



HaNi-Crop: A Harmonized and Gridded Global Dataset of Crop-Specific Nitrogen Inputs from Nitrogen Fertilizer and Manure

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Abstract. Crop-specific dataset on nitrogen (N) inputs from synthetic fertilizer and manure are critical for assessing crop productivity, nutrient use efficiency, and environmental impacts, as crops differ substantially in their N demands and utilization. However, existing datasets remain limited in their simultaneous coverage of crop-group specificity, spatial resolution, long-term temporal coverage, and fertilizer-form differentiation. These limitations have constrained comprehensive global and regional assessments of crop-specific greenhouse gas emissions, N use efficiency, N budgets, and agrifood-system resilience. Based upon the History of Anthropogenic Nitrogen Inputs (HaNi) data infrastructure (Tian et al., 2022), we present HaNi-Crop, a harmonized global dataset of crop-specific N inputs from synthetic fertilizer and manure for 21 major crop groups at a spatial resolution of $0.1^\circ \times 0.1^\circ$, spanning the period of 1961–2023. This dataset integrates national and sub-national fertilizer and manure statistics, crop harvested-area maps, fertilizer product information, and spatial allocation procedures to generate annual gridded estimates of crop-specific N application rates differentiated by $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ forms. Globally, synthetic fertilizer N inputs to cropland increased sharply from 11 Tg N yr^{-1} in the early 1960s to more than 100 Tg N yr^{-1} by 2023, while manure N inputs increased from 14 to 23 Tg N yr^{-1} . Throughout 1961–2023, three major cereal crops—wheat, maize, and rice, consistently accounted for approximately half of global synthetic fertilizer N inputs. Among N fertilizer forms, $\text{NH}_4^+\text{-N}$ inputs increased from 8 to nearly 90 Tg N yr^{-1} , while the inputs for $\text{NO}_3^-\text{-N}$ fertilizers only increased from 3 to about 12 Tg N yr^{-1} . Overall, the HaNi-Crop dataset provides a critical foundation for crop-specific greenhouse gas accounting, Earth system and agroecosystem



modeling, and N budget analyses to enhance food security, environmental sustainability, and climate mitigation. The dataset is publicly available at <https://doi.org/10.5281/zenodo.21364978> (Hao et al., 2026).

1 Introduction

Nitrogen (N) is an essential nutrient for crop growth, and large-scale use of synthetic N fertilizers following the development of the Haber-Bosch process has fundamentally transformed global crop production (Erisman et al., 2008; Foley et al., 2011; Galloway & Cowling, 2021). Over the past six decades, global agricultural N inputs from synthetic fertilizers and manure have increased dramatically, contributing substantially to global food security for a growing world population (Frink et al., 1999; Bouwman et al., 2013; Tian et al., 2022; FAO, 2025d). However, the overuse of N fertilizer also intensifies perturbations to the global N cycle and generates widespread environmental impacts, such as greenhouse gas emissions, water and air pollution, soil acidification, and biodiversity loss (Matson et al., 1997; Tian et al., 2016; de Vries, 2021; FAO, 2025e). Because different crop species have distinct N demands and utilization characteristics, the application rate and form of N inputs vary substantially among crops, production regions, and management practices (Shcherbak et al., 2014; Xu et al., 2024). These differences in fertilizer N management lead to large spatial and temporal heterogeneity in agricultural N cycling and N losses (Wang et al., 2024). For example, crop-specific N management substantially influences crop yield and N use efficiency (NUE), as well as N losses of nitrous oxide (N₂O), ammonia (NH₃), and nitrous acid (HONO) losses to the environment (Uwizeye et al., 2020; Gong et al., 2024; FAO, 2025b). Therefore, there is an urgent need to develop a spatially explicit, global crop-specific N inputs dataset that accounts for both synthetic fertilizer and manure application, to support more robust crop-specific assessments of crop yield, N budgets, and greenhouse gas emissions at regional and global scales (Galloway et al., 2008; L. Liu et al., 2022). Long-term crop-specific N datasets are also increasingly needed by Earth system models and agroecosystem models to support historical greenhouse gas inventories and nutrient interaction assessments at the global scale (Gu et al., 2023).

The Food and Agriculture Organization of the United Nations (FAO) and the International Fertilizer Association (IFA) have regularly compiled national fertilizer statistics and cropland nutrient budgets since 1961 (FAO, 2025a; Ludemann et al., 2022, 2024). Several studies have attempted to spatially allocate these national statistics using crop distribution maps and empirical allocation approaches. Tian et al. (2022) developed gridded estimates of historical anthropogenic N inputs to cropland, while Mueller et al. (2012) and West et al. (2014) produced crop-specific fertilizer and manure datasets for circa 2000. Nishina et al. (2017) further distinguished fertilizer N into



NH_4^+ and NO_3^- forms at the global scale, with Adalibieke et al. (2023) extending the specific N inputs to include fertilization placement and type. More recently, CROPGRIDS (Tang et al., 2024) and NPKGRIDS (Nguyen et al., 2024) have updated high-resolution global datasets of crop harvested area and crop-specific fertilizer application rates to circa 2020. Despite these advances, important data gaps remain, including: short temporal coverage, coarse crop-specific harvest distribution, incomplete representation of manure applications, and lack of harmonization across data sources with fertilizer chemical forms (Thomas et al., 2015). Furthermore, few datasets provide annually resolved, harmonized global maps of crop-specific N inputs spanning the post-1960 period of rapid agricultural intensification.

To address these limitations, we developed HaNi-Crop, a harmonized and gridded global dataset of crop-specific N inputs from synthetic fertilizer and manure for 21 major crop groups at $0.1^\circ \times 0.1^\circ$ spatial resolution, spanning 1961-2023. Building upon the History of Anthropogenic Nitrogen Inputs (HaNi) framework (Tian et al., 2022), this crop-specific N inputs dataset integrates national and sub-national fertilizer and manure statistics, crop harvested-area maps, fertilizer product information, and spatial allocation procedures to produce annual gridded estimates of N application amounts and rates. In addition, synthetic fertilizer N is partitioned into NH_4^+ and NO_3^- forms to better support assessments of crop-specific N cycling and associated environmental impacts (Houlton et al., 2007). The HaNi-Crop dataset is primarily intended to support regional and global applications, including Earth system modeling, agricultural N budgeting, N use efficiency assessments, and greenhouse gas emission analyses (Erisman et al., 2008; Friedlingstein et al., 2025). By providing long-term, spatially explicit, and crop-resolved representations of agricultural N inputs, this dataset can improve understanding of the evolution and spatial heterogeneity of cropland N management and its implications for food production, environmental quality, and climate change mitigation (Jägermeyr et al., 2021; Tian et al., 2024).

2 Materials and methods

Our workflow follows the overall data processing framework, which integrates multiple datasets and analytical steps to generate consistent, long-term, and spatially explicit estimates of crop-specific N inputs (Fig. 1). The framework encompasses data harmonization, temporal interpolation, spatial allocation, and consistency adjustment with national statistics. The synthetic fertilizer inputs were further classified into NH_4^+ -N and NO_3^- -N



forms to support subsequent analysis of form-specific N inputs. The following sections describe in detail the procedures for constructing annual gridded maps of crop-specific N inputs from synthetic fertilizer and manure.

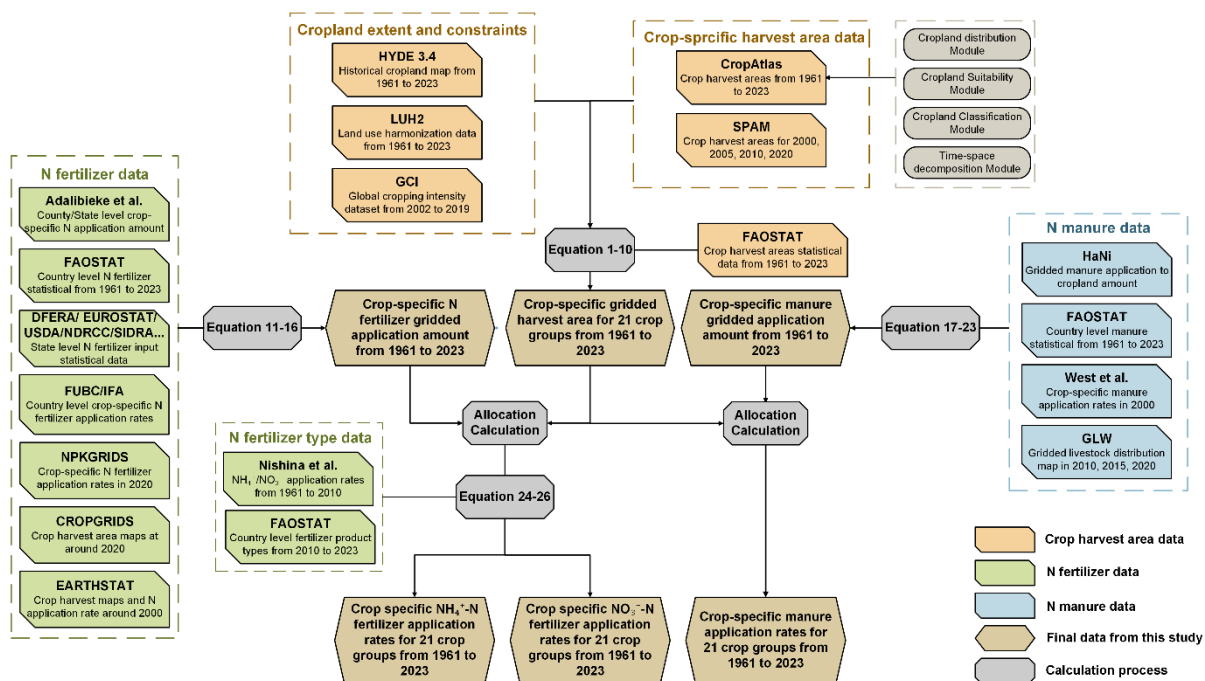


Figure 1. Workflow of the development of crop-specific N and manure dataset.

2.1 Data Sources

The crop-specific N dataset was reconstructed by integrating multiple global and regional data sources, and the key datasets are summarized in Table 1, including country-level fertilizer use statistics, crop distribution maps, and regional grid boundary data for synthetic fertilizer and manure application rates. To ensure consistency with FAO-reported national N fertilizer statistics, FAO crop items were harmonized into 21 representative crop groups throughout this study: barley, cassava, cotton, groundnuts, maize, millet, oil palm fruit, potatoes, pulses, rapeseed, rice, rye, sorghum, soybean, sugarbeets, sugarcane, sunflower, wheat, fruits, vegetables, and others in Table 2.



110 **Table 1. Summary of the main data sources used in this study.**

Data Description	Spatial Resolution	Reference
Country-level cropland N fertilizer by product and manure inputs from 1961 to 2023	Country Level	FAOSTAT (2025a)
Specific-crop harvest area from 1961 to 2023	Country Level	FAOSTAT (2024)
The Global Administrative Unit Layers (GAUL)	Prefectural Level	Franceschini et al. (2025)
NPGRIDS crop-specific N application rates at circa 2020	0.05 degree	Nguyen et al. (2024)
CROPGRIDS crop-specific harvest area at circa 2020	0.05 degree	Tang et al. (2024)
HYDE3.4 historical cropland area from 1961 to 2023	5-arc-min	Klein Goldewijk et al. (2017)
HYDE3.4 historical population from 1961 to 2023	5-arc-min	Klein Goldewijk et al. (2017)
Global cropping intensity dataset from 2001 to 2019	250m	Liu et al. (2021)
Sub-national N application amount from 1961 to 2020	5-arc-min	Adalibieke et al. (2023)
MRF global gridded crop harvested area at circa 2000	5-arc-min	Monfreda et al. (2008)
FUBC N fertilizer application rates from 1978 to 2019	Country Level	Ludemann et al. (2022)
SPAM crop-specific harvest area and yield 2000, 2005, 2010, and 2020	5-arc-min	Yu et al. (2020)
NH ₄ ⁺ and NO ₃ ⁻ application rates from 1961 to 2010	Country Level	Nishina et al. (2017)
Crop-specific N fertilizer application rates at circa 2000	5-arc-min	Mueller et al. (2012)
Crop-specific manure application rates at circa 2000	5-arc-min	West et al. (2014)
The Gridded Livestock of the World (GLW) for 2010, 2015, and 2020	5-arc-min	Gilbert et al. (2018)
Rates of N application to cropland from 1961 to 2009	Country Level	Lassaletta et al. (2014)
Global area equipped for irrigation from 1961 to 2023	5-arc-min	Mehta et al. (2024)
Gridded global dataset for GDP from 1990 to 2022	30 arc-sec	Kummu et al. (2025)
Country-level GDP from 1961 to 2023	Country Level	World Bank Open Data
National N budget from 2000 to 2020	Country Level	DEFRA; EUROSTAT; USDA; SIDRA; Australian Bureau of Statistics; NBS of China

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112 These 21 crop groups were selected to balance crop-level specificity with data availability and to remain consistent
113 with the FAO crop classifications used in national harvested-area and fertilizer-use statistics by FAOSTAT for
114 1961-2023 (FAO, 2025a). Because national fertilizer and manure input statistics are not always reported
115 separately for cropland and pasture, we partitioned national total N inputs using cropland-pasture allocation rates
116 from previous studies and updated FAOSTAT cropland nutrient balance data. Specifically, we first adopted the
117 cropland-pasture allocation ratios reported in Lassaletta et al. (2014) and then updated these ratios where country-
118 specific information was available from Ludemann et al. (2024). For countries lacking updated cropland-pasture
119 partitioning information after 2009, we retained the 2009 relative application intensity between cropland and
120 pasture and recalculated annual allocation fractions using annual cropland and pasture areas. This approach allows
121 post-2009 changes in cropland and pasture areas to influence the allocation ratios of national N inputs, while
122 preserving the relative application intensity between cropland and pasture inferred from the most recent available
123 partitioning data. Corresponding crop harvest area basemaps were derived from the Crop Atlas of Agricultural
124 Map (CropAtlas) to align fertilizer inputs and crop distributions at the same spatial resolution. These harmonized
125 datasets together formed the foundational data sources for downscaling N inputs to specific crop types and gridded
126 spatial units. To validate the crop-specific fertilizer application rates, we compared them with national survey data
127 from the fertilizer use by crop database (FUBC), covering more than 60 countries (Ludemann et al., 2022).



2.2 The construction of the Crop Specific Harvest Area

Table 2. Crop types considered for N fertilizer and manure use rate in this study

Crop class	Classification	Item Code (FAO)
Wheat	Cereals	Wheat (15)
Maize	Cereals	Maize, corn (56)
Soybean	Legume	Soya beans (236)
Rice	Cereals	Rice (27)
Cotton	Cash crops	Seed cotton, unginned (328)
Barley	Cereals	Barley (44)
Millet	Cereals	Millet (79)
Rye	Cereals	Rye (71)
Sorghum	Cereals	Sorghum (83)
Rapeseed	Oil crops	Rapeseed (270)
Oil Palm Fruit	Oil crops	Oil palm fruit (254)
Cassava	Root & Tuber	Cassava, fresh (125)
Potatoes	Root & Tuber	Potatoes (116)
Sugar Beets	Root & Tuber	Sugar beet (157)
Sugarcane	Cash crops	Sugar cane (156)
Groundnuts	Legume	Groundnuts, excluding shelled (242)
Sunflower	Oil crops	Sunflower seed (267)
Pulses	Legume	Beans, dry (176), Broad beans and horse beans, dry (181), Peas, dry (187), Chick peas, dry (191), Cow peas, dry (195), Pigeon peas, dry (197), Lentils, dry (201), Bambara beans, dry (203), Vetches (205), Lupins (210), Other pulses n.e.c. (211)
Vegetables	Horticultural	Cabbages (358), Artichokes (366), Asparagus (367), Lettuce and chicory (372), Spinach (373), Cassava leaves (378), Tomatoes (388), Cauliflowers and broccoli (393), Pumpkins, squash and gourds (394), Cucumber and gherkins (397), Eggplants (399), Chillies and peppers, green (401), Onion and shallots, green (402), Onion and shallot, dry (403), Green garlic (406), Leeks and alliaceous (407), Other beans, green (414), Peas, green (417), Broad beans and horse beans, green (420), String beans (423), Carrots and turnips (426), Okra (430), Green corn (446), Other vegetables fresh n.e.c. (463)
Fruits	Horticultural	Locust beans, carobs (461), Bananas (486), Plantains (489), Oranges (490), Tangerines, mandarins, clementines (495), Lemons and limes (497), Pomelos and grapefruits (507), Other citrus n.e.c. (512), Apples (515), Pears (521), Quinces (523), Apricots (526), Sour cherries (530), Cherries (531), Peaches and nectarines (534), Plums and sloes (536), Other stone fruits n.e.c. (541), Other pome fruits n.e.c. (542), Strawberries (544), Raspberries (547), Gooseberries (549), Currants (550), Blueberries (552), Cranberries (554), Other berries and



		fruits of the genus vaccinium n.e.c. (558), Grapes (560), Watermelons (567), Cantaloupes and other melons (568), Figs (569), Mangoes, guavas and mangosteens (571), Avocados (572), Pineapples (574), Dates (577), Persimmons (587), Cashewapple (591), Kiwi fruits (592), Papayas (600), Other tropical fruits n.e.c. (603), Other fruits n.e.c. (619)
Others	Others	Oats (75), Buckwheat (89), Quinoa (92), Fonio (94), Triticale (97), Canary seed (101), Mixed grain (103), Cereals n.e.c. (108), Sweet potatoes (122), Yautia (135), Taro (136), Yams (137), Edible roots and tubers with high starch or inulin content, n.e.c., fresh (149), Other sugar crops n.e.c. (161), Cashew nuts, in shell (217), Chestnuts, in shell (220), Almonds, in shell (221), Walnuts, in shell (222), Pistachios, in shell (223), Kola nuts (224), Hazelnuts, in shell (225), Areca nuts (226), Other nuts (excluding wild edible nuts and groundnuts), in shell, n.e.c. (234), Coconuts, in shell (249), Olives (260), Karite nuts (sheanuts) (263), Castor oil seeds (265), Rape or colza seed (270), Tung nuts (275), Jojoba seeds (277), Safflower seed (280), Sesame seed (289), Mustard seed (292), Poppy seed (296), Melonseed (299), Tallowtree seeds (305), Kapok fruit (310), Seed cotton, unginned (328), Linseed (333), Hempseed (336), Other oil seeds, n.e.c. (339), Chicory roots (459), Coffee, green (656), Cocoa beans (661), Tea leaves (667), Maté leaves (671), Hop cones (677), Pepper (Piper spp.), raw (687), Chillies and peppers, dry (Capsicum spp., Pimenta spp.), raw (689), Vanilla, raw (692), Cinnamon and cinnamon-tree flowers, raw (693), Cloves (whole stems), raw (698), Nutmeg, mace, cardamoms, raw (702), Anise, badian, coriander, cumin, caraway, fennel and juniper berries, raw (711), Ginger, raw (720), Other stimulant, spice and aromatic crops, n.e.c. (723), Peppermint, spearmint (748), Pyrethrum, dried flowers (754), Flax, raw or retted (771), True hemp, raw or retted (777), Jute, raw or retted (780), Kenaf, and other textile bast fibres, raw or retted (782), Ramie, raw or retted (788), Sisal, raw (789), Agave fibres, raw, n.e.c. (800), Abaca, manila hemp, raw (809), Other fibre crops, raw, n.e.c. (821), Unmanufactured tobacco (826)

N application for fertilizer and manure is more directly associated with planted or sown area than with harvested area, because harvested area excludes crop areas that were planted but not successfully harvested. However, the globally consistent long-term crop-specific planting data are not available for all crops and years. We therefore used reconstructed harvested area as a proxy for fertilized crop area, consistent with the crop-area variable reported in FAOSTAT and widely used global crop mapping datasets. We first constrained annual cropland distribution maps from 1961 to 2023 by integrating LUH2 (Hurtt et al., 2020) and HYDE 3.4 datasets (Klein Goldewijk et al., 2017) following an approach of the HaNi dataset (Tian et al., 2022) to reduce unrealistic spatial allocation. In this reconstruction, the HYDE 3.4 dataset (Klein Goldewijk et al., 2017) was used to preserve fine-scale spatial heterogeneity in cropland distribution, whereas LUH2 was used to provide temporally continuous annual cropland-area constraints. Because the spatial resolutions of the datasets are not consistent, all cropland constraints were generated on the $0.1^\circ \times 0.1^\circ$ target grid. HYDE 3.4 cropland area was first conservatively remapped from its native 5-arcmin resolution to the $0.1^\circ \times 0.1^\circ$ target grid and used as the spatial allocation weight:

$$A_{j,y}^{HYDE} = \sum_h A_{h,y}^{HYDEori} \cdot \omega_{h,j} \quad (1)$$

where $A_{j,y}^{HYDE}$ is the HYDE-derived cropland area in $0.1^\circ \times 0.1^\circ$ target grid cell j and year y , $A_{h,y}^{HYDEori}$ is the original HYDE cropland area in 5-arcmin grid cells h , and $\omega_{h,j}$ is the fraction of HYDE grid cell h overlapping target grid



cell j . This conservative remapping preserved the total HYDE cropland area while converting the fine-scale HYDE pattern to the target resolution. Because the original LUH2 variable is reported as cropland fraction, the LUH2 cropland area in each coarse grid cell was calculated as the product of the LUH2 cropland fraction and the corresponding grid-cell land area:

$$A_{k,y}^{LUH2} = F_{k,y}^{LUH2} \times A_k^{land} \quad (2)$$

where $A_{k,y}^{LUH2}$ is the LUH2-derived cropland area in coarse grid cell k and year y , $F_{k,y}^{LUH2}$ is the LUH2 cropland fraction, and A_k^{land} is the land area for the same resolution in LUH2 in grid cell k . The LUH2 annual cropland area was then redistributed to $0.1^\circ \times 0.1^\circ$ target grid cells according to their cropland shares derived from the HYDE dataset. We next redistributed the LUH2-derived annual cropland area from the native $0.25^\circ \times 0.25^\circ$ grid to the $0.1^\circ \times 0.1^\circ$ target grid. This redistribution was performed using area-weighted conservative remapping, in which HYDE-derived cropland area on the 0.1° grid was used as the spatial allocation weight.

$$A_{j,y}^{cropland} = \sum_k \left[A_{k,y}^{LUH2} \cdot \frac{A_{j,y}^{HYDE} \cdot \phi_{j,k}}{\sum_{j'} A_{j',y}^{HYDE} \cdot \phi_{j',k}} \right] \quad (3)$$

where $A_{j,y}^{cropland}$ is the reconstructed cropland area in $0.1^\circ \times 0.1^\circ$ target grid cell j and year y , $A_{k,y}^{LUH2}$ is the LUH2 cropland area in $0.25^\circ \times 0.25^\circ$ grid cell k , and $\phi_{j,k}$ is the fraction of $0.1^\circ \times 0.1^\circ$ grid cell j overlapping LUH2 grid cell k , and $\phi_{j',k}$ is the fraction of $0.1^\circ \times 0.1^\circ$ grid cell j' overlapping LUH2 grid cell k . The denominator represents the total HYDE-derived cropland allocation weight within the LUH2 grid cell k . This procedure redistributes the LUH2 annual cropland area to the target grid while preserving the fine-scale cropland spatial pattern from HYDE. If a LUH2 grid cell contained positive cropland area but no corresponding HYDE cropland weight, the LUH2 cropland area was distributed according to the land-area overlap among target grid cells within that LUH2 cell. This fallback procedure prevented the loss of LUH2 cropland area in regions where HYDE and LUH2 cropland extents were spatially inconsistent. The final annual cropland maps preserve the fine-scale spatial heterogeneity of HYDE while remaining consistent with LUH2 annual cropland totals. These maps were then used as spatial constraints for crop-specific harvested-area allocation, ensuring that reconstructed crop harvested areas.

Gridded crop-specific harvested areas $A_{g,j,t}^{init}$ for 17 crops except pulses, fruits, and vegetables from 1961 to 2023 in this study were derived from the CropAtlas dataset, which integrates $0.1^\circ \times 0.1^\circ$ distribution maps with national and sub-national harvest area statistics. The CropAtlas dataset consists of four core modules and one optional module: a cropland distribution module, a crop suitability module, a spatial disaggregation module, and a spatiotemporal fusion module. The cropland distribution module estimates time-varying cropland area



distributions by integrating multiple cropland observation and cropland map products to avoid spatial estimation biases resulting from the use of a single model across large spatial scales. In CropAtlas, this cropland layer is used as a physical constraint for crop allocation, limiting the total crop area assigned to each grid cell and reducing dependence on any single cropland product. The module further uses an adaptive rotated quadtree strategy to divide the land surface according to cropland density, allowing cropland-area estimation to be conducted within spatially adaptive regions rather than under a single global model structure. This design is intended to reduce spatial bias associated with applying one uniform model across highly heterogeneous cropland systems (Koldasbayeva et al., 2024). The crop suitability module estimates the plausible spatial distribution of individual crops using crop occurrence samples and the MaxEnt species distribution model (Yu et al., 2022). Both presence and absence information are considered to reduce overestimation of crop suitability, and model performance is evaluated using metrics such as Kappa and True Skill Statistic (Yoon & Lee, 2023). In this study, crop suitability was used only as one component of the spatial allocation framework to indicate where each crop was more likely to occur under soil and climate conditions. These allow us to reconstruct historical crop-specific harvested-area distributions that remain consistent with reported crop statistics. The spatial disaggregation module allocates crop statistics reported at national, provincial, or county levels to grid cells. CropAtlas uses the dissever algorithm (Malone et al., 2012), which includes an initialization step and an iterative correction step. In the initialization step, administrative polygons containing crop statistics are rasterized, and grid-cell crop areas are fitted within each polygon using weighted generalized additive models or machine-learning models with environmental predictors. The difference between fitted grid-cell values and reported statistics is evaluated using a penalized residual sum of squares. In the iterative step, fitted values are corrected according to the statistical residuals, and the model is repeatedly refitted until convergence. The spatiotemporal fusion module, which employs the Spatiotemporal Discrete Cosine Transform method, further refines the initial crop distributions by integrating existing crop-specific maps derived from remote-sensing products, geospatial statistical datasets, or agricultural survey-based maps. CropAtlas therefore uses the output of the spatial disaggregation module as the baseline distribution and applies pixel-level fusion to incorporate available crop-specific maps where they provide additional spatial detail. In this study, the CropAtlas-derived products were used as spatial allocation priors rather than as error-free observations of crop harvested area. Specifically, they provided crop-specific harvested-area proportion maps $P_{i,j,y}$ at $0.1^\circ \times 0.1^\circ$ resolution for 17 crop groups, which did not include crop groups including vegetables, fruits, pulses, and others. Compared with single-year datasets such as EARTHSTAT and CROPGRIDS, CropAtlas provides temporally continuous and spatially detailed allocation weights from 1961 onward. By integrating crop statistics, cropland-area constraints, crop suitability, and multi-source spatial data



fusion, this approach provides a more constrained and internally consistent basis for reconstructing historical crop-specific harvested-area distributions, which is important for dynamically allocating crop-specific synthetic fertilizer and manure N inputs over time. Considering the used $P_{i,j,y}$ maps remain spatial allocation uncertainty from cropland mapping, crop suitability modelling, statistical downscaling, and the fusion of heterogeneous crop maps, we therefore included an uncertainty analysis accounting for alternative spatial allocation assumptions and cropland-constraint sensitivity.

Next, we generated continuous annual gridded harvested-area maps for vegetables, fruits, pulses, and other crop groups from 1961 to 2023, using SPAM reference maps for 2000, 2005, 2010, and 2020 (Yu et al., 2020). These SPAM maps provide spatially explicit harvested-area distributions for each crop group and were used as within-country spatial allocation templates for different time periods. For each country, crop group, and year, the annual FAO-reported national harvested area was distributed to grid cells according to the relative harvested-area distribution in the corresponding SPAM reference map. Specifically, the SPAM maps for 2000, 2005, 2010, and 2020 were used as spatial allocation templates for 1961-2003, 2004-2007, 2008-2015, and 2016-2023, respectively. This procedure preserved annual changes in national harvested area reported by FAO with the assumption that the relative spatial distribution of each crop group within a country remained unchanged within each reference period. The initial gridded harvested area was calculated as:

$$A_{g,j,y}^{init} = A_{g,c,y}^{FAO} \cdot \frac{A_{g,j,y^*}^{SPAM}}{\sum_{j \in c} A_{g,j,y^*}^{SPAM}}, \quad j \in c \quad y^* = \begin{cases} 2000, & 1961 \leq y \leq 2003 \\ 2005, & 2004 \leq y \leq 2007 \\ 2010, & 2008 \leq y \leq 2015 \\ 2020, & 2016 \leq y \leq 2023 \end{cases} \quad (4)$$

where $A_{g,j,y}^{init}$ is the initially allocated harvested area of crop group g in grid cell j and year y . A_{g,j,y^*}^{SPAM} is the SPAM harvested area of crop group g in grid cell j for reference year y^* . $A_{g,c,y}^{FAO}$ is the national harvested area of crop group g in country c and year y based on FAOSTAT. The notation $j \in c$ indicates all grid cells j located within country c , and the $\sum_{j \in c} A_{g,j,y^*}^{SPAM}$ represents the total SPAM harvested area of crop group g within country c , ensuring that the allocated gridded harvested area sums to the FAO national total. For countries in which the selected SPAM reference map contained no harvested area for a given crop group, but positive harvested area reported by FAO, we used the nearest alternative SPAM reference year with non-zero harvested area. To further constrain the gridded harvested-area allocation process, we incorporated cropping-intensity information to account for multiple cropping systems. Because harvested areas can exceed physical cropland areas where multiple cropping occurs, the upper bound for each grid cell was not defined as cropland area alone. Instead, we



used the annual global cropping intensity dataset GCI (Liu et al., 2021) to derive an effective harvested-area capacity for each $0.1^\circ \times 0.1^\circ$ grid cell. The original cropping intensity maps at 250 m resolution classify each pixel as non-cropping, single cropping, double cropping, or triple cropping. For each $0.1^\circ \times 0.1^\circ$ grid cell, we calculated the areas of 250 m pixels classified as single, double, and triple cropping. Non-cropping pixels were excluded from the calculation of the cropping-intensity multiplier. The effective cropping intensity of grid cell j in year y was calculated as:

$$CI_{j,y} = \frac{1 \cdot A_{1,j,y}^{CI} + 2 \cdot A_{2,j,y}^{CI} + 3 \cdot A_{3,j,y}^{CI}}{A_{1,j,y}^{CI} + A_{2,j,y}^{CI} + A_{3,j,y}^{CI}} \quad (5)$$

where $CI_{j,y}$ is the effective cropping-intensity multiplier, and $A_{1,j,y}^{CI}$, $A_{2,j,y}^{CI}$, and $A_{3,j,y}^{CI}$ are the areas of 250 m pixels classified as single, double, and triple cropping within 0.1° grid cell j , respectively. If a reconstructed cropland grid cell had no valid cropping-intensity pixels, we assigned a conservative value of $CI_{j,y} = 1$, representing single cropping. For years outside the temporal coverage used in this study, the nearest available cropping-intensity map was used as the spatial template. Specifically, the 2001 cropping-intensity pattern was used for years before 2001, and the 2019 pattern was used for 2020-2023. The harvested area capacity of each 0.1° grid cell was then defined as the reconstructed annual cropland area multiplied by the effective cropping-intensity multiplier:

$$U_{j,y} = A_{j,y}^{cropland} \cdot CI_{j,y}^{CI} \quad y^{CI} = \begin{cases} 2002, & 1961 \leq y < 2002 \\ y, & 2002 \leq y \leq 2019 \\ 2019, & 2020 \leq y \leq 2023 \end{cases} \quad (6)$$

where $U_{j,y}$ is the maximum allowable total harvested area in grid cell j and year y , $A_{j,y}^{cropland}$ is the reconstructed physical cropland area, and $CI_{j,y}^{CI}$ is the effective cropping-intensity multiplier from the selected cropping-intensity reference year. This constraint allows total harvested area to exceed physical cropland area in multi-cropping regions, while preventing unrealistic expansion of harvested area in individual grid cells. The initial harvested-area maps $A_{g,j,y}^{init}$ from CropAtlas and SPAM were then adjusted simultaneously for all 21 crop categories under the grid-cell harvested-area capacity constraint. The capacity constraint was applied to the summed harvested area across all crop categories rather than to each crop separately, because the physical constraint applies to the total harvested area that can be supported by local cropland area and cropping intensity. At each iteration, the total harvested area in grid cell j was calculated as:

$$S_{j,y}^{(r)} = \sum_{m=1}^{21} A_{m,j,y}^{(r)} \quad (7)$$



where $S_{j,y}^{(r)}$ is the summed harvested area across all 21 crop categories in grid cell j and year y at iteration r , and $A_{m,j,y}^{(r)}$ is the harvested area of crop category m at iteration r . If $S_{j,y}^{(r)}$ exceeded $U_{j,y}$, all crop categories in that grid cell were proportionally reduced using:

$$\widetilde{A}_{m,j,y}^{(r)} = A_{m,j,y}^{(r)} \cdot \min\left(1, \frac{U_{j,y}}{S_{j,y}^{(r)}}\right) \quad (8)$$

where $\widetilde{A}_{m,j,y}^{(r)}$ is the capacity-corrected harvested area after proportional reduction. This step preserved the crop composition within each over-capacity grid cell while ensuring that the summed harvested area did not exceed $U_{j,y}$. The removed harvested area for each crop category was then redistributed within the same country to grid cells with remaining capacity. The remaining capacity in each grid cell was calculated as:

$$R_{j,y}^{(r)} = \max\left(0, U_{j,y} - \sum_{m=1}^{21} \widetilde{A}_{m,j,y}^{(r)}\right) \quad (9)$$

where $R_{j,y}^{(r)}$ is the remaining harvested-area capacity in grid cell j . For each crop category, country, and year, the residual area to be redistributed was calculated as:

$$E_{m,c,y}^{(r)} = A_{m,c,y}^{\text{FAO}} - \sum_{j \in c} \widetilde{A}_{m,j,y}^{(r)} \quad (10)$$

where $E_{m,c,y}^{(r)}$ is the remaining harvested area of crop category m in country c that needs to be redistributed to preserve the FAO national total. This reduction-and-redistribution procedure was repeated until two convergence criteria were satisfied: (1) the summed harvested area across all 21 crop categories in each grid cell did not exceed the harvested-area capacity $U_{j,y}$, and (2) the country-level harvested area of each crop category matched the FAOSTAT national harvested area. The final allocation was therefore consistent with FAOSTAT national statistics while being constrained by reconstructed annual cropland extent and maximum allowable total harvested area.

2.2 The Construction of the Crop-Specific N Fertilizer Application Rate

We first adopted the global sub-national N fertilizer application amounts by administrative units from Adalibieke et al. (2021, 2023) during 1961-2020. For 2021-2023, these ratios were updated where newly available country-specific or sub-national fertilizer statistics were available from multiple sources such as DEFRA (Department for Environment Food and Rural Affairs) (DEFRA, 2026), EUROSTAT (Statistical office of the European Union) (DEFRA, 2026), USDA (United States Department of Agriculture) (USDA, 2026), SIDRA (Brazilian Institute of



Geography and Statistics) (*SIDRA*, 2026), the Australian Bureau of Statistics (*Australian Bureau of Statistics*, 2026), National Bureau of Statistics of China (*NBSC*, 2026) and other national reports, as summarized in Table 1. For countries without updated sub-national information after 2020, the 2020 allocation ratios were retained for 2021-2023. The resulting allocation ratios were used to disaggregate national total N fertilizer use to province-, district-, or county-level fertilizer application amounts, ensuring consistency with national fertilizer consumption statistics while incorporating updated administrative-level information where available. For each administrative unit p within country c , the sub-national fertilizer amount was calculated as:

$$N_{p,c,y}^{stat} = \left(\frac{N_{p,c,y}^{amount}}{\sum_{p \in c} N_{p,c,y}^{amount}} \right) \cdot N_{c,y}^{stat}, \quad y \in [1961, 2023] \quad (11)$$

where $N_{p,c,y}^{stat}$ is the estimated N fertilizer input for administrative unit p in country c and year y is the administrative-level fertilizer use reported by Adalibieke et al. (2023) and updated country-level sources, used to calculate the sub-national allocation share. and $N_{c,y}^{stat}$ is the national total N fertilizer use for country c in year y . The denominator $\sum_{p \in c} N_{p,c,y}^{amount}$ represents the sum of fertilizer use across all administrative units within country c , ensuring that the disaggregated sub-national estimates sum to the national total. To construct crop-specific N fertilizer input baseline maps, we disaggregated total administrative-unit N inputs among the 21 crop groups using validated crop-specific fertilizer allocation products for 2000 and 2020 that demonstrated spatial consistency and temporal compatibility (Mueller et al., 2012; Nguyen et al., 2024). Details of the crop groups are provided in Table 2. The baseline maps were used to assign administrative-level total N inputs to individual crop groups. These two baseline years therefore served as spatiotemporally consistent baseline anchors for reconstructing crop-specific N fertilizer inputs over the full study period. For each baseline year, crop-specific fertilizer amounts at the administrative-unit level were first derived from the corresponding harvested areas. These crop-specific administrative fertilizer amounts were then spatially distributed to grid cells using the crop-specific harvested-area maps $A_{i,j,y}$ as spatial allocation weights, where i denotes the crop group, j denotes the grid cell, and y represents the benchmark year. In cases where N fertilizer data for the target county and their neighbors were missing, but complete data were available at the higher administrative level (e.g., provincial or subnational regions like state), we estimated the total N fertilizer application for the target provincial- or prefectural-level data using a weighted average of neighboring administrative. Conceptually, this crop-specific fertilizer allocation framework is like the scenario-based spatial disaggregation approaches described in Yu et al. (2022) and Nguyen et al. (2024) shown in Table 3, in which administrative-level fertilizer totals are redistributed to crop-specific grid cells using



spatial allocation weights derived from crop distribution datasets. This approach accounts for potential differences in cropping systems and socioeconomic conditions between provincial or subnational regions and considers the assumption that changes in crop N fertilizer application rates are proportional to changes in the provincial or subnational regions level total N fertilizer.

Table 3. Scenarios considered for constructing N application rates use in this study.

Starting Level	Condition	Action	Priority
County/Prefectural	Data available	County/Prefectural actual data	1
	Data missing, but neighboring County/Prefectural data available	Neighboring County/Prefectural average	2
	No neighboring County/Prefectural data available	State/Provincial average	3
	State/Provincial data unavailable	Country average	4
State/Provincial	Data available	State/Provincial actual data	1
	Data missing, but neighboring State/Provincial data available	Neighboring State/Provincial average	2
	No neighboring State/Provincial data available	Country average	3
	Country data unavailable	Regional average	4
Country	Data available	Country actual data	1
	Data missing	Regional average	2

To reconstruct annual crop-specific N fertilizer amounts for each administrative unit, we developed an ordinary least squares regression model using the 2000 and 2020 crop-specific fertilizer baseline maps as training observations. The model relates baseline regional N fertilizer amounts to crop harvested areas, crop-specific yield (Institute (IFPRI), 2019, 2025; Institute (IFPRI) & Analysis (IIASA), 2025; Institute (IFPRI), 2026) area equipped for irrigation (Mehta et al., 2024), cropland area, population (Klein Goldewijk et al., 2017), agricultural GDP, and a normalized temporal term. A log-transformed response variable was used to reduce the influence of unreasonable fertilizer amount distributions and to ensure positive predicted values after back-transformation. The estimation model is expressed as follows:

$$\ln N_{fer,c,r,y}^{obs} = \beta_0 + \beta_1 \ln H A_{c,r,y} + \beta_2 (\ln H A_{c,r,y})^2 + \beta_3 \ln Y_{c,r,y} + \beta_4 (\ln Y_{c,r,y})^2 + \beta_5 \ln Irr_{r,y} + \beta_6 \ln Pop_{r,y} + \beta_7 \ln AgriGDP_{r,y} + \beta_8 \ln Cropland_{r,y} + \beta_9 T_y + \varepsilon_{c,r,y} \quad (12)$$

$$N_{fer,c,r,y}^{est} = \exp \left(\widehat{\beta}_0 + \widehat{\beta}_1 \ln H A_{c,r,y} + \widehat{\beta}_2 (\ln H A_{c,r,y})^2 + \widehat{\beta}_3 \ln Y_{c,r,y} + \widehat{\beta}_4 (\ln Y_{c,r,y})^2 + \widehat{\beta}_5 \ln Irr_{r,y} + \widehat{\beta}_6 \ln Pop_{r,y} + \widehat{\beta}_7 \ln AgriGDP_{r,y} + \widehat{\beta}_8 \ln Cropland_{r,y} + \widehat{\beta}_9 T_y \right) \quad (13)$$



where $N_{fer,c,r,y}^{obs}$ and $N_{fer,c,r,y}^{est}$ are the observed and estimated crop-specific N fertilizer application amounts for crop group c in administrative region r and year y , respectively. $HA_{c,r,y}$ represents crop-specific harvested area, $Y_{c,r,y}$ denotes crop-specific yield, $Irr_{r,y}$ is the area equipped for irrigation, $Pop_{r,y}$ represents population, $AgriGDP_{r,y}$ denotes agricultural gross domestic product, and $CropLand_{r,y}$ represents cropland area. $\beta_0 - \beta_9$ are regression coefficients, and $\varepsilon_{c,r,y}$ is the residual error term. The model coefficients were estimated using ordinary least squares (OLS) regression based on administrative regions with available crop-specific fertilizer baseline data in 2000 and 2020. The fitted model was subsequently applied to reconstruct annual crop-specific fertilizer application amounts for 1961-2023. Predicted regional fertilizer amounts were then spatially allocated to grid cells according to the proportional distribution of crop harvested area within each administrative region, ensuring consistency between regional fertilizer totals and subregional crop spatial patterns. As the input datasets for crop-specific yield contain only a few baseline years, we generated a continuous time series yield from 1961 to 2023 using FAOSTAT national statistics with the assumption that all administrative units within a given country follow similar temporal trajectories of yield growth with the following function:

$$Y_{i,j,y}^{adj} = Y_{i,j,y_0(y)}^{SPAM} \cdot \frac{Y_{i,c,y}^{FAO}}{Y_{i,c,y_0(y)}^{SPAM}}, \quad y_0(y) = \begin{cases} 2000, & 1961 \leq y \leq 2003 \\ 2005, & 2004 \leq y \leq 2007 \\ 2010, & 2008 \leq y \leq 2015 \\ 2020, & 2016 \leq y \leq 2023 \end{cases} \quad (14)$$

where $Y_{i,j,y}^{adj}$ is the adjusted gridded yield for crop i in grid cell j year y after temporal extension. $Y_{i,j,y_0(y)}^{SPAM}$ is the SPAM gridded baseline yield map for crop i in reference year y_0 . $Y_{i,c,y_0(y)}^{SPAM}$ is the national yield for crop i in country c in the SPAM reference year y_0 . $Y_{i,c,y}^{FAO}$ is the FAOSTAT national yield statistics (FAO, 2024) for crop i in country c and year y . We harmonized the SPAM gridded yield maps (Yu et al., 2020) and harvest-area data to the same spatial resolution using the same processing framework as that used for reconstructing the SPAM vegetable and fruit harvested area.

After estimating the initial crop-specific N fertilizer input $N_{i,p,y}^{fert,est}$ for each crop group within each administrative unit, we adjusted these estimates to match the reported total N fertilizer use $N_{p,y}^{stat}$ for all crops in the same administrative unit. The adjusted crop-specific fertilizer amount was calculated as:

$$N_{i,p,c,y}^{fert,adj} = N_{i,p,c,y}^{fert,est} \cdot \frac{N_{p,c,y}^{stat}}{\sum_{i=1}^{21} N_{i,p,c,y}^{fert,est}} \quad (15)$$



where $N_{i,p,c,y}^{fert,adj}$ is the adjusted fertilizer input for crop group i in administrative unit p , country c , and year y ; $N_{i,p,c,y}^{fert,est}$ is the initially estimated crop-specific fertilizer input; $N_{p,c,y}^{stat}$ is the reported total fertilizer input for all crops in administrative unit p ; and $\sum_{i=1}^{21} N_{i,p,c,y}^{fert,est}$ is the total initially estimated fertilizer input across all 21 crop groups in that administrative unit. The scaling factor aligns crop-specific estimates with the administrative fertilizer statistics. The crop-specific N fertilizer application rate was then calculated as:

$$R_{i,j,y}^{fert} = \frac{N_{i,p,c,y}^{fert,adj}}{\sum_{j \in p} A_{i,j,y}}, \quad j \in p, p \in c \quad (16)$$

where $R_{i,j,y}^{fert}$ is the N fertilizer application rate for crop group i in grid cell j and year y . $N_{i,p,c,y}^{fert,adj}$ is the adjusted N fertilizer input for crop group i in administrative unit p , country c , and year y . $A_{i,j,y}$ is the harvested area of crop group i in grid cell j and year y . The denominator $\sum_{j \in p} A_{i,j,y}$ represents the total harvested area of crop group i across all grid cells within administrative unit p . The notation $j \in p$ and $p \in c$ indicates that grid cell j belongs to administrative unit p , and administrative unit p belongs to country c . This calculation assumes a uniform fertilizer application rate for each crop group within the same administrative unit.

2.3 The Construction of the Crop Specific Manure Application Rate Maps

Previous manure application data generally available only as national totals, with limited crop-specific and sub-national information. Most studies estimated manure application by using the same ratio of N fertilizer to manure at a certain scale. But the ratio of manure utilization for legumes (like soybeans) is far lower than that for cereal crops. To account for local manure availability, we used gridded livestock distributions from Gridded Livestock of the World (GLW4) (Gilbert et al., 2018) together with FAOSTAT livestock population data (FAO, 2025d) and Intergovernmental Panel on Climate Change (IPCC) Tier 1 methodology for manure N excretion factors (Allan et al., 2021) to estimate the manure N produced by livestock in each grid cell or administrative unit. The resulting livestock manure availability was used as an upper constraint on local manure application and avoids unrealistic long-distance manure redistribution.

Following the HaNi (Tian et al., 2022) framework, grid-level livestock manure N production $M_{j,y}^{prod}$ was estimated using the GLW basemap, FAOSTAT national livestock population data (FAO, 2025c), and IPCC Tier 1 N excretion factors. The calculation included eight livestock categories: buffaloes, cattle, chickens, ducks, goats, horses, pigs, and sheep. For each category, national FAOSTAT populations were downscaled to grid cells based



on the relative GLW4 livestock density within each country and multiplied by the corresponding N excretion factor. The resulting manure production map was used as a local manure availability constraint. We then spatialized the FAOSTAT national total manure N applied to cropland (FAO, 2025a) using cropland area and baseline manure application intensity (West et al., 2014). Where the initially allocated manure application exceeded local manure availability, the excess manure was redistributed within the same country to grid cells with remaining manure availability. Our crop-specific allocation scheme allows manure inputs to vary among crop types, thereby capturing differences in application intensity, such as the lower manure use associated with legumes relative to cereal crops. We first derived a crop-specific baseline manure allocation weight from the crop-specific manure application rates of West et al. (2014) and harvested-area maps around 2000 from EARTHSTAT (Monfreda et al., 2008). For each administrative unit p , the baseline manure amount for crop group i was calculated as:

$$N_{i,p,2000}^{base} = \sum_{j \in p} A_{i,j,2000}^{harv} \cdot R_{i,j,2000}^{West} \quad (17)$$

where $N_{i,p,2000}^{base}$ is the baseline manure N applied to crop group i in administrative unit p in 2000, $A_{i,j,2000}^{harv}$ is the harvested area of crop group i in grid cell j , and $R_{i,j,2000}^{West}$ is the crop-specific manure N application rate from West et al. (2014). In grid cells where manure application amounts could not be matched with reconstructed harvested areas, we applied the same gap-filling procedure as described in Table 3, under the assumption that all cultivated areas may receive both synthetic fertilizer and manure inputs. These baseline crop-specific manure amounts were then converted into crop allocation shares within each administrative unit:

$$B_{i,p} = \frac{N_{i,p,2000}^{base}}{\sum_{i=1}^{21} N_{i,p,2000}^{base}} \quad (18)$$

where $B_{i,p}$ represents the baseline manure allocation share of crop group i in administrative unit p . This term captures crop-specific differences in manure application preference and is used as a fixed crop preference weight in the subsequent dynamic allocation.

Next, we spatialized the FAOSTAT national total manure N applied to cropland to grid cells using a baseline manure allocation weight derived from cropland area and baseline manure application intensity. The baseline grid-level manure application intensity and the grid-level manure N amount were calculated as:

$$\bar{R}_{j,2000}^{manure} = \frac{\sum_{i=1}^{21} A_{i,j,2000}^{harv} \cdot R_{i,j,2000}^{West}}{\sum_{i=1}^{21} A_{i,j,2000}^{harv}} \quad (19)$$



$$N_{j,y}^{manure,ini} = N_{c,y}^{FAO,manure} \cdot \frac{\bar{R}_{j,2000}^{manure} \cdot A_{j,y}^{cropland}}{\sum_{j \in c} (\bar{R}_{j,2000}^{manure} \cdot A_{j,y}^{cropland})}, \quad j \in c \quad (20)$$

where $N_{j,y}^{manure,ini}$ is the initial total manure N applied to cropland in grid cell j and year y , $N_{c,y}^{FAO,manure}$ is the FAOSTAT national total manure N applied to cropland in country c and year y , $\bar{R}_{j,2000}^{manure}$ is the baseline manure application intensity derived from West et al. (2014), and $A_{j,y}^{cropland}$ is the reconstructed cropland area in grid cell j . The denominator normalizes the allocation weights within each country, ensuring that the gridded manure N amounts to the FAOSTAT national total.

$$N_{j,y}^{manure,total} = \min(N_{j,y}^{manure,ini}, M_{j,y}^{prod}) \quad (21)$$

When $N_{j,y}^{manure,ini}$ exceeded $M_{j,y}^{prod}$, the excess manure was distributed within the same country to grid cells with remaining manure availability, while preserving the FAOSTAT national manure total. The grid-level total manure N was then allocated among the 21 crop groups according to both baseline crop-specific manure preference and annual harvested-area distribution. Specifically, the manure N amount allocated to crop group i in grid cell j and year y was calculated as:

$$N_{i,j,y}^{manure} = N_{j,y}^{manure,total} \cdot \frac{B_{i,p(j)} \cdot A_{i,j,y}^{harv}}{\sum_{i=1}^{21} B_{i,p(j)} \cdot A_{i,j,y}^{harv}} \quad (22)$$

where $N_{i,j,y}^{manure}$ is the manure N amount allocated to crop group i in grid cell j and year y , $N_{j,y}^{manure,total}$ is the total manure N applied to cropland in grid cell j and year y , $B_{i,p(j)}$ is the baseline manure allocation share of crop group i in the administrative unit p containing grid cell j , and $A_{i,j,y}^{harv}$ is the harvested area of crop group i in grid cell j and year y . This allocation allows crop-specific manure inputs to vary with annual harvested-area changes while retaining crop-specific manure application preferences derived from the baseline data. Finally, we aggregated manure N applied to cropland within the same global administrative unit as those used in the fertilizer dataset. The crop-specific manure application rate was then calculated as:

$$R_{i,j,y}^{manure} = \frac{N_{i,j,y}^{manure}}{A_{i,j,y}^{harv}} \quad (23)$$

where $R_{i,j,y}^{manure}$ is the manure N application rate for crop group i in grid cell j and year y . Grid cells with zero harvested area for a given crop group were assigned no manure application for that crop. This procedure generated annual crop-specific manure application amount and rate maps for 21 crop groups from 1961 to 2023, while maintaining consistency with FAOSTAT national manure totals and crop-specific harvested-area distributions.



2.4 Characterizing NH_4^+ and NO_3^- Application Rates in N Fertilizer

Nishina et al. (2017) provides country-level estimates of NH_4^+ and NO_3^- based on N fertilizer consumption from 1961 to 2010. We extended these estimates to 2023 following the same method, using country-level fertilizer product consumption data from FAOSTAT (FAO, 2025a). Due to the lack of statistical data for sub-national area, we collected national consumption data for 15 types of synthetic N fertilizers including Ammonia anhydrous, Ammonium nitrate, Ammonium sulphate, Calcium ammonium nitrate (CAN), Diammonium phosphate (DAP), Fertilizers n.e.c., Monoammonium phosphate (MAP), NPK fertilizers, Other Nour fertilizers, Other NK compounds, Other NP compounds, Potassium nitrate, Sodium nitrate, Urea and Urea ammonium nitrate solute. Based on the product-specific fractions listed in Table 4, total synthetic N fertilizer consumption for each country was partitioned into NH_4^+ -N and NO_3^- -N components. Since the FAOSTAT fertilizer product statistics before 2002 are provided through the Fertilizer Archive, whose product categories are not fully consistent with those used in Table 4. Therefore, we used Nishina et al. (2017) as the primary source for 1961-2001 and FAOSTAT fertilizer product data as the primary source for 2011-2023. The overlapping period 2002–2010 was used to harmonize the two data sources as calculated with a country-specific scaling factor for fertilizer N form within each country c using the 2010 values:

$$R_{c,2010} = \frac{F_{c,2010}^{\text{FAOSTAT}}}{F_{c,2010}^{\text{Nishina}}} \quad (24)$$

where $R_{c,2010}$ is the scaling factor for fertilizer NH_4^+ -N form in country c , $F_{c,2010}^{\text{FAO}}$ is the fraction derived from FAOSTAT fertilizer product data in 2010, and $F_{c,2010}^{\text{Nishina}}$ is the corresponding fraction from Nishina et al. (2017). We then defined a linear transition weight for the overlapping period 2002-2010:

$$\alpha_y = \frac{y - 2002}{2010 - 2002}, \quad y = 2002, 2003, \dots, 2010 \quad (25)$$

where α_y increases linearly from 0 in 2002 to 1 in 2010, the adjusted Nishina-based fraction was then calculated as:

$$F_{c,y}^{\text{adjusted}} = F_{c,y}^{\text{Nishana}} \cdot \left[(1 - \alpha_{c,y}) + \alpha_{c,y} \cdot R_{2010,y} \right], \quad y = 2002, 2003, \dots, 2010 \quad (26)$$

where $F_{c,y}^{\text{adjusted}}$ is the adjusted fraction of fertilizer NH_4^+ -N form in country c in year y . This approach retains the temporal pattern of the Nishina et al. (2017) dataset during the transition period while gradually scaling it to match the FAOSTAT-derived estimate in 2010. For the countries including Côte d'Ivoire, Dominica, and other 12 countries lacking post-2002 FAOSTAT fertilizer product consumption data, missing NH_4^+ -N and NO_3^- -N fractions were filled using continent averages. Specifically, countries were grouped into eight agricultural regions:



Africa, East Asia, Eastern Europe, Latin America, North America, South Asia, the rest of Europe and Oceania, and Western Asia. The mean $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ fractions within each region were used to fill missing national values. Subsequently, we applied a third-order polynomial function to the full time-series data of each country c to ensure temporal smoothness and to minimize abrupt or random fluctuations. Due to the lack of detailed information on fertilizer application types for individual crops, we assumed that all crops within a country received fertilizers in the same proportion as NH_4^+ and NO_3^- . The final N fertilizer application rate for each crop was then calculated based on the $F_{c,y}^{\text{adjusted}}$ after spline smoothing. For countries lacking reported data after 2010 in FAOSTAT, which accounted for approximately 11% of country-year records, such as the Bahamas, Cape Verde, and French Guiana. We divided the globe into eight representative agricultural regions, namely Africa, East Asia, Eastern Europe, Latin America, North America, South Asia, the rest of Europe and Oceania, and Western Asia. The mean NH_4^+ and NO_3^- N fertilizer application rate within each region was used to replace missing national values.

Table 4. N contained fertilizer application types and ratios used in this study

Name	Ratio ($\text{NH}_4^+:\text{NO}_3^-$)	Name	Ratio ($\text{NH}_4^+:\text{NO}_3^-$)
Ammonia anhydrous	0	Other nitrogenous fertilizers	1
Ammonium nitrate	0.5	Other NK compounds	1
Ammonium sulphate	1	Other NP compounds	1
Calcium ammonium nitrate (CAN)	0.5	Potassium nitrate	0
Diammonium phosphate (DAP)	1	Sodium nitrate	0
Fertilizers n.e.c.	1	Urea	1
Monoammonium phosphate (MAP)	1	NPK fertilizers	1
Urea and ammonium nitrate solute	0.75		

2.5 Uncertainty analysis

We considered three uncertainty components in the reconstructed crop-specific N fertilizer dataset. First, baseline fertilizer allocation uncertainty was considered because the 2000 and 2020 crop-specific fertilizer baseline maps provide the observational anchor for model calibration and temporal reconstruction. Uncertainty in these benchmark products may arise from differences in source datasets like the category in fruits and vegetables in SPAM, subnational statistical completeness, N allocation procedures by pasture and cropland, and spatial disaggregation methods. Because the regression framework was calibrated directly against these benchmark fertilizer maps, uncertainties in the baseline allocation products can propagate into the estimated regression



coefficients, reconstructed regional fertilizer amounts, and subsequent gridded fertilizer application rates throughout the full 1961-2023 reconstruction period. Here, multiplicative perturbations were applied to the baseline fertilizer allocation datasets during each Monte Carlo realization. Perturbation factors were sampled from log-normal distributions centered at unity to preserve positive fertilizer amounts and proportional spatial relationships, with a coefficient of variation of 20% ($CV = 0.20$) applied to represent moderate uncertainty in the benchmark allocation products. The perturbed baseline maps were subsequently used in the reconstruction framework to propagate baseline allocation uncertainty into both regional and gridded uncertainty estimates. Second, regression coefficient uncertainty was propagated by sampling alternative coefficient vectors from the multivariate normal distribution defined by the fitted regression coefficients and their associated variance-covariance matrix. This procedure accounts for parameter estimation uncertainty arising from limited observations, spatial heterogeneity among administrative units, and correlations among predictor variables within the regression framework. Third, residual predictive uncertainty was incorporated into the Monte Carlo ensemble to represent unexplained regional variability, local management heterogeneity, and model structural error not explicitly captured by the selected predictors. For each Monte Carlo realization, an additive residual term was randomly sampled from a normal distribution with zero mean and standard deviation equal to the residual standard error of the fitted crop-specific regression model. This residual perturbation is associated with unrepresented management practices, local socioeconomic conditions, and incomplete explanatory variables. For each crop group, the Monte Carlo ensemble consisted of $n = 800$ realizations. Each realization included baseline fertilizer allocation perturbation, regression coefficient sampling, residual perturbation, crop-specific rate reconstruction, and aggregation to regional and global uncertainty statistics. Predicted regional fertilizer amounts were converted to fertilizer application rates using crop-specific harvested area. To avoid physically unrealistic fertilizer intensities caused by extremely small, harvested areas or local allocation artifacts, a maximum fertilizer application threshold of 700 kg N ha^{-1} was applied during the uncertainty propagation procedure (Cui et al., 2021).

To evaluate the robustness of the reconstruction model, we performed a spatial masking validation experiment. We divided the world into eight representative agricultural regions: Africa, East Asia, Eastern Europe, Latin America, North America, South Asia, Rest Europe & Oceania, and West Asia. For each crop group and baseline year, we selected a fixed proportion to mask our administrative units ($p = 20\%$) and randomly withheld and treated them as missing. The reconstruction model was fitted using the remaining 80% of observations and then used to predict fertilizer amounts for the withheld regions. This procedure was repeated 100 times for each crop. Model performance was evaluated using RMSE and R^2 in log space. Uncertainty estimates were summarized at multiple scales. At the administrative-region level, the Monte Carlo ensemble was summarized using the ensemble



mean, standard deviation, coefficient of variation, median, and 95% uncertainty interval. For global uncertainty, fertilizer amounts were first summed across all regions within each Monte Carlo realization, and global uncertainty statistics were then calculated from the resulting ensemble distribution. Spatial uncertainty maps were generated by converting regional uncertainty estimates to gridded fertilizer application rates using crop-specific harvested area. The resulting uncertainty products for both N fertilizer and manure application in this study were subsequently used to characterize crop-specific, regional, and temporal uncertainty patterns with three significant digits in the discussion section, including regional 95% uncertainty intervals, global coefficient-of-variation trajectories, and uncertainty interval widths.

3 Results

3.1 Temporal trends in total N fertilizer and manure application

The global N inputs from synthetic fertilizers and manure increased substantially between 1961 and 2023, although their magnitudes and temporal trajectories differed markedly (Fig. 2). Synthetic N fertilizer input increased by nearly an order of magnitude, from approximately 12 Tg N yr⁻¹ in 1961 to about 100 Tg N yr⁻¹ in 2023. The most rapid increases occurred from the 1960s to the 1980s, followed by slower growth and a tendency toward stabilization at high levels after 2000. In contrast, manure N input increased more gradually, from approximately 13 Tg N yr⁻¹ in the 1960s to about 22 Tg N yr⁻¹ in the recent decade. Thus, the long-term increase in total cropland N input was driven primarily by synthetic N fertilizer, while manure represented a smaller but persistent component of total N inputs. Over the 1961-2023 period, the global average synthetic fertilizer N application rate per unit harvested area increased steadily from approximately 12 kg N ha⁻¹ to over 67 kg N ha⁻¹, whereas the corresponding manure N application rate remained relatively stable at around 15 kg N ha⁻¹.

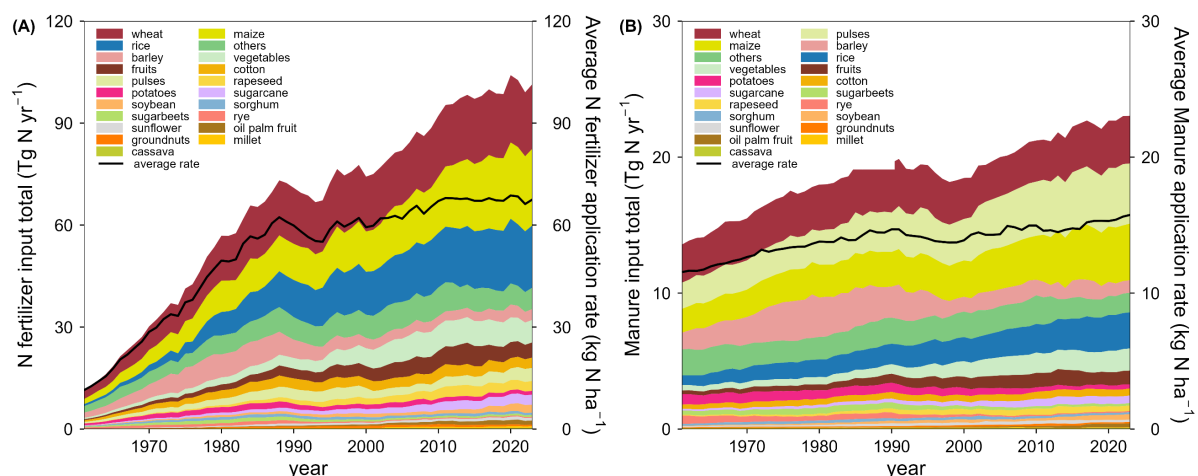


Figure 2. Total N inputs from synthetic fertilizer (A) and manure (B) on cropland from 1961 to 2023. The black line shows the global average application rate across all crop groups.

The crop composition of global N inputs from fertilizer and manure changed markedly between 1961 and 2023 (Fig. 3 and Table S1). Cereal crops remained the dominant recipients of both N sources, although the magnitudes and compositional trajectories differed. Mean decade synthetic fertilizer N input to cereals increased from about 12 Tg N yr⁻¹ in the 1960s to about 63 Tg N yr⁻¹ in the recent decade, while their share of global fertilizer N input remained relatively stable at around 60%. Maize, wheat, and rice together accounted for about 58% of global fertilizer N input in the most recent decade. In contrast, manure N input to cereals increased more modestly, from approximately 8 to 11 Tg N yr⁻¹, while their share of global manure N input remained half of the total manure N input. Non-cereal crops became increasingly important, particularly in synthetic N fertilizer use. Fertilizer N inputs to fruits and vegetables increased from 1 Tg N yr⁻¹ during to over 12 Tg N yr⁻¹ in the recent decade, raising their combined share of global fertilizer N input from 6% to 12%. In the most recent decade, vegetables and fruits received approximately 7 and 5 Tg N yr⁻¹, respectively. Synthetic fertilizer N inputs to oil crops and legumes—including rapeseed, sunflower, oil palm fruit, groundnuts, and pulses increased from approximately 1 to 11 Tg N yr⁻¹, with their combined share rising from 6% to nearly 11%. These crop groups were even more prominent in manure allocation, accounting for 25% of global manure N input in the most recent decade, compared with about 16% during the 1960s. Overall, synthetic fertilizer N input was more concentrated in maize, wheat, rice, and horticultural crops, whereas manure N was distributed more broadly across crop groups. In the most recent decade, maize, wheat, and rice together accounted for about 44% of global manure N input, substantially lower than their 58% share of synthetic fertilizer N input. Pulses alone accounted for approximately 19% of manure N input but only about 3% of synthetic fertilizer N input, highlighting the distinct crop allocation patterns of the two N sources.

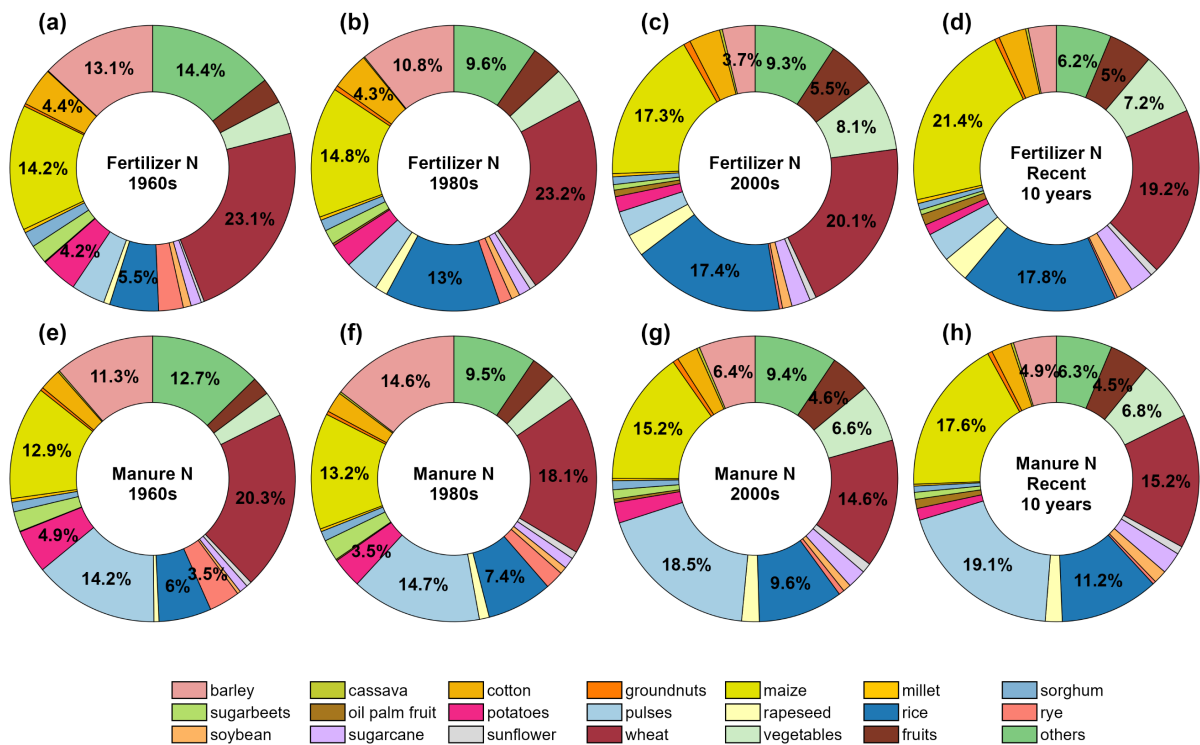


Figure 3. Changes in the percentage contribution of N fertilizer and manure to total N inputs by crop group from the 1960s to the recent decade. Panels (a)–(d) show synthetic fertilizer N shares for the 1960s, 1980s, 2000s, and recent decade, respectively; panels (e)–(h) show the corresponding manure N shares.

Synthetic fertilizer N was dominated by $\text{NH}_4^+\text{-N}$ throughout the study period (Fig. 4). Annual $\text{NH}_4^+\text{-N}$ input increased from approximately 8 Tg N yr^{-1} in 1961 to 90 Tg N yr^{-1} in 2023, whereas $\text{NO}_3^-\text{-N}$ input increased from approximately 3 to 12 Tg N yr^{-1} . Consequently, the contribution of $\text{NH}_4^+\text{-N}$ to total fertilizer N increased from approximately 76% in 1961 to 88% in 2023, with the $\text{NO}_3^-\text{-N}$ share declining to only 12% in recent years. The crop distributions of the two fertilizer N forms were broadly similar but differed in magnitude. Mean annual $\text{NH}_4^+\text{-N}$ inputs to maize, wheat, and rice increased from approximately 7 Tg N yr^{-1} during the 1960s to almost 52 Tg N yr^{-1} in the recent decade, accounting for about 45% and 59% of global $\text{NH}_4^+\text{-N}$ input, respectively. Over the same periods, $\text{NO}_3^-\text{-N}$ inputs to these three crops increased from about 1.6 to 7 Tg N yr^{-1} and their combined share rose from 37% to 57%.



Non-cereal crops also accounted for increasing proportions of both fertilizer N forms. The combined share of fruits and vegetables increased from nearly 7% to 12% for $\text{NH}_4^+\text{-N}$ and from 6% to 11% for $\text{NO}_3^-\text{-N}$ in the past 63 years. Similarly, the combined contribution of oil crops and legumes increased from approximately 6% to 11% for both N forms. In the most recent decade, cotton and sugarcane together accounted for 6% of $\text{NH}_4^+\text{-N}$ and 5% of $\text{NO}_3^-\text{-N}$ inputs, whereas roots and tubers accounted for only 4% together. Overall, the increasing dominance of $\text{NH}_4^+\text{-N}$ was accompanied by a growing concentration of both fertilizer N forms in the three major cereals, together with moderate increases in their allocation to horticultural crops, oil crops, and legumes.

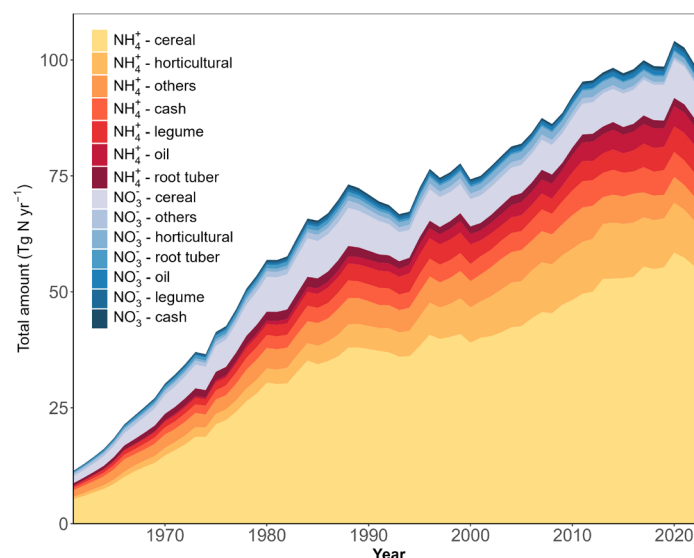


Figure 4. Changes in NH_4^+ and NO_3^- N fertilizer use inputs from 1961 to 2023. Crop groups are defined as follows: cereals, including barley, maize, millet, rice, rye, sorghum, and wheat; legumes, including pulses, soybean, and groundnuts; roots and tubers, including cassava, potatoes, and sugar beets; oil crops, including rapeseed, sunflower, and oil palm fruit; cash crops, including cotton and sugarcane; horticultural crops, including vegetables and fruits; and others, including all remaining crop types.

3.2 Global patterns and temporal dynamics of crop-specific fertilizer and manure application

Globally, about 50% of crop-growing areas experienced increases in both fertilizer and manure application rates from the 1960s to the past decade across the 21 crop types. The largest increases were concentrated in major agricultural regions of the Northern Hemisphere, particularly East and South Asia, Western Europe, and the United States (Fig. 5). In these regions, N fertilizer application rates increased substantially relative to the 1960s, often exceeding $100 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ in major grain-producing areas. Manure application rates also increased, although the magnitude of change was smaller. For maize, strong increases in synthetic fertilizer inputs were



observed across the U.S. Corn Belt, central and eastern China, and parts of southern Brazil. Manure inputs also increased in several maize-growing regions, particularly North America, Europe, and parts of East Asia, where both N fertilizer and manure rose by over 75% relative to the 1961 baseline. For example, in the U.S. Midwest, N inputs increased by approximately $80 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ to over $125 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. Across the Southern Hemisphere, Brazil, Argentina, and Australia show consistent positive changes of over 20% in N fertilizer applications, whereas large areas of Sub-Saharan Africa and Central Asia remain comparatively stable, with changes below $150 \text{ kg N ha}^{-1} \text{ yr}^{-1}$. In Africa, fertilizer input rates for major cereals remained broadly stable at less than $35 \text{ kg N ha}^{-1} \text{ yr}^{-1}$ over the study period, but manure application increased significantly in East African countries. For wheat, application rates of both synthetic fertilizer and manure increased by over 40% in northern China, India, and western Europe; North America and the Middle East show about 20% to 30% growth, while eastern Europe and parts of Australia exhibit only slight increases. For maize, both N fertilizer and manure application rates showed widespread increases of more than 30% across the U.S. Corn Belt, central and eastern China, and southern Brazil.

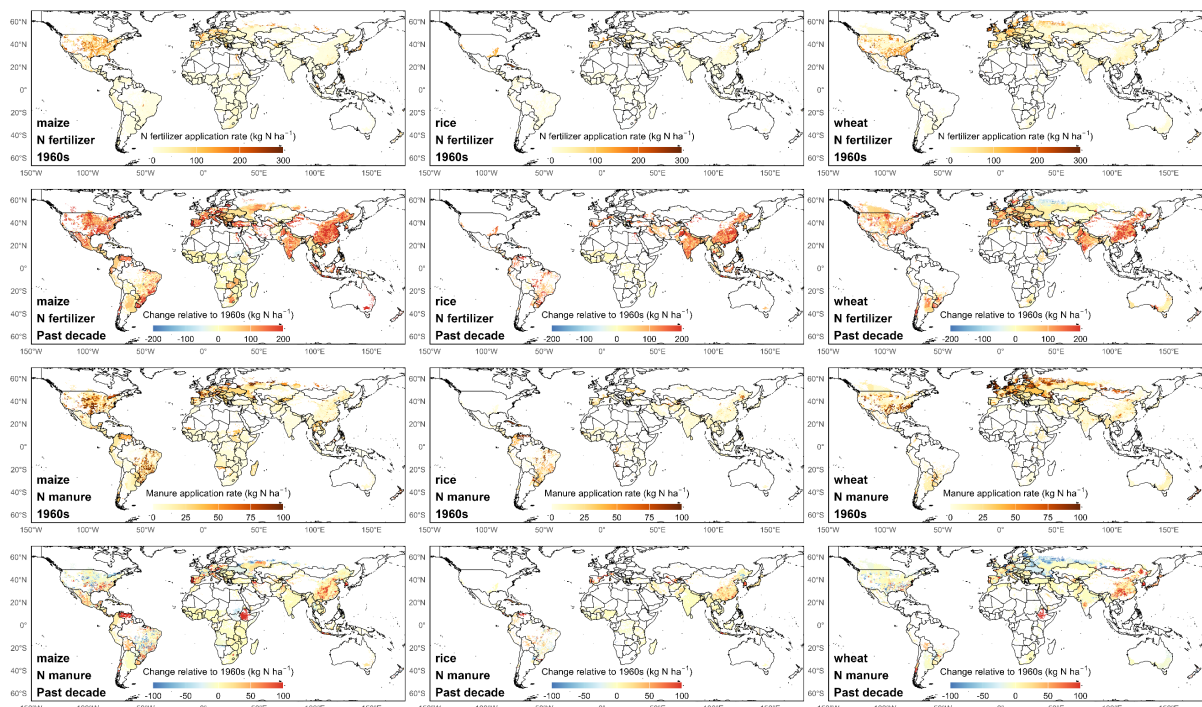


Figure 5. Mean manure and N fertilizer application rates for maize, rice, and wheat in the 1960s and their changes in the past decade



By comparison, eastern Europe and southern Africa record modest fertilizer increases of about 10%, paired with a more pronounced rise in manure use of around 32%, suggesting a relative shift toward organic N sources in those systems. For rice, strong positive changes of about 42% for both synthetic and manure N dominate South and Southeast Asia, particularly India, Bangladesh, Vietnam, and southern China. Overall, East Asia, especially the North China Plain and Yangtze River Basin, shows the largest global increases in N inputs to major cereals, with both fertilizer and manure contributions rising by nearly 48% over the study period, while regions with smaller percentage changes often compensate through rising manure contributions even where synthetic fertilizer growth is limited.

3.3 National and temporal N fertilizer and manure use application for specific crops

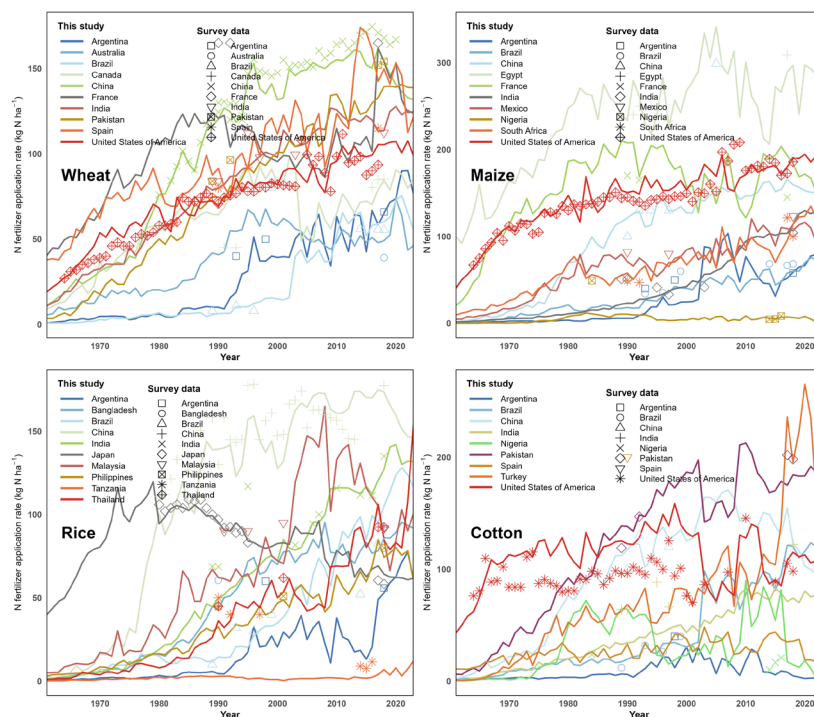


Figure 6. Comparison of crop-specific N fertilizer application rates estimated in this study with independent survey datasets for wheat, maize, rice, and cotton at the country level.

Between 1961 and 2023, crop-specific N fertilizer application rates increased in many major producing countries, although the magnitude and timing of these changes varied strongly by crop and region (Fig. 6). The comparison with independent survey datasets showed good agreement for the four major crops. These comparisons indicate



that the reconstructed dataset captures the broad spatial and temporal variability in national crop-specific fertilizer N application rates, although uncertainty is greater for cotton. In China, both the reconstructed and survey data showed substantial increases in fertilizer N application to major cereals. In the matched survey records, wheat increased from about 70 kg N ha⁻¹ yr⁻¹ in the 1980s to around 130-150 kg N ha⁻¹ yr⁻¹ after 2010. Rice showed a similar increase, from roughly 100 kg N ha⁻¹ yr⁻¹ in the early records to about 150-170 kg N ha⁻¹ yr⁻¹ during the 2000s and 2010s. Cotton in China was represented by fewer survey records, but available values were generally around 130 kg N ha⁻¹ yr⁻¹. India exhibited a later and generally more gradual increase. By 2018, reconstructed application rates reached approximately 114 kg N ha⁻¹ yr⁻¹ for wheat and maize and 127 kg N ha⁻¹ yr⁻¹ for rice, closely corresponding to survey estimates. In contrast, the reconstructed cotton rate for India remained lower than the survey estimate, indicating greater uncertainty for this crop. Long-term agreement was particularly evident for maize in the United States, where reconstructed application rates increased from approximately 65 kg N ha⁻¹ yr⁻¹ in 1964 to 190 kg N ha⁻¹ yr⁻¹ in 2018, compared with corresponding survey values of 67 and 186 kg N ha⁻¹ yr⁻¹. In South Asia, Pakistan also showed relatively high fertilizer rates for wheat, rice, maize, and cotton in recent observations, particularly for cotton and maize. Overall, the validation results demonstrate that the dataset reproduces major national trajectories in crop-specific fertilizer N use, while discrepancies for particular crops and countries highlight the remaining uncertainty associated with limited survey coverage and heterogeneous fertilizer-management practices.

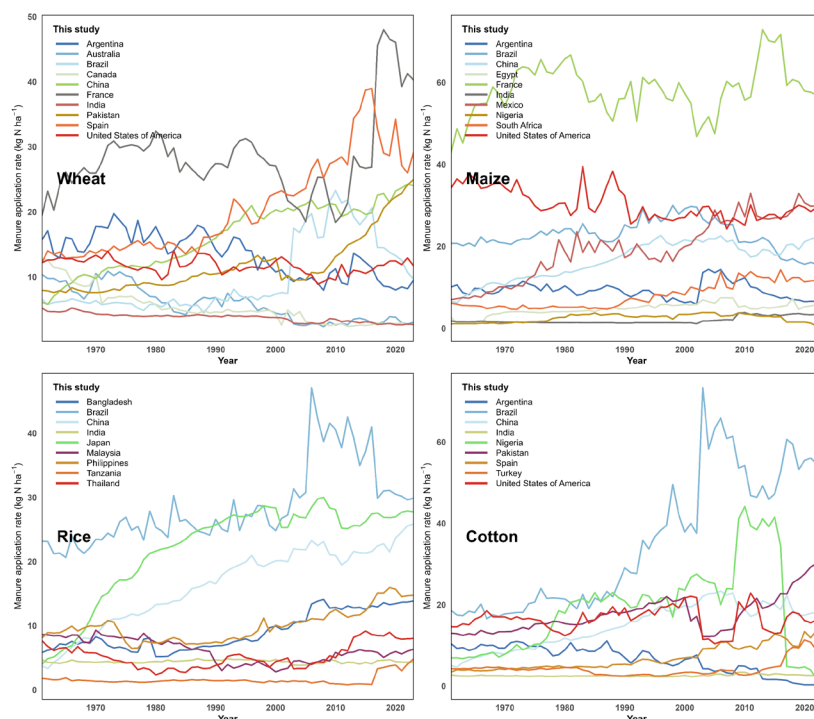


Figure 7. Country-level manure N application rates for wheat, maize, rice, and cotton from 1961 to 2023.

Manure N application rates exhibited temporal trajectories distinct from those of synthetic fertilizer N (Fig. 7) and were typically lower and changed more gradually, although substantial differences occurred among crops and countries. In China, mean manure N application rates increased between the 1960s and the most recent decade from approximately 8 to 22 kg N ha⁻¹ yr⁻¹ for wheat, maize, rice, and cotton in recent years. Pakistan also showed marked increases for wheat and cotton, with application rates rising from approximately 10 to 2 kg N ha⁻¹ yr⁻¹. In contrast, maize manure application N rates in the United States and Brazil declined from the 1960s to the recent decade. Cotton showed particularly divergent trajectories, increasing from approximately 20 to 50 kg N ha⁻¹ yr⁻¹ in Brazil but declining from about 10 to less than 1 kg N ha⁻¹ yr⁻¹ in Argentina.



3.4 Validation and comparison with other crop-specific datasets

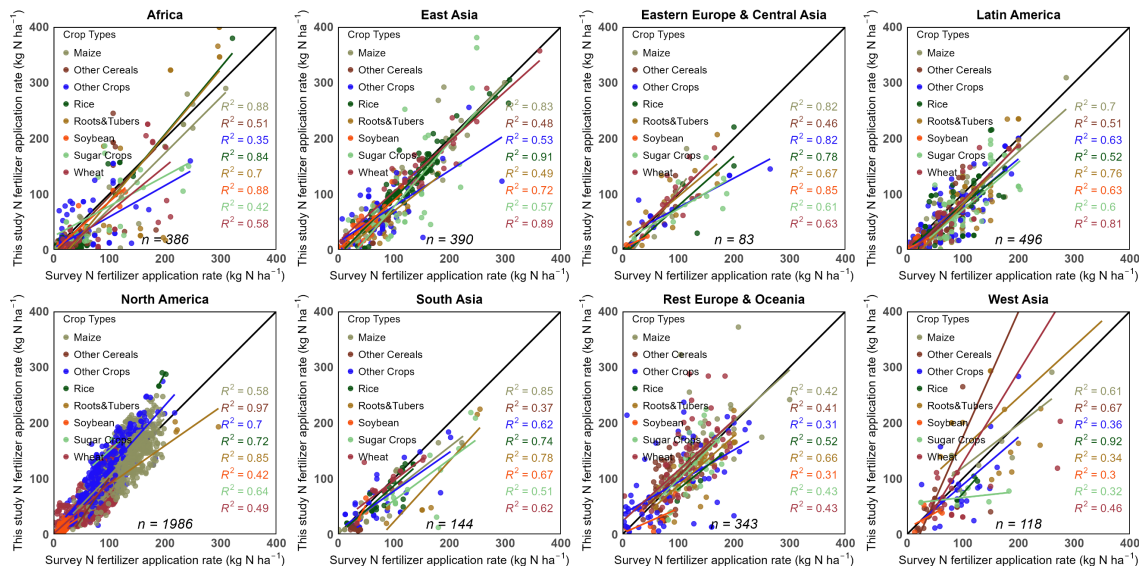
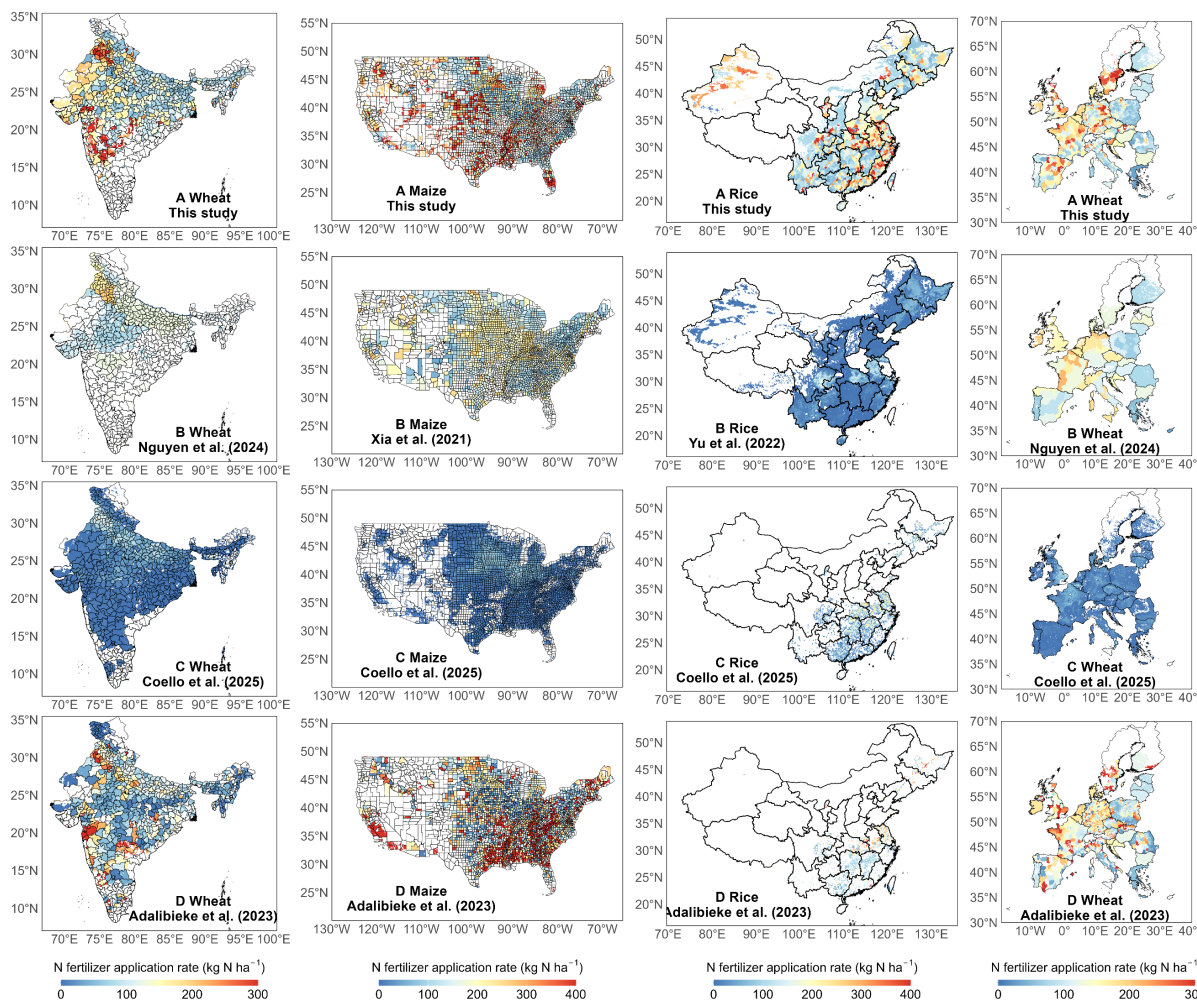


Figure 8. Crop-specific validation of N fertilizer application rate across eight regions using national and subnational survey data. Each point represents a paired observation between survey and N fertilizer application rates in this study. Colored regression lines represent crop-specific linear fits between survey and N fertilizer application rates in this study within each region; the black diagonal line indicates the 1:1 reference line.

To evaluate the robustness and credibility of crop-specific N fertilizer application estimations, we compared our results with independent survey data from national and subnational sources across eight representative agricultural regions: Africa, East Asia, East Europe, Latin America, North America, South Asia, Rest Europe & Oceania and West Asia (Fig. 8). The validation datasets included records from the USDA, the Cost-Benefit Report published by the National Development and Reform Commission of China (NDRC), and reports from FUBC fertilizer use by crop. For each region, we calculated the coefficient of determination (R^2) from regressions between our estimates and survey observations across matched crop-specific records. In Africa, East Asia, and North America, our estimates showed strong agreement with survey data, with regression slopes close to unity and R^2 values exceeding 0.85, indicating a good consistency between our gridded estimates and independent survey-based records. West Asia showed the weakest agreement with survey data, as well as large uncertainty in the reconstructed crop-specific N input estimates for this region. Typically, major cereals such as maize, wheat, and rice demonstrate the most robust validation performance across all regions, with our modelled fertilizer application rates closely matching reported values, reflecting the reliability of our estimates for these crop groups.



658 Compared with four previously published datasets, our estimates show more explicit temporal and spatial patterns
 659 of crop-specific N fertilizer application reported in earlier studies, particularly in terms of long-term performance
 660 (Fig. 9; Figs. S10-S16).



661 **Figure 9. Spatial comparison of N fertilizer application rates for rice, maize, and wheat between our study**
 662 **and previously published datasets. Panel A shows the estimate from this study. Panel B shows the crop-**
 663 **specific estimates from Yu et al. (2022) for rice, Xia et al. (2021) for maize, Nguyen et al. (2024) for wheat;**
 664 **Panel C presents the dataset from Coello et al. (2025); and Panel D presents estimates from Adalibieke et**
 665 **al. (2023).**

666 In this study, more explicit temporal and spatial patterns of crop-specific N fertilizer application are partly
 667 attributable to the use of CropAtlas crop-specific harvested-area maps as spatial allocation constraints (Fig. S9).



Our reconstructed harvested area maps are highly consistent with remote-sensing crop products, which provide reasonable constraints for long-term N input reconstruction. For example, the comparison with independent high-resolution remote-sensing crop products demonstrates that our reconstructed harvested-area maps reliably capture the major crop-specific production zones and spatial gradients. For rice, our maps reproduce the major rice-growing regions in central, eastern, southern, and northeastern China, and further reflect spatial differences associated with single- and double-rice systems shown by the CCD-Rice product at 30m resolution (Shen et al., 2025). For maize, the reconstructed harvested area captures the dominant concentration of maize cultivation in the U.S. Corn Belt, particularly across the central Midwest, and shows strong spatial agreement with the 10 m maize distribution from Li et al. (2026). For wheat, our estimates identify the major wheat-growing areas across northern India and the Indo-Gangetic Plain, consistent with the 30 m wheat map of Fu et al. (2025). These agreements suggest that the CropAtlas-based harvested-area constraints provide reliable spatial information for crop-specific allocation and help reduce the misallocation of fertilizer inputs to areas where the target crop is unlikely to be grown, thereby improving the spatial realism of reconstructed crop-specific N fertilizer application maps.



4 Discussion and conclusion

4.1 Temporal changes in crop-specific N fertilizer and manure application

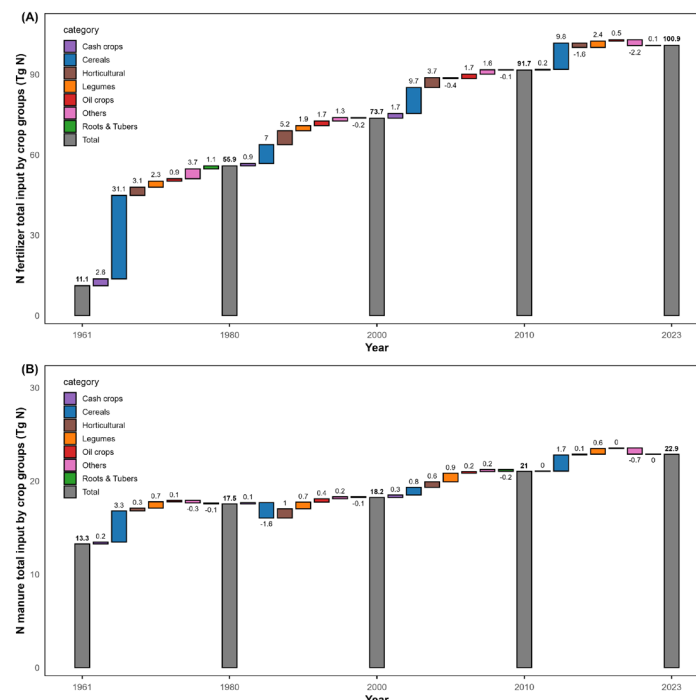


Figure 10. Increasing trends of total N fertilizer and manure application inputs by crop groups

The marked improvement of this dataset is to provide a spatially explicit, crop-specific, and temporally continuous reconstruction of N inputs from 1961 to 2023 due to the use of intensive, spatialized sub-national crop-specific fertilizer and manure N inputs data (Fig. 10). Our dataset is not only consistent with the original fertilizer and manure statistics but also provides details on where, for which crops, and at what rates N inputs were allocated over the past 63 years. Our crop-specific N dataset is expected to support crop models and biogeochemical models for more precise assessments of terrestrial C-N interaction simulations such as crop yields, N losses, or greenhouse gas emissions, capturing historical trends. Integrating intensive sub-national statistical data and our reconstructed crop-specific harvested areas, we employed multiple ordinary least squares (OLS) regression models to reconstruct historical N input datasets and found that our crop-specific N input dataset successfully captured the interannual variations in both fertilizer and manure inputs across different crop groups and nations. This conclusion was supported by significant correlations between baseline and predicted $\ln(N)$ amounts for several



globally important or spatially concentrated crop groups, including vegetables, fruits, rice, rapeseed, and wheat, although weaker fits were observed for oil palm fruit and sunflower. (Fig. S1).

However, our results also showed that roots and tuber crop groups in this study pose challenges for model fitting due to small variations and low fertilizer N inputs. These crops often grow in regions with limited N application and water resources, which may limit our model to predicting N inputs mainly based on irrigation and economic factors (Piao et al., 2010). Because errors in high-input regions have a disproportionate effect on national and global N budgets, we specifically evaluated whether the reconstruction preserved the spatial structure of high N input hotspots in the baseline maps. For each crop group, we selected grid cells in the upper 20% of baseline N input amounts and their reconstructed values to compare with the baseline values using Spearman rank correlation. Across the 21 crop groups, the median Spearman rank correlation was about 0.76, with 16 crop groups showing correlation values greater than 0.70 (Fig. S2). Notably, higher consistency was found not only for major crops with sufficient data in baseline maps but also for millet, pulses, vegetables, groundnuts, oil palm fruit, and fruits. In this study, the 2000 and 2020 baseline products were developed using partially different input datasets and allocation procedures. Overall, they exhibit consistent large-scale spatial patterns of fertilizer intensity, country-level gradients, and hotspot distributions, supporting their joint use as temporal anchors for historical reconstruction. The country-level distribution of N application rates also suggests that global fertilization did not simply converge toward a uniform rate.

To validate our model performance during a long-term period, we evaluate the temporal changes of national N application rates across countries. We found a higher CV for fertilizer N inputs in earlier 2000 and indicated an accuracy decrease in this period. This might be explained by limited statistics and a lack of remote-sensing products for accurate crop harvest area (Fig.S3). The crop-specific spread cross-country pattern indicates an uneven change pattern in fertilizer and manure N inputs for different crop groups and countries (Fig. S4 and S5), highlighting the importance of adopting more fine-scale sub-national statistics and crop-specific data to reveal the fine spatiotemporal variations in N inputs (Kallenberg et al., 2026). Globally, cross-country variation in N inputs to cereal crops has gradually narrowed over time, indicating more uniform fertilizer N inputs, which has the potential to increase crop yields in low-N input countries and improve NUE in countries with high N inputs (Zhang et al., 2015). However, the rapid increase in N inputs in some regions also implies potential environmental risks (Harris et al., 2022). In comparison, cross-country variation in manure N inputs for major crops remained relatively stable, suggesting that manure N use efficiency needs to be further improved (Steinfeld & Gerber, 2010). Together, these results highlight the importance of our crop-specific N fertilizer dataset in distinguishing fertilizer types, crop types, and long-term temporal changes.



4.2 N fertilizer and manure use by different crop types

Our crop-specific N input dataset highlights that N input data should not be treated as a single cropland-wide variable without crop-specific categories (Cao et al., 2026). Although the national totals of N fertilizer and manure use are constrained by statistical data, this study reconstructs the global N use in cropland among crops and across space and time. The results indicate that global N intensification has been highly crop-selective: much of the increase in N fertilizer use was allocated to a small number of major cereal crops, especially maize, rice, and wheat, whereas manure inputs were distributed more broadly across crop groups and remained closely linked to livestock manure excretion availability (Mueller et al., 2017). This crop selectivity has important implications for global N-cycle modelling. Many terrestrial biogeochemical and crop models represent N inputs at the grid-cell level but often lack crop-specific information (Kaltenegger & Winiwarter, 2020). If a common N application rate is applied uniformly across all croplands within a grid cell, N inputs may be over-allocated to low-input crops and under-allocated to high-input crops. This is particularly important for cereals and horticultural crops, which receive high fertilizer N inputs in many intensively managed systems, and for legumes or root and tuber crops, which often have lower fertilizer N demand or different nutrient management practices (Fan et al., 2012). The distinction between fertilizer and manure N input is important because they reflect different production systems and management constraints. Synthetic fertilizer N is more closely associated with commercial and high-yield cropping systems, and its expansion reflects the increasing dependence of many cereal and horticultural systems on N inputs (Raun & Johnson, 1999). In contrast, manure N input is constrained by livestock distribution, manure production, transport limitations, and the spatial coupling between crop and livestock systems (Hilimire, 2011). As a result, manure allocation reflects not only crop nutrient demand but also local crop–livestock production structures. Some crop systems may have high manure shares because they are embedded in mixed crop–livestock systems, whereas other high-input crop systems rely mainly on synthetic fertilizer because manure supply is spatially disconnected from crop production (Wang et al., 2026). This spatial mismatch is particularly relevant for evaluating manure recycling, nutrient circularity, and mitigation options, because increasing manure use is not simply a matter of replacing N fertilizer globally; it depends on whether manure production is spatially close to cropland, whether crops can efficiently use manure nutrients, and whether transport and nutrient-management constraints can be overcome (Li et al., 2012). Therefore, this dataset can help identify regions where manure recycling is limited by spatial mismatch between livestock and crop production.

The increasing contribution of horticultural crops, oil crops, and some legumes also demonstrates the need to move beyond a cereal-only view of global N management (Zhao et al., 2022). Although maize, rice, and wheat remain dominant in total N use, non-cereal crops have become increasingly important in the global N budget; for



example, vegetables and fruits may contribute disproportionately to local N surplus and water-quality risks (Goulding, 2000; Zhang et al., 2021). These crop-specific shifts would be difficult to diagnose from national fertilizer statistics alone. The crop-specific separation of $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ further strengthens the relevance of the dataset for process-based modelling. Different fertilizer N forms enter soil N transformations through different pathways and can influence nitrification, denitrification, nitrate leaching, and N_2O emissions (Zhu et al., 2025). The dataset shows that NH_4^+ -based fertilizer dominates global fertilizer N inputs, especially in major cereal systems, but NO_3^- -based fertilizers remain important in specific regions and crops. This distinction is useful for models that explicitly simulate soil mineral N pools. However, this component also has uncertainty because fertilizer product information is available mainly at the country level. In this study, country-level fertilizer-form proportions were applied across crops within each country, which is necessary given current data limitations but may not fully capture crop-specific product choices by farmers. Overall, this dataset converts national and sub-national N statistics into a long-term, crop-specific, and spatially explicit representation of N inputs. This makes it possible to assess N use efficiency and environmental losses relative to N management (Cassman et al., 2002). At the same time, the crop-specific estimates should be interpreted in light of uncertainties in the underlying harvested-area maps, fertilizer allocation procedures, fertilizer-form assumptions, and manure availability constraints. Despite these limitations, its primary utility lies in serving as optimized input for global biogeochemical modeling and large-scale N budget assessments, rather than as a product for field-scale fertilizer recommendations.

4.3 Uncertainty and limitations in crop-specific N input reconstruction

Several sources of uncertainty remain in the reconstruction of the crop-specific N input dataset (Figs. S6-S9). These uncertainties arise from both the statistical datasets used as constraints and the spatial allocation assumptions to transform national and sub-national totals into gridded crop-specific time series. Our dataset should be interpreted as a spatially explicit reconstruction that integrates available statistical data on crop-specific fertilizer inputs, manure inputs, and crop area, rather than as a direct survey of field-scale N management. The first source of uncertainty is associated with the crop-specific allocation of synthetic N fertilizer. Long-term crop-specific fertilizer N statistics are not available for some countries, and sub-national statistics are also spatially and temporally incomplete. We therefore relied on a combination of national fertilizer totals, sub-national allocation ratios, harvested-area maps, and regression-based estimates to reconstruct crop-specific fertilizer inputs. In regions lacking observed fertilizer rates, missing values were inferred using neighboring administrative units by assuming that they are in the same situation. This approach allows the construction of a complete global time



series, but it also assumes that nearby administrative units with similar crops and socioeconomic conditions have comparable fertilizer management. Such assumptions may underrepresent fine-scale variability caused by local fertilizer access, farm size, irrigation, soil fertility, extension services, and farmer management decisions (Liu et al., 2022). A second limitation relates to the use of harvested areas as the spatial basis for fertilizer and manure rate calculation, which might slightly overestimate application rates per cropland area because harvested areas exclude crop failure and abandoned fields. Because consistent, long-term, crop-specific planted-area datasets are not available at global scale, the use of harvested area in this study is consistent with the crop-area statistics available from FAO and most global crop mapping products. Future datasets would benefit from incorporating planted or sown areas where available, particularly in regions with crop failure risks. A third source of uncertainty is associated with the spatial reconstruction of manure inputs. Manure application is more difficult to map than synthetic fertilizer because it depends on livestock distribution, manure production, collection, storage, transport, and crop-livestock integration (Potter et al., 2010). We spatialized national manure totals using livestock-based manure availability, cropland distribution, and baseline manure application patterns for a single reference year. This constrained manure allocation by local availability and reduced unrealistic long-distance redistribution but could not fully capture management differences such as storage losses, grazing systems, and crop preferences (Godde et al., 2021). Therefore, uncertainties are likely larger in mixed crop-livestock regions and where manure markets or long-distance transport are important but poorly documented. In addition, N forms including $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ fractions were derived from country-level statistics and then applied to all crops within each country because crop-specific fertilizer product data are generally unavailable. This assumption may obscure differences in fertilizer form among crops, regions, and production systems (Davidson, 2012). Future improvements will accordingly require crop- and region-specific fertilizer product surveys on fertilizer types, timing, and splitting of fertilizer applications (Cui et al., 2021).

Uncertainty also arises from the crop distribution maps used to allocate N inputs. CropAtlas, SPAM, and other crop-area products provide essential spatial allocation weights, but they are themselves affected by uncertainties in cropland mapping, crop classification, statistical downscaling, and temporal interpolation or extrapolation (Kallenberg et al., 2026). These uncertainties propagate directly into crop-specific N input maps because fertilizer and manure amounts are distributed according to crop harvested areas. This is particularly important for crops with fragmented spatial distributions, multiple cropping systems, or limited remote-sensing reference data. Future work should incorporate more independent crop maps, explicitly distinguish crop ecotypes such as winter and spring wheat or single- and double-rice systems, and improve representation of cropping intensity and planted-area distributions. Despite these limitations, our reconstruction preserves the major large-scale patterns needed



for global modelling applications. These diagnostics help identify where the dataset is more reliable and where caution is needed, especially for regional interpretation or crop groups with sparse observations. Future improvements should prioritize the collection and harmonization of field-level and sub-national fertilizer survey data, especially in regions with limited data. In addition, incorporating distinctions among crop types such as winter and spring wheat, spring and winter maize, or single-, double-, and triple-cropping rice systems with explicit accounting for their spatially heterogeneous planting area distributions would substantially enhance the accuracy of N allocation. Moreover, integrating socio-economic factors such as fertilizer prices, policy incentives, and access to extension services could help better capture drivers of fertilizer use and identify leverage points for sustainable intensification. Better spatial data on livestock systems, manure transport, and manure application destinations would also reduce uncertainty in organic N allocation. As more high-resolution crop maps, planted-area datasets, and management surveys become available, future versions of the dataset could provide more accurate crop-specific N inputs to support sustainable N management at regional and global scales.

5 Data availability

The crop-specific N fertilizer and manure application rate datasets in this study are available at <https://doi.org/10.5281/zenodo.21364978> (Hao et al., 2026).

6 Summary

This study presents a global, annual, crop-specific dataset of N inputs from synthetic fertilizer and manure at $0.1^\circ \times 0.1^\circ$ resolution for 1961–2023 and further distinguishes N fertilizer into NH_4^+ -N and NO_3^- -N components based on fertilizer product information. By integrating national and sub-national statistics, the dataset reconstructs long-term crop-specific N input patterns across global croplands in the past six decades. Compared with existing global datasets, this product improves temporal continuity, crop specificity, and spatial details. Independent comparisons with survey-based datasets indicate that the reconstructed N application rates generally agree with observed crop-specific fertilizer use at national and sub-national scales. Nevertheless, uncertainties remain due to incomplete sub-national statistics, assumptions in spatial allocation, and limited crop-specific fertilizer product information and should be considered when applying the dataset to regional analyses. The dataset is primarily intended to support global and regional modelling applications, including crop-specific N budgeting, N use efficiency assessment, nutrient surplus and deficit analysis, soil N dynamics, and greenhouse gas emission modelling, particularly for N_2O . It can provide improved N input data for process-based agroecosystem and terrestrial biosphere models, such as DLEM (You et al., 2022), ORCHIDEE-CNP (Sun et al., 2021), BRTSim (Pasut et al.,



2021) and modelling frameworks used in the Global Carbon Budget (Friedlingstein et al., 2025) or Global N₂O Budget (Tian et al., 2024), and Nitrogen Model Intercomparison Project (NMIP) (Tian et al., 2018). Overall, this dataset provides a consistent and spatially explicit foundation for studying long-term cropland N dynamics and evaluating N management strategies globally.

Author contributions

HT conceived and designed this work. WH performed the study and developed the dataset. HS, XY, NP, and SP contributed to data curation and methodology. FNT, WA, MB, PC, FM, KN, AU, and FZ contributed data resources, domain expertise, and interpretation of the results. All authors contributed to writing the paper.

Competing interests

Some authors are members of the editorial board of the journal Earth System Science Data.

Disclaimer

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