Agriculture sector:

Emissions from Synthetic Fertilizer, Crop Residue, and Manure Application

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August 2025 Update: This sector in previous releases only estimated synthetic fertilizer emissions. Climate TRACE has updated and added crop residue and manure application sectors.

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, residue, and manure emission calculation. To enhance the precision of our emission estimations in future release, we are going to use higher-tier emission factors collected from literature.

2. Materials and Method

In this section, we describe the datasets and methods used to quantify greenhouse-gas emissions from synthetic nitrogen fertilizer, crop residue management, and manure application across all crops, and to simulate soil organic carbon (SOC) stock changes **only for maize**. 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*
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.

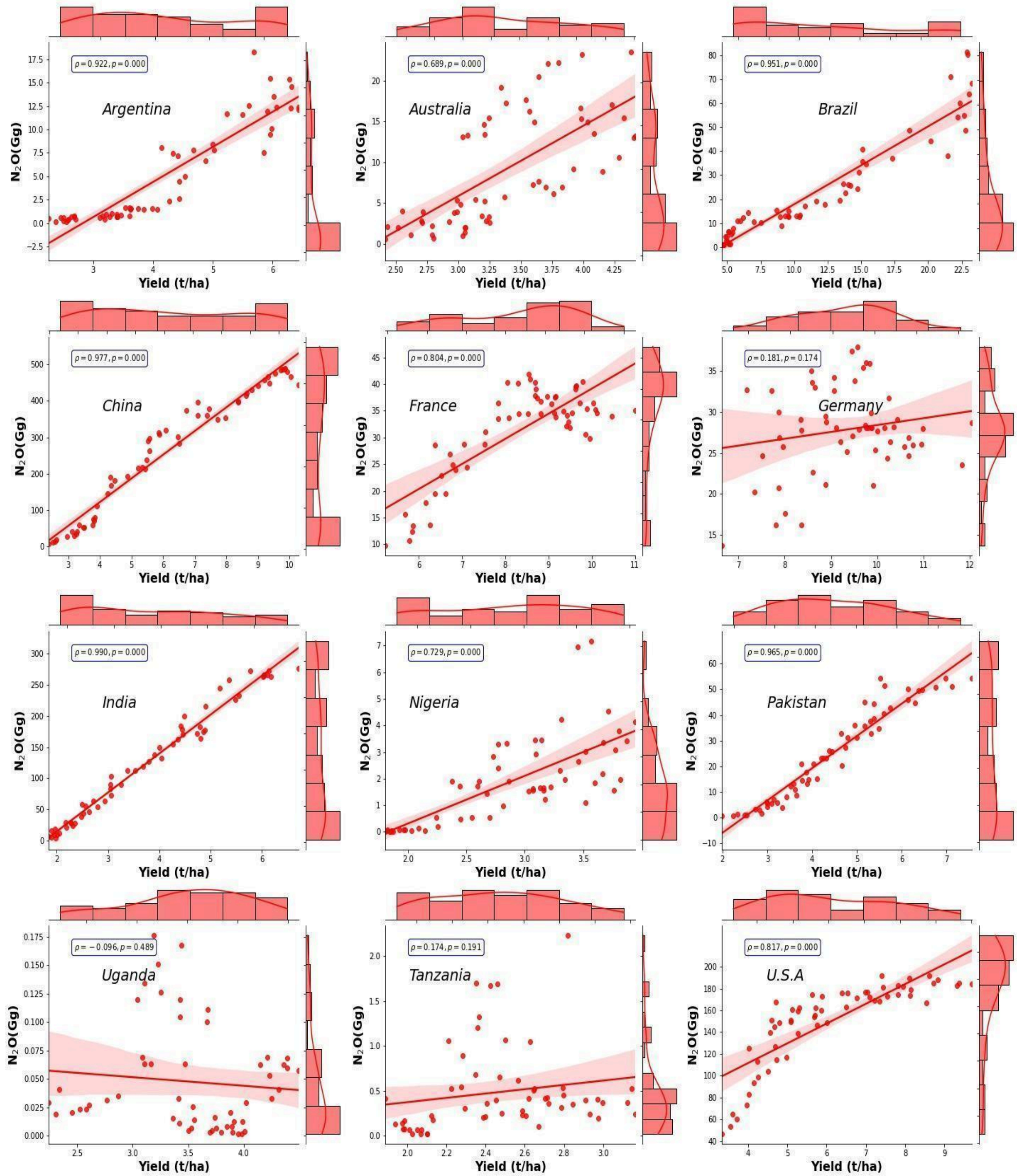


Figure 1 Correlation graph between country-level direct N_2O emissions due to synthetic N fertilizer and crop yield using FAOSTAT data from 1961-2018. (Units- y-axis: gigagram, x-axis: tonnes/ha).

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, a2015 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 emissions from burned residue, 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.

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). Emission factors (EFs) manure 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.

SOC Changes in maize using SALUS

In the latest update from last year, we integrated the process-based SALUS model (Basso et al., 2006), which simulates coupled plant and soil biogeochemistry processes to estimate SOC changes from maize cropping systems. 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/). Synthetic nitrogen fertilizer rate for maize is from our dataset, as detailed in Section 2.2.5. Manure data was based on a published study Adalibieke et al. (2023), while crop residue fraction is from Smerald et al. (2023). Tillage practices are from a published study, Porwollik et al. (2019) and irrigation data is from AQUASTAT (FAOSTAT) for areas equipped with irrigation systems. The maize growing season data was generated using AI techniques, as reported in a recent study Franch et al. (2021).

2.1 Data (Synthetic Fertilizer)

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 emissions on a national scale, methodically organized into three distinct segments: model development, calibration, and validation, culminating in the final output. Table 3 details the datasets used for the calculation of annual emissions at a finer gridded scale, approximately 10 kilometers, employing the IPCC Tier 1 emission factor set at 1%. Table 4 outlines the datasets harnessed to derive a spatio-temporally heterogeneous, crop-specific emission factor at an even higher resolution of approximately 4 kilometers.

Table 2 Model development, validation data used for estimation of N_2O emissions from synthetic N fertilizer.

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
Model calibration	***Unit***	***Source***
Total N fertilizer at country scale	Kton	IFASTAT
Validation	***Unit***	***Source***
Direct N_2O emission at country scale	Gg	FAOSTAT
Direct N_2O emission at country scale	Kton	UNFCCC
Output	***Unit***	***Source***
Direct N_2O emission at country scale	tCO_2eq /Gg	Model generated

Table 3 Model development, validation data used for estimation of gridded N_2O emissions at ~10 km resolution.

Model development	***Unit***	***Source***
Crop-specific N fertilizer rate at country scale	Kg/ha	This study
Gridded crop-specific harvest area	ha	Grogan et al., 2022
Validation	***Unit***	***Source***
N fertilizer amount at state level USA	Kg	USDA
Output	***Unit***	***Source***
Gridded N fertilizer amount	Kg	Model generated
Gridded direct N_2O emission	tCO_2eq /Gg	Model generated

Table 4 Model development data used for estimation of gridded Emission factor and N_2O emissions at ~4 km resolution .

Model development	***Unit***	***Source***
Global N_2O/EF dataset	-	CGIAR
Gridded crop-specific N fertilizer amount	Kg	This study
Crop calendar	date	FAOSTAT
NDVImax	-	Landsat
Annual Precipitation	mm	TerraClimate
Silt	(%)	SoilGrids
Clay	(%)	SoilGrids
Sand	(%)	SoilGrids
pH	-	SoilGrids
Cation Exchange Capacity (CEC)	-	SoilGrids
Topographic Wetness Index (TWI)	-	MERIT Hydro
Output	***Unit***	***Source***
Gridded crop-specific EF	Kg	Model generated
Gridded crop-specific direct N_2O emission	tCO_2eq /Gg	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.

2.4 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 6; 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 (Synthetic fertilizers emissions)

3.1 Country scale

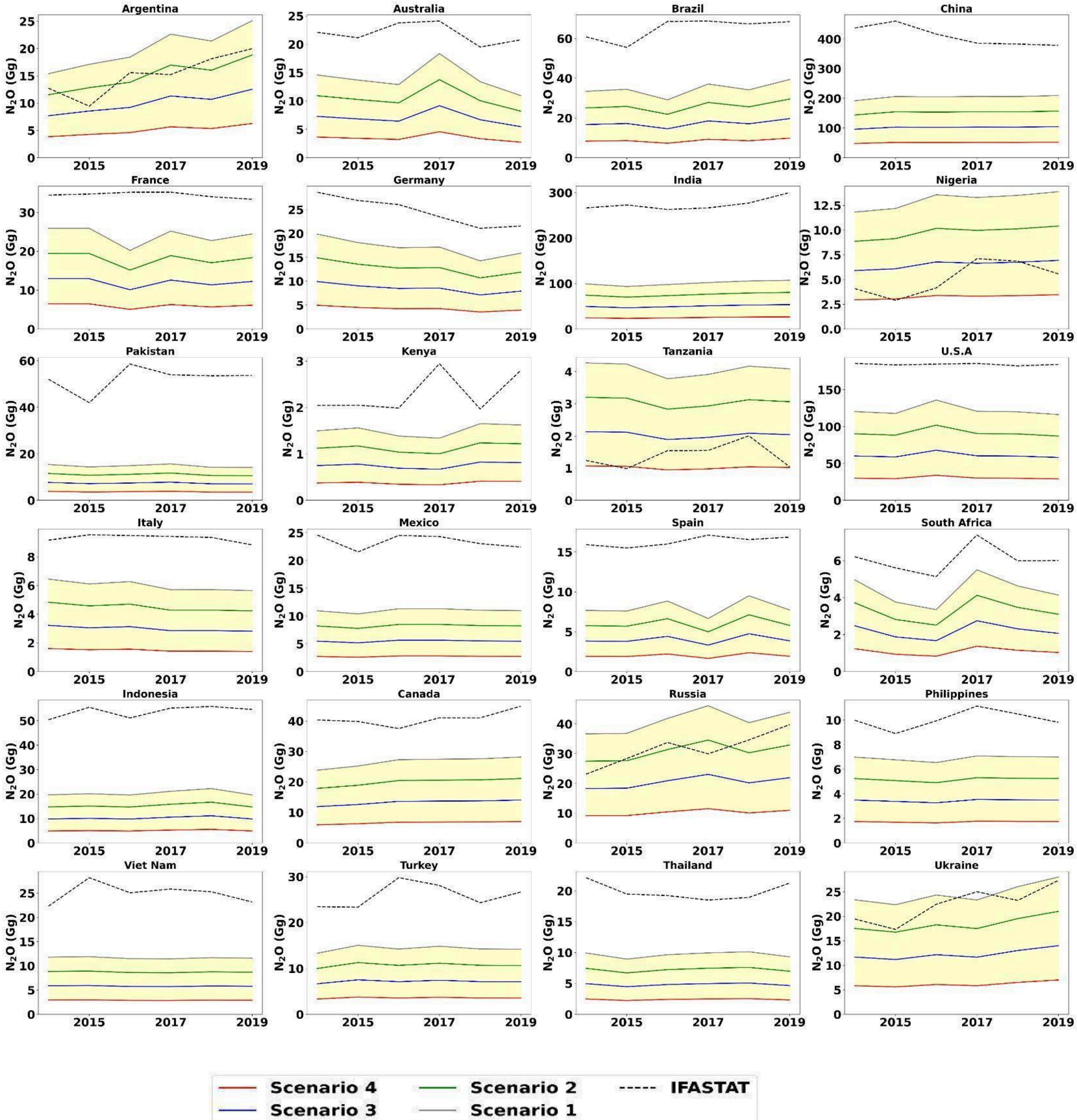
We compared N_2O derived from the N_{FERT} amounts in different scenarios to the IFASTAT observation data at the country-level (Figure 9a). IFASTAT provides N fertilizer consumption data at the country scale. We converted fertilizer consumption data to N_2O emissions by applying the IPCC (2006) emission factor. Figure 9b, 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 9b 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.

a)



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b)

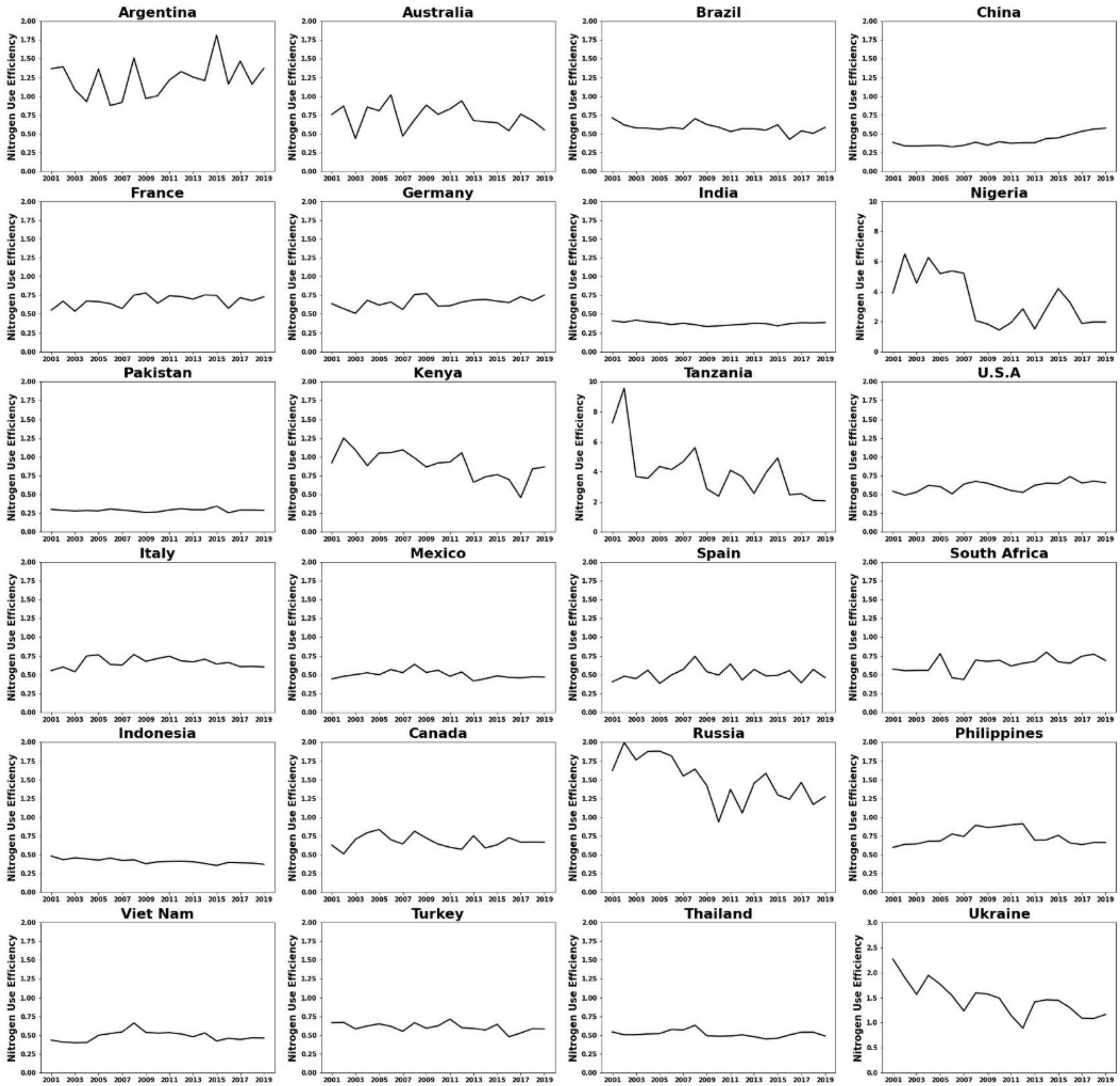


Figure 9 a) Time-series (2014-2019) of N_2O from IFASTAT and N_2O estimated from scenarios 1, 2, 3 and 4. Note, y-scales, N_2O (Gg) are different for each country; **b)** Nitrogen use efficiency (NUE) for each country based on scenario 1 N_{FERT} and IFASTAT. Note, y-scales are different for each country.

In this study, we include 103 countries, which represent the majority of total synthetic nitrogen fertilizer use at global scale (~99%). According to our estimation, total direct N_2O emissions from synthetic nitrogen fertilizer use combined for 103 countries are 1,623, 1,610, 1,636, 1,585, 1,600, and 1,652 gigagrams (Gg) for years 2015, 2016, 2017, 2018, 2019, and 2020 respectively.

China, India, and the U.S.A. are the top three emitter countries for the period 2015 to 2020 contributing more than 50% of total emissions every year (Table 6). Including the next set of highest emitters - Brazil, Pakistan, Indonesia, and Canada - the total percentage contribution reaches more than 60% of total emissions (>900 Gg) every year (Table 6).

Table 6 List of the 7 countries which contributed at least 69% to the total global direct N_2O emissions due to synthetic nitrogen fertilizers during the period of 2015-2020. Values are measured as percent (country total/global total *100).

Country	**Percent contribution to total emission by year**					
	2015 (%)	**2016 (%)**	**2017 (%)**	**2018 (%)**	**2019 (%)**	**2020 (%)**
China	29.1	28.2	25.3	24.0	23.6	22.8
India	16.3	16.7	16.3	16.6	17.3	19.0
U.S.A	11.2	11.9	10.6	11.6	11.3	11.2
Brazil	3.7	3.3	4.7	4.1	4.5	4.3
Pakistan	3.2	2.6	3.5	3.3	3.3	3.3
Indonesia	3.1	3.3	3.4	3.6	3.1	3.2
Canada	2.5	2.4	2.4	2.7	2.5	2.7

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 10). 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.

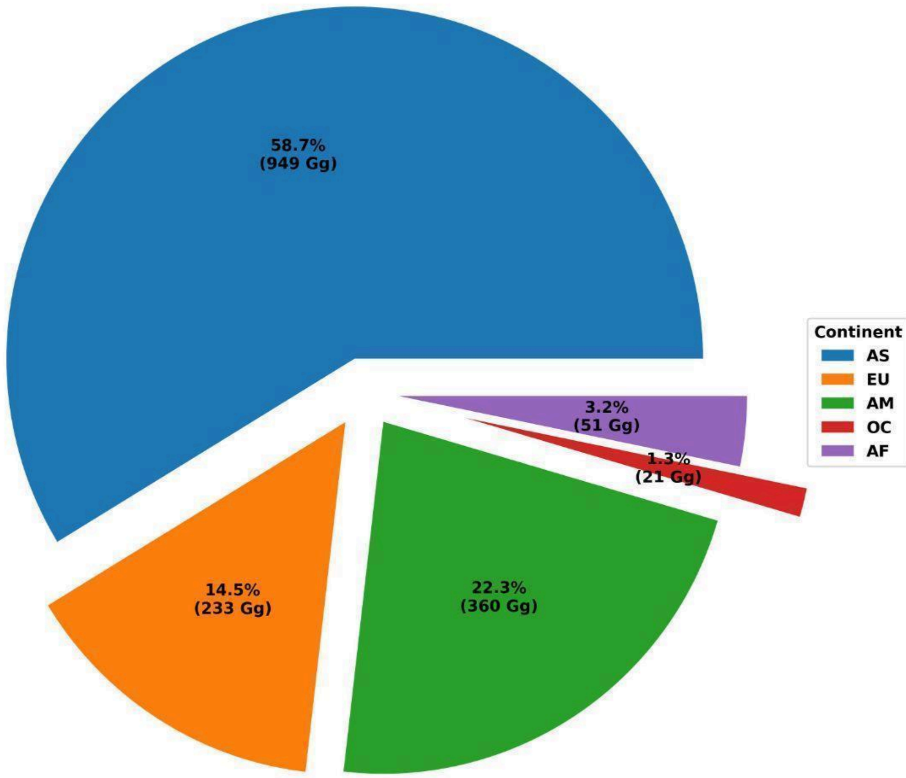
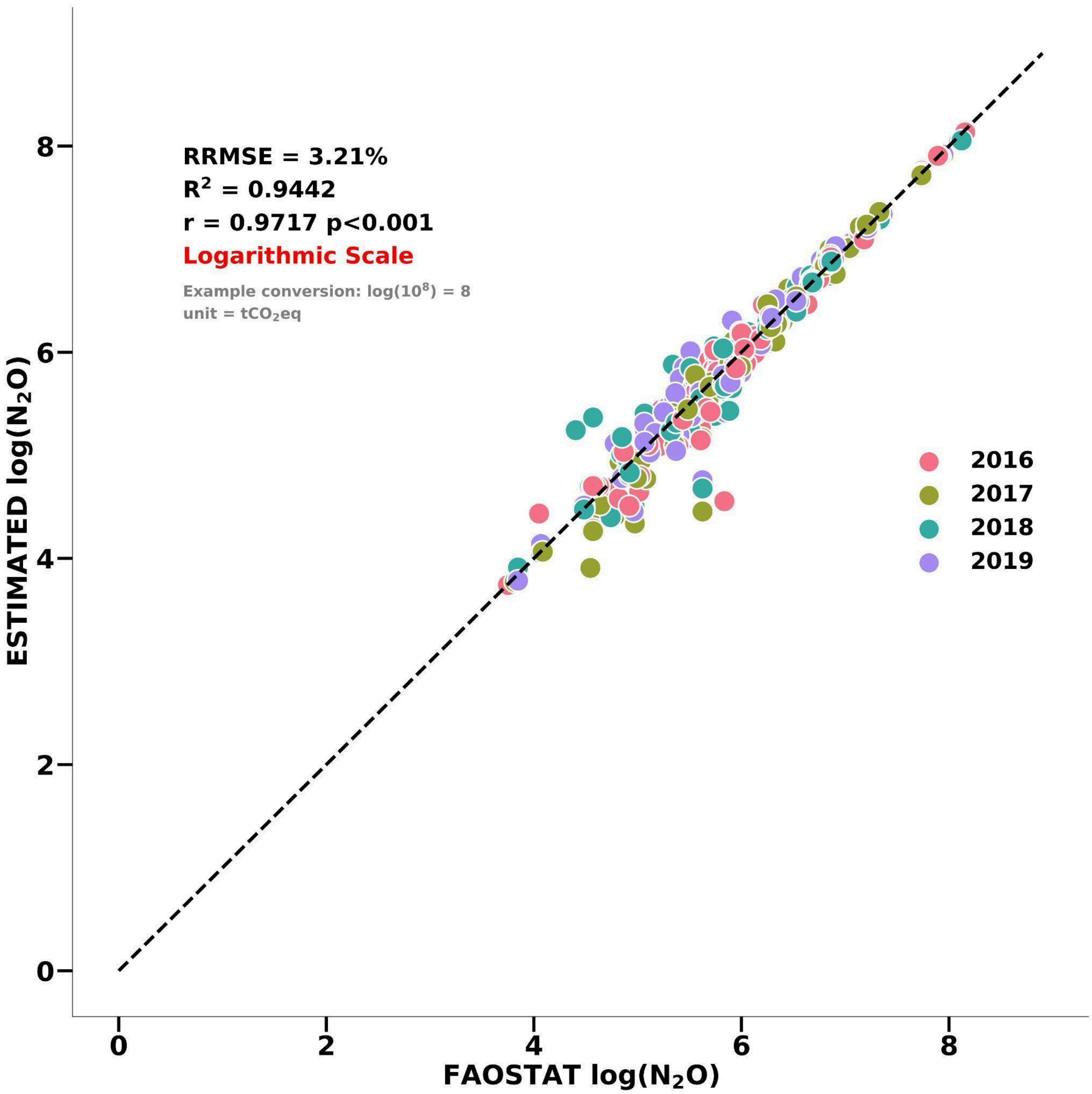


Figure 10 Average percentage contribution of each continent to global total direct N_2O emissions averaged over the period of 2015-2020. In parentheses are the average amount of emissions (Gg) for the same period. Legend key as follows: Asia (AS), Europe (EU), America (AM), Africa (AF), and Oceania (OC).

Our predicted N_2O emissions are independently compared against country-level estimates provided by FAO and UNFCCC inventories (Figure 11). 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' direct 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 0.94 and 0.96, 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 6). 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.



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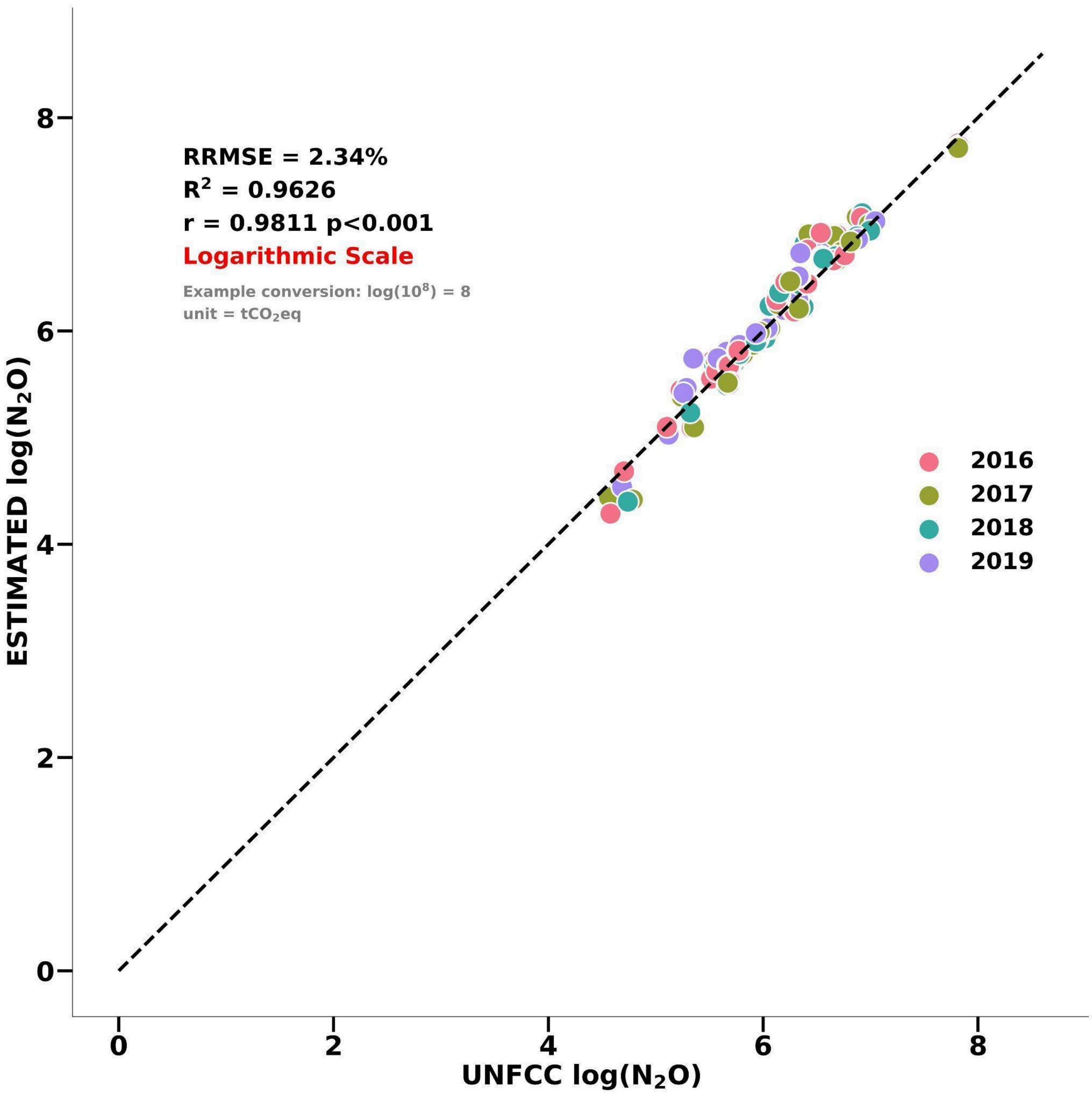

Figure 11 The model predicted N_2O validation with FAOSTAT (top image) and UNFCCC (bottom image) at the country-level for the time period 2016-2019. Dashed black line is the 1:1: line, indicating perfect agreement. Note, each figure has different scales.

To further analyze the results, we compared a time series of emissions for 24 countries from 2015 to 2019 with FAO and UNFCCC inventory (Figure 12). These 24 countries are selected from each of the five continents (Asia, America, Europe, Africa, and Oceania). According to our calculation, in total, these 24 countries represented 84%-86.4%, total global emissions between 2015 and 2020.

The discrepancies between our estimates and UNFCCC might be due to the difference in method. For example, countries like the USA use different approaches for national scale N_2O emissions assessments, which involve process-based models, such as the DAYCENT (Del Grosso et al., 2012), along with the IPCC emission factor. For some countries UNFCCC emission values are not available between 2015 to 2019, and we compared our emission with FAOSTAT only. In China, which is the highest emitting country (as discussed earlier), our estimates underestimate emissions as compared to FAOSTAT. However, both are showing decreases in emission levels from 2015 to 2019. Other high emitting countries like India and Pakistan show a close match to FAOSTAT estimates.

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.

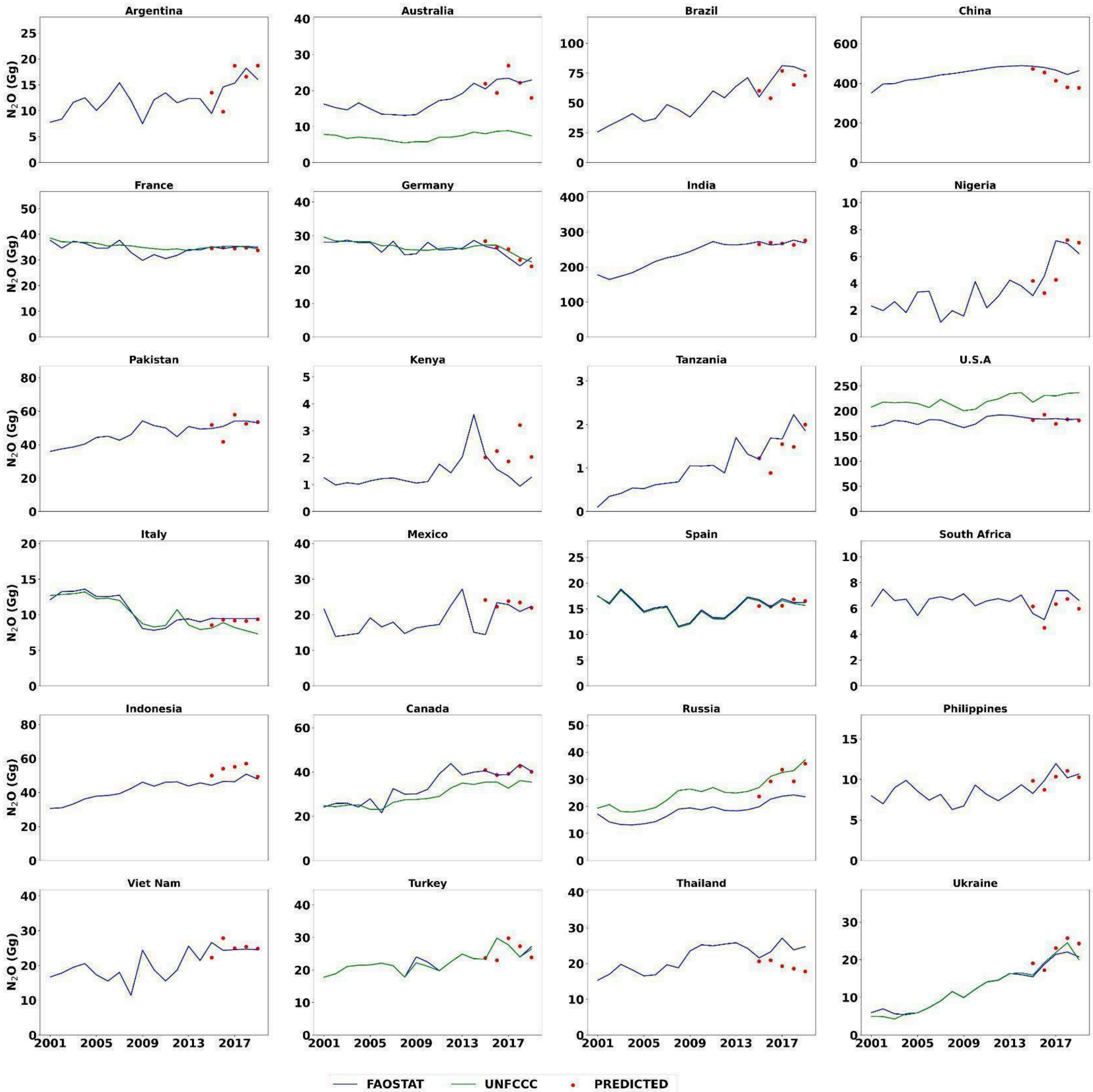

Figure 12 Time-series comparison of model-predicted N_2O emissions (red-dots) with FAO (blue-line) and UNFCCC inventory (green-line). Units- y-axis: Gigagram; x-axis: Year. Note: y-scales are different for each country. For the x-axis, FAO and UNFCCC data is plotted for the time period 2001-2019 and the model calculated emissions are for the time period 2016-2019.

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 2022 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 2021 grid-level data is displayed in Figure 13. 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 N2O 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.

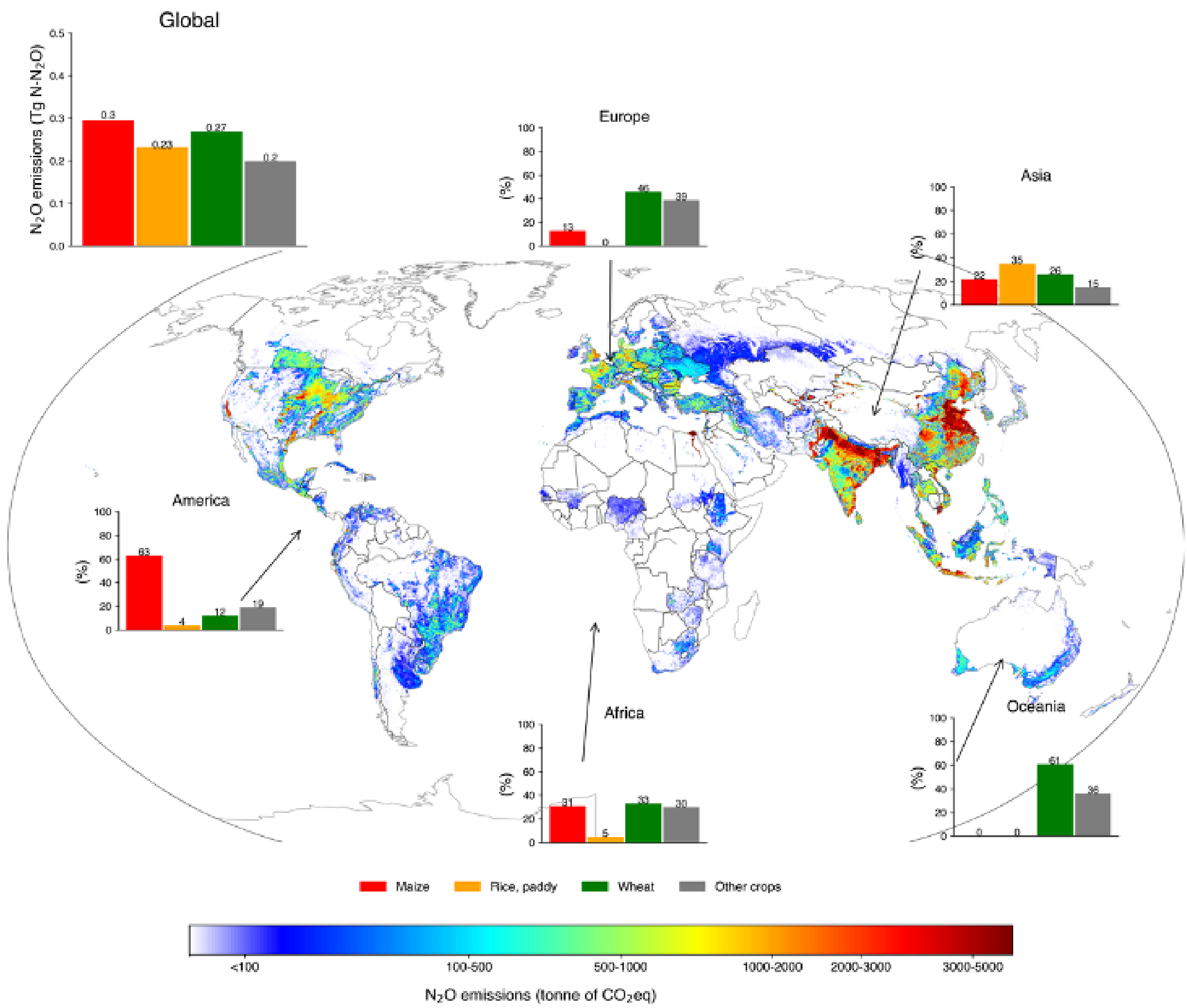

Figure 13 Total nitrogen fertilizer applied at grid scale 0.083° resolution (~10 km) for 2023. Units: Kg/ha grid area.

4. Conclusion

In this study, we developed a novel data-based model to estimate direct N2O emissions from synthetic nitrogen fertilizer use on a country scale. This model assumes that crop nitrogen uptake is proportional to fertilizer application. Our estimates covered 103 countries, accounting for approximately 99% of global synthetic nitrogen fertilizer usage. From 2015 to 2020, total direct N_2O emissions were recorded as follows: 1,623, 1,610, 1,636, 1,585, 1,600, and 1,652 gigagrams (Gg) respectively. The seven largest contributors to these emissions were China, India, the USA, Brazil, Pakistan, Indonesia, and Canada, jointly responsible for over 60% of the total (>900 Gg annually). At the continental level, Asia, America, and Europe emerged as significant emitters, collectively accounting for 95.5% (1,542 Gg) of the global emissions averaged over the study period.

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.

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).

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

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

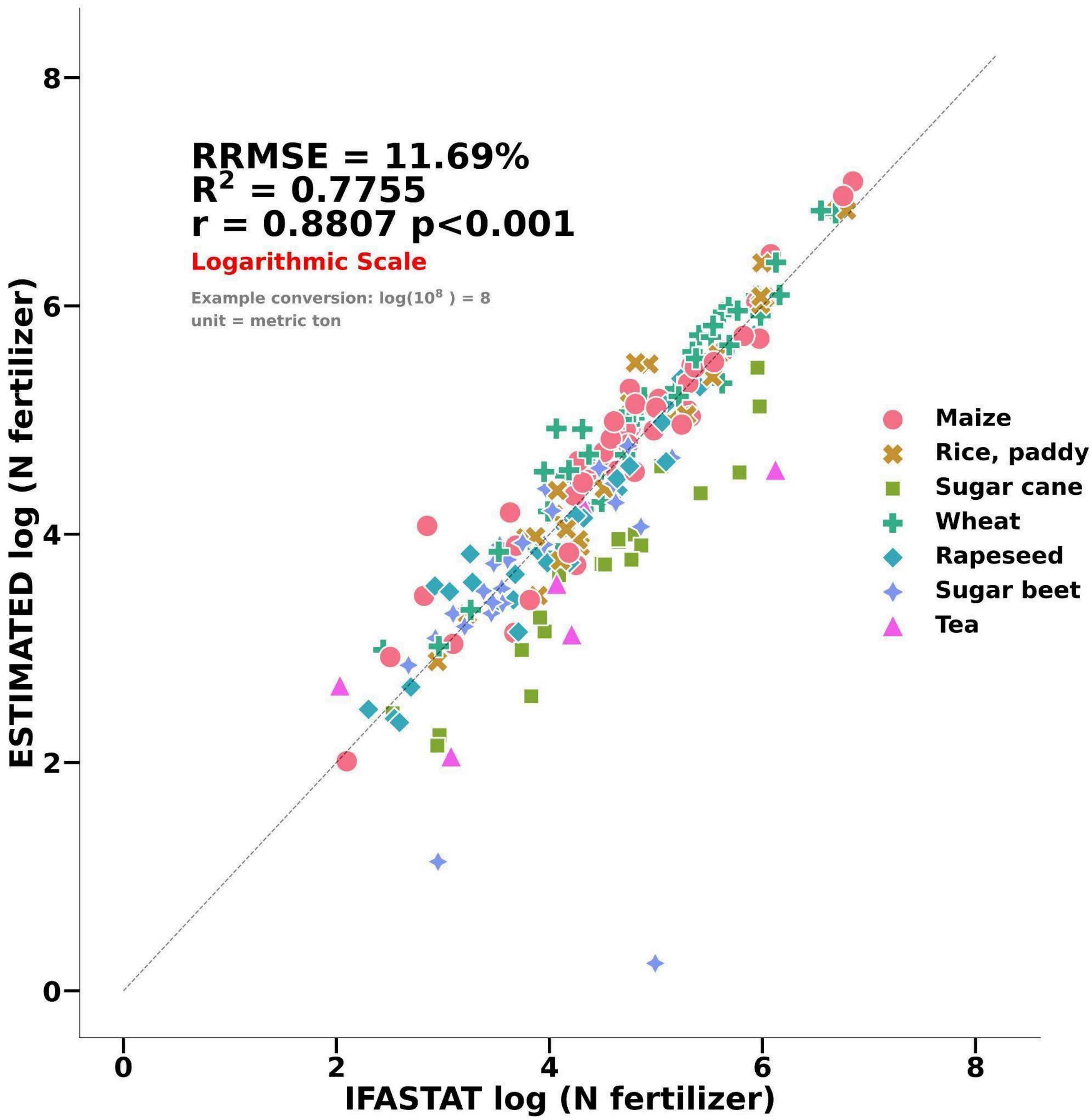

Figure S1 Comparison of crop-specific Nitrogen fertilizer at country scale between our study and IFASTAT for 2018. Units- y-axis and x-axis: kiloton (1000 metric ton).

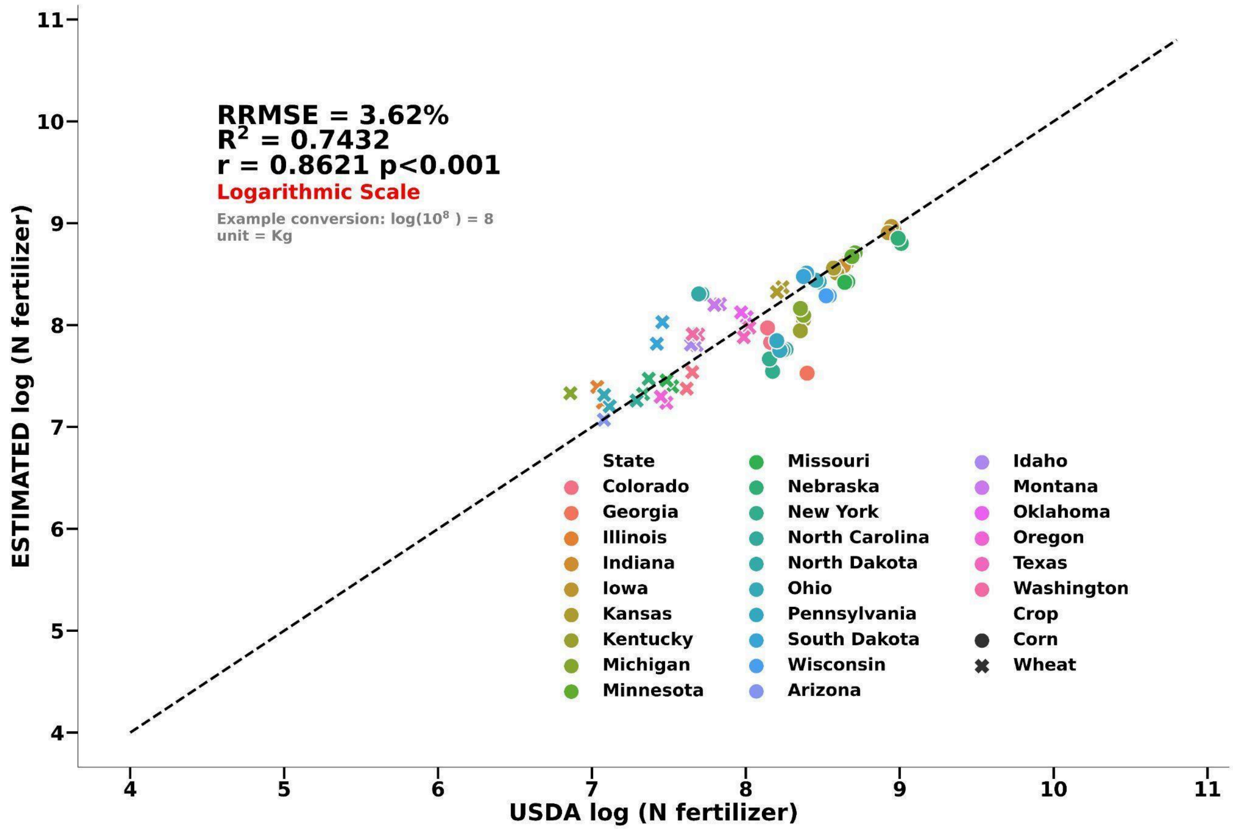

Figure S2 Comparison of crop-specific Nitrogen fertilizer at state scale between our study and USDA for 2015-2018.

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 metadata 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
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

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Data citation format: Sharma, P. 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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