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International trade substantially reshapes methane emissions from rice cultivation

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Rice cultivation is a major source of methane, a potent greenhouse gas with significant climate implications. Official inventories report emissions based on domestic production, often overlooking the role of international trade in redistributing methane. Major exporters shift a substantial portion of emissions to consumers via trade. We provide a methane-focused global assessment of trade-adjusted emissions from rice cultivation, showing that international trade has increasingly reshaped the geographic distribution of rice-related methane emissions over the long term, with nearly 9% redistributed internationally in 2023, almost tripling since 1990. Regions previously considered low-emitting, including Europe, the Middle East, and parts of Africa, now carry a larger consumption-based methane footprint, with the EU27 nearly doubling its production-based emissions, Africa showing the largest divergence among continents, and the Middle East's footprint driven almost entirely by imports. To ensure effective mitigation, policy frameworks should integrate trade- adjusted methane estimates so that commitments such as the Global Methane Pledge reflect the full lifecycle of rice production and consumption.

Rice cultivation is a major contributor to global methane (CH_4) emissions from anaerobic decomposition in flooded soils, accounting for about 8% of anthropogenic CH_4 emissions, with strong regional variation linked to water management, organic inputs and rice varieties[1]. As a staple for nearly half the global population, rice underpins food security. Although its share in global primary crop production declined from 10% in 2000 to 8% in 2023[2], absolute demand continues to grow, particularly in Africa and Asia[3]. This trend highlights the urgency of tackling rice-related CH_4 emissions within climate policy.

Rice CH_4 emissions depend on agroecological, climatic and management conditions. Flooded paddies provide ideal anaerobic environments for methanogenic bacteria, with water management, soil organic matter, temperature and rice variety as key determinants[4–7]. Alternate wetting and drying (AWD) can reduce CH_4 emissions significantly compared with continuous flooding, while some hybrid varieties show lower intensities[8,9]. The widespread use of continuous flooding in Southeast Asia explains its role as a major global source.[5]

Process-based models such as CH_4MOD demonstrate how local climate, soil and cultivation practices shape fluxes, underscoring the need for region-specific emission factors[6,10,11]. Generalized factors introduce large uncertainties, constraining inventory accuracy and mitigation planning. While Emissions Database for Global Atmospheric Research (EDGAR) (https://edgar.jrc.ec.europa.eu/,last access: October 2025) provides harmonized global estimates, advances in spatial data, updated IPCC 2019 factors and improved agricultural statistics[12] enable more refined regional and national inventories, supporting targeted interventions.

International trade further reshapes CH_4 footprints[13,14]. Conventional inventories allocate emissions only to producers, ignoring cross-border flows. This distinction is particularly relevant for agricultural commodities traded internationally, as production-based inventories may not reflect the drivers of emissions embodied in global consumption patterns. Previous studies have shown that consumption-based perspectives can significantly alter the distribution of responsibility[15] and can complement territorial inventories by providing additional insight into demand-driven pressures and opportunities for shared responsibility[16,17]. Rice, largely traded from Asia to Africa and the Middle East, allows importers to outsource part of their footprint. A consumption-based perspective reveals an alternative distribution of emissions and raises equity concerns[5,18–22]. Increasing trade of rice shifts emissions from producing to consuming countries[13,23] raising the question of the need for trade-adjusted estimates.

Global initiatives such as the Global Methane Pledge (GMP) (https://www.globalmethanepledge.org/, last access: October 2025) and Nationally Determined Contributions (NDCs) (https://unfccc.int/NDCREG, last access: October 2025) aim for a 30% methane reduction by 2030 across agriculture, energy and waste. Trade-adjusted estimates can complement existing approaches by linking emissions to demand and supporting cooperative mitigation efforts.

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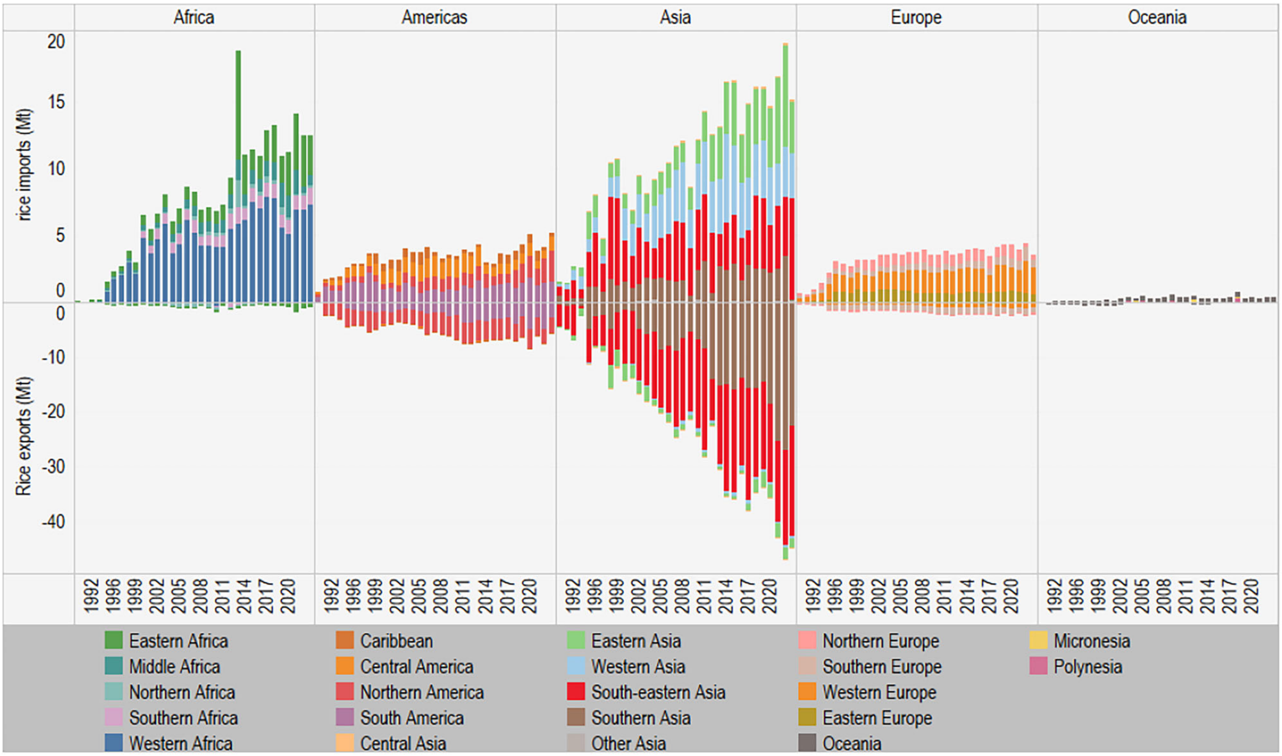

Fig. 1 | Global rice imports and exports in main regions and subregions, 1990–2023. Source: FAOSTAT (last access October 2025).

Despite progress, gaps persist. Inventories rarely analyse emission intensities per hectare or per ton of rice, and coarse default factors fail to capture variation in water regimes, climate, soils and varieties[5,24,25]. Addressing these gaps is essential for more accurate estimates and effective mitigation.

While previous global assessments (e.g. ref. 5) have provided multi-gas, multi-commodity estimates of rice-related emissions across production, trade, and consumption or proxy-based approaches, including virtual land methods (e.g. ref. 26), this study presents a methodological enhancement of these analyses by applying inventory-consistent methane emissions based on EDGAR and the IPCC 2019 Refinement. By combining the most recent FAOSTAT (https://www.fao.org/faostat/en/#data/QCL, last access: October 2025) rice production and trade statistics with the updated EDGAR 2025[27], we distinguish production-based and trade-adjusted (consumption oriented) CH_4 emissions, quantify trade-driven redistribution, and assess emission intensities per hectare and per unit of production. Unlike[14], who applied earlier EDGAR inventories within an economy-wide input–output framework, and other studies that applied economic supply-chain or multi-regional input-output (MRIO) based approaches[5,23,28] our method is crop-specific and relies on physical bilateral rice flow data. This enables a more detailed and biophysically consistent assessment of rice-related methane emissions, providing a transparent and policy relevant representation of international CH_4 displacement.

Results

Rice global production trends

Since 1990, global rice production grew by 54%, reaching nearly 800 million tonnes (Mt) in 2023, driven by population demand and agricultural intensification (FAOSTAT, https://www.fao.org/faostat/en/#data/QCL, last access: October 2025). An illustration of rice production trends by country over period 1990–2023 as well as top ranking yield countries and rice harvest area in 2023, is shown in Figure S1.

Africa shows the fastest growth, increasing 236%, particularly in Middle Africa (+373%) and Western Africa (+339%), while Europe declined, with Eastern Europe down 50% and EU27 by nearly 6%. In Asia, the main producer, growth was 50%, with Southeast Asia up 75% and Eastern Asia declining 29%. The top 15 producers, including India, China, and Bangladesh, have consistently dominated output, maintaining global leadership over 1990–2023 (FAOSTAT, https://www.fao.org/faostat/en/#data/QCL, last access: October 2025).

Among the top rice producers, India and China have shown particularly noteworthy but contrasting developments in rice cultivation dynamics. In 2023, for the first time, India slightly overtook China in total rice production, reaching 207Mt, an important increase considering that, in 1990, India's rice production was only about 60% of China's.

India's rice production increase of 85% over the period was primarily driven by a 65% rise in yield, supported by modest area expansion (+12%). In contrast, China reduced the area under rice cultivation by 13% between 1990 and 2023, though yield improved by nearly 25%, leading to a modest total production increase of 8.6%.

Global rice trade

Global rice trade plays a crucial role in ensuring that demand is met in regions where domestic production is insufficient[29]. An analysis of world rice imports reveals that the trade is highly diversified, involving a wide array of importing countries. In 2023, global rice imports have reached 66 Mt, whereas exports were nearly 86 Mt, with an increase by 22 and 17 times since 1990 respectively.

Figure 1 illustrates the evolution of global rice imports and exports across major world regions and subregions from 1990 to 2023. Africa stands out as an increasingly significant rice importing region, with notable growth after the early 2000s, particularly driven by imports in Western and Eastern Africa. In contrast, Asia shows a dual role as both a major importer and exporter. South and Southeast Asia are dominant net exporters, underlining the role of countries like India, Thailand, and Vietnam as global rice suppliers. Meanwhile, other Asian subregions, including Western and parts of Eastern Asia, appear as consistent importers, illustrating strong intra-regional trade flows. The Americas display a relatively balanced picture, with moderate levels of both imports and exports. South America, including exporters like Brazil and Uruguay, contributes to the region's trade surplus,

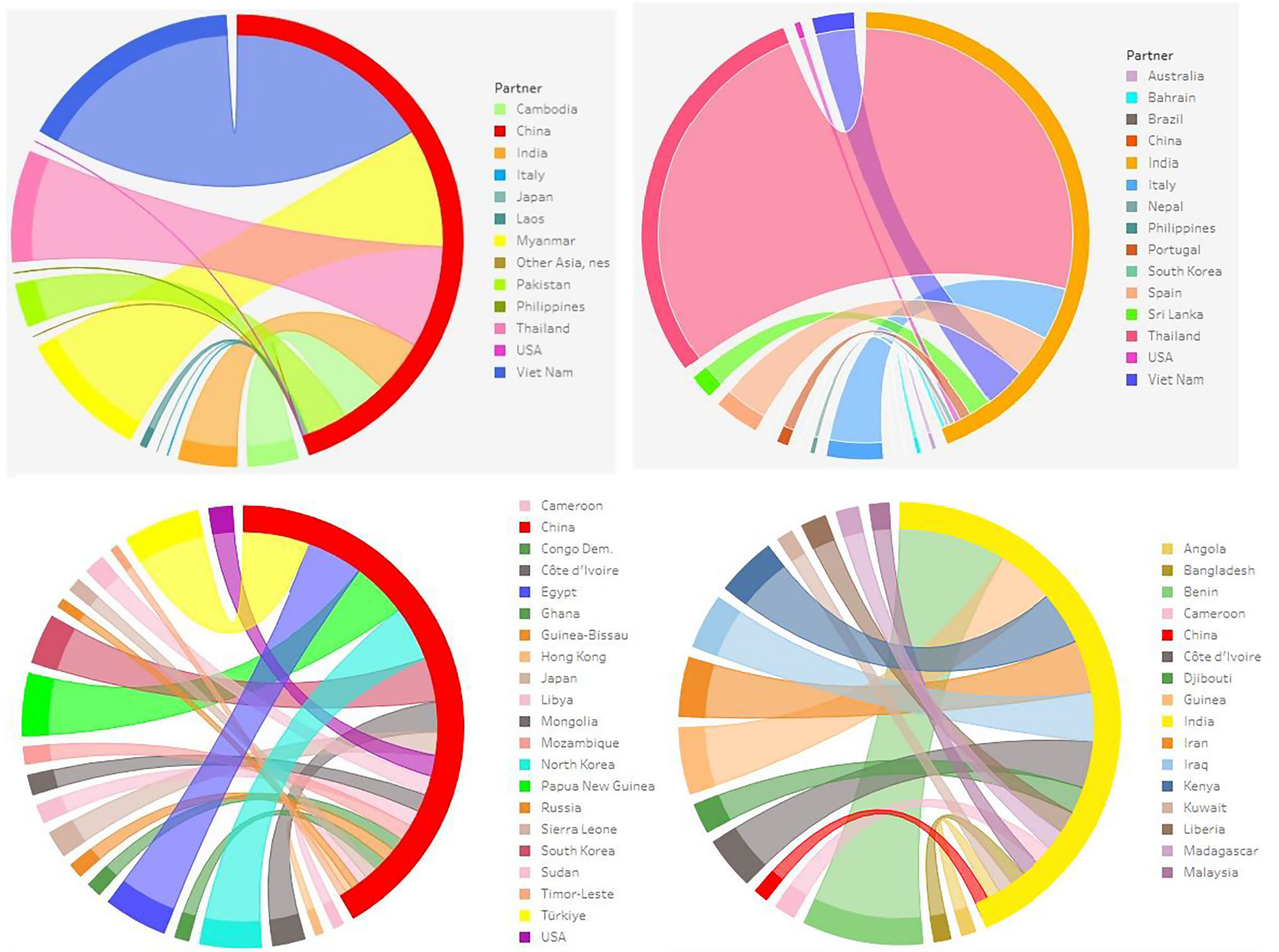

Fig. 2 | China (left) and India (right) rice imports (above) and exports (below) by partner, 2023. Source: FAOSTAT (last access October 2025), JRC elaboration.

whereas Central America and the Caribbean rely more heavily on imports. Europe, particularly Western Europe, has seen a steady increase in rice imports over the period, and virtually no exports.

Indonesia stands as the largest rice importer, accounting for approximately 8% of global rice imports, followed by China at 7.0%, Benin and the Philippines, each with around 4%. (see Figure S2) Other significant importers include Malaysia, Saudi Arabia, and the United States, each contributing about 3.5– 3.8% to global rice imports.

The global rice export landscape is notably more concentrated than imports, with a smaller set of countries supplying the vast majority of internationally traded rice (see Fig. S3). In 2023, India accounted for about one-third of total global rice exports, making it by far the largest exporter. Thailand and Viet Nam (just above 16% and 14%, respectively), and Pakistan (nearly 9%), together raised the combined share of the top four exporters to over 70%. The United States contributed about 5%, while Cambodia, China, Myanmar, Brazil, Uruguay, and Italy each held smaller shares ranging from 1% to 3%, with all remaining countries together making up less than 1%.

China's and India's rice trade by partner countries

China and India, the world's two largest rice producers, present markedly different profiles in terms of rice trade patterns, both in their import sources and export destinations, as shown in Fig. 2. Over the years, India has strengthened its position as a net exporter of rice, with production increasingly exceeding domestic consumption. Meanwhile, in 2020, China became a net importer of rice for the first time since 2010 (FAOSTAT, https://www.fao.org/faostat/en/#data/QCL, last access: October 2025), marking a major shift in its trade pattern.

In 2023, China's rice imports were primarily sourced from regional producers, with Vietnam (36%), Myanmar (about 21%) and Thailand (nearly 18%) together accounting for nearly 75% of country rice imports. India (around 9%), Cambodia (about 8%), and Pakistan (7%) followed. This composition indicates China's preference for sourcing rice primarily from Southeast and South Asian countries, with an apparent emphasis on proximity and regional trade links.

In contrast, India's rice imports in 2023 were dominated by Thailand, which alone accounted for about two-thirds of the total. Other notable partners included Italy (around 9%), Spain (around 8%), Viet Nam (about 7%), Sri Lanka (4%), Portugal (2%), and the USA (1%). The relatively considerable share of European countries in India's rice imports (nearly 20%) is noteworthy and reflects India's increasing interest in specialty or high-value rice varieties such as arborio or other non-basmati premium segments.

European Union rice trade by partner countries

In 2023, EU27 rice imports reached nearly 2.3 Mt and exports 1.0 Mt, representing approximately threefold and two-fold increases since 1990 with eight EU27 Member States rice production: Italy (1.4 Mt), Spain (0.3 Mt), Greece (0.2 Mt), Portugal (0.2 Mt), France (0.1 Mt), Bulgaria (0.1 Mt), Romania (< 0.1 Mt), and Hungary (< 0.1 Mt). Except for Italy and Greece, consistent net exporters, and Bulgaria, which became a net exporter after 2006, all other producers are net importers. Italy's exports are dominated by

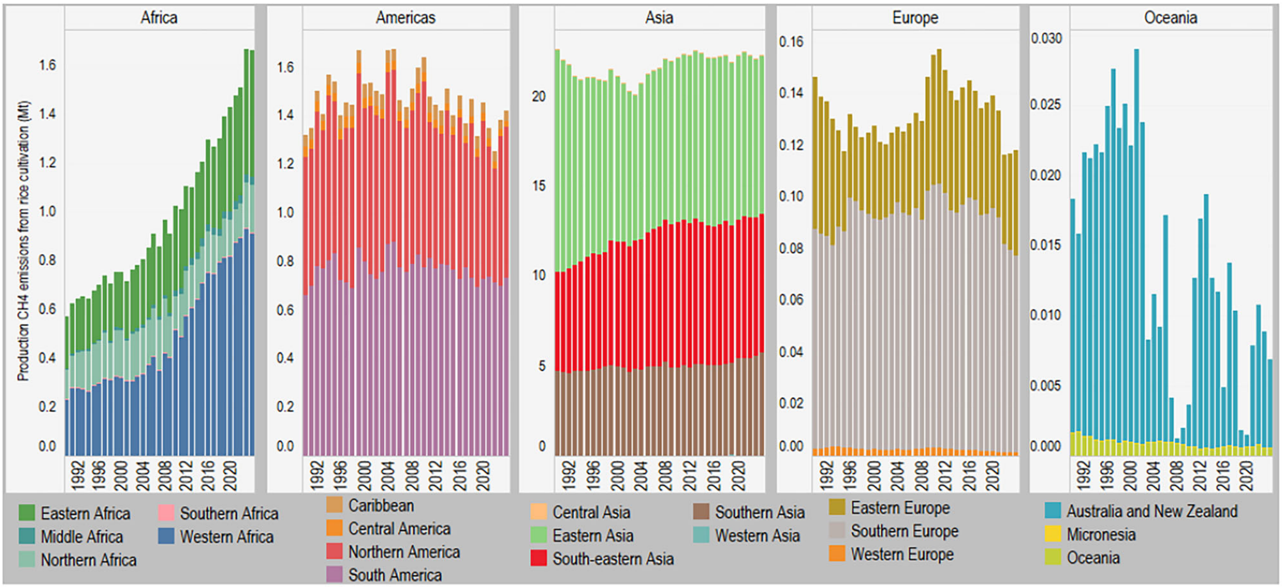

Fig. 3 | Global CH_4 emissions from rice cultivation by subregions, 1990–2024 (Mt). Source: EDGAR 2025, last access: October 2025.

Japonica varieties (e.g., arborio, carnaroli), while domestic demand also covers indica, parboiled, basmati, and fragrant rice.

In 2023, Italy's imports came mainly from Pakistan (30.5%), India (11.2%), Myanmar (9%), and Thailand (8.3%), with exports primarily to France (24.5%), Germany (22.7%), the Netherlands (6.9%), and the UK (8.3%). Spain has shown shifting trade patterns, with imports rising strongly after 2020. In 2023, imports originated mainly from Myanmar (23.8%), Argentina (15.7%), Uruguay (11.8%), Pakistan (11%), and Brazil (9.2%). Exports went largely to EU27 partners and the UK, with Belgium (22.6%), France (16.3%), Portugal (13.6%), Netherlands (6.4%), Germany (4.9%), and the UK (16.8%) as main destinations. Greece also remains a net exporter, with imports in 2023 mostly from Myanmar (29.2%), Pakistan (22.5%), Cambodia (12.3%), and Italy and India (9% each). Its exports target EU markets, chiefly Bulgaria (24%), Italy (15%), Poland (10.8%), Czechia (9.9%), and the Netherlands (6.6%).

Global production-based CH_4 emissions from rice cultivation

Global CH_4 emissions from rice cultivation in 2024 are estimated at 25.5 Mt, a 3.5% increase compared with 1990. Uncertainty in these production-based estimates is relatively high compared with other sectors, reflecting variability in emission factors and cultivation practices, as documented in refs. 30, 31. For rice cultivation, cultivation-system-specific uncertainties adopted in EDGAR yield propagated uncertainties of approximately ±26–28% for the dominant irrigated and rainfed systems. Figure 3 illustrates the CH_4 emissions from rice cultivation by subregions.

Africa recorded the largest rise since 1990, at 191%, while Oceania showed the largest decline, at 62.5%. Europe's emissions fell by 19%, Asia's by only 1%, and the Americas increased by nearly 8%. Within Africa, Middle and Western Africa experienced the sharpest growth, at 447% and 291%, respectively, with regional emissions surpassing those of the Americas after 2020.

Asia remains dominant, contributing over 87% of global rice CH_4 emissions in 2024, slightly below its 1990 share of 92%. Southeastern Asia increased its share by 10 percentage points since 1990, approaching Eastern Asia, which had previously contributed more than half of the region's emissions. In 2024, Eastern and Southeastern Asia together accounted for nearly 74% of Asia's CH_4 emissions. In the Americas, South America remained the leading contributor with about half of regional emissions, while North America accounted for 43% during 1990–2023. At the country level, India's production growth coincided with a 17% rise in CH_4 emissions, whereas China achieved a 27.5% decline due to reduced rice area and adoption of improved water and residue management practices.

Regional CH_4 emission patterns, highlighting irrigated versus rainfed systems, are shown in Figure S4. Asia—particularly China, India, and Southeast Asia—dominates global emissions, with irrigated systems as the primary source. Similar observations have been reported in India, where CH_4 emissions vary strongly with water regime and soil management[7]. In Africa, emissions are more dispersed, and rainfed rice plays a larger role, especially in West and East Africa. In the Americas, irrigation dominates in South America (e.g., Argentina, Uruguay) and the United States, while Central America has mixed systems. Oceania, mainly Australia, relies almost entirely on irrigated rice. In Europe, including the EU27, rice cultivation is almost exclusively irrigated, concentrated in southern countries such as Italy, Spain, and Greece. Figure S5 shows the relative contributions of each subregion within the five regions and EU27 in 2024.

Global production-based CH_4 emission intensity patterns

Regional differences in CH_4 emission intensities from rice cultivation in 2023, expressed both per unit area and per unit production, reveals distinct global patterns (see Fig. 4). The highest CH_4 emission intensities per unit of area (left panel) are observed in USA, Bulgaria, Italy, Turkmenistan, Afghanistan, Tajikistan, Sudan, and Egypt. High CH_4 emissions per unit of area occur where rice fields remain flooded for long periods with little intermittent drainage, conditions that promote CH_4 production in paddy soils[12,25];

The lowest CH_4 emission intensities per unit of area were observed in India, several African countries, and others such as Turkey, Bolivia, and France. Intermediate values were recorded in China, Mexico, Brazil, Spain, Hungary, Romania, Ukraine, Russia, and Australia.

By contrast, the highest CH_4 intensities per tonne of rice were found in parts of sub-Saharan Africa and the Near East, largely due to low yields in rainfed or marginal systems, which increase the CH_4 footprint per unit of harvested rice. Countries combining low CH_4 emissions per tonne with competitive yields represent the most efficient systems. These findings confirm that high-yield systems are not necessarily the highest emitters per hectare, suggesting scope for yield improvements without proportional increases in emissions. A 2022 World Bank study[32] similarly showed that intensive rice cultivation in the United States (California, Mississippi River Valley), northern Italy, and parts of South America achieves high yields without corresponding increases in emission intensity. High-yield areas, moreover, do not always coincide with the largest cultivation areas.

India provides a notable case: while its rice production growth coincided with a rise in absolute CH_4 emissions, the country maintained one of

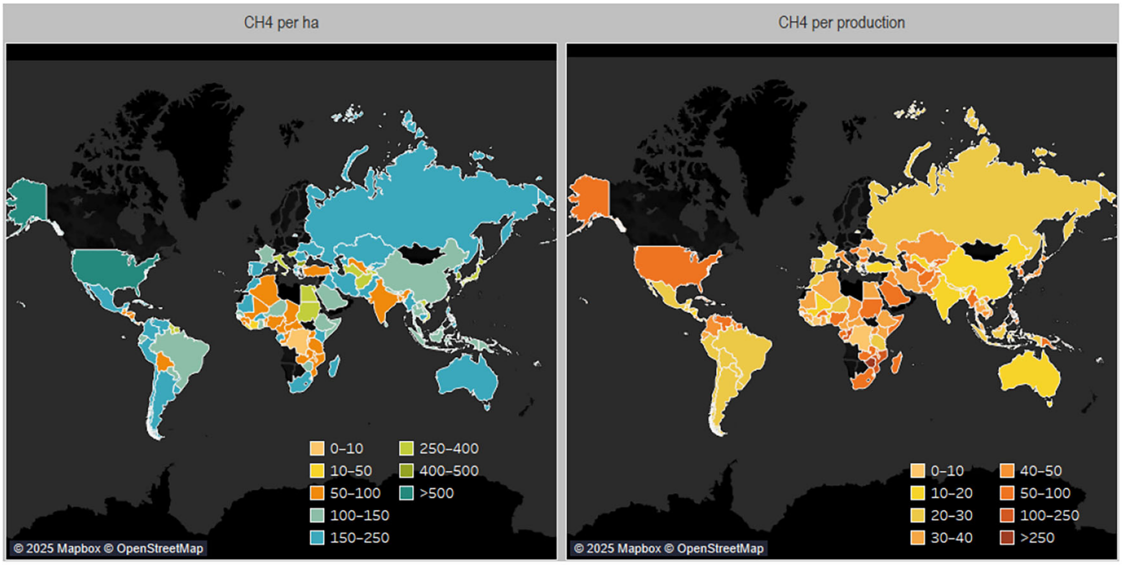

Fig. 4 | CH_4 emissions intensities by country and region—per hectare (left) and per production (right), kg CH_4/unit. Source: EDGAR 2025, FAOSTAT (last access October 2025).

the lowest CH_4 intensities per hectare globally, 79 kg CH_4/ha in 2023, due to its reliance on rainfed and partially irrigated systems, with only two-thirds of its rice area irrigated. In contrast, China's rice cultivation, almost entirely irrigated and therefore CH_4-intensive, recorded 279 kg CH_4/ha in 2023. Yet total CH_4 emissions declined due to reduced rice area and adoption of improved water and residue management practices.

Trade-adjusted CH_4 emissions embodied in global rice trade

Countries producing rice with high CH_4 intensities and exporting large volumes are effectively "exporting" emissions to consumer markets. The role of trade in redistributing methane emissions from rice has tripled over three decades: in 1990, only 3.3% of rice-related methane emissions were shifted through trade, whereas by 2023 this had risen to nearly 9%. Five countries—India, Thailand, Pakistan, the United States, and Myanmar—accounted for 90% of net exported CH_4, indicating a highly concentrated trade structure, where a small number of exporters dominate global methane redistribution. As these estimates are derived by reallocating production-based emission intensities through bilateral trade flows, uncertainties in the underlying production estimates propagate to the trade-adjusted results. Additional uncertainty arises from the use of FAOSTAT bilateral trade statistics and the assumptions adopted for the trade matrix (see Methods section).

As shown in Fig. 5, top importers include the Philippines, Indonesia, Malaysia, China, and Côte d'Ivoire. Although the number of net exporters is small compared with importers, most emissions embedded in trade originate from exports.

India, the largest rice exporter, contributed a dominant share of trade-related CH_4 emissions. Thailand, Vietnam, Pakistan, and the USA followed, with the latter standing out for its smaller export volumes but very high emission intensities. Myanmar, Cambodia, Brazil, and Uruguay also contributed, each representing 2–3% of global rice exports. Conversely, import-dependent regions with limited domestic production, such as Africa, the Middle East, and much of Europe, show trade-adjusted emissions far exceeding production-based ones.

China illustrates a shift from exporter to net importer after 2019. Although domestic CH_4 emissions fell due to reduced cultivation area and improved practices, the country increasingly "imports" emissions through foreign supply. Japan shows a similar trend since 2020, with imports rising as domestic production declined, leading to negative decoupling between production and consumption footprints. In import-dependent regions such as Africa, the Middle East and the EU27, trade-adjusted methane emissions substantially exceed production-based values, highlighting the disproportionate role of rice imports in shaping national methane footprints (Figs. S6–S7). At the continental level, Africa shows the steepest divergence, with modest production-based emissions but rising trade-adjusted values linked to growing imports. Europe also displays low production-based emissions but nearly double trade-adjusted emissions, reflecting its dependence on imports. By contrast, the Americas remain net exporters, with production-based emissions above trade-adjusted ones, particularly in the USA, Brazil, and Uruguay. Oceania shows smaller differences.

Over time, Africa and Europe experienced the fastest growth in trade-adjusted emissions, underscoring shifting global trade impacts (Fig. S6). Within the EU27 (Fig. S7), Italy remains a net exporter, with production-based emissions nearly 42% higher than trade-adjusted ones in 2023. Spain recently shifted toward higher trade-adjusted than production-based emissions, while in most other Member States, including France, Romania, and Hungary, consumption-related emissions dominate. At the EU27 level, trade-adjusted emissions are nearly twice as high as production-based emissions, despite a 6% decline compared with 2020. Embedded CH_4 emissions in rice trade between sub regions are shown in Sankey diagrams (Figs. S8–S11) in the supplementary material. Exports from South and Southeast Asia dominate methane transfers to Africa and parts of Europe, while North and South America play a central role in trade-related methane flows to Central America and Africa. This indicates that a small number of bilateral trade relationships account for a large share of global methane redistribution.

Discussions

Methodological positioning: physical trade flows versus MRIO approaches

Most studies on consumption-based GHG accounting rely on MRIO models to trace emissions through complex global supply chains[5,18,33,34]. While powerful, these approaches depend on aggregated economic sectors and harmonized monetary trade data, which often rely on aggregated sectoral and monetary representations, making it challenging to fully capture biophysical and practice- specific drivers of agricultural CH_4 emissions[34–37]. This limitation is particularly critical for rice, where emissions are strongly influenced by local cultivation practices and biophysical conditions that are not explicitly represented in monetary input–output structures[6,11,24,38]. Even physically extended models such as FABIO[39] operate at aggregated crop

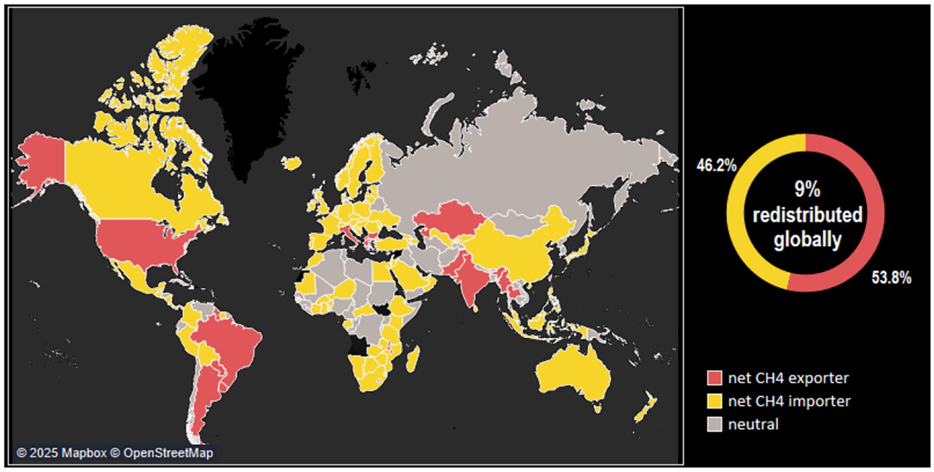

Fig. 5 | Net CH_4 rice emissions exporters and importers and their share in global emissions redistribution, 2023. Source: EDGAR 2025, FAO-STAT (last access October 2025).

groups and broader food-system scales, which still limits crop- and practice-specific attribution of CH_4 emissions. Detailed crop-specific consumption-based CH_4 accounting and trade-related emission transfers are still limited[40,41] in part because global CH_4 inventories are less complete and less harmonised than those for CO2[28,42,43];

To the best of our knowledge, this study provides the first global, crop-specific assessment of CH_4 emissions from rice cultivation integrating both production-based and trade-adjusted perspectives for the period 1990–2023, using a physical trade-flow approach rather than an MRIO framework. By directly linking bilateral rice trade volumes with production-based CH_4 intensities, this method preserves the physical characteristics of the system and enables transparent tracing of emission transfers between producing and consuming countries. While not intended to replace MRIO models, it offers a complementary, physically grounded perspective that is particularly suited to process-driven, location-specific agricultural emissions such as those from rice cultivation.

Decoupling methane emissions from rice area and yield

Production-based CH_4 emissions from rice cultivation correlate strongly with harvested area, since flooded soils provide the anaerobic substrate for methane formation. By contrast, yield shows no consistent global relationship with emissions (see Fig. S12). Between 1990 and 2023, global rice yields rose by 34% while CH_4 emissions increased by only ~3%, indicating a partial decoupling between production growth and emissions. Similar patterns have been observed previously, with stable global emissions despite yield gains, due to both improvements in management practices and continued reliance on high-emitting systems[1,5,24]

Country-level evidence confirms this divergence. China, Japan and Brazil combined yield growth with emission declines: China achieved a 25% yield increase alongside a 27% emission reduction, Japan modest yield gains (+ 8%) with nearly a 28% decline, and Brazil a 270% yield increase with a 43% decrease in emissions. Indonesia also shows partial decoupling, while Vietnam, Bangladesh and the USA experienced rising emissions despite higher yields. Cambodia stands out, with yield increasing by 165% and emissions by 200%. These contrasting trends confirm that yield growth alone is not a reliable proxy for mitigation, since water management and organic inputs remain the dominant drivers[24,44,45]. Future atmospheric conditions (higher CO_2 and warmer temperatures) can increase CH_4 intensity even if yields rise[46]. Evidence from China shows that practices such as mid-season drainage and improved varieties enabled yield increases with lower CH_4 intensity[25,47]. In contrast, reliance on continuously flooded systems in parts of South and Southeast Asia has intensified emissions alongside productivity growth[4].

Broader implications for inventories, trade and equity

These diverging country pathways illustrate the interplay between intensification, irrigation practices and trade in shaping national CH_4 inventories. India has expanded production and exports with moderate emissions growth and relatively low per-hectare intensities. China has reduced domestic emissions through land contraction and improved practices, but its rising reliance on imports has shifted part of its footprint abroad. Production-based inventories correctly capture territorial emissions but overlook their redistribution through trade. This is particularly evident for the EU27, the Middle East and Africa, which appear nearly emission-free in inventories but are substantial consumers of methane embodied in imports.

Our trade-adjusted estimates indicate a clear long-term increase in the importance of trade, with the share of global rice-cultivation CH_4 emissions redistributed internationally rising from 3.3% in 1990 to around 10% in recent years and reaching 9% in 2023. The redistribution share remained relatively stable during 2015–2023, ranging from 9.0% to 10.4%. Over 2000–2016, corresponding to the study period considered by[26], the redistribution share averaged approximately 7.8%, broadly comparable with their estimate that nearly 6% of rice-related environmental pressures, including methane, were embodied in international trade. Table S1 compares the present study with previous studies on embodied agricultural emissions, with particular emphasis on[26]. The comparison highlights differences in temporal coverage, methodological approaches, system boundaries, and emission datasets that likely contribute to the differing estimates. Exporting countries such as India, Vietnam and Thailand bear the production burden of emissions that sustain consumption elsewhere. This raises questions of equity and responsibility, since mitigation pledges under the Global Methane Pledge are tied to territorial inventories and thus underestimate the role of consumption[5,13,18,34]. Although the estimated 9% redistribution of methane emissions through rice trade may appear modest in relative terms, it is substantial given the scale of rice cultivation contribution within the global methane budget.

Policy implications, limitations and future directions

Integrating trade-adjusted perspectives into methane accounting would improve the attribution of responsibility. Current systems place the full burden on producers, overlooking demand-driven emissions. Consumption-based metrics highlight, for example, that the EU27—almost emission-free on a production basis—still carries a meaningful footprint through imports. From a policy perspective, trade-adjusted methane estimates can inform both supply- and demand-side mitigation[13,18]. For importing regions such as the EU27, consumption-related emissions highlight opportunities for demand-side action, while for exporting countries, results point to the value of supporting low-emission rice production practices[4,10,11]. These findings support shared-responsibility frameworks, in which both producing and consuming regions contribute to mitigation efforts[34].

Further improving the resolution of trade-adjusted assessments is important: distinguishing rice types, cultivation systems and irrigation regimes would refine results, as these factors strongly influence CH_4 intensity[5,10] and may contribute to larger uncertainties in countries with heterogeneous production systems. Enhanced cooperation between producers and consumers could also reflect shared drivers of emissions, including support for low-emission practices or cropping systems in exporting regions, and sustainable procurement in importing ones. Integrating these perspectives in climate strategies could help strengthen the effectiveness of mitigation efforts.

This study also has limitations. Emission intensities are applied at the national level and do not capture sub-national heterogeneity in practices, potentially under- or overestimating embodied methane emissions where exports are concentrated in specific cultivation systems. Trade-adjusted estimates rely on reported bilateral trade data and do not account for re-exports, stock changes, or informal flows, which may over-attribute emissions to trading hubs and underestimate emissions in final consuming countries. The analysis focuses solely on methane emissions from rice cultivation and does not include upstream or downstream supply-chain emissions, unlike MRIO or life-cycle approaches, which may affect interpretation.

A broader implication of our findings concerns their role within emerging food-system GHG accounting. Frameworks such as EDGAR-FOOD[48] allocate emissions across the entire food chain, from primary production to processing, packaging, transport, retail, cooking and waste. Our analysis focuses solely on rice cultivation (production) and its reallocation through trade, which represent only one component of the full food-system footprint. As noted by ref. 49, food-system emissions extend beyond primary production to processing, packaging, transport, retail and cooking. While this study focuses on production and trade components of rice-related CH_4, future work could integrate these additional stages to capture full life- cycle emissions, connecting crop-specific analyses with broader food-system accounting frameworks.

Method

Production-based CH_4 emissions

In the 2025 version of EDGAR, methane emissions from rice cultivation are estimated at the country level using an enhanced Tier 1 methodology, approaching a Tier 2 method consistent with the updates of 2006 IPCC Guidelines in the 2019 Refinements document[12,50] incorporating also input data beyond the global defaults, such as reported or literature-based values for cultivation periods, water regimes, and organic amendment practices, to improve spatial detail and representativeness. The approach follows the refined methodology outlined in the IPCC 2019 Refinement, Chapter 5 of the Cropland volume, and incorporates improved data sources and scaling factors for key parameters affecting CH_4 emissions. As such, EDGAR rice emissions may now differ from CH_4 estimates from other global data sources that apply a Tier 1 methodology (e.g., FAO or approaches similar to ref. 26), reflecting the increased level of detail in EDGAR's approach. This difference is entirely consistent with the methodological improvements in EDGAR (mentioned above and described in detail below) and should not be interpreted as under- or overestimation. It simply reflects the transition from a coarse Tier 1 approach to a more detailed, Tier 2–like methodology. EDGAR methane rice cultivation emissions are calculated using the following general equation:

$$CH4 = \sum\nolimits_{ijk} (EF_{ijk} * \ t_{ijk} * A_{ijk} * 10^{-6} \tag{1}$$

where:

CH_4 = Annual CH_4 emissions from rice cultivation (Gg CH_4 yr^{-1})

EF_{ijk} = Daily emission factor under specific conditions (kg CH_4 ha^{-1} day^{-1})

t_{ijk} = Cultivation period (days)

A_{ijk} = Annual harvested rice area (ha)

i, j, k = Combinations of ecosystem type, water management regime, and organic amendment use

The daily emission factor (EF) for a given set of conditions is computed as:

$$EF = EF_c * SF_w * SF_p * SF_o \tag{2}$$

where:

EFc = Baseline emission factor for continuously flooded fields without organic amendments

SFw = Scaling factor for the water regime during the cultivation period

SFp = Scaling factor for water regime during the pre-season

SFo = Scaling factor for the type and amount of organic amendments

Harvested area and rice yields are obtained from FAOSTAT https://www.fao.org/faostat/en/#data/QCL, last access: October 2025), updated annually. The total area is disaggregated by water regime into irrigated (IRR), rainfed (RNF), and upland (UPL) systems using a combination of national inventory reports[51] IPCC default shares[52,53] and regional data such as the Global Upland Rice Area 2019 dataset[54] (see Fig. S13). Cultivation periods are sourced primarily from the International Rice Research Institute (IRRI) and complemented by Table 5.11A in the 2019 IPCC Refinement.

The default EFc values are sourced from Table 5.11 in the IPCC 2006 Guidelines and updated values in the IPCC 2019 Refinement. EDGAR includes an expanded country-specific list of EFc values, while for countries without specific data, the default global average (1.19 kg CH_4 ha^{-1} day^{-1})[12] is applied.

SFw and SFp values are derived from IPCC 2006 Tables 5.12 and 5.13 and their corresponding updates in the 2019 Refinement. These factors adjust emissions based on varying water regimes during and before cultivation. The scaling factor SFo reflects the impact of type and quantity of organic amendments and is computed as:

$$SF_o = [1 + \Sigma i(ROAi * CFOAi)]^{0.59} \tag{3}$$

where:

ROA_i = Application rate of amendment i (t ha^{-1}; dry weight for straw, fresh weight otherwise)

$CFOA_i$ = Conversion factor for amendment i, relative to straw incorporated shortly before cultivation

From the literature, the ratio grain to straw varies between 0.7 and 1.4[55] depending on rice variety and growth. The improved EDGAR methodology on CH_4 emissions includes the following formula sourced from[24], to calculate the application rate of organic amendment in dry weight for each country.

$$ROA = 3.43 * \ln\left(Yield_{dm}\right) + 1.36 \tag{4}$$

Here, $Yield_{dm}$ represents the rice yield in dry matter, calculated as the product of reported yield and a drying coefficient of 0.89. If $Yield_{dm}$ is below 1 t ha^{-1}, a conservative default SFo of 2.0 is applied, as per IPCC (1997).

Two scenarios are considered for the CFOA parameter:

- Case 1: All straw incorporated within 30 days before cultivation (CFOA_1 = 1)
- Case 2: All straw incorporated >30 days before cultivation (CFOA_2 = 1)

For most countries, Case 1 is assumed (see Fig. 6). For China, a specific weighted average based on country practices is applied. The selection of Case 1 or Case 2 is supported by comparison with national GHG inventory submissions and FAO statistics. In total, 67 countries apply Case 1 for SFo; For 9 countries (Australia -AUS, Azerbaijan -AZE, Bangladesh -BGD, Costa Rica -CRI, Liberia -LBR, Mozambique-MOZ, Mauritius-MUS, Togo-TGO, Turkey-TUR), EDGAR does not apply any scaling factor for organic amendments due to insufficient data in UNFCCC submissions. Case 2 for SFo; is applied to 45 countries. More details on regional parameters are shown in

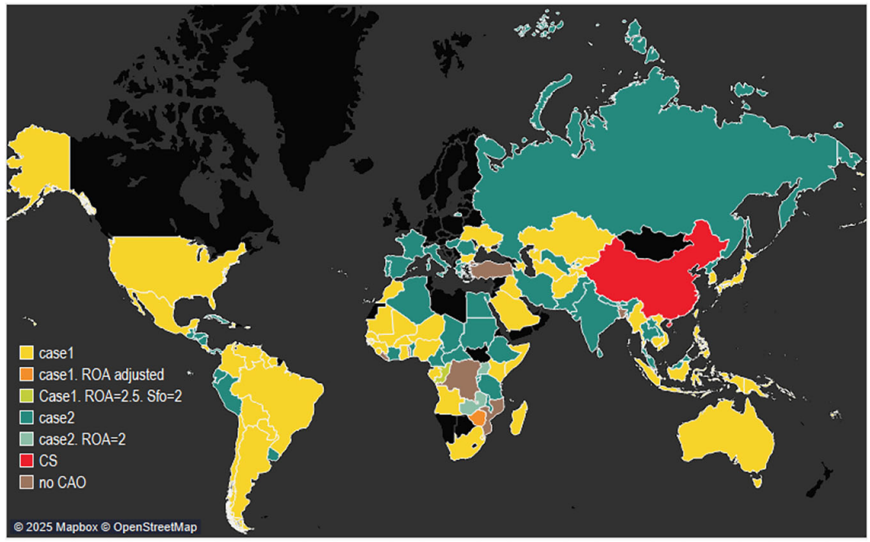

Fig. 6 | Organic amendment cases applied in EDGAR methodology. Source: EDGAR 2025.

Table 1 | Regional key parameters for CH_4 emissions from rice cultivation (EDGAR methodology)

Region	EFc (kg CH4/ ha/day)	Typical t (days)	Dominant Water Regimes	SFw	SFp	SFo Case Applied
East Asia	1.19–1.32	110-130	Irrigated, continuously flooded	0.45–0.6	0.89–1.22	CHN-specific; JPN, KOR, TWN Case 1
Southeast Asia	0.85–1.19	92–155	Irrigated + rainfed	0.45–0.6	0.89–1	7 countries Case 1; 3 countries Case 2
South Asia	1.19	112–141	Flooded and intermittently drained	0.45–0.78	0.89–1.22	5 countries Case 2, BGD no CAO
Other Asia	1.19–1.3	97–144	Mostly irrigated	0.45–2	0.89–2	7 countries Case 1; 2 countries Case 2; TUR no CAO
Europe	1.19 & 1.56	97–145	Irrigated	0.6	0.89–1.22	BGR & UKR Case 1; 9 countries Case 2
Africa	1.19	100–212	Rainfed + upland	0.45-1	0.89–1.22	22 countries Case 1; 15 countries Case 2; 4 countries no CAO
North America	1.19 & 1.27	98–183	Irrigated	0.45–0.6	0.89–1.22	Case 2
South America	1.19–1.32	107–170	Irrigated flooded	0.45–0.78	0.89–1.22	9 countries Case 1; 3 countries Case 2
Oceania	1.19–1.3	89–122	Rainfed + irrigation	0.45–0.78	0.89–1.22	Case 1

IPCC 2006 and 2019 Refinement, UNFCCC Annex I and non Annex I reporting (National Communications, Biennial Reports); FAOSTAT, USDA, IRRI.

Table 1. Accounting for sub-national heterogeneity in production improves the accuracy of emissions embedded in trade[56], a consideration important when using regional rice emission factors. Compared to earlier EDGAR releases, the current methodology introduces:

- Expanded country-specific EFc values
- Dynamic estimation of organic amendment application based on yield (see Fig. 1)
- Integration of cultivation period data from IRRI and IPCC refinements
- Broader incorporation of national and international datasets for disaggregating water regimes and cropping systems
- Incorporation of regional differences.

Trade-adjusted (consumption-based) CH_4 emissions

While national GHG inventories traditionally report production-based CH_4 emissions—assigning emissions to the country where rice is cultivated—this approach neglects the climate responsibility embedded in international rice trade. To better capture consumption-driven emissions, we estimate trade-adjusted (or consumption-based) CH_4 emissions by reallocating emissions based on rice import and export flows.

This methodological approach is grounded in the broader framework of consumption-based emissions accounting, which has been applied extensively to CO_2 and increasingly to non-CO_2 gases such as CH_4 and N_2O[13] and[34] provided the conceptual foundation for trade-adjusted GHG inventories, showing that reallocating emissions along trade flows gives a more accurate picture of climate responsibility[18]. Extended these principles to agricultural systems, using a proportional allocation method to quantify CH_4 and N_2O emissions embedded in international trade of livestock and crops. Their work demonstrated the feasibility and policy relevance of assigning emissions per tonne of product based on the average national emission intensity in the exporting country. Studies focused more directly on CH_4 -such as ref. 57 -showed that trade-adjusted CH_4 emissions can account for up to a quarter of national consumption footprints in some countries, underscoring the importance of including agricultural trade in CH_4 accounting. We reallocate emissions associated with traded rice using the approach applied at[57]

$$CH4cons\,i,t = CH4prod\,i,t + \Sigma j\left(\frac{Ii,j,t}{Pj,t}\;x\;CH4prod\,j,t\right) - \Sigma k\left(\frac{Ei,k,t}{Pi,t}\;x\;CH4prod\,i,t\right) \quad (5)$$

where:

CH_4cons,i,t–CH_4 emissions embodied in consumption for country i (Reporter) in year t

CH_4prod,i,t–: CH_4 emissions from domestic rice cultivation in country i (Reporter) in year t

Table 2 | Mapping of UN Comtrade and FAOSTAT trade codes for rice

Comtrade and FAOSTAT trade codes fo	Comtrade and FAOSTAT trade codes fo
100610–Paddy rice (in husk)	27—Rice
100620–Brown rice (husked)	28—Husked rice
100630–White rice (semi or wholly milled)	29—Rice milled (husked) 31—Rice milled
100640- Broken rice	32—Rice broken

UN Comtrade (https://comtradeplus.un.org/TradeFlow), FAOSTAT (https://www.fao.org/faostat/en/#data, last access October 2025.

CH_4prod,j,t -: CH_4 emissions from domestic rice cultivation in country j (Partner) in year t

i,j,t–Volume of rice imported by country i (Reporter) from country j (Partner) in year t

Ei,k,t -: Volume of rice exported by country i (Reporter) to country k (Partner) in year t

Pi,t: Total rice production in country i (Reporter) in year t

Pj,t: Total rice production in country j (Partner) in year t

Main assumptions applied here are: (i) uniform emission intensity within countries as exported rice is assumed to reflect the national-average CH_4 intensity; (ii) trade data consistency as only reported bilateral trade flows are considered (re-exports and processed rice products are excluded); (iii) due to data limitations, no differentiation by rice type or water regime is applied.

For countries with no domestic rice production, there are no territorial (production-based) CH_4 emissions from rice. However, their consumption-based CH_4 footprint is entirely due to CH_4 emissions embedded in imported rice, reflecting emissions from the countries where that rice was cultivated. Emissions from countries that re-export rice but lack domestic rice production are excluded from the consumption-based CH_4 emissions, as no CH_4 is generated within those countries' rice cultivation.

For each country and year from 1990 to 2023, we compute both the production-based and consumption- based CH_4 emissions from rice cultivation. The difference between the two (Eq. 6) represents the net transfer of CH_4 emissions associated with international rice trade.

$$\Delta CH_4^{trade}(i,t) = CH_4^{cons}(i,t) - CH_4^{prod}(i,t) \quad (6)$$

A positive difference indicates that a country is a net importer of CH_4 emissions embodied in rice, meaning it consumes more rice-associated CH_4 emissions than it produces domestically. Conversely, a negative difference implies that the country is a net exporter of CH_4 emissions, thus bearing the production-related climate burden of rice that is ultimately consumed elsewhere.

Assumptions on trade matrix

This study draws on internationally recognized datasets to assess rice production, trade flows, and associated CH_4 emissions. Data on area harvested, yield, production, and domestic supply were obtained from FAOSTAT. These indicators provide a consistent and comprehensive overview of national rice production systems. For rice trade flows (imports and exports), we have tested both UN Comtrade and FAOSTAT trade data. After mapping the codes of both data sources as shown in Table 2, FAO data are used.

We would expect the reported import and export quantities between two trading partners to match. However, in practice, discrepancies are common due to differences in data completeness, methodological approaches, and the temporal alignment of trade records (https://www.fao.org/faostat/en/#data/TCL/metadata, last access October 2025).

To ensure consistency in the calculation of global CH_4 emissions from rice, including trade-adjusted emissions, we conducted a sensitivity analysis based on three approaches: (i) the Import approach, which uses the import matrix and mirrors it to represent exports; (ii) the Export approach, which uses the export matrix and mirrors it to represent imports; and (iii) the Import-Export (I&E) approach, which relies on both import and export data as reported by countries.

The Import and Export approaches preserve the global total of CH_4 emissions, which is essential given that the goal of trade adjustment is to redistribute emissions across countries without altering the global sum. These approaches also support transparency and replicability of the methodology. Although the I&E approach does not strictly conserve the global emission total, the relative deviation remains small and consistently negative—ranging between approximately −0.07% and −1.8% during the 1990–2023 period.

When comparing the I&E approach with the Import and Export approaches, we found that for most countries, the Import approach is more closely aligned with the I&E approach. However, for certain countries, such as Spain, the Export approach provides a less dispersive match (see Fig. S2). We adopted the Import–Export (I&E) matrix as our standard for trade-adjusted emissions as the deviations in global CH_4 totals were low.

Data availability

The EDGAR 2025 methane production-based emissions[27] are available on the EDGAR website and can be accessed at the following link https://edgar.jrc.ec.europa.eu/emissions_data_and_maps, last access: October 2025. The EDGAR 2025 methane trade-adjusted emissions[58] can be found at https://zenodo.org/records/21163104, last access: 03/07/2026. UN Comtrade data can be found at https://comtradeplus.un.org/TradeFlow, last access: October 2025. FAOSTAT 2025 data can be found at https://www.fao.org/faostat/en/#data, last access: October 2025.

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Author contributions
M.B. and M.C. defined the structure, objectives, and overall approach of the paper. M.B. developed the methodology for improving EDGAR methane emissions from rice cultivation. M.B. also wrote the initial draft of the manuscript, performed data analysis, prepared all figures and tables and was responsible for implementing revisions and improvements throughout the review process. F.P. implemented and tested the improved EDGAR 2025 rice methane methodology. F.P. collected all necessary input data (sourced by FAO) for the EDGAR 2025 methane estimations, including area, yield, and trade data, and developed all trade matrices used in the paper. M.C. contributed to defining the structure, objectives, and overall approach of the paper, ensuring the scientific robustness of the analysis by providing also relevant literature and guidance. F.N.T and A.L provided useful and detailed review that helped improving the manuscript quality and its main messages.

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