Model-based evaluation of methane emissions from paddy fields in East Asia

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Abstract

Evaluating regional budgets of methane (CH\(_4\)), a potent greenhouse gas and short-lived climate forcer, is an important task for future climate management. This study estimated historical CH\(_4\) emissions from paddy fields in East Asia by using a process-based terrestrial biogeochemical model driven by climate and land-use data. To capture the range of estimation uncertainty, this study used two CH\(_4\) emission schemes, four paddy field maps, and two seasonal inundation methods for a total of 16 simulations. The mean CH\(_4\) emission rate during 2000–2015 was estimated to be 5.7 Tg CH\(_4\) yr\(^{-1}\), which is similar to statistical inventories and other estimates. However, the large standard deviation (± 3.2 Tg CH\(_4\) yr\(^{-1}\)) among the simulations implies that serious estimation uncertainties remain. Three factors — CH\(_4\) emission scheme, paddy field map, and inundation seasonality — were responsible for the disparity of the estimates. Because of the lack of historical management data, the model simulation did not show a decreasing trend in the agricultural CH\(_4\) emissions. A sensitivity analysis for temperature indicated that a 1–2 °C temperature rise (typical warming in mitigation-oriented scenarios) would substantially enhance CH\(_4\) emissions. However, a sensitivity analysis for water management indicated that a lower water-table depth would largely mitigate the emission increase. Additional studies to improve agricultural datasets and models for better paddy field management are still needed.

Key words: Greenhouse gas, Paddy field map, Process-based model, Uncertainty

1. Introduction

Methane (CH\(_4\)) is the second most potent anthropogenic greenhouse gas and plays important roles in atmospheric chemistry as a short-lived climate forcer (IPCC, 2021). Atmospheric CH\(_4\) concentrations increased from 700 ppb in ca. 1900 to 1880 ppb in 2020, mainly because of the increase of emissions from human activities such as fossil fuel mining, waste management, and agriculture (Saunois et al., 2020; Chandra et al., 2021). However, serious gaps remain in our understanding of the global CH\(_4\) budget. For example, researchers have not reached a consensus about the mechanism responsible for decadal-scale variations in the growth rates of atmospheric CH\(_4\) concentrations (Nisbet et al., 2019). Because effective climatic mitigation by reduction of emissions must be based on reliable greenhouse gas budgets, there is a need to elucidate sources, sinks, spatial distributions, and temporal variability of the concentrations of the target gases.

Irrigated paddy fields are among the major sources of CH\(_4\) because waterlogging during periods of irrigation favors methanogenesis under anaerobic conditions. Because paddy fields are distributed across a vast area of Asia, which is under the influence of a monsoonal climate and increasing human pressure, the CH\(_4\) budget of Asia has attracted particular attention (Wassmann et al., 2000; Minamikawa et al., 2006). However, because the distribution of paddy fields and the practices used to manage them are complicated, large uncertainties remain in current estimates of CH\(_4\) emissions, even those used in national inventories (Zhang et al., 2017). Field measurements made in paddy fields, using chamber and micrometeorological techniques, have indicated that CH\(_4\) emissions show large spatiotemporal variability that depends on environmental and management conditions (e.g., Miyata et al., 2000; Tokida et al., 2010; Kajura et al., 2018; Chaichana et al., 2018). At the regional scale, previous studies have attempted to estimate CH\(_4\) emissions from Asia by using inventory-based and modeling approaches. For example, Matthews et al. (2000) applied a process-based paddy field model, Methane Emissions from Rice Ecosystems (MERES), to major countries in Asia and, for example, estimated CH\(_4\) emissions from China to be 3.73 Tg CH\(_4\) yr\(^{-1}\) (baseline scenario). Yan et al. (2003) estimated paddy field CH\(_4\) emissions from Asian countries using data from the Food and Agriculture Organization (FAO) and national inventories (i.e., statistics). Ito et al. (2019) assessed the CH\(_4\) budget of East Asia with a bottom-up approach using inventories, a biogeochemical model, and land-cover data; they estimated that agricultural soils (chiefly in paddy fields) released 15.8 Tg CH\(_4\) yr\(^{-1}\), which is about 26% of total anthropogenic CH\(_4\) emissions from this region. Few studies, however, have evaluated paddy field emissions and included the range of uncertainty associated with the data and models in a systematic manner.
The goal of this study was to estimate CH₄ emissions from paddy fields in East Asia using a contemporary biogeochemical model, taking into consideration the uncertainty associated with the distribution of paddy fields and assumptions about agricultural practices. Compared with an inventory-based approach, the model-based approach has advantages with respect to spatially explicit mapping, direct use of climate and satellite data, and linkage to future projections. By comparing simulation results, we aimed to investigate the range of uncertainty associated with input data and estimation models. Our expectation was that the results of this study could be used to harmonize climate management with agricultural food production.

2. Methods

2.1. Research area and paddy field maps

Figure 1 shows an overview of the estimation procedure used in this study. We assessed CH₄ emissions from paddy fields in East Asia, comprising Japan, China, South Korea, North Korea, Mongolia, Chinese Taipei, and Hong Kong. We used maps of paddy fields from four sources (Table 1): 1) the Center for Sustainability and the Global Environment, University of Wisconsin (UW-SAGE), 2) MIRCA2000, 3) the Institute of Industrial Science, University of Tokyo (UT-IIS), and 4) the National Institute for Environmental Studies (NIES). Maps of UW-SAGE and MIRCA2000 were derived from country-based paddy field areas. The total areas of paddy fields are therefore consistent with statistics, but their spatial distributions are functions of disaggregation (down-scaling) methods. In contrast, maps of UT-IIS and NIES were derived from analyses of satellite images. Those maps were made with spatially explicit data and had high spatial resolution, but their total areas were not constrained by statistical data. For model simulation, all the paddy maps were converted to paddy fraction (0–1) maps with a mesh of 0.5° × 0.5°. Historical changes of paddy field area were taken into account by using the global land-use dataset of Hurd et al. (2020). We assumed a constant ratio of the area of paddy fields to the area of other crops within each grid cell. Paddy field area was therefore assumed to have varied through time in parallel with the changes of total cropland fraction.

2.2. Biogeochemical model

A process-based terrestrial ecosystem model, Vegetation Integrative Simulator for Trace gases (VISIT; Inatomi et al., 2010; Ito and Inatomi, 2012) was used to simulate CH₄ emissions from paddy fields. The model has been used in regional and global studies of terrestrial CH₄ budgets and validated with atmospheric and field measurement data (e.g., Patra et al., 2011, 2016; Chandra et al., 2021). The model simulates atmosphere-ecosystem exchanges of greenhouse gases and biogeochemical processes of natural and agricultural ecosystems; their area-fraction-weighted value equals the total flux at each grid. The model consists of biogeophysical (e.g., radiation budget) and biogeochemical schemes, and it simulates the cycles of water, carbon, and nitrogen. In the cropland fraction of each mesh, agricultural practices such as planting, harvesting, and fertilizer input are considered in a simplified manner (Ito et al., 2018). Consideration of agricultural practices at fine scales such as plot-by-plot differences in rice cultivars was beyond the scope of this regional study.

The model simulates CH₄ exchange between the atmosphere and ecosystem, as explained briefly below. Oxidative uptake of CH₄ by methanotrophic microbes is assumed to occur in upland soils, and production and emission of CH₄ by methanogenic microbes is assumed to occur in wetland soils (Ito and Inatomi, 2012). This study focused on emissions from paddy fields (artificial wetlands), and emissions from natural wetlands and uptake by upland soils were not included. The paddy field CH₄ emissions were simulated with two schemes implemented in the VISIT model. One was the simple scheme of Cao et al. (1996), which considers the depth of water table (i.e., the aerobic and anaerobic fractions of the soil) in a single-layer model of bulk soil. The scheme calculates uptake by the aerobic fraction of the soil and production by the anaerobic fraction; the total CH₄ flux through the soil profile is calculated by summation, irrespective of transport pathways. In this scheme, daily CH₄ emission rate was calculated; the monthly CH₄ emission rate was then obtained by multiplying this value by the number of days in the month. The second scheme, the Walter–Heimann scheme (Walter and Heimann, 2000), has a more mechanistic structure that simulates soil vertical profiles of CH₄ concentrations and transport with a multi-layer model. This scheme considered three CH₄ transport pathways: diffusion, ebullition, and plant-mediated transport. Diffusion flux was calculated by using Fick’s first law, and ebullition was assumed to occur when the CH₄ concentration of each soil layer exceeded 500 µmol L⁻¹. Plant-mediated transport depended on plant characteristics such as growth stage and rooting depth (Walter and Heimann, 2000). In the Walter-Heimann scheme, hourly CH₄ fluxes were estimated and then converted to monthly rates by multiplying by 24 hours (in a day) and the number of days in the month. This study used a

| Table 1. Summary of paddy field maps used in this study. |
|---|---|---|
| Name | Description | Paddy field area (10⁵ km²) |
| UW-SAGE | Spatial disaggregation of country-based cropland area (Monfreda et al., 2008). Static map for the year 2000. Original spatial resolution is 5 minutes in latitude and longitude. | 476.2 |
| UT-IIS | Satellite-based land-use classification using MODIS data (Takeuchi and Yasuoka, 2006). Static map for the years 2001–2005. Original spatial resolution is about 1 km. | 242.7 |
| MIRCA2000 | Harmonization of national statistics, UW-SAGE, and FAO data. Maximum monthly mean areas were used (Portmann et al., 2010). Static map for the year 2000. Original spatial resolution is 5 minutes in latitude and longitude. | 303.6 |
| NIES | Satellite-based land-use classification using Sentinel-1 and -2 data (Inoue et al., 2020). Static map for the year 2018. Original spatial resolution is about 30 m. | 312.1 |
multi-layer soil model (20 layers, each with a thickness of 5 cm), and a diffusion equation was numerically solved at a 0.01-h time step. In both schemes, CH₄ production was assumed to be sensitive to temperature and the associated parameter Q₁₀ was 2. Vegetative growth and photosynthetic production, which provide substrates for CH₄ production, were obtained from the carbon cycle scheme of the VISIT model.

2.3. Simulations and analyses

Simulations encapsulating the East Asia region were conducted at a spatial resolution of 0.5° × 0.5° in latitude and longitude during the period from January 1901 to December 2020 with a monthly time step. The spatial resolution is coarse in terms of spatial heterogeneity in paddy field conditions, but it is standard for regional and global modeling studies. Climate conditions (temperature, precipitation, vapor pressure, and cloudiness) were derived from the global historical dataset CRU TS 4.05 (Harris et al., 2020). For the paddy field fraction at each grid, seasonal changes in the inundated soil fraction (by irrigation in croplands and by flooding in wetlands) were determined by two methods. The first method involved remote sensing by satellite, Special Sensor Microwave/Imager (SSM/I) on board the United States Air Force Defense Meteorological Satellite Program. Prigent et al. (2001) developed a global map of inundation (for both natural wetlands and paddy fields) using the dataset of passive microwave measurements. The second method estimated seasonal changes in the inundated soil fraction based on the time from planting (start of irrigation) to harvest (end of irrigation), which was determined with the rule-based estimation dataset of Iizumi et al. (2019). We used the planting and harvest dates with the highest probabilities (Fig. S1) and assumed a rice variety with medium characteristics. Note that both inundation seasonality methods allowed for multi-cropping (i.e., cropping and harvesting two or three times in one year), which occurs in subtropical areas. For both inundation methods, average seasonal variation patterns were repeatedly used through the simulation period to cover the historical period. It was assumed that the water table of the inundated fraction was 3 to 4 cm above the soil surface in both schemes, whereas the position of the drained fraction was about 0.5 m below the surface.

The baseline simulations were conducted using combinations of the two CH₄ emission schemes, two inundation seasonalities, and four maps of paddy fields: for a total of 16 cases (Fig. 1). The mean (composite) and standard deviation (SD) were calculated from these results, and monthly CH₄ emissions and interannual variability were examined. By applying a country-boundary mask to the data, results for East Asia were extracted and compared with previous estimates and statistical inventories, e.g., FAOSTAT (FAO, 2021) and EDGAR (Crippa et al., 2020). Moreover, several sensitivity simulations were conducted to assess the responses of CH₄ emissions to climate change and human management. Assuming global warming and water management, air and soil temperatures were raised by 1 or 2 °C, and the corresponding depths of the water table lowered by 6 cm throughout the year, respectively. These conditions were chosen to demonstrate the estimation sensitivity in a simplified manner and to examine the potential effect of water management for mitigation of warming-caused CH₄ emissions.

3. Results and discussion

3.1. Paddy field maps

The average (± SD) total paddy field area in East Asia determined from the maps was 333,648 ± 99,941 km² in 2000; see Table 1 for the areas of each map. The average area is a bit lower than previously reported values; for example, Yan et al. (2003) reported a value of 350,110 km². The estimated average paddy field area of Japan, 15,813 km² (SD = 9,650 km²), was comparable with the area of rice planting in the national statistics (16,137 km², 2005–2015; Ministry of Agriculture, Forestry and Fisheries [MAFF], 2018). The four maps (Fig. 2) showed similar
spatial distributions of paddy fields in East Asia. The fractions of paddy fields were higher in central China (e.g., the Yangtze River delta), southern China (e.g., Sichuan basin), and the plains of Japan and South Korea. However, there were marked differences in several regions. For example, the UW‑SAGE map indicated that the proportion of paddy fields was high in southern China, whereas the NIES map indicated that the proportion was high in northern China.

3.2. Mean CH₄ emissions

The average (± SD) of the 16 baseline total CH₄ simulated emissions from paddy fields in East Asia for 2005–2015 was 5.68 ± 3.23 Tg CH₄ yr⁻¹. The estimates ranged from 2.04 Tg CH₄ yr⁻¹ for the case using the UT‑IIS paddy field map, Cao scheme, and satellite‑derived inundation to 13.74 Tg CH₄ yr⁻¹ for the case using the UW‑SAGE paddy field map, Walter–Heimann scheme, and crop‑calendar‑based inundation (Fig. 3). Because of its large area of paddy fields, China dominated the regional CH₄ emissions, with 5.14 ± 2.88 Tg CH₄ yr⁻¹ (90.6% of regional emissions). Although emissions from Japanese paddy fields were much smaller, 0.24 ± 0.21 Tg CH₄ yr⁻¹, Japan was the second largest contributor in East Asia.

A composite CH₄ emission map based on the 16 simulations (Fig. 4) showed that high emissions occurred in paddy fields in central and southern China (including double‑cropping areas), western Chinese Taipei, South Korea, and southwestern Japan. The distribution of emissions appeared to be largely attributable to the distribution of paddy fields and partly to differences in CH₄ emission schemes and inundation seasonality (Fig. S2). For example, in central China, the Walter–Heimann scheme led to higher CH₄ emissions than the Cao scheme, even though...
the same paddy field map was used. The simulations using the UW-SAGE paddy field map showed higher CH$_4$ emissions from southern China. Also, the use of crop calendar-based inundation seasonality resulted in higher CH$_4$ emissions in northern China, South Korea, and most of Japan.

Mean values of the simulated CH$_4$ emissions were roughly similar with statistics and previous estimates (Table 2). For example, the regional and country-based rates were close to those reported by FAOSTAT (5.9 Tg CH$_4$ yr$^{-1}$ for East Asia, 5.3 Tg CH$_4$ yr$^{-1}$ for China, and 0.336 Tg CH$_4$ yr$^{-1}$ for Japan). Although the FAOSTAT values are slightly higher than the means, they are within the range of model-based values. The EDGAR v6.0 estimates are much higher, 14.7 Tg CH$_4$ yr$^{-1}$ for East Asia, 13.5 Tg CH$_4$ yr$^{-1}$ for China, and 0.66 Tg CH$_4$ yr$^{-1}$ for Japan. It should be noted that these values are for agricultural soils and did not include emissions from manure management and enteric fermentation (livestock). Therefore, the large discrepancy is likely attributable to assumptions in agricultural activities and emission factors used in compiling the dataset. The estimated emissions from paddy fields in Japan by the GIO (2021), which used the DNDC–Rice model for estimation (e.g., Fujimoto et al., 2010; Katayanagi et al., 2016), are much

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**Table 2.** Comparison of CH$_4$ emission estimates.

| Data            | Paddy field emissions (Tg CH$_4$ yr$^{-1}$) | Range                  | Period                        | Notes and references                |
|-----------------|-------------------------------------------|------------------------|-------------------------------|-------------------------------------|
| **East Asia**   |                                           |                        |                               |                                     |
| FAOSTAT         | 5.9                                       |                        | 2005–2015                     | Emissions from rice cultivation     |
| Thompson et al. (2015) | 13.6                                     |                        | 2000–2010                     | Prior data from EDGAR              |
| This study      | 5.68                                      | 2.0 – 13.7             | 2005–2015                     | VISIT model                         |
| **China**       |                                           |                        |                               |                                     |
| Matthews et al. (2000) | 3.73                                    | 3.35 – 8.64            |                                | MERES model                         |
| Yan et al. (2003) | 7.668                                    |                        |                               | Inventory analysis                  |
| Chen et al. (2013) | 8.11                                     | 5.2 – 11.36            |                                | Field data synthesis                |
| Peng et al. (2016) | 7.4                                      | 6.0 – 8.8              | 2010                          | Inventory with domestic data        |
| Saunois et al. (2020) | 7.3                                      | 5.3 – 15.0             | 2008–2017                     | GCP synthesis, average of 5 inventories |
| Gong and Shi (2021) | 11.45                                    |                        | 2015                          | Inventory                          |
| FAOSTAT         | 5.3                                       |                        | 2005–2015                     | Emissions from rice cultivation     |
| This study      | 5.14                                      | 2.0 – 13.7             | 2005–2015                     | VISIT model                         |
| **Japan**       |                                           |                        |                               |                                     |
| Yan et al. (2003) | 0.416                                     |                        |                                | Inventory analysis                  |
| Hayano et al. (2013) | 0.288                                    |                        | 1990                          | DNDC-Rice model                     |
| Katayanagi et al. (2017) | 0.519                                    | 0.431 – 0.607          | 1990–2010                     | DNDC-Rice model                     |
| Sasai et al. (2017) | 0.2566                                   |                        | 2001–2010                     | BEAMS model                         |
| GIO (2021)      | 0.5761                                    |                        | 2009–2015                     | UNFCCC inventory                    |
| FAOSTAT         | 0.336                                     |                        | 2005–2015                     | Emissions from rice cultivation     |
| This study      | 0.238                                     | 0.057 – 0.834          | 2005–2015                     | VISIT model                         |

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**Fig. 4.** Composite means of the 16 baseline estimates of annual CH$_4$ emissions from paddy fields (weighted by area fraction).
higher than the mean value of the present study, but they are within the range of baseline simulations.

3.3. Seasonal and interannual variability

Each simulation showed a clear seasonal change in paddy field CH$_4$ emissions, but with different amplitudes (Fig. 5a). Such seasonal change is consistent with that observed by chamber and tower-based measurements conducted in East Asia (e.g., Miyata et al., 2005; Lou et al., 2008; Tokida et al., 2010). Interestingly, maximum CH$_4$ emissions occurred in different months among the simulations. For example, simulations using the Walter–Heimann scheme and satellite-based inundation showed peak emissions in June, whereas those using the Cao scheme peaked in July or August. Emissions simulated with satellite-derived inundations showed a small, secondary peak in October. The results extracted at a single grid point (Fig. S3) showed the underlying mechanisms of the large seasonal variation simulated by the Walter–Heimann scheme. Under warm and humid summer conditions, microbial production resulted in higher CH$_4$ concentrations in soil layers and then large ebullition emissions. Also, active rice growth enhanced the plant-mediated emissions. In contrast, the Cao scheme simulated modest seasonal variations associated with the response of the CH$_4$ production rate to temperature and water-table conditions.

The simulated annual CH$_4$ emissions were stable or gradually increased during the last few decades, from 4.55 Tg CH$_4$ yr$^{-1}$ in 1970 to 5.81 Tg CH$_4$ yr$^{-1}$ in 2020 (Fig. 5b). The trends in the simulations were caused largely by the increase of paddy field area and the temperature rise during this period. In contrast, statistical inventories (FAOSTAT and EDGAR) showed gradually decreasing trends. This discrepancy between the model estimates and inventory was attributable to the fact that the model estimates ignored historical changes in management practices. For example, Kai et al. (2011) estimated that CH$_4$ emissions from paddy fields in the Northern Hemisphere decreased by 15.5 ± 1.9 Tg CH$_4$ yr$^{-1}$ between 1984 and 2005, probably because

Fig. 5. Seasonal and interannual changes in CH$_4$ emissions from paddy fields in East Asia. Results of 16 simulations and their averages are shown. Interannual variability was compared with those in inventories (FAOSTAT, Peng et al. (2016), and EDGAR v6.0). Note that Peng et al. (2016) data represent CH$_4$ emissions from only China only. WH: Walter–Heimann.
of increases in fertilizer input and reductions in water use for irrigation. In contrast, Sheng et al. (2021) implied that CH₄ emissions from paddy field and aquaculture increased, at the rate of 0.13 ± 0.05 Tg CH₄ yr⁻¹ after 2012 based on atmospheric observation and model inversion. The mean emissions of the 16 simulations since 2000 were close to the FAOSTAT emissions, but the simulated emissions were less than FAOSTAT emissions in the 1970s through 1990s.

3.4. Sensitivity analysis
Temperature rise, which mimics global warming, resulted in higher CH₄ emissions from paddy fields, and the responsiveness of emissions differed between schemes. The Walter–Heimann scheme showed a larger response to warming (+1 °C, +0.6 Tg CH₄ yr⁻¹; +2 °C, +1.1 Tg CH₄ yr⁻¹) than the Cao scheme (+1 °C, +0.2 Tg CH₄ yr⁻¹; +2 °C, +0.4 Tg CH₄ yr⁻¹). These results indicate that the ambitious climate mitigation target of a 2 °C temperature increase in the Paris Agreement may not be sufficient to prevent a climate-induced increase of CH₄ emissions. Such increases in CH₄ emissions may imply a positive climatic feedback loop, making it difficult to achieve the mitigation target for climatic stabilization (e.g., Nisbet et al., 2019).

A drawdown of the water-table depth, which mimics the effects of water management, resulted in lower CH₄ emissions from paddy fields, but the sensitivity of emissions differed between emission schemes (Fig. 6). A draw down of 6 cm caused total emissions to decrease by 1.1 Tg CH₄ yr⁻¹ (43% below the baseline) according to the Cao scheme and by 1.4 Tg CH₄ yr⁻¹ (23% below the baseline) according to the Walter-Heimann scheme. Although the experiment assumed a uniform drawdown for simplicity, the results implied that water management was a plausible option to reduce greenhouse gas emissions from East Asian paddy fields. Optimization of water management practices (e.g., drainage in midsummer rather than in winter) would make reduction in emissions more effective.

3.5. Limitations and uncertainty
The estimated rate of CH₄ emissions from paddy fields in East Asia, 5.7 Tg CH₄ yr⁻¹, is relatively low in comparison with other estimates and inventories, but it is plausible because recent studies, including those by inversion estimation with atmospheric measurement data, imply that previous inventories overestimated CH₄ emissions from East Asia (e.g., Thompson et al., 2015). However, the large disparity among the baseline simulations (a coefficient of variation of 57%) implies that serious uncertainties remain in the present estimates. The disparity could be attributed to three main factors—paddy field maps, inundation seasonality, and CH₄ emission schemes—each of which made substantial contributions. The disparities attributable to the CH₄ emission schemes (max. – min. = 4.6 Tg CH₄ yr⁻¹) and paddy field maps (4.3 Tg CH₄ yr⁻¹) were similar; the disparity attributable to inundation seasonality (2.1 Tg CH₄ yr⁻¹) was smaller but still substantial. The disparities suggest that an estimate based on a single set of input data and just one scheme can be seriously biased. Therefore, use of multiple datasets and schemes is certainly recommended to obtain a less biased result and to examine uncertainty.

The uncertainty associated with the CH₄ emission schemes has been recognized and assessed by several intercomparison studies for wetlands (e.g., Bohn et al., 2015). The schemes differ in model structure (bulk soil or multi-layer), separation of CH₄ emission pathways, and sensitivities to plant activity and environmental conditions. In the present study, two distinct schemes (Cao and Walter-Heimann) were driven by the same depth of the water table, temperature, and plant activity, but the results differed considerably. The difference was likely mainly caused by different sensitivities to the depth of the water table, because the three CH₄ transport pathways (diffusion, ebullition, and plant-mediated transport) of the Walter–Heimann scheme respond in complicated ways to water table depth. Moreover, the results of sensitivity simulations for warming indicate that the two schemes differ in temperature sensitivity. The Walter-Heimann scheme showed higher temperature sensitivity, because of amplification by plant-mediated and ebullition emissions (e.g., Fig. S3). The effect of inundation seasonality on the estimation of paddy field CH₄ emissions has

![Fig. 6. Results of the sensitivity experiments for the changes in depths of water tables (−6 cm) and temperatures (+1 and +2 °C). Differences from the baseline simulation are shown.](image)
not been assessed previously, but its importance for model-based estimation was disclosed in this study. Satellite-derived inundation seasonality is expected to be spatially explicit, but it can be influenced by land cover and observational errors (Prigent et al., 2001). In contrast, the model-estimated crop calendar can account for agricultural practices, but it can be influenced by model-specific assumptions (e.g., threshold temperatures). The present study highlighted the importance of the inundation (irrigation) calendar, which accounts for agricultural practices and is constrained by observations.

The uncertainties associated with paddy field mapping are derived from the classification algorithms and data quality, as reviewed by Dong and Xiao (2016). The present study used four maps, two produced by disaggregation of national statistics and two by satellite land-cover classification. Apparently, the use of maps showing broader paddy field areas (e.g., UW-SAGE) resulted in higher CH\textsubscript{4} emissions from East Asia. The four maps differed with respect to production years (e.g., UW-SAGE for 2000 and NIES for 2018), and the two satellite-based maps used data from different satellites (Terra MODIS by UT-IIS and Sentinel-1 and -2 by NIES). Inoue et al. (2020) pointed out that accurately separating paddy fields from other land-cover types (e.g., croplands and pastures) on a flat plain is technically difficult, even with the use of up-to-date, high resolution optical and microwave images. It is fortunate that the use of the recent paddy field map by Inoue et al. (2020) made possible an estimation of CH\textsubscript{4} emissions (5.3 Tg CH\textsubscript{4} yr\textsuperscript{-1}) that could be compared with the multi-map mean value. Improving paddy field maps by taking account of temporal variations is a prerequisite for reliable estimation of CH\textsubscript{4} emissions.

The comparison of CH\textsubscript{4} emission time-series between model estimation and statistical inventories (Fig. 5b) clarified the importance of historical changes in paddy field area and management practices. For example, in Japan, the total rice planting area decreased from 2.84 × 10\textsuperscript{4} km\textsuperscript{2} in 1970 to 1.47 × 10\textsuperscript{4} km\textsuperscript{2} in 2016 (MAFF, 2018). A quantitatively similar area decrease was also found in China, from 3.4 million km\textsuperscript{2} in 1980 to 3 million km\textsuperscript{2} in 2010, especially in southern regions (Liu et al., 2013; Clauss et al., 2016). The increase of rice production during the same period implied that technical improvements of agricultural practices accompanied the northward shift of central production areas (Deng et al., 2019). However, the simplified method of estimating temporal changes in paddy field area (i.e., a constant paddy field fraction in cropland) used in this study could not capture such characteristic changes in paddy field area. Including technological shifts in fertilizer use, planting variety, tillage, and water management are even more difficult, although previous studies imply the importance of taking account of technological shifts in estimating CH\textsubscript{4} emissions from paddy fields during the past few decades (e.g., Denier van der Gon, 2000; Li et al., 2002). This study used representative data that were applicable to biogeochemical models to examine the possibilities and limitations of the present approach. More data related to rice cultivation and land use are becoming available for use by crop models: e.g., MIRCA2000 (Portmann et al., 2010), RiceAtlas (Laborte et al., 2017), and LUH2 (Hurtt et al., 2020). In future studies, exchanges of CH\textsubscript{4} and other trace gases may be estimated using such comprehensive datasets of agricultural practices.

Limitations were also found in the model-based estimates of this study. For example, this study did not account for differences between rice cultivars, which differ in morphological and physiological properties (e.g., tiller number, root depth, and shoot length) as well as their CH\textsubscript{4} emission rates (e.g., Watanabe et al., 1995; Butterbach-Bahl et al., 1997). The CH\textsubscript{4} production schemes used in this study did not include the effect of substrate limitations, and therefore the model could not simulate the impact of manure input. Moreover, use of monthly time-steps in the simulation may be inadequate, although it reduced computational costs and made multiple simulations possible. As shown in Fig. S3, the model simulation had difficulty in capturing the effects of meteorological conditions, rice growth stages, and management practices such as intermittent irrigation. Selecting and breeding cultivars and sophisticated water management are considered potentially effective mitigation options (e.g., Yagi et al., 1997; Souza et al., 2021). Improving biogeochemical models to capture agricultural processes in paddy fields and other croplands is therefore important to future projections, including mitigation options.

4. Conclusions

This study confirmed that the paddy fields of East Asia are a substantial source of CH\textsubscript{4} emissions in the regional CH\textsubscript{4} budget, although the present estimate is lower than previous, inventory-based estimates (e.g., FAOSTAT and EDGAR). This study clarified the effectiveness of using multiple datasets and schemes to reduce the bias in estimates of CH\textsubscript{4} emissions from paddy fields. The spatial map of CH\textsubscript{4} emissions (e.g., Fig. 4) should be useful to identify emission hot spots and mitigation targets. The bulk emission factor (i.e., total annual emission / paddy field area / mean cultivation period [112 days; IPCC, 2019]) was obtained from the present results to be 1.52 (1.45–1.57 among maps) kg CH\textsubscript{4} ha\textsuperscript{-1} d\textsuperscript{-1}, which is slightly higher than the default value of 1.32 for East Asia in the IPCC Guidelines for National Greenhouse Gas Inventories (error range: 0.89–1.96 kg CH\textsubscript{4} ha\textsuperscript{-1} d\textsuperscript{-1}; IPCC, 2019). This model-based study may thus contribute to greenhouse gas accounting by providing spatially explicit emission maps and an independent estimate of budgets and emission factors, but the need to consider the remaining uncertainties in the current greenhouse gas accounting applies to other emission sectors and regions. This study therefore demonstrated the necessity of additional research to elucidate greenhouse gas budgets via studies of biogeochemical processes, analyses of geographical data, and modeling. For example, recent advances of in situ CH\textsubscript{4} flux measurement techniques and database compilation (e.g., Delwiche et al., 2021) should enable us to conduct model validation not only at a point scale but also at a regional scale. Advances in satellite remote sensing of atmospheric CH\textsubscript{4} concentrations would also facilitate examinations of spatiotemporal variations of surface CH\textsubscript{4} exchanges by various emission sectors (e.g., Zhang et al., 2020; Wang et al., 2021). Close collaborations among researchers conducting between multi-scale observations and modeling should play a pivotal role in accomplishing that task.
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