

Input uncertainty overshadows cropland greenhouse gas accounting and mitigation tracking

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Input uncertainty overshadows cropland greenhouse gas accounting and mitigation tracking

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Abstract

Tracking agricultural greenhouse gas (GHG) mitigation to achieve the Paris Agreement goal requires robust emission baselines. Here we test the impact of choice of input datasets on emission baselines. We tested 1,284 source-specific input-dataset combinations across 11,100 gridded emission maps through an IPCC Tier 1/2 framework at 5 arcmin resolution, covering cropland GHG from nitrogen inputs (synthetic fertilizer, manure and crop residues), rice paddies, and drained peatland, to characterize the dataset-driven uncertainty. The range of total emissions across input datasets was 1.9 Gt CO₂eq yr⁻¹, comparable to the central estimate of total cropland GHG emissions circa 2020 (2.4 Gt CO₂eq yr⁻¹) and to the assessed annual technical mitigation potential of these sources by 2050 (1.8 Gt CO₂eq yr⁻¹). For countries responsible for 99% of rice CH₄, 72% of nutrient N₂O and 50% of peatland emissions among those with an assessed mitigation potential, the variation of national emission estimates across input datasets exceeded the country's technical mitigation potential for the same source. This makes it extremely challenging to confidently monitor reductions in emissions from these sources. Activity dataset choice was the leading contributor to variance for every source (84-100% of ANOVA sum-of-squares), substantially exceeding climate, hydrology, or emission-factor zonation. The uncertainty carried a distinct spatial fingerprint, concentrated in identifiable sub-national hotspots: the Indo-Gangetic Plain for nutrient N₂O, monsoon-Asia rice basins for CH₄, and tropical peat-forest margins for peatland CO₂. These findings show

an urgent need to harmonize and standardize agricultural activity datasets, because consistent input data are a prerequisite to reliably track national cropland mitigation.

Main

Achieving the Paris Agreement’s primary goal of holding global warming “well below 2 °C above pre-industrial levels” requires coordinated and accountable emission reductions across both fossil-fuel and land-based sectors^{1,2}. Following current policies, the annual emission gap to remain below 2 °C by 2035 is estimated at 21 (9-26) Gt CO₂eq³. The land-based sector of agriculture, forestry, and other land uses (AFOLU) has expanded and intensified throughout the past century and now accounts for around 6.5 Gt CO₂eq yr⁻¹ (~11%) of global net anthropogenic GHG emissions³, of which approximately 2.5 Gt CO₂eq yr⁻¹ comes from cropland circa 2020⁴. The Glasgow and Dubai climate decisions identify agricultural emissions as near-term mitigation priorities². More than 120 (~65%) countries include agricultural mitigation options in their Nationally Determined Contributions (NDCs)⁵. Agriculture’s mitigation potential is estimated at roughly 2 Gt CO₂eq yr⁻¹ by 2035³.

Tracking collective progress under these commitments rests on the Paris Agreement’s Global Stocktake (Article 14), the periodic assessment that quantifies the emission gap between current ambition and the “well below 2 °C” trajectory and motivates strengthened NDCs in successive rounds⁶. The quantification of the emission gap depends on an accurate aggregated baseline, that is a global emission trajectory built up from national and regional contributions. When the same source is computed using different input datasets, the aggregated baseline carries a material uncertainty component that propagates directly into the assessment of the emission gap, and therefore into the case for strengthening NDCs in the next round. When this baseline uncertainty is large relative to the abatement being tracked, it can obscure the accounting of collective progress.

Existing assessments of cropland GHG uncertainty have focused largely on IPCC emission factor ranges and process-model spread^{4,7–10}. Model intercomparisons show global estimates of cropland direct N₂O, rice CH₄, and drained peatland CO₂ vary by 35–50%^{8,11,12}, and IPCC Tier 1/2 factors carry 30–200% uncertainty ranges¹³. The complementary contribution from input datasets, produced by heterogeneous methods (e.g. statistical downscaling, machine learning, expert rules, national inventories) that can disagree both in totals and in spatial allocation^{4,14–16}, has received less systematic attention at the global and regional scales. Yet the input products themselves disagree substantially in national totals and in how they distribute activity data across space. Across products, global estimates of cropland nitrogen (N) fertilizer use, manure application, crop residue handling, and peatland extent diverge by 10–60%⁴. Such disagreement can directly propagate into emissions estimates.

No prior study has quantified how the choice of input dataset, with the same emission model, propagates uncertainty across all major cropland GHG sources on a common spatial framework. Here we systematically characterize input data robustness across the five major cropland GHG sources: synthetic fertilizer, manure, and crop residue direct and indirect N₂O; rice paddy CH₄; and drained peatland cultivation CO₂, CH₄, N₂O, in an integrated assessment. We compile multiple datasets per source and propagate the full combinatorial space of input choices through an IPCC Tier 1/2 framework at 5 arcmin (~10 km) resolution *circa* 2020 so dataset choices can be compared on a common basis across sources and input layers. We quantify how dataset choice propagates uncertainty into emission estimates at global, regional, and pixel scales, and benchmark country-level ranges against the mitigation potentials reported by Roe et al¹⁷. The analysis identifies the input layers whose disagreement contributes most to each source, the geographies where that disagreement concentrates, and the targeted data investments that would most efficiently reduce uncertainty in emissions accounting for agriculture.

Activity input choice dominates variance

Across all combinations, the central estimate of total cropland GHG emissions is 2.4 Gt CO₂eq yr⁻¹ *circa* 2020, with a dataset-driven range of 1.9 Gt (minimum-maximum: 1.7-3.6 Gt; relative range, i.e. range divided by mean: 81%) across input combinations (Fig. 1, Table 1). Two sources dominate the budget: drained peatlands emit 0.91 Gt CO₂eq yr⁻¹ (0.51-1.7 Gt, 129%) and rice paddies 0.76 Gt CO₂eq yr⁻¹ (0.55-1.14 Gt, 77%). Each carries a dataset-driven range comparable to its central estimate. Fertilizer N₂O (direct + indirect) is the third largest source at 0.5 Gt CO₂eq yr⁻¹, yet its range across datasets is comparatively narrow (0.06 Gt, 11%). Manure and crop residue N₂O are smaller absolute sources (~0.1 Gt each) but proportionally far more uncertain (51–58%). This contrast reflects a methodological commonality: three of the four fertilizer products (Cao, Coello and Adalibieke) are anchored to FAOSTAT and IFASTAT national fertilizer consumption statistics and NPKGRIDS is validated against them, so all four converge to within ~4% on global totals, whereas manure and crop residue datasets have no equivalent global anchor, so inter-product differences propagate directly into emission totals. Regional decomposition shows that East Asia & Pacific and South Asia together account for more than half of every source's dataset-driven range, reflecting the concentration of rice cultivation, intensive fertilizer use, and peatland conversion in monsoon Asia (Fig. 1b-f). Europe & Central Asia and North America additionally show large disagreements among manure and crop residue products for N₂O (Supplementary Figure 2).

ANOVA decomposition of the 1,284 input-dataset combinations (Methods) reveals a consistent pattern across sources: activity dataset choice contributes more variance than climate forcing or hydrology product for every source examined (Extended Table 1). Across all five sources, fertilizer products account for 18% of the variance, peatland

112 products for 38%, and rice calendar for 19%, together 76% of the total variance. The
113 magnitude of the dominant driver differs by source.

114 For the combined N₂O budget (1,152 combinations spanning four fertilizer products, two
115 manure products, two residue products, four cropland extent products, six climate
116 models, three runoff products and two irrigation maps), 88% of the variance in total N₂O
117 is attributable to N input product choice and 10% to climate model (Extended Table 1).
118 Of the total N₂O variance, fertilizer products, despite their relatively narrow uncertainty
119 range, account for 61% owing to their dominant absolute share, while crop residue and
120 manure products each contribute 14%.

121 For rice CH₄, growing-season calendar choice (RiceAtlas, Hybrid-MARC and Hybrid-
122 RICA) explains 60% of variance, manure product 26%, five rice area products
123 (SPAM2020 V2, CROPGRIDS, Coello, Adalibieke and GlobalRice20) 14%, and water-
124 regime source less than 0.1%. The small water-regime variance is constrained by data
125 availability: the two currently available water-regime products (Cao and Carlson) draw
126 on closed national rice-system statistics for major Asian producers, so their agreement at
127 the country scale primarily reflects shared inputs rather than independent convergence.
128 RiceAtlas produces systematically higher emissions than the Hybrid calendars across all
129 five area products, primarily because it records additional multi-cropping systems in
130 subtropical and tropical Asia, extending the flooding duration before and during
131 cultivation, as reflected in the uncertainty hotspots across monsoon Asia (Fig. 4a;
132 Supplementary Section 5).

133 For drained peatlands, the peatland-extent product alone accounts for nearly all variance,
134 with the six peatland maps (FAO Organic Soil, GFW, GPM, Cao, PEATMAP and
135 PeatML) spanning a factor of three. The overlap with cropland, controlled jointly by the
136 peatland-extent and cropland products, drives the resulting spread in drained-peatland
137 area.

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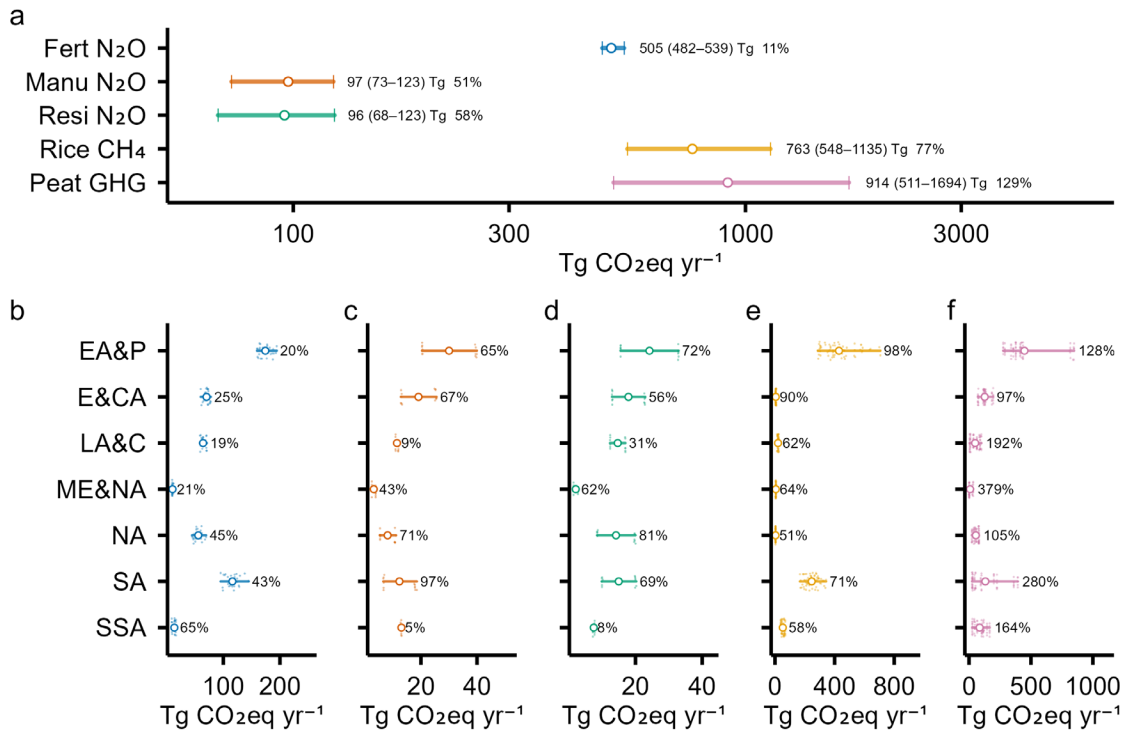


Figure 1. Global and regional cropland GHG emissions ranges from input dataset choice. (a) Global dataset-driven range for five sources (note that the x-axis uses a logarithmic scale). (b–f) Regional breakdown by World Bank region for each source. Horizontal segment represents the range from minimum to maximum emissions, open circle is the mean, and jittered dots represent individual combinations. Labels at right of bar show mean (min–max) Tg CO₂eq yr⁻¹ and relative range (%). Region abbreviations: EA&P, East Asia & Pacific; E&CA, Europe & Central Asia; LA&C, Latin America & Caribbean; ME&NA, Middle East & North Africa; NA, North America; SA, South Asia; SSA, Sub-Saharan Africa.

Table 1. Global cropland GHG emissions from five sources: mean, range across input-dataset combinations, and relative range (range divided by mean) across input dataset choices. The five-source total sums each source's independent minimum and maximum.

Source	Pathway	Mean Tg CO ₂ eq	Min Tg CO ₂ eq	Max Tg CO ₂ eq	Range Tg CO ₂ eq	Relative range %
Fertilizer N ₂ O	Source total	506	483	540	57	11
Fertilizer N ₂ O	Direct (non-rice)	321	302	347	45	14

Fertilizer N ₂ O	Direct (rice)	35	33	37	4.4	13
Fertilizer N ₂ O	Leaching	111	108	114	5.4	5
Fertilizer N ₂ O	Volatilization	38	36	42	5.8	15
Manure N ₂ O	Source total	98	73	123	49	51
Manure N ₂ O	Direct (non-rice)	47	36	59	23	48
Manure N ₂ O	Direct (rice)	6	4.4	8.1	3.7	60
Manure N ₂ O	Leaching	25	19	32	13	51
Manure N ₂ O	Volatilization	19	14	24	10	55
Residue N ₂ O	Source total	96	69	124	55	58
Residue N ₂ O	Direct (non-rice)	56	41	71	29	53
Residue N ₂ O	Direct (rice)	8.4	4.6	12	7.5	89
Residue N ₂ O	Leaching	31	22	41	18	59
Rice CH ₄	Source total	763	548	1135	588	77
Peatland GHG	Source total	914	511	1694	1183	129
Peatland GHG	CO ₂	816	455	1518	1063	130
Peatland GHG	CH ₄	27	16	49	33	122
Peatland GHG	N ₂ O	71	40	127	87	123
All 5 sources	Total (envelope)	2376	1684	3616	1932	81

150

151 Extended Table 1. Attribution of dataset-driven uncertainty to input drivers. Each row is
152 an input driver within an emission pathway. All values are outputs of the input-dataset
153 combination ensemble. Driver range is the mean range in emissions (Tg CO₂eq yr⁻¹)
154 across that driver's options when all other inputs are held fixed, averaged over all
155 combinations of the other inputs. Pathway % is the driver's share of the ANOVA sum of
156 squares within the pathway, normalized so that the drivers of each pathway sum to 100%.
157 Source %, Roe class % and Total % weight these shares by the pathway's mean emission
158 relative to the source, to the Roe et al. (2021) mitigation category (nutrient N₂O, rice
159 CH₄, drained peatland GHG) and to the five sources total, respectively.

Roe class	Source	Pathway	Input driver	Driver range Tg CO ₂ eq	Pathway %	Source %	Roe class %	Total %
Nutrient	Fertilizer	Direct N ₂ O (non-rice)	Climate model	16	19	12	8.6	2.5
Nutrient	Fertilizer	Direct N ₂ O (non-rice)	Crop extent	2.2	0.2	0.1	0.09	0.03
Nutrient	Fertilizer	Direct N ₂ O (non-rice)	Fertilizer product	26	81	51	37	11
Nutrient	Fertilizer	Direct N ₂ O (rice)	Climate model	0.3	0.5	0.03	0.02	0.01
Nutrient	Fertilizer	Direct N ₂ O (rice)	Crop extent	0.9	0.3	0.02	0.02	0
Nutrient	Fertilizer	Direct N ₂ O (rice)	Fertilizer product	2.7	99	6.9	5.0	1.5
Nutrient	Fertilizer	Indirect N ₂ O (leaching)	Climate model	0.01	0	0	0	0
Nutrient	Fertilizer	Indirect N ₂ O (leaching)	Crop extent	0.7	0.2	0.05	0.03	0.01
Nutrient	Fertilizer	Indirect N ₂ O (leaching)	Fertilizer product	5.0	90	20	14	4.2
Nutrient	Fertilizer	Indirect N ₂ O (leaching)	Runoff dataset	1.7	10	2.2	1.6	0.5
Nutrient	Fertilizer	Indirect N ₂ O (volatilization)	Climate model	2.2	23	1.7	1.2	0.4
Nutrient	Fertilizer	Indirect N ₂ O (volatilization)	Crop extent	0.2	0.2	0.02	0.01	0
Nutrient	Fertilizer	Indirect N ₂ O (volatilization)	Fertilizer product	3.4	77	5.8	4.2	1.2
Nutrient	Manure	Direct N ₂ O	Climate model	0.2	0	0	0	0
Nutrient	Manure	Direct N ₂ O	Crop extent	0.4	0.2	0.1	0.02	0
Nutrient	Manure	Direct N ₂ O	Manure product	26	100	54	7.6	2.2
Nutrient	Manure	Indirect N ₂ O (leaching)	Crop extent	0.3	0.2	0.05	0.01	0

Nutrient	Manure	Indirect N2O (leaching)	Manure product	12	100	26	3.6	1.1
Nutrient	Manure	Indirect N2O (leaching)	Runoff dataset	0.7	0.2	0.05	0.01	0
Nutrient	Manure	Indirect N2O (volatilization)	Climate model	0.5	0.1	0.02	0	0
Nutrient	Manure	Indirect N2O (volatilization)	Crop extent	0.2	0.2	0.04	0.01	0
Nutrient	Manure	Indirect N2O (volatilization)	Manure product	9.7	100	19	2.7	0.8
Nutrient	Residue	Direct N2O	Climate model	0.3	0	0	0	0
Nutrient	Residue	Direct N2O	Crop extent	0.3	0.2	0.1	0.02	0.01
Nutrient	Residue	Direct N2O	Residue product	36	100	67	9.2	2.7
Nutrient	Residue	Indirect N2O (leaching)	Crop extent	0.2	0.2	0.07	0.01	0
Nutrient	Residue	Indirect N2O (leaching)	Residue product	18	100	33	4.5	1.3
Nutrient	Residue	Indirect N2O (leaching)	Runoff dataset	0.8	0.2	0.07	0.01	0
Peatland	Peatland	Peatland GHG	Climate model	2.4	0	0	0	0
Peatland	Peatland	Peatland GHG	Cropland area	21	0	0	0	0
Peatland	Peatland	Peatland GHG	Peatland product	1162	100	100	100	38
Rice	Rice	Rice CH4	Area product	151	14	14	14	4.4
Rice	Rice	Rice CH4	Manure product	149	26	26	26	8.4
Rice	Rice	Rice CH4	Rice calendar	254	60	60	60	19
Rice	Rice	Rice CH4	Water regime source	7.4	0	0	0	0

Dataset uncertainty ranges are of the same order of magnitude as estimated mitigation potential at national scale

The Global Stocktake sums national baselines and mitigation pledges into a single global trajectory to guide policy. The dataset-driven uncertainty in any country's baseline counts the same as real abatement, obscuring the next round of mitigation pledges in the aggregated accounts. We benchmark each country's source range against its technical mitigation potential (the full biophysical ceiling) and cost-effective mitigation potential (the subset achievable below US\$100 per tCO₂eq, a more realistic and actionable target for policy) for the matching category based on an integrated assessment model study¹⁷.

Summed across the five emission sources, the cropland dataset-driven range (1.9 Gt CO₂eq yr⁻¹) is comparable to the annual mitigation potential of the entire agriculture sector (crop, livestock, and agroforestry systems) expected to be achieved by 2035³, and exceeds the annual technical potential of these five sources by 2050 estimated by Roe et al. (0.99 Gt CO₂eq yr⁻¹ cost-effective and 1.8 Gt CO₂eq yr⁻¹ technical mitigation) (Fig. 2). Rice CH₄ ranges by 0.59 Gt CO₂eq yr⁻¹, about 3.4 times the cost-effective rice mitigation potential (0.17 Gt) and roughly 2.4 times the technical potential (0.24 Gt). Nutrient N₂O spans 0.16 Gt yr⁻¹ (fertilizer, manure, and crop residue; 0.74× its cost-effective potential and 0.65× its technical potential), while peatland spans 1.18 Gt yr⁻¹ (2.0× and 0.9×).

Global aggregates understate the problem, because the largest emitters are disproportionately affected. Against technical mitigation potential, countries whose dataset-driven range exceeds the matching mitigation potential account for 72% of nutrient N₂O, 99% of rice CH₄ and 50% of peatland emissions among countries with an assessed mitigation potential; against cost-effective potential, the corresponding shares are 73%, 99% and 58%, respectively (Fig. 2). For rice, every major producer is affected: China (range 199 Tg versus 38 Tg technical potential; 5.2 times), Indonesia (79 versus 26 Tg; 3.0 times), India (129 versus 54 Tg; 2.4 times), and Bangladesh (36 versus 27 Tg; 1.3 times). For peatland, the exceedance concentrates in the tropical-peat economies of Nigeria and the Democratic Republic of the Congo, whereas China and the United States account for most of the affected emissions. In these countries the dataset-driven range is large relative to the assessed potential, so the contribution they make to the collective total is sensitive to the dataset chosen, underscoring the value of consistent input data when national estimates are aggregated.

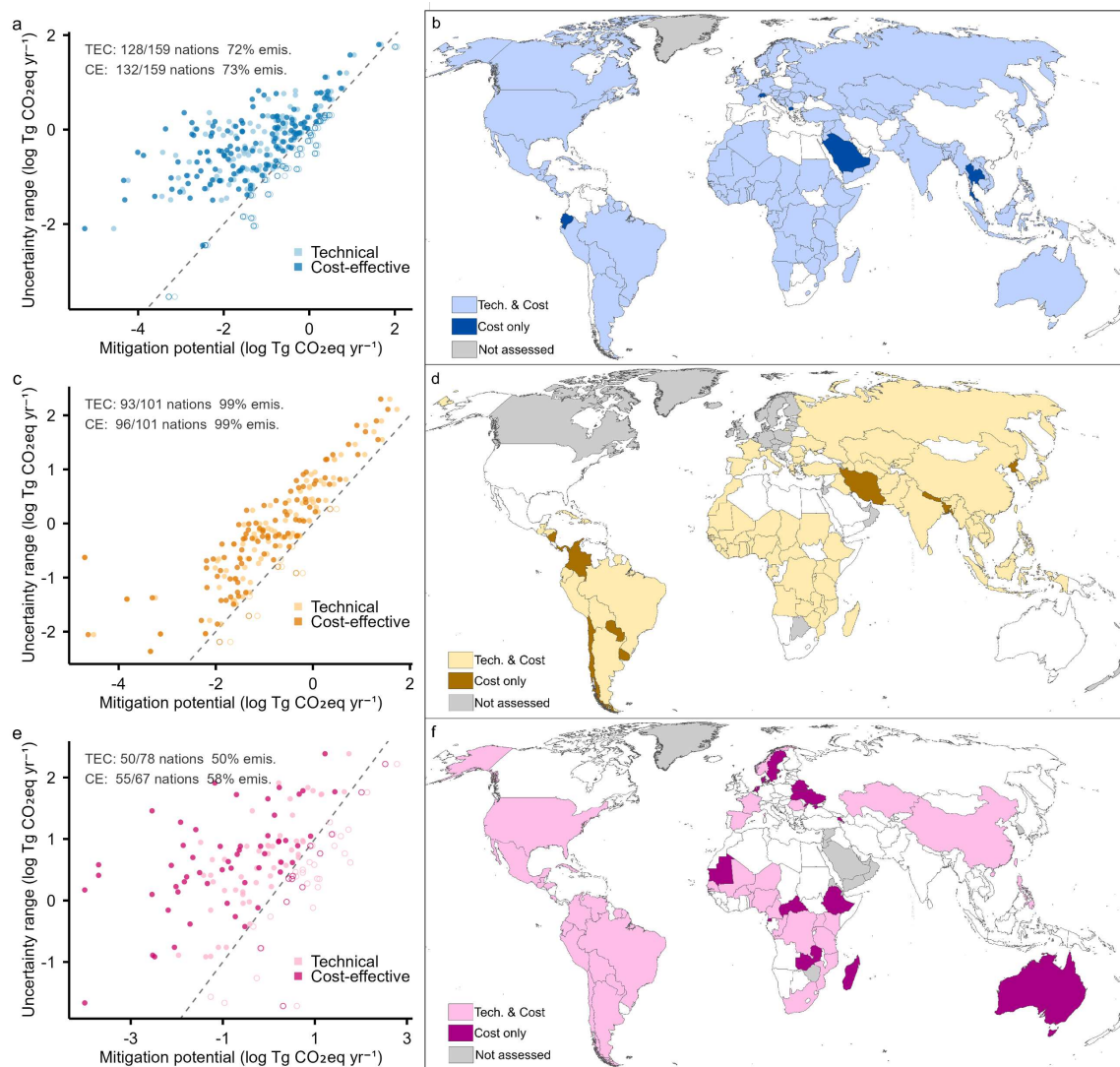


Figure 2. Country-level dataset uncertainty relative to mitigation potential, by emission source. Scatter of country-level dataset-driven uncertainty range vs. country mitigation potential from Roe et al. (2021) on log-log axes, nutrient N₂O (a), rice CH₄ (c), drained peatland (e). Light shade represents technical potential (any cost), dark shade represents cost-effective potential (below US\$100/tCO₂eq). Filled circles above the 1:1 diagonal are nations whose dataset-driven range exceeds their mitigation potential. Panel annotations report the count of nations and share of source emissions affected; counts differ between technical and cost-effective potential where Roe et al. (2021) report cost-effective potential for fewer countries (e). (b, d, f) Corresponding maps of nations whose dataset-driven range exceeds the mitigation potential: light shade, both technical and cost-effective potential; dark shade, cost-effective potential only; grey, not assessed.

Spatial hotspots of emission disagreement

For nutrient N_2O , dataset disagreement broadly tracks the global crop- and livestock-dense agricultural zones (Fig. 3). Hotspots of fertilizer N_2O uncertainty ($> 5 \text{ Gg CO}_2\text{eq yr}^{-1}$) concentrate over eastern China, Southeast Asia, South Asia, the U.S. Midwest, southern Brazil, and parts of Europe, driven predominantly by disagreement among fertilizer products (Fig. 3a). Climate models contribute to considerable uncertainty along the wet/dry zone boundaries in central China and India, northern Europe, and the U.S. Midwest. Manure and crop residue N_2O disagree ($> 0.5 \text{ Gg CO}_2\text{eq yr}^{-1}$) across similar regions of Asia, Europe, North America, and southern Brazil, but at smaller magnitude than fertilizer and dominated by the manure and crop residue products (Fig. 3b,c).

For rice CH_4 , the hotspot pattern ($> 30 \text{ Gg CO}_2\text{eq yr}^{-1}$) follows the calendar-driven variance (Fig. 4a, Supplementary Section 5). Because harmonized calendar comparisons were restricted by data availability, calendar-driven discrepancies were evaluated specifically within monsoon Asia, meaning global rice CH_4 variance is conservatively constrained. Disagreement concentrates in the multi-cropping rice systems of monsoon Asia: the Yangtze, Pearl, and Mekong basins, the Ganges-Brahmaputra delta, and the Philippines, Java and South Sumatra in insular Southeast Asia, where RiceAtlas resolves additional short-season crops that the Hybrid calendars miss.

For drained peatland, disagreement is the most spatially extensive of the five sources in both extent and intensity (Fig. 4b, Supplementary Section 6). Across the major tropical peat domains: equatorial insular Southeast Asia (Indonesia and Malaysia), the Congo Basin, and the Niger delta, the six peatland products diverge by more than $50 \text{ Gg CO}_2\text{eq yr}^{-1}$ per pixel. Because they differ both in peatland distribution and in the per-pixel area density, the disagreement is broad and diffuse rather than confined to sharp boundaries, extending across northeastern China, central India, much of Europe, the northern U.S., Canada, and southern Brazil with $10\text{-}50 \text{ Gg CO}_2\text{eq yr}^{-1}$ discrepancies. It is pixel-scale divergence in cropland-peatland overlap that propagates into the large global product spread.

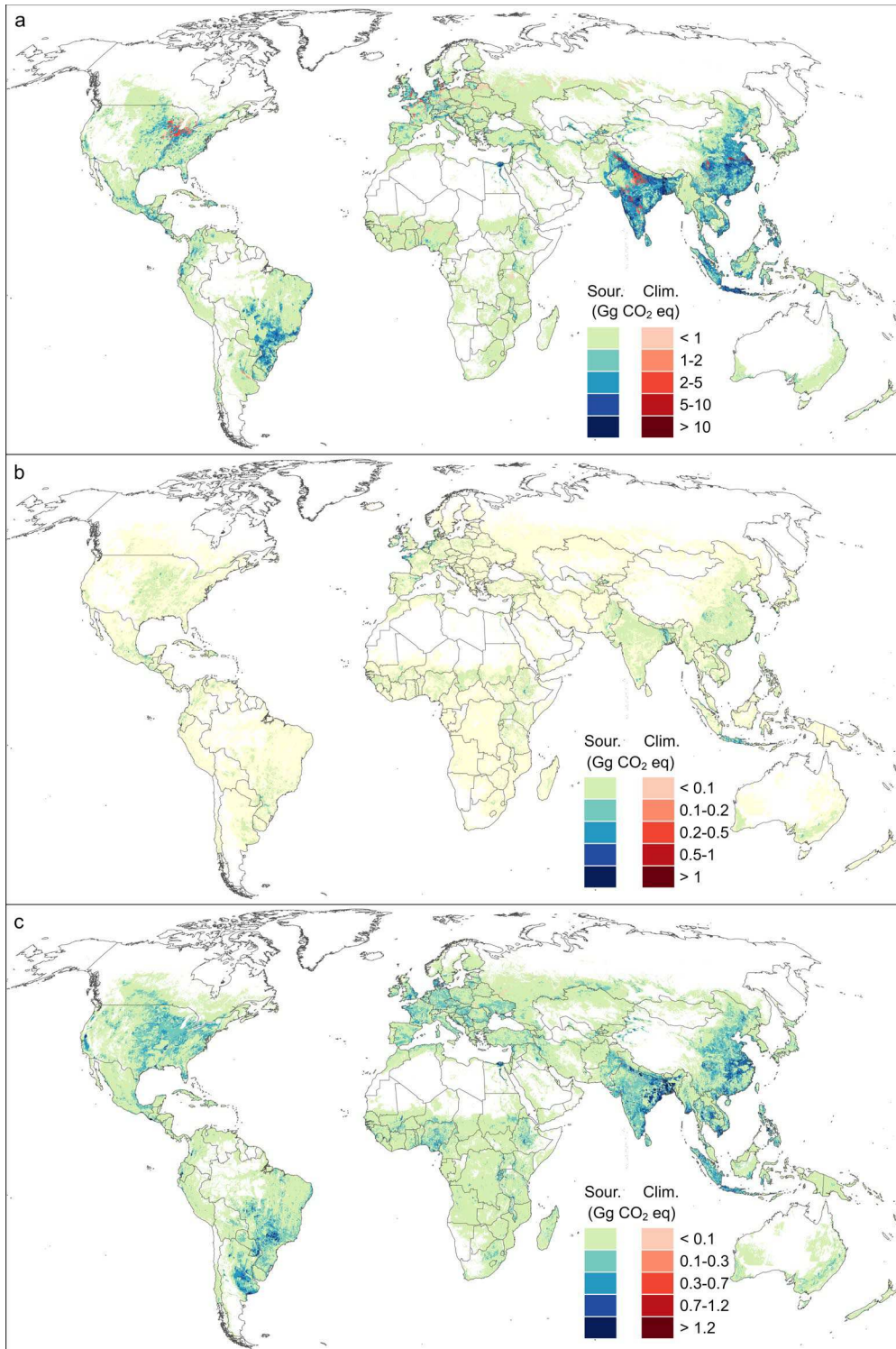


Figure 3. Spatial fingerprint of input uncertainty for cropland N_2O . Maps of uncertainty range by dominant factors for (a) fertilizer N_2O , (b) manure N_2O , and (c) crop residue N_2O . Source (Sour.; bluish) refers to uncertainty dominated by the synthetic fertilizer, manure or crop residue dataset; climate (Clim.; reddish) refers to uncertainty dominated by climate zone. Colour intensity indicates the magnitude of the uncertainty range.

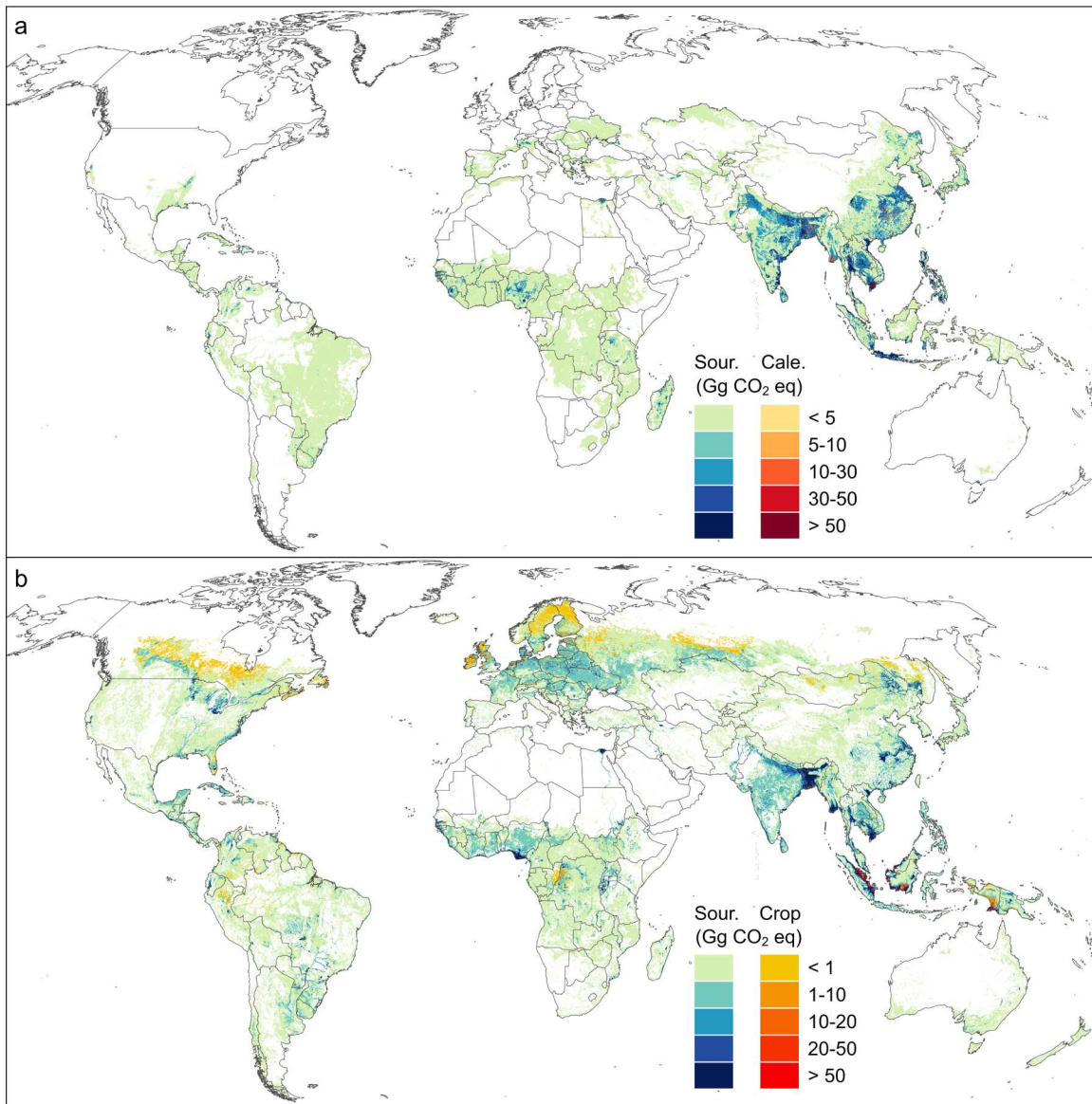


Figure 4. Spatial fingerprint of input uncertainty for cropland CH₄ and peatland GHG. Maps of uncertainty range for (a) rice CH₄ and (b) drained peatland GHG. Source product (Sour.; bluish) refers to uncertainty dominated by the rice area and peatland datasets, respectively; calendar (Cale.; reddish), by the rice calendar; crop (Crop; reddish), by the cropland dataset. Colour intensity indicates the magnitude of the uncertainty range.

Spatial aggregation shapes emissions source uncertainty

How a dataset is spatially resolved, from pixel values, through subnational or national aggregation, to national crop-specific constraints, changes the uncertainty it carries. We examine this from two complementary angles: the magnitude of the change in estimated emissions at each aggregation or constraint level (Fig. 5), and the spatial structure of

where the products actually diverge (Fig. 6, Supplementary Sections 3-11). They show both how much uncertainty a given data treatment removes and where the residual disagreement remains, informing the data improvement that would most directly translate into reduced uncertainty.

The four fertilizer products, each built independently but drawing largely on FAOSTAT/IFASTAT statistics, converge to within ~4% of one another (Supplementary Table 3), so the residual uncertainty in fertilizer N₂O may arise primarily from how that well-constrained total is distributed in space rather than from disagreement in its magnitude. For fertilizer N₂O, the aggregation level on which a product is built matters more than is commonly assumed. Because different aggregations redistribute the same national total across space, it shifts the estimate wherever emissions are resolved with spatially explicit factors, as in IPCC Tier 2 and Tier 3 accounting. The within-product variations range from a CV of 0.03-0.14% (Coello) and 0.1-0.7% (NPKGRIDS) to an order of magnitude larger for Cao (0.5-1.0%) and Adalibieke (1.3-2.0%; Fig. 5a), reflecting how much each product's spatial distribution changes between aggregation levels. The effect is unevenly distributed in space: re-aggregation shifts regional totals by up to several percent, particularly where cropland spans contrasting wet and dry climate zones, such as North America and South Asia (Fig. 5b). The latitudinal view sharpens the picture, the four products agree closely on the shape of the fertilizer N₂O profile but diverge in magnitude at the Northern subtropical peak around 20-40° N (Fig. 6a,b), the same intensively cropped belt that dominates the global total. This challenges the common assumption that national statistics provide an adequate constraint: applying a national average rate uniformly misplaces nitrogen within countries that propagates artificial spatial variance into spatially explicit Tier 2 and Tier 3 estimates. The priority is therefore to extend subnational disaggregation, paired with field- or survey-based validation so that finer resolution does not impart false confidence.

For rice CH₄, calendar choice dominates the uncertainty (60% of variance), but a second layer in the water-regime dimension is masked by data limitations and country-level aggregation. Allowing within-country water-regime shares to vary widens national ranges by 3-7% for major producers: 11 Tg CO₂eq yr⁻¹ in India, 4.6 Tg in China, 2.8 Tg in Viet Nam and 3.8 Tg in Indonesia (Fig. 5c,d). Maximum- and minimum-redistribution profiles remain similar across latitude, but local differences exceed 5 Gg CO₂eq yr⁻¹ per pixel in monsoon Asia (Fig. 6c,d), indicating that local water regime uncertainty rearranges emissions within countries without changing their totals. As noted above, the small variance at aggregated scales attributed to water regime source reflects data limitations. Many Asian countries report a high adoption rate of multiple drainage practices, whereas many non-traditional rice producers simply assume continuously flooded conditions for the whole country. This suggests that the current water regime classification requires expanded regime classes to represent reality. Rice CH₄ uncertainty is therefore reducible along two axes: an observation-anchored growing-season calendar for the dominant term,

294 and better-resolved water-regime classifications and mapping for the within-country
295 distribution.

296 For drained peatland, spatial constraint has by far the largest effect. At the raw raster-
297 intersection level with no constraints, the six peatland-extent products span 511-1,672 Tg
298 CO₂eq yr⁻¹, a factor of 3.3 (Fig. 5e). Applying national peatland drainage constraints from
299 the UNEP Global Peatlands Assessment (UNGPA) compresses the spread to 908-1,083
300 Tg, a factor of 1.2, an 85% reduction in inter-product range obtained entirely from
301 existing national land-use statistics, with no new measurement. The spatial and latitudinal
302 disagreement explains why a residual persists even with the constraint: product
303 disagreement is bimodal, concentrated both in the northern temperate-boreal peatland belt
304 (45-55° N) and in the equatorial tropics (Fig. 6e,f), reflecting genuine differences in
305 where each product places peat rather than a uniform scaling offset. GFW at raw level
306 overcounts overlap by ~54% relative to its own nationally constrained estimate, and FAO
307 organic soils undercounts by ~44%. National constraints reconcile the totals but not the
308 placement, so peatland is at once the source whose magnitude is most readily narrowed
309 and the one whose spatial attribution remains least certain.

310 One cross-cutting input layer runs through all three source groups: cropland distribution.
311 The spatial allocation of nutrient N depends on the cropland map used to identify cropped
312 pixels and crop types; rice CH₄ depends on the rice extent product; and drained-peatland
313 GHG depends on the intersection of cropland and peatland extent. In our experiment, the
314 five cropland and rice distribution products (SPAM2020 V2, CROPGRIDS, Coello,
315 Adalibieke, and GlobalRice20) appear as the area dimension in rice CH₄, and also
316 condition the spatial pattern of nutrient N₂O and drained peatland GHG. Distributing the
317 same N inventory across the four cropland products changes national and global nutrient
318 N₂O totals by less than 1%, indicating that N-input rate product, rather than the cropland
319 extent, drives uncertainty in the source totals. However, the cropland product reorganizes
320 where N falls within countries and across climate zones, which matters for spatially
321 explicit Tier 2 and Tier 3 estimates and for local mitigation and verification. Harmonizing
322 cropland distribution datasets would therefore improve local attribution across nutrients,
323 rice, and peatland simultaneously, a longer-term complement to the source-specific
324 priorities (calendars, manure/ crop residue methodology, peatland national reporting)
325 identified above.

326

327

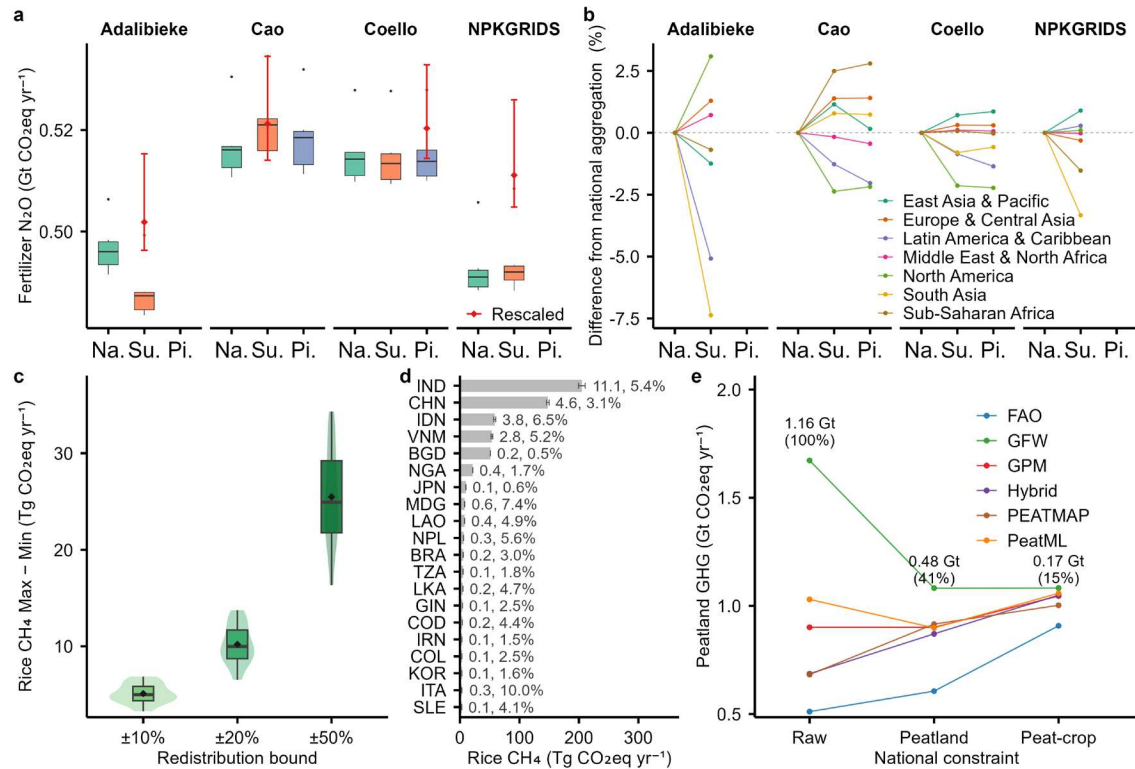


Figure 5. Spatial aggregation shapes uncertainty differently by source. (a) Fertilizer N_2O global emissions by spatial aggregation level (Na., national; Su., subnational; Pi., pixel), separately for the four fertilizer products. (b) Regional difference in fertilizer N_2O emissions (CO_2eq) from the national aggregation baseline (%) by product. (c) Rice CH_4 range under bounded within-country redistribution of water regimes, in which pixel-level regime fractions may deviate from the national fraction by up to $\pm 10\%$, $\pm 20\%$ or $\pm 50\%$ (0.1, 0.2, 0.5) while national totals are preserved. (d) Top 20 rice-emitting nations by mean emission, with the within-country water regime 0.5 redistribution range as error bars. (e) Drained peatland GHG across three national-constraint levels: raw, peatland-constrained, and peat-crop-constrained.

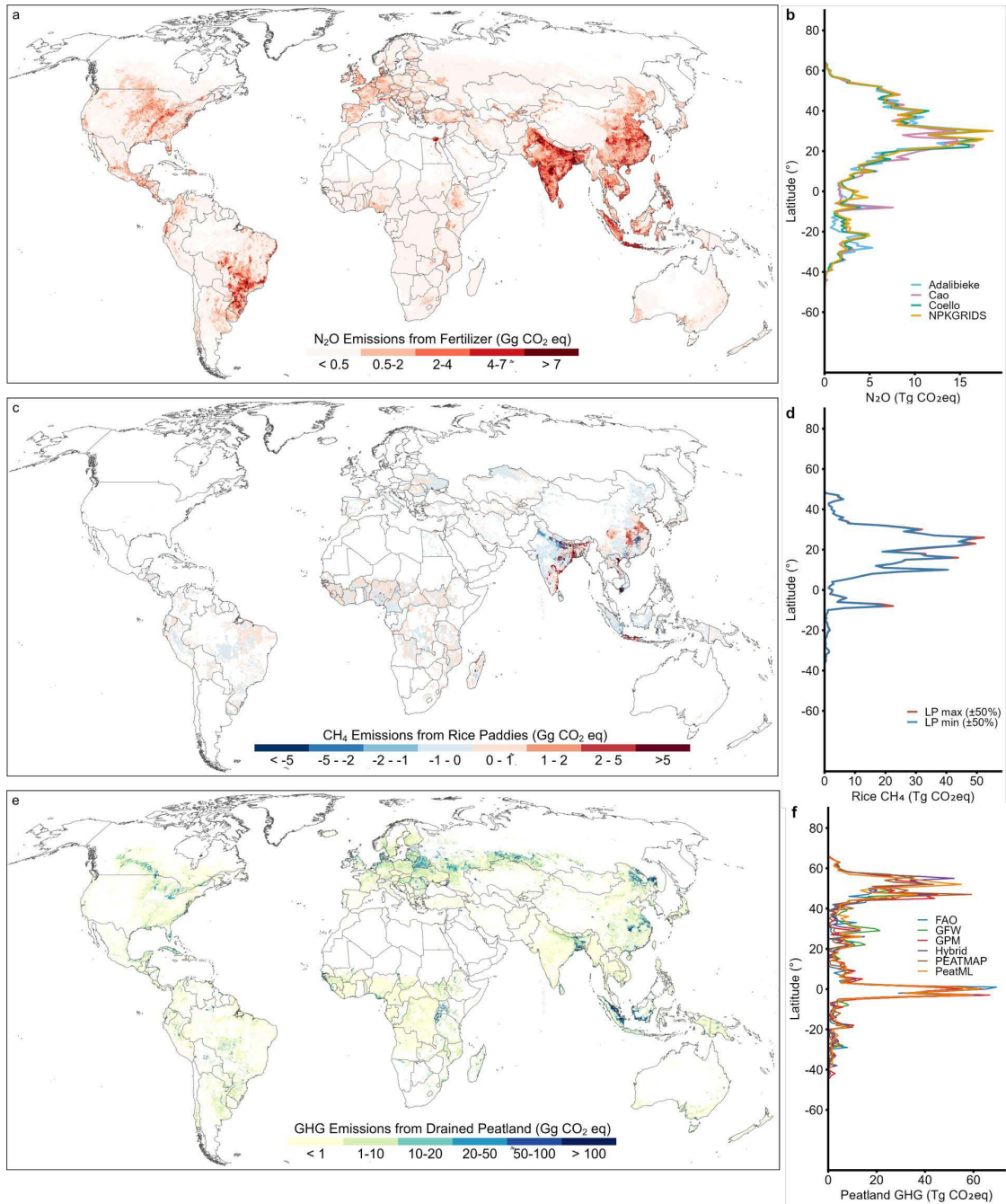


Figure 6. Spatial and latitudinal profiles of dataset-driven uncertainty. For each source, the pixel-level uncertainty range (max - min per pixel) is shown as a map alongside its latitude-band emission profile. (a, b) Fertilizer N₂O: range across the four fertilizer products with national total rescaled. (c, d) Rice CH₄: difference between the maximum and minimum within-country water regime redistribution scenarios at the ±50% bound (negative where the minimum scenario is locally higher). (e, f) Drained peatland GHG: range across the six extent products with UN national report constraints.

Discussion

Cropland GHG accounting has been refined largely through better emission factors and process models^{10,18,19}. With the underlying input data held fixed, process-model and emission-factor intercomparisons have reported considerable discrepancies, yet we find that the input layer alone generates a comparable or larger variability. Across all five sources, the choice among published, equally credible activity datasets moves the estimate more than the effects of climate forcing, hydrology, or emission factor zonation. At global and country level, the dataset-driven range is comparable to the mitigation potential assessed for meeting the primary Paris Agreement goal³. This makes it extremely challenging to confidently measure progress in mitigating GHG in cropland. The Global Stocktake builds its global trajectory by aggregating national contributions, so input-data spread of this magnitude can obscure the aggregate signal it is meant to detect⁶. The corollary is encouraging: since this uncertainty arises mainly from divergent input data rather than from poorly constrained biophysical processes, much of it can be reduced through systematic data harmonization and targeted observation, on a timescale relevant to the next Global Stocktake.

Datasets anchored to a shared statistical reference converge, narrowing the estimated uncertainty, whereas those lacking such an anchor diverge (Supplementary Table 3). Three of the four synthetic fertilizer products downscale FAOSTAT/IFASTAT national totals, and all four agree to within ~4% globally, whereas manure and crop residue products differ by 48-58% because they encode different livestock management and residue handling assumptions. Rice calendar products diverge where they resolve different cropping intensities, and the six peatland-extent maps differ by a factor of three because they combine soil, remote sensing, and inventory evidence in ways that are incompatible across products. These are structured and methodological differences rather than random error, implying that harmonization would reduce these biases.

Variability across datasets alone, however, does not equate to confidence. Datasets may agree because they are independently correct or merely because they share the same upstream inputs. They may diverge through genuine methodological diversity or through sparse observation. We therefore score each input against five evidence criteria: observational coverage, product independence, validation, temporal representativeness, and spatial-resolution adequacy, and read these alongside the measured variability, following the IPCC evidence agreement construct for confidence²⁰ (Extended Table 2). Synthetic fertilizer N₂O splits into two different claims under this framework. The national total it applies to is independently grounded in FAOSTAT/IFASTAT trade accounting and is genuinely robust, but the gridded pattern is associated with false confidence, since three of the four products allocate it spatially using the same single crop-distribution map. Manure and crop residue N₂O combine high variability with weak evidence. Across all products behind these two drivers, not one has been validated

389 against an independent field- or pixel-level N measurement, so their spread is a true
390 uncertainty hotspot and the priority for new measurement. Rice calendar and peatland
391 extent products are equally divergent but better evidenced, with independent surveys,
392 retrievals and maps that genuinely disagree. Therefore, their variation is a well-
393 understood and reducible sensitivity. However, the two rice water regime products agree
394 almost perfectly at the national scale only because they share sparse and closed national
395 statistics, a false confidence that the pixel-level divergence in Fig. 6c exposes.

396 Two layers of action follow. The more immediate layer is source-specific: peatland
397 uncertainty collapses by ~85% once existing national land-use statistics are applied; rice
398 CH₄ needs an observation-anchored growing-season calendar and better-resolved water
399 regime mapping; nutrient N₂O needs methodologically harmonized fertilizer, manure and
400 crop residue inventories and continued subnational disaggregation. The second layer is
401 cross-cutting: the cropland distribution product is the shared spatial substrate beneath N
402 nutrient allocation, rice extent, and the cropland-peatland intersection, and harmonizing it
403 would reduce the sub-national disagreement on which spatially explicit accounting
404 depends. Crucially, the spatial fingerprints show these investments need not be global,
405 targeting the sub-national hotspots that carry most of the disagreement would capture
406 most of the benefit.

407 Several limitations to these conclusions should be noted. We apply fixed IPCC Tier 1/2
408 emission factors to global gridded input products throughout, which isolate dataset-driven
409 uncertainty from emission-factor parameter uncertainty and from the structural
410 uncertainty of process-based biogeochemical models. The input data layers we evaluate,
411 fertilizer, manure, crop residue, cropland distribution, rice extent and growing season
412 calendar, rice water regime, and peatland extent, are the foundational data used at every
413 IPCC tier¹³, including the country-specific Tier 3 systems operated by major emitters.
414 The input data uncertainty patterns identified here are therefore properties of the
415 underlying data infrastructure rather than artefacts of the Tier 1/2 framing. Because Tier
416 1/2 emission factors scale linearly with activity data, non-linear responses represented in
417 process-based Tier 3 models, for example to soil nitrogen surplus or water-table depth,
418 could amplify the propagation of input divergence beyond the ranges reported here. Our
419 scope is also bounded to these layers and does not include other management dimensions,
420 such as nutrient management, tillage, cover cropping, biochar amendment, irrigation
421 management. Addition of these dimensions is likely to widen the reported ranges;
422 therefore, the dataset-driven ranges we report are in this sense a conservative lower
423 bound. The dataset-driven ranges we report bear directly on the Paris Agreement's gap-
424 assessment mechanism. Aggregating national emission baselines into a single global
425 trajectory, the basis on which the Global Stocktake quantifies the gap to a well below 2
426 °C pathway, requires that those baselines be computed on comparable input data. Within-
427 dataset temporal trend detection within a single country, under a fixed methodology held
428 constant over time, is a complementary question that would require multi-year inputs and

is a natural extension. Each source is assessed independently; cross-source interactions such as overlapping cropland definitions are not propagated, so combined-source uncertainty estimates are also conservative.

More broadly, the credibility of land-sector climate commitments now rests as much on data infrastructure as on ambition. A country can pledge, implement, and report genuine abatement and still see it vanish into the noise of incompatible input datasets.

Establishing open-access, version-controlled agricultural activity datasets, especially for crop calendars, water regimes, and organic soil extent, is a practical prerequisite for the UNFCCC Enhanced Transparency Framework. Without baseline data harmonization ahead of the second Global Stocktake, genuine national mitigation will remain indistinguishable from input dataset noise. The atlas and priority ordering offered here are a starting point for that work.

Extended Table 2. Evidence strength assessment

Driver	Spa tial	Per iod	Proce ssing	valid ation	indep endency	Varia bility	evid ence	quadrant
Fertilizer	2	2.5	2	1.5	1	11	1.8	False confidence
Manure	2.5	2.5	1.5	1	2	51	1.9	True uncertainty hotspot
Crop residue	2	2.5	2.5	1	2	58	2	True uncertainty hotspot
Rice calendar	2.7	2.3	2.7	2.7	3	77	2.7	Well-understood sensitivity
Water regime	1	1	2	1	1	0.1	1.2	False confidence
Peatland extent	3	2.2	2	2	3	129	2.4	Well-understood sensitivity
Cropland distribution	3	3	2	2.3	2	11	2.5	Robust

Methods

Emission framework

We estimated cropland GHG emissions at 5 arcmin resolution (~10 km at the equator) using IPCC 2019 Refinement Tier 1 and Tier 2 emission factors. Direct N₂O was computed for non-rice and rice crops separately, with wet/dry climate-zone-specific factors. Indirect N₂O followed the IPCC leaching and volatilization pathways. Rice CH₄ used the IPCC flooded-rice equation with water regime specific factors and growing season duration from the chosen calendar. Peatland emissions (CO₂, CH₄, N₂O) applied tropical and temperate/boreal factors per unit drained area. All emissions were converted to CO₂-equivalent using IPCC AR6 100-year global warming potentials for non-fossil sources (CH₄ = 27.0; N₂O = 273), enabling variance attribution by source based on its contribution to global warming.

Input datasets, combinations and sensitivity scenarios

We compiled multiple global datasets for each emission driver, selecting products with broad spatial coverage circa 2020 and differing methodologies (Supplementary Table 1). We distinguished input-dataset combinations, that is choices among input products, from sensitivity scenarios that test spatial aggregation level, within-country water regime redistribution and national peatland constraint level on top of them (Supplementary Table 2). The analysis comprises 1,284 combinations (576 fertilizer, 288 manure and 288 crop residue N₂O, 60 rice CH₄ and 72 drained peatland) and 1,728 sensitivity-scenario runs, together producing 11,100 gridded emission maps. The country-level comparison and the variance decomposition used combinations only. The nutrient N₂O total sums the fertilizer, manure and crop residue combinations (576 + 288 + 288 = 1,152) that share a cropland, climate, runoff and irrigation choice.

We tested the sensitivity of IPCC emission factors to combinations of climate, hydrology, and irrigation inputs. These included six bias-corrected ISIMIP2b climate models (ENSEMBLE, GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M) for the wet/dry climate zone classification. Runoff (GLDAS, G-RUN, ERA5-Land) and irrigation fraction datasets (AQUASTAT, IWU) were collected for indirect N₂O *via* leaching.

Four global crop-specific harvested area products (SPAM2020 V2, CROPGRIDS, Coello and Adalibieke) were used as cropland extent for N input N₂O. Rice CH₄ used the rice layers of these four products with an additional rice product (GlobalRice20). Two physical area products (SPAM2020 V2 and CROPGRIDS) defined the cropland overlap for drained peatland emissions.

Four global crop-specific fertilizer N products, Cao, NPKGRIDS, Coello, and Adalibieke were compiled. Two manure N and two crop residue N products were also compiled,

both derived from Cao and Adalibieke. We grouped crops into rice and non-rice by harvest area-weighted average for these three N input layers to minimize the calculation while implementing full IPCC emission factors. To examine the effects of spatial aggregation levels on the product uncertainty, we processed each product, as sensitivity scenarios on its native cropland, at three to four spatial aggregation levels (national, subnational, pixel, and national-rescaled, in which national totals were rescaled to FAOSTAT 2020 national fertilizer consumption while each product's within-country distribution was preserved).

Gridded N-input products are conventionally built by anchoring pixel values to national or sub-national activity statistics (for example FAOSTAT and IFASTAT). To separate the uncertainty contributed by the N input rate from that contributed by the cropland extent onto which it is mapped, we generated the full cross-product of the N input and cropland extent datasets. For each N input product (four fertilizer, two manure, two crop residue) and each of the four cropland distribution products, the N input product's pixel rates were transferred onto the target cropland extent using an area-weighted moving window (~50 km) with subnational constraints, rescaled within each subnational unit so that its N total matched the N input product's own subnational total, and capped at an agronomic maximum threshold of 700 kg N ha⁻¹ yr⁻¹ to avoid downscaling artifacts where a subnational total is allocated to a small cropland area⁴. Following the conventional anchoring described above, this preserved each product's subnational nitrogen inventory while exchanging only the spatial cropland template, so that the N input product and the cropland extent product entered the variance decomposition as independent factors whose contributions could be attributed separately. Identity pairs, in which a product is mapped on its native cropland, retained the original rate. Direct and indirect N₂O were then computed for all 32 product-by-cropland pairings (sixteen fertilizer, eight manure and eight crop residue) across the six climate models.

For rice CH₄, the combinations comprised five rice-area products, three growing season calendars (RiceAtlas, Hybrid-MARC and Hybrid-RICA), two water regime sources (Cao and Carlson) and two manure products at their native (pixel) level, with residue fixed to Cao. We fixed residue because the two available products differ by about 100%. To prevent poorly constrained residue products from dominating the uncertainty analysis, we excluded residue variability. This exclusion should not be interpreted as evidence that its contribution is negligible, and the rice CH₄ range reported here is therefore a conservative lower bound. Sensitivity scenarios (720 runs) applied within-country water regime redistribution at 0.1, 0.2 and 0.5 bounds, each as a maximum and a minimum while preserving national regime fractions, to every combination at both manure aggregation levels.

We collected six peatland extent products (FAO Organic Soil, GFW, GPM, Cao, PEATMAP, PeatML) to intersect with two cropland physical area products (SPAM2020

V2 and CROPGRIDS) for drained peatland emissions. To examine the impacts of spatial constraints on drained peatland emissions, three integration levels (raw, national-controlled peatland, national-controlled drained peatland for cultivation) were tested. We rescaled the pixels within each country to match the national total peatland area for national-controlled peatland and rescaled the peatland-cropland intersection to match the national total drained peatland area for national-controlled drained peatland levels.

Variance decomposition

We performed Type I sum-of-squares ANOVA in R (lm function) for each emission pathway, with the global emission of each combination ($\text{Gg CO}_2\text{eq yr}^{-1}$) as the response and the input choices as categorical main effect predictors. The predictors entered in the following order: N input product, cropland extent product and climate model for direct N_2O , with water regime source added for fertilizer N_2O from rice; N input product, cropland extent product, climate model, runoff product and irrigation map for indirect leaching; N input product, cropland extent product and climate model for volatilization; water regime source, rice extent product, growing season calendar and manure product for rice CH_4 ; and peatland extent product, cropland extent product and climate model for drained peatland. Interaction terms were omitted from global sum-of-squares decomposition because additive main effects accounted for 97–100% of global variance ($R^2 = 0.97\text{--}1.00$); however, spatial non-additive interactions between activity layers and climate masks were preserved in the pixel-level sensitivity maps. Each driver's share is its sum of squares normalized so that the drivers of a pathway sum to 100% (shares therefore describe the variance explained by main effects), and source-level, Roe-class and five-source shares were obtained by weighting these pathway shares by each pathway's mean emission relative to the corresponding aggregate (Extended Table 1). Regional ANOVA uses country-level World Bank region groupings. Because the combination designs are balanced with full factorials, main effect sums of squares are independent of entry order; Type III sums of squares (car::Anova) reproduced the Type I shares exactly.

Structural range and mitigation-potential comparison

The dataset-driven uncertainty range for each source was defined as the maximum minus minimum emission across all combinations of input products for that source. Country-level ranges and means were computed by summing pixel emissions within country boundaries.

National mitigation potentials were taken from Roe et al. (2021) for the aligned categories, nutrient management (fertilizer + manure + residue N_2O), rice cultivation (rice CH_4), and peatland restoration. These potentials are top-down estimates synthesized across integrated-assessment and bottom-up studies rather than spatially explicit products built on the same activity data, so the comparison presented is an illustrative benchmark

of magnitude rather than an equivalent reconciliation. We treated it as context for interpreting published mitigation estimates rather than a validation or revision of them. Two ratios were computed per country–source pair: ratio for technical potential (any cost) and ratio for cost-effective potential (\$50–150/tCO₂, 2050 horizon). Countries with ratio greater than 1 are those whose dataset-driven range exceeds the matching mitigation potential. We reported this extent both as a count of countries and as a share of global source emissions originating from such countries.

Evidence-strength assessment

To distinguish genuine robustness from apparent consensus caused by shared upstream data, we paired the dataset-driven variability results with a structured qualitative evidence-strength score. For each driver, individual products were scored on five criteria (1 = Low, 2 = Medium, 3 = High): (i) spatial resolution adequacy for the heterogeneity of the process; (ii) period representativeness for the target period (~2020), (iii) processing for estimating grounded in direct measurement or census versus modelling or assumption; (iv) validation against independent data not used to construct the product; and (v) independence among products, reflecting whether the alternative datasets trace to methodologically distinct source chains rather than shared upstream statistics. Driver-level scores for criteria (i)–(iv) were the mean across products, whereas criterion (v) is a single driver-level judgment. The evidence composite was the unweighted mean of all five driver-level scores. Drivers were placed in a 2×2 matrix crossing evidence strength (split at 2 on the 1-3 scale) against dataset-driven relative range (split at 30 %): Robust (low variability, high evidence), False confidence (low variability, low evidence), Well-understood sensitivity (high variability, high evidence), and True uncertainty hotspot (high variability, low evidence). Per-product scores are provided in Supplementary Table 4.

Spatial aggregation-level analysis

For each fertilizer product, we computed the within-product uncertainty ranges across alternative spatial aggregation variants (pixel, national, subnational, national-rescaled where available), holding all other inputs fixed. For rice CH₄, we computed the within-(area × calendar) range across the three water regime redistribution values (0.1, 0.2, 0.5) and across the two water-regime sources (Cao, Carlson). For peatland, we computed the inter-product range at each of three integration levels (raw, national-controlled peatland, national-controlled drained peatland) and compared the range across products at each level. The cropland distribution dimension enters all three sources: as the spatial downscaling layer for fertilizer N totals, as the rice-extent layer for rice CH₄ area, and as the cropland extent of the cropland × peatland intersection for drained peatland GHG.

Data and code availability

All input datasets are publicly available from the sources listed with access links in Supplementary Table 1. Global, regional and national emissions for all input-dataset combinations and sensitivity scenarios, and the country-level comparison with mitigation potentials are provided as Supplementary Data. The gridded emission maps (11,100 maps) are intermediate outputs that can be regenerated from the public inputs with the Supplementary Software and are available from the corresponding authors on request.

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