novel methodology for estimating annual, crop-specific N_2O emissions at various spatial resolutions, circumventing the reliance on imprecise self-reported nitrogen fertilizer data. Our approach primarily utilizes crop productivity metrics, offering a more dependable data source. These metrics reflect the raw materials designated for immediate consumption or integration into broader food systems and supply chains.

The methodology presented has undergone several iterative refinements. Initially, we established a technique for approximating crop-specific nitrogen fertilizer use at a national level. This process employed indicators such as crop yield, cultivated area, and nitrogen use efficiency (NUE). We calculated a country's NUE for a given prediction year based on the prior year's NUE—adjusted using IFASTAT data—and the percentage change in a specific crop's productivity across two consecutive years. Subsequently, we applied the IPCC Tier 1 emission factor to translate nitrogen fertilizer quantities into emission figures. Despite its independence from reported values, this strategy operates at a country-scale, restricting our capacity to identify emission-intensive areas or 'hotspots' within a country. To address this limitation, we devised a strategy for disaggregating national crop-specific nitrogen fertilizer data to a grid scale. This finer resolution was achieved using the detailed crop-specific harvested area data generated by the Global Agro-Ecological Zones (GAEZ) Version 3 model (refer to section 2.2.4).

As part of our update for this sector, we extend our analysis beyond synthetic-nitrogen fertilizer by quantifying several additional sources and sinks of greenhouse-gas and air-quality pollutants-crop residue and manure application. Crop residue retained on the field is assumed to mineralize and release N_2O, while residue that is open-burned produces N_2O, CH_4, and primary $PM_{2.5}$. All fluxes are resolved at a monthly timestep on a 5-arc-minute (~10 km) grid. Direct soil N_2O resulting from manure applications to cropland is calculated with the same spatial and temporal resolution. Only for maize, we also simulate annual changes in SOC stocks with the process-based SALUS model, thereby capturing the CO_2 sink (or source) associated with carbon accrual or loss at the same spatial level.

Nevertheless, the application of the IPCC Tier 1 emission factor continued at this gridded level for synthetic fertilizer, crop residue, and manure application emission calculation. To enhance the precision of our emission estimations, we applied IPCC disaggregated EFs for wet and dry regions.

Beginning in October 2025, Climate TRACE integrated emission reducing solutions (ERSs) across the agricultural sector to complement baseline emission estimates with mitigation scenarios. ERSs capture how changes in farming practices or technologies could lower emissions from synthetic fertilizer use, manure applied to soils, and crop residue management. These additions build on the IPCC 2019 Refinement (IPCC 2019a; IPCC 2019b) and reflect updated knowledge of soil processes, crop management, and mitigation options at global and regional scales. In this release, ERSs considered include the use of nitrification and urease inhibitors, controlled-release fertilizers, and organic substitutions for synthetic inputs; alternative manure application methods such as injection, digestate application, and fraction management; and residue management practices tailored to residue quality and incorporate on timing. Each of these strategies is supported by meta-analyses and field studies, and together they provide a transparent, evidence-based framework to quantify potential emission reductions in agriculture.

2. Materials and Method

In this section, we describe the datasets and methods used to quantify greenhouse-gas emissions globally from 2015 to 2025 for synthetic nitrogen fertilizer, crop residue management, and manure application across all crops, and to simulate soil organic carbon (SOC) stock changes **only for maize in 2023**. We also outline our approach for estimating non-GHG emissions of primary $PM_{2.5}$ produced by crop-residue burning.

Synthetic fertilizer

The approach utilized here primarily relies on crop productivity data to estimate N_2O emissions, which is considered a reliable source of information as crop productivity indicates raw materials going for direct consumption or into the food systems and supply chain. We hypothesized that crop productivity could be used as a proxy for estimating N_2O emissions for a country. To investigate this, we selected a subset of high-income, upper-middle-income, lower-middle-income, and low-income countries and classified them by their development level as measured by per capita gross national income (GNI) by the United Nations (UNESCAP, 2020).

To understand the relationship between the average crop productivity and direct N_2O emissions within these selected countries, two variables were used. First, we estimated average crop productivity within the country by accumulating total annual production and harvested area for all the primary crops as defined in FAOSTAT data from 1961-2018 and extracted country-level annual direct N_2O emission data from FAOSTAT for the same period. Then, we compared crop productivity (tons/ha) to direct N_2O emission for each selected country (Figure 1).

Table 1 Pearson correlation coefficients and their significance level between average crop productivity and direct N_2O emission for each country. Correlation coefficients with an asterisk are statistically significant ($p<0.01$).

GNI level	Country	Correlation coefficient (ϱ)
High-income	Australia	0.69*
	France	0.80*
	Germany	0.18
	U.S.A	0.82*

GNI level	Country	Correlation coefficient (ϱ)
Upper-middle-income	Argentina	0.92*
	China	0.97*
	Brazil	0.95*
Lower-middle-income	India	0.99*
	Nigeria	0.73*
	Pakistan	0.96*
Low-income	Uganda	-0.09
	Tanzania	0.17

Our analysis found that the average crop productivity and direct N_2O emissions from synthetic fertilizers data were highly correlated for countries in the upper-middle-income and lower-middle-income countries (Table 1). For example, India, China, Argentina, Brazil, and Pakistan have correlation coefficients greater than 0.9. In the high-income countries group, the U.S.A, one of the significant synthetic nitrogen fertilizer users (after China and India), shows a correlation of 0.82 (Figure 1). On the other hand, this relationship was not significant in low-income countries like Uganda and Tanzania. The reason behind this is the minimal use of nitrogen fertilizer in cropland; less than 1% of farmers in most African countries apply fertilizers (Nkonya et al., 2011). One exception was Germany, which belongs to the high-income group and shows no significant relationship between productivity and direct N_2O emissions for reasons unknown to us. In our initial analysis, countries that are significant users of synthetic nitrogen fertilizer, like China, India, U.S.A, Brazil, Pakistan, France, and Australia, which represent 66% of total global nitrogen fertilizer use (FAOSTAT, 2019), show a strong correlation between crop productivity and direct N_2O emissions from synthetic fertilizers. Overall, this analysis supports our hypothesis that crop productivity has a strong correlation with direct N_2O emissions from synthetic fertilizers and it can be used as a proxy to estimate direct N_2O emissions.

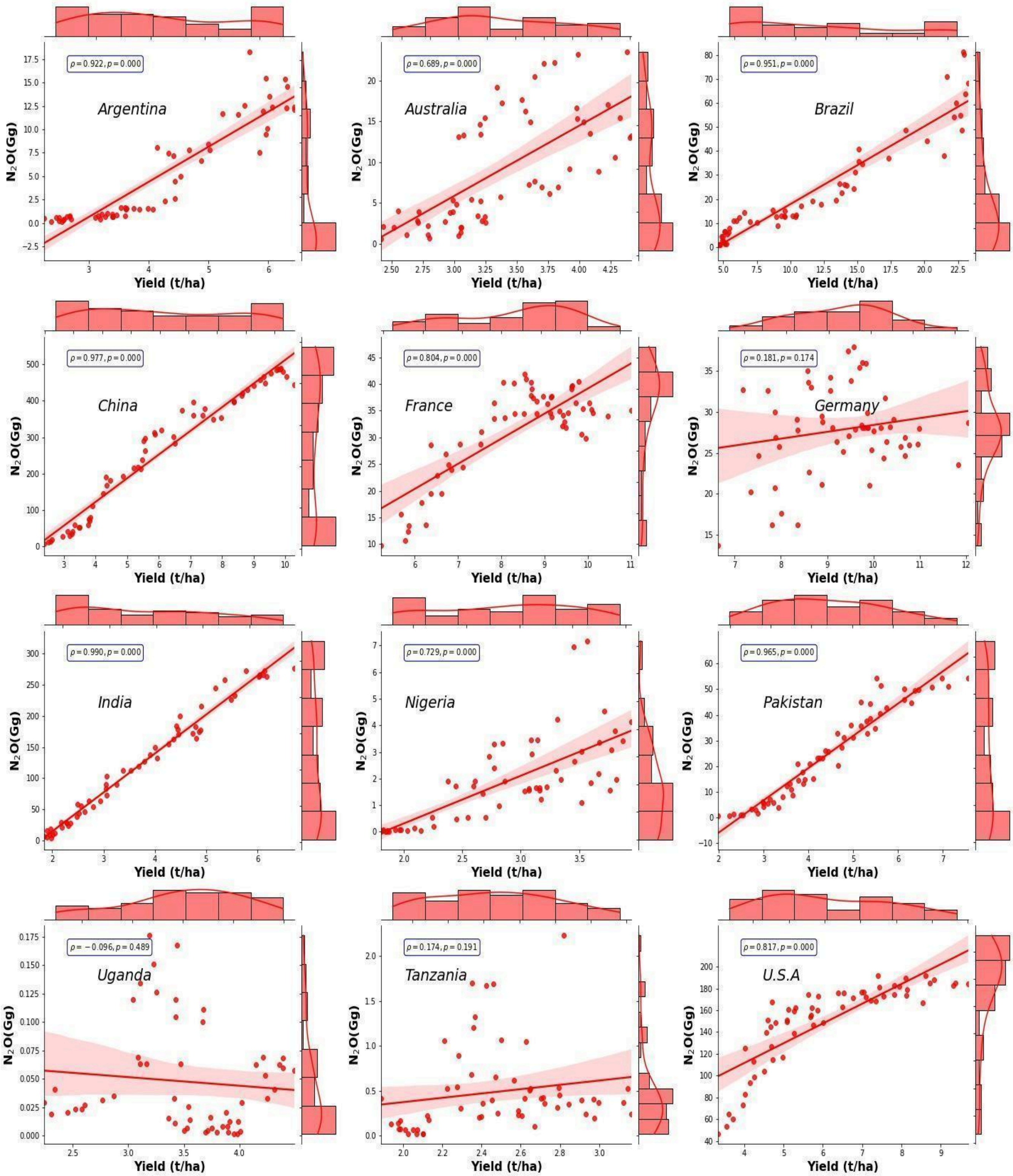

Figure 1 Correlation graph between country-level direct N_2O emissions due to synthetic N fertilizer and crop yield using FAOSTAT data from 1961-2023. (Units- y-axis: gigagram, x-axis: tonnes/ha).

Crop residue

Residue Production

To estimate crop residue production, we followed the approach outlined in Smerald et al. (2023). First, national-level crop-specific production and harvested area data was compiled from FAOSTAT and USDA. To represent the crop spatial patterns, a 2015 gridded crop-specific production and harvested area data was utilized from GAEZ. To represent recent years, we assumed that the spatial patterns of crop production and harvested area remained consistent, and scaled the GAEZ gridded values by the ratio of country-level production and area from FAOSTAT/USDA to GAEZ. This yielded spatially explicit maps of crop-specific production and harvested area. To derive crop-specific residue production maps, the approach developed by Smerald et al. (2023 was applied to the gridded maps.

Partitioning Residue into Retained and Burned Fractions

To partition the total residue production into fractions that are retained on the soil surface and those that are burned, we adopted the spatially explicit gridded residue treatment fractions provided by Smerald et al. (2023). These fractions were applied to the residue production maps to generate separate layers for residue left on the ground and residue subjected to open burning.

Emission Calculations for N_2O, CH_4, and $PM_{2.5}$

Annual Estimates:
For N_2O emissions from residue left on the field, the nitrogen content of the residue was first estimated followed by using the IPCC Tier 1 approach or parameters from Lassaletta et al. (2014). Emission factors (EFs) for crop residue were then applied to compute direct N_2O emissions.

For burned residue emissions, the dry matter content of the residue was estimated and IPCC Tier 1 emission factors was applied to calculate emissions of N_2O, CH_4, and $PM_{2.5}$.

Monthly Estimates:
To downscale annual emissions to a monthly resolution, separate methods for residue left on the ground and residue burned were applied.

- For N_2O emissions from retained residue, we used the monthly distribution pattern of soil N_2O emissions from EDGAR, applying these fractions to our annual totals.
- For burned residue, monthly crop area burned estimates from Hall et al. (2024) were used. These monthly fractions were used to temporally disaggregate the annual emissions from burning. Figure 2 (adapted from Hall et al., 2024). The resulting monthly emission distributions are produced by our analysis and shown for three major emitting countries in Figure 3.

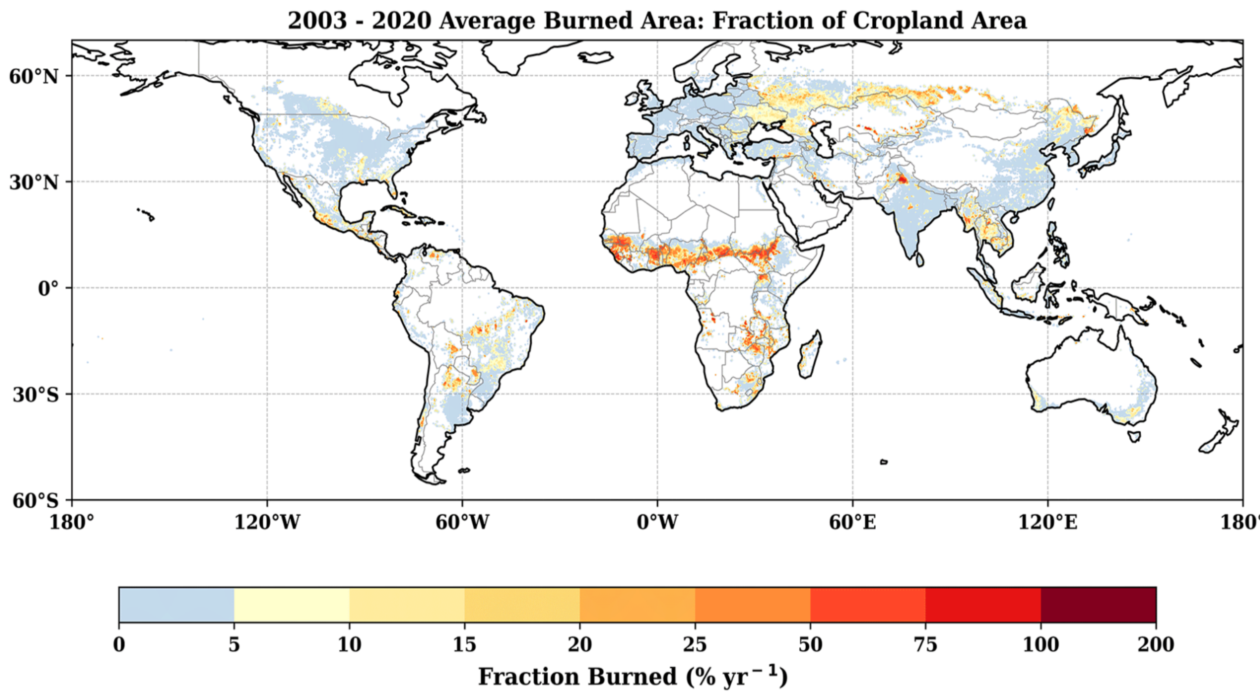

Figure 2. Average annual area burned (2003–2020), expressed as the fraction of cropland within each 0.25° grid cell that burns each calendar year. Grid cells with more than 100 % cropland burned area are seen within double-cropping regions or within grid cells where neighboring fields are on different harvest cycles. Source- Hall et al. (2024).

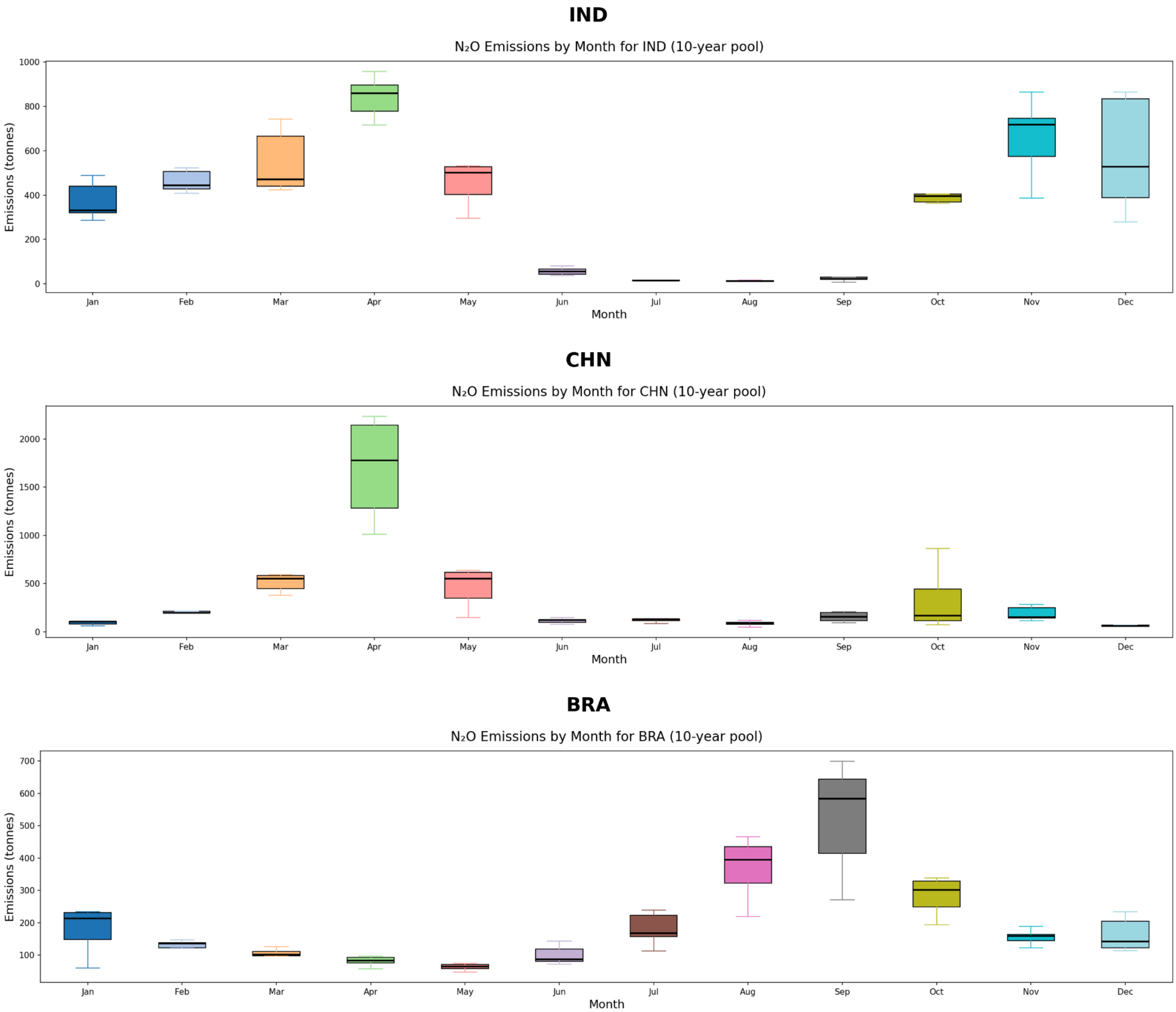

Figure 3. Examples of monthly residue burning emissions for 3 of the 6 major countries (India, China, and Brazil).

Manure

To estimate N_2O emissions from manure applied to cropland, we adopted a straightforward approach. First, we obtained national-level data on manure application from FAOSTAT. We then downscaled this data to a gridded resolution using the method described in Adalibieke et al. (2023). Manure emission factors (EFs) were then applied using IPCC Tier 1 approach to compute direct N_2O emissions. To distribute the emissions temporally, we applied the monthly distribution pattern of soil N_2O emissions from EDGAR to our gridded annual estimates, thereby generating monthly emission maps.

Gridded annual SOC Changes using SALUS

We integrated the process-based **S**ystem **A**pproach for **L**and **U**se **S**ustainability (SALUS) model (Basso et al., 2006, 2015, and 2025), which simulates coupled plant and soil biogeochemistry processes to estimate SOC changes from cropping systems (Figure 4). To run SALUS on a global scale, we utilized various datasets. Weather data is from the Prediction Of Worldwide Energy Resources (NASA/POWER) project at NASA Langley Research Center (https://power.larc.nasa.gov/), which aggregates global data at a 1° grid. Soil input data is from SoilGrids (https://www.soilgrids.org/). Crop residue left on the ground is provided as input in the SALUS biogeochemistry model (Figure 5) , while crop residue fraction left on the ground is from Smerald et al. (2023) (see above). Tillage practices are from a published study, Porwollik et al. (2019). Crop residue is considered as input to fresh organic matter (FOM) pool. This fresh organic material is further divided into sub-pools based on quality and decomposition characteristics: soluble compounds (Rapid), cellulose (Intermediate), and lignin (Slow). Each sub-pool has different turnover rates and C/N ratios, allowing the model to dynamically distribute residue based on C/N ratio and lignin content. The ACTIVE pool, which includes microbial biomass and highly labile by-products of microbial metabolism, undergoes rapid decomposition. The SLOW pool contains microbial by-products that are moderately resistant to further decomposition. Products of microbe metabolism that are extremely resistant to further break down reside as a PASSIVE pool. A portion of decomposing SOM respired as CO2 from each pool.

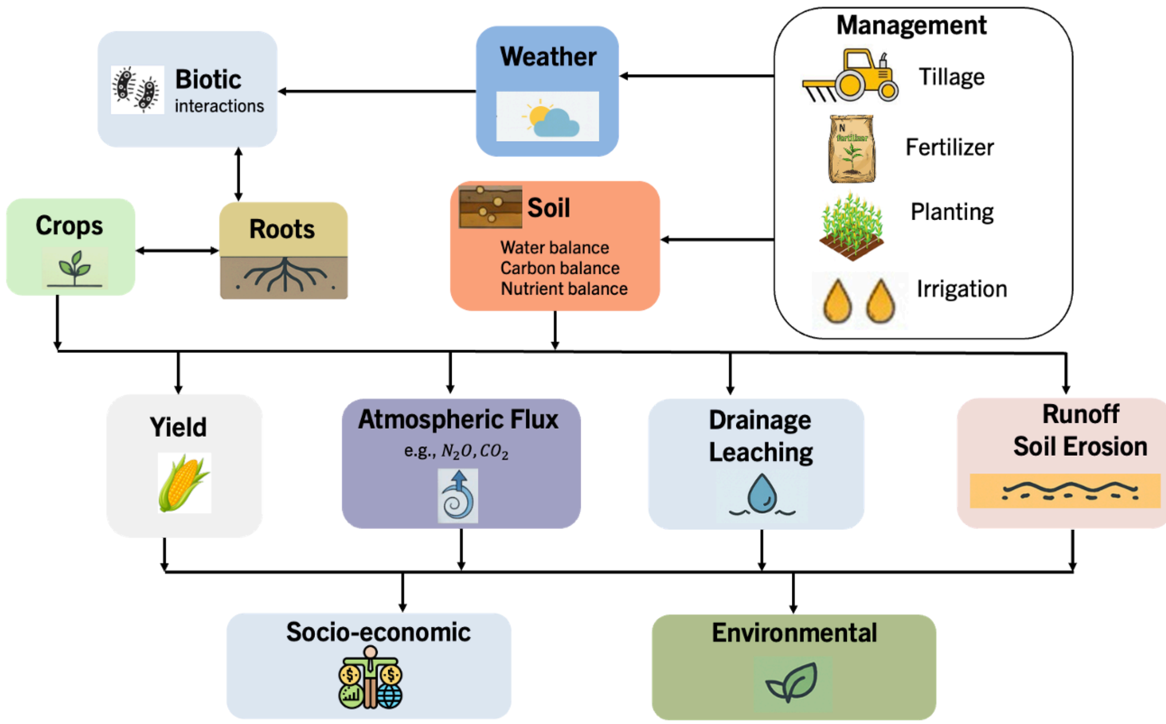

Figure 4. Process-based SALUS schematic (Basso et al., **2015, 2025)**.

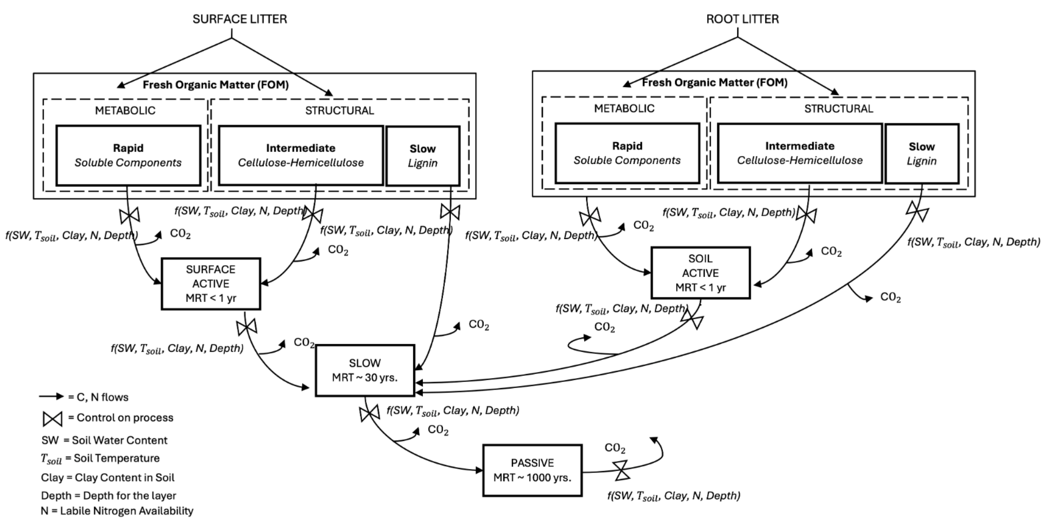

Figure 5. SALUS Soil Organic Carbon dynamics (Basso et al., **2015, 2025)**

Updated country specific emission factors for direct N_2O emissions for synthetic fertilizers, manure applied to soil, crop residue left on soil

To enhance the accuracy and confidence in our direct N_2O emissions estimates from synthetic fertilizers, manure applied to soils, and crop residues retained on fields, we replaced the default Tier 1 emission factor (1%) with country-specific emission factors derived from the literature (Menegat et al., 2022).

Crop-specific production

To support country- and grid-level estimates that depend on crop production, we assembled a consistent set of gridded inputs at ~10 km (0.1°) resolution and monthly time steps. Weather was sourced from ERA5‑Land Daily Aggregated (ECMWF/ERA5_LAND/DAILY_AGGR) via Google Earth Engine. Daily values from January 2015 through August 2025 were aggregated to monthly means for temperature (2 m minimum/maximum/average, converted to °C) and monthly totals for precipitation (mm), then stacked into 128‑band GeoTIFFs (Jan‑Aug for each year). Static biophysical properties (silt, clay, sand, pH, bulk density, organic carbon) were taken from SoilGrids at the same spatial resolution. Harvest-area rasters for each crop/year (2015–2025) were used to mask cultivated pixels. These inputs are used by a spatial Long Short-Term Memory (LSTM) network (a type of recurrent neural network designed to capture temporal dependencies) to predict 2025 crop production, which in turn informs emission estimates that use production-linked activity data.

We implemented a sequence-to-one regression model using a two-layer LSTM with 96 hidden units and dropout regularization (0.15). Each pixel's feature sequence consisted of:

- Dynamic weather inputs (8 time steps × 4 variables)
- Static soil layers (repeated across time steps)
- Year-specific harvest area values

The target variable was crop production (tonnes per hectare). Input features were normalized (z-score) across all training years, and target production values were standardized.

Table 3 summarizes the variables, units, and sources. All rasters were reprojected and aligned to a common grid (EPSG:4326). Outputs are GeoTIFFs aligned to the production raster grid.
Table 3. Model development data used for estimation of gridded crop‑specific production for 2025 at ~10 km resolution.

2.1 Data
The provided dataset is essential for creating a model that estimates annual emissions across various spatial scales. Table 2 presents a comprehensive list of datasets employed for the estimation of annual/monthly crop-specific emissions at gridded scale (~ 10km) until year 2024. Because no crop-specific production dataset was available for 2025, we generated estimates using our machine-learning approach described above. Table 3 lists the inputs used to calculate crop-specific production at the same ~10 km resolution.

Table 2 Data used for estimation of N_2O emissions from synthetic N fertilizer, crop-residue, manure.

Model development	***Unit***	***Source***
Crop-specific yield	Mg/ha,Mg	FAOSTAT
Crop-specific harvest area	ha	FAOSTAT
Crop-specific production	Mg	FAOSTAT, USDA Foreign Agriculture Service
Crop-specific N content	Kg N/ton	Lassaletta *et al.,* 2014
Gridded crop-specific harvest area	ha	Grogan et al., 2022
Total N fertilizer at country scale	Kton	IFASTAT
Crop residue fraction retained/burned	fraction	Smerald et al., 2023
Emission Factor Tier 1 (N_2O) residue burnt	unit of emission/unit of activity	IPCC, 2019
Emission Factor disaggregated dry and wet region (N_2O) for synthetic N fertilizer, residue left on ground, and manure	unit of emission/unit of activity	IPCC, 2019
Monthly crop area burned	Mha	Hall et al., 2024
National Manure applied to cropland	Kg	FAOSTAT
Manure applied gridded distribution	Kg/ha	Adalibieke et al., 2023
Monthly fraction of annual emission of soil N_2O emissions	fraction	EDGAR

Table 3 Model development data used for estimation of gridded crop-specific production for 2025 at ~10 km resolution .

Model development	***Unit***	***Source***
Minimum temperature (2m)	°C	ECMWF/ERA5_LAND/DAILY_AGGR
Maximum temperature (2m)	°C	ECMWF/ERA5_LAND/DAILY_AGGR
Average temperature (2m)	°C	ECMWF/ERA5_LAND/DAILY_AGGR
Total precipitation	mm	ECMWF/ERA5_LAND/DAILY_AGGR

Model development	*Unit*	*Source*
Crop-specific harvest area	ha	FAOSTAT
Silt	(%)	SoilGrids
Clay	(%)	SoilGrids
Sand	(%)	SoilGrids
pH	-	SoilGrids
Bulk Density	g/cm3	SoilGrids
Organic carbon	(%)	SoilGrids
Output	***Unit***	***Source***
Gridded crop-specific Production 2025	t/ha	Model generated

2.1.1 FAOSTAT & UNFCCC

FAOSTAT is a data center for FAO (Agency of United Nations), which provides free access to food and agriculture statistics (including crop, livestock, and forestry sub-sectors) for over 245 countries and covers time periods from 1961 to the most recent year available. At the time of this writing, the most recent year for reported synthetic fertilizer emissions per country is 2019. FAOSTAT compiles this dataset using annual questionnaires sent to country focal points within the national statistical systems. The following datasets were used for this study:

a) Crop-specific yield, production, and harvest area data were extracted for primary crops for >100 countries. Primary crops include >150 types; however, 12 nitrogen-fixing (i.e., soybean) crops were excluded from this study as they do not require synthetic N fertilizer application. Instead, these nitrogen-fixing crops obtain N from the atmosphere via the nitrogen fixation process. This information was used in model development (Table 2). For recent years where FAOSTAT crop production data is not updated (results tend to be delayed by 2 years), we use data from USDA Foreign Agriculture Service for global-scale crop production and harvest data. The updated crop data is for the following crops ('Almond', 'Apples', 'Barley', 'Coffee, green', 'Maize (corn)', 'Millet', 'Oats', 'Rice', 'Rye', 'Sorghum', 'Wheat'), which cover a major part of the world crop production.

b) To validate our country-scale emissions, direct N_2O emissions data were extracted from FAOSTAT & UNFCCC for years 2015 to 2019. FAOSTAT calculates direct N_2O emission using Tier 1 approaches, based on generalized emission factors and other parameter values that are specified either globally or regionally. The Tier 1 method employs the default (simplest) method described in the IPCC Guidelines and the default emission factors and other parameters provided by the IPCC. UNFCCC direct N_2O emission data (available via FAOSTAT) was reported by the countries using Tier 2 and 3 methods suggested by IPCC. Both tier estimates were used to validate the modeled approach (Table 2).

2.1.2 IFASTAT

IFASTAT is a data center for the International Fertilizer Association (IFA; https://www.ifastat.org/). This is the only global fertilizer association and has a membership of some 400 entities, encompassing companies across the fertilizer value chain from producers through traders and distributors and service providers to advisors, research organizations and NGOs. Country scale N fertilizer consumption data was extracted from IFASTAT, which is based on a survey conducted every year, sent to country correspondents, including fertilizer associations, fertilizer companies, consultants, experts, and university researchers.

2.1.3 Gridded crop-specific harvest area

Grogen (2022) created a global gridded dataset for the harvested area, production, and yields for 26 distinct crops (Table S2), corresponding to the year 2015. They integrated data from the GAEZ Version 4 global gridded dataset with publicly available information from the FAOSTAT database. This mapping was detailed to a 5-minute resolution and differentiated between irrigated and rainfed crop production systems.

2.1.4 Emission Reduction Solutions

Nitrous oxide (N_2O) from synthetic fertilizer use, crop residue management, and manure application is the primary focus of ERSs in this sector. Each subsector is approached separately with tailored strategies designed to mitigate emissions while maintaining crop productivity. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

2.1.4.1 Synthetic Fertilizer

A range of ERSs target fertilizer-driven N_2O emissions by improving synchronization between nitrogen supply and plant uptake. A potentially effective solution is the adoption of nitrification and urease inhibitors, which slow microbial conversion processes and reduce gaseous losses. Another widely tested option is the use of slow- or controlled-release fertilizers that provide nitrogen in forms less susceptible to volatilization and leaching. Finally, partial or complete substitution of synthetic fertilizers with organic amendments (such as manure or compost) can lower net emissions when managed carefully. Meta-analyses confirm average reductions of ~25–35% across systems depending on soil, crop, and management conditions (Grados et al., 2022). These adjustments were applied to country-level fertilizer baselines and averaged to generate sector-wide ERS estimates.

2.1.4.2 Crop Residue Management

ERSs for residues are based on residue quality (carbon-to-nitrogen ratio, C:N) and placement.

Studies have demonstrated that avoiding immediate incorporation of fresh, low C:N residues (<25) significantly lowers N_2O emissions compared to conventional practices. For medium C:N residues (50–75), surface retention or shallow incorporation is preferred, avoiding overlap with fertilizer applications. High C:N residues (≥75) are best retained as mulch or shallowly incorporated alongside delayed or split fertilizer applications. Shakoor et al. (2020) found emission factor reductions of up to 75% under optimized residue management strategies. Modeled ERS estimates were derived by scaling baseline emission factors with log response ratios from the literature, yielding avoided emissions compared to the "business as usual" residue treatment.

2.1.4.3 Manure Application

ERSs for manure management focus on altering application methods and pre-treatment strategies. Options include injection or incorporation of slurry below the soil surface, application of digestate instead of raw slurry, separation into liquid fractions with lower solids, and treatment or composting of solids before application. Global meta-analyses (Hou et al., 2015) show that these practices can reduce emission factors by 20–80% depending on context. For example, injection of slurry reduced modeled N_2O emissions in China, India, and the USA by nearly 80% compared to surface spreading. ERS calculations applied published effect sizes to baseline emission factors for each country and climate zone, representing a "best case scenario" of avoided emissions.

Together, these ERSs were incorporated into the modeling framework to represent potential reductions under adoption scenarios. While adoption varies widely across regions, the methods provide a transparent and evidence-based approach to estimating mitigation potential in agriculture.

2.1.4.4 Cropland Burning

The ERS for cropland burning focuses on residue removal without burning. There are many potential uses of residues currently intended for burning, including animal feed, use as a substrate for mushroom cultivation, or biochar production. The applicability of alternative residue uses depends on local infrastructure and economic conditions. There are many contexts where the logistics of planting a subsequent crop, a lack of infrastructure, or limited local demand drivers make residue removal technically or economically infeasible. Future iterations of the ERS will attempt to make more location specific recommendations for the optimal use of residues and the relative environmental impacts of those alternate scenarios. For the first implementation of ERS in Cropland Burning, a simple GHG quantification approach was selected, whereby the biomass burned activity value is set to zero (self-defined) to represent a scenario where no crop residues are burned. This scenario represents the impact of 100% adoption of residue removal, which is an aggressive assumption given the feasibility challenges discussed herein.

2.4 Verifying modeled emissions estimates

To verify the modeled country-level N_2O emission estimates, FAOSTAT and UNFCCC direct N_2O emissions data were used. A time-series analysis was performed for 24 countries, representing the significant portion of N_2O emissions globally, and a direct modeled emissions to FAOSTAT or UNFCCC comparison was performed (Figure 12). In addition, for all the countries (where data were available) one to one comparison is performed with FAOSTAT and UNFCCC (Figure 8; discussed in detail in next section). The spatially gridded direct N_2O emissions were not compared to other emissions estimates (i.e., *in-situ* measurements) due to a lack of globally gridded distributed data at the time of this work. However, we used USDA crop-specific state level N fertilizer data in the USA to validate our estimated N fertilizer amount aggregated at state level. Our estimates from corn and wheat are compared for 25 states in the USA including years from 2015-2018 (Figure S2).

3. Results & Discussion

For the results, only synthetic fertilizers emissions are provided. The other sectors - Crop Residue and Manure Application.

3.1 Country scale

IFASTAT provides N fertilizer consumption data at the country scale. We converted fertilizer consumption data to N_2O emissions by applying the IPCC (2006) emission factor. Figure 4, shows the country scale NUE (calculated in section 2.1.2). For Asian countries, like India, China, Pakistan, and Indonesia, the direct emissions (or N fertilizer) observed is much higher than scenario 1, suggesting primary crops take up a very low percentage of N fertilizer applied (low Nitrogen Use Efficiency: NUE<<1).

On the other hand, direct emissions for Tanzania, Kenya, and Nigeria, are closer to scenario 4 for most years, suggesting a small fraction of N uptake comes from synthetic N fertilizer (lower N application) in these countries (N mining: NUE >1). Soil N mining or fertility loss results from over exploitation of agricultural land without giving back the lost N to the soil. Limited access of synthetic N fertilizer and increasing population pressure led to severe loss of soil nutrient fertility in these countries. This problem of nutrient mining and loss of soil fertility in many African countries is highlighted in previous studies (Vitousek et al., 2009, Liu et al., 2010).

In countries like the U.S.A, France, Canada, Germany, Australia, Italy, and South Africa, observed emissions are closer to scenario 1, suggesting these countries have higher nutrient efficiency (Moderate Nitrogen Use Efficiency: NUE < 1) as compared to Asian countries. One of the reasons might be due to the use of better nutrient management practices in these countries.

According to our analysis, in the last two decades, NUE for most countries have not varied significantly, except for countries like Nigeria and Tanzania, where synthetic fertilizer is not the primary source of crop N uptake, and extra N comes from the agricultural soil nutrient storage. Lassaletta et al. (2014) showed the NUE trends for the past 50 years for 124 countries and found higher crop yield than fertilization (NUE >1; N mining) for 18 countries such as Canada, Morocco, Algeria, Iraq, and Mozambique in the 1960–1980 period (Lassaletta et al., 2014). Also, in recent years of his study period, NUE higher than 1 have been observed in 10 African countries and former Soviet Union countries, Afghanistan and Paraguay. Argentina is the only country with NUE higher than 1 for the whole period of his study. Our study and results shown in Figure 6 suggests NUE is greater than 1 for countries like 1) Argentina, 2) Nigeria and Tanzania (African countries), 3) Russia and Ukraine (former Soviet Union countries), aligning well with analysis from Lassaletta et al. (2014). Note that our calculated NUE ignores other N inputs beyond synthetic fertilizer (i.e., N manure, deposits), which could influence our assessment of NUE in systems that rely on organic amendments.

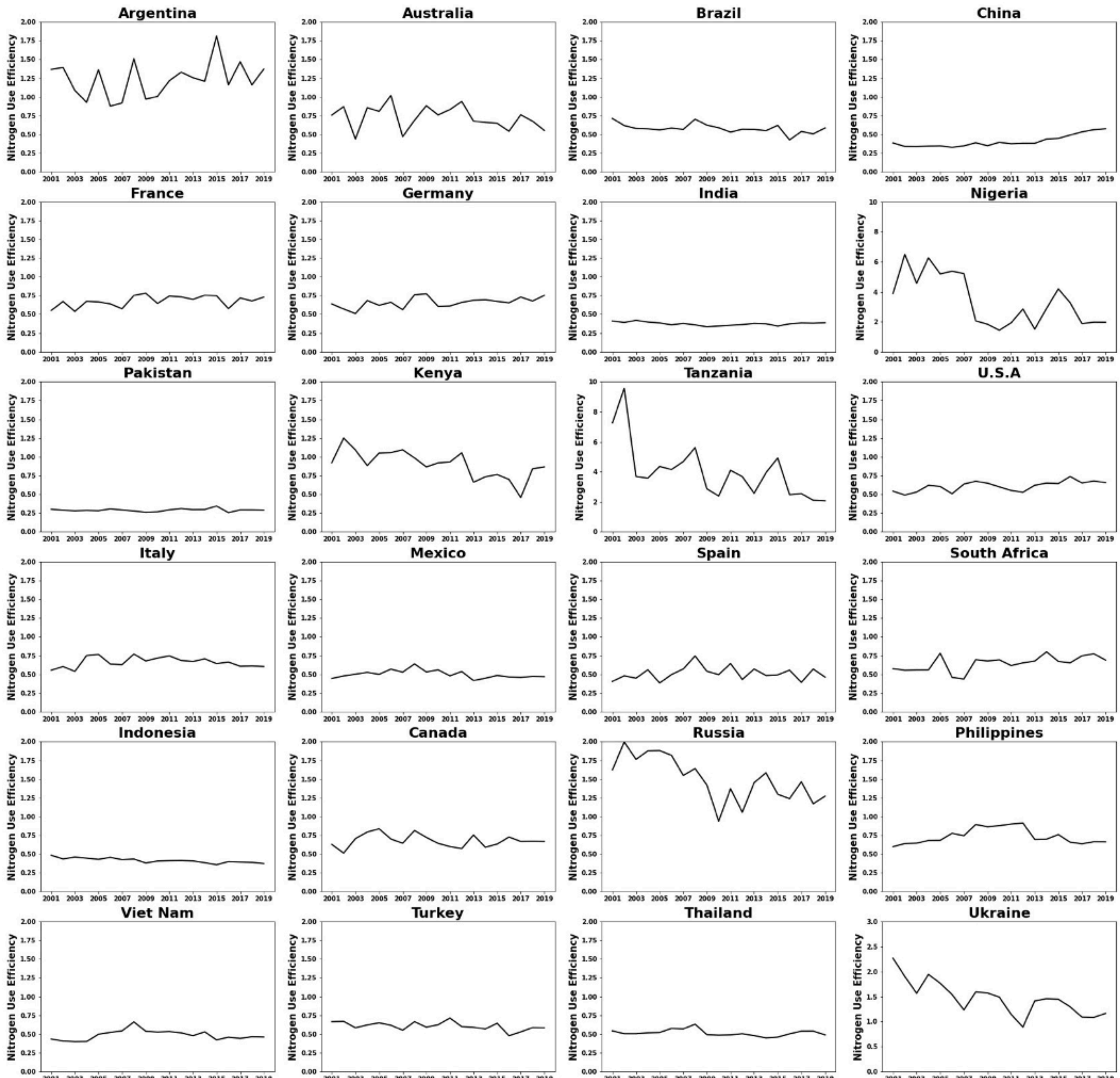

Figure 6 Nitrogen use efficiency (NUE) for each country based on scenario 1 N_{FERT} and IFASTAT. Note, y-scales are different for each country.

In this study, we include 103 countries, which together represent nearly all global synthetic nitrogen fertilizer use (~99%). According to our estimation, the combined direct N_2O emissions from synthetic nitrogen fertilizer use for these 103 countries were approximately 1,774, 1,747, 1,761, 1,801, 1,902, and 1,851 gigagrams (Gg) for the years 2017, 2018, 2019, 2020, 2021, and 2022, respectively.

China, India, and the U.S.A. remain the top three emitter countries during this period, contributing more than 40% of total emissions each year (Table 4). Including the next set of high emitters, Brazil, Mexico, Indonesia, and Canada, the total percentage contribution reaches about 59% of global emissions each year (Table 4).

Table 4 List of the 7 countries which contributed at least 59% to the total global total N_2O emissions due to synthetic nitrogen fertilizers during the period of 2017-2022. Values are measured as percent (country total/global total *100).

	Percent contribution to total emission by year					
Country	**2017 (%)**	**2018 (%)**	**2019 (%)**	**2020 (%)**	**2021 (%)**	**2022 (%)**
China	16.7	14.7	14.8	15.6	14.4	13.8
India	11.7	12.4	12.8	13.5	13.9	13.6
U.S.A	9.8	10.5	10.3	10.4	10.1	8.7
Brazil	7.8	7.6	8.2	7.6	8.9	10.6
Mexico	4.3	4.2	4.2	3.9	4.1	4.1
Indonesia	4.0	4.1	4.1	3.9	3.5	4.1
Canada	3.5	3.9	4.0	4.1	3.9	3.8

In addition to country-level estimation, the accumulated emissions per year at a continent level for Asia (AS), Europe (EU), America (AM), Africa (AF), and Oceania (OC) are provided in Table S1. AS is the highest emitting continent with a total emission of 949 Gg or 58.7% of total global emissions(averaged over the study period). AM, EU, AF, and OC emit 360 Gg (22.3%), 233 Gg (14.5%), 51 Gg (3.2%), and 21 Gg (1.3%), respectively (Figure 7). Even though AF is quite significant in the land area, it only represents 3.2 % of total global emissions due to the limited access to synthetic use N fertilizers in African countries. AS and AM continents collectively represent more than 80% of the total global emissions.

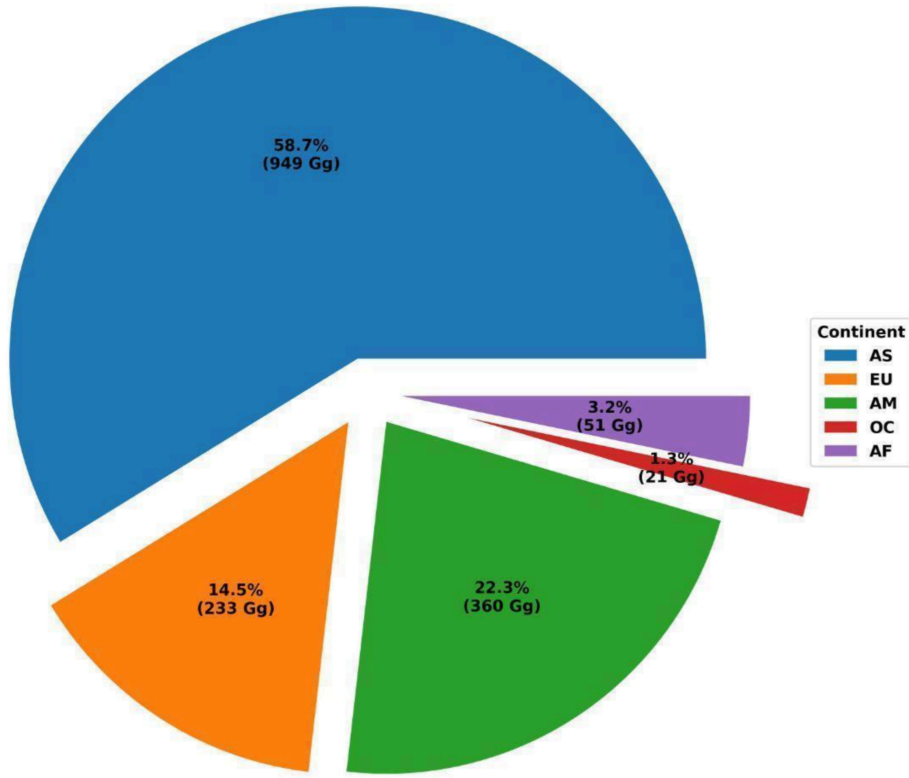

Figure 7 Average percentage contribution of each continent to global total direct N_2O emissions averaged over the period of 2015-2020. In parentheses are the average amount of emissions (Gg) for the same period. Legend key as follows: Asia (AS), Europe (EU), America (AM), Africa (AF), and Oceania (OC).

Our predicted N_2O emissions are independently compared against country-level estimates provided by FAO and UNFCCC inventories (Figure 8). FAO and UNFCCC provide direct N_2O emissions estimation from synthetic nitrogen fertilizer use at country scale. FAO estimates are computed at Tier 1 following the 2006 Guidelines for National GHG Inventories of the Intergovernmental Panel on Climate Change (IPCC, 2006). The primary data source for FAO is national data collected via the FAO Fertilizers questionnaire sent to FAO focal points in the national government. The UNFCCC provides direct N_2O emissions from managed agricultural soils reported by the countries. In this inventory, Annex I group countries' total N_2O emissions from agricultural soil are calculated by combining IPCC's higher tier approaches (Tier 2 and 3). UNFCCC has limited countries which separately report direct emissions for the category of inorganic N fertilizers applied to managed soil.

Overall, the model estimated emissions correlate with FAO and UNFCCC data inventory with an R^2 of 0.91 and 0.86, respectively ($p<0.001$). As discussed earlier, according to our estimations, China, India, U.S.A, and Brazil are the top four emitters globally (Table 4). When we compared our estimation with the FAO database, we are slightly underestimating the emissions for a few countries. However, our estimates are close to UNFCCC for the other two countries, India and U.S.A. For countries like the U.S.A and Australia, our estimates are more comparable to FAO than UNFCCC, which might be because we are following the IPCC Tier 1 approach to calculate the final direct emissions from N fertilizer amounts like FAO. UNFCCC reporting countries use IPCC's higher tier approaches (Tier 2 and 3) for emission estimates.

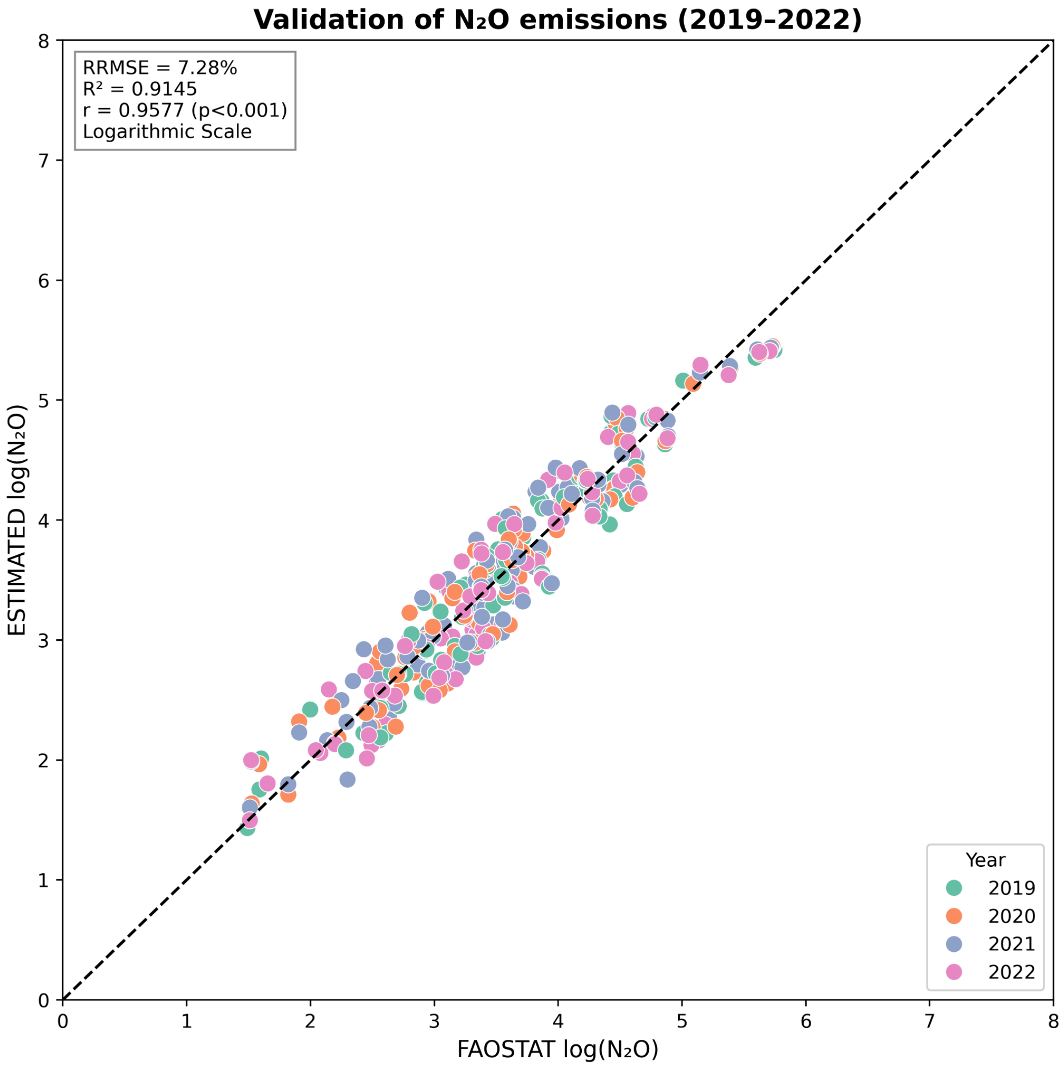

Figure 8 cont.

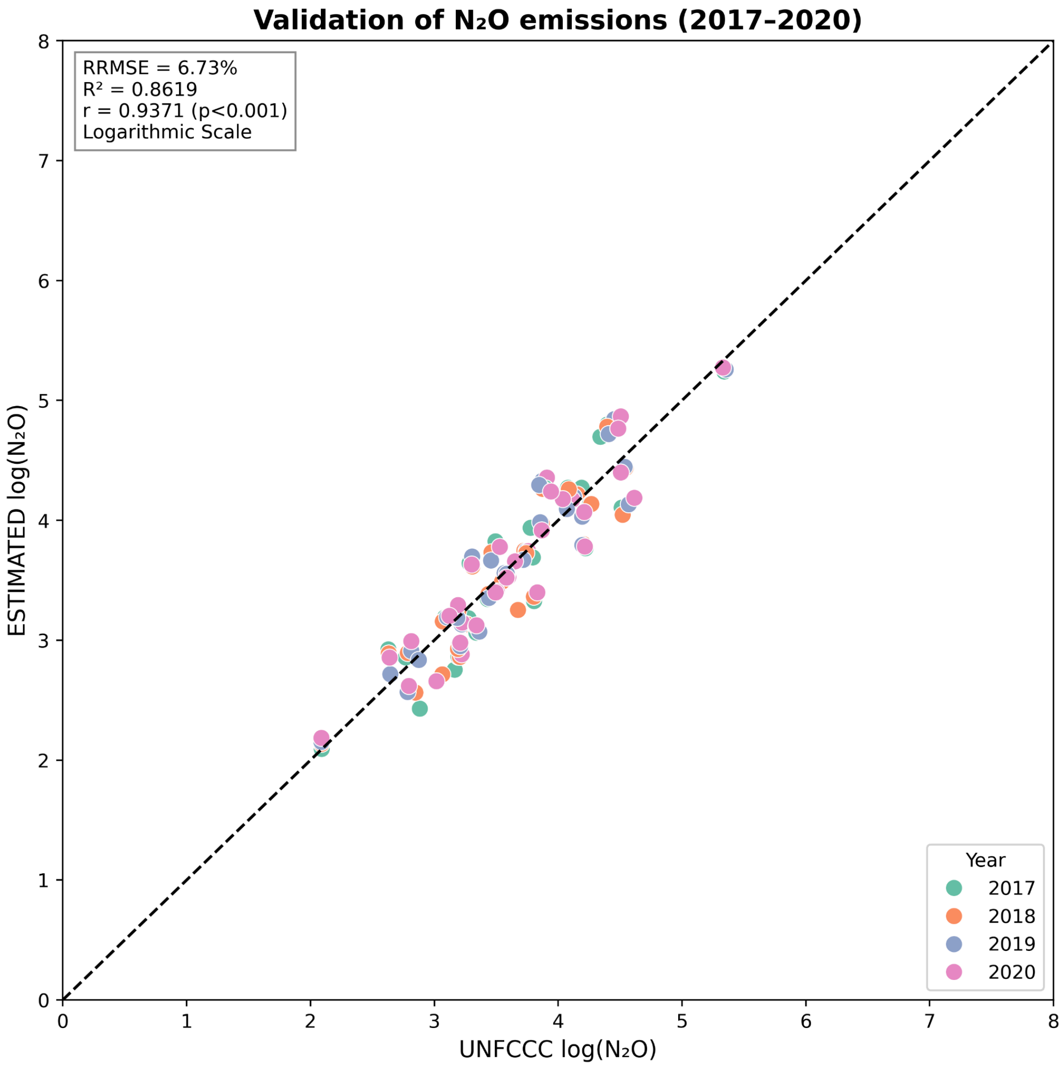

Figure 8 The model predicted N_2O validation with FAOSTAT (top image) and UNFCCC (bottom image) at the country-level for the time period 2017-2022. Dashed black line is the 1:1: line, indicating perfect agreement. Note, each figure has different scales.

To further evaluate the performance of our estimates, we compared a continuous time series of N_2O emissions for 8 initially selected countries over the period 2001–2022 against FAO and UNFCCC inventories (Figure 9). From this set, we retained only those countries for which data were available in all three sources (FAO, UNFCCC, and model predictions), ensuring a consistent basis for comparison.

According to our calculations, these countries account for the majority of global synthetic fertilizer–derived N_2O emissions, contributing between 84% and 86% of global totals during 2015–2020. Overall, our predicted emissions track well with both FAO and UNFCCC inventories, though discrepancies are evident in some cases due to methodological differences. For instance, the United States relies on higher-tier national methods (including process-based models such as DAYCENT; Del Grosso et al., 2012), leading to divergence from the Tier 1–based FAO and our estimates. In China, the highest-emitting country, our predictions show slightly lower values compared to FAO, though both series indicate a downward trend after 2015. India and Pakistan, in contrast, align closely with FAO estimates.

These comparisons highlight that while absolute levels vary across inventories, the temporal dynamics and relative changes are generally consistent, supporting the robustness of our model in capturing long-term emission trends across key emitter countries.

In addition to time-series comparison, to further analyze the changes in emissions in the last five years, we have compared the percentage change in emissions between five years from 2015 to 2019 to FAO and UNFCCC (if available; Table S2). Positive or negative percent change indicates increase or decrease in emissions level between 2015 and 2019, respectively. According to our estimates 14 countries out of 24 are showing the same sign (positive or negative) of percent change in emissions compared with FAO or UNFCCC. Another contrasting difference between our method and FAO estimates is the temporal variability in the emissions. Our model suggests high temporal variability in emissions for countries like Argentina, Australia, and Brazil compared to FAO estimates. The reason could be that our predicted NUE for crops depends on the change in crop yield from one year to another. Therefore, if yield changes from one year to another within a country, as it normally does, changes in the emissions are reflected in our estimates. To further validate our estimations, we compared crop-specific country-level N fertilizer amounts of 7 crops (Maize, Wheat, Rice, Sugar cane, Rapeseed, Tea, Sugar beet) with IFASTAT data for 59 countries (Figure S1). Out of these 7 crops, Maize receives the maximum amount of N fertilizers, representing 20 % of global N fertilizer used on all the crops, followed by wheat with 18% and rice 16 % (IFA report, 2022). These three crops alone represent more than 50% of the total N fertilizer used globally. Our estimates show statistically significant correlation with IFASTAT data inventory with an R^2 of 0.94.

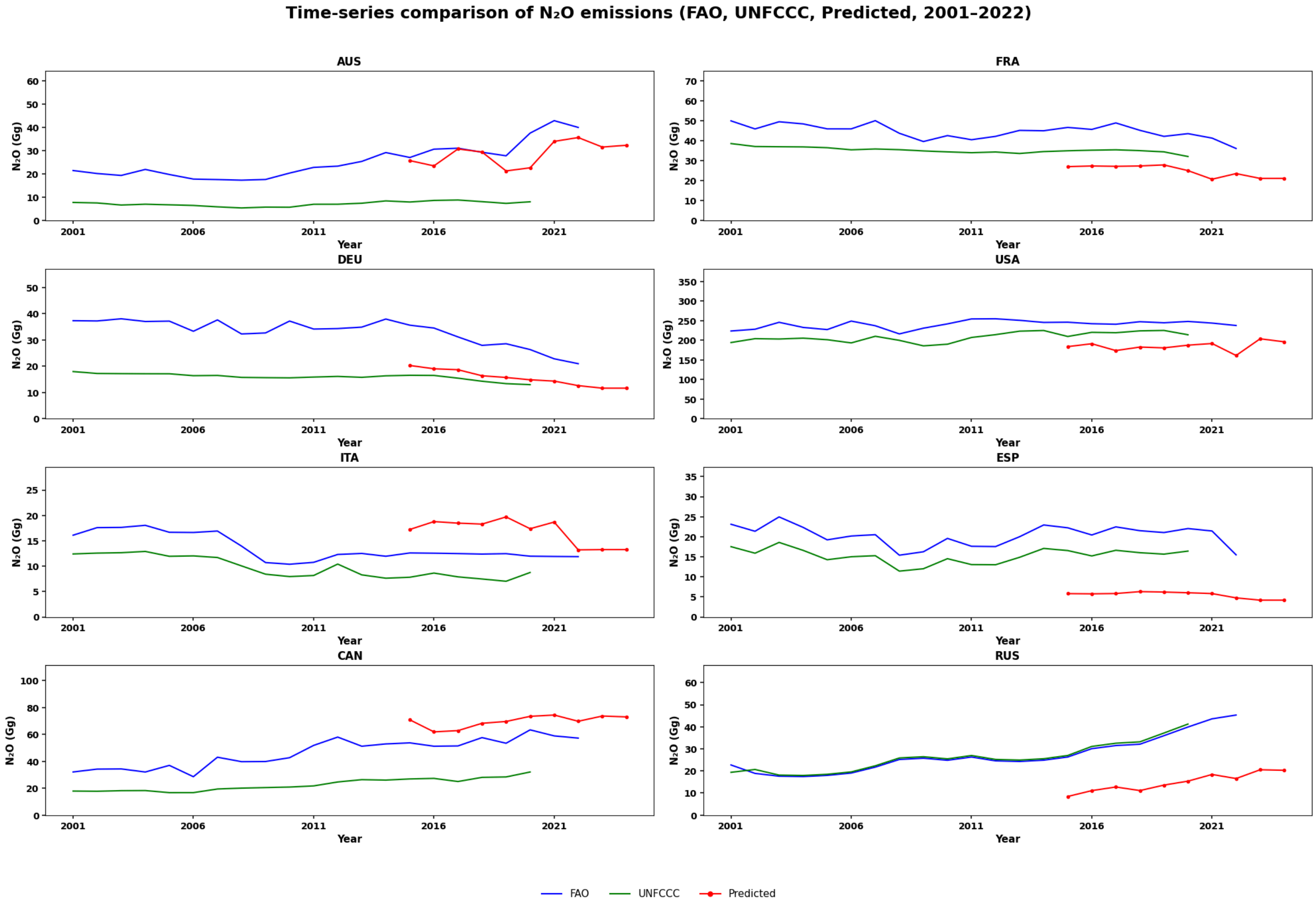

Figure 9 Time-series comparison of model-predicted N_2O emissions (red-dots) with FAO (blue-line) and UNFCCC inventory (green-line). Units- y-axis: Gigagram; x-axis: Year. Note: y-scales are different for each country. For the x-axis, FAO and UNFCCC data is plotted for the time period 2001-2022 and the model calculated emissions are for the time period 2015-2022.

3.2 Gridded emission estimate using IPCC tier 1 EF (~10 km)

In this section, we will explore the gridded N_2O emission map with an approximate resolution of 10 kilometers, created using the methodology outlined in section 2.2.5. This map is part of our broader effort to produce crop-specific N_2O emission maps for each year from 2015 to 2025 hosted on the Climate TRACE website, https://climatetrace.org/. Here, we focus on the cumulative emissions for all crops within each grid cell for the year 2021. An example of 2023 grid-level data is displayed in Figure 10. The map readily highlights emission hotspots, enabling us to pinpoint regions of intense N_2O output. Notably, the Gangetic Plain in India emerges as a significant hotspot, reflecting its status as one of the most agriculturally productive regions in the world. In the United States, areas such as the Corn Belt and the California Valley stand out as prominent emission centers. These regions are known for their intensive agricultural activities, which correlate with higher N_2O emissions. By identifying these hotspots, we can better target mitigation strategies and understand the regional contributions to global N2O emissions. Furthermore, to delineate the contribution of individual crops to the total emissions, we categorized the crops into four types: maize (depicted in red), rice (yellow), wheat (green), and other crops (grey), both at continental and global scales. Globally, maize, wheat, and rice are the predominant contributors, accounting for 80% of total emissions. On the continental scale, the patterns vary: in the Americas, maize is the primary contributor, responsible for 63% of emissions. In Asia, rice stands out as the leading emitter, although wheat (26%) and maize (22%) also have substantial shares. Europe's emissions are mostly dominated by wheat and a diverse array of other crops, together accounting for approximately 85% of the continent's total emissions. In contrast, Africa presents a more balanced emission profile, with wheat, maize, and other crops each having a roughly equivalent impact on the total N2O output. This nuanced understanding of crop-specific contributions is vital for formulating targeted emission reduction strategies across different regions. Identifying emission hotspots is crucial for effectively tackling N_2O emissions from agriculture, as it allows for a focused approach to mitigation. By zeroing in on areas with the highest emissions, resources and strategies can be deployed more efficiently, ensuring the greatest possible impact on reducing greenhouse gases. This precise targeting not only makes economic sense but also facilitates the crafting of localized solutions that respect the nuances of individual agricultural systems, crop types, and environmental conditions.

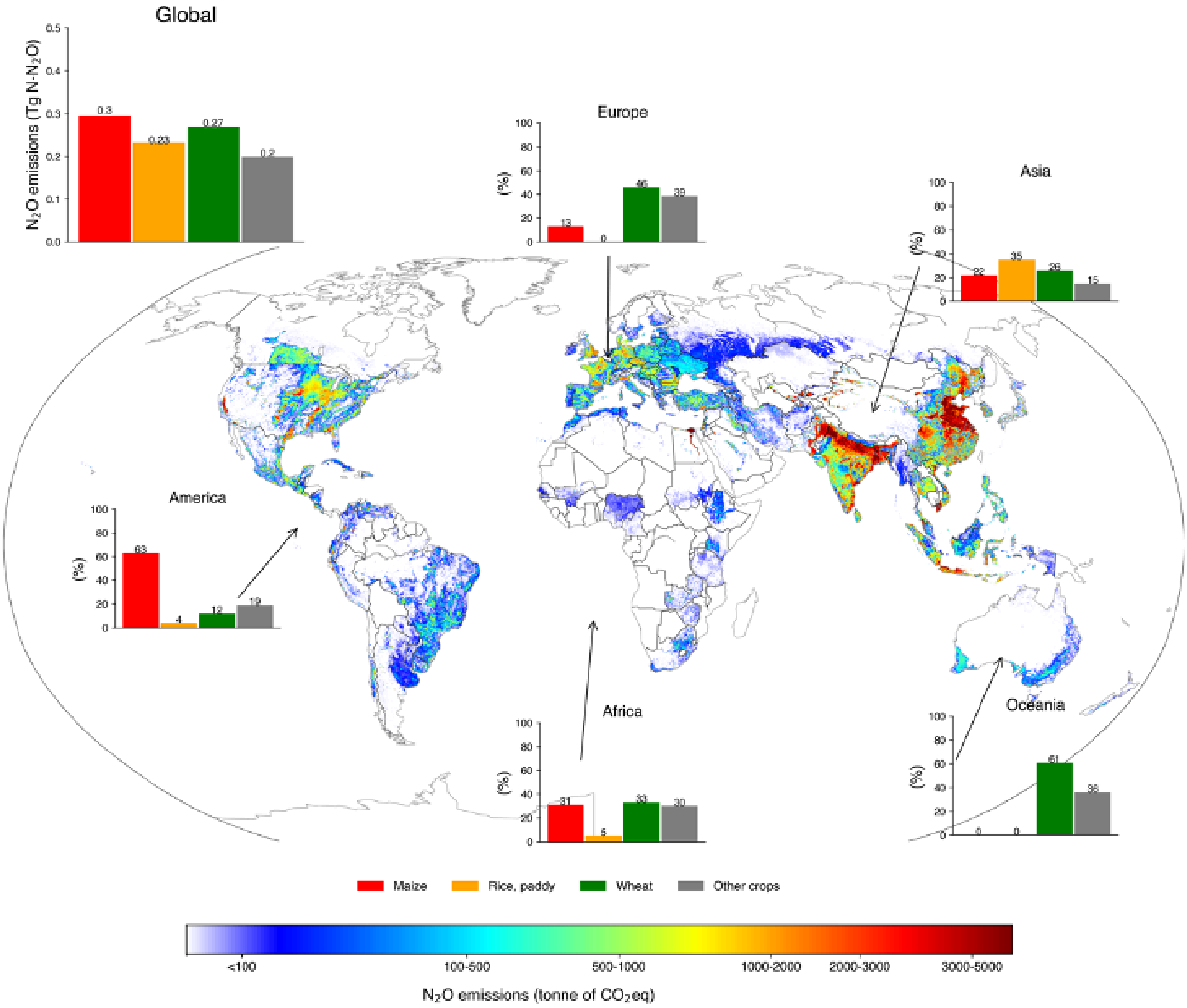

Figure 10 Total nitrogen fertilizer applied at grid scale 0.083° resolution (~10 km) for 2023. Units: Kg/ha grid area.

3.3 Emissions Reduction Solutions (ERS)

Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.

3.3.1 ERS For Synthetic Fertilizer

Baseline N_2O emissions from synthetic nitrogen application were estimated using the IPCC Tier 1 EF (1%), reflecting conventional broadcast application without mitigation. In the ERS scenario, controlled-release fertilizers were modeled to slow nitrogen availability and better match crop demand. Meta-analysis evidence (Grados et al., 2022) suggests reductions of 25–35% depending on conditions. Results show that emissions fell markedly in China, India, and the USA, with the largest absolute savings in regions of high fertilizer intensity (Figure 11).

These three countries were selected because they represent the highest fertilizer consumers globally, together contributing a major share of global synthetic N_2O emissions. Focusing on them illustrates how mitigation strategies can deliver the largest absolute savings where fertilizer use is most concentrated. This highlights the role of technological innovation in reducing fertilizer-related emissions while sustaining crop yields.

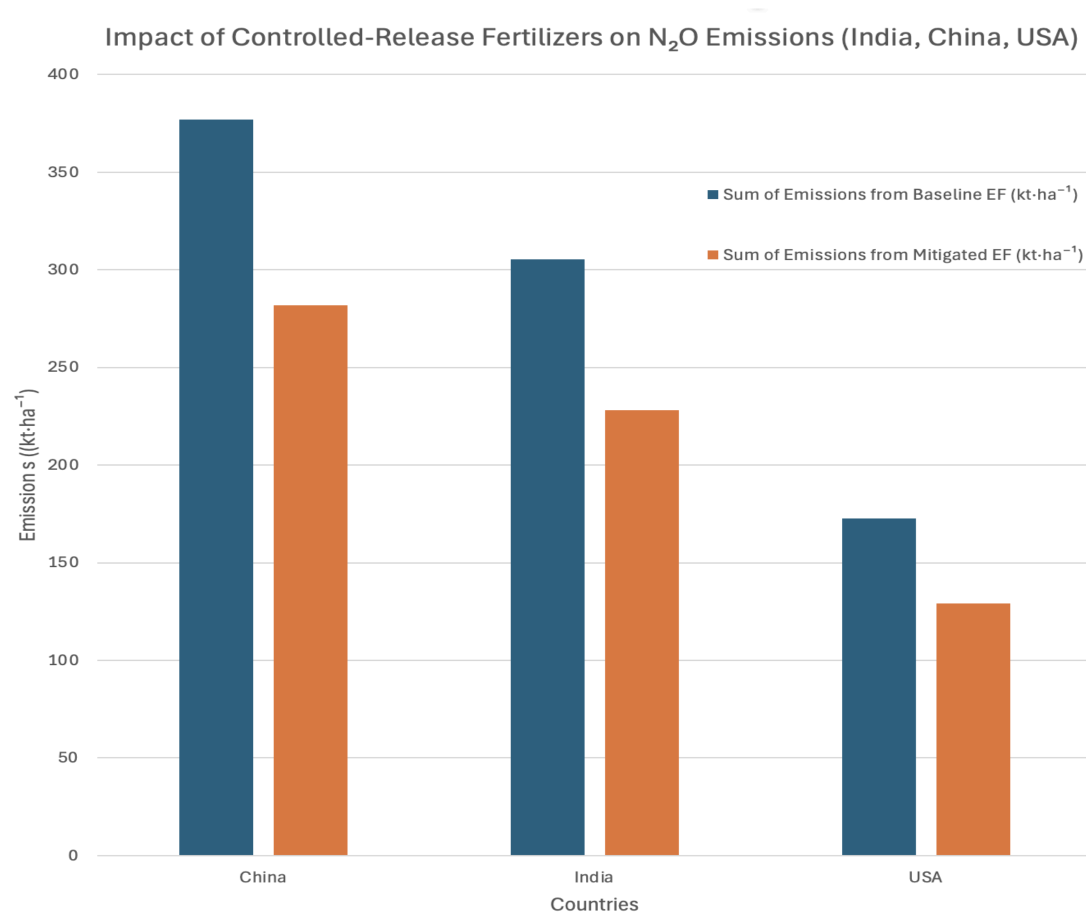

Figure 11. Distribution of N_2O emissions from synthetic fertilizer application at ~10 km resolution (0.083°) for 2024, with regional crop contributions (maize, rice paddy, wheat, and other crops) shown as inset bar charts. Units: kt N_2O–N ha^{-1} yr^{-1}. Countries employing specific strategies in this figure don't necessarily match what is employed on the Climate TRACE website.

3.3.2 ERS for Manure Applied to Soils

Baseline emissions from manure applied to cropland were calculated using Tier 1 IPCC defaults, which assume surface application under average field conditions. The ERS scenario tested injection or incorporation of manure, which alters soil oxygen dynamics and limits denitrification losses. Literature (Hou et al., 2015) shows this practice can cut N_2O emissions by up to 70–80%. Modeled outcomes for China, India, and the USA reveal significant reductions, with China benefiting most due to large manure inputs (Figure 12). These findings demonstrate the mitigation leverage of management shifts in manure handling, where emissions are tied to waste treatment practices rather than synthetic inputs.

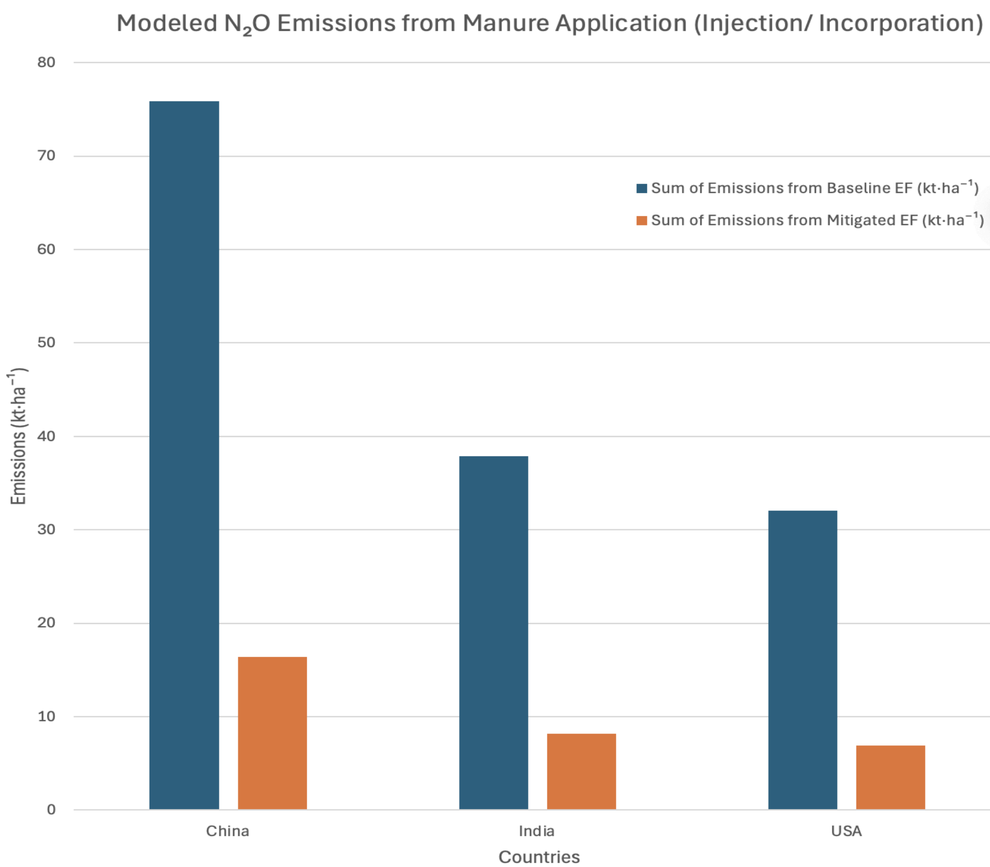

Figure 12 Modeled N_2O emissions from manure application under baseline conditions (IPCC Tier 1 EF) and a mitigated scenario using injection/incorporation as an Emission Reduction Strategy (ERS) for China, India, and the USA. Units: kt·ha^{-1} yr^{-1}. Countries employing specific strategies in this figure don't necessarily match what is employed on the Climate TRACE website.

3.3.3 ERS for Crop Residues

Residue-driven emissions were modeled with IPCC Tier 1 EF (1%), which does not account for residue quality. In reality, residue C:N strongly influences microbial activity and decomposition rates. The ERS scenario applied optimized management of low C:N (<25) residues, delaying incorporation to avoid coinciding with peak fertilizer application. Evidence (Shakoor et al., 2020) indicates potential reductions of up to 75%. Results for China, India, and the USA show clear declines in emissions, especially in systems with abundant cereal residues (Figure 11). This underscores the importance of aligning residue practices with crop nutrient cycles, offering mitigation without reducing residue returns to the soil.

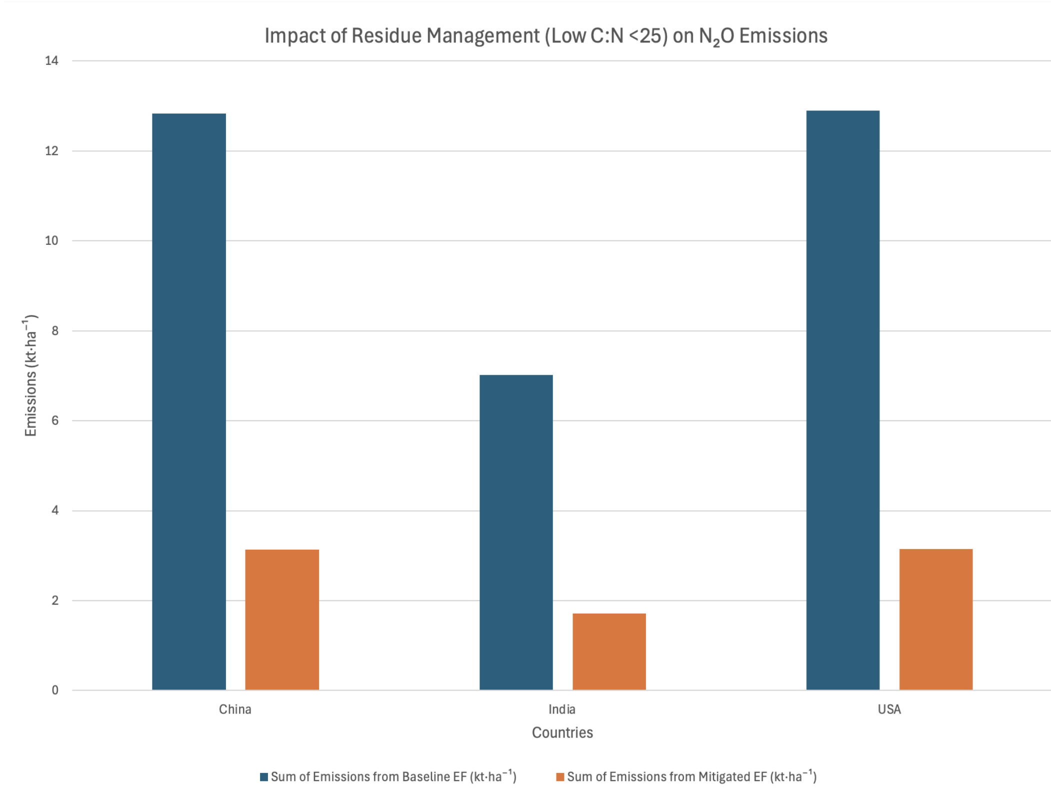

Figure 13 Distribution of N_2O emissions from manure application to soils at ~10 km resolution (0.083°) for 2024, with regional contributions shown as inset bar charts. Units: kt N_2O–N ha^{-1} yr^{-1}. Countries employing specific strategies in this figure don't necessarily match what is employed on the Climate TRACE website.

4. Conclusion

In this study, we include 103 countries, which together represent nearly all global synthetic nitrogen fertilizer use (99%). For 2017–2022, we report percentage contributions of countries to the global total of direct N_2O emissions from synthetic N fertilizer. Across this period, China, India, and the U.S.A. consistently rank as the top three emitters, jointly contributing >40% of global emissions each year (Table 4). When the next four high emitters, Brazil, Mexico, Indonesia, and Canada are included, the combined share is approximately 59% each year (Table 4). Country-level shares vary year to year (e.g., China 16.7 to 13.8%, India 11.7 to 13.6%, USA 9.8 to 8.7%), but these seven countries consistently account for the majority of global emissions.

We refined our approach by estimating crop-specific emissions using gridded harvest areas and nitrogen fertilizer rates. This refined approach sheds more light on regional emission hotspots. For instance, India's Gangetic Plains and the USA's Corn Belt are identified as major contributors to their respective countries' emissions (Figure 10).

To further enhance our estimates, we integrated experimental emission factors (EF) from literature and global networks with remote-sensing data (including soil and climate factors) into machine learning algorithms. This allowed us to develop crop-specific, heterogeneous EFs that are more dynamic than the static 1% IPCC Tier 1 EF. Our method revealed significant differences in emission patterns when compared to those estimated using the IPCC's method. For example, the Gangetic Plains in India, which are identified as a major hotspot by the IPCC, were less prominent in our model. Additionally, our approach generally resulted in lower country-scale emissions estimates compared to those of the IPCC. Our goal is to enhance the precision of emission estimates using advanced tools like machine learning and remote sensing. We validated our estimates against various datasets to ensure reliability. Although our methodology differs significantly from that of the FAO or UNFCCC, it shows good correlation with other global emission inventories. This validation process builds more trust in current emissions inventories while identifying emerging inconsistencies. Our next step involves a dual-focus approach. Firstly, we plan to enhance our methodology by integrating additional features, such as a process-based model encompassing elements like nitrate, ammonium, and biomass. This inclusion will aid Machine Learning in better understanding the variability of emissions. Secondly, we will explore more experimental datasets in data-deficient regions such as Africa and South America. This ongoing improvement will progressively enhance our confidence in emission estimates.

Another area for potential improvement is reducing uncertainties related to crop yield and harvest area data. Currently, we rely on FAOSTAT, which is self-reported by countries. This reliance can be problematic, as countries might underreport or overreport their agricultural areas. For instance, Seto et al. (2000) highlighted significant discrepancies in China between satellite-derived and government-reported agricultural land area. The satellite-derived estimates for total agricultural land in ten counties were 115% greater than those reported in government yearbooks. This example illustrates the need for more reliable data sources in areas like sub-Saharan Africa, where national standards for agricultural data collection are often inadequate (Carletto et al., 2013).

Extending beyond baseline estimates, the integration of Emission Reduction Solutions (ERSs) provides a pathway to mitigate agricultural N_2O emissions**.** For synthetic fertilizers, strategies such as nitrification and urease inhibitors, slow/controlled-release fertilizers, and partial substitution with organics have shown 25–35% reductions in emission factors (Grados et al., 2022). For crop residues, aligning management practices with residue quality (C:N ratio) and timing of incorporation can lower emissions by as much as 75% (Shakoor et al., 2020). For manure application, alternative methods such as injection, digestate use, and fraction management reduce losses by 20–80% (Hou et al., 2015). Together, these ERSs highlight practical, evidence-based options that can complement productivity while delivering meaningful mitigation. Adoption, however, faces regional and practical challenges. In low-income regions, access to inputs and infrastructure limits the potential of ERSs, even though baseline emissions are already low. In high-input systems, economic costs, regulatory frameworks, and farmer adoption behaviors play a central role in determining scalability. Residue strategies may compete with local uses such as fodder or fuel, while manure solutions require investments in handling and treatment systems. In conclusion, applying ERSs alongside refined emission modeling presents an opportunity to substantially reduce agricultural N_2O emissions while maintaining crop productivity. While not a complete solution on their own, these strategies collectively offer scalable, regionally adaptable tools that bring the sector closer to aligning food security with climate mitigation goals.

5. Acknowledgements

This study was funded by Climate TRACE.

6. Supplementary materials

Table S1 Total direct N_2O emissions due to synthetic nitrogen fertilizers for 5 continents for years 2015-2020 (all values rounded to one decimal place). Note, only countries modeled are included in the continent estimates.

	Total emission (Gg)					
Continent	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Asia	985.7	969.9	954.2	910.0	918.9	960.5
America	349.5	348.4	363.3	362.1	362.5	378.0
Europe	219.9	226.9	239.3	238.0	240.1	239.1
Africa	46.4	45.8	52.4	52.6	60.0	54.4
Oceania	21.9	19.4	27.0	22.2	18.0	19.7

Table S2 GAEZ crop classification

1. Wheat	10. Yams and other roots	19. Olives
2. Rice	11. Sugarbeet	20. Cotton
3. Maize	12. Sugarcane	21. Tobacco
4. Sorghum	13. Pulses	22. Banana
5. Millet	14. Soybean	23. Stimulants
6. Barley	15. Rapeseed	24. Vegetables
7. Other cereals	16. Sunflower	25 CropsNES
8. Potato and Sweet potato	17. Groundnut	26 Fodder crops
9. Cassava	18. Oil Palm fruit	

Table S3 Comparison for the percent change in emissions at country scale between the 5 years period from 2015 to 2019 for this study and other inventories.

	% Change in emissions from 2015 to 2019		
Country	**Our study**	**FAOSTAT**	**UNFCCC**
Argentina	38.61	69.35	Not available
Australia	-18.03	12.05	-7.22
Brazil	21.21	39.39	Not available
China	-20.21	-4.63	Not available
France	-2.25	-0.68	-1.55
Germany	-26.23	-12.36	-18.24
India	4.08	-1.53	Not available
Nigeria	68.15	101.98	Not available
Pakistan	3.30	6.90	Not available
Kenya	0.91	-38.94	Not available
Tanzania	63.24	54.7	Not available
U.S.A	-0.35	-0.51	8.64
Italy	9.54	-0.48	-9.85
Mexico	-9.08	55.15	Not available

Country	% Change in emissions from 2015 to 2019		
	Our study	FAOSTAT	UNFCCC
Spain	6.23	-3.41	-5.38
South Africa	-2.87	18.30	Not available
Indonesia	-1.24	8.25	Not available
Canada	-1.83	-0.54	-0.03
Russian Federation	51.12	18.73	37.71
Philippines	4.55	29	Not available
Vietnam	11.65	-7.91	Not available
Turkey	0.91	16.35	13.18
Thailand	-13.75	14.55	Not available
Ukraine	27.51	34.27	25.54

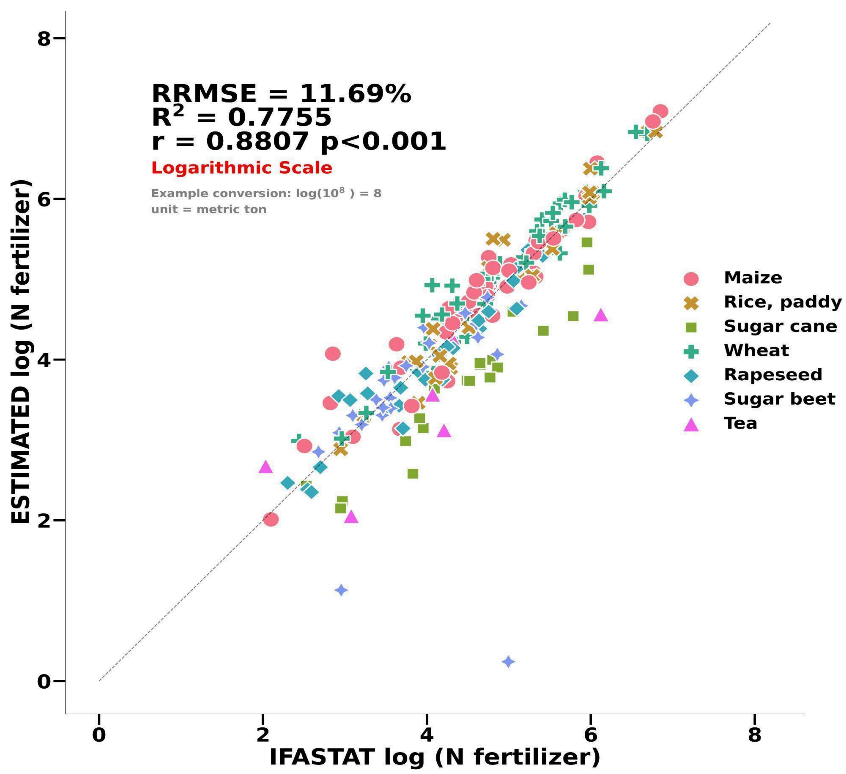

Figure S1 Comparison of crop-specific Nitrogen fertilizer at country scale between our study and IFASTAT for 2018. Units- y-axis and x-axis: kiloton (1000 metric ton).

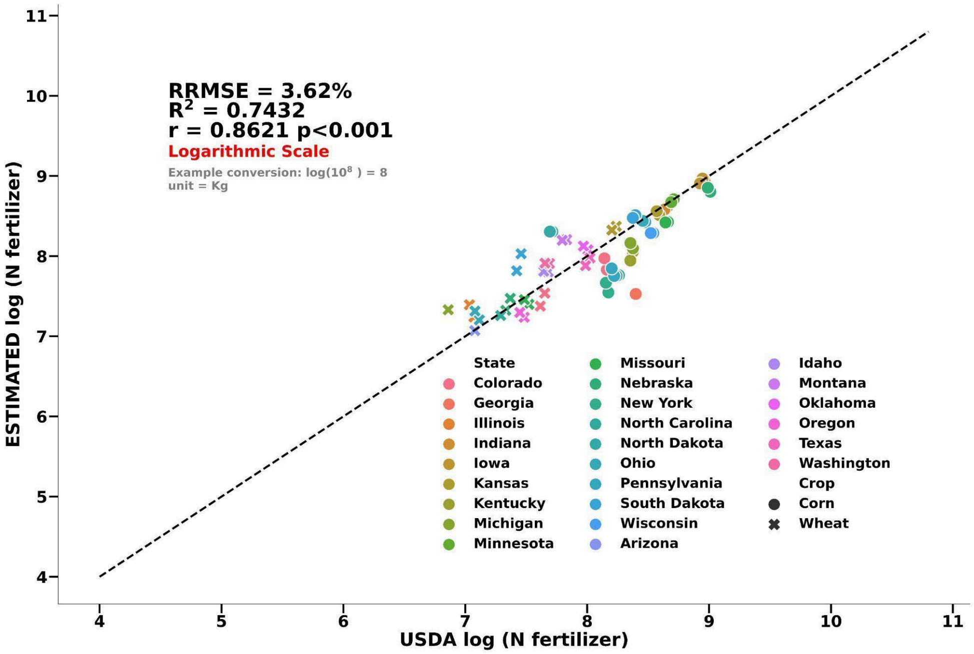

Figure S2 Comparison of crop-specific Nitrogen fertilizer at state scale between our study and USDA for 2015-2018.

Supplementary metadata section

Crop-specific direct N_2O emission are reported at two different spatial resolution (country and asset level) on the Climate TRACE website:

- Country scale crop-specific (include 140 crops in total) direct N_2O emission due to synthetic N fertilizer use in the croplands at 20 and 100 years GWPs
- Asset level crop-specific (140 crops combined in 26 types) direct N_2O emission due to synthetic N fertilizer use in the croplands at 20 and 100 years GWPs

Emissions estimates were reported for years 2015 to 2022, with 2015 backfilled with 2016 data. This sector does not include direct emissions produced from N fertilizer use within pasture. All data is freely available on the Climate TRACE website (https://climatetrace.org/). A detailed description of what is available is described in Table S1 and S2.

Table S4 General dataset information for country scale emissions.
file name: country-climate-trace_synthetic-fertilizer-application.csv.

General Description	Definition
Sector definition	*Crop-specific direct N_2O emission*
UNFCCC sector equivalent	*3.D.1.1 Inorganic N fertilizers*
Temporal Coverage	*2015 – 2022*
Temporal Resolution	*Annual*

Data format(s)	*CSV*
Coordinate Reference System	*None. ISO3 country code provided*
Number of countries available for download and percent of global emissions (as of 2022)	*103 total countries emission representing ~99% of this sector's emissions*
Ownership	*Country*
What emission factors were used?	*IPCC tier 1*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here:https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf

Table S5 Source level description confidence and uncertainty.

Data attribute	Confidence Definition	Uncertainty Definition
type	● *Medium*: if estimate is modeled and not validated ● *High*: if estimate type is modeled and validated	Not used; N/A
capacity_description	● *Medium*: if estimate type was modeled based on published data	Given as an interval with an lower and upper bound of value
activity_description	● *Medium*: if estimate is modeled and not validated ● *High*: if estimate type is modeled and validated for crop-specific N fertilizer amount	Given as an interval with an lower and upper bound of value
CO2_emissions_factor	Not used; N/A	Not used; N/A
CH4_emissions_factor	Not used; N/A	Not used; N/A
N2O_emissions_factor	*Medium*: based on IPCC emissions factors	IPCC uncertainty estimates, expressed as a percentage above or below the mean estimate (i.e. +/-XX%), or as an interval with an upper and lower bound of values.
other_gas_emissions_factor	Not used; N/A	Not used; N/A
CO2_emissions	Not used; N/A	Not used; N/A
CH4_emissions	Not used; N/A	Not used; N/A

Data attribute	Confidence Definition	Uncertainty Definition
N2O_emissions	● *Medium*: if estimate is modeled and not validated ● *High*: if estimate type is modeled and validated total amount with UNFCCC	Given as an interval with an lower and upper bound of value
other_gas_emissions	Not used; N/A	Not used; N/A
total_CO2e_100yrGWP	● *Medium*: if estimate is modeled and not validated ● *High*: if estimate type is modeled and validated total amount with UNFCCC	Given as an interval with an lower and upper bound of value
total_CO2e_20yrGWP	● *Medium*: if estimate is modeled and not validated ● *High*: if estimate type is modeled and validated total amount with UNFCCC	Given as an interval with an lower and upper bound of value

Table S6 Main ERSs employed for this sector. Strategies include [short list: e.g., nitrification/urease inhibitors, controlled-release fertilizers, optimized residue placement, injection/incorporation of manure]. The "Relative N_2O emission factor" values are derived from meta-analyses (Hou et al., 2015; Shakoor et al., 2020; Grados et al., 2022) and represent global mean ratios if the respective strategy were employed across cropland systems. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

strategy_name	strategy_description	mechanism	Relative N_2O emission factor	confidence
Adopt nitrification/urease inhibitors	Apply nitrification and/or urease inhibitors with synthetic N. Works best with correct timing, incorporation, and moisture management.	retrofit	0.642	high
Adopt slow/controlled-release fertilizers	Replace conventional urea with polymer-coated or other controlled-release fertilizers. Suited to high leaching/volatilization risk.	retrofit	0.748	medium

Data citation format: Sharma, P., Trivedi, R., and Basso, B. (2025). *Emissions from Synthetic Fertilizer, Crop Residue, and Manure Application.* Department of Earth and Environmental Sciences, Michigan State University, USA, Climate TRACE Emissions Inventory.

https://climatetrace.org [Accessed date].

Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

- HKG (China, Hong Kong Special Administrative Region) and MAC (China, Macao Special Administrative Region) are reported at GADM level 0 (country/national);
- Kosovo has been assigned the ISO3 code 'XKX';
- XCA (Caspian Sea) has been removed from GADM level 0 and the area assigned to countries based on the extent of their territorial waters;
- XAD (Akrotiri and Dhekelia), XCL (Clipperton Island), XPI (Paracel Islands) and XSP (Spratly Islands) are not included in the Climate TRACE dataset;
- ZNC name changed to 'Turkish Republic of Northern Cyprus' at GADM level 0;
- The borders between India, Pakistan and China have been assigned to these countries based on GADM codes Z01 to Z09.

The above usage is not warranted to be error free and does not imply the expression of any opinion whatsoever on the part of Climate TRACE Coalition and its partners concerning the legal status of any country, area or territory or of its authorities, or concerning the delimitation of its borders.

Disclaimer: The emissions provided for this sector are our current best estimates of emissions, and we are committed to continually increasing the accuracy of the models on all levels. Please review our terms of use and the sector-specific methodology documentation before using the data. If you identify an error or would like to participate in our data validation process, please contact us.

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