Biogeosciences Discuss., 12, 9341–9368, 2015
www.biogeosciences-discuss.net/12/9341/2015/
doi:10.5194/bgd-12-9341-2015

Biogeosciences Discussions
Open Access

The ability of atmospheric data to resolve discrepancies in wetland methane estimates over North America

S. M. Miller[1], A. E. Andrews[2], J. Benmergui[3], R. Commane[1], E. J. Dlugokencky[2], G. Janssens-Maenhout[4], J. R. Melton[5], A. M. Michalak[6], C. Sweeney[7], and D. E. J. Worthy[8]

[1]Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA, USA
[2]Global Monitoring Division, Earth Systems Research Laboratory, National Oceanic and Atmospheric Administration, Boulder, CO, USA
[3]School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA
[4]Institute for Environment and Sustainability, European Commission Joint Research Centre, Ispra, Italy
[5]Climate Processes Section, Environment Canada, Victoria, Canada
[6]Department of Global Ecology, Carnegie Institution for Science, Stanford, CA, USA
[7]Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, CO, USA
[8]Climate Research Division, Environment Canada, Toronto, Canada

Received: 14 May 2015 – Accepted: 19 May 2015 – Published: 23 June 2015

Correspondence to: S. M. Miller (scot.m.miller@gmail.com)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Existing estimates of methane fluxes from North American wetlands vary widely in both magnitude and distribution. In light of these disagreements, this study uses atmospheric methane observations from the US and Canada to analyze seven different bottom-up, wetland methane estimates reported in a recent model comparison project. We first use synthetic data to explore how well atmospheric observations can constrain wetland fluxes. We find that observation sites can identify an atmospheric pattern from Canadian wetlands but not reliably from US wetlands. The network can also identify the spatial distribution of fluxes in Canada at multi-province spatial scales. Based upon these results, we then use real data to evaluate the magnitude, temporal distribution, and spatial distribution of each model estimate. Most models overestimate the magnitude of fluxes across Canada. Most predict a seasonality that is too narrow, potentially indicating an over-sensitivity to air or soil temperatures. In addition, the LPJ-Bern model has a spatial distribution that is most consistent with atmospheric observations. Unlike most models, LPJ-Bern utilizes land cover maps, not just remote sensing inundation data, to estimate wetland coverage. A flux model with a constant spatial distribution outperforms most other existing flux estimates across Canada.

1 Introduction

Methane fluxes from wetlands play a critical role in global climate change. Methane is the second-most important long-lived greenhouse gas; the radiative forcing of the current atmospheric burden is approximately 26 % of carbon dioxide. Wetlands are possibly the largest single source of this gas to the atmosphere and account for roughly 30 % of global emissions (Ciais et al., 2013).

Despite the important role of wetland methane fluxes in climate change, existing estimates of this source disagree markedly on the magnitude, seasonality, and spatial distribution of fluxes, from regional to global scales. In fact, a recent global model

BGD
12, 9341–9368, 2015

comparison project named WETCHIMP (Wetland and Wetland CH_4 Inter-comparison of Models Project) found large discrepancies among existing methane wetland models (Fig. 1, Melton et al., 2013; Wania et al., 2013). For example, existing estimates of maximum global wetland coverage differ by over a factor of 6 – from 4.1×10^6 to 26.9×10^6 km^2 . Furthermore, estimates of global natural wetland fluxes range from 92–264 Tg CH_4 yr^{-1}. The relative magnitude of these uncertainties increases at sub-global spatial scales. As a case in point, methane estimates for Canada's Hudson Bay Lowlands (HBL) range from 0.2 to 11.3 Tg CH_4 yr^{-1}. These disagreements in current methane estimates do not bode well for scientists' abilities to accurately predict future changes in wetland fluxes due to climate change (Melton et al., 2013).

A number of studies have used chamber measurements of methane to parameterize or evaluate biogeochemical methane models (e.g., Livingston and Hutchinson, 2009). However, these measurements usually encompass fluxes from a very small spatial scale, and fluxes can vary by an order of magnitude over one meter or less (Waddington and Roulet, 1996; Hendriks et al., 2010). Methane data collected in the atmosphere, by contrast, sees the cumulative effect of methane fluxes across a much broader region (e.g., Kort et al., 2008; Pickett-Heaps et al., 2011; Miller et al., 2014). Hence, atmospheric data can provide an important tool for evaluating existing methane flux estimates across different countries or continents.

The present study compares the WETCHIMP methane flux estimates against atmospheric methane data from 2007–2008 through two sets of analyses. First, we construct progressively demanding synthetic data experiments to explore how well available data can constrain wetland fluxes. Can the atmospheric data identify methane patterns from wetlands over distracting patterns in the atmosphere? These patterns include methane from anthropogenic sources or random noise due to model and measurement errors. If yes, can the observation sites detect spatial variability in the wetland fluxes? We seek to understand whether large uncertainties in wetland methane estimates point to a paucity of methane data – data capable of calibrating or evaluating the models. In the alternative, perhaps these disagreements would be much smaller if ex-

BGD
12, 9341–9368, 2015

isting biogeochemical models leveraged all available data. To answer these questions, we utilize a modeling approach based upon the Bayesian Information Criterion (BIC), described in greater detail in Sect. 2.2 (Shiga et al., 2014; Fang et al., 2014; Fang and Michalak, 2015).

Based on the synthetic experiments, we conduct a second set of analyses using real atmospheric data. We use this data to evaluate the magnitude, seasonal cycle, and spatial distribution of each WETCHIMP methane estimate. Of the seven available models, which have a magnitude, seasonal cycle, or spatial distribution that is most consistent with the available data? We investigate this question over the US and Canada using methane data collected from towers and regular aircraft flights operated by NOAA and its partners and from towers operated by Environment Canada.

2 Methods

This section first describes the atmospheric methane data and the atmospheric model that allows direct comparison between the data and various flux estimates. Subsequent sections describe how we use these tools to construct both the synthetic and real data experiments outlined in the introduction (Sect. 1).

2.1 Data and atmospheric model

The present study utilizes atmospheric methane observations at Environment Canada and NOAA observation sites (Fig. 2). These include regular measurements from tower and aircraft platforms, a total of 14 703 observations from 2007–2008. The observations used here are identical to those in Miller et al. (2013, 2014).

We then employ an atmospheric transport model to relate methane fluxes at the Earth's surface to atmospheric concentrations at the observation sites. The modeling approach here combines the Weather Research and Forecasting (WRF) meteorological model and a particle-following model known as STILT, the Stochastic Time-Inverted

BGD
12, 9341–9368, 2015

Lagrangian Transport model (e.g., Lin et al., 2003; Nehrkorn et al., 2010; Hegarty et al., 2013). WRF-STILT generates a set of footprints; these footprints quantitatively estimate the sensitivity of each observation to fluxes at each surface location (with units of ppb per unit surface flux). We multiply the footprints by a flux model and add this product to an estimate of the "background" concentration – the methane concentration of air entering the North American regional domain. The resulting modeled concentrations can be compared directly against atmospheric methane observations. This modeling setup is identical to Miller et al. (2013, 2014). Both the observations and the WRF-STILT model are described in greater detail in those papers and in the Supplement.

Using this setup, we can compare predicted methane concentrations using the WETCHIMP flux estimates (Fig. 1) against observed atmospheric concentrations. Of the WETCHIMP models, seven provide a flux estimate for boreal North America and six provide an estimate for temperate North America. These models include CLM4Me (Riley et al., 2011), DLEM (Tian et al., 2010), LPJ-Bern (Spahni et al., 2011), LPJ-WHyMe (Wania et al., 2010), LPJ-WSL (Hodson et al., 2011), ORCHIDEE (Ringeval et al., 2010), and SDGVM (Singarayer et al., 2011). All model outputs have a temporal resolution of one month. These models are described in Melton et al. (2013); Wania et al. (2013), and the Supplement.

2.2 Model selection framework

This study employs two synthetic data experiments to explore the sensitivity of atmospheric observations to wetland fluxes: can the observations detect an atmospheric pattern from wetlands fluxes over distracting patterns from anthropogenic emitters? If yes, can the observations detect spatial variability in wetland fluxes from different regions? We build a modeling approach based upon the BIC to answer these questions.

The BIC is a model selection technique, and various forms of the BIC are used widely in statistical regression analysis (e.g., Schwarz, 1978; Ramsey and Schafer, 2012). It scores all possible combinations of explanatory variables based on model-

BGD
12, 9341–9368, 2015

data fit, and it penalizes combinations that have a greater number of variables. The best combination or candidate model has the lowest BIC score.

We use a form of the BIC that has been adapted for use within a geostatistical inverse modeling framework (e.g., Gourdji et al., 2008; Miller et al., 2014). The implementation here parallels that of Fang et al. (2014) and Shiga et al. (2014):

$$\mathrm{BIC} = \underbrace{\ln|\mathbf{\Psi}| + (z - \mathbf{HX}\boldsymbol{\beta})^{\mathrm{T}}\mathbf{\Psi}^{-1}(z - \mathbf{HX}\boldsymbol{\beta})}_{\text{negative log-likelihood}} + \underbrace{p\ln(n)}_{\text{penalty term}} \tag{1}$$

The first term in Eq. (1) is the negative log-likelihood, a measure of how well the model fits the data. In that term, z ($n \times 1$) represents the observations minus background concentrations, $\mathbf{H}$ ($n \times m$) the footprints, $\mathbf{X}$ ($m \times p$) a matrix of p explanatory variables, $\boldsymbol{\beta}$ ($p \times 1$) a set of coefficients assigned to those variables, and $\mathbf{\Psi}$ ($n \times n$) a covariance matrix derived from an atmospheric inversion framework. The data (z), footprints ($\mathbf{H}$), and parameters that define the covariance matrix ($\mathbf{\Psi}$) are taken from Miller et al. (2013, 2014) (refer to the Supplement). The second term in Eq. (1) penalizes the BIC score of a particular model based upon the number of explanatory variables (p).

We employ this model selection framework to understand which explanatory variables from an anthropogenic emissions inventory and from the WETCHIMP ensemble are required to describe either synthetic or real methane data at North American observation sites.

2.3 Synthetic data experiments

The experiments described in this section use synthetic data generated at each of the observation sites. We use anthropogenic emissions estimates for the US and Canada from Miller et al. (2013, 2014), respectively, and use one of the WETCHIMP models as the wetland flux estimate. We then multiply these fluxes by $\mathbf{H}$ to create the synthetic data at the measurement locations. We further add in error that is randomly generated from the covariance matrix $\mathbf{\Psi}$ – error that represents uncertainties in the fluxes, the

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |
BGD
12, 9341–9368, 2015
Uncertainties in wetland methane estimates over North America
S. M. Miller et al.
Title Page
Abstract Introduction
Conclusions References
Tables Figures
◀ ▶
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

measurements, and the atmospheric transport model, among other error sources (refer to the Supplement).

The synthetic experiments ask progressively demanding questions that test the limits of available data. In experiment one, we examine whether methane observations can detect patterns in the atmosphere due to wetland fluxes from different regions. When given multiple possible explanatory variables (including data from the EDGAR anthropogenic emissions inventory), will the model selection framework choose a wetland estimate? If yes, the observations can identify a pattern in atmospheric methane due to wetland fluxes, and that pattern is large enough to be visible over other signals in the atmosphere. If not, then either the contribution of wetlands at that site is small, or the observations cannot differentiate atmospheric patterns due to wetlands over other atmospheric patterns due to anthropogenic sources or model-measurement errors. This setup follows Shiga et al. (2014), who explored the detectability of atmospheric patterns from anthropogenic CO_2 emissions.

For this test, we generate the synthetic data using one of the WETCHIMP models. We then allow the model selection framework to select wetland fluxes and/or the EDGAR data used to generate the synthetic fluxes. We divide the wetland fluxes into four regions (Fig. 2) and four seasons (winter, spring, summer, fall). The model selection can choose none, some, or all of these sixteen wetland variables. We run this experiment 1000 times, generating new synthetic data each time, and calculate the percentage of all trials in which the model selection chooses a wetland model. In this experiment, the coefficients ($\boldsymbol{\beta}$) are fixed to one. Note that several of the WETCHIMP models overestimate the magnitude of fluxes (Sect. 4.2), so we only use models with a smaller magnitude to generate the synthetic data in this experiment (CLM4Me, DLEM, SDGVM, and LPJ-WSL).

In experiment two, we investigate whether the observation network is sensitive to spatial variability in the wetland fluxes, independent of magnitude or seasonality. In this setup, we do not fix the coefficients ($\boldsymbol{\beta}$) but rather estimate coefficients that minimize the log-likelihood in Eq. (1). We also include a spatial constant or intercept term in $\mathbf{X}$

BGD
12, 9341–9368, 2015

that can change by month. As a result of this setup, the magnitude and seasonality of the intercept can be adjusted to match the data, but any spatial variability in the fluxes can only come from the wetland model. As in experiment one, the model selection framework can choose among 16 wetland variables – variables that represent different regions and seasons. If model selection chooses a wetland variable, then the spatial distribution in that variable is necessary to reproduce the synthetic data. If not, then the observations are not sensitive to spatial variability in wetland fluxes for that region/season. This approach follows that of Fang et al. (2014), who employed a model selection framework to evaluate the spatial distribution of biospheric CO_2 flux models.

2.4 Real data experiments

If experiment two is successful on synthetic data, we then apply the experiment to real data. We use the model selection framework to determine which, if any, bottom-up models have a spatial distribution that can describe the methane observations more effectively than a spatial constant.

We also include a number of model-data time series to evaluate both the magnitude and seasonality of the fluxes. We model methane concentrations at a number of US and Canadian observation sites using WRF-STILT, WETCHIMP, and EDGAR v4.2FT2010 (Olivier and Janssens-Maenhout, 2012; European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL), 2013). We average the observations and model output at the monthly scale and then compare the magnitude of these model estimates for each month against the averaged observations.

Several studies indicate that EDGAR may underestimate emissions in certain regions of the US and Canada (e.g., Kort et al., 2008; Miller et al., 2013, 2014; Wecht et al., 2014). Therefore, we scale the magnitude of EDGAR v4.2FT2010 to match wintertime observations (November–April) at each site using a standard major axis (SMA) regression. During those months, fluxes from wetlands are small and any model biases are likely due to anthropogenic emissions. We then apply this scaling factor, estimated for each site from winter data, to anthropogenic emissions in all seasons. Miller et al. (2013) found that anthropogenic emissions in the US lack significant seasonality, so the wintertime scaling factors should be applicable to other seasons.

We further compare the seasonality of existing bottom-up models against the seasonality of a recent inverse modeling estimate by Miller et al. (2014). We plot the monthly methane budget as a fraction of the annual total for both the bottom-up models and the inversion estimate. We only conduct this analysis for wetland flux regions that are visible to the observation network (synthetic experiments one and two).

Note that inter-annual variability in existing methane flux models is small relative to the differences among these models; as a result, conclusions from the 2 year study period (2007–2008) likely hold for other years. For example, the inter-annual variability in the total US/Canadian budget is ±7.3–9.7 % (standard deviation), depending upon the model in question (Note that LPJ-Bern has even larger inter-annual variation due to an issue with model spin-up described in Wania et al., 2013).

3 Results and discussion: synthetic experiments

The synthetic experiments presented here explore the limits of existing atmospheric data for constraining wetland fluxes. We first leverage synthetic data to examine whether the atmospheric observation sites can distinguish an atmospheric pattern from wetland fluxes above other patterns due anthropogenic emissions or simulated model, measurement, and emissions uncertainties. If atmospheric observations are to constrain wetland methane fluxes, those observations must, at minimum, identify an atmospheric pattern from wetland fluxes from other distracting patterns in the model and/or data.

The results of this experiment are summarized in Fig. 3a. The four columns in Fig. 3a display the results from an individual season in each of four geographic regions. In this experiment, the observation network can detect a summertime methane pattern from wetlands in both Eastern and Western Canada in greater than 75 % of all trials. In the eastern US, the model selection framework chooses a wetland model in 50–75 % of all trials in multiple different seasons. By contrast, the observations are least sensitive to wetland fluxes in the western US, and the model selection framework chooses wetland fluxes from that region in less than 25 % of all trials irrespective of the season. This result may be due, in part, to the relatively dry climate and scant wetlands in much of the west. The methane signal from resource extraction and/or agriculture may also overshadow any patterns from wetlands.

The results also contain a number of seasonal trends. Of any region, the observation network is best able to constrain the seasonal cycle in eastern Canada. The largest wetland fluxes estimated for the US and Canada are in Ontario and Quebec. It is therefore unsurprising that the network is so sensitive to fluxes from this region, even though there are relatively few observation sites in the area. In other regions, the observation network is less sensitive to wetlands during the winter, fall, and spring seasons. For example, the model selection framework chooses a wetland model in less than 25 % of all trials during the winter in all regions.

The density of the observation network may also play a role in these results. Wetlands in the Eastern US are sparse relative to Canada, but the higher density of observations in the Eastern US may contribute to a moderate success rate (> 50 %) for that region. A recent observation network expansion could play a key role in future efforts to constrain wetland fluxes across these regions. Environment Canada has recently been expanding their observation network across western and Arctic Canada (i.e., Saskatchewan, Alberta, Northwest Territories, and Nunavut). In addition, Earth Networks has begun to install new observation sites across the eastern US in a privately-funded initiative.

Compared to experiment one, the second experiment asks a more demanding question of the observation network: is the observation network sensitive to spatial variability in the wetland fluxes from each region? Alternately, can a spatially-constant model reproduce the synthetic atmospheric observations as well? Existing bottom-up

BGD
12, 9341–9368, 2015

estimates disagree markedly on the spatial distribution of wetland fluxes, but perhaps atmospheric data can provide guidance.

Figure 3b displays the results of this experiment for each region and season. The available data is only sensitive to spatial variability in certain cases. The model selection framework chooses a wetland model in $> 75\%$ of all trials in eastern Canada during summer and fall and in western Canada during summer. In remote regions of northern Ontario and Quebec, large wetland fluxes dominate variability in atmospheric methane. Hence, it is understandable that observations are most sensitive to the spatial distribution of fluxes in this region. By contrast, the observation network is largely insensitive to spatial variability in wetland fluxes across the US; in most instances, the model selection framework favors a spatially-constant model over a wetland model for the two US regions.

These results indicate that the observation network has limited capacity to evaluate wetland fluxes over the US. Across Canada, the results are far more promising, despite the relative sparsity of the observation network there. Existing bottom-up methane estimates are highly uncertain across Canada, and the synthetic experiments indicate that atmospheric observations can reduce these uncertainties.

4 Results and discussion: comparisons with atmospheric data

4.1 Spatial flux patterns

We first compare the spatial distribution of the existing wetland flux estimates against methane data from the atmospheric observation network. We apply experiment two to real data and report the results for regions and seasons that had a high success rate in the synthetic experiment. That experiment examined whether the spatial variability in a wetland model is more useful at describing the atmospheric data than a spatial constant. We now apply this question to real data: do the WETCHIMP models have spatial variability that describe the real data better than a spatial constant? If so, which models? This approach indicates whether each model contributes positive information on the location of wetland fluxes.

The results of this real data experiment are displayed in Table 1. This table only lists the regions and seasons that had a success rate > 75 % in synthetic data experiment two. If a wetland model describes the distribution of fluxes better than a spatial constant in those regions/seasons, then the model selection framework should select that model.

Only a small number of WETCHIMP models are able to describe the distribution of wetland fluxes (as seen via the atmospheric observations) better than a spatial constant – between 0–28 % of the available models depending upon the region and season. The model selection framework chooses LPJ-Bern in eastern Canada and LPJ-Bern and SDGVM in western Canada. The spatial patterns in the remaining WETCHIMP models do not perform better than a spatial constant when compared to atmospheric data.

The LPJ-Bern and SDGVM models have several unique spatial characteristics that could explain these results. Over eastern Canada, the LPJ-Bern model concentrates the largest fluxes in the HBL. Other models, by contrast, often distribute the fluxes more broadly across Ontario and Quebec or put the largest fluxes in Ontario outside of the HBL. In western Canada, the LPJ-Bern and SDGVM models distribute fluxes broadly across both northern Saskatchewan and Alberta. A number of other estimates like DLEM or CLM4Me assign relatively small fluxes in these provinces relative to other regions.

The LPJ-Bern and SDGVM models share another common characteristic: both model wetland area independently instead of relying solely on remote sensing inundation datasets. LPJ-WSL, ORCHIDEE, DLEM, and CLM4Me use remote sensing inundation datasets like GEIMS (Global Inundation Extent from Multi-Satellites, Prigent et al., 2007) to construct a wetland map. Other models, like LPJ-Bern and LPJ-WHyMe also use land cover maps and/or land surveys to estimate wetland (or at least methane-producing) area. SDGVM estimates this area using a dynamic model of soil moisture

(Melton et al., 2013; Wania et al., 2013). Wetland maps generated using these different approaches show substantial differences. Remote sensing datasets estimate relatively high levels of inundation in regions of Canada that are non-forested or have many small lakes (see further discussion in Melton et al., 2013; Bohn et al., 2015). Other modeling approaches, by contrast, assign more wetlands over regions with high water tables but little surface water. As a result of these differences, models like LPJ-Bern assign more wetlands and methane fluxes in the HBL relative to other regions of eastern Canada.

4.2 Flux magnitude

We next compare the magnitude of predicted concentrations using the WETCHIMP models against atmospheric observations. Unlike previous sections that utilized model selection, this section employs several simple model-data timeseries, displayed in Fig. 4. We model methane concentrations at a number of US and Canadian observation sites using WRF-STILT, the WETCHIMP flux estimates, and anthropogenic emissions from the EDGAR v4.2FT2010 inventory. This model estimate consists of several components: the background (in green) is the estimated concentration of methane in clean air before entering the model domain as in Miller et al. (2013, 2014). The estimated contribution of anthropogenic emissions from EDGAR v4.2FT2010 is added to this background (in red). Note that the estimated scaling factors for EDGAR (Sect. 2.4) are 1.7 ± 0.3 at Chibougamau, 5.6 ± 0.5 at East Trout Lake, 2.4 ± 0.3 at Fraserdale, and 2.5 ± 0.3 at Park Falls. The contribution of wetland fluxes from the WETCHIMP models is then added to the previous inputs, and the sum of all components (blue lines) can be compared directly against measured concentrations.

The various WETCHIMP flux estimates produce very different modeled concentrations at the observation sites (Fig. 4). Overall, modeled concentrations with the WETCHIMP fluxes usually exceed the methane measurements during summer. At Chibougamau, Fraserdale, and Park Falls in early summer, all six WETCHIMP models predict methane concentrations that equal or exceed the observations. The ORCHIDEE, LPJ-WHyMe, and LPJ-Bern models always exceed the measurements during summer

BGD
12, 9341–9368, 2015

while DLEM and SDGVM better match the observations at these sites. In contrast to these results, a recent study by Bohn et al. (2015) found that the ensemble average is not biased over the Western Siberian Lowlands relative to inverse modeling estimates. The models also show a large spread in that region.

Methane models that overestimate fluxes in North America do not always compensate with smaller fluxes elsewhere. For example, the ORCHIDEE model not only estimates large fluxes over North America but also estimates higher fluxes over the tropics than any other model (Melton et al., 2013). Hence, the disagreement in magnitude over North America not only reflects uncertainty in the global distribution of wetland fluxes but also reflects uncertainty in the global wetland budget.

4.3 Seasonal cycle

Bottom-up methane flux estimates show variable performance when compared against atmospheric observations, and the temporal distribution of these estimates is no exception. Figure 5 compares the seasonal cycle of the existing estimates over Canada's HBL. Eastern Canada is one of the largest wetland regions in North America (Fig. 1), and unlike other regions, the observation network there can detect a clear wetland signal through most of the seasonal cycle (Fig. 3).

In this region, the bottom-up estimates diverge on the seasonal cycle of fluxes. Most estimates predict peak fluxes in July or August, though two variations of the LPJ model predict seasonal peaks in September and October (LPJ-WHyMe and LPJ-Bern, respectively). Discrepancies among models are also notable during the fall and spring seasons. For example, fluxes in June account for anywhere between 6 and 21 % of the annual methane budget, depending upon the model. Fluxes in October account for between 1 and 23 % of the annual budget.

The figure also displays the seasonality of an inverse modeling estimate from Miller et al. (2014) for comparison. That estimate incorporates observations from Chibougamau and Fraserdale, atmospheric measurement sites that are strongly influenced by fluxes from the HBL. The discrepancies among the WETCHIMP models often exceed

BGD
12, 9341–9368, 2015

the 95 % confidence interval of the inversion estimate. On whole, the WETCHIMP estimates have a narrower seasonal cycle than the inversion estimate, which assigns comparatively larger fluxes to the fall and spring shoulder seasons. A recent inverse modeling study of the Western Siberian Lowlands found parallel results for that region – existing models also under-predict the shoulder seasons relative to summer months (Winderlich, 2012; Bohn et al., 2015).

Numerous possible explanations could underly this discrepancy. For example, the bottom-up models could be too sensitive to soil/air temperature, and may therefore shut off methane emissions too early. Compared to the inversion estimate, the bottom-up models predict small or minimal fluxes during fall/spring months when air temperatures are near freezing but soils are still unfrozen (Fig. S3). According to estimates from the North American Regional Reanalysis (NARR) (Mesinger et al., 2006), surface soils in the HBL (0 and 10 cm depth) begin to thaw in April and are largely unfrozen in May (Fig. S3). In the fall, surface soils (0 cm depth) begin to freeze in November, but deeper soils (10 and 40 cm) remain largely unfrozen until December. Compared to the bottom-up models, the inversion estimate predicts a wider seasonal window, a result that is consistent with soil freeze/thaw.

5 Conclusions

A recent model comparison study revealed substantial differences in existing estimates of wetland methane fluxes – differences at global to regional scales. In the first component of this study, we use two increasing stringent synthetic data experiments to understand how sensitive the atmospheric observation network is to regional-scale wetland fluxes. We find that the network can reliably identify an atmospheric pattern from Canadian wetlands. The network can identify a methane pattern from the eastern US in 50–75 % of trials and rarely from the western US. The network can also detect spatial variability in the Canadian wetland source but rarely in the US wetland source. This analysis also accounts for distracting signals or patterns in the atmosphere from

BGD
12, 9341–9368, 2015

anthropogenic sources or simulated modeling errors. These results indicate that uncertainties in current methane models can be reduced, if those models begin to leverage available methane data. Furthermore, these discrepancies indicate a disconnect between scientists who build process-based and/or biogeochemical models and scientists who collect or use atmospheric methane data. Improved collaboration between these two groups could help reduce present uncertainties in natural methane fluxes, at least over Canada.

In a second component of the study, we evaluate each existing bottom-up methane model at regional scale using real atmospheric data. We find that only 0–28 % of all models have a spatial pattern that describes the atmospheric data more effectively than a constant. The LPJ-Bern and SDGVM models have spatial distributions that are most consistent with atmospheric observations, depending upon the region and season of interest. In addition, almost all existing models overestimate the magnitude of wetland methane fluxes when compared against atmospheric data at individual observation sites. The ensemble of models also appears to estimate a seasonal cycle that is too narrow across the HBL, a large region of methane fluxes in North America. Overall, this study indicates numerous areas for improvement in existing bottom-up wetland methane estimates.

The Supplement related to this article is available online at doi:10.5194/bgd-12-9341-2015-supplement.

Acknowledgements. We thank Marc Fischer and Sebastien Biraud of Lawrence Berkeley Labs and John Miller of NOAA; these collaborators operate several sites in the US greenhouse gas observation network. We also thank Steven Wofsy of Harvard University and Thomas Nehrkorn of Atmospheric and Environmental Research. The National Aeronautics and Space Administration (NASA) Advanced Supercomputing Division provided key computing resources and assistance. This work was supported by the Department of Energy Computational Science Graduate Fellowship Program of the Office of Science and National Nuclear Security Administration in the Department of Energy under contract DE-FG02-97ER25308. This work was also supported by a National Science Foundation Graduate Research Fellowship.

References

Andrews, A. E., Kofler, J. D., Trudeau, M. E., Williams, J. C., Neff, D. H., Masarie, K. A., Chao, D. Y., Kitzis, D. R., Novelli, P. C., Zhao, C. L., Dlugokencky, E. J., Lang, P. M., Crotwell, M. J., Fischer, M. L., Parker, M. J., Lee, J. T., Baumann, D. D., Desai, A. R., Stanier, C. O., De Wekker, S. F. J., Wolfe, D. E., Munger, J. W., and Tans, P. P.: CO_2, CO, and CH_4 measurements from tall towers in the NOAA Earth System Research Laboratory's Global Greenhouse Gas Reference Network: instrumentation, uncertainty analysis, and recommendations for future high-accuracy greenhouse gas monitoring efforts, Atmos. Meas. Tech., 7, 647–687, doi:10.5194/amt-7-647-2014, 2014. 9365

Bohn, T. J., Melton, J. R., Ito, A., Kleinen, T., Spahni, R., Stocker, B. D., 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., Zhuang, Q., and Kaplan, J. O.: WETCHIMP-WSL: intercomparison of wetland methane emissions models over West Siberia, Biogeosciences, 12, 3321–3349, doi:10.5194/bg-12-3321-2015, 2015. 9354, 9355, 9356

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., and Canadell, J.: Carbon and Other Biogeochemical Cycles – Final Draft Underlying Scientific Technical Assessment, chap. 6, IPCC Secretariat, Geneva, 2013. 9343

European Commission, Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL): Emission Database for Global Atmospheric Research (EDGAR), release EDGARv4.2 FT2010, available at: http://edgar.jrc.ec.europa.eu (last access: 14 June 2015), 2013.

Fang, Y. and Michalak, A. M.: Atmospheric observations inform CO_2 flux responses to enviroclimatic drivers, Global Biogeochem. Cy., 29, GB005034, doi:10.1002/2014GB005034, 2015. 9345

Fang, Y., Michalak, A. M., Shiga, Y. P., and Yadav, V.: Using atmospheric observations to evaluate the spatiotemporal variability of CO_2 fluxes simulated by terrestrial biospheric models, Biogeosciences, 11, 6985–6997, doi:10.5194/bg-11-6985-2014, 2014. 9345, 9347, 9349

Gourdji, S. M., Mueller, K. L., Schaefer, K., and Michalak, A. M.: Global monthly averaged CO_2 fluxes recovered using a geostatistical inverse modeling approach: 2. Results including auxiliary environmental data, J. Geophys. Res.-Atmos., 113, D21115, doi:10.1029/2007JD009733, 2008. 9347

Hegarty, J., Draxler, R. R., Stein, A. F., Brioude, J., Mountain, M., Eluszkiewicz, J., Nehrkorn, T., Ngan, F., and Andrews, A.: Evaluation of Lagrangian particle dispersion models with measurements from controlled tracer releases, J. Appl. Meteorol. Clim., 52, 2623–2637, 2013. 9346

Hendriks, D. M. D., van Huissteden, J., and Dolman, A. J.: Multi-technique assessment of spatial and temporal variability of methane fluxes in a peat meadow, Agr. Forest Meteorol., 150, 757–774, doi:10.1016/j.agrformet.2009.06.017, 2010. 9344

Hodson, E. L., Poulter, B., Zimmermann, N. E., Prigent, C., and Kaplan, J. O.: The El Niño–Southern Oscillation and wetland methane interannual variability, Geophys. Res. Lett., 38, L08810, doi:10.1029/2011GL046861, 2011. 9346

Kort, E. A., Eluszkiewicz, J., Stephens, B. B., Miller, J. B., Gerbig, C., Nehrkorn, T., Daube, B. C., Kaplan, J. O., Houweling, S., and Wofsy, S. C.: Emissions of CH_4 and N_2O over the United States and Canada based on a receptor-oriented modeling framework and COBRA-NA atmospheric observations, Geophys. Res. Lett., 35, L18808, doi:10.1029/2008gl034031, 2008. 9344, 9349

Lin, J., Gerbig, C., Wofsy, S., Andrews, A., Daube, B., Davis, K., and Grainger, C.: A near-field tool for simulating the upstream influence of atmospheric observations: the Stochastic Time-Inverted Lagrangian Transport (STILT) model, J. Geophys. Res.-Atmos., 108, 4493, doi:10.1029/2002jd003161, 2003. 9346

Livingston, G. and Hutchinson, G.: Enclosure-based measurement of trace gas exchange: applications and sources of error, chap. 2, in: Methods in Ecology, Wiley, London, 14–51, 2009. 9344

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., Zürcher, S., Brovkin, V., van Bodegom, P. M., Kleinen, T., Yu, Z. C., and Kaplan, J. O.: Present state of global wetland extent and wetland methane modelling: conclusions from a model inter-comparison project (WETCHIMP), Biogeosciences, 10, 753–788, doi:10.5194/bg-10-753-2013, 2013. 9344, 9346, 9354, 9355

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

Mesinger, F., Dimego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., Jovi, D., Woollen, J., Rogers, E., Berbery, E. H., Ek, M. B., Fan, Y., Grumbine, R., Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., and Shi, W.: North American regional reanalysis, B. Am. Meteorol. Soc., 87, 343–360, doi:10.1175/BAMS-87-3-343, 2006. 9356

Miller, S. M., Wofsy, S. C., Michalak, A. M., Kort, E. A., Andrews, A. E., Biraud, S. C., Dlugokencky, E. J., Eluszkiewicz, J., Fischer, M. L., Janssens-Maenhout, G., Miller, B. R., Miller, J. B., Montzka, S. A., Nehrkorn, T., and Sweeney, C.: Anthropogenic emissions of methane in the United States, P. Natl. Acad. Sci. USA, 110, 20018–20022, doi:10.1073/pnas.1314392110, 2013. 9345, 9346, 9347, 9349, 9350, 9354

Miller, S. M., Worthy, D. E. J., Michalak, A. M., Wofsy, S. C., Kort, E. A., Havice, T. C., Andrews, A. E., Dlugokencky, E. J., Kaplan, J. O., Levi, P. J., Tian, H., and Zhang, B.: Observational constraints on the distribution, seasonality, and environmental predictors of North American boreal methane emissions, Global Biogeochem. Cy., 28, 146–160, doi:10.1002/2013GB004580, 2014. 9344, 9345, 9346, 9347, 9349, 9350, 9354, 9355, 9368

Nehrkorn, T., Eluszkiewicz, J., Wofsy, S. C., Lin, J. C., Gerbig, C., Longo, M., and Freitas, S.: Coupled Weather Research and Forecasting-Stochastic Time-Inverted Lagrangian Transport (WRF-STILT) model, Meteorol. Atmos. Phys., 107, 51–64, doi:10.1007/s00703-010-0068-x, 2010. 9346

Olivier, J. and Janssens-Maenhout, G.: CO_2 emissions from fuel combustion, 2012 edn., chap. III, in: Greenhouse-Gas Emissions, International Energy Agency, Paris, III.1 – III.51, 2012.

Pan, L. L., Bowman, K. P., Atlas, E. L., Wofsy, S. C., Zhang, F., Bresch, J. F., Ridley, B. A., Pittman, J. V., Homeyer, C. R., Romashkin, P., and Cooper, W. A.: The stratosphere-troposphere analyses of regional transport 2008 experiment, B. Am. Meteorol. Soc., 91, 327–342, doi:10.1175/2009BAMS2865.1, 2010. 9365

Pickett-Heaps, C. A., Jacob, D. J., Wecht, K. J., Kort, E. A., Wofsy, S. C., Diskin, G. S., Worthy, D. E. J., Kaplan, J. O., Bey, I., and Drevet, J.: Magnitude and seasonality of wetland methane emissions from the Hudson Bay Lowlands (Canada), Atmos. Chem. Phys., 11, 3773–3779, doi:10.5194/acp-11-3773-2011, 2011. 9344

Prigent, C., Papa, F., Aires, F., Rossow, W. B., and Matthews, E.: Global inundation dynamics inferred from multiple satellite observations, 1993–2000, J. Geophys. Res.-Atmos., 112, D12107, doi:10.1029/2006JD007847, 2007. 9353

Ramsey, F. and Schafer, D.: The Statistical Sleuth: A Course in Methods of Data Analysis, Cengage Learning, Boston, 3rd edn., 2012. 9346

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

Riley, W. J., Subin, Z. M., Lawrence, D. M., Swenson, S. C., Torn, M. S., Meng, L., Mahowald, N. M., and Hess, P.: Barriers to predicting changes in global terrestrial methane fluxes: analyses using CLM4Me, a methane biogeochemistry model integrated in CESM, Biogeosciences, 8, 1925–1953, doi:10.5194/bg-8-1925-2011, 2011. 9346

Ringeval, B., de Noblet-Ducoudré, N., Ciais, P., Bousquet, P., Prigent, C., Papa, F., and Rossow, W. B.: An attempt to quantify the impact of changes in wetland extent on methane emissions on the seasonal and interannual time scales, Global Biogeochem. Cy., 24, GB2003, doi:10.1029/2008GB003354, 2010. 9346

Schwarz, G.: Estimating the dimension of a model, Ann. Stat., 6, 461–464, doi:10.1214/aos/1176344136, 1978. 9346

Shiga, Y. P., Michalak, A. M., Gourdji, S. M., Mueller, K. L., and Yadav, V.: Detecting fossil fuel emissions patterns from subcontinental regions using North American in situ CO_2 measurements, Geophys. Res. Lett., 41, 4381–4388, doi:10.1002/2014GL059684, 2014. 9345, 9347, 9348

Singarayer, J. S., Valdes, P. J., Friedlingstein, P., Nelson, S., and Beerling, D. J.: Late Holocene methane rise caused by orbitally controlled increase in tropical sources, Nature, 470, 82–85, doi:10.1038/nature09739, 2011. 9346

Spahni, R., Wania, R., Neef, L., van Weele, M., Pison, I., Bousquet, P., Frankenberg, C., Foster, P. N., Joos, F., Prentice, I. C., and van Velthoven, P.: Constraining global methane emissions and uptake by ecosystems, Biogeosciences, 8, 1643–1665, doi:10.5194/bg-8-1643-2011, 2011. 9346

Tian, H., Xu, X., Liu, M., Ren, W., Zhang, C., Chen, G., and Lu, C.: Spatial and temporal patterns of CH_4 and N_2O fluxes in terrestrial ecosystems of North America during 1979–2008: application of a global biogeochemistry model, Biogeosciences, 7, 2673–2694, doi:10.5194/bg-7-2673-2010, 2010. 9346

Waddington, J. and Roulet, N.: Atmosphere-wetland carbon exchanges: scale dependency of CO_2 and CH_4 exchange on the developmental topography of a peatland, Global Biogeochem. Cy., 10, 233–245, doi:10.1029/95GB03871, 1996. 9344

Wania, R., Ross, I., and Prentice, I. C.: Implementation and evaluation of a new methane model within a dynamic global vegetation model: LPJ-WHyMe v1.3.1, Geosci. Model Dev., 3, 565–584, doi:10.5194/gmd-3-565-2010, 2010. 9346

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.,

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

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., and Kaplan, J. O.: Present state of global wetland extent and wetland methane modelling: methodology of a model inter-comparison project (WETCHIMP), Geosci. Model Dev., 6, 617–641, doi:10.5194/gmd-6-617-2013, 2013. 9344, 9346, 9350, 9354

Wecht, K. J., Jacob, D. J., Frankenberg, C., Jiang, Z., and Blake, D. R.: Mapping of North American methane emissions with high spatial resolution by inversion of SCIAMACHY satellite data, J. Geophys. Res.-Atmos., 119, 7741–7756, doi:10.1002/2014JD021551, 2014. 9349

Winderlich, J.: Setup of a CO_2 and CH_4 measurement system in Central Siberia and modeling of its results, PhD thesis, University of Hamburg, Hamburg, Germany, available at: http://ediss.sub.uni-hamburg.de/volltexte/2012/5533/pdf/Dissertation.pdf (last access: 14 June 2015), 2012. 9356

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

Table 1. Spatial patterns chosen by the model selection framework.

Region	Season	Models chosen over a constant	Model name(s)
E. Canada	Summer	1 of 7	LPJ-Bern
E. Canada	Fall	0 of 7	
W. Canada	Summer	2 of 7	LPJ-Bern, SDGVM

BGD
12, 9341–9368, 2015

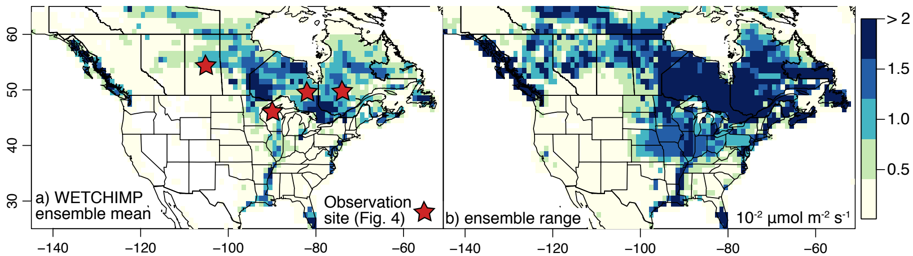

Figure 1. Mean of the annual methane fluxes estimated by the WETCHIMP models **(a)** and the range of fluxes estimated by the ensemble **(b)**. Note that the range in estimates is larger than the mean. The fluxes shown above are averaged over an entire grid cell, not per m^2 of wetlands.

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

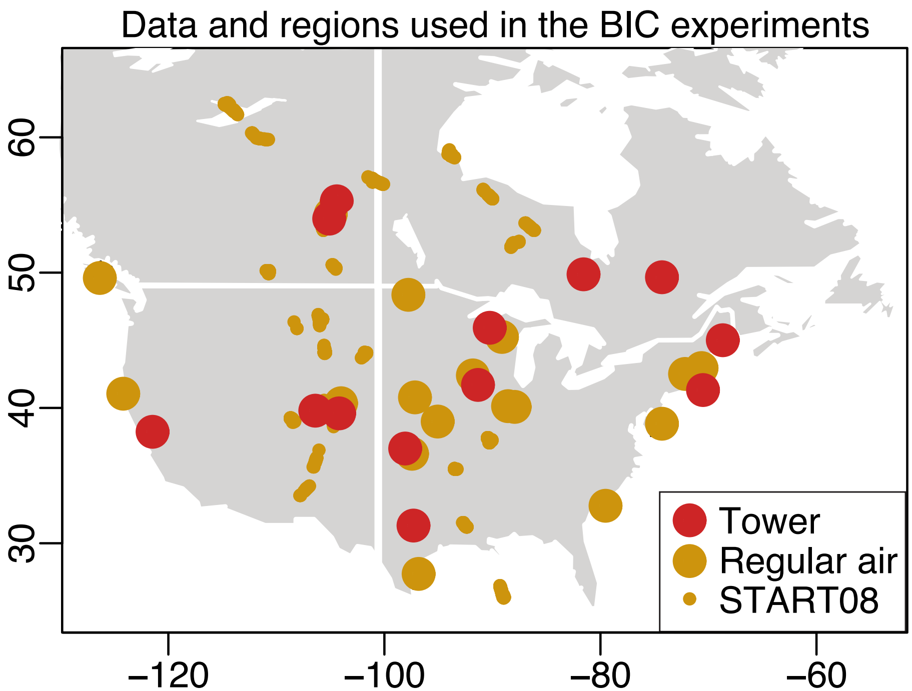

Figure 2. The US and Canadian atmospheric methane observation network for 2007–2008 (14 703 total observations). Small yellow dots indicate observations from the START08 measurement campaign (Pan et al., 2010). Larger dots indicate tower and aircraft sites with regular observations over the two year period (Andrews et al., 2014). The grey background delineates the four regions used in the synthetic data experiments (Sect. 2.3).

BGD
12, 9341–9368, 2015

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

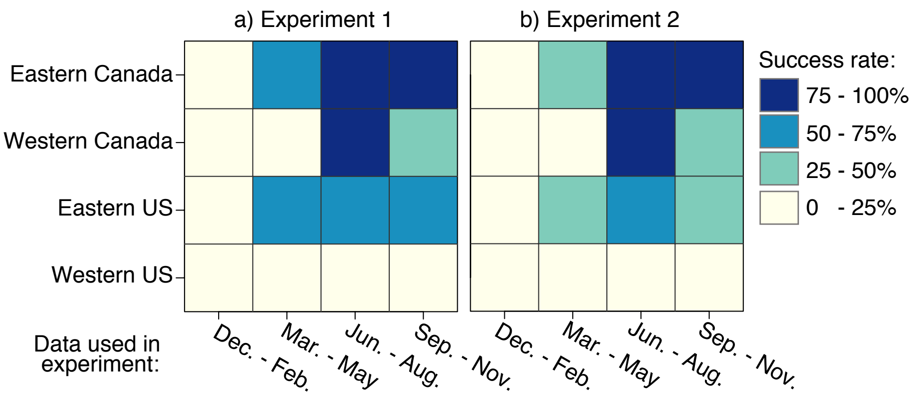

Figure 3. This figure displays the results of the synthetic data experiments. These experiments examine whether the observation network can **(a)** identify a methane pattern from wetland fluxes and **(b)** identify spatial variability in the wetland fluxes. The figure shows the percentage of trials that are successful. Darker shades indicate that the network is more sensitive to fluxes in the given region and season.

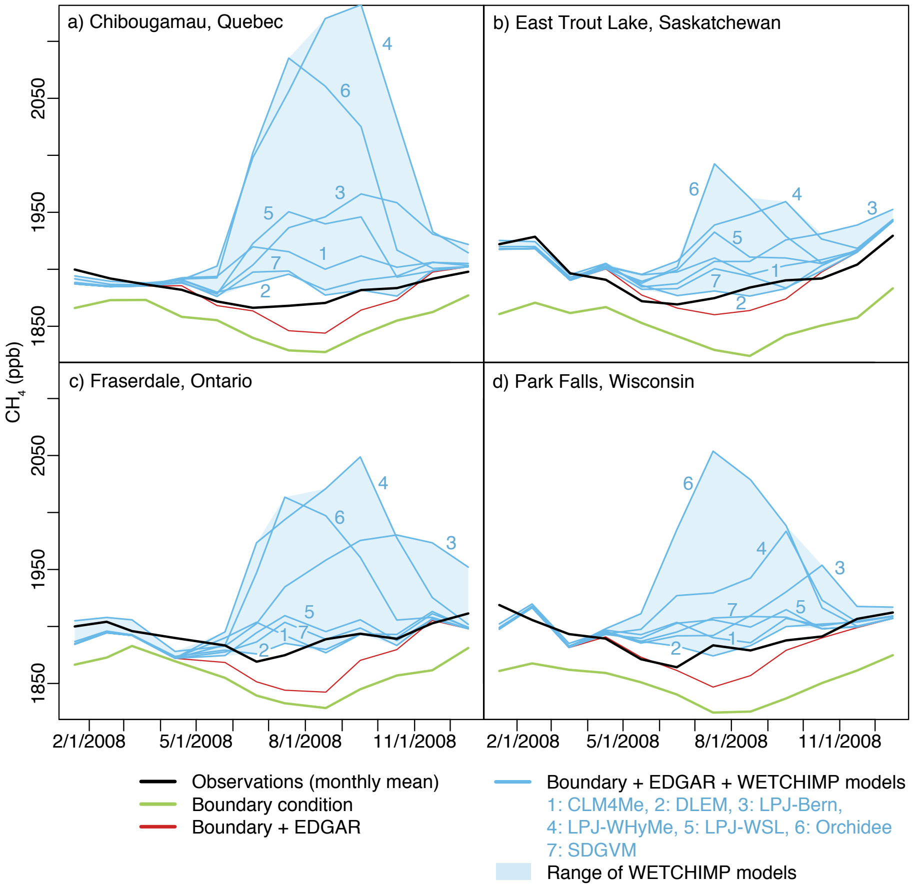

Figure 4. These time series compare atmospheric methane measurements at several observation sites against model estimates using the WETCHIMP ensemble and the EDGAR v4.2FT2010 anthropogenic emissions inventory. The range of estimates from the various WETCHIMP models is large.

BGD
12, 9341–9368, 2015

Uncertainties in wetland methane estimates over North America

S. M. Miller et al.

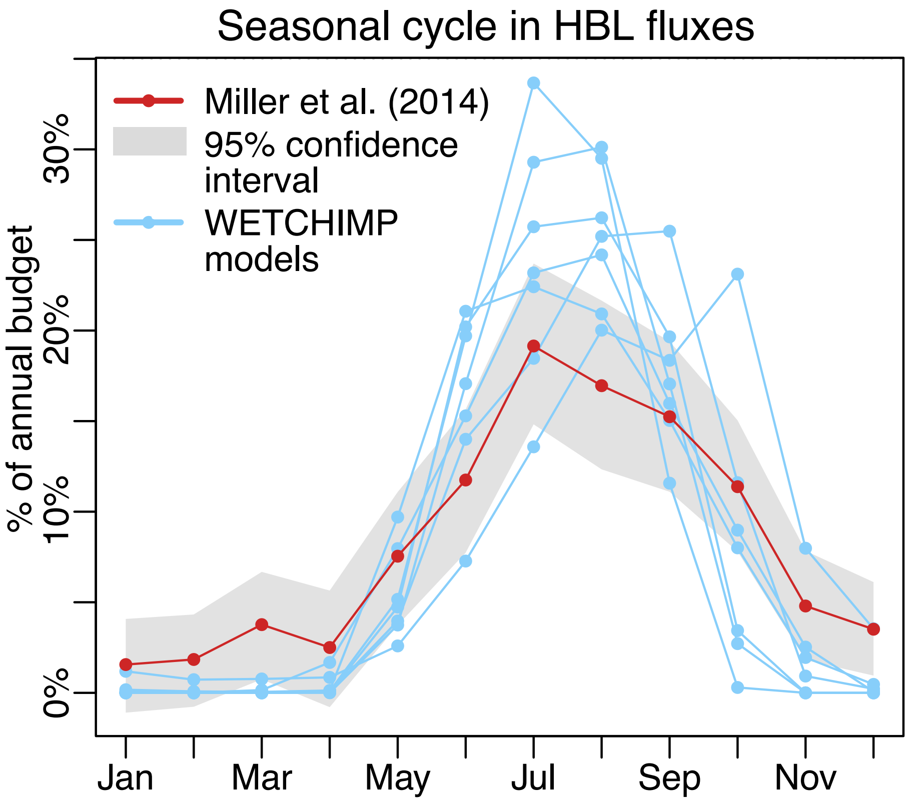

Figure 5. The seasonal cycle in methane fluxes estimated for the Hudson Bay Lowlands (HBL; 50–60° N, 75–96° W). We include both the WETCHIMP estimates and an inverse modeling estimate from Miller et al. (2014). Each month is displayed as a percentage of the annual budget estimated by a given model. This approach highlights differences in the seasonality of the models and controls for differences in magnitude. In general, the WETCHIMP models estimate a narrower seasonal cycle relative to Miller et al. (2014).

BGD
12, 9341–9368, 2015