A global wetland methane emissions and uncertainty dataset for atmospheric chemical transport models.

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Abstract. Wetland emissions remain one of the principal sources of uncertainty in the global
atmospheric methane (CH_4) budget, largely due to poorly constrained process controls on CH_4
production in waterlogged soils. Process-based estimates of global wetland CH_4 emissions and their
associated uncertainties can provide crucial prior information for model-based top-down CH_4 emission
estimates. Here we construct a global wetland CH_4 emission model ensemble for use in atmospheric
chemical transport models. Our $0.5° \times 0.5°$ resolution model ensemble is based on satellite-derived
surface water extent and precipitation re-analyses, nine heterotrophic respiration simulations (eight
carbon cycle models and a data-constrained terrestrial carbon cycle analysis) and three temperature
parameterizations for the period 2009-2010; an extended ensemble subset – based solely on
precipitation and the data-constrained terrestrial carbon cycle analysis – is derived for the period 2001-
2015. We incorporate the mean of the full and extended model ensembles into GEOS-Chem and
compare model against surface measurements of atmospheric CH_4; model performance (site-level and
zonal mean anomaly residuals) compares favourably against published wetland CH_4 emissions
scenarios. We find that uncertainties in carbon decomposition rates and wetland extent together account
for more than 80% of the primary uncertainty in the timing, magnitude and seasonal variability of
wetland CH_4 emissions, although uncertainty in the temperature CH_4:C dependence is a significant

contributor to seasonal variations in mid-latitude wetland CH_4 emissions. The combination of satellite, carbon cycle models and temperature dependence parameterizations provides a physically informed structural a priori uncertainty critical for top-down estimates of wetland CH_4 fluxes: specifically, our ensemble can provide enhanced information on the prior CH_4 emissions uncertainty and the error

5   covariance structure, as well as a means for using posterior flux estimates and their uncertainties to quantitatively constrain global wetland CH_4 emission biogeochemical process controls.

1 Introduction

10   Methane (CH_4) is a potent greenhouse gas, with a global warming potential of more than 25 times that of CO_2 on a 100-year time horizon (Myhre et al., 2013). The global CH_4 budget and growth rate remain poorly understood, largely due to poorly resolved evolution of atmospheric CH_4 sources and sinks (Nisbet et al., 2014). Wetland CH_4 emissions are the largest natural source of atmospheric CH_4, amounting to roughly 20 – 40% of global CH_4 emissions (Ciais et al., 2013). The large disparities

15   between a range of top-down and bottom up wetland CH_4 estimates (Kirschke et al., 2013; Melton et al., 2013) arise from large uncertainties in the timing, distribution and the underlying processes controlling net wetland CH_4 production.

        In wetland soils, CH_4 is produced by the decomposition of organic matter in anaerobic (oxygen depleted) environments. The dominant processes controlling the seasonal and inter-annual variations

20   include carbon availability (soil C substrate) and decomposition rate, wetland inundation extent, and temperature (Yvon-Durocher et al., 2014). Other important controls on wetland CH_4 emissions include the presence of macrophytes (Laanbroek 2010), organic C decomposition rates (Miyajima et al., 1997) and soil pH (Singh et al., 2000), amongst other factors. The link between terrestrial carbon-water cycling and wetland CH_4 emissions is of particular interest from a terrestrial greenhouse gas emissions

25   standpoint: inter-annual variations in terrestrial carbon cycling (Le Quéré et al., 2013) can affect wetland CH_4 emissions on seasonal-to-century timescales (Hodson et al., 2011). The role of carbon cycle dynamics in global wetland CH_4 emissions is increasingly recognized: temporal variations in gross primary production influence short-term carbon supply (such as carbon inputs from root exudates

and fine litter), as well as long-lived carbon stores (such as wood litter turnover or soil organic C) in wetland soils (Riley et al., 2011; Bloom et al., 2012; Melton et al., 2013). The combined response of CO_2 and CH_4 fluxes to climatic variability remains poorly characterized. For example, increasing temperatures in boreal ecosystems could lead to higher carbon uptake, increased respiration and drier

5 soils (Watts et al., 2014), and it is currently unclear whether these processes amount to an amplifying or dampening effect on boreal CH_4 emissions. From a greenhouse gas balance standpoint, quantifying the global-scale process links between terrestrial carbon cycling and wetland CH_4 emissions is crucial to characterizing the combined terrestrial biosphere CO_2 and CH_4 flux response to climatic variability.

Quantification of regional wetland CH_4 emissions remains challenging. While wetland CH_4

10 emissions are relatively well constrained on a global scale (Kirschke et al., 2013), regional CH_4 fluxes are difficult to detect, due to their comparatively diffuse nature – relative to anthropogenic point sources – and the scarcity of direct measurements of wetland CH_4 emissions. From a bottom-up perspective, challenges in wetland CH_4 modelling stem from order-of-magnitude uncertainties on wetland CH_4 emissions factors and their spatio-temporal dependence on biogeochemical process controls.

15 Nonetheless, for top-down CH_4 emission estimates, prior knowledge of wetland CH_4 emissions and their associated uncertainty is critical in the formulation of Bayesian atmospheric CH_4 inversions. Atmospheric inversions combine CH_4 measurements from surface, aircraft and satellites (Wecht et al., 2014b; Jacob et al., 2016) and the prior probability on the magnitude and uncertainty characteristics of CH_4 emissions (Bousquet et al., 2011; Pison et al., 2013; Fraser et al., 2014; Turner et al., 2015): these

20 CH_4 inversions typically formulate wetland CH_4 emission uncertainty as a spatio-temporally uncorrelated and normally distributed CH_4 prior. However, inter-model similarities reveal significant levels of emergent correlations in the timing, magnitude and spatial variability of wetland CH_4 emissions. For example, the Wetland CH4 Inter-comparison of Models Project (WETCHIMP) model ensemble (Melton et al., 2013) reveals varying levels of spatial and temporal agreement between

25 models; these correlations stem from large-scale patterns in biogeochemical process controls (such as temperature, inundation and carbon cycling). Given the relatively large WETCHIMP CH_4 emission uncertainties (model range is typically 150-300% of model mean over major wetland areas, and greater elsewhere), this prior 'biogeochemical covariance' can potentially amount to a critical constraint on

atmospheric CH_4 inversions: such a covariance structure can be incorporated in an atmospheric inversion cost-function (Michalak et al., 2005) or as a means for improving attribution of posterior CH_4 fluxes to wetland CH_4 emissions (Wecht et al., 2014a).

5   Here we propose a process-informed wetland CH_4 emission ensemble based on multiple terrestrial biosphere models, wetland extent scenarios and CH_4:C temperature dependencies. In contrast to a conventional process-based model inter-comparison approach, our ensemble statistics are derived by exhaustively combining a range of temperature, carbon and wetland extent parameterizations. An advantage of our approach is that it provides a prior probability distribution of biogeochemical process control uncertainty: our ensemble can be further constrained – based top-down CH_4 emission estimates

10 – to quantify the combined probability distribution of carbon models, CH_4:C temperature dependencies and wetland extent scenarios.

       We formulate a full (2009-2010) and extended (2001-2015) estimate of wetland CH_4 emission magnitude and its associated biogeochemical covariance structure, based on knowledge of the global wetland CH_4 source and the primary biogeochemical process controls. We validate and compare the

15 wetland CH_4 emissions ensemble against a suite of regional studies, and we use a global atmospheric chemical transport model (GEOS-Chem, Bey et al., 2001) to evaluate the CH_4 emissions ensemble relative to existing wetland CH_4 emission models (sections 2 and 3). Finally, we summarize the strengths and limitations of our wetland emissions ensemble and outline its potential applications in global atmospheric inversion frameworks (section 4).

20

2. Wetland CH_4 model ensemble

       The wetland CH_4 emissions ensemble provides CH_4 fluxes and associated uncertainty estimates based on four wetland extent parameterizations, nine terrestrial biosphere models of heterotrophic

25 respiration and three CH_4:C temperature parameterization. Global monthly $0.5° \times 0.5°$ emissions and their associated uncertainty structure span 2009-2010 (full ensemble, henceforth FE); we also evaluate a subset of the model ensemble spanning 2001-2015 (extended ensemble, henceforth EE). We validate FE

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and EE emissions against a range of regional CH_4 emission estimates, and we test the updated GEOS-Chem model against 104 surface CH_4 measurement sites.

2.1 Wetland CH_4 emissions & uncertainty

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We derive wetland CH_4 emissions F $(mg\ CH_4\ m^{-2}\ day^{-1})$ at time t and location x as:

$$F(t,x) \ = \ s\ A(t,x)R(t,x)q_{10}^{\frac{T(t,x)}{10}} \tag{1}$$

10 where $A(t,x)$ is the wetland extent fraction, $R(t,x)$ is the total C heterotrophic respiration at time for a unit area at time t, $q_{10}^{T(t,x)/10}$ is the temperature dependence of the ratio of C respired as CH_4 (where q_{10} represents the relative CH_4:C respiration for a 10°C increase) and s is a global scale factor. This empirical parameterization provides first order constraints on the role of carbon, water and temperature variability on the global spatial and temporal variability of wetland CH_4 emissions. Variants of the
15 equation 1 parameterization have been used within a range of wetland CH_4 emission models (e.g., Hodson et al., 2011, Pickett-Heaps et al., 2011, Melton et al., 2013 amongst others).

In our approach, wetland CH_4 emissions statistics within each 0.5°×0.5° gridcell are derived based on a 108-member ensemble of wetland CH_4 emission simulations. The 108-member FE is based on 3 CH_4:C temperature dependencies, 9 heterotrophic respiration configurations and 4 wetland extent
20 scenarios (3×9×4 = 108); the six-member EE ensemble is a subset of FE, based on data availability during 2001-2015 (see table 1 for summary). For each ensemble member, the magnitude and uncertainty of s is optimized to match global estimates of the annual wetland CH_4 source (Kirshke et al., 2013).

The heterotrophic respiration configurations are derived from 8 terrestrial biosphere models used
25 in the Multi-scale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP BG1 simulations, see Huntzinger et al., 2013 and Wei et al., 2014 for model and experiment details) and the global CARbon DAta-MOdel fraMework (CARDAMOM) terrestrial carbon analysis (Bloom et al., 2016). V1.0 outputs from the MsTMIP are available for the period 1900-2010 (Huntzinger et al., 2015); the

CARDAMOM analysis was extended to span 2001-2015 based on the Bloom et al., (2016) methodology (see Appendix A for details). Since MsTMIP and CARDAMOM respiration estimates vary intrinsically as a function of temperature, q_{10} only accounts for the temperature dependence of the fraction of C respired as CH_4. We prescribe three CH_4:C temperature dependencies (table 1) which are

5 broadly equivalent to a ±50% range on the CH_4:CO_2 temperature dependence reported by Yvon-Durocher et al., (2014).

Here we use two spatial (i = 1,2) and two temporal (j = 1,2) wetland extent parameterizations approaches to represent the uncertainty associated with the role of hydrology on wetland CH_4 emissions. We parameterize wetland extent as the product of a static extent constraint $w_i(x)$ and a

10 normalized time-varying scale factor $h_{ij}(x,t)$, in the following manner

$$A(x,t) = w_i(x)h_{ij}(x,t), \qquad\qquad (2)$$

$w_1(x)$ is the sum of all GLOBCOVER wetland and freshwater land cover types (all flooded,

15 water-logged, and inland water body land-cover types; Bontemps et al., 2011) and $w_2(x)$ the Global Wetland and Lakes Database (GLWD) maximum recorded wetland and freshwater body extent map by Lehner & Doll (2004).

For $h_{*j}(x,t)$, we use (a) the Surface WAter Microwave Product Series (SWAMPS) multi-satellite surface water product (Schroeder et al., 2015; j=1), and (b) monthly ERA-interim precipitation

20 (j=2): for i = 1 (i = 2), $h_{ij}(x,t)$ is normalized such that mean (maximum) $h_{ij}(x,t)$ is equal to 1. We note that the two hydrological proxies provide contrasting advantages and disadvantages. Satellite-retrieved surface water extent provides an observation-based constraint on the spatial and temporal extent of wetlands and freshwater bodies. While our temporal scaling of static wetland and freshwater extent mitigates the role of spatial biases in satellite-retrieved inundation, vegetation cover remains a major

25 confounding variable in satellite-constrained wetland extent (Schroeder et al., 2015). Moreover, satellites cannot directly observe subsurface soil saturation, even though these soils amount to significant CH_4 fluxes to the atmosphere (Turetsky et al., 2014). On the other hand, precipitation does not provide a direct constraint on the wetland and freshwater extent; however, it provides an aggregate

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constraint on ecosystem hydrological variability and wall-to-wall coverage across the globe. We henceforth refer F as "wetland CH_4 emissions"; however, we recognize that lakes, rivers and reservoirs account for ~20% of the total wetland and freshwater body extend (Lehner and Döll, 2004). We discuss the implications of including non-wetland freshwater bodies in $w_i(x)$ section 4.

5   For each of the 108 FE ensemble configurations (c = 1 – 108), and 6 EE ensemble configurations (c = 1-6), we derive s_c such that:

$$S_c = \frac{G}{\Sigma_x \Sigma_t F_{x,t,c} A_x \frac{\Delta t}{n}} \qquad (3)$$

10   where $F_{x,t,c}$ are the cth ensemble member fluxes at grid-cell x and time t, A_x is the area of grid-cell x, Δt is the timestep (1 month), n is the number of years, and G is the global total CH_4 emitted from wetlands. We derive s_c such that each ensemble members are scaled to G = 175 Tg CH_4 yr^{-1} throughout the duration of FE (2009-2010): this is consistent with the Kirschke et al., (2013) mean 2000-2009 top-down wetland CH_4 emission estimates (175 Tg CH_4 yr^{-1}).

15   We derive the CH_4 flux ensemble mean and 5th – 95th percentile ranges at location x and time t based on all 108 $F_{x,t,c}$ ensemble members. For the percentile range calculations, we propagate the global mean wetland CH_4 emission uncertainty by Kirschke et al., (2013) (minimum-to-maximum range = 142 – 208 Tg CH_4 yr^{-1}, or 175 Tg CH_4 yr^{-1} ±19%). We create an expanded ensemble (FE$_{exp}$) by randomly perturbing all 108 model s$_c$ values by a factor of U(0.81,1.19) 1000 times, where U() denotes

20   a random number sampled from a continuous uniform distribution spanning the bracketed numbers. We use the expanded ensemble FE$_{exp}$ to derive the ensemble's spatiotemporal error covariance structure: the quantitative derivation and qualitative interpretation of the error covariance structure is fully described in appendix B.

        We attribute the uncertainty of the timing and magnitude of $F(x,t)$ (maximum CH_4 emission

25   month, mean CH_4 emissions and CH_4 emission variability) to carbon decomposition, wetland extent and CH_4:C temperature dependence uncertainty; the derivation of the "primary uncertainty" within each

zonal band (i.e. the dominance of carbon, water or temperature as the dominant source of uncertainty) is fully described in Appendix C.

2.2 GEOS-Chem atmospheric CH$_4$ simulations

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We evaluate the FE and EE wetland CH$_4$ emission means against the World Data Centre for Greenhouse Gases (WDCGG) CH$_4$ measurement sites by incorporating these into the 4°×5° resolution GEOS-Chem atmospheric chemical and transport model (version 10.01; *acmg.seas.harvard.edu/geos*). We benchmark the FE and EE runs against GEOS-Chem simulations with the GEOS-Chem wetland

10 CH$_4$ emission inventory (Pickett-Heaps et al., 2011; henceforth GC) and the Bloom et al., (2012) satellite-constrained wetland emissions (henceforth BL), as these emission estimates have been in a range of atmospheric chemical transport model simulations (Fraser et al., 2013; Turner et al., 2015; Wilson et al., 2016 amongst others). We perform each GEOS-Chem forward run for the period 2009-2010 with a four-year (2005-2009) spin-up period. The non-wetland CH$_4$ sources in GEOS-Chem

15 consist of biofuel, fossil fuel, livestock, waste, Rice (EDGAR v4.2; European Comission, 2011), fires (Global Fire Emissions Database version 4; van der Werf et al., 2010), soil C sinks and termites (Fung et al., 1991) .The non-wetland CH$_4$ fluxes are the same in each run, with the exception of rice source in run BL (as global wetland and rice emissions are treated as one source by Bloom et al., 2012). While model CH$_4$ surface concentrations are strongly influenced by wetland CH$_4$ magnitude, timing and

20 distribution (Bloom et al., 2012, Meng et al., 2015), comparisons between GEOS-Chem outputs and surface CH$_4$ measurement may also be affected by errors in non-wetland CH$_4$ emissions and in transport. However, Wecht et al. (2012) and Turner et al. (2015) show that the GEOS-Chem emissions and transport provide an unbiased representation of the observed latitudinal background. The global inversion of Turner et al. (2015) using GEOS-Chem emissions as prior further shows no large errors in

25 non-wetland emissions that would confound the analysis presented here.

For each of the four runs (FE, EE, GC and BL), we use the Wecht et al., (2014a) 1st Jan 2005 initial conditions for atmospheric CH$_4$ concentrations in GEOS-Chem. For each simulation, we performed a four-year spin-up period (2005-2009) using 2009 emissions to reduce the potential

inconsistency between initial conditions and the global distribution of wetland CH_4 emissions; this spin-up ensures that the relative variations in Jan 1st 2009 CH_4 concentrations for each run are broadly consistent with each emission scenario. We save GEOS-Chem atmospheric CH_4 concentrations every 3 hours. We compare mean monthly GEOS-Chem output against all WDCGG sites below 500m altitude

5   (104 sites with monthly 2009-2010 data in total); this minimizes the topographic mismatch due to vertical CH_4 representation in the model. For each site, the nearest 4°×5° GEOS-Chem grid-cell is used for comparison.

3. Results, Comparison and Validation

10

Mean full ensemble (FE) global wetland emissions are largely accounted for by three high-latitude regions, three tropical regions, and sub-tropical southeast Asia (Figure 1a). North America, Scandinavia and Siberia median (5th – 95th percentiles) CH_4 fluxes amount to 8% (3 – 30%), 2% (0 – 6%) and 2% (1 – 6%) of global emissions; Amazon wetland emissions amount (30%; 21 – 38%) account for the

15   largest tropical emission source, followed by the Indonesian archipelago (13%; 7 – 22%), and central Africa (12%; 7 –24%); subtropical southeast Asia emissions account for 5% (1 – 10%). High-latitude (>50°N) and tropical emissions amount to 11% (4 – 29%) and 68% (43 – 84%) of global wetland CH_4 emissions, respectively. High-latitude FE emissions exhibit a peak at 60°N (Figure 1b) similar to the GEOS-Chem wetland CH_4 emissions inventory (Pickett-Heaps et al., 2011; GC) and further north than

20   the Bloom et al., (2012) emissions (BL). Tropical emissions for all three emission datasets peak within 0° – 5°S. A comparison between zonal mean emissions (Figure 2) reveals differences of less than 1 Tg/yr/°lat between FE and the extended ensemble (EE) s; the FE zonal mean is comparable to the BL in the near-equatorial tropics and significantly (with respect to the FE model ensemble 90% confidence range) lower everywhere else; the FE zonal mean is comparable to GC in high-latitude and temperate

25   regions, but significantly lower than GC in the tropics and southern hemisphere.

All CH_4 emission models show similar patterns in the temporal distribution of CH_4 emissions in high-latitude and temperate regions (with CH_4 emissions peaking between July and September, Figure 3).

9

We note that the larger CH_4 fluxes in the BL emissions over Asia and Oceania are due to rice paddy CH_4 emissions. The CH_4 emission models exhibit 1-month differences in the timing of maximum seasonal CH_4 emission across the high-latitudes (generally between June and August). In tropical South America $0° – 20°S$ latitudes, FE and EE emissions peak March –May, which is comparable to BL

5 (March); and overall earlier than GC ($5°S – 20°S$ emission peak in September). There is a considerable disagreement between northern tropical Africa emission variability amongst all models. Subtropical Asia FE and EE emissions ($20°N – 30°N$) peak in June-August, earlier than BL emissions (August-September) and comparable to GC emissions (June).

10 We compare mean FE and EE (2009-2010) wetland emissions against a range of independent wetland CH_4 regional emission estimates (Figure 4). Emissions from Siberian wetlands (Glagolev et al., 2011) Hudson bay lowlands (Pickett-Heaps et al., 2011), and Amazon river basin (Melack et al., 2004) are within 25th – 75th percentile estimates of FE and EE wetland CH_4 emissions; Chang et al., (2014)(May-September 2012) wetlands are higher (2.1 Tg CH_4 yr^{-1}) but within the 5th -95th percentile range of FE

15 and EE wetland CH_4 emission estimates. BL (2009-2010) and GC (2009-2010) estimates are also within 5th – 95th percentile ranges. With the exception of Amazon river basin estimates, the FE and EE emission estimate uncertainty is larger than the Melton et al., (2013) wetland CH_4 emission model (WETCHIMP 1993-2004) range. We note the temporal mismatch between the wetland emission estimates shown in Figure 4: however, we expect inter-annual variation in wetland CH_4 emissions (e.g.

20 Bloom et al., 2010; Melton et al., 2013) to be substantially smaller than the FE and EE estimate uncertainty.

On a zonal basis, the "primary uncertainty" – i.e. the dominant source of uncertainty within each band – in mean CH_4 emissions and the timing of maximum CH_4 emissions is almost completely dominated

25 carbon decomposition and wetland extent uncertainties (Figure 5). Seasonal variability of CH_4 emissions is also largely dominated by carbon and extent uncertainties, although the temperature CH_4:C dependence is the dominant source of uncertainty in temperate latitudes. At latitudes $> 20°N$, wetland extent is the dominant source of uncertainty in mean CH_4 emissions, while temperature CH_4:C

dependence accounts for less than 10% of the primary uncertainty attribution. At all latitudes > 10°S, carbon decomposition accounts for the vast majority of the primary uncertainty in the timing of wetland CH_4 emissions.

5   We summarizing the FE_{exp} global error covariance structure as an error correlation matrix between mean monthly 2009-2010 emissions across boreal & arctic (>55°N) temperate (23°N – 55°N), tropical (23°S – 23°N) and southern hemisphere (<23°S) latitudes (Figure 6); the error correlation matrix quantitatively summarizes similarities in the spatial and temporal patterns between ensemble members, relative to the ensemble mean (see appendix B for description and interpretation). The FE_{exp} error

10 correlation matrix highlights positively correlated ensemble member CH_4 emissions within each region, with larger correlations (generally r>0.8) between emissions separated by 1-2 months; tropical emissions exhibiting the largest overall temporal correlations (r>0.5). Tropical and boreal & arctic CH_4 emissions are overall anti-correlated, however no temporal patterns emerge between these anti-correlations.

15

Mean 2009-2010 observed and GEOS-Chem forward model run CH_4 concentrations (with FE, EE, BL and GC wetland emissions) are broadly consistent on a latitudinal basis. The observed and modelled zonal atmospheric CH_4 concentration anomaly (relative to mean global 2009-2010 CH_4 concentrations) is shown in Figure 7 (zonal profile root-mean-square errors – RMSE – are 6.4 ppb, 6.6 pbb, 8.4 ppb, 9.2

20 ppb for FE, EE, BL and GC relative to the observed CH_4 anomaly zonal profile). Within the primary wetland CH_4 emission latitudes (10°S – 80°N; Figure 2), all mean CH_4 model estimates are within the mean standard deviation of observed CH_4, except GC at >60°N and all models at 80°N. The median site-level correlation (Pearson's r) between observed and model de-trended CH_4 concentrations for FE (0.79; 5th – 95th percentiles = -0.15 - 0.97) is highest, followed by EE (0.77; 5th - 95th percentiles = -

25 0.24 - 0.96), BL (0.75; 5th - 95th percentiles = -0.08 - 0.99) and GC (0.72; 5th - 95th percentiles = -0.24 - 0.93). The median RMSE between observed and model de-trended CH_4 concentrations for FE (10.98 ppb; 5th - 95th percentiles = 2.81 - 53.11 ppb) and EE (11.61ppb 5th - 95th percentiles = 4.01 - 51.69) are lower than BL (12.29 ppb; 5th - 95th percentiles = 2.35 - 49.31 ppb) and GC (median =

12.95 ppb; 5th - 95th percentiles = 5.06 - 50.98). FE and EE improvements (relative to GC and BL Pearson's r and RMSE) are primarily in northern hemisphere high-latitudes latitudes (>50°N; Figure 8). FE Pearson's r and RMSE suggest better performance than GC in southern hemisphere extra-tropical latitudes (<23°S); BL is comparable to FE and outperforms EE across southern hemisphere latitudes.

5

4. Discussion

4.1 Model limitations

10 Densely vegetated wetland areas are likely to amount to a large component of the global wetland CH_4 sources; high-carbon density (and high temperatures in the case of tropical wetlands) result in high CH_4 emissions under inundated conditions. However, satellite-derived observations of surface water area (Schroeder et al., 2015) are ill-equipped to observe densely vegetated wetland areas, as the passive microwave sensors become increasingly sensitive to vegetation moisture within high biomass
15 ecosystems (Sippel et al., 1994). For example, estimates of Amazon river basin wetland CH_4 emissions range between 16% - 29% (5th – 95th percentiles) of the global wetland emissions source; high biomass density in this region (Saatchi et al., 2011) may be a significant source of inundation area bias. Therefore, while we incorporate prior information on the mean and maximum wetland extent to scale the satellite-derived inundation fraction, we anticipate that errors in seasonal and inter-annual
20 inundation variability are likely to be larger within densely vegetated wetland areas. We are optimistic that current and upcoming missions such as SMAP and BIOMASS (Entekhabi et al., 2010; Le Toan et al., 2011) combined with data integration approaches (Schroeder et al., 2015; Fluet-Chouinard et al., 2015) can potentially provide additional constraints required to extend current inundation datasets and to improve current surface inundation detection capabilities.

25

The MsTMIP model ensemble provides a first-order estimate of the magnitude and variability of C decomposition within each 0.5°×0.5° grid-cell. Here we highlight 4 potentially major sources of error: (a) differences in aerobic:anaerobic turnover rates of major (labile and recalcitrant) C pools (b)

systematic differences in wetland and non-inundated area carbon uptake within each $0.5°\times0.5°$ grid-cell, (c) systematic differences in dead organic matter C stocks and accumulation between wetland and non-inundated areas, and (d) lateral flows of C into (or out of) wetland areas. Top-down estimates of seasonal and inter-annual terrestrial CO_2 fluxes (e.g. Liu et al., 2014) could be used to independently

5 assess the validity of heterotrophic respiration from the MsTMIP models and CARDAMOM. In turn, top-down CH_4 and CO_2 flux retrievals, and range of in-situ and regional-scale CH_4 flux estimates (Schriel-Uijl et al., 2011; Chang et al., 2014; Budishchev et al., 2014; amongst others) can be combined to assess whether our empirical parameterization is able capture regional, seasonal and inter-annual wetland CH_4 emission variability and their link to the broader terrestrial carbon cycle. Finally, in

10 succession to eddy covariance tower site analyses of CO_2 respiration dependence on temperature (Mahecha et al., 2010), we anticipate that CH_4 eddy covariance measurements will provide critical site-level constraints on the temperature dependence of wetland CH_4 emissions.

Rice paddies likely amount to <20% of wetland CH_4 emissions, and the majority of rice paddy areas are

15 implicitly excluded from our analysis: GLOBCOVER distinguishes between natural and irrigated water bodies, and GLWD explicitly excludes rice paddy extents in China (which alone accounts for a large portion of global rice paddy CH_4 emissions). However, satellite-based inundation fraction retrievals are unable to distinguish the temporal variability of co-located agriculture and natural wetland inundation extent; moreover $0.5°\times0.5°$ carbon cycle model resolution may be insufficient to resolve spatial

20 differences in wetland and agricultural C cycling. Inadvertent inclusion of co-located rice CH_4 emissions is therefore a potential source of bias in our approach. We note that the distinction between wetland and rice CH_4 emissions has yet to be consistently addressed in global wetland CH_4 emission quantification efforts (see Bloom et al., 2010; Hodson et al., 2011; Melton et al., 2013, and references therein).

25

CH_4 production in non-wetland freshwater bodies, such as very small ponds (Holgerson and Raymond 2016), lakes (Wik et al., 2016) and rivers (Bastviken et al., 2011) is potentially a significant – albeit highly uncertain – term in the global CH_4 budget (Kirshke et al., 2013; Bridgham et al., 2013). Our

approach implicitly accounts for non-wetland freshwater body emissions, since their extent is incorporated in grid-cell scaling factors (see Eq. 2). We recognise the challenge in explicitly distinguishing between wetlands and non-wetland freshwater body CH_4 emissions, as well as the associated physical and biogeochemical process controls: the spatial and temporal characterization of

5   wetland and non-wetland freshwater extent remains challenging from the current spatial resolution (~25km) of surface inundation retrievals (Prigent et al., 2007; Schroeder et al., 2015). Equally, from a carbon perspective, 0.5°×0.5° carbon cycle model resolution is insufficient to resolve spatial variability in wetland and non-wetland freshwater body extent (Lehner and Döll, 2004). Contingent on future resolution enhancements in surface inundation and carbon cycle models, we recommend further

10   investigation on the adequate distinction and estimation of non-wetland freshwater CH_4 emissions for atmospheric CH_4 chemical transport modelling applications.

By constraining global emission estimates to the Kirshke et al., (2013) model range, our approach does not challenge the global annual CH_4 source and uncertainty (175 Tg CH_4 yr^{-1}; range = 142 – 206 Tg

15   CH_4 yr^{-1} or ±19%); rather, it places constraints on spatial and temporal wetland CH_4 source variability. Since the global uncertainty is substantially smaller than regional, zonal and grid scale uncertainties (Figures 1,2 and 4), we highlight that new or improved constraints on the global wetland CH_4 source are unlikely to substantially influence our regional or grid-scale CH_4 flux confidence range estimates.

20   *4.2 Applications*

Based on comparisons against measured CH_4 concentrations and a range of regional and global CH_4 emission estimates (Figures 2-4, 7-8), we have shown that the FE and EE wetland CH_4 emission ensembles robustly represent the global magnitude and uncertainty of wetland CH_4 emissions. The ensemble configurations of inundation extent, carbon decomposition and temperature dependence have

25   together provided a characterization of the dominant source of uncertainty in global wetland CH_4 estimates (Figure 5). The approach outlined here provides a framework for producing prior emission estimates and associated uncertainty. The error covariance structure – along with the CH_4 observing system capabilities (Wecht et al., 2014a) – can be used to devise an optimal strategy for spatially and/or

temporally aggregating CH_4 fluxes in an atmospheric inversion framework. Retrieved CH_4 flux from assimilating atmospheric CH_4 observations in an inverse modelling framework (e.g. Fraser et al., 2013) could in turn provide a quantitative constraint on the wetland ensemble: the FE and EE model members can be treated as an ensemble of probable biogeochemical process hypotheses that can be weighted

5   against atmospheric constraints. In contrast to conventional wetland CH_4 emission estimates (Riley et al., 2011; Pickett-Heaps et al., 2011) and model inter-comparisons (Melton et al., 2013), top-down CH_4 flux estimates can constrain the joint probability distribution of FE and EE carbon models, wetland extent parameterizations, and temperature dependencies.

10 We anticipate extensions of the FE beyond the 2009-2010 time period, contingent on the extensions of the MsTMIP and SWAMPS dataset beyond 2010 and 2012 respectively. In light of continued satellite CH_4 retrievals from GOSAT (Parker et al., 2011; Butz et al., 2011) and upcoming satellite CH_4 measurement from TROPOMI on-board ESA Sentinel 5 precursor (Veefkind et al., 2012), we anticipate that the FE and EE datasets will provide key process-based prior knowledge in future atmospheric CH_4

15 inversions.

Appendix A: CARDAMOM extension

20 CARDAMOM heterotrophic respiration was derived from the Bloom et al., (2016) global terrestrial C cycle 1°×1° analysis. CARDAMOM retrieved C state and process variables for the period 2001-2010 were used to run the ecosystem carbon balance model DALEC2 (Bloom & Williams 2015) to span 2001-2015. The 2011-2015 ERA-interim meteorological drivers and MODIS burned area were obtained as described by Bloom et al., (2016). The CARDAMOM output consists of 4000 heterotrophic

25 respiration realisations at each monthly time-step: for each time-step, we use the median CARDAMOM heterotrophic respiration output. We downscale the data to a 0.5°×0.5° resolution using a nearest neighbour interpolation.

Appendix B: Error correlation structure

We derive the model ensembles' space-time $n \times n$ error correlation matrix **M** as follows:

5    $M_{ij} = cor(\mathbf{A}_{i,*} \mid \mathbf{A}_{j,*})$ (A1)

where n corresponds to the number of space and time wetland CH_4 emission aggregations, and i, j span $1-n$,. $A_{(i,m)}$ and $A_{(j,m)}$ correspond to the total CH_4 flux for model m within the ith and jth space-time aggregations (i.e. total wetland CH_4 emissions within a given time & area); $\mathbf{A}_{i,*}$ and $\mathbf{A}_{j,*}$ are $1 \times N$

10   vectors, where N is the number of models within the ensemble. the "cor()" operator denotes the Pearson's correlation coefficient between the two bracketed vectors. For Figure 6, $A_{1,m}$ we aggregate model wetland CH_4 emissions for each month across four zonal bands: Boreal & Arctic (>55°N) Temperate (23°N – 55°N), Tropical (23°S – 23°N) and Southern Hemisphere (<23°S). **Interpretation:** a perfect correlation between the ith and jth indices ($M_{ij} = 1$) indicates that models are consistently over-

15   or under-predicting CH_4 emissions at times-and-locations i and j relative to the ensemble mean; a perfect anti-correlation ($M_{ij} = -1$) indicates that models consistently over-predicting CH_4 emissions at time-and-location i consistently under-predict CH_4 emissions at time-and-location j (relative to the ensemble mean) and vice versa.

20   **Appendix C: Primary process uncertainty**

We quantify the primary process uncertainty of wetland CH_4 emission state variables (s = 1-3; 1. maximum emission month, 2. mean CH_4 emissions and 3. seasonal variability (standard deviation)) to wetland emission controls (e = 1-3; 1. model carbon decomposition, 2. CH_4:C temperature dependence

25   and 3. wetland extent parameterization) at location x as follows:

$$R_{x,s,e} = \sum_{c=1}^{N} \frac{\max(\mathbf{M}_{x,s,m_c}) - \min(\mathbf{M}_{x,s,m_c})}{N} \quad\quad\quad\quad (A2)$$

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where $R_{x,s,e}$ is the mean range of state variable s across the ensemble given a fixed emission control e; $\mathbf{M}_{x,s,*}$ is a vector of all ensemble member state variables s at location x; $\mathbf{m}_c$ denotes the indices of ensemble subset driven by cth emission control e; N are the number of configurations for each e (the ensemble configuration details are show in Table 1). For example, $R_{100,1,1}$ is the mean range of seasonal

5   CH_4 variability ($s=3$) for a fixed carbon model configuration ($e=1$) at the 100th gridcell ($x=100$). We attribute the zonal primary uncertainty of state variable s to emission control e as:

$$P_{z,s,e} = \frac{\sum_{x_z} r_{x_z,s,e} F_{x_z}}{\sum_{x_z} F_{x_z}} \times 100\% \qquad\qquad (A3)$$

10   where x_z are the pixels x within 5° zonal band z, F_{x_z} is the mean 2009-2010 area-integrated CH_4 flux (Eq. 1 in main text). $r_{x_z,s,e} = 1$ if $R_{x_z,s,e} = \min(\mathbf{R}_{x_z,s,*})$ otherwise $r_{x_z,s,e} = 0$; the "min()" function denotes the minimum element of the bracketed vector; i.e. e is the largest source of uncertainty when the mean range in state variable s is smallest for a fixed e. $P_{z,s,e}$ denotes the percentage of zonal band z where emission control e is the greatest source of uncertainty for each s.

15

Data availability

The full ensemble (FE), extended ensemble (EE) presented here are currently available upon request and will become publicly available through the NASA DAAC. MsTMIP monthly 0.5°×0.5° datasets

20   were obtained from *nacp.ornl.gov/MsTMIP.shtml*. ERA-interim datasets were obtained from *apps.ecmwf.int/datasets/data/interim-full-mnth*. CARDAMOM 2001-2010 heterotrophic respiration outputs are available at *datashare.is.ed.ac.uk/handle/10283/875*; 2011-2015 heterotrophic extensions outputs are available upon request. Inundation datasets were obtained from *wetlands.jpl.nasa.gov*. The GLWD dataset was obtained from *gcmd.gsfc.nasa.gov*. The GLOBCOVER dataset was obtained from

25   *due.esrin.esa.int*. The WDCGG data was obtained from *ds.data.jma.go.jp/gmd/wdcgg*.

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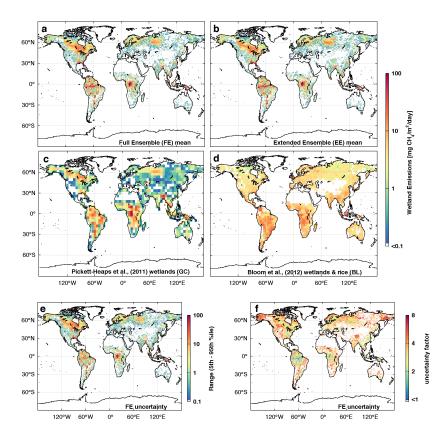
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10 **Figure 1. Top row:** 2009-2010 full model ensemble (FE, left) and extended model ensemble (EE, right) mean wetland CH_4 emissions; **Middle row:** 2009-2010 emissions from the GEOS-Chem wetland

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CH$_4$ emissions inventory (GC, left) model and satellite-constrained estimates by Bloom et al., (2012) (BL, right). **Bottom row**: Mean 2009-2010 FE 5th – 95th percentile range (left) and uncertainty factor (5th – 95th percentile range normalized by mean 2009-2010 emissions, right).
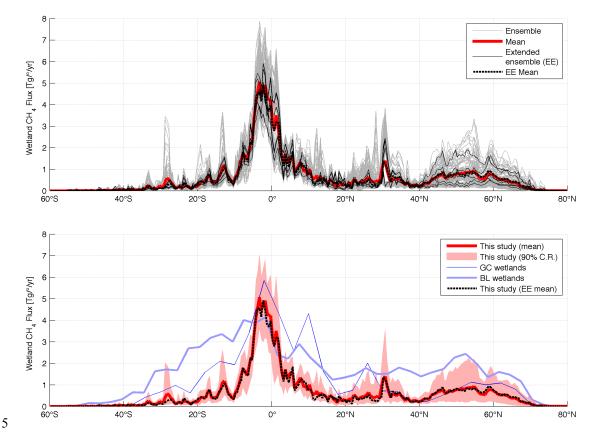

Figure 2. Top: Zonal profile of full ensemble (FE, red) extended ensemble (EE, black dashed line) and mean wetland CH$_4$ emissions from 108 ensemble members (grey). **Bottom:** mean FE (red), mean EE (black dashed line) and 90% FE confidence range (pink), GEOS-Chem wetland emission inventory (GC) and the Bloom et al., (2012) emissions (BL).

Figure 3. Seasonal mean zonal profiles for this study (full ensemble: FE; extended ensemble: EE) Bloom et al., (2012) wetland emissions (BL) and GEOS-Chem wetland emissions inventory (GC) for North & South America (left column; 180°W – 35°W); Europe & Africa (center column; 35°W – 55°E) and Asia & Oceania (right column; 55°E – 180°E). The black dotted line denotes the maximum emissions month within each 5° latitude bin.
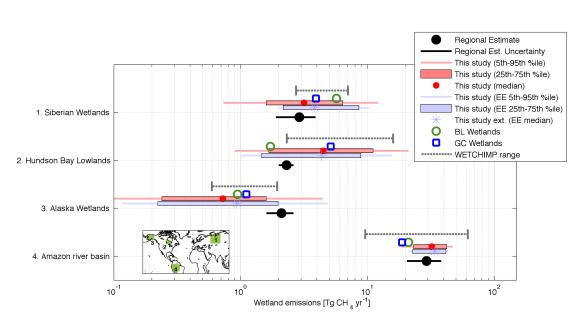
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Figure 4. Comparison between mean annual regional wetland CH$_4$ emission estimates (1. Glagolev et al., 2011; 2. Picket Heaps et al., 2011; 3. Chang et al., 2014; 4. Melack et al., 2004) and global wetland emission datasets by Bloom et al., 2012 emissions (BL), the GEOS-Chem wetland CH$_4$ emission inventory (GC); this study (full ensemble: FE; extended ensemble: EE), and the range of WETCHIMP models (Melton et al., 2013). The regions (1-4) are shown in the inset map.
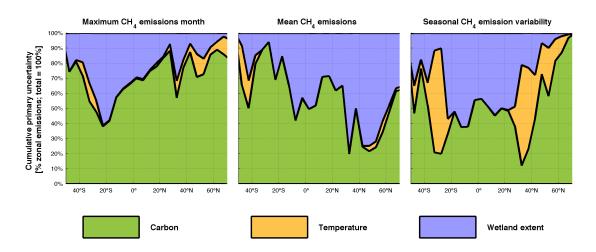
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Figure 5. Primary uncertainty attribution of maximum CH4 emissions month (left), magnitude (center) and seasonal variability (right), to carbon decomposition, temperature CH4:C dependence (q_{10}) and wetland extent parameterization, within 5° latitude bins. The derivation of primary uncertainties is described in Appendix C.
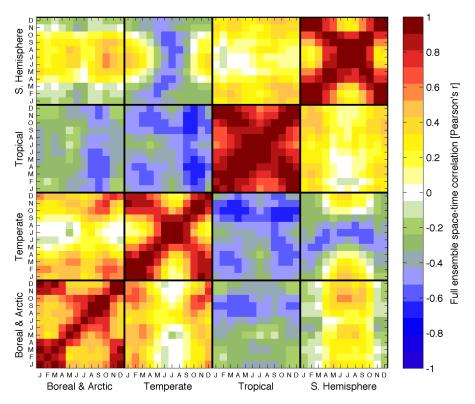
Figure 6. Full ensemble (FE) spatial and temporal error covariance, summarized as monthly error correlation across boreal & arctic (>55°N) temperate (23°N – 55°N), tropical (23°S – 23°N) and southern hemisphere (<23°S) latitudes. A correlation between two location-and-time indices indicates

5 the degree to which models consistently over- or under-predict wetland CH_4 emissions relative to the ensemble mean. The non-zero off-diagonal correlation patterns emerge as a function of varying biogeochemical commonalities across ensemble members, such as wetland CH_4 dependencies on temperature, carbon availability and wetland extent. Negative correlations between tropical and northern hemisphere extratropical (i.e. temperate, boreal and arctic) wetlands emerge as a function of a

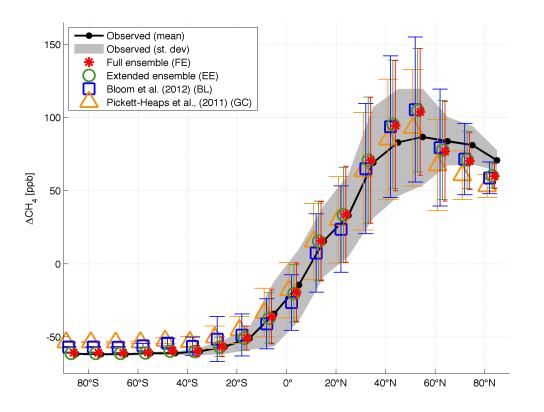10 global constraint on wetland CH_4 emissions (175 Tg CH_4 yr^{-1} ± 19%).

Figure 7. Mean 2009-2010 CH_4 measurements and model CH_4 zonal anomalies (ΔCH_4), relative to the mean 2009-2010 global CH_4 concentration. The black dots denote mean WDCGG network observed CH_4 concentrations within 5° latitude bins; the grey envelope denotes the mean 2009-2010 standard deviation across all sites within 5° latitude bins. The coloured symbols and error bars denote the GEOS-Chem equivalent model concentrations statistics based on the FE and EE ensembles (this study), Bloom et al., (2012) (BL) and the GEOS-Chem emission inventory (GC) wetland CH_4 emissions datasets.
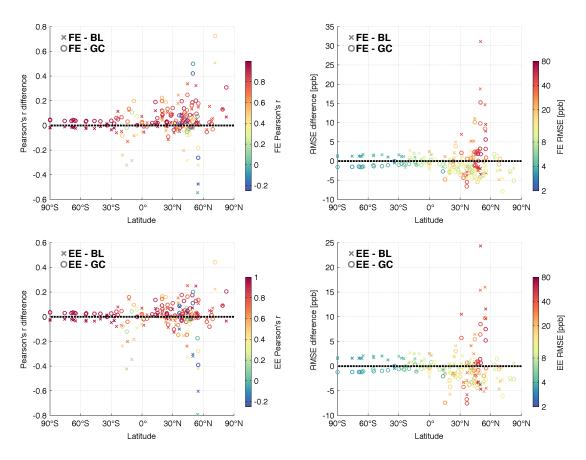
Figure 8. Symbol colours denote the monthly de-trended CH₄ model-observation Pearson's r correlation (left column) and RMSE (right column) for the FE (top-row) and EE (bottom-row) wetland CH₄ emissions (CH₄ observations are from the WDCGG measurement site network). The y-axis denotes the difference between FE/EE and model runs with Bloom et al., (2012) wetland CH₄ emissions (BL) and the GEOS-Chem wetland CH₄ emissions inventory (GC).

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Tables

Table 1: Wetland CH_4 model ensemble configurations

Parameter	Description		Ensemble configurations
s	Global scaling factor[*]		N/A (all configurations are scaled to 175 Tg CH_4 yr^{-1})
A	Wetland extent	*Spatial Extent*	2 spatial extent parameterization (scaled using GLOBCOVER and GLWD)
		Temporal Variability	SWAMPS inundation extent[**]
			ERA-interim precipitation
R	Heterotrophic respiration		8 MsTMIP terrestrial C models[**]
			CARDAMOM terrestrial C cycle analysis
$q_{10(c)}$	Temperature-dependent CH_4 respiration fraction.		3 CH_4:C temperature parameterizations: $q_{10(c)} = [1,2,3]$

[*]Global scaling factor is derived such that the global annual CH_4 emissions amount to 175 Tg CH_4 yr^{-1}.

5 [**] These datasets are only used in the 2009-2010 "Full Ensemble" (FE).