

Agriculture sector: Rice Cultivation Emissions Estimates Using Sentinel-1A and -2A/B



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Update November 2025: This methodology employs the rice field detection and updates from the August 2025 journal article “[High-resolution maps of rice cropping intensity across Southeast Asia](#)” by Ginting, F.I., Rudiyanto, R., Fatchurrachman et al. (2025). Please refer to that article for additional information. For previous publications detailing the Sentinel approach, please refer to [Automated near-real-time mapping and monitoring of rice extent, cropping patterns, and growth stages in Southeast Asia using Sentinel-1 time series on a Google Earth Engine platform](#)” (Rudiyanto et al. 2019) and “[High-Resolution Mapping of Paddy Rice Extent and Growth Stages across Peninsular Malaysia Using a Fusion of Sentinel-1 and 2 Time Series Data in Google Earth Engine](#)” (Fatchurrachman et al. 2022). A summary of these approaches is described in the [Climate TRACE GitHub methodology repository](#).

1. Introduction

The Climate TRACE coalition’s aim is to track global greenhouse gas (GHG) emissions and make emissions data publicly available as a tool for climate action. The agricultural sector is a major contributor to global GHG emissions, contributing around 11.7% of total emissions; within agriculture, rice cultivation is the third-highest contributor, at over 1% of total global emissions (Ge, Friedrich and Vigna, 2024). Rice cultivation primarily emits methane (CH_4), a potent GHG with a 100-year global warming potential (GWP) nearly 30 times that of carbon dioxide. Rice is generally grown in flooded paddies, creating anaerobic conditions ideal for bacteria that feed on decomposing organic matter and emit methane as a byproduct. Given that rice is a key staple crop in much of the world, it is crucial to be able to track methane production from rice cultivation and to investigate potential methods for mitigating those emissions.

Climate TRACE generates rice cultivation GHG emissions estimates using three different methods. The highest resolution of these modeling approaches is conducted using Sentinel-1A synthetic aperture radar (SAR) and Sentinel-2A/B 10m spatial resolution time-series data. The data from these satellites were applied to estimate rice cultivation emissions in the largest rice producing countries for 2022 to 2024 and, in some cases, 2021. A second model was developed that used 500m data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua satellites (read more at <https://modis.gsfc.nasa.gov/about/>). Rice cultivation emissions were estimated for years 2015 to 2021 using this method. Finally, for countries and years not modeled using the first two approaches, appropriate emission factors derived from

literature review were applied to country-level data provided by The Food and Agriculture Organization (FAO) FAOSTAT.

This document describes the high-resolution approach to estimating rice cultivation emissions using Sentinel-1A synthetic SAR and -2A/B, as well as an analysis of Emissions Reductions Strategies (ERSs) that can be used to mitigate rice cultivation GHG emissions. Rice is grown in flooded paddies to help suppress weeds that would undermine crop yields. Water can originate from irrigation infrastructure or seasonal flooding, or a rice field can exist within permanent deep water conditions. While long-term flooded conditions are effective at weed suppression, they provide ideal conditions for methane-generating microorganisms to thrive, generating higher methane emissions. Methane emissions from rice paddies also respond to the nutrient balance in the fertilizer applied. While most farmers primarily focus on the nitrogen content of fertilizers, phosphorus deficiency in rice systems has consequences both for productivity and methane emissions. Phosphorus can help create the conditions for methane consuming methanotrophs, micro-organisms that are limited in phosphorus deficient systems.

Thus, rice cultivation ERSs include strategies designed to strike a balance between reducing methane production from flooding and phosphorus deficiency and maintaining weed suppression and strong rice yields.

- Irrigated rice paddies: Alternate Wetting and Drying (AWD) is an irrigation management technique that can help prevent the development of microorganisms that generate methane under prolonged flooding conditions. Through repeated draining and flooding, rice systems can suppress weeds that threaten crop yields while meaningfully controlling methane emissions (Zhao et al., 2024).
- Non-irrigated rice paddies: Balanced Fertilizer Composition involves balancing fertilizer applications to have a combination of phosphorus and potassium in addition to nitrogen can reduce methane emissions from rice paddies. When combined with potassium and phosphorus soil amendments, a balanced fertilizer application can reduce net emissions 21-28% depending on the number of harvests within a production system (Zhu et al., 2022).

2. Materials and methods

2.1 Materials

2.1.1 Emissions factors

From 2015 to 2021, emissions estimates were refined by national emission factors (EFs), (see Table S2). Subsequently, for 2022 through 2024, emission factors were further customized for three countries—China, Vietnam, and Thailand—where sub-national EFs or higher temporal frequencies were available. These country-specific factors were applied to capture local

variations in rice cultivation practices (Katoh, 1999; Thoung Vo, 2020; Sun, 2020). The sub-national EFs used for these countries are detailed in Tables S3 to S5.

2.1.2 Satellite data and indices used

Southeast Asia contains much of the world's rice cultivation area, producing around 29% of rice methane emissions globally (Ginting et al., 2025) through a diverse range of different rice production practices, including smallholder production systems. Thus, a precise approach was developed to accurately estimate harvested areas across Southeast Asia. Since 2023, Universiti Malaysia Terengganu (UMT) has applied these methods for modeling in rice production regions in South Asia, Europe, North America, and South America (See Table S1 for details).

Data comes from a combination of optical (Sentinel-2) and Synthetic Aperture Radar (SAR) (Sentinel-1) remote sensing, which integrates the unique benefits of both types of imagery. High-resolution (10-meter) maps of rice cropping intensity, taking into account repeated harvests throughout the entire growing season, were generated from Sentinel time-series data from January 2020 to December 2021 using the Local Unsupervised Classification with Phenological Labelling (LUCK-PALM) algorithm (Ginting et al., 2025). The Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI) from Sentinel-2 were used to capture rice phenology and flooding of rice fields, respectively. Sentinel-1 SAR time-series data were used to calculate monthly median VH backscatter, and European Space Agency (ESA) Worldcover 2020 land cover data was leveraged to mask non-cropland areas. For more detailed information on these methods, refer to the published article in *Scientific Data* at <https://www.nature.com/articles/s41597-025-05722-1>.

Currently, the Sentinel modeling approach covers:

- 2021: 14 countries,
- 2022: 31 countries,
- 2023: 39 countries
- 2024: 60 countries* including expanded coverage in Europe, South America, and the African continent. See Table S1 for details.

*of which 39 have been published in Climate TRACE data as of November 2025 due to availability of historical data. See table S1 for country-specific information.

Where Sentinel imagery was unavailable (primarily for years 2015-2020), harvested rice area estimates were based on MODIS data with a spatial resolution of 500 meters, covering the majority of rice-producing regions (see Table S1).

2.1.3 FAOSTAT rice data

Country-level rice cultivation data was acquired from the Food and Agriculture Organization database (FAOSTAT) to supplement rice production information where satellite data was not applied to countries. Refer to Table S1 for more detailed information on where this method was applied.

2.2 Methods

2.2.1 Estimating rice emissions

The Climate TRACE coalition estimates annual rice cultivation emissions for a country i (E_i) each year using the IPCC (1997) approach, calculated as follows (Eq.1):

$$(Eq. 1) \quad E_i = (A_1 * EF_1)_i + (A_2 * EF_2)_i + (A_3 * EF_3)_i$$

Where:

- A_1, A_2, A_3 are the harvested rice areas for the first, second, and third seasons, respectively (in hectares).
- EF_1, EF_2, EF_3 are the emission factors for the respective seasons (in tons per hectare).

The harvested rice areas for different seasons and regions were determined based on rice cropping intensity using remote sensing technology. The emission factors were obtained from published data.

2.2.2 Incorporating ERS into model

The ERS strategy to apply to each asset was determined by satellite data supplemented with literature review. For countries in Southeast Asia, rice fields (assets) were identified as rainfed rice, irrigated rice, and/or deep-water rice. For countries outside of Southeast Asia, literature references provided the dominant type of rice production within each country. For assets and countries with >50% of rice production area under irrigation, the AWD strategy was applied, and for all other assets, the Balanced Fertilizer Composition strategy was applied. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

2.2.3 Alternate wetting and drying (AWD)

AWD was incorporated into the ERS dataset for rice cultivation after the emissions modeling process as an adjustment to the CH₄ emissions factor for each asset. The updated emissions factor is applied to some percentage of the harvested area (activity) within each grid cell, depending on whether that location is known to be partially or entirely irrigated.

The AWD strategy is estimated to reduce the combined GWP-adjusted emissions of N₂O + CH₄ by an average of 46.9% compared to continuous flooding, according to a 2024 meta-analysis of studies (this accounts for a reduction in CH₄ emissions and an increase in N₂O emissions) (Zhao et al., 2024). In order to ensure both impacts were represented despite having no quantified N₂O emissions in this subsector, we reduced the CH₄ emissions of each asset with the AWD strategy by 46.9%, resulting in a new-to-old ratio of CH₄ emissions of 0.531. To account for assets with different percentages of irrigated rice, we used the following structure:

- Assets where the rice production area was observed or estimated to have been irrigated >95% were assigned the *awd95pct* strategy. The methane emissions were reduced by 46.9%, and this reduction was applied to 95% of the harvested area in these assets.
- Assets where the rice production area was observed or estimated to have been irrigated >=50% but less than 95% were assigned the *awd50pct* strategy. The emissions were reduced by 46.9%, and this reduction was applied to 50% of the harvested area in these assets.
- Assets where the rice production areas were observed or estimated to have been irrigated <50% were assigned Balanced Fertilizer Composition ERSs, as explained in the next section.

2.2.4 Balanced fertilizer composition

Balanced fertilizer composition was also incorporated after the emissions modeling process as an adjustment to the CH₄ emissions generated by the rice cultivation activity for each asset. This strategy is estimated by a 36-year field trial study published in 2022 to reduce CH₄ emissions by an average of 21.2% for early-season harvests and 28.6% for late-season harvests (Zhu et al., 2022). We have data on how many yearly harvests each rice production asset undergoes (either one, two, or three). Thus, we scaled these emissions reductions as follows:

- Rice fields with a single yearly harvest (early-season) were assigned the *rfeearly* strategy, with CH₄ emissions reduced by 21.2%. These reductions were assigned to 100% of the rice harvest area in the asset.
- Rice fields with two yearly harvests (early-season and late-season) were assigned the *rfrmiddle* strategy, with CH₄ emissions reduced by 24.9%, which is the average of early-season (21.2%) and late-season (28.6%) emissions reductions. These reductions were assigned to 100% of the rice harvest area in the asset.
- Rice fields with three yearly harvests (early-season, middle-season, and late-season) were assigned the *rfrlate* strategy, with CH₄ emissions reduced by 26.1%. This emissions

reduction was calculated by averaging the emissions reductions for one early season (21.2%) harvest and two late season harvests (2*28.6%). These reductions were assigned to 100% of the rice harvest area in the asset.

2.2.5 Calculating emissions after incorporating ERS

Rice cultivation emissions adjusted for ERSs are calculated as shown in Equations 2 and 3.

$$(Eq. 2.) \quad EF_{ERS} = EF * R_{EF}$$

where EF_{ERS} is the methane emissions factor after implementing ERS,
 EF is the methane emissions factor before implementing ERS,
and R_{EF} is the new-to-old emissions factor ratio.

$$(Eq. 3.) \quad emissions_{ERS} = EF_{ERS} * [A_{max} * A] + EF * [(1 - A_{max}) * A]$$

Where $emissions_{ERS}$ is the adjusted annual methane emissions after implementing ERS,
 A_{max} is the ratio of maximum activity affected by the ERS to total activity,
and A is the annual activity of the asset.

2.2.6 Verifying ERS estimates

The proposed rice cultivation ERSs are considered scenario-based: approaches that are shown (in limited deployment and studies) to reduce methane emissions, but are not fully implemented. In the future, methods to observe and verify AWD may be implemented using remote sensing tools. Time series wetness indices combined with in-situ moisture readings have been demonstrated to provide a prediction of AWD adoption (Lovell 2019). As these practices begin deployment within carbon offset projects, it is likely that several scalable remote sensing tools may be available to cost effectively monitor implementation, but given low current adoption rates of AWD, attempts to implement and validate remote sensing detection strategies in new geographies is challenging.

The composition of fertilizer applied to rice fields cannot be directly observed, though there may be opportunities to use independent evidence via fertilizer consumption data at a country or site specific scale that could provide insight into the adoption of fertilizer-based strategies.

3. Results

3.1 Sentinel Results

The high-resolution Sentinel approach developed by Ginting, F.I., Rudiyanto, R., Fatchurrachman et al. (2025) yields promising results, with an overall rice cropping intensity identification accuracy of 98.3%. The model is able to track rice growth over time within a growing year, enabling detection of rice cropping intensity (whether a rice field was harvested one, two, or three times within a year; see Figure 1). Rice growth is tracked using NDVI; the number of NDVI peaks within a year corresponds to the cropping intensity (Ginting et al., 2025). This approach allows Climate TRACE emissions estimates to vary based on the cropping intensity of a rice field (see Eq. 1), yielding high accuracy compared to previous methods.

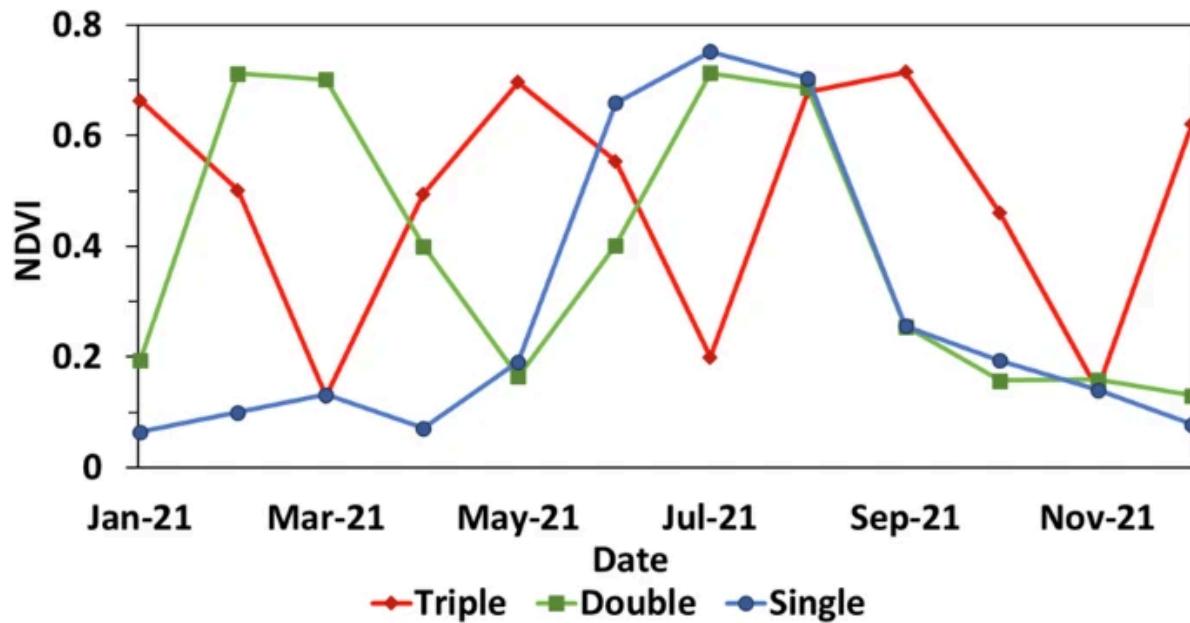


Figure 1. Plot showing NDVI over the year 2021 for single (blue lines), double (green lines) and triple (red lines) rice cropping intensities (Ginting et al., 2025).

Results from the Sentinel model indicate that the vast majority of rice cropping area is concentrated in South and Southeast Asia, with India (53,457,705 hectares) and China (28,198,771 hectares) representing the largest shares by far of the 159,384,573 total hectares of harvested area in 2024. Other countries where rice is a staple crop, including Thailand, Bangladesh, Myanmar, and Indonesia, follow distantly (see Figure S2).

3.2 Rice cultivation emissions results

Total methane emissions from rice cultivation estimated using the Sentinel-1&2 methods outlined in this document fall at 24,906,589 tons; 25,223,626 tons, and 26,121,589 tons for 2022, 2023, and 2024 respectively. The countries producing the highest shares of those emissions are primarily located in South and Southeast Asia; China, India, Thailand, Indonesia, and

Bangladesh were the top five producers of rice cultivation methane emissions in 2024. Notably, Brazil is the only non-Asian country that falls within the top ten producers of rice cultivation methane emissions for 2024. Refer to Figure S6 (a,b) for more detailed information.

3.3 Example results from applying ERSs

There is currently no feasible method to monitor implementation of AWD or fertilizer practices in rice cultivation; thus, it's difficult to compare actual modeled emissions from assets with and without ERSs applied. Instead, Table 1 compares 2024 methane emissions and emissions factors for a handful of assets with *potential* emissions and emissions factors if ERSs were to be applied to those assets. The AWD strategy (with 95% of activity affected) yields the largest potential emissions reduction, at 44.55%, but all strategies demonstrate meaningful emissions reduction potential. Post-ERS emissions and emissions factors in Table 1 were calculated as shown in Eq. 2 and Eq. 3 in section 2.3.3 above.

Table 1. Comparison of actual modeled 2024 annual emissions and estimated 2024 annual emissions if each ERS were to be applied. Annual activity is defined as the total harvested rice area (in hectares) of an asset in a given year, taking into account multiple harvests if applicable.

Asset ID	Max activity affected by ERS	CH4 EF ratio (new to old)	Strategy ID	Annual activity	CH4 EF before ERS	Annual CH4 emissions before ERS (tonnes)	CH4 EF after ERS	Annual CH4 emissions after ERS (tonnes)	Percent change in annual CH4 emissions from ERS
RUS.1.7_1	0.95	0.531	awd95pct	7797	0.081	631.531	0.043	350.153	- 44.55 %
KHM.14.4_2	0.5	0.531	awd50pct	784	0.145	113.994	0.077	87.262	- 23.45 %
JPN.10_1	1	0.788	rfrearly	27479	0.470	12909.674	0.370	10172.823	- 21.20 %
BGD.1.1_1	1	0.751	rfrmiddle	125225	0.168	21062.723	0.126	15818.105	- 24.90 %
BGD.3.14_1	1	0.739	rfrlate	124522	0.168	20944.935	0.124	15459.655	- 26.10 %

4. Discussion of ERS impacts on rice cultivation emissions

Alternate Wetting and Drying (AWD) only works in rice paddies with irrigation systems capable of modulating flooding rates, which is not practical in rainfed systems or in permanent waterways. Acidic soils or soils with low soil organic carbon also may experience yield reductions under these methods. One study estimates that approximately 60% of fields where AWD has been evaluated experience a win-win of yield gains, water efficiency, and emissions reductions (Gao et al., 2024). It is a fairly elegant solution where the correct infrastructure is available, but some lower-resourced regions where irrigation allotments are less dispatchable or

where irrigation infrastructure is less developed may struggle to implement the solution. There can also be up front capital barriers to this solution. The practice is not yet wide-spread enough to impact global emissions estimates, though its efficacy has been well documented.

Unlike plentiful nitrogen, phosphorus is available in more limited quantities, which makes Balanced Fertilizer Composition potentially less accessible to operations without the capital to procure phosphorus fertilizers, even if the potential yield boost may help improve the economic case for these management changes. There is limited data on this solution in continuously flooded rice operations, where limited oxygen availability creates adverse conditions for sustaining methanotrophs, potentially limiting the effectiveness of Balanced Fertilizer Composition (Zhu et al., 2022). Highly acidic conditions may also discourage production of methanotrophs, limiting the methane efficacy of this solution (Zhu et al., 2022). While this solution will work in many contexts (P and K are thoroughly documented as important soil nutrients), global phosphorus shortages limit the ability of this solution to scale across global rice production systems. Targeting the solution to the most phosphorus deficient soils (that are not overly acidic) in intermittently flooded systems will ensure maximum yield and emissions benefits are realized.

5. Conclusion

Emissions Reductions Solutions for rice cultivation include Alternate Wetting and Drying (AWD) and Balanced Fertilizer Composition. AWD is an ideal solution for irrigated rice paddies with balanced soils and adequate infrastructure. Alternately flooding and drying the rice paddy reduces the prevalence of ideal conditions for methane-generating microorganisms to flourish, thus reducing emissions by 46.9% compared to continuous flooding (Zhao et al., 2024). AWD can also improve crop yields (Gao et al., 2024). Balanced Fertilizer Composition involves adding phosphorus to fertilizer plans, which creates ideal conditions for methane-consuming microorganisms called methanotrophs. This strategy can reduce overall methane emissions by between 21.2% and 26.1%, depending on the number of times a paddy is harvested (Zhu et al., 2022). This strategy is, however, limited in scalability by global phosphorus shortages.

6. Supplementary materials

Table S1 The different spatial resolutions for modeled countries by year. 500m = MODIS modeling approach. 10m = Sentinel-1A/B and -2A/B modeling approach. A country with a “N/A” for a specific year, or for any country not shown, used FAOSTAT to estimate rice emissions for that specific country and year.

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Bangladesh	500m	10m	10m	10m						
Bhutan	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
Brazil	500m	10m	10m	10m						
Bulgaria*	N/A	10m								
Burkina Faso*	N/A	10m								
Burundi*	N/A	10m								
Cambodia	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Cameroon*	N/A	10m								
China	500m	10m	10m	10m						
Ecuador	N/A	10m	10m	10m						
Egypt	N/A	10m	10m	10m						
Ethiopia	N/A	10m	10m	10m						
France*	N/A	10m								
Gambia*	N/A	10m								
Greece*	N/A	10m								
Guinea*	N/A	10m								

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Guinea-Bissau*	N/A	10m								
Guyana	N/A	10m	10m							
Hungary*	N/A	10m								
India	500m	10m	10m	10m						
Indonesia	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Iran (Islamic Republic of)	500m	10m	10m	10m						
Italy	500m	10m	10m	10m						
Japan	500m	10m	10m	10m						
Kenya*	N/A	10m								
Korea (the Democratic People's Republic of)	500m	10m	10m	10m						
Korea (the Republic of)	500m	10m	10m	10m						
Lao People's Democratic Republic (the)	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Madagascar	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
Malawi*	N/A	10m								
Malaysia	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Mali	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
Mauritania*	N/A	10m								
Mexico	N/A	10m	10m							
Morocco*	N/A	10m								
Myanmar	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Nepal	500m	10m	10m	10m						
Niger*	N/A	10m								
Nigeria	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
North Macedonia*	N/A	10m								
Pakistan	500m	10m	10m	10m						
Peru	N/A	10m	10m							
Philippines (the)	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Portugal*	N/A	10m								
Russia	N/A	10m	10m							
Rwanda*	N/A	10m								
Senegal*	N/A	10m								
Sierra Leone*	N/A	10m								
Spain	500m	10m	10m	10m						
Sri Lanka	500m	10m	10m	10m						
Suriname	N/A	10m	10m							
Taiwan (Province of China)	500m	10m	10m	10m						
Thailand	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m
Timor-Leste	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
Turkey	N/A	10m	10m							
Uganda*	N/A	10m								

Country	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
United Republic of Tanzania	N/A	N/A	N/A	N/A	N/A	N/A	10m	10m	10m	10m
United States of America (the)	500m	10m	10m	10m						
Uruguay	N/A	10m	10m	10m						
Viet Nam	500m	500m	500m	500m	500m	500m	10m	10m	10m	10m

*Country modeled but not yet published in Climate TRACE rice cultivation data due to availability of historical data.

Table S2 Seasonally integrated methane (CH₄) emission factors (EFs) in various conditions and locations of the world that were used in this study. Mean emission factors and standard deviation (SD) are provided.

Country	ISO3 country	Mean CH ₄ Emission (kg CH ₄ /ha/season)	SD CH ₄ Emission (kg CH ₄ /ha/season)	References
Bangladesh	BGD	168.2	80.4	(Islam <i>et al.</i> , 2020)
Bhutan	BTN	81	42.5	India EF
Brazil	BRA	430.1	149.6	(Camargo <i>et al.</i> , 2018; Zschornack <i>et al.</i> , 2018)
Bulgaria	BGR	292	116	Italy EF
Burkina Faso	BFA	183.6	51.04	Africa EF (Mboyerwa, 2022)
Burundi	BDI	183.6	51.04	Africa EF (Mboyerwa, 2022)
Cambodia	KHM	145.3	31	(Vibol and Towprayoon, 2010)
Cameroon	CMR	183.6	51.04	Africa EF (Mboyerwa, 2022)
Ecuador	ECU	430.1	149.6	Brazil EF
Egypt	EGY	183.6	51.04	(Mboyerwa, 2022)
Ethiopia	ETH	183.6	51.04	(Mboyerwa, 2022)
France	FRA	292	116	Italy EF

Country	ISO3 country	Mean CH₄ Emission (kg CH₄/ha/season)	SD CH₄ Emission (kg CH₄/ha/season)	References
Gambia	GMB	183.6	51.04	Africa EF (Mboyerwa, 2022)
Greece	GRC	292	116	Italy EF
Guinea	GIN	183.6	51.04	Africa EF (Mboyerwa, 2022)
Guinea-Bissau	GNB	183.6	51.04	Africa EF (Mboyerwa, 2022)
Guyana	GUY	430.1	149.6	Brazil EF
Hungary	HUN	292	116	Italy EF
India	IND	81	42.5	(Bhatia <i>et al.</i> , 2005; Kritee <i>et al.</i> , 2018; Oo <i>et al.</i> , 2018)
Indonesia	IDN	339.8	102.1	(Setyanto <i>et al.</i> , 2018)
Iran (Islamic Republic of)	IRN	81	42.5	India EF
Italy	ITA	292	116	(Lagomarsino <i>et al.</i> , 2016; Mazza <i>et al.</i> , 2016; Meijide <i>et al.</i> , 2017)
Japan	JPN	469.8	302.4	(Camargo <i>et al.</i> , 2018; Toma <i>et al.</i> , 2019)
Kenya	KEN	183.6	51.04	Africa EF (Mboyerwa, 2022)
Korea (the Democratic People's Republic of)	PRK	349.4	93	Korea (the Republic of) EF
Korea (the Republic of)	KOR	349.4	93	(Gutierrez, Kim and Kim, 2013; Lim <i>et al.</i> , 2021)
Lao People's Democratic Republic (the)	LAO	78.3	31.6	Thailand EF
Madagascar	MDG	183.6	51.04	Africa EF (Mboyerwa, 2022)
Malawi	MWI	183.6	51.04	Africa EF (Mboyerwa, 2022)
Malaysia	MYS	178.3	118.5	(Fazli and Man, 2014)
Mali	MLI	183.6	51.04	Africa EF (Mboyerwa, 2022)

Country	ISO3 country	Mean CH ₄ Emission (kg CH ₄ /ha/season)	SD CH ₄ Emission (kg CH ₄ /ha/season)	References
Mauritania	MRT	183.6	51.04	Africa EF (Mboyerwa, 2022)
Mexico	MEX	202	121.9	USA EF
Morocco	MAR	183.6	51.04	Africa EF (Mboyerwa, 2022)
Myanmar	MMR	30.1	12.5	(Win <i>et al.</i> , 2020)
Nepal	NPL	81	42.5	India EF
Niger	NER	183.6	51.04	Africa EF (Mboyerwa, 2022)
Nigeria	NGA	183.6	51.04	Africa EF (Mboyerwa, 2022)
North Macedonia	MKD	292	116	Italy EF
Pakistan	PAK	81	42.5	India EF
Peru	PER	430.1	149.6	Brazil EF
Philippines (the)	PHL	258	192.7	(Alberto <i>et al.</i> , 2014; Sander, Samson and Buresh, 2014; Sibayan <i>et al.</i> , 2018)
Portugal	PRT	405.7	202.9	Spain EF
Russia	RUS	81	42.5	India EF
Rwanda	RWA	183.6	51.04	Africa EF (Mboyerwa, 2022)
Senegal	SEN	183.6	51.04	Africa EF (Mboyerwa, 2022)
Sierra Leone	SLE	183.6	51.04	Africa EF (Mboyerwa, 2022)
Spain	ESP	405.7	202.9	(Moreno-García, Guillén and Quílez, 2020; Martínez-Eixarch <i>et al.</i> , 2021)
Sri Lanka	LKA	81	42.5	India EF
Suriname	SUR	430.1	149.6	Brazil EF
Taiwan (Province of China)	TWN	112	91.4	(Chang, 2001)

Country	ISO3 country	Mean CH₄ Emission (kg CH₄/ha/season)	SD CH₄ Emission (kg CH₄/ha/season)	References
Timor-Leste	TLS	339.8	102.1	(Setyanto <i>et al.</i> , 2018)
Turkey	TUR	81	42.5	India EF
Uganda	UGA	183.6	51.04	Africa EF (Mboyerwa, 2022)
United Republic of Tanzania	TZA	183.6	51.04	Africa EF (Mboyerwa, 2022)
United States of America (the)	USA	202	121.9	(Hatala <i>et al.</i> , 2012; Humphreys <i>et al.</i> , 2019; Della Lunga <i>et al.</i> , 2021; Karki <i>et al.</i> , 2021)
Uruguay	URY	430.1	149.6	Brazil EF

Table S3 summarizes emissions factors and their standard deviation for five regions in China (Sun 2020). For regions where it is common to have multiple rice harvests, unique emissions factors were provided to help illustrate seasonal variation. These emissions factors were applied to modeled harvested area estimates to characterize annual methane emissions.

Table S3 China subnational EFs reported in Sun (2020)

Region	Season	Mean (kg CH ₄ /ha)	Standard Deviation
South China	Early Season	50.5	83.41
	Late-rice	182.3	156.65
	All Rice	116.4	146.14
Southwest China	Single Rice	244	220.36
	All Rice	244	220.36
Yangtze River	Early Season	99.2	140.68
	Late-rice	224.8	224.03
	Single Rice	188.5	173.32
	All Rice	174	188.75
Northeast	Single Rice	74.4	133.62
Huang-Huai-Hai	Single Rice	43.2	15.41

Table S4 Thailand subnational estimated seasonal rice field methane rates. Major and second refers to “wet season rice cropping” and “dry season rice cropping”, respectively (Katoh, 1999). Table modified from Katoh (1999). Blank cells indicate no value given. Asterisk with numbers refer to citations- *1 = Yagi et al. (1994), *2 = Katoh et al. (1999a), and *3 = Katoh et al. (1999b). A season with a “N/A” indicates no value provided.

Site	Year	Rice cultivation	Flooding period (day)	CH4 flux (mg m ⁻² hr ⁻¹)	Estimated seasonal emission (g m ⁻² season ⁻¹)	
					Second	Major
Khon kaen	1991	Major *1	97	16.4	N/A	50.8
		Second *1	109	19.4	38.2	N/A
Khlong Lugang	1991	Second *1	83	3.1	6.1	N/A
Chai Net	1991	Major *1	94	1.1	N/A	2.5
Bang Khen	1992	Major *2	106	21.8	N/A	55.5
		Second *2	120	4.3	12.4	N/A
	1994	Second	118	6.7	19	N/A
Phitsanulok	1992	Major *3	98	7.4	N/A	17.4
	1993	Second *3	113	6.6	17.9	N/A
San Pa Thong	1993	Major *3	103	16.1	N/A	39.8
	1994	Second *3	101	8.8	21.3	N/A
Phtae	1993	Major *3	128	22.2	N/A	68.2
	1994	Second *3	127	15.9	48.5	N/A
Khon Kaen	1994	Major *3	129	19.8	N/A	61.3
	1995	Second *3	96	15.1	34.8	N/A
Surin	1994	Major *3	123	13.3	N/A	39.3
	1995	Second*3	120	15.4	44.4	N/A
Mean					26.9	41.8

Table S5 Vietnam subnational emission factors reported in Thoung Vo (2020). In each of these regions, rice production involved multiple harvests. Unique emissions factors were provided to help illustrate seasonal variation in emissions across successive harvests. These emissions factors were applied to modeled harvested area estimates to characterize annual methane emissions.

Region of Vietnam	Season	Average emissions (kg ha ⁻¹ season ⁻¹)	Standard Deviation
North	Early	271	150
	Late	404	173
Central	Early	321	237
	Middle	321	237
South	Early	174	82
	Middle	277	116
	Late	356	481

Table S6 Rice cultivation Strategy ERS Table. Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.

native_strategy_id	strategy_name	strategy_description	mechanism	max_activity_affected_ratio	ch4_emissions_factor_new_to_old_ratio
awd95pct	Alternate Wetting and Drying	Alternate Wetting and Drying involves periodic soil drying and flooding to achieve intermittent rather than continuous flooding during rice production, inhibiting the production of micro-organisms prone to produce methane.	retrofit	0.95	0.531
awd50pct	Alternate Wetting and Drying	Alternate Wetting and Drying involves periodic soil drying and flooding to achieve intermittent rather than continuous flooding during rice production, inhibiting the production of micro-organisms prone to produce methane.	retrofit	0.5	0.531
rfrearly	Balanced Fertilizer Composition	Changes in fertilizer composition (to include K and P in addition to N) encourages the production of micro-organisms that help control CH4.	retrofit	1	0.788
rfrmiddle	Balanced Fertilizer Composition	Changes in fertilizer composition (to include K and P in addition to N) encourages the production of micro-organisms that help control CH4.	retrofit	1	0.751

native_strategy_id	strategy_name	strategy_description	mechanism	max_activity_affected_ratio	ch4_emissions_factor_new_to_old_ratio
rfrlate	Balanced Fertilizer Composition	Changes in fertilizer composition (to include K and P in addition to N) encourages the production of micro-organisms that help control CH4.	retrofit	1	0.739

Table S7 Rice cultivation Strategy ERS Crosswalk Table: This table provides an example of an asset for each ERS discussed. *Note: Only rank 1 strategies are provided for assets on the Climate TRACE website and additional strategies will be made available in future releases.*

asset_identifier	max_activity_affected_ratio	ch4_emissions_factor_new_to_old_ratio	strategy_id	strategy_name
RUS.1.7_1	0.95	0.531	awd95pct	Alternate Wetting and Drying
KHM.14.4_2	0.5	0.531	awd50pct	Alternate Wetting and Drying
JPN.10_1	1	0.788	rfrearly	Balanced Fertilizer Composition
BGD.1.1_1	1	0.751	rfrmiddle	Balanced Fertilizer Composition
BGD.3.14_1	1	0.739	rfrlate	Balanced Fertilizer Composition

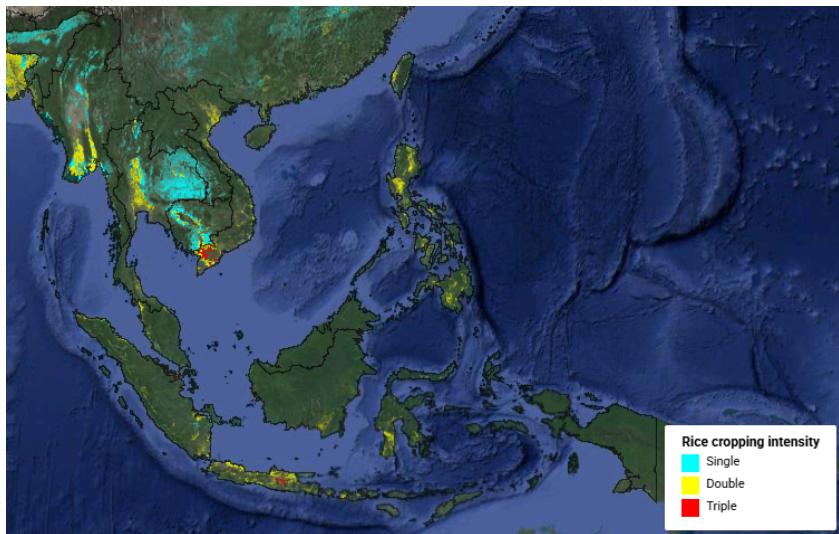
Figure S1 illustrates the spatial distribution of rice cropping intensity for 2024 across different regions: (a) 60 key rice-producing countries. Figure S1 continues below and shows the following regions: (b) Southeast Asia, (c) East Asia, (d) South Asia, (e) the USA, (f) South America, (g) East Africa, (h) West Africa, and (i) Europe. The data is derived from Sentinel-1 and Sentinel-2A/B imagery with a 10m spatial resolution. In Southeast Asia, which is situated in the tropical zone, there is significant variation in cropping intensity, ranging from single (light blue) to double (yellow) and triple (red) rice cropping. In contrast, most other regions are predominantly characterized by single cropping intensity, mainly due to climatic conditions.

(a) Rice cropping intensity across 60 countries (<https://ee-rudiyanto.projects.earthengine.app/view/globalriceintensity2024>)



Figure S1 continued. Spatial distribution of rice cropping intensity for the year 2024 in (a) 60 countries as the main rice producer, (b) Southeast Asia, (c) East Asia, (d) South Asia, (e) the USA, (f) South America, (g) East Africa, (h) West Africa, and (i) Europe. countries derived from Sentinel-1 and Sentinel-2A and -2B at (10m spatial resolution). Colors indicate rice cropping: single (light blue), double (yellow), and triple (red). Figure S1b to S1i are continued on the following pages below.

(b) Southeast Asia



(c) East Asia

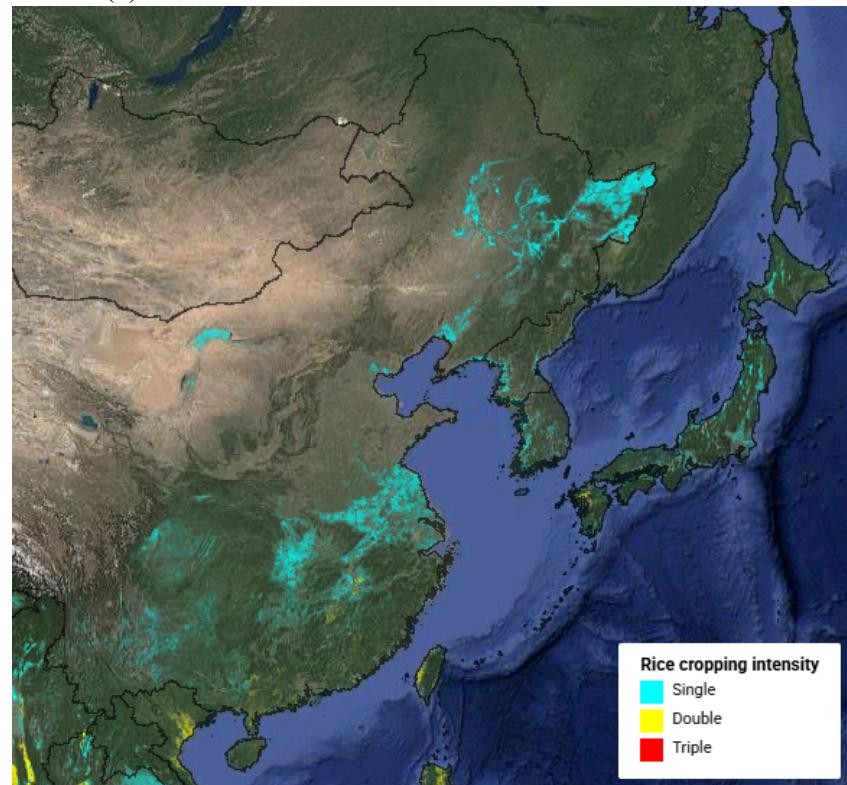
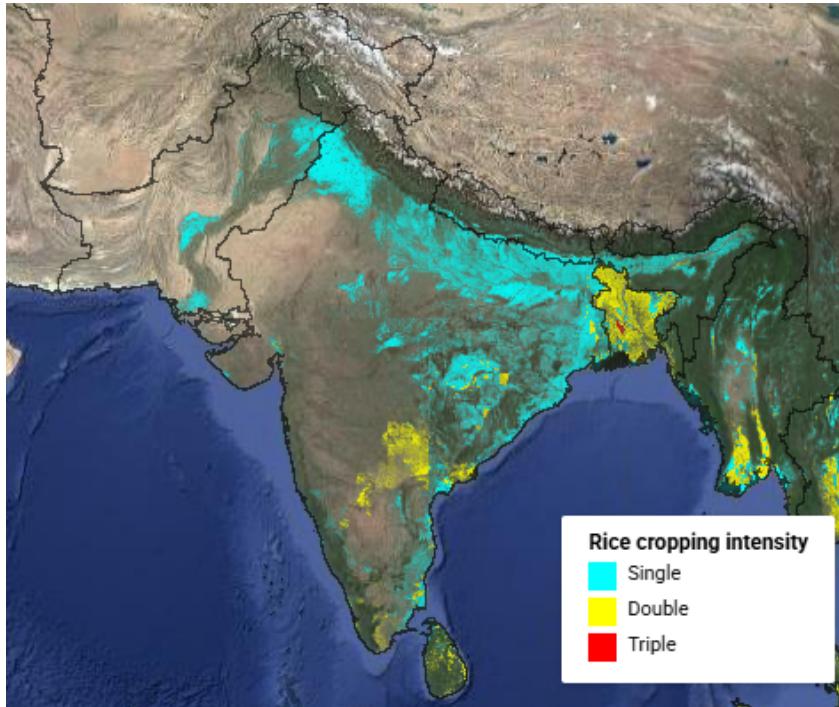


Figure S1 cont.

(d) South Asia

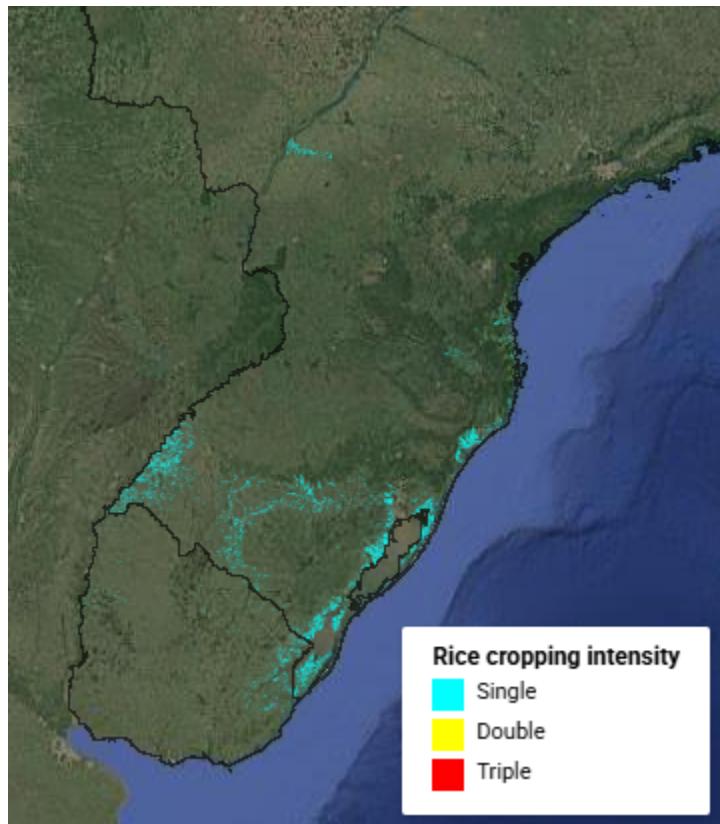


(e) USA (California, Arkansas, Missouri, Mississippi, Louisiana, Texas)



Figure S1 cont.

(f) South America (South regions of Brazil and Uruguay)



(g) East Africa (Tanzania, Kenya, Uganda, Rwanda, Burundi, Malawi, and Madagascar)

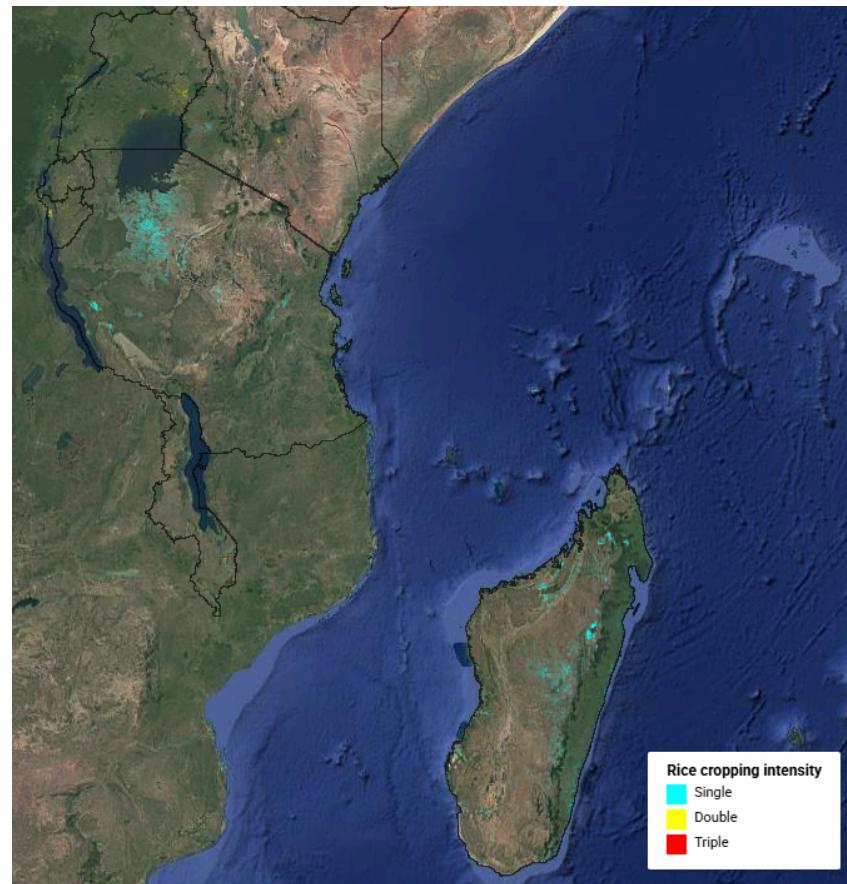


Figure S1 cont.

(h) West Africa (Senegal, Gambia, Guinea-Bissau, Guinea, Sierra Leone, Mali, Burkina Faso, Niger, and Nigeria)

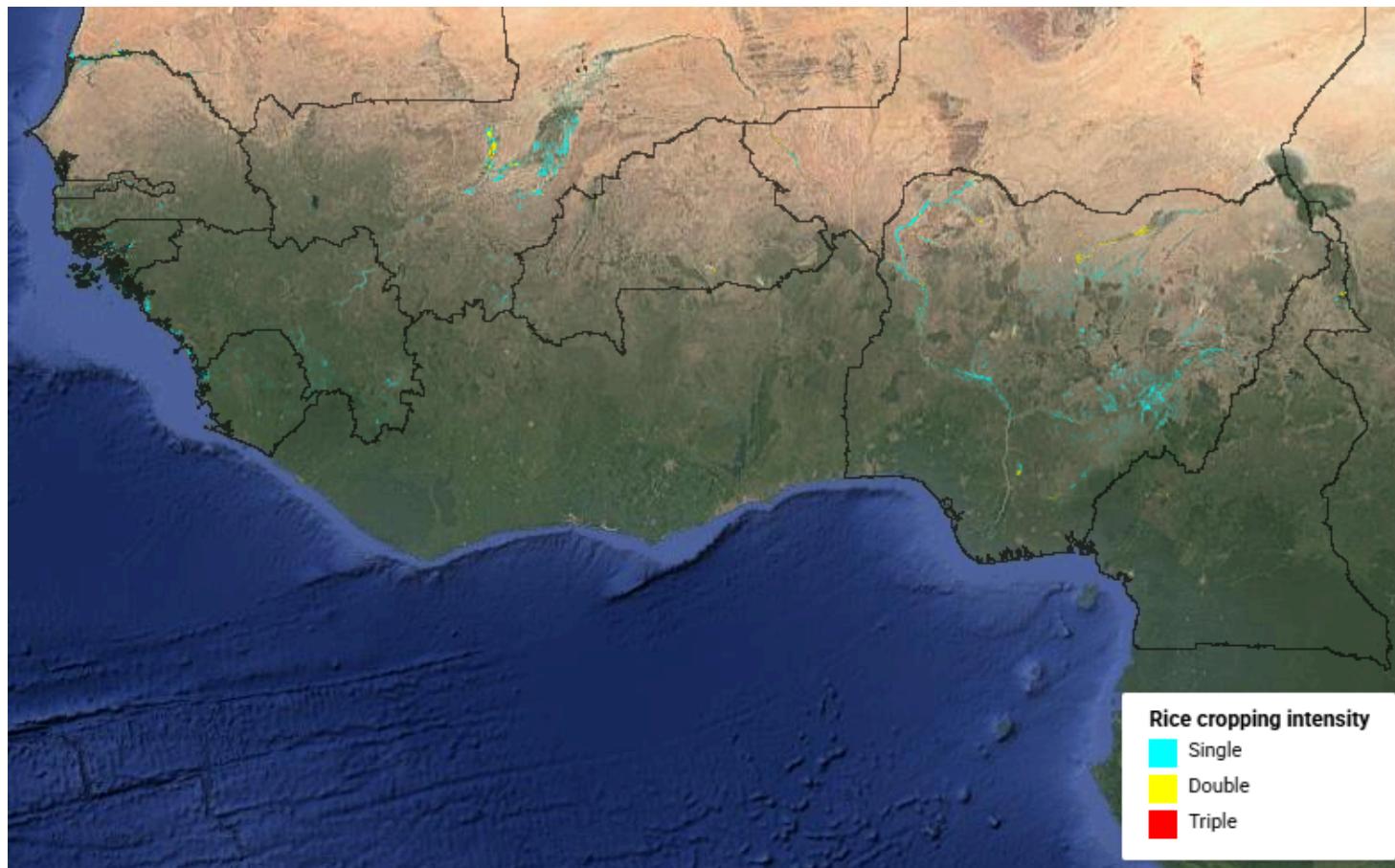


Figure S1 cont.

(i) Europe (Portugal, Spain, France, Italy, Greece, North Macedonia, Hungary, Bulgaria, Turkiye, and Russia)



Figure S1 cont.

Figure S2 presents a dot plot of the annual harvested rice area for 2024 across 60 countries, derived from calculations based on the rice cropping intensity shown in Figure S1a. The total harvested rice area for 2024 amounts to 159,384,573 hectares. This dot plot highlights significant disparities among major rice-producing nations. India leads with a harvested area of 53,457,705 hectares, followed by China with 28,198,771 hectares, underscoring the dominance of these two countries in global rice production. Thailand and Bangladesh also stand out, with harvested areas of 12,602,198 and 11,069,231 hectares, respectively. Other notable contributors include Myanmar (9,421,720 hectares), Indonesia (8,609,632 hectares) and Vietnam (5,495,160 hectares). The data indicates that Southeast Asian countries, particularly those in the tropical region, have substantial harvested areas, reflecting their favorable climatic conditions for rice cultivation. In contrast, countries like the USA, Brazil, and several European nations exhibit significantly lower harvested areas, highlighting their lesser reliance on rice as a staple crop.

(a)

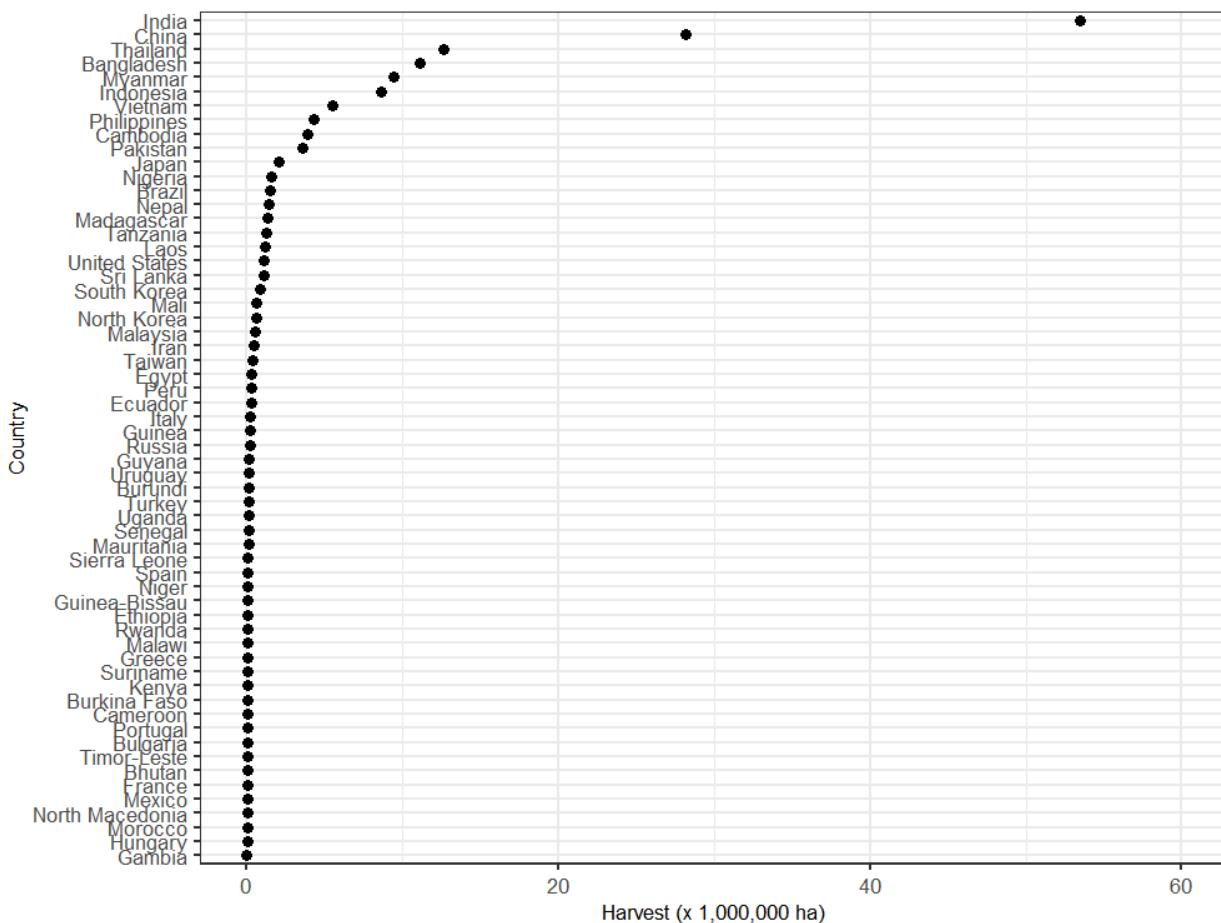


Figure S2 cont.

(b)

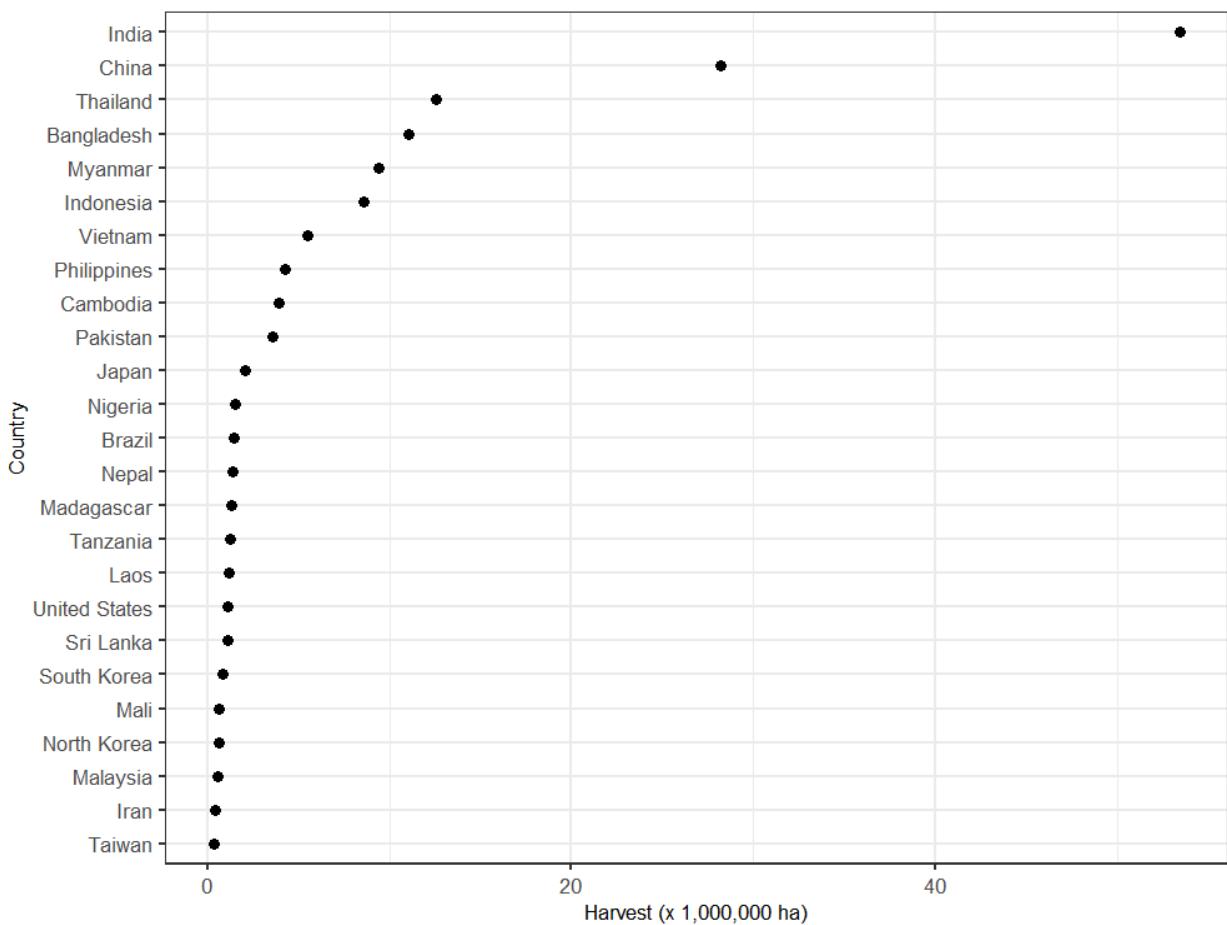


Figure S2. Annual harvested rice area for 2024 across (a) 60 countries and (b) top 25 countries, derived from calculations based on rice cropping intensity shown in **Figure S1a**. FAOSTAT data is not available for 2024.

Based on the provided data comparing harvested rice areas in 2023 from both Paddy Watch and FAO in **Figure S3a**, significant variations are evident among the 36 countries listed. The total harvested rice area reported by Paddy Watch across these countries is 155,811,388 hectares, while the FAO reports a total of 151,420,832 hectares. This discrepancy is primarily attributed to the estimated harvested area in India, where Paddy Watch reports 52,900,000 hectares, significantly higher than the FAO's estimate of 47,828,000 hectares. The remaining countries exhibit relatively similar harvested rice areas across both sources. **Figure S3b** shows the correlation between harvested rice areas reported by Paddy Watch and FAOSTAT for 2023. There is a strong positive linear relationship between the two data sources, with an R^2 value of 0.99. However, the notable divergence in India's figures emphasizes the challenges of obtaining consistent agricultural data and illustrates how different methodologies and data sources can lead to varying estimates of harvested rice area.

(a)

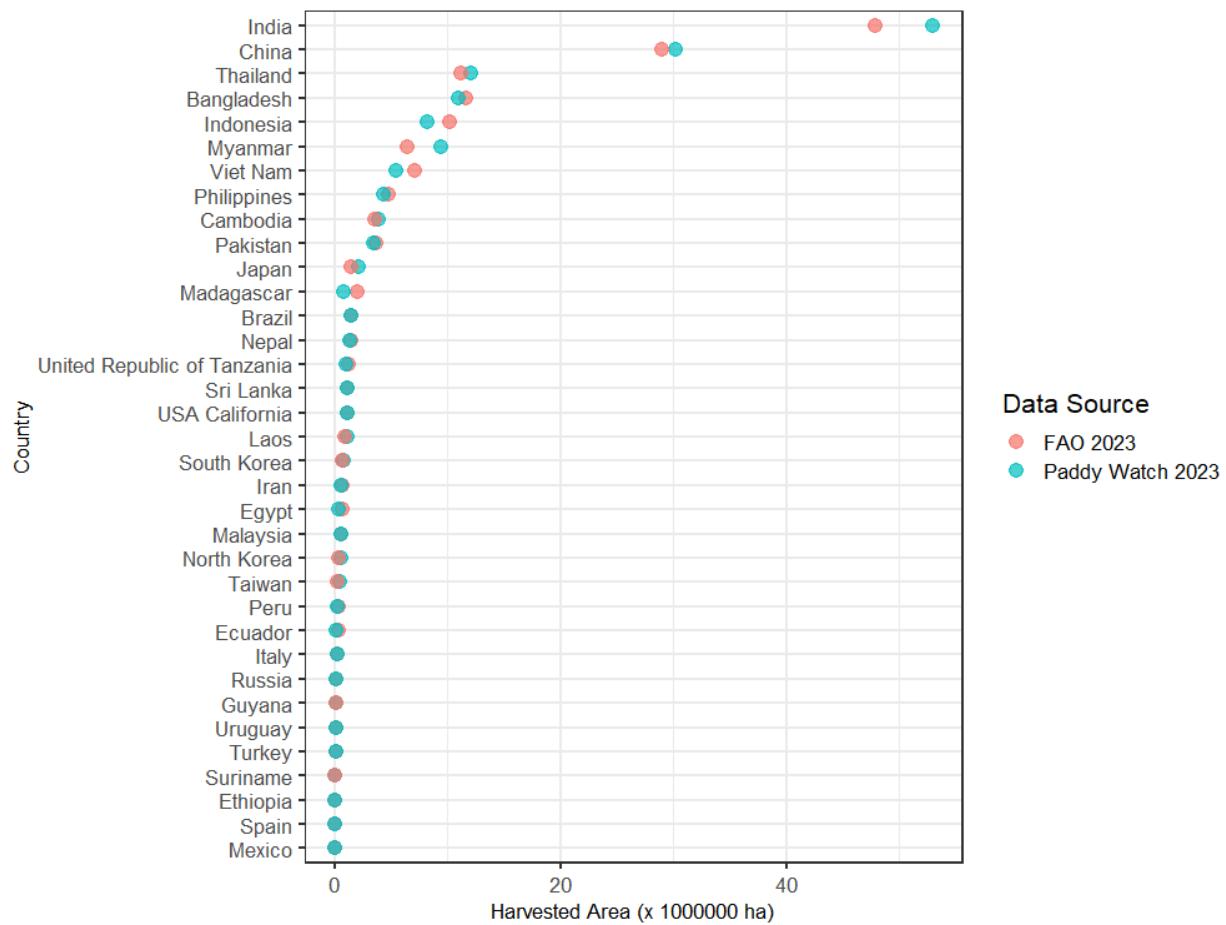


Figure S3 continued

(b)

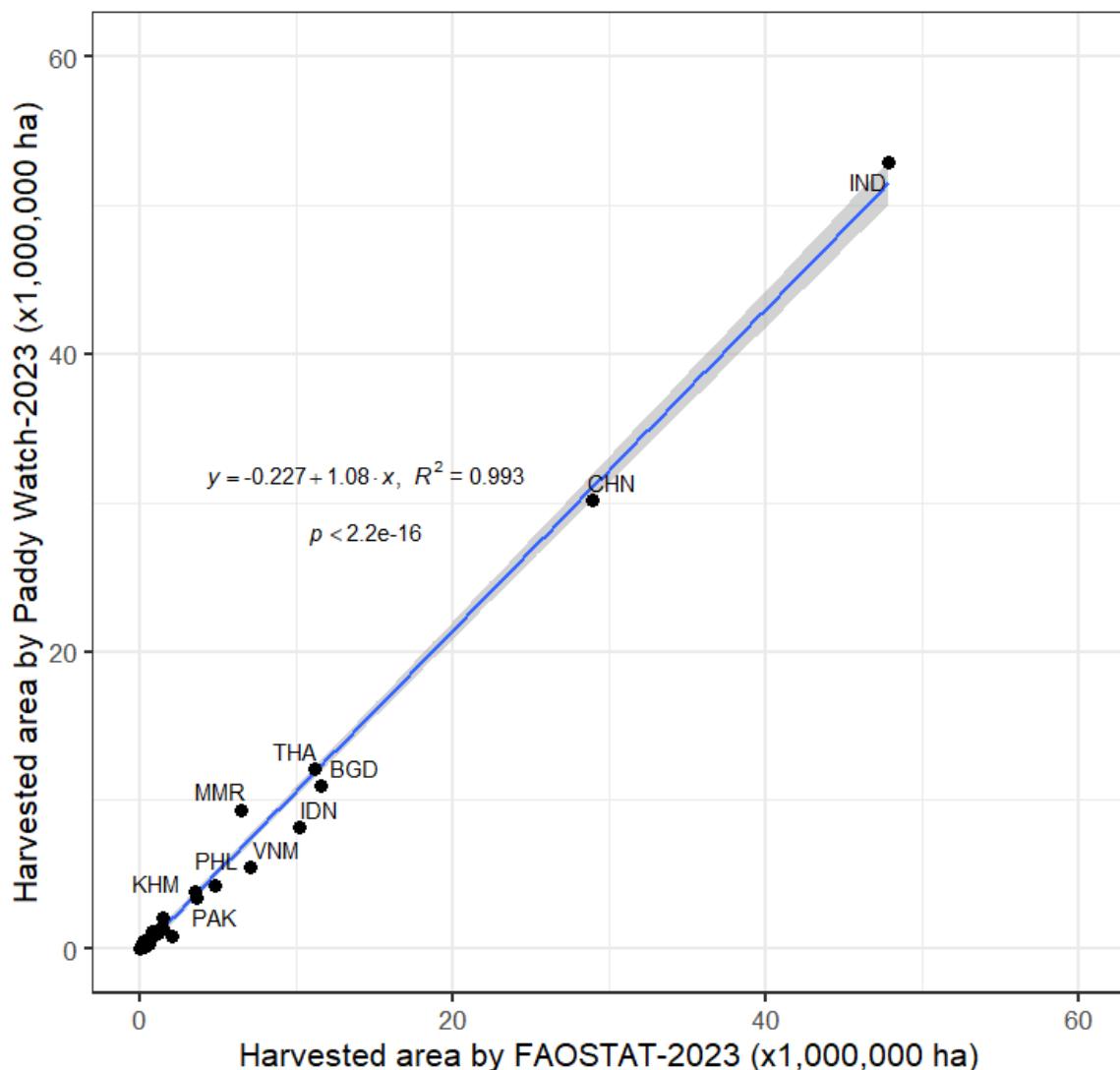
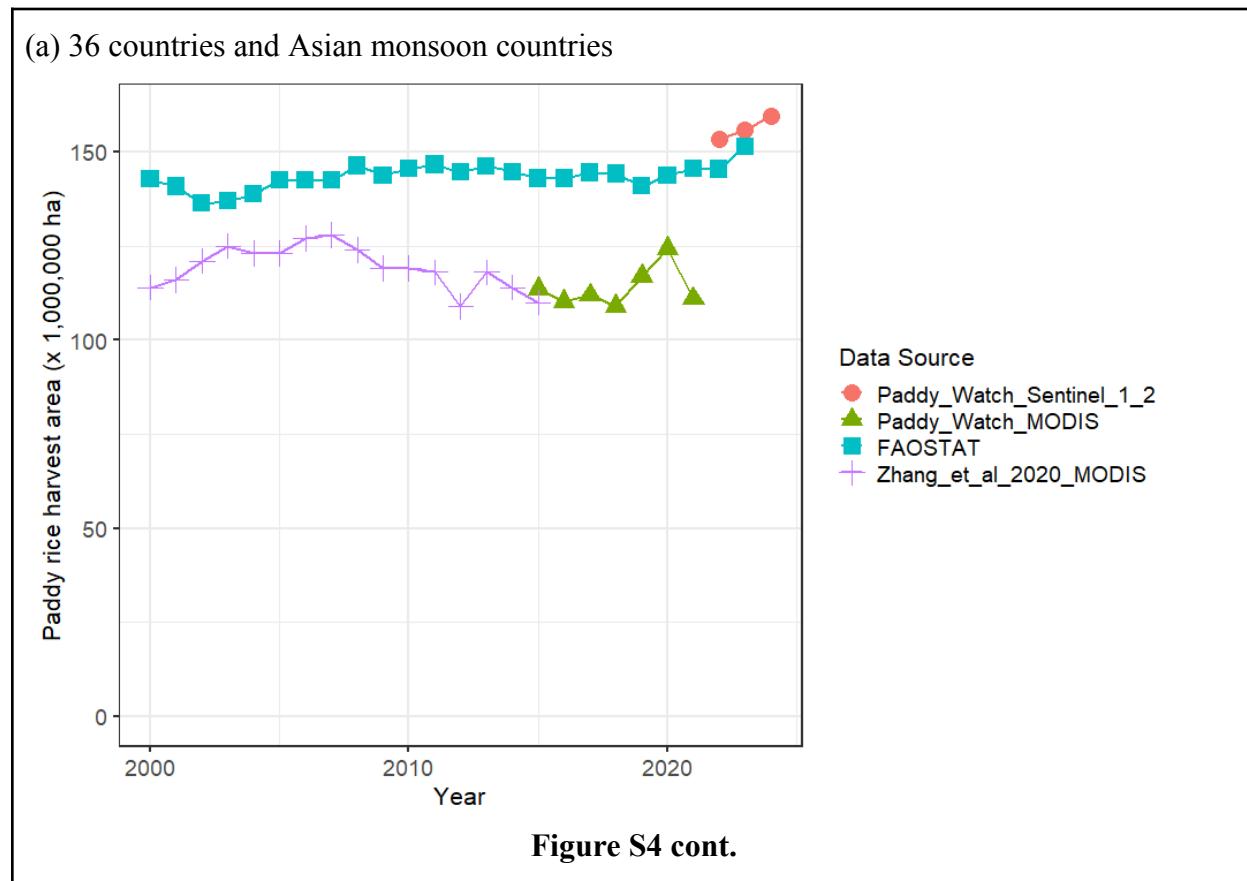


Figure S3. (a) Annual harvested rice area for 2023 across 36 countries; (b) Correlation analysis of annual harvested area between Paddy watch and FAOSTAT data for 2023. The shaded area represents the 95% confidence interval.

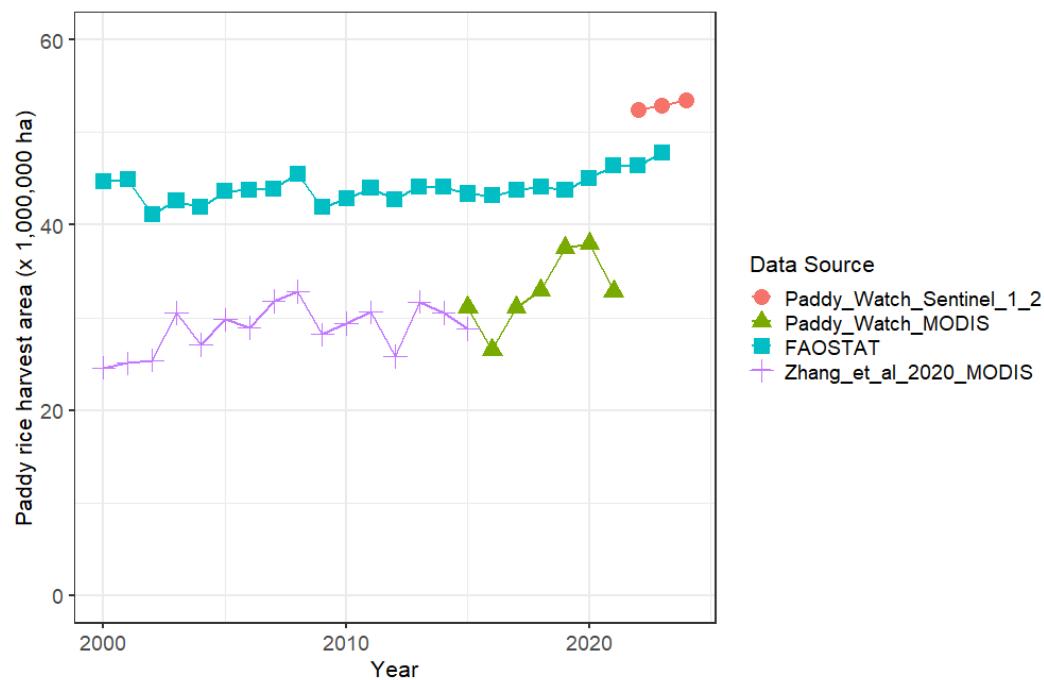
Figure S4 illustrates the annual harvested paddy rice area derived from multiple data sources, showcasing trends from 2015 to 2025. Panel (a) presents data for 36 countries within the Asian monsoon region, integrating information from Paddy Watch using MODIS (2015-2021) and Sentinel-1 and Sentinel-2 (2022-2024), alongside FAOSTAT data for the years 2000 to 2023 and Zhang et al. (2020) for 2000 to 2015. Panel (b) focuses specifically on India, while panel (c) highlights data for China. These figures are larger than the harvested rice area recorded from MODIS data for 2020, which was 124,271,392 hectares, and also exceed the FAOSTAT estimate of 145,408,328 hectares. This increase can be attributed to not only the inclusion of additional countries but also the enhanced spatial resolution, which improves from 500 meters with MODIS

to 10 meters with Sentinel-1/2. This finer resolution allows for more accurate capture of smaller rice fields typically found across Asia.

For India (**Figure S4b**), there is a significant difference between the estimates from Paddy Watch (Sentinel-1/2) and FAOSTAT. Paddy Watch reported a harvested rice area of 52,900,000 hectares for 2022, while FAOSTAT provided a lower estimate of 47,828,000 hectares for the same year. This discrepancy underscores the variability in data sources and methodologies used for estimating agricultural production.



(b) India



(c) China

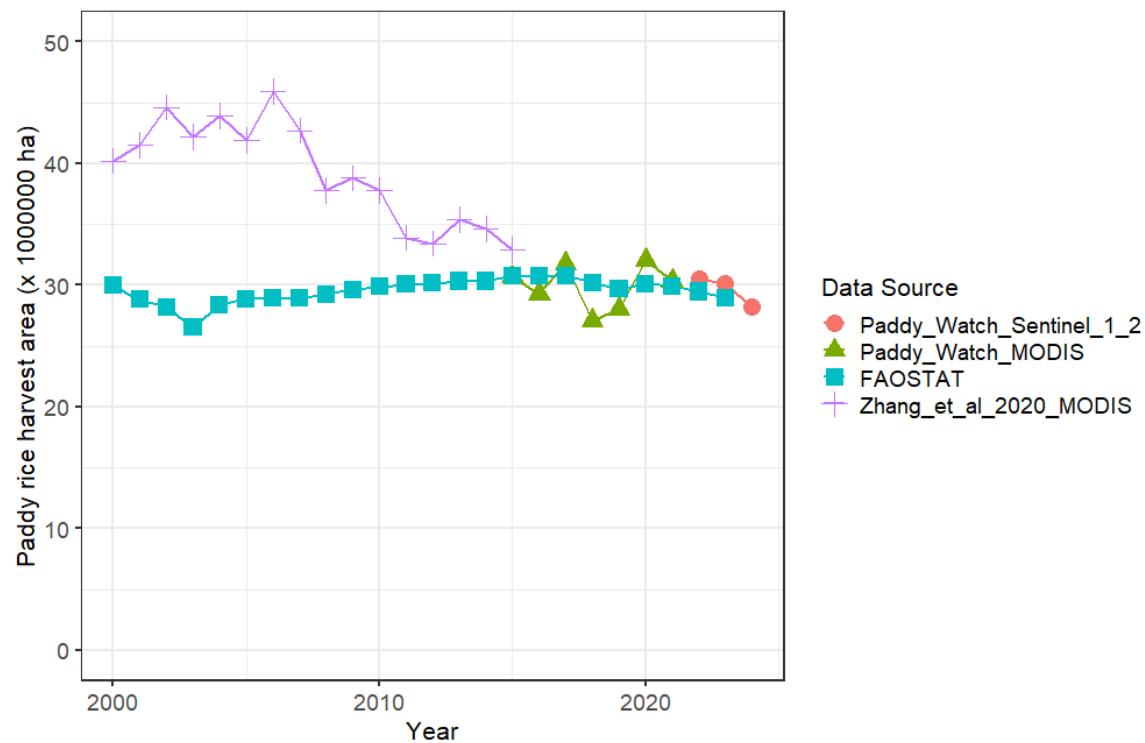


Figure S4. Annual harvested paddy rice area based on Paddy Watch using MODIS (2015 - 2021) and Sentinel-1 and 2 (2022-2024); FAOSTAT data (2000 - 2023) and Zhang et al. (2020) (2000 - 2015) for (a) 36 countries and Asian monsoon countries, (b) India and (c) China.

Figure S5 illustrates the spatial distribution of annual CH₄ emission estimates for the year **2024** from rice cultivation across different regions and countries. The data focuses on 60 of the main rice-producing countries, grouped into several geographic categories: Southeast Asia, East Asia, South Asia, the USA, South America, and Africa. CH₄ emissions from rice cultivation across 60 countries for 2024, derived from calculations based on the spatial distribution of CH₄ emissions from rice cultivation shown in **Figure S6**. In 2024, China and India emerged as the top contributors to CH₄ emissions from rice cultivation, with emissions of 4,712,261 tons and 4,286,663 tons, respectively, highlighting their roles as leading rice producers. Southeast Asian countries, including Thailand (4,001,391 tons), Indonesia (2,778,604 tons), and Bangladesh (1,850,612 tons), also significantly contribute to global emissions due to similar agricultural practices. Moderate contributors such as Vietnam (1,687,665 tons) and the Philippines (1,107,668 tons) further emphasize the region's importance. The notable emissions from Japan (1,009,923 tons) and emerging contributors like Brazil (609,785 tons) and Cambodia (558,655 tons).

(a) Emission for 60 countries (<https://ee-rudiyanto.projects.earthengine.app/view/globalricech4emission2024>)



Figure S5. Spatial distribution of annual CH₄ emission estimates for the year 2024 from rice cultivation in (a) 60 countries as the main rice producer and, continued below, for specific regions: (b) Southeast Asian, (c) East Asian, (d) South Asian, (e) USA, (f) South America, (g) Africa, and (i) Europe countries derived from Paddy Watch using Eq. (1). Yellow colors = lower CH₄ emissions and redder (warmer) colors indicate higher CH₄ emissions. Figures S5b to S5i are on the following pages below.

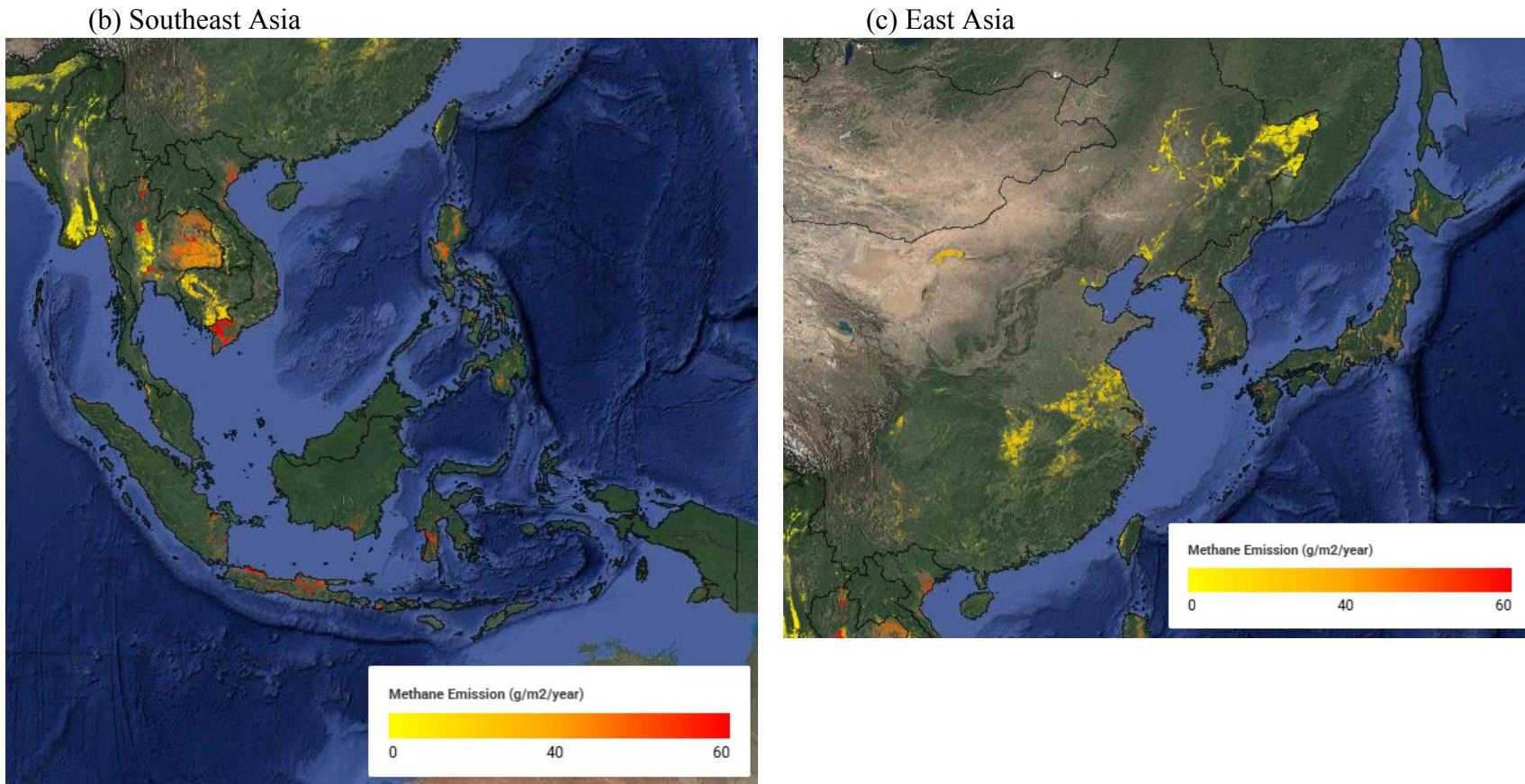
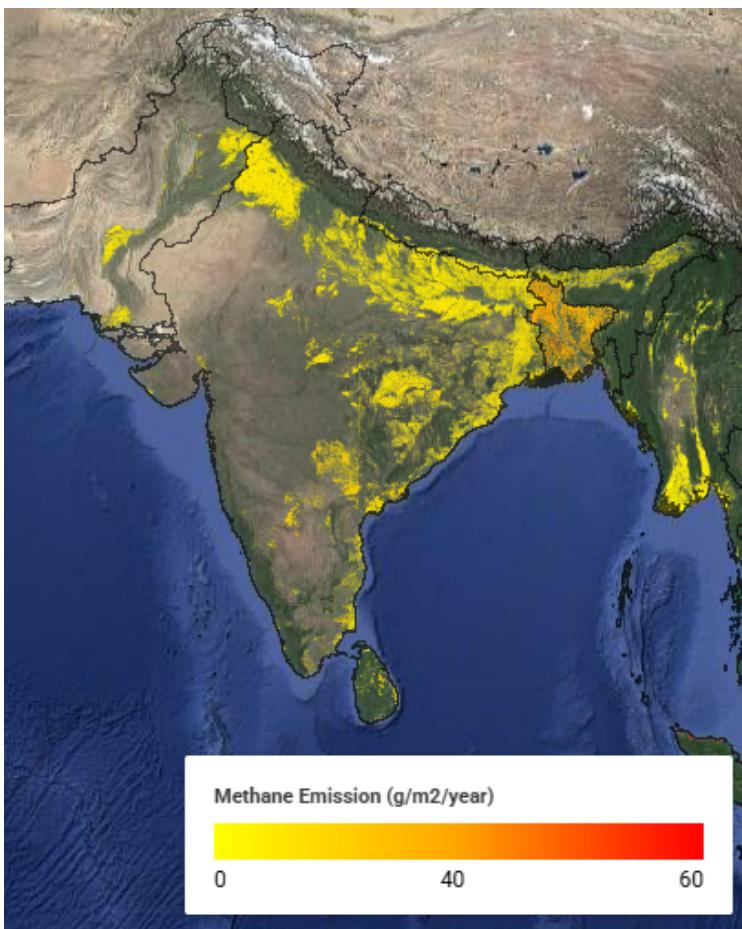


Figure S5 cont.

(d) South Asia



(e) USA (California, Arkansas, Missouri, Mississippi, Louisiana, Texas)

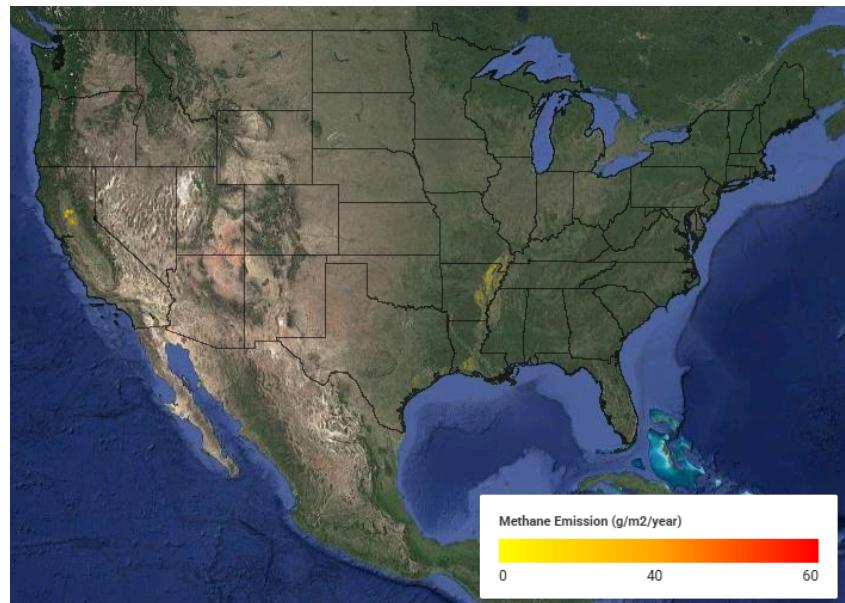
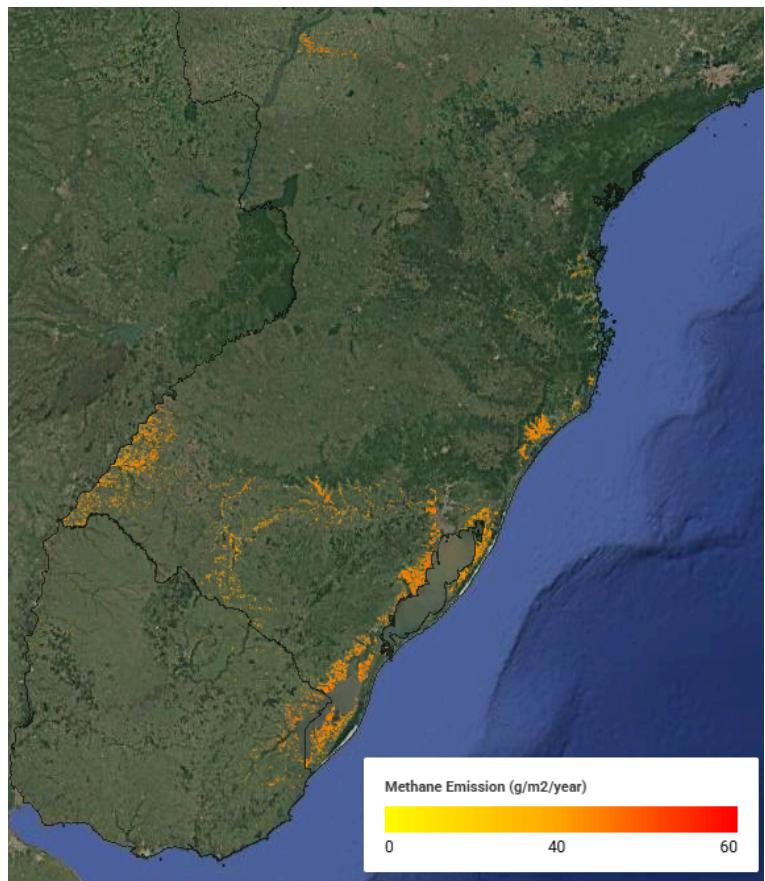


Figure S5 cont.

(f) South America (South regions of Brazil and Uruguay)



(g) Africa (Tanzania, Kenya, Uganda, Rwanda, Burundi, Malawi, and Madagascar)

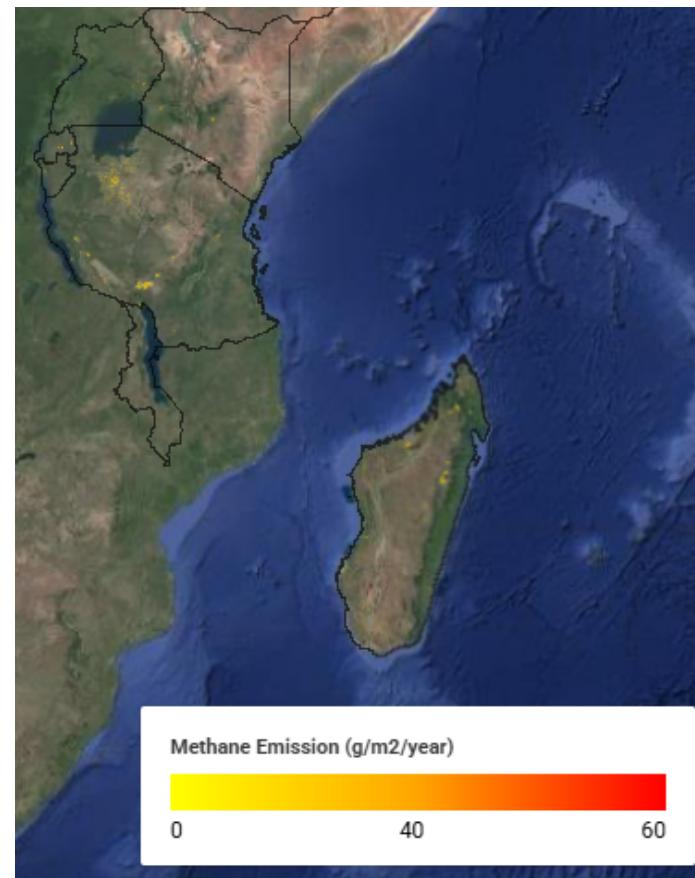


Figure S5 cont.

(h) West Africa (Senegal, Gambia, Guinea-Bissau, Guinea, Sierra Leone, Mali, Burkina Faso, Niger, and Nigeria)



Figure S5 cont.

(i) Europe (Portugal, Spain, France, Italy, Greece, North Macedonia, Hungary, Bulgaria, Turkiye, and Russia)



(a)

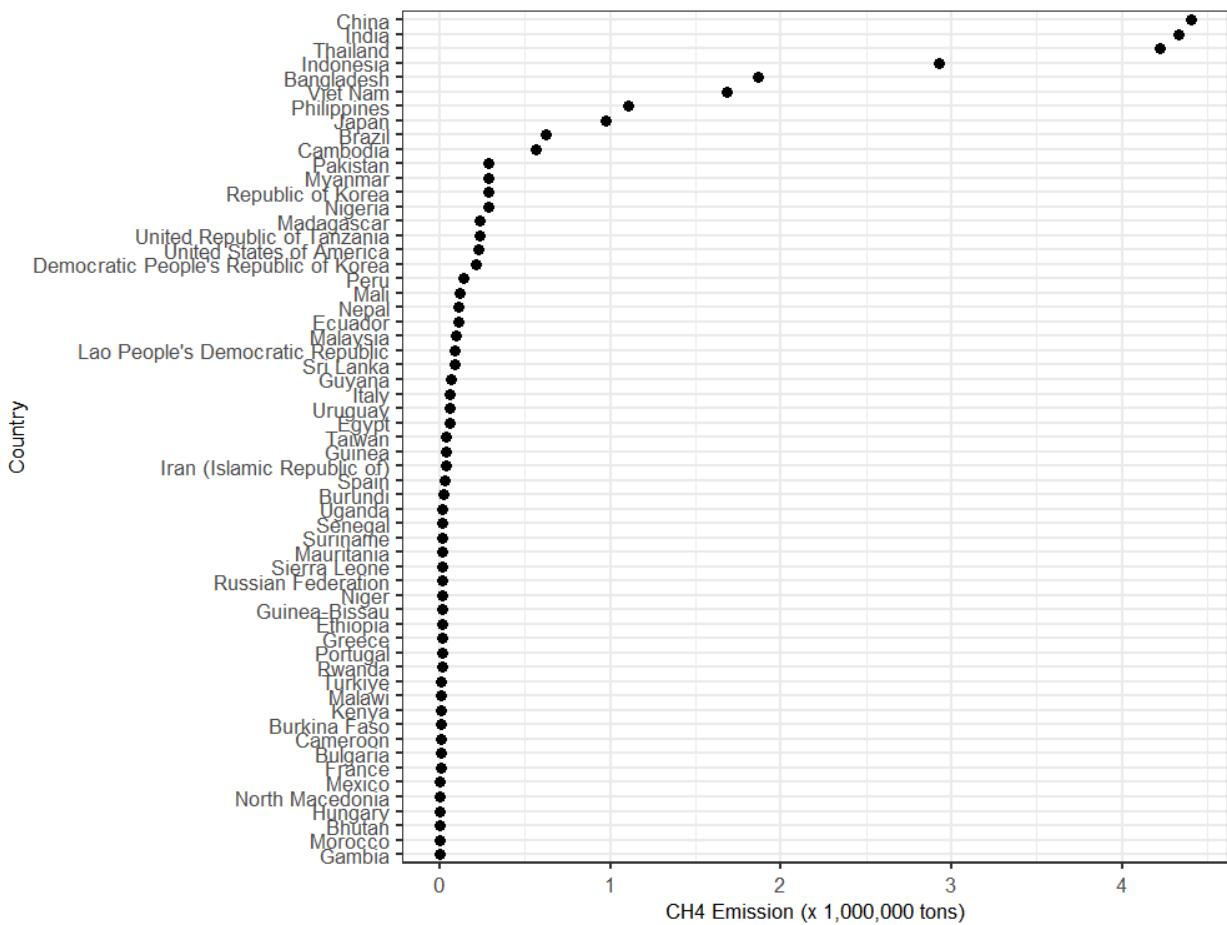


Figure S6 cont.

(b)

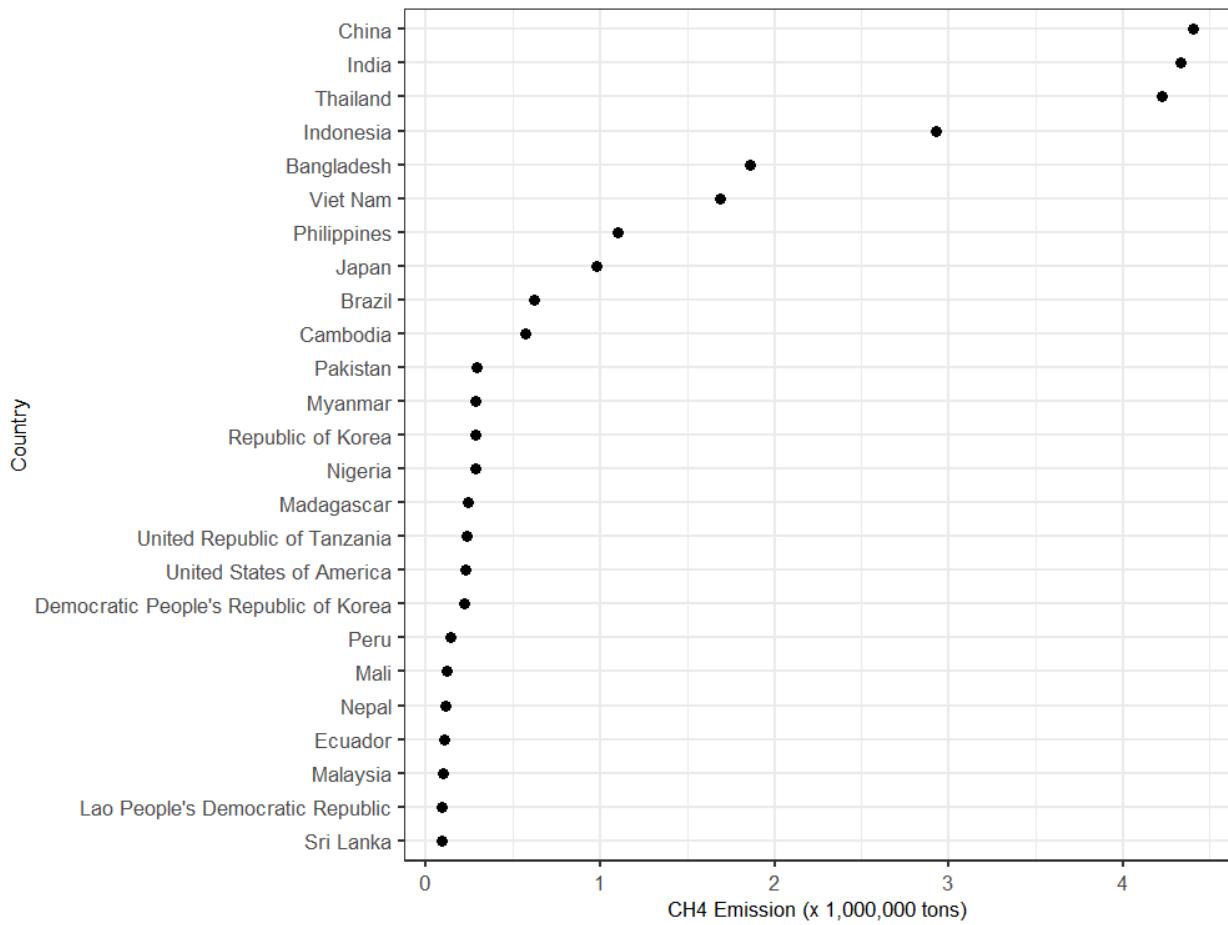


Figure S6. CH₄ emissions from rice cultivation across (a) 60 countries and (b) top 25 countries for 2024, derived from calculations based on the spatial distribution of CH₄ emissions from rice cultivation shown in **Figure S5a**.

Figure S7 illustrates annual CH₄ emissions from rice cultivation, integrating various data sources across different time periods. The emissions are derived from Paddy Watch using MODIS (2015-2021) and Sentinel-1 and Sentinel-2 (2022-2024), alongside FAOSTAT data (2000-2022) and Zhang et al. (2020) (2000-2015), divided into three key segments: (a) a comprehensive overview of 60 countries, including those influenced by the Asian monsoon; (b) a focused examination of emissions in India; and (c) a detailed analysis of emissions in China. The total CH₄ emissions from rice cultivation are 24,906,589 tons; 25,223,626 tons, and 26,121,589 tons for 2022, 2023, and 2024 respectively, derived from Sentinel-1/2 data, which exceed the MODIS estimate of around 20,000,000 tons for 2015-2020. A similar pattern is observed for India (Figure S8a). Conversely, CH₄ emissions from rice cultivation in China are reported at 4,712,261 tons for 2023, and 4,402,034 tons for 2024 lower than the MODIS estimate of approximately 7,000,000 tons for 2015-2020. These discrepancies are attributed not only to differences in harvested rice area but also to the use of different emission factors (EFs). Despite these variations, the estimates still fall within the confidence intervals.

(a) 60 countries and Asian monsoon countries

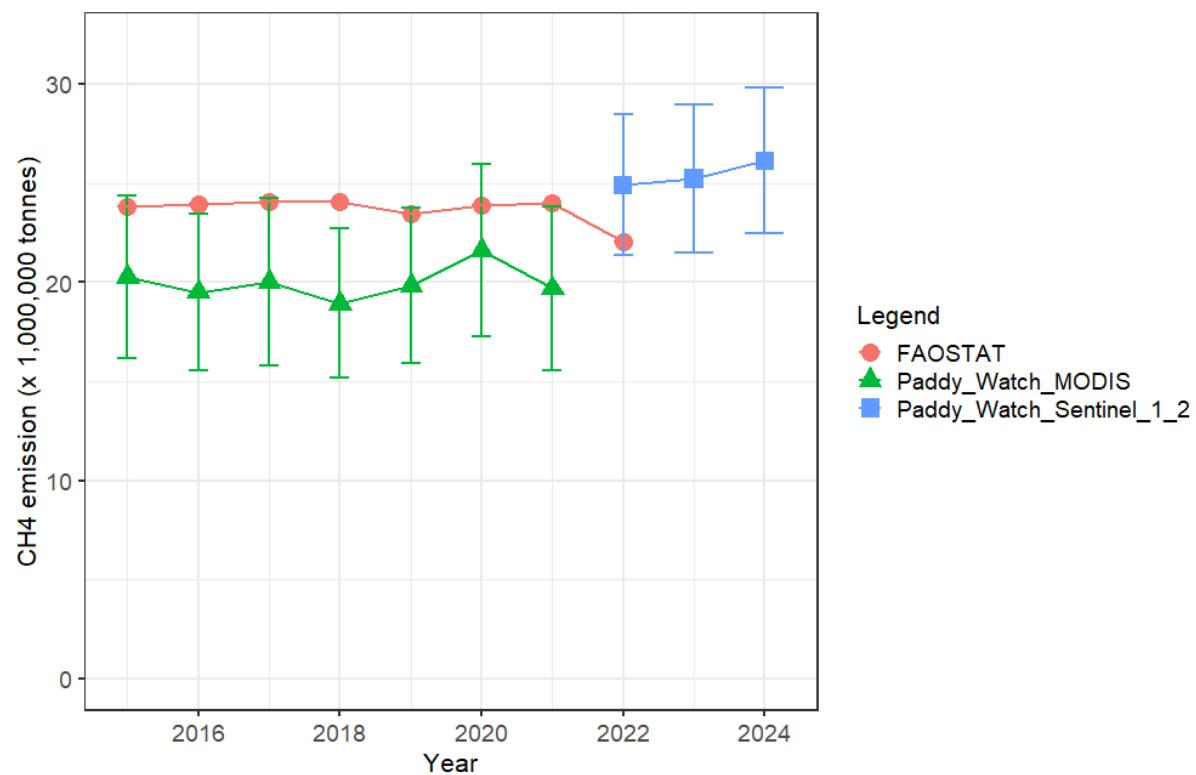


Figure S7 cont.

(b) India

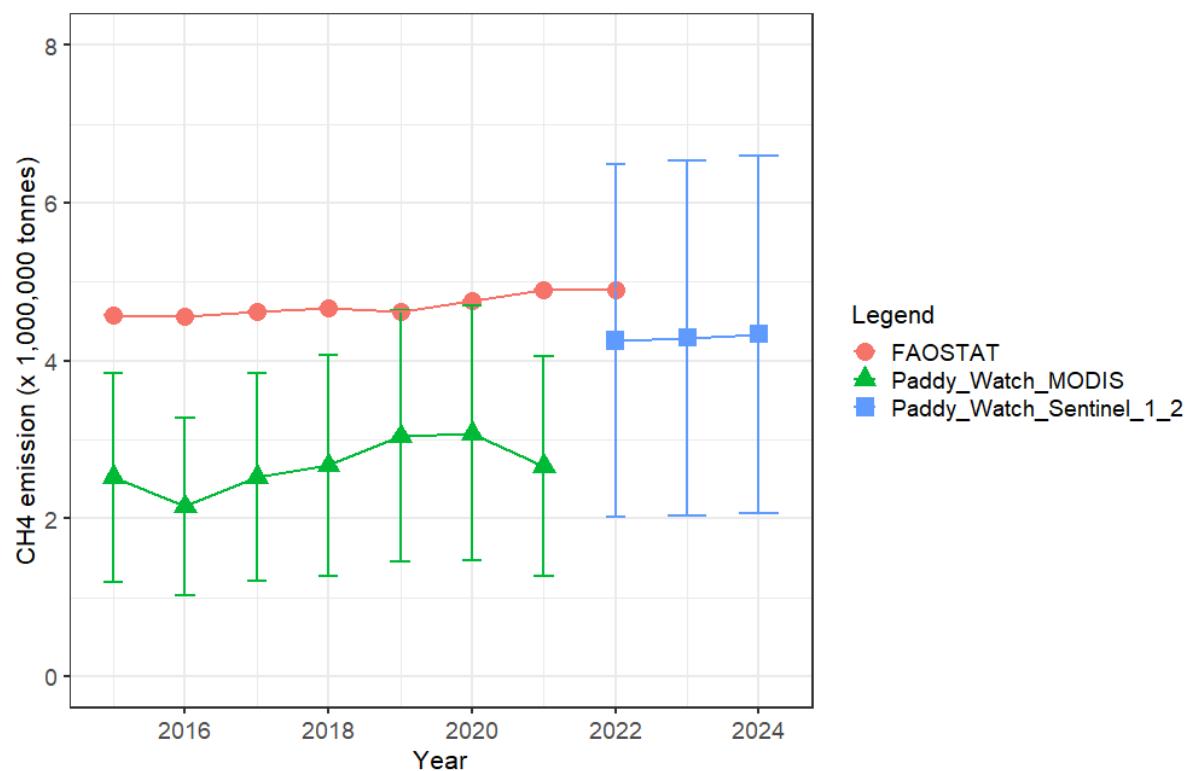


Figure S7 cont.

(c) China

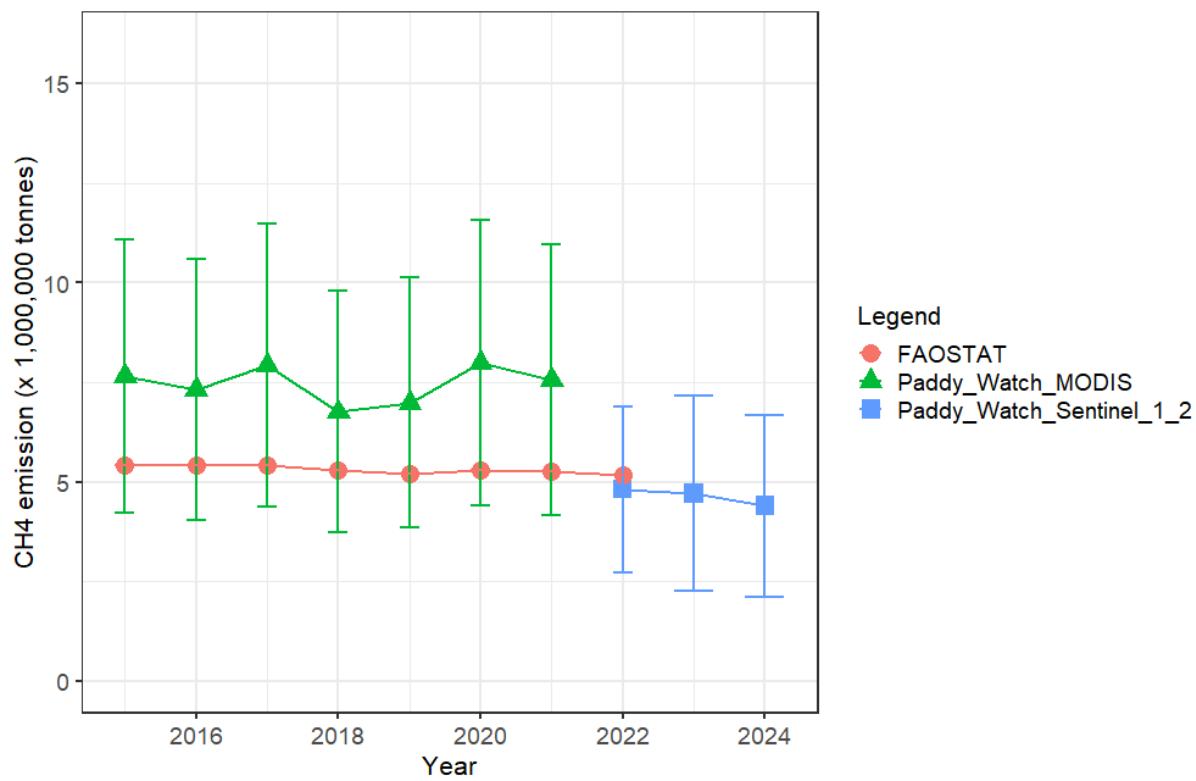


Figure S7. Annual CH_4 emission from rice cultivation based on Paddy Watch using MODIS (2015 - 2021) and Sentinel-1 and 2 (2022-2024); FAOSTAT data (2000 - 2022) and Zhang et al. (2020) (2000 - 2015) for (a) 23 countries and Asian monsoon countries, (b) India and (c) China.

6.1 Metadata

The Agriculture sector: “Rice Cultivation Emissions Estimates using Sentinel-1A and -2A/B” reports the following data on the Climate TRACE website:

- Country-level CH₄, and 20 and 100 year GWPs emissions from rice cultivation.

Emissions estimates were reported for years 2021 to 2024 for select countries, with previous years combined with MODIS-generated and/or FAOSTAT generated emissions data (see Table S1). Other approaches to estimate rice emissions are in the [Climate TRACE GitHub methodology repository](#). The data generated here has been combined with the other approaches to estimate rice cultivation emissions globally. All data is freely available on the Climate TRACE website (<https://climatetrace.org/>). A detailed description of what is available is described in Table S6. Note, uncertainty definitions are defined in Table S2 and S3, the standard deviation associated with each country. Confidence definitions are in the tables below.

Table S8 Metadata for Rice Cultivation Emissions Estimates.

General Description	Definition
Sector definition	<i>Country-level rice cultivation emissions</i>
UNFCCC sector equivalent	<i>3.C Rice Cultivation</i>
Temporal Coverage	<i>2021 – 2024 (see Table S1)</i>
Temporal Resolution	<i>Annual (original); Monthly (on website, see Temporal Disaggregation of Emissions Data for the Climate TRACE Inventory)</i>
Data format	<i>CSV</i>
Coordinate Reference System	<i>None. ISO3 country code provided</i>
Number of assets/countries available for download	<i>14 to 39 countries, varies by year (see Table S1)</i>
Ownership	<i>Country</i>
What emission factors were used?	<i>IPCC CH. 10 and 11 EFs</i>
What is the difference between a “0” versus “NULL/none/nan” data field?	<i>“0” values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modeled, this is represented by “NULL/none/nan”</i>
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	<i>Climate TRACE uses IPCC AR6 CO₂e GWPs. CO₂e conversion guidelines are here: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf</i>

Confidence values are based on the level of information detail used to estimate emissions, which is defined as the following:

- Subgroup 1: 10m resolution, regional EF
- Subgroup 2: 10m resolution, country level EF
- Subgroup 3: 10m resolution, Tier 1 EF or EF from neighboring country
- Subgroup 4: 500m resolution, country level EF
- Subgroup 5: 500m resolution, Tier 1 EF or EF from neighboring country
- Subgroup 6: backfilled by Climate TRACE

Low to very high confidence values for each group are shown in Table S7 and country specific confidences are shown in Table S8.

Table S9 Confidence definitions for rice cultivation emissions by subgroup number.

Data attributes	Definitions	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	Subgroup 5	Subgroup 6
type				Not used; NA			
capacity_description				Not used; NA			
capacity_factor_description				Not used; NA			
activity_description	Area harvested	High	High	High	Medium	Medium	Low
CO2_emissions_factor				Not used; NA			
CH4_emissions_factor	T CH ₄ per harvested ha	High	Medium	Low	Medium	Low	Low
N2O_emissions_factor				Not used; NA			
other_gas_emissions_factor				Not used; NA			
CO2_emissions				Not used; NA			
CH4_emissions	T CH ₄	High	Medium	Medium	Medium	Medium	Low
N2O_emissions				Not used; NA			
other_gas_emissions				Not used; NA			
total_CO2e_100yrGWP	Based on CH ₄ emissions	High	High	High	Medium	Medium	Low
total_CO2e_20yrGWP	Based on CH ₄ emissions	High	High	High	Medium	Medium	Low
other_1	Area of single crop	Very High	Very High	Very High	Very High	Very High	Not used; NA
other_2	Area of double crop	Very High	Very High	Very High	Very High	Very High	Not used; NA

Data attributes	Definitions	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	Subgroup 5	Subgroup 6
other_3	Area of triple crop	Very High	Not used; NA				

Table S10 Country specific confidence definitions for rice cultivation emissions.

Country	ISO3	Sub group	capacity	capactiy_factor	activity	CO2_emissions_factor	CH4_emissions_factor	N2O_emissions_factor	other_gas_emissions_factor	CO2_emissions	CH4_emissions	N2O_emissions	other_gas_emissions	total_CO2e_100yrGWP	total_CO2e_20vrGWP	other_1	other_2	other_3
China	CHN	1	NA	NA	High	NA	High	NA	NA	NA	High	NA	NA	High	High	Very High	Very High	Very High
Vietnam	VNM	1	NA	NA	High	NA	High	NA	NA	NA	High	NA	NA	High	High	Very High	Very High	Very High
Thailand	THA	1	NA	NA	High	NA	High	NA	NA	NA	High	NA	NA	High	High	Very High	Very High	Very High
Bangladesh	BGD	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Brazil	BRA	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Spain	ESP	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Indonesia	IDN	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
India	IND	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Iran (Islamic Republic of)	IRN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Italy	ITA	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Japan	JPN	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Cambodia	KHM	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Korea (the Republic of)	KOR	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Lao People's Democratic Republic (the)	LAO	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Sri Lanka	LKA	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Myanmar	MMR	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Malaysia	MYS	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Nepal	NPL	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Pakistan	PAK	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Philippines (the)	PHL	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Korea (the Democratic People's Republic of)	PRK	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High

Country	ISO3	Sub group	capacity	capaciy_factor	activity	CO2_emissions_factor	CH4_emissions_factor	N2O_emissions_factor	other_gas_emissions_factor	CO2_emissions	CH4_emissions	N2O_emissions	other_gas_emissions	total_CO2e_100yrGWP	total_CO2e_20yrGWP	other_1	other_2	other_3
Taiwan (Province of China)	TWN	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
United States of America (the)	USA	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Ethiopia	ETH	5	NA	NA	Medium	NA	Low	NA	NA	NA	Medium	NA	NA	Medium	Medium	Very High	Very High	Very High
Egypt	EGY	5	NA	NA	Medium	NA	Low	NA	NA	NA	Medium	NA	NA	Medium	Medium	Very High	Very High	Very High
Turkey	TUR	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Madagascar	MDG	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Tanzania	TZA	2	NA	NA	High	NA	Medium	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Uruguay	URY	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Surinam	SUR	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Peru	PER	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Guyana	GUY	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Ecuador	ECU	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Russia	RUS	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Mexico	MEX	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Bhutan	BTN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Bulgaria	BGR	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Burkina Faso	BFA	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Burundi	BDI	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Cameroon	CMR	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
France	FRA	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Gambia	GMB	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Greece	GRC	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Guinea	GIN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High

Country	ISO3	Sub group	capacity	capaciy_factor	activity	CO2_emissions_factor	CH4_emissions_factor	N2O_emissions_factor	other_gas_emissions_factor	CO2_emissions	CH4_emissions	N2O_emissions	other_gas_emissions	total_CO2e_100yrGWP	total_CO2e_20yrGWP	other_1	other_2	other_3
Guinea-Bissau	GNB	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Hungary	HUN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Kenya	KEN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Malawi	MWI	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Mali	MLI	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Mauritania	MRT	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Morocco	MAR	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Niger	NER	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Nigeria	NGA	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
North Macedonia	MKD	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Portugal	PRT	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Rwanda	RWA	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Senegal	SEN	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Sierra Leone	SLE	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Timor-Leste	TLS	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Uganda	UGD	3	NA	NA	High	NA	Low	NA	NA	NA	Medium	NA	NA	High	High	Very High	Very High	Very High
Backfilled Countries		6	NA	NA	Low	NA	Low	NA	NA	NA	Low	NA	NA	Low	Low	NA	NA	NA

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

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

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