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Methane emissions from global wetlands: An assessment of the uncertainty associated with various wetland extent data sets

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HIGHLIGHTS

- Discrepancies in wetland extent are the major source of CH₄ emission uncertainty.
- Tropics contribute the largest portion of estimated CH₄ emissions from global wetland.
- Improved estimate of wetland area and CH₄ emission in tropics are most critical.
- Global scale wetland data set with higher spatial and temporal resolution is desired.

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ABSTRACT

A wide range of estimates on global wetland methane (CH₄) fluxes has been reported during the recent two decades. This gives rise to urgent needs to clarify and identify the uncertainty sources, and conclude a reconciled estimate for global CH₄ fluxes from wetlands. Most estimates by using bottom-up approach rely on wetland data sets, but these data sets show largely inconsistent in terms of both wetland extent and spatiotemporal distribution. A quantitative assessment of uncertainties associated with these discrepancies among wetland data sets has not been well investigated yet. By comparing the five widely used global wetland data sets (GLISS, GLWD, Kaplan, GIEMS and SWAMPS-GLWD), in this study, we found large differences in the wetland extent, ranging from 5.3 to 10.2 million km², as well as their spatial and temporal distributions among the five data sets. These discrepancies in wetland data sets resulted in large bias in model-estimated global wetland CH₄ emissions as simulated by using the Dynamic Land Ecosystem Model (DLEM). The model simulations indicated that the mean global wetland CH₄ emissions during 2000–2007 were 177.2 ± 49.7 Tg CH₄ yr⁻¹, based on the five different data sets. The tropical regions contributed the largest portion of estimated CH₄ emissions from global wetlands, but also had the largest discrepancy. Among six continents, the largest uncertainty was found in South America. Thus, the improved estimates of wetland extent and CH₄ emissions in the tropical regions and South America would be a critical step toward an accurate estimate of global CH₄ emissions. This uncertainty analysis also reveals an important need for our scientific community to generate a global scale wetland data set with higher spatial resolution and shorter time interval, by integrating multiple sources of field and satellite data with modeling approaches, for cross-scale extrapolation.

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1. Introduction

Carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O) account for more than 87% of the radioactive forcing (RF) due to long-lived greenhouse gases (LLGHGs) (WMO, 2015). Among them,

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methane ranks as the second largest RF (Ciais et al., 2013). The global warming potential (GWP) of CH₄ is 28 times higher than that of CO₂ at 100-year time horizon (Myhre et al., 2013). In 2014, the global abundance (as mole fractions) of CH₄ had already reached 1833 ± 1 ppb, an increase of 154% since pre-industrial time (WMO, 2015). The relative increase of CH₄ is 1.8 and 2.1 times higher than that of CO₂ and N₂O, respectively. The shorter lifetime (~9 years) and higher GWP make CH₄ a good candidate to reduce the human-induced climate warming (Dlugokencky et al., 2011; Tian et al., 2016). In addition, methane also determines the oxidizing capacity of troposphere by removing hydroxyl radical and subsequently changing the level of water vapor through CH₄ oxidation and the climate influence of HFCs and HCFCs in the stratosphere (Ciais et al., 2013; Montzka et al., 2011). Thus, the change of atmospheric CH₄ concentration could cause a quick response to the climate (Tian et al., 2016).

Among all natural and anthropogenic sources, wetlands are the single largest CH₄ source and contribute 40%–50% of total CH₄ emissions (Bohn et al., 2015; Kirschke et al., 2013; Saunio et al., 2016). Despite the crucial role of anthropogenic emission from a long-term perspective, CH₄ emission from wetlands likely dominated the inter-annual variability of CH₄ sources and determined the fluctuation of atmospheric CH₄ in the recent two decades (Bousquet et al., 2006; Pison et al., 2013). Previous research has intensively examined CH₄ emission from wetland ecosystems through bottom-up (BU: e.g., inventory, statistical extrapolation of local flux measurements, process-based modeling) and top-down (TD: atmospheric inversions) approaches (Kirschke et al., 2013; Tian et al., 2016). Furthermore, recent progress in deriving CH₄ flux from field measurements, eddy-covariance and aircraft data allows for extensive observation-based evaluation. Nonetheless, wetlands are responsible for the largest absolute uncertainty from all the CH₄ emission categories, with a range of 107 Tg CH₄ yr⁻¹, approximately 49.3% of the global total estimate (Kirschke et al., 2013). Likewise, large discrepancies exist in spatial-temporal variation of estimated CH₄ emission (Kirschke et al., 2013; Melton et al., 2013; Mitsch et al., 2013). One of the large uncertainties in estimates of CH₄ emission comes from differences in wetland spatial extent being used (Bohn et al., 2015; Kirschke et al., 2013; Melton et al., 2013).

To determine the extent of global wetlands, terrestrial ecosystem models in general either simulate the extent through a hydrological module or use the wetland spatial data from inventory or remote sensing observations (Melton et al., 2013). However, model-simulated wetland extent tends to overestimate the wetland area and shows distinct patterns in spatial and temporal distribution compared to observed data sets (Melton et al., 2013; Stacke and Hagemann, 2012), which is partially attributed to the simplicity of model structure, parameterization, absence of several important processes and wetland determination schemes (Melton et al., 2013; Wania et al., 2013). Wetland extent data sets derived from inventory or satellite observations are broadly used in land ecosystem models to estimate CH₄ emission and other biogeochemical processes at regional scale (Banger et al., 2015; Ito and Inatomi, 2012; Melton et al., 2013; Pison et al., 2013; Zhuang et al., 2015). Although identified, insufficient attention has been paid to the discrepancies among wetland data sets and estimates of CH₄ emission caused thereby (Bridgman et al., 2013).

Here, we take one step toward unraveling the uncertainties caused by use of different wetland data sets. The Dynamic Land Ecosystem Model (DLEM), which has been widely used to estimate multiple greenhouse gas fluxes (Tian et al., 2015b), was chosen to quantify CH₄ emission from global wetlands. The objectives of this study were to 1) examine the difference in the magnitude, spatial and temporal patterns of wetland distributions among the five data

sets, 2) compare the differences in magnitude, spatial and temporal patterns of modeled CH₄ fluxes as driven by the five wetland data sets, and 3) determine the uncertainties caused by wetland data sets and discuss potential strategies to reduce the uncertainties.

2. Methodology

2.1. Wetland data sets

In this study, we collected five wetland data sets, which were well recognized and used by different studies to estimate the CH₄ emission and related biogeochemical processes in wetlands (Bergamaschi et al., 2007; Bloom et al., 2017; Bohn et al., 2015; Ito and Inatomi, 2012; Kirschke et al., 2013; Melton et al., 2013; Ringeval et al., 2011; Spahni et al., 2011; Zhu et al., 2015).

The first three data sets were all static in time. Matthews and Fung (1987) developed the first data set of the global distribution of wetlands in Goddard Institute for Space Studies (GISS) and classified wetlands into five types (forested bog, non-forested bog, forested swamp, non-forested swamp, and alluvial formations) with a spatial resolution of $1^\circ \times 1^\circ$. Lehner and Döll (2004) developed the Global Lakes and Wetlands Database (GLWD). GLWD provides a global coverage of maximum wetland extent, with a spatial resolution of $30'$. Based on land cover types and land area fraction, nine wetland categories were classified in GLWD, including: (1) freshwater marsh, floodplain, (2) swamp forest, flooded forest, (3) coastal wetland, (4) pan, brackish/saline wetland, (5) bog, fen, mire, (6) intermittent wetland/lake, (7) 50–100% wetland, (8) 25–50% wetland, and (9) wetland complex (0–25% wetland) (Lehner and Döll, 2004). We used the mean fractions, i.e., 75%, 37.5%, and 12.5%, to represent grid scale wetland fractions for categories 7, 8, and 9, respectively. By using five major data sources (the Canadian peatland database (Tarnocai et al., 2000), the U. S. National Land Cover Dataset (Vogelmann et al., 2001), Global land Cover 2000 dataset (JRC, 2003), CORINE90 Land Cover dataset (ETCET, 2000), and GLWD (Lehner and Döll, 2004)), Kaplan (2007) produced a global wetland map for 2003–2007, with a spatial resolution of $0.5^\circ \times 0.5^\circ$ (<http://arve.unil.ch/pub/wetlands/index.html>).

Based on a multi-satellite observation methodology, Papa et al. (2010) and Prigent et al. (2012) generated the Global Inundation Extent from Multi-Satellites (GIEMS) data set, which included both natural wetland and artificial wetland (referred to “paddy field”). GIEMS, for the first time, provided the global coverage and monthly change of inundation extent from 1993 to 2007, and was later used in the Wetland CH₄ Intercomparison of Models Project (WETCH-IMP) (Melton et al., 2013), in which the inland water bodies, like lakes and rivers were excluded. Recently, a global fractional surface water data set based on the Surface Water Microwave Product Series Version 2.0 (SWAMPS) was developed to represent monthly land surface water fraction during 2000–2012 (Schroeder et al., 2015). Poulter et al. (2017) integrated GLWD with SWAMPS to develop a new global wetland data set (SWAMPS-GLWD), which has been used to quantify CH₄ fluxes from wetlands at both regional (Bohn et al., 2015) and global scale (Bloom et al., 2017).

These five wetland data sets have all been widely used to represent global wetland area and distribution and to estimate wetland carbon and CH₄ fluxes. Considering the large difference in wetland area, type, and spatial distribution patterns among the five data sets, the estimation of CH₄ fluxes based on these data sets could differ significantly. Therefore, large uncertainty in global CH₄ fluxes could arise from the choosing of wetland data sets. In our study, we transformed these data sets to the same spatial resolution of $0.5^\circ \times 0.5^\circ$ for driving an ecosystem model. When comparing the wetland extent of dynamic wetland data sets with static wetland

data sets, we first calculated the maximum occurrence of wetland area in each year and get the 15-year and 13-year averages in GIEMS and SWAMPS-GLWD to represent their wetland extents, respectively.

2.2. Dynamic Land Ecosystem Model (DLEM)

The DLEM is comprised of five major components: (1) biophysics, (2) plant physiology, (3) soil biogeochemistry, (4) vegetation dynamics, and (5) land use, land management practices and disturbance. The DLEM can make daily, spatially-explicit estimations of the exchange of water, carbon and nitrogen fluxes between land and the atmosphere and at the land-ocean interface. The major components and related processes have been well described in previous publications (Lu and Tian, 2013; Ren et al., 2011; Tian et al., 2010a, 2012, 2015b, 2015c).

In the DLEM, the CH₄-related processes are assumed to occur in the top 50 cm of soil. The DLEM only accounts for CH₄ produced from dissolved organic carbon (DOC), which comes from the decomposition of vegetative litter and soil organic matter, and the byproduct of gross primary production (GPP). In the DLEM, the net CH₄ fluxes were collectively determined by CH₄ production, oxidation, and transport from soil to the atmosphere.

Methane production is calculated using the Michaelis–Menten equations, and is a function of DOC, soil pH, temperature, and soil moisture content. Methane oxidation occurs through three pathways, including atmospheric CH₄ oxidation (refers to the oxidation of CH₄ transported from the atmosphere), CH₄ oxidation in the soil pore water, and CH₄ oxidation during plant-mediated transport. Methane is assumed to be transported from soil pore to the atmosphere via ebullition, diffusion, and plant-mediated transport. More detailed information about the DLEM simulation of CH₄ fluxes was described in Tian et al. (2010b).

The CH₄ module in the DLEM has already been extensively validated and applied at various spatial scales, including site, regional, and global scales (Banger et al., 2015; Lu and Tian, 2013; Pan et al., 2014, 2015; Ren et al., 2011; Tian et al., 2010b, 2015b; Xu and Tian, 2012). The DLEM's performance in simulating daily and annual CH₄ fluxes has been evaluated against estimates from field observational data, inventory studies, other process-based and inverse models (Banger et al., 2015; Bohn et al., 2015; Tian et al., 2011; Xu et al., 2010). These evaluations have indicated that the DLEM can generally capture the magnitude and temporal variation of CH₄ fluxes.

2.3. Other model input data

To run the DLEM, geo-referenced data with spatial resolution of 0.5° are grouped into two broad categories, which includes (1) dynamic data at daily time-step (e.g., climate data -maximum, minimum, and mean air temperature, precipitation, relative humidity, and shortwave solar radiation, and AOT40 O₃ index), and at annual time-step (e.g., data sets of atmospheric chemical components - atmospheric CO₂ concentration, and nitrogen deposition; data sets of land use and land management practices), and (2) one phase static data (e.g., data set of soil properties - soil texture, soil pH, and soil bulk density; and other ancillary data, such as river network and topographic data). More specifically, daily climate data was derived from CRUNCEP 6-hourly climate data sets (<http://forge.ipsl.jussieu.fr/orchidee/wiki/Documentation/Forcings>). Atmospheric CO₂ concentration was obtained from Ice core and NOAA observations (<https://www.esrl.noaa.gov/gmd/ccgg/trends/global.html>). Atmospheric ozone index (AOT40- Accumulated Ozone exposure over a Threshold of 40 ppb) was used to represent the influences of tropospheric ozone exposure on vegetation

photosynthesis (Felzer et al., 2005; Ren et al., 2007). The AOT40 data was obtained from Felzer et al. (2005). Atmospheric nitrogen deposition data was interpolated based on the three time periods (1860, 1993 and 2050) of global nitrogen deposition maps (Dentener et al., 2006). The interpolation methods have been described in Tian et al. (2015a) and Wei et al. (2014). The geo-referenced information for the soil physical properties was derived from FAO/IIASA/ISRIC/ISSCAS/JRC (2012). The land use and land cover data were collected from HYDE 3.1 (Klein Goldewijk et al., 2011). More detailed information about these data sets and the analysis of spatial and temporal patterns were shown in Zhang et al. (2016).

2.4. Model experimental design

To address the uncertainties of global and regional-scale estimations of CH₄ emission due to different wetland extent data, we conducted ten simulations in total (using each wetland data set to run two simulations). We used averaged climate data from 1901 to 1930 and kept all other input variables constant at the level in 1900 to drive the model until DLEM reach equilibrium state and get the initial condition in 1900. Then, the model was run another 900 years for the spin-up with de-trended climate data from 1901 to 2012, which was to smooth the transition between equilibrium and the transient run. In the transient simulations, we considered multiple environmental changes during 1901–2012 to estimate CH₄ emission from wetlands. For one-phase static wetland data sets (GISS, GLWD, and Kaplan), we assumed the wetland extent didn't change over time. For time-series dynamic wetland data sets (GIEMS and SWAMPS-GLWD), we extracted the seasonal trend from long-term mean wetland extent and applied it to the study period beyond the observation period.

2.5. Analysis and statistical methods

The period 2000–2007 (the overlapped period from the dynamic wetland data sets) was chosen to quantify the uncertainties in the estimated CH₄ emission by using different wetland data sets. When comparing the inter-annual variation of estimated CH₄ emission from different data sets, we subtracted the averaged CH₄ emission ($F_{\text{avg}, 2000-2007}$) during the overlapped period (2000–2007) from estimated CH₄ emission from each year (F_{year}) to determine the anomalous fluxes ($F_{\text{year}} - F_{\text{avg}, 2000-2007}$). The cross-data standard deviation for wetland extent or estimated CH₄ emission refers to the standard deviation that is derived from different wetland data sets, either in depicting wetland extent or estimating wetland CH₄ emission ($SD = \sqrt{\frac{\sum (F_i - F_{\text{avg}})^2}{4}}$, i indicates different wetland data sets).

3. Results

3.1. Wetland area, extent and uncertainties

Our results showed that the mean global wetland area of five wetland data sets was 7.8 ± 2.2 (Avg. ± 1 std. Dev.) million km² and varied from 5.3 million km² (GISS) to 10.2 million km² (SWAMPS-GLWD). All data sets showed that the low latitude (LL, 30°S–30°N) had the largest wetland area (3.4 ± 1.1 million km², Fig. 1a), which accounted for about $43 \pm 4\%$ of the total wetland area. However, the wetland area in the LL varied from ~1.9 million km² in GISS (37% of the global wetland area) to ~4.3 million km² in GIEMS (47% of the global wetland area). The middle latitude (ML, 30° - 60°N and S) accounted for around $36 \pm 1\%$ of the global wetland area ($\sim 2.8 \pm 0.9$ million km²). The estimated wetland area from GISS and Kaplan

Fig. 1. Wetland distribution at (a) high latitude region (HLR, 60°–90° N and S), middle latitude region (MLR, 30°–60° N and S) and low latitude region (LLR, 30°S –30°N), and (b) continental scale for different wetland data sets. Note: Data labels above the bar represent the fraction of estimated wetland area in (a) each region and (b) continent to the global wetland area.

matched well (1.8–2.0 million km²), which was much lower than the estimate from GLWD, GIEMS (3.2–3.4 million km²) and SWAMPS-GLWD (3.9 million km²). The high latitude (HL, 60°–90° N and S) accounted for 20 ± 5% of the global total wetland area. GISS, GLWD, and GIEMS all suggested that the wetland area was around 1.4–1.5 million km²; Kaplan had the smallest wetland area (~1.1 million km²) and SWAMPS-GLWD had the largest (~2.1 million km²). From the latitudinal distribution, all the data set except GIEMS showed a peak wetland distribution around 60°N–66°N, where large areas of peatland distributed (Fig. 1), but GIEMS showed large wetland extent in 20°N–33°N owing to the inclusion of rice paddy land.

At the continental scale, all data sets except GIEMS had about one-third of wetland area in Asia, while GIEMS had 43% of wetland area due to its inclusions of rice paddy land (Fig. 1b). Larger discrepancies in wetland extent were found in northeast China, and India. North America accounted for about 28 ± 8% of the global wetland area, which was two times higher than that in Africa (14 ± 3%) and South America (14 ± 1%). Europe and Oceania together shared approximately 10% of the global wetland area. There was a large difference in wetland extent among the five data sets in Northern Europe, the Hudson Bay Lowland (HBL) and the

West Siberian Lowland (WSL) (Fig. 2b).

The temporal variation in wetland extent can be observed from dynamic wetland data sets (GIEMS and SWAMPS-GLWD). For both data sets, a decreasing trend was found in South America. GIEMS showed a decreasing trend in Canada, the WSL, India and East China in summer (June ~ August, JJA) during 1993–2007 (Fig. 3). SWAMPS-GLWD showed an apparent increase at the northern high latitude, especially in the HBL and the WSL in spring (March ~ May, MAM), summer and autumn (September ~ November, SON) during 2000–2012 (Fig. 3). The wetland extent from SWAMPS-GLWD declined in Alaska, Alberta, and Northwest Territories of Canada in summer and autumn. The wetland extent in swamp forest and floodplain extent in South America showed a decreasing trend for all seasons during 2000–2012. The largest decline of wetland extent from GIEM (~18,060 km²/yr) was found at the 30°N–60°N zone in summer. The wetland extent in LL showed a decreasing trend in four seasons, with a rate ranging from 13,011 km²/yr in spring to 16,392 km²/yr in autumn. SWAMPS-GLWD data indicated a significant reduction of wetland area in LL, with a rate ranging from 7177 km²/yr in spring to 17,846 km²/yr in autumn during 2000–2012. On the contrary, there was an increasing trend at the 30°N–90°N zone in winter (December ~ February, DJF), spring and

Fig. 2. The spatial distribution of mean wetland fraction (top) and standard deviation (bottom) based on the 5 wetland data sets.

autumn. For the intra-annual variations, both data sets indicated that wetland area reached the maximum in August, and minimum in December.

3.2. Methane emission magnitudes and uncertainties

We evaluate the uncertainty coming from wetland extent and it turns out that the simulated CH_4 emissions from global wetlands were $177.2 \pm 49.7 \text{ Tg CH}_4 \text{ yr}^{-1}$, with the maximum emissions using GLWD data set ($263.4 \text{ Tg CH}_4 \text{ yr}^{-1}$) and the minimum using GIEMS data set ($141.3 \text{ Tg CH}_4 \text{ yr}^{-1}$) (Fig. 4). At the regional scale, LL had the largest portion ($\sim 72 \pm 7\%$) of estimated CH_4 emission and the largest uncertainty ($128.3 \pm 38.5 \text{ Tg CH}_4 \text{ yr}^{-1}$), ranging from $91.0 \text{ Tg CH}_4 \text{ yr}^{-1}$ (GIEMS) to $187.9 \text{ Tg CH}_4 \text{ yr}^{-1}$ (GLWD). ML and HL contributed $\sim 25 \pm 6\%$ and $\sim 9 \pm 2\%$ of the total emissions, respectively. The mean CH_4 emission in ML was $43.8 \pm 13.6 \text{ Tg CH}_4 \text{ yr}^{-1}$, with lower estimation using GISS ($31.6 \text{ Tg CH}_4 \text{ yr}^{-1}$) and Kaplan

($32.2 \text{ Tg CH}_4 \text{ yr}^{-1}$) data sets and higher estimation using SWAMPS-GLWD ($56.9 \text{ Tg CH}_4 \text{ yr}^{-1}$) and GLWD ($59.9 \text{ Tg CH}_4 \text{ yr}^{-1}$) data sets. For the HL, CH_4 emission was $14.8 \pm 3.4 \text{ Tg CH}_4 \text{ yr}^{-1}$, ranging from $11.8 \text{ Tg CH}_4 \text{ yr}^{-1}$ (Kaplan and GIEMS) to $20.0 \text{ Tg CH}_4 \text{ yr}^{-1}$ (SWAMPS-GLWD).

Among the six continents, South America contributed the largest portion of estimated wetland CH_4 emission ($\sim 53.5 \pm 23.2 \text{ Tg CH}_4 \text{ yr}^{-1}$) despite it only covered 14% of global wetland area, followed by Asia ($\sim 47.4 \pm 11.3 \text{ Tg CH}_4 \text{ yr}^{-1}$), Africa ($\sim 34.9 \pm 13.8 \text{ Tg CH}_4 \text{ yr}^{-1}$), and North America ($\sim 30.2 \pm 13.3 \text{ Tg CH}_4 \text{ yr}^{-1}$) (Table 1 & Fig. 4). Europe and Oceania contributed the least portions of the CH_4 emission, which was 6.4 ± 3.1 and $4.8 \pm 1.6 \text{ Tg CH}_4 \text{ yr}^{-1}$, respectively.

The largest uncertainties in CH_4 emission were found in South America and Africa. In South America, the large uncertainty was mainly due to the high estimation using GLWD data set ($\sim 93.0 \text{ Tg CH}_4 \text{ yr}^{-1}$), which was about two times larger than those using other

Trend of Wetland Fraction (1993–2007)

Trend of Wetland Fraction (2000–2012)

Fig. 3. Seasonal trends of wetland fraction from GIEMS during 1993–2007 (top) and SWAMPS-GLWD during 2000–2012 (bottom). *Notes:* The wetland fraction denotes the fraction of wetland area within a grid cell at resolution of 0.5° by 0.5° longitude/latitude, which is around 55.6 km × 55.6 km at the equator. DJF, MAM, JJA, SON represents December ~ February (winter), March ~ May (spring), June ~ August (summer), and September ~ November (autumn), respectively.

Fig. 4. Wetland CH₄ emission at global and continental scales using different wetland data sets.

Table 1Estimated wetland CH₄ emission during 2000–2007 at global and continental scales using different wetland data sets.

Tg CH ₄ yr ⁻¹	GISS	GLWD	Kaplan	GIEMS	SWAMPS-GLWD	Mean
Global	146.5	263.4	165.9	141.3	169.1	177.2 ± 49.7
Asia	34.8	57.1	41.5	61.3	42.3	47.4 ± 11.3
North America	16.7	51.1	25.9	23.1	34.3	30.2 ± 13.3
Europe	11.6	4.3	4.2	6.0	5.9	6.4 ± 3.1
Africa	35.2	51.5	43.3	15.5	28.9	34.9 ± 13.8
South America	42.7	93.0	46.0	33.1	52.7	53.5 ± 23.2
Oceania	5.5	6.5	5.0	2.2	4.8	4.8 ± 1.6

Note: The period 2000–2007 (the overlapped period from the dynamic wetland data sets) was chosen to quantify the uncertainties in the estimated CH₄ emission among all wetland data sets.

data sets (33.1 Tg CH₄ yr⁻¹ from GIEMS ~ 52.7 Tg CH₄ yr⁻¹ from SWAMPS-GLWD). In Africa, an even larger uncertainty in CH₄ emission was found, ranging from ~51.5 Tg CH₄ yr⁻¹ (GLWD) to ~15.5 Tg CH₄ yr⁻¹ (GIEMS). In Asia, lower estimations were found using GISS (34.8 Tg CH₄ yr⁻¹), Kaplan (41.5 Tg CH₄ yr⁻¹) and SWAMPS-GLWD (42.3 Tg CH₄ yr⁻¹) data sets as input, while higher estimations were obtained using GLWD (57.1 Tg CH₄ yr⁻¹) and GIEMS (61.3 Tg CH₄ yr⁻¹) data sets. In North America, the highest estimation was obtained using GLWD (~51.1 Tg CH₄ yr⁻¹) data set, which was over three times higher than using GISS (~16.7 Tg CH₄ yr⁻¹) data set. In contrast, in Europe, the highest estimation was derived using GISS (~11.6 Tg CH₄ yr⁻¹) data set, which was over two times higher than those using GLWD (~4.3 Tg CH₄ yr⁻¹) and Kaplan (~4.2 Tg CH₄ yr⁻¹) data set. In Oceania, CH₄ emission was similar from all data sets (4.8–6.5 Tg CH₄ yr⁻¹), except GIEMS (~2.2 Tg CH₄ yr⁻¹).

In general, we found that GLWD data set had larger wetland area in South America, Africa, Oceania, and North America than other data sets, and GIEMS data set had larger wetland area in Asia, while GISS data set had larger wetland area in Europe, which was roughly consistent with the model estimated divergence in CH₄ emissions.

3.3. Temporal variation in CH₄ emissions

Temporal patterns of CH₄ emission were greatly different between the static and dynamic wetland data sets. The CH₄ anomalies from all static wetland data sets (i.e., GISS, GLWD and Kaplan) showed similar inter-annual variations at all latitudinal bands since wetland extents were not changed with time and the inter-annual variations was mainly owing to the changing environmental factors.

The largest inter-annual variation in CH₄ emissions occurred in the LL (Fig. 5). The CH₄ emissions from the three static wetland data sets showed a significant increasing trend with a mean rate of 0.32 Tg CH₄ yr⁻¹ during 1993–2005. On the contrary, the simulated CH₄ fluxes using GIEMS demonstrated a significant decreasing trend with a rate of 0.92 Tg CH₄ yr⁻¹ during 1993–2005. After 2007, the patterns of inter-annual variation in CH₄ emissions were similar using GISS, GLWD, Kaplan, and SWAMPS-GLWD data sets, but with different magnitudes. For the ML, the simulation with GIEMS showed higher and positive CH₄ emissions anomalies before 1997, opposite to that from other data sets. For the HL, the simulated CH₄ emission anomalies based on all data sets showed a reduction from 1993 to 1997, and followed by a small fluctuation during

Fig. 5. Modeled wetland CH₄ emission anomalies (i.e., annual number – mean value) using different wetland data sets at high latitude region (HLR, 60°–90° N and S), middle latitude region (MLR, 30°–60° N and S) and low latitude region (LLR, 30°S–30°N).

1998–2012, with the highest positive anomalies in 2005, 2007 and 2012.

The simulations with GLWD and SWAMPS-GLWD data sets showed the highest monthly CH_4 emissions from global wetlands as compared to other data sets. Although the magnitudes were different, the estimated CH_4 emissions using all data sets showed a similar intra-annual/seasonal variation (Fig. 6). Methane emissions decreased slightly from January to February, then increased and reached a peak in July and August and declined thereafter. Around 60% of annual emissions occurred during May–October.

4. Discussion

4.1. The uncertainty source of wetland data sets

There are large discrepancies in both the magnitude and spatial distributions of wetland extents among the five data sets used in this study (Zhu and Gong, 2014). This may be primarily due to the inconsistency in: 1) the definition and classification of wetland types, 2) the duration and time of the wetland data sets coverage, and 3) the purposes and methods of generating wetland data sets.

Three static wetland datasets (GISS, GLWD, Kaplan) defined and classified wetlands in distinct ways. Yet, the dynamic wetland datasets (GIEMS and SWAMPS-GLWD) were determined by the inundated fractions (Prigent et al., 2012). Static wetland data sets were unable to capture the seasonal variation over time, whereas around 60% of the wetlands were inundated only in a portion of the year (Prigent et al., 2016). In addition, GLWD has been argued to overestimate the wetland extent in arid or semiarid regions (Lehner and Döll, 2004; Melton et al., 2013) and in the northwest of WSL; however, it tended to underestimate the wetland area in the tundra region (Bohn et al., 2015). Still, GLWD was considered as the best choice to represent global wetland extent and types due to its high spatial resolution (1 km) and more detailed wetland categories (Prigent et al., 2016).

The wetland data sets were generated for different time periods (from early 1980s to early 2010s). Due to intensive human perturbations (e.g., wetland drainage and land conversion) and variations in climate (e.g., precipitation, temperature, soil freezing and thawing time), wetland extent could vary greatly year by year (Melton et al., 2013; Niu et al., 2012; Paudel et al., 2016; Prigent et al., 2016; Wei and Wang, 2016). For example, wetland has been drained for cultivation and decreased by 33% in China during 1978–2008 (Niu et al., 2012; Wei and Wang, 2016); however, wetland area may not change dramatically in some other regions, such as the northern Alaska (Hall et al., 1994).

In general, there are three approaches towards generating the regional/global wetland extent data sets, including field investigations and statistical extrapolation, remote sensing monitoring, and model simulations. Field investigations and statistical extrapolation may reasonably capture the wetland extent for small regions, while still have challenges in mapping the fine-scale heterogeneity of wetland with high spatial/temporal resolution and large area coverage (Prigent et al., 2016; Terentieva et al., 2016). The wetland data sets from multi-satellite observations, considered the dynamic inundation extent at global scale, but cannot accurately represent the wetland without standing water (such as peatland) but with the water table beneath the land surface, some small wetlands with less than 10% fractional coverage of a grid cell, and the inundation area under dense forest canopy (Melton et al., 2013; Prigent et al., 2016; Terentieva et al., 2016). However, those areas could still produce considerable amounts of CH_4 . Thus, it is important to be cautious when using the dynamic wetland datasets in peatland-intensive area.

4.2. Uncertainties in modeled CH_4 emissions by using different wetland data sets

The lack of consistence in wetland extent and distribution among different data sets caused the large uncertainty range in modeled CH_4 emissions (Bohn et al., 2015; Bousquet et al., 2006; Ito and Inatomi, 2012; Melton et al., 2013; Wania et al., 2013). To determine the estimated CH_4 emission per unit wetland area bias, we calculate the relative magnitude of the estimation uncertainties, which was defined as $\frac{F_{\text{CH}_4 i} - F_{\text{CH}_4 \text{mean}}}{\text{Area}_i - \text{Area}_{\text{mean}}}$. Here i indicates different wetland data set. For the dynamic wetland data sets, the wetland area from GIEMS and SWAMPS-GLWD were determined by averaged annual maximum inundation extent, thus the higher estimation of wetland extent did not necessarily reflect the higher wetland extent throughout the year. But for the static wetland the relative magnitude of the uncertainties ranged from 5.9 g $\text{CH}_4 \text{ m}^{-2} \text{ yr}^{-1}$ (Kaplan) to 97.6 g $\text{CH}_4 \text{ m}^{-2} \text{ yr}^{-1}$ (GLWD). The higher bias of CH_4 emission per unit wetland area from GLWD is owing to large wetland area distributed in the tropical and subtropical regions, where CH_4 producing capability was markedly larger than other places. Despite only 14% coverage of global wetland, our study revealed that both South America and Africa, where averaged CH_4 producing capabilities per unit wetland area are generally larger than other continents, contributes the greatest unknown in the global wetland CH_4 budget.

Among a range of explanations, CH_4 emission from wetlands has long been proposed as the dominant contributor to the recent

Fig. 6. Intra-annual variation of estimated wetland CH_4 emission using different wetland data sets.

variation of global CH₄ burden. Our study also found a contrasting inter-annual variation pattern in CH₄ fluxes between static wetland data sets and two dynamic wetland data sets. Thus, the ability of bottom-up approaches to estimate the inter-annual and intra-annual variation of CH₄ fluxes from the global wetlands relies on our understanding of the long-term dynamics of wetland extents and how different climatic factors could affect/control both temporal variation of wetland extents and the CH₄ producing capabilities per unit area.

4.3. Comparisons with other studies

The selected wetland data sets in this study have been broadly used in many previous studies at both global and regional scales (Bohn et al., 2015; Ito and Inatomi, 2012; Matthews and Fung, 1987; Ringeval et al., 2010; Saunio et al., 2016; Wania et al., 2013). Unsurprisingly therefore, the estimated global wetland CH₄ emission revealed a large range (127.2 ± 4.8 – 264 ± 12 Tg CH₄ yr^{−1}) by using different data sets as inputs (Ito and Inatomi, 2012; Melton et al., 2013; Ringeval et al., 2011; Tian et al., 2015b; Wania et al., 2013), whereas our estimation was 177.2 ± 49.7 Tg CH₄ yr^{−1}. Analyzing the largest high-latitude wetland, Bohn et al. (2015) suggested that GISS and SWAMPS-GLWD underestimated the non-inundated peatland area, but overestimated the permanent wetland area by including water body due to the polluted signal from remotely sensed observations (Bohn et al., 2015; Prigent et al., 2012). On the other hand, for the second largest boreal wetland (HBL), the estimated CH₄ emissions ranged from 2.2 ± 0.2 to 11.3 ± 7.9 Tg CH₄ yr^{−1} using GIEMS data set (Melton et al., 2013), and our study suggested a similar estimation ranging from 1.9 ± 0.1 to 8.5 ± 0.5 Tg CH₄ yr^{−1} in the HBL by using different data sets.

4.4. Implication and future directions

The results of this analysis compare the similarity and dissimilarity among existing wetland data sets and identify some common patterns among them, identify the regions/continents with the largest/least uncertainty in wetland extents and CH₄ emissions, and bring forth some strategies for future development of more reliable wetland data sets for CH₄ research. The information derived can be readily fed back to future researchers in particularly to select appropriate wetland data sets for their specific research objections and regions.

In theory, it should then be possible to capture the dynamic changes of wetland extent at global scale. But finding a way to do this still faces challenge nowadays. Several key characteristics of the future wetland data sets are desired: 1) shorter time step in delineating wetland extent and variations (from annual to monthly or even daily), 2) larger area coverage (from regional to continental and global), and 3) higher spatial resolution. Poor delineation of wetland extent and distribution has greatly affected the estimation accuracy of simulated CH₄ fluxes. To reduce the present uncertainties and generate a more robust global wetland data set, future research efforts will need to integrate multiple sources of data from ground and satellite observations with multiple approaches (inventory, bottom-up and top-down modeling) for spatial and temporal extrapolation.

Future research could couple different existing data sets with some ongoing efforts (e.g., soil moisture monitoring from SMAP-Soil Moisture Active Passive satellite) to improve the wetland extent in the regions we identified as poorly by current wetland data sets. GIEMS is a remote sensing product that primarily captures visible surface water while the Northern Circumpolar Soil Carbon Database (NCSCD) estimates peatland distribution (and peatlands may not have visible surface water) (Hugelius et al.,

2013). Coupling these two data sets with field observation could improve the estimation of peatland distribution meanwhile considering seasonal variation. High-resolution mapping of global surface water data sets, which provides surface water change at 30-m resolution over the past 32 years (Pekel et al., 2016), together with SMAP, which provides the near real-time soil moisture data set with high spatial/temporal resolution, could use as a reference to examine the change in wetland extent.

Implication of multi-scale studies, such as extensive field investigation together with high resolution satellite images, could improve map accuracy from 56% to 79% (Terentieva et al., 2016). Thus, the identification of wetland areas at field or watershed scale could be used as ground truth data for training data and generate more accurate regional estimations (Terentieva et al., 2016).

In addition, the integration of multiple approaches is critical to bridge the knowledge gap, particularly for the regions that are poorly documented but with large amount of CH₄ emission from a global perspective. The presence of wetlands could be inferred from satellite observation (e.g., SCIAMACHY- Scanning Imaging Absorption Spectrometer for Atmospheric Cartography), which identifies the hotspots with large CH₄ emission, such as South America and Africa (Bergamaschi et al., 2007, 2009; Melton et al., 2013). However, large uncertainties of estimated CH₄ emission in those regions were partially attributed to inconsistent wetland extent from different data sets, such as South America, where dense forest canopy coverage mingles the satellite (e.g., GIEMS and SWAMPS-GLWD) signals for accurately detecting. It is urgent to collect more information about inter-annual and seasonal variation of wetland extent and CH₄ emission at both site and regional scale in these identified regions with larger uncertainties. At present, several process-based models are applied to estimate wetland distribution within its model structure, such as SDGVM and UVic-ESCM (Melton et al., 2013). To improve the modeling accuracy of wetland extent, it is critical to improve the representation of hydrological processes and their regulations to CH₄ fluxes, including more explicit representation of key hydrological processes, implementation of both horizontal and lateral water flows, and the incorporation of several important controls, such as freezing and thawing. These improvements from modeling group could contribute to reduce wetland data delineation-induced error. For example, the extant wetland data sets could not provide the information of wetland variation at finer scale, such as within-month or even daily, and model estimation provides primary characteristics of soil moisture at these time steps (Song et al., 2012). Thus, we need better model representation to understand and estimate dynamic hydrological cycles related to the changing wetland area. The integration of multiple approaches, such as inventory, bottom-up and top-down approaches could benefit from each other.

5. Conclusion

This study quantified the uncertainties in wetland area and distributions, as well as the estimated wetland CH₄ emissions by using five widely used wetland data sets. There were extensive disagreements on the wetland distribution from the tropical to the northern high latitude region among five wetland data sets. The large uncertainty in wetland extents resulted in a large range of estimated CH₄ emission from wetlands. The tropical regions contributed the largest portion of estimated CH₄ emission from wetlands, but also have the largest discrepancy. Despite over half of the wetland located in the extra-tropical regions, improved understanding of both wetland extent and wetland CH₄ emission in the tropical regions is essential to address the wetland's contribution to the CH₄ budget in the context of global perspective. At continental scale, South America and Africa showed the largest

uncertainty in the global wetland CH₄ estimate because the actual wetland extent and temporal variations are uncertain.

Similar inter-annual variation of CH₄ emissions was found in model simulations using the static wetland data sets, but it is significantly different from the model results using the dynamic wetland data sets. The large uncertainty range of estimated CH₄ emission implies an urgent need to improve the accuracy of wetland extent data sets. Future wetland data sets with high temporal and spatial resolutions are desired. Considering the improved techniques and ongoing wetland monitoring activities, it is imperative to integrate multiple sources of data from ground and satellite observations with multiple approaches (inventory, bottom-up and top-down modeling) for spatial and temporal extrapolation.

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References

- Banger, K., Tian, H.Q., Zhang, B.W., Lu, C.Q., Ren, W., Tao, B., 2015. Biosphere-atmosphere exchange of methane in India as influenced by multiple environmental changes during 1901–2010. *Atmos. Environ.* 192–200.
- Bergamaschi, P., Frankenberg, C., Meirink, J.F., Krol, M., Dentener, F., Wagner, T., Platt, U., Kaplan, J., Körner, S., Heimann, M., 2007. Satellite cartography of atmospheric methane from SCIAMACHY on board ENVISAT: 2. Evaluation based on inverse model simulations. *J. Geophys. Res. Atmos.* 112.
- Bergamaschi, P., Frankenberg, C., Meirink, J.F., Krol, M., Villani, M.G., Houweling, S., Dentener, F., Dlugokencky, E.J., Miller, J.B., Gatti, L.V., 2009. Inverse modeling of global and regional CH₄ emissions using SCIAMACHY satellite retrievals. *J. Geophys. Res. Atmos.* 114.
- Bloom, A.A., Bowman, K.W., Lee, M., Turner, A.J., Schroeder, R., Worden, J.R., Weidner, R., McDonald, K.C., Jacob, D.J., 2017. A global wetland methane emissions and uncertainty dataset for atmospheric chemical transport models (WetCHARTs version 1.0). *Geosci. Model Dev.* 10, 2141–2156.
- Bohn, T.J., Melton, J.R., Ito, A., Kleinen, T., Spahni, R., Stocker, B., Zhang, B., Zhu, X., Schroeder, R., Glagolev, M.V., Maksyutov, S., Brovkin, V., Chen, G., Denisov, S.N., Eliseev, A.V., Gallego-Sala, A., McDonald, K.C., Rawlins, M.A., Riley, W.J., Subin, Z.M., Tian, H.Q., Zhuang, Q., Kaplan, J.O., 2015. WETCHIMP-WSL: inter-comparison of wetland methane emissions models over West Siberia. *Biogeosciences* 12, 3321–3349.
- Bousquet, P., Ciais, P., Miller, J.B., Dlugokencky, E.J., Hauglustaine, D.A., Prigent, C., Van der Werf, G.R., Peylin, P., Brunke, E.G., Carouge, C., Langenfelds, R.L., Lathiere, J., Papa, F., Ramonet, M., Schmidt, M., Steele, L.P., Tyler, S.C., White, J., 2006. Contribution of anthropogenic and natural sources to atmospheric methane variability. *Nature* 443, 439–443.
- Bridgman, S.D., Cadillo-Quiroz, H., Keller, J.K., Zhuang, Q.L., 2013. Methane emissions from wetlands: biogeochemical, microbial, and modeling perspectives from local to global scales. *Glob. Change Biol.* 19, 1325–1346.
- Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., Chhabra, A., DeFries, R., Galloway, J., Heimann, M., Jones, C., Le Quere, C., Myneni, R.B., Piao, S.L., Thornton, P., 2013. Carbon and other biogeochemical cycles. In: *Climate change 2013: the physical science basis*. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 465–570.
- Dentener, F., Drevet, J., Lamarque, J.F., Bey, I., Eickhout, B., Fiore, A.M., Hauglustaine, D., Horowitz, L.W., Krol, M., Kulshrestha, U.C., Lawrence, M., Galy-Lacaux, C., Rast, S., Shindell, D., Stevenson, D., Van Noije, T., Atherton, C., Bell, N., Bergman, D., Butler, T., Cofala, J., Collins, B., Doherty, R., Ellingsen, K., Galloway, J., Gauss, M., Montanaro, V., Müller, J.F., Pitari, G., Rodriguez, J., Sanderson, M., Solomon, F., Strahan, S., Schultz, M., Sud, K., Szopa, S., Wild, O., 2006. Nitrogen and sulfur deposition on regional and global scales: a multi-model evaluation. *Glob. Biogeochem. Cy* 20, 1–21. <http://dx.doi.org/10.1029/2005GB002672>.
- Dlugokencky, E.J., Nisbet, E.G., Fisher, R., Lowry, D., 2011. Global atmospheric methane: budget, changes and dangers. *Philos. T R. Soc. A* 369, 2058–2072.
- ETCTE, 2000. Corine Land Cover Database (Version 12/2000 Extended Coverage), the European Topic Centre on Terrestrial Environment. European Environment Agency.
- FAO/IIASA/ISRIC/ISSCAS/JRC, 2012. Harmonized World Soil Database (Version 1.2). FAO, Rome, Italy and IIASA, Laxenburg, Austria.
- Felzer, B., Reilly, J., Melillo, J., Kicklighter, D., Sarofim, M., Wang, C., Prinn, R., Zhuang, Q., 2005. Future effects of ozone on carbon sequestration and climate change policy using a global biogeochemical model. *Clim. Change* 73, 345–373.
- Hall, V.J., Frayer, E.W., Wilen, O.B., 1994. Status of Alaska Wetlands. U. S. Fish and Wildlife Service Alaska Region.
- Hugelius, G., Tarnocai, C., Broll, G., Canadell, J., Kuhry, P., Swanson, D., 2013. The Northern Circumpolar Soil Carbon Database: spatially distributed datasets of soil coverage and soil carbon storage in the northern permafrost regions. *Earth Syst. Sci. Data* 5, 3–13.
- Ito, A., Inatomi, M., 2012. Use of a process-based model for assessing the methane budgets of global terrestrial ecosystems and evaluation of uncertainty. *Biogeosciences* 9, 759–773.
- JRC, 2003. Global Land Cover 2000 Database. European Commission, Joint Research Centre, Ispra, Italy. <http://www.gvm.jrc.it/glc2000>.
- Kaplan, J.O., 2007. A composite map of global wetland distribution at 0.5 degree resolution. Digital dataset available at: <http://arve.epfl.ch/pub/wetlands/index.html>.
- Kirschke, S., Bousquet, P., Ciais, P., Saunoy, M., Canadell, J.G., Dlugokencky, E.J., Bergamaschi, P., Bergmann, D., Blake, D.R., Bruhwiler, L., Cameron-Smith, P., Castaldi, S., Chevallier, F., Feng, L., Fraser, A., Heimann, M., Hodson, E.L., Houweling, S., Josse, B., Fraser, P.J., Krummel, P.B., Lamarque, J.F., Langenfelds, R.L., Le Quere, C., Naik, V., O'Doherty, S., Palmer, P.I., Pison, I., Plummer, D., Poulter, B., Prinn, R.G., Rigby, M., Ringeval, B., Santini, M., Schmidt, M., Shindell, D.T., Simpson, I.J., Spahni, R., Steele, L.P., Strode, S.A., Sud, K., Szopa, S., van der Werf, G.R., Voulgarakis, A., van Weele, M., Weiss, R.F., Williams, J.E., Zeng, G., 2013. Three decades of global methane sources and sinks. *Nat. Geosci.* 6, 813–823.
- Klein Goldewijk, K., Beusen, A., van Drecht, G., de Vos, M., 2011. The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. *Glob. Ecol. Biogeogr.* 20, 73–86.
- Lehner, B., Döll, P., 2004. Development and validation of a global database of lakes, reservoirs and wetlands. *J. Hydrology* 296, 1–22.
- Lu, C.Q., Tian, H.Q., 2013. Net greenhouse gas balance in response to nitrogen enrichment: perspectives from a coupled biogeochemical model. *Glob. Change Biol.* 19, 571–588.
- Matthews, E., Fung, I., 1987. Methane emission from natural wetlands: global distribution, area, and environmental characteristics of sources. *Glob. Biogeochem. Cy* 1, 61–86.
- Melton, J.R., Wania, R., Hodson, E.L., Poulter, B., Ringeval, B., Spahni, R., Bohn, T., Avis, C.A., Beerling, D.J., Chen, G., Eliseev, A.V., Denisov, S.N., Hopcroft, P.O., Lettenmaier, D.P., Riley, W.J., Singarayer, J.S., Subin, Z.M., Tian, H., Zurcher, S., Brovkin, V., van Bodegom, P.M., Kleinen, T., Yu, Z.C., Kaplan, J.O., 2013. Present state of global wetland extent and wetland methane modelling: conclusions from a model inter-comparison project (WETCHIMP). *Biogeosciences* 10, 753–788.
- Mitsch, W.J., Bernal, B., Nahlik, A.M., Mander, Ü., Zhang, L., Anderson, C.J., Jørgensen, S.E., Brix, H., 2013. Wetlands, carbon, and climate change. *Landsch. Ecol.* 28, 583–597.
- Montzka, S.A., Dlugokencky, E.J., Butler, J.H., 2011. Non-CO₂ greenhouse gases and climate change. *Nature* 476, 43–50.
- Myhre, G., Shindell, D., Bréon, F.M., Collins, W., Fuglestad, J., Huang, J., Koch, D., Lamarque, J.F., Lee, D., Mendoza, B., Nakajima, Y., Robock, A., Stephens, G., Takemura, T., Zhang, H., 2013. Anthropogenic and natural radiative forcing. In: *Climate change 2013: the physical science basis*. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, p. 423.
- Niu, Z., Zhang, H., Wang, X., Yao, W., Zhou, D., Zhao, K., Zhao, H., Li, N., Huang, H., Li, C., 2012. Mapping wetland changes in China between 1978 and 2008. *Chin. Sci. Bull.* 57, 2813–2823.
- Pan, S.F., Tian, H.Q., Dangal, S.R.S., Ouyang, Z.Y., Tao, B., Ren, W., Lu, C.Q., Running, S., 2014. Modeling and monitoring terrestrial primary production in a changing global environment: toward a multiscale synthesis of observation and simulation. *Adv. Meteorology* 2014, 1–17.
- Pan, S.F., Tian, H.Q., Yang, Q.C., Yang, J., Lu, C.Q., Tao, B., Ren, W., Ouyang, Z.Y., 2015. Responses of global terrestrial evapotranspiration to climate change and increasing atmospheric CO₂ in the 21st century. *Earth's Future* 3, 15–35.
- Papa, F., Prigent, C., Aires, F., Jimenez, C., Rossow, W., Matthews, E., 2010. Interannual variability of surface water extent at the global scale, 1993–2004. *J. Geophys. Res.* 115, D12111, [10.1029/2009JD012674](https://doi.org/10.1029/2009JD012674).
- Paudyal, R., Mahowald, N.M., Hess, P.G., Meng, L., Riley, W.J., 2016. Attribution of changes in global wetland methane emissions from pre-industrial to present using CLM4. 5-BGC. *Environ. Res. Lett.* 11, 034020.
- Pekel, J.-F., Cottam, A., Gorelick, N., Belward, A.S., 2016. High-resolution mapping of global surface water and its long-term changes. *Nature* 540, 418–422.
- Pison, I., Ringeval, B., Bousquet, P., Prigent, C., Papa, F., 2013. Stable atmospheric methane in the 2000s: key-role of emissions from natural wetlands. *Atmos. Chem. Phys.* 13, 11609–11623.

- Poulter, B., Bousquet, P., Canadell, J., Ciais, P., Peregon, A., Saunio, M., Arora, V., Beerling, D., Brovkin, V., Jones, C., Joos, F., Gedney, N., Ito, A., Kleinen, T., Koven, C., McDonald, K., Melton, J., Peng, C., Peng, S., Prigent, C., Schroder, R., Riley, W., Saito, M., Spahni, R., Tian, H., Taylor, L., Viovy, N., Wilton, D., Wiltshire, A., Xu, X., Zhang, B., Zhang, Z., Zhu, Q., 2017. Global wetland contribution to 2000–2012 atmospheric methane growth rate dynamics. *Environ. Res. Lett.* (submitted for publication).
- Prigent, C., Lettenmaier, D.P., Aires, F., Papa, F., 2016. Toward a high-resolution monitoring of continental surface water extent and dynamics, at global scale: from GIEMS (Global Inundation Extent From Multi-Satellites) to SWOT (Surface Water Ocean Topography). *Remote Sens. Water Resour.* 149–165.
- Prigent, C., Papa, F., Aires, F., Jimenez, C., Rossow, W.B., Matthews, E., 2012. Changes in land surface water dynamics since the 1990s and relation to population pressure. *Geophys. Res. Lett.* 39, 1–5.
- Ren, W., Tian, H.Q., Liu, M.L., Zhang, C., Chen, G.S., Pan, S.F., Felzer, B., Xu, X.F., 2007. Effects of tropospheric ozone pollution on net primary productivity and carbon storage in terrestrial ecosystems of China. *J. Geophys. Res.-Atmos.* 112, 1–17.
- Ren, W., Tian, H.Q., Xu, X.F., Liu, M.L., Lu, C.Q., Chen, G.S., Melillo, J., Reilly, J., Liu, J.Y., 2011. Spatial and temporal patterns of CO₂ and CH₄ fluxes in China's croplands in response to multifactor environmental changes. *Tellus B* 63, 222–240.
- Ringeval, B., de Noblet-Ducoudré, N., Ciais, P., Bousquet, P., Prigent, C., Papa, F., Rossow, W.B., 2010. An attempt to quantify the impact of changes in wetland extent on methane emissions on the seasonal and interannual time scales. *Glob. Biogeochem. Cy* 24, 1–24.
- Ringeval, B., Friedlingstein, P., Koven, C., Ciais, P., Noblet-Ducoudré, N.D., Decharme, B., Cadule, P., 2011. Climate-CH₄ feedback from wetlands and its interaction with the climate-CO₂ feedback. *Biogeosciences* 8, 2137–2157.
- Saunio, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J.G., Dlugokencky, E.J., Etiope, G., Bastviken, D., Houweling, S., Janssens-Maenhout, G., Tubiello, F.N., Castaldi, S., Jackson, R.B., Alexe, M., Arora, V.K., Beerling, D.J., Bergamaschi, P., Blake, D.R., Brailsford, G., Brovkin, V., Bruhwiler, L., Crevoisier, C., Crill, P., Covey, K., Curry, C., Frankenberg, C., Gedney, N., Höglund-Isaksson, L., Ishizawa, M., Ito, A., Joos, F., Kim, H.S., Kleinen, T., Krummel, P., Lamarque, J.F., Langenfelds, R., Locatelli, R., Machida, T., Maksyutov, S., McDonald, K.C., Marshall, J., Melton, J.R., Morino, I., Naik, V., O'Doherty, S., Parmentier, F.J.W., Patra, P.K., Peng, C., Peng, S., Peters, G.P., Pison, I., Prigent, C., Prinn, R., Ramonet, M., Riley, W.J., Saito, M., Santini, M., Schroeder, R., Simpson, I.J., Spahni, R., Steele, P., Takizawa, A., Thornton, B.F., Tian, H., Tohjima, Y., Viovy, N., Voulgarakis, A., van Weele, M., van der Werf, G.R., Weiss, R., Wiedinmyer, C., Wilton, D.J., Wiltshire, A., Worthy, D., Wunch, D., Xu, X., Yoshida, Y., Zhang, B., Zhang, Z., Zhu, Q., 2016. The global methane budget 2000–2012. *Earth Syst. Sci. Data* 8, 697–751.
- Schroeder, R., McDonald, K.C., Chapman, B.D., Jensen, K., Podest, E., Tessler, Z.D., Bohn, T.J., Zimmermann, R., 2015. Development and evaluation of a multi-year fractional surface water data set derived from active/passive microwave remote sensing data. *Remote Sens.* 7, 16688–16732.
- Song, C., Xu, X., Sun, X., Tian, H., Sun, L., Miao, Y., Wang, X., Guo, Y., 2012. Large methane emission upon spring thaw from natural wetlands in the northern permafrost region. *Environ. Res. Lett.* 7, 034009.
- Spahni, R., Wania, R., Neef, L., van Weele, M., Pison, I., Bousquet, P., Frankenberg, C., Foster, P.N., Joos, F., Prentice, I.C., van Velthoven, P., 2011. Constraining global methane emissions and uptake by ecosystems. *Biogeosciences* 8, 1643–1665.
- Stacke, T., Hagemann, S., 2012. Development and validation of a global dynamical wetlands extent scheme. *Hydrology Earth Syst. Sci.* 16, 2915–2933.
- Tarnocai, C., Kettles, I.M., Lacelle, B., 2000. Peatlands of Canada Database. Geological Survey of Canada Open File Report 3834.
- Terentieva, I.E., Glagolev, M.V., Lapshina, E.D., Sabrekov, A.F., Maksyutov, S., 2016. Mapping of West Siberian taiga wetland complexes using Landsat imagery: implications for methane emissions. *Biogeosciences* 13, 4615–4626.
- Tian, H., Lu, C., Ciais, P., Michalak, A.M., Canadell, J.G., Saikawa, E., Huntzinger, D.N., Gurney, K.R., Sitch, S., Zhang, B., Yang, J., Bousquet, P., Bruhwiler, L., Chen, G., Dlugokencky, E., Friedlingstein, P., Melillo, J., Pan, S., Poulter, B., Prinn, R., Saunio, M., Schwalm, C.R., Wofsy, S.C., 2016. The terrestrial biosphere as a net source of greenhouse gases to the atmosphere. *Nature* 531, 225–228.
- Tian, H., Lu, C., Yang, J., Banger, K., Huntzinger, D.N., Schwalm, C.R., Michalak, A.M., Cook, R., Ciais, P., Hayes, D., Huang, M., Ito, A., Jain, A.K., Lei, H., Mao, J., Pan, S., Post, W.M., Peng, S., Poulter, B., Ren, W., Ricciuto, D., Schaefer, K., Shi, X., Tao, B., Wang, W., Wei, Y., Yang, Q., Zhang, B., Zeng, N., 2015a. Global patterns and controls of soil organic carbon dynamics as simulated by multiple terrestrial biosphere models: current status and future directions. *Glob. Biogeochem. Cy* 29, 775–792.
- Tian, H.Q., Chen, G.S., Liu, M.L., Zhang, C., Sun, G., Lu, C.Q., Xu, X.F., Ren, W., Pan, S.F., Chappelka, A., 2010a. Model estimates of net primary productivity, evapotranspiration, and water use efficiency in the terrestrial ecosystems of the southern United States during 1895–2007. *For. Ecol. Manag.* 259, 1311–1327.
- Tian, H.Q., Chen, G.S., Lu, C.Q., Xu, X.F., Ren, W., Zhang, B.W., Banger, K., Tao, B., Pan, S.F., Liu, M.L., Zhang, C., Bruhwiler, L., Wofsy, S.C., 2015b. Global methane and nitrous oxide emissions from terrestrial ecosystems due to multiple environmental changes. *Ecosyst. Health Sustain.* 1, 1–20.
- Tian, H.Q., Lu, C.Q., Melillo, J., Ren, W., Huang, Y., Xu, X.F., Liu, M.L., Zhang, C., Chen, G.S., Pan, S.F., Liu, J.Y., Reilly, J., 2012. Food benefit and climate warming potential of nitrogen fertilizer uses in China. *Environ. Res. Lett.* 7, 044020.
- Tian, H.Q., Xu, X.F., Liu, M.L., Ren, W., Zhang, C., Chen, G.S., Lu, C.Q., 2010b. Spatial and temporal patterns of CH₄ and N₂O fluxes in terrestrial ecosystems of North America during 1979–2008: application of a global biogeochemistry model. *Biogeosciences* 7, 2673–2694.
- Tian, H.Q., Xu, X.F., Lu, C.Q., Liu, M.L., Ren, W., Chen, G.S., Melillo, J., Liu, J.Y., 2011. Net exchanges of CO₂, CH₄, and N₂O between China's terrestrial ecosystems and the atmosphere and their contributions to global climate warming. *J. Geophys. Res.-Biogeo* 116, 1–13.
- Tian, H.Q., Yang, Q.C., Najjar, R.G., Ren, W., Friedrichs, M.A.M., Hopkinson, C.S., Pan, S.F., 2015c. Anthropogenic and climatic influences on carbon fluxes from eastern North America to the Atlantic Ocean: a process-based modeling study. *J. Geophys. Res. Biogeosciences* 120, 757–772.
- Vogelmann, J.E., Howard, S.M., Yang, L., Larson, C.R., Wylie, B.K., Van Driel, N., 2001. Completion of the 1990s national land cover data set for the conterminous United States from landsat thematic mapper data and ancillary data sources. *Photogrammetric Eng. Remote Sens.* 67, 650–652.
- Wania, R., Melton, J.R., Hodson, E.L., Poulter, B., Ringeval, B., Spahni, R., Bohn, T., Avis, C.A., Chen, G., Eliseev, A.V., Hopcroft, P.O., Riley, W.J., Subin, Z.M., Tian, H., van Bodegom, P.M., Kleinen, T., Yu, Z.C., Singarayer, J.S., Zürcher, S., Lettenmaier, D.P., Beerling, D.J., Denisov, S.N., Prigent, C., Papa, F., Kaplan, J.O., 2013. Present state of global wetland extent and wetland methane modelling: methodology of a model inter-comparison project (WETCHIMP). *Geosci. Model Dev.* 6, 617–641.
- Wei, D., Wang, X., 2016. CH₄ exchanges of the natural ecosystems in China during the past three decades: the role of wetland extent and its dynamics. *J. Geophys. Res. Biogeosciences* 121, 2445–2463.
- Wei, Y., Liu, S., Huntzinger, D.N., Michalak, A.M., Viovy, N., Post, W.M., Schwalm, C.R., Schaefer, K., Jacobson, A.R., Lu, C., Tian, H., Ricciuto, D.M., Cook, R.B., Mao, J., Shi, X., 2014. The North American carbon Program multi-scale synthesis and terrestrial model intercomparison project – Part 2: environmental driver data. *Geosci. Model Dev.* 7, 2875–2893.
- WMO, 2015. World meteorological organization greenhouse gas bulletin. Citeseer. ISSN: 2071-0896.
- Xu, X.F., Tian, H.Q., 2012. Methane exchange between marshland and the atmosphere over China during 1949–2008. *Glob. Biogeochem. Cy* 26.
- Xu, X.F., Tian, H.Q., Zhang, C., Liu, M.L., Ren, W., Chen, G.S., Lu, C.Q., Bruhwiler, L., 2010. Attribution of spatial and temporal variations in terrestrial methane flux over North America. *Biogeosciences* 7, 3637–3655.
- Zhang, B., Tian, H., Ren, W., Tao, B., Lu, C., Yang, J., Banger, K., Pan, S., 2016. Methane emissions from global rice fields: magnitude, spatiotemporal patterns, and environmental controls. *Glob. Biogeochem. Cy* 30, 1246–1263.
- Zhu, P., Gong, P., 2014. Suitability mapping of global wetland areas and validation with remotely sensed data. *Sci. China Earth Sci.* 57, 2283–2292.
- Zhu, Q., Peng, C., Chen, H., Fang, X., Liu, J., Jiang, H., Yang, Y., Yang, G., 2015. Estimating global natural wetland methane emissions using process modelling: spatio-temporal patterns and contributions to atmospheric methane fluctuations. *Glob. Ecol. Biogeogr.* 24, 959–972.
- Zhuang, Q., Zhu, X., He, Y., Prigent, C., Melillo, J.M., McGuire, A.D., Prinn, R.G., Kicklighter, D.W., 2015. Influence of changes in wetland inundation extent on net fluxes of carbon dioxide and methane in northern high latitudes from 1993 to 2004. *Environ. Res. Lett.* 10, 095009.