

AUTHOR RESPONSES TO REVIEWER COMMENTS

Title: Monthly Gridded Data Product of Northern Wetland Methane Emissions Based on Upscaling Eddy Covariance Observations

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We thank the reviewers for their comments on our manuscript. The comments helped us to identify the weaknesses and unclear sections in our manuscript and hence helped us to improve the text. We address the individual comments point-by-point below. The comments are with **bold** font whereas the responses to the comments are with normal font.

Reviewer #1

(1) Evaluation of the products is too simplistic. It would be nice to illustrate the statistics for model-observation comparison spatially, which means to make a plot to see the spatial patterns of R², NSE, RE and BE.

There are two hot spots for CH₄ emission across the circumpolar region (Hudson Bay lowlands and western Siberian lowlands). But unfortunately, there is only one site from each hot spot area. Why don't the authors select these two sites for the time series comparison, like what is shown in Figure 5? I notice that Figure 4 indicates regression lines between model and observations for these two sites have large deviations from the 1:1 line.

RESPONSE: Good idea. We will add a figure showing the spatial patterns of the suggested statistical metrics (i.e. R², NSE, RE and BE). However, one should note that BE is already shown in Fig. 7 of the manuscript. Also, in order to avoid effects of differences in wetland maps, we will add only the comparison between LPX-Bern and RF-DYPTOP since they are based on the same wetland map.

The second point the reviewer raises in the comment is also most valid. It would make sense to select the sites from Hudson Bay lowlands (HBL) and western Siberian lowlands (WSL) (CA-JBL and RU-Vrk, respectively) for time series comparison. However, we opted not to do that since we have only limited amount of monthly data points from these two sites (four and five data points, respectively) and hence time series plots would not be very informative. Hence, we opt not to add these sites to Fig. 5 of the manuscript.

CHANGES IN MANUSCRIPT: added a figure (Fig.8 in the revised manuscript) showing maps of the statistical metrics (NSE, R² and RE) comparing LPX-Bern and RF-DYPTOP.

(2) Why does the study only select two years of observations? As most observations in the Arctic have only been collected during growing seasons, there are not many monthly data points left within two years. Therefore, it is difficult to say how significant the regression relationships between model and observation in each site is.

RESPONSE: We used all the available observations for model development and validation, not only 2013-2014. The upscaling work flow was as follows: 1) we gathered all available CH₄ flux eddy covariance observations from northern wetlands, 2) developed random forest (RF) machine learning model utilizing all this data, 3) used the RF model and spatial maps of CH₄ flux drivers to upscale the measurements for two years (2013 and 2014). This can be seen in the multi-year time series figure 5 where RF model predictions are validated against all the available data from four EC sites. Also, the main RF model validation figure (Fig. 4) contains all the available observations from the years 2005-2016, not only 2013-2014.

For upscaling, we selected only the two years 2013 and 2014 mainly since in these two years, the largest overlapping fraction of the available observations were made.

CHANGES IN MANUSCRIPT: In order to clarify this point we will emphasise in the abstract, Sect. 2.3.1 and Sect. 4.2.1 that all the available data from all the years were used in the model development and validation.

(3) Why do the authors compare RF-GLWD with LPJ-Bern and WetCHARTs? I don't see the point of making such a comparison, because they are not based on the same wetland map.

RESPONSE: We partly agree with the reviewer that direct point-by-point comparison of products not based on the same wetland map adds complexity. Yet, here, we wanted to emphasise the fact that the underlying wetland maps have a big impact on the estimated spatial distribution of wetland CH₄ emissions. Furthermore, it is unclear which wetland map is most accurate for the study domain and hence upscaling with as many wetland maps as feasible is warranted. Hence, we opt to keep the comparison as it is.

CHANGES IN MANUSCRIPT: We will add the following sentence to the first part of Sect. 3.3.: " While the wetland maps differ, there is no consensus on which is more accurate, so comparisons indicate the uncertainty in upscaling emanating from uncertainties in wetland distribution."

(4) I noticed the input variables listed in table 1 comprise of some categorical variables. Can the authors describe more details about how RF use such information? Can the authors consider making an RF model based on individual wetland type or biome type? Moreover, why don't these input variables include water table position, which is important drivers for CH₄ emissions, particularly to explain spatial heterogeneity?

RESPONSE: During the training of a RF model the mean squared error (MSE) between training data and RF model output is minimized. The categorical variables are used in the split nodes to divide the data into two in such a way that the MSE is minimized after the split. Let us take a simple example: we develop a RF model with three input variables, snow cover (SC), wetland type (WT) and air temperature (Ta). SC and WT are categorical variables, whereas Ta is a continuous variable. After training, a single decision tree for regressions in a RF model could look like in Fig. 1 below. The output from this one tree would be the mean of the training data in each leaf node. The output from RF model is then an average of the output from all the trees in the RF model.

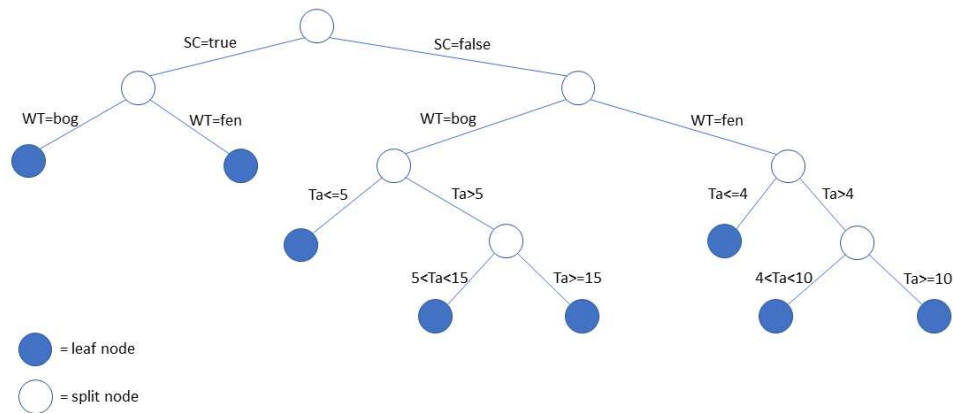


Figure 1. Example of a decision tree for regression with three input variables: SC, WT and Ta. SC and WT are categorical variables, whereas Ta is a continuous variable. The output from this particular regression tree is the mean of the training data in each leaf node.

In principle one could make an RF model on individual wetland or biome type. Yet, in our study, the categorical variables, wetland or biome type, did not increase the overall performance of the developed model and hence they were not included as drivers in the model used in upscaling.

We agree that the water table depth (WTD) is likely an important driver for the wetland CH₄ emissions, though a growing body of literature shows temperature to dominate for spatial variation and short-term variation. This is already discussed in the manuscript (Sect. 4.2.1). However, WTD measurements were not available in many of the study sites preventing us from using it for our upscaling procedure.

CHANGES IN MANUSCRIPT: add text in Sect. 2.1 on how RF model uses different input variables (categorical, continuous).

Specific comments:

Page 2

Line 11: utilize random forest (RF) -> utilize a random forest (RF)

RESPONSE: thanks, will be corrected.

Line 16: What does “confidence interval” refer to? a random forest ensemble? Please specify it.

RESPONSE: Yes, it refers to 95 % confidence interval of the random forest ensemble. We will specify this in the text.

Line 27: constraint -> constrain

RESPONSE: Thanks, will be corrected.

Reviewer #2

The authors have produced a gridded product of monthly CH₄ fluxes from Northern (>=45) wetlands using a random forest (machine learning) algorithm. The random forest model was trained against a number of predictor variables such as nighttime Land Surface Temperature, absence or presence of permafrost, potential sunshine, sedge cover and biome class. Eddy covariance measurements of CH₄ from 25 sites was used to optimize model performance during the training. The fluxes were then upscaled using three different wetland maps and compared against previous studies and two process models. There results are comparable to these. The manuscript is well written and explanatory, highlights uncertainties and discuss data in a good way. The product have potential to become valuable to process modellers as a benchmarking product further on, which is also the aim of the study. I have a few thoughts that could be considered before the final report is submitted.

RESPONSE: Thanks, we acknowledge the positive feedback.

1) The most important predictor variable is the nighttime land surface temperature (LSTn). While this is interesting and maybe not completely unexpected I lack the discussion around this. Is there a mechanism behind the nighttime temperature or is it an outcome of the machine learning algorithm? For instance, I would assume that most process based models would use daily temperature as that would be better correlated with ecosystem productivity.

RESPONSE: Most likely it is just an outcome of the machine learning algorithm and the available data. The results using other temperature variables (e.g. daytime land surface temperature (LSTd) or daily mean air temperature (Ta)) as drivers instead of LSTn were almost as good as with LSTn when evaluated against the independent validation data. Possibly with slightly different data set (more sites) other temperature variables (e.g. Ta) might have been more important drivers for the CH₄ flux variability. However, we opted to use LSTn since this variable was selected by the driver selection procedure used in this study (Sect. 3.1).

However, it might also be that LSTn is a better proxy of the temperature controlling the CH₄ production and oxidation processes in the soil (and hence emissions), since it is less affected by the daytime solar heating than LSTd and Ta. Hence it might better reflect the more dampened temperatures deeper in the soil than the more variable LSTd or Ta. However, this is left for future studies to clarify.

CHANGES IN MANUSCRIPT: Shortly mention in Sect. 3.1. that the selection of LSTn as a primary driver instead of e.g. daily mean air temperature was most likely an outcome of the algorithm and data used in this study.

2) In the upscaling process you initially calculate the flux density per grid cell and then use the wetland maps to produce the amount of CH₄ per grid cell. As the maps used contribute highly to the uncertainties in these amounts I would consider to add a map of the flux densities. Such a map could also be used as a benchmark product by bottom-up models.

RESPONSE: Yes, we agree a map of flux densities would be a valuable addition to the published data set. Initially, we did not include such map since it is difficult to judge for which grid cells the flux densities would be included in the published data set. Of course, RF models can be used to calculate CH₄ flux densities for every grid cell on the globe, but are not very informative for grid cells with

zero wetland coverage. Hence we opted to show only maps where flux densities are scaled by wetland coverage to produce the CH₄ emitted per grid cell.

We will add a map of flux densities to the published data set, but limit the data set only to grid cells with significant (>5% grid cell coverage) wetland coverage based on the three wetland maps available.

CHANGES IN MANUSCRIPT: No changes to the manuscript, but we will add wetland CH₄ flux densities to the published data set.

3) The comparison to the process models contains uncertainty both in the wetland map used as pointed out by referee 1, but also in the climate forcing data of the models. This should maybe at least be clarified if a comparison should be made.

RESPONSE: Good point, we will clarify that there are several sources of uncertainty when comparing process models and the upscaled products, one of them being the different climate forcing data used in the models.

CHANGES IN MANUSCRIPT: Add short text on the different sources of uncertainty when the upscaled products are compared against process models (Sect. 3.3).

4) In the introduction the contribution of CH₄ emissions from natural wetland is discussed (page 2, line 30-33). Although it might be implicitly understood, I lack a clarification that these are global estimates.

RESPONSE: Thanks, we will clarify that the first part of the introduction discusses global wetland emissions.

CHANGES IN MANUSCRIPT: Clarify in the Introduction that the emission estimates from Saunois et al. (2016) are global estimates.

Technical corrections: 1) I cannot find where the abbreviation of SC is defined. I assume that it stands for sedge cover?

RESPONSE: SC stands for snow cover flag. We will define the abbreviation in Sect. 2.3.2 where we introduce the used satellite products.

2) Page 14, line 11 th an -> than

RESPONSE: Thanks, will be corrected.

3) Page 14 line 12. Consider not using ... for timespans. Use instead, e.g., years 2008-2011

RESPONSE: Thanks, will be corrected

4) Page 14, line 15, same as 3)

RESPONSE: See our response above.

5) Also why not use subscript for ecosystem respiration Reco -> R_{eco} ?

RESPONSE: Thanks we will change Reco to R_{eco} everywhere in the text.

Monthly Gridded Data Product of Northern Wetland Methane Emissions Based on Upscaling Eddy Covariance Observations

Olli Peltola¹, Timo Vesala^{2,3}, Yao Gao¹, Olle Rättyä⁴, Pavel Alekseychik⁵, Mika Aurela¹, Bogdan Chojnicki⁶, Ankur R. Desai⁷, Albertus J. Dolman⁸, Eugenie S. Euskirchen⁹, Thomas Friborg¹⁰, Mathias Göckede¹¹, Manuel Helbig^{12,13}, Elyn Humphreys¹⁴³, Robert B. Jackson¹⁵⁴, Georg Jocher^{165*}, Fortunat Joos¹⁷⁶, Janina Klatt¹⁸⁷, Sara H. Knox¹⁹⁸, [Natalia Kowalska^{6*}](#), Lars Kutzbach²⁰⁺⁹, Sebastian Lienert¹⁷⁶, Annalea Lohila^{1,2}, Ivan Mammarella², Daniel F. Nadeau²¹⁰, Mats B. Nilsson¹⁶⁵, Walter C. Oechel²²⁺²³², Matthias Peichl¹⁶⁵, Thomas Pypker²⁴³, William Quinton²⁵⁴, Janne Rinne²⁶⁵, Torsten Sachs²⁷⁶, Mateusz Samson⁶, Hans Peter Schmid¹⁸⁷, Oliver Sonnentag¹³²⁷, Christian Wille²⁷⁶, Donatella Zona²²⁺²⁸, Tuula Aalto¹

¹ Climate Research Programme, Finnish Meteorological Institute, P.O. Box 503, 00101 Helsinki, Finland

² Institute for Atmosphere and Earth System Research/Physics, PO Box 68, Faculty of Science, FI-00014, University of Helsinki, Finland

³ Institute for Atmospheric and Earth System Research/Forest Sciences, PO Box 27, Faculty of Agriculture and Forestry, FI-00014, University of Helsinki, Finland

⁴ Meteorological Research, Finnish Meteorological Institute, P.O. Box 503, 00101 Helsinki, Finland

⁵ Natural Resources Institute Finland (LUKE), FI-00790 Helsinki, Finland

⁶ Department of Meteorology, Faculty of Environmental Engineering and Spatial Management, Poznan University of Life Sciences, 60-649 Poznan, Poland

⁷ Department of Atmospheric and Oceanic Sciences, University of Wisconsin-Madison, 1225 W Dayton St, Madison, Wisconsin 53706 USA, 608-265-9201, desai@aos.wisc.edu

⁸ Department of Earth Sciences, Faculty of Sciences, Vrije Universiteit Amsterdam, Boelelaan 1085, 1081 HV Amsterdam, the Netherlands

⁹ University of Alaska Fairbanks, Institute of Arctic Biology, 2140 Koyukuk Dr., Fairbanks, AK 99775

¹⁰ Department of Geosciences and Natural Resource Management, University of Copenhagen, Denmark

¹¹ Max Planck Institute for Biogeochemistry, Jena, Germany

¹² School of Geography and Earth Sciences, McMaster University, Hamilton, ON, Canada

¹³ [Département de géographie, Université de Montréal, Montréal, QC H2V 3W8, Canada](#)

¹⁴³ Department of Geography & Environmental Studies, Carleton University, Ottawa, ON, Canada

¹⁵⁴ Department of Earth System Science, Woods Institute for the Environment, and Precourt Institute for Energy, Stanford University, Stanford, CA 94305, USA

¹⁶⁵ Department of Forest Ecology and Management, Swedish University of Agricultural Sciences, Umeå, Sweden

¹⁷⁶ Climate and Environmental Physics, Physics Institute and Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland

¹⁸⁷ Institute of Meteorology and Climatology – Atmospheric Environmental Research (IMK-IFU), Karlsruhe Institute of Technology (KIT), Kreuzeckbahnstrasse 19, 82467 Garmisch-Partenkirchen, Germany

¹⁹⁸ Department of Geography, The University of British Columbia, Vancouver, Canada

²⁰⁺⁹ Institute of Soil Science, Center for Earth System Research and Sustainability, Universität Hamburg, Hamburg 20146, Germany

²¹⁰ Department of Civil and Water Engineering, Université Laval, Quebec City, Canada

²²⁺²³² Global Change Research Group, Dept. Biology, San Diego State University, San Diego, CA 92182, USA

²³² Department of Geography, College of Life and Environmental Sciences, University of Exeter, Exeter, EX4 4RJ, UK

²⁴³ Department of Natural Resource Sciences, Thompson Rivers University, Kamloops, BC, Canada

²⁵⁴ Cold Regions Research Centre, Wilfrid Laurier University, Waterloo, ON, Canada

²⁶⁵ Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden

²⁷⁶ GFZ German Research Centre for Geosciences, Potsdam, Germany

²⁷ ~~Département de géographie, Université de Montréal, Montréal, QC H2V 3W8, Canada~~

²⁸ Department of Animal and Plant Sciences, University of Sheffield, Western Bank, Sheffield, S10 2TN, United Kingdom

*~~Georg Joehner~~ now at: Department of Matter and Energy Fluxes, Global Change Research Institute, Czech Academy of Sciences, Bělidla 986/4a, 603 00 Brno, the Czech Republic

Correspondence to: Olli Peltola (olli.peltola@fmi.fi)

Abstract. Natural wetlands constitute the largest and most uncertain source of methane (CH₄) to the atmosphere, and a large fraction of them are found in the northern latitudes. These emissions are typically estimated using process ('bottom-up') or inversion ('top-down') models. However, estimates from these two types of models, yet the two are not independent of each other since usually the top-down estimates rely on the a priori estimation of these emissions obtained with coming from the process models. Hence, independent, spatially-explicit validation data is needed. validation data of the large-scale emissions are would be needed.

Here we utilize a random forest (RF) machine learning technique to upscale CH₄ eddy covariance flux measurements from 25 sites to estimate CH₄ wetland emissions from the northern latitudes (north of 45 °N). Eddy Covariance data from 2005 - 2016 are used for model development. The model is then used to predict emissions during 2013 and 2014, during years 2013 and 2014. The predictive performance of the RF model is evaluated using the leave-one-site-out cross-validation scheme. T and the performance (Nash-Sutcliffe model efficiency = 0.47) is comparable to previous studies upscaling net ecosystem exchange of carbon dioxide and studies comparing where process model outputs are compared against site-level CH₄ emission data. The global distribution of wetlands is one major source of uncertainty for upscaling CH₄. Thus t Three wetland distribution maps are utilized in the upscaling, and Depending on the wetland distribution map, t the annual emissions for the northern wetlands yield 31.72 (22.3-41.2, 95 % confidence interval calculated from a RF model ensemble), 30.61 (21.4-39.9) or 37.68 (25.9-49.5) Tg(CH₄) yr⁻¹, depending on the map used. To further evaluate the uncertainties of the upscaled CH₄ flux data products it is we also compared them against output from two process models (LPX-Bern and WetCHARTs) and methodological issues related to CH₄ flux upscaling are discussed. The monthly upscaled CH₄ flux data products is are available for further usage at: <https://doi.org/10.5281/zenodo.2560163> <https://doi.org/10.5281/zenodo.2560164>.

1 Introduction

Methane (CH₄) is the second most important anthropogenic greenhouse gas in terms of radiative forcing after carbon dioxide (CO₂): 34 times (GWP₁₀₀, including climate-carbon feedbacks) as strong as CO₂ according to IPCC (Ciais et al., 2013). CH₄ and has contributed ~20% to of the cumulative GHG related global warming (Etminan et al. 2016). Deriving constraints on CH₄ its sources and sinks is thus of utmost importance. The net atmospheric CH₄ budget is well constrained by precise CH₄ mole fraction measurements around the globe, yet the contribution of individual sources and sinks to this aggregated budget

remains poorly understood. ~~This is~~ primarily due to lack of data to constraint the modelling results (Saunois et al., 2016). In order to make more accurate predictions of the atmospheric CH₄ budget in a changing climate, the response of the various sources and sinks to different drivers needs to be better identified and quantified.

Natural wetlands are the largest and quantitatively most uncertain source of CH₄ to the atmosphere (Saunois et al., 2016). An ensemble of land surface models estimated global CH₄ emissions from wetlands for the period 2003-2012 to be 185 Tg(CH₄) yr⁻¹ (range 153-227 Tg(CH₄) yr⁻¹) and for the same period inversion models estimated it to be 167 Tg-(CH₄) yr⁻¹ (range 127-202 Tg(CH₄) yr⁻¹) (Saunois et al., 2016). This discrepancy between bottom-up (process models) and top-down (inversion models) estimates, as well as the range of variability, exemplifies the large uncertainty of the current estimate for natural wetland CH₄ emissions. Sources of this uncertainty can be roughly divided into two categories: 1) uncertainty related to the global areal extent of wetlands (e.g. Petrescu et al 2010. Bloom et al., 2017a; Zhang et al., 2016) and 2) uncertainties related to the key CH₄ emission drivers and responses to these drivers (e.g. Bloom et al., 2017a; Saunois et al., 2017). Evaluation of the emission estimates is thus urgently needed, and ~~the results~~ from these efforts will lead to refined feed-on-improvements in process models. Process model improvements will also directly affect the uncertainty of inversion results since they provide important a priori information to the inversion models (Bergamaschi et al., 2013).

Boreal and arctic wetlands comprise up to 50 % of the total global wetland area (e.g. Lehner and Döll, 2004) and ~~these wetlands~~ in these northern latitudes make a substantially contribution to total terrestrial wetland CH₄ emissions (ca. 27 %, based on the sum of regional budgets for bBoreal North America, Europe and Russia in Saunois et al., 2016). In wetlands, CH₄ is produced by methanogenic Archaea under anaerobic conditions and hence the production takes place predominantly under water saturated conditions (e.g. Whalen, 2005). The microbial activity and the resulting CH₄ production is thus controlled by quality and quantity of the available substrates, competing electron acceptors and temperature (Le Mer and Roger, 2001). Once produced, the CH₄ can be emitted to the atmosphere via three pathways: ebullition, molecular diffusion through soil matrix and water column, or plant transport. If plants capable of transporting CH₄ are present, plant transport is generally the dominating emission pathway ~~largest of the three~~ (Knoblauch et al., 2015; Kwon et al., 2017; Waddington et al., 1996; Whiting and Chanton, 1992). A ~~Importantly, a~~ large fraction of CH₄ transported via molecular diffusion is oxidized into CO₂ by methanotrophic bacteria in the aerobic layers of wetland soils and hence never reaches the atmosphere (Sundh et al., 1995), whereas CH₄ transported via ebullition and plant transport can largely bypass oxidation (Le Mer and Roger, 2001; McEwing et al., 2015). Furthermore, processes related to permafrost dynamics (e.g. active layer thaw, thermokarst ~~processes~~) and snow cover dynamics (e.g., snow melt, insulation) have an impact on CH₄ flux seasonality and variability ~~in general~~ (Friborg et al., 1997; Helbig et al., 2017; Mastepanov et al., 2008; Zona et al., 2016; Zhao et al 2016). Hence wetland CH₄ emissions to the atmosphere largely depend on ~~are largely controlled by the a subtle~~ interplay between various controls including water table position, temperature, vegetation composition, methane consumption, availability of substrates and competing electron acceptors.

During the past two decades, eddy covariance (EC) measurements of wetland CH₄ emissions have become more common, due to rapid development in sensor technology (e.g. Detto et al., 2011; Peltola et al., 2013, 2014). The latest generation of low-power and -maintenance instruments are rugged enough for long-term field deployment ~~and can function without grid power~~ (Nemitz et al., 2018; McDermitt et al., 2010), ~~thus the increasing the~~ number of sites where CH₄ flux measurements ~~have been made is increasing can be collected~~. Due to this progress, EC CH₄ flux synthesis studies ~~have been~~ are now emerging (Petrescu et al., 2015; Knox et al., in review). Similar progress was made with CO₂ and energy flux measurements in the 1990s and now these measurements form the backbone of the global EC measurement network FLUXNET (<https://fluxnet.fluxdata.org/>), whose data has provided invaluable insights into terrestrial carbon and water cycles. Some of the most important results have been obtained by upscaling FLUXNET observations using machine learning algorithms to evaluate terrestrial carbon balance components and evapotranspiration (Beer et al., 2010; Bodesheim et al., 2018; Jung et al., 2010, 2011, 2017; Mahecha et al., 2010). These results are now widely used by the modelling community to evaluate process model performance (e.g. Wu et al., 2017) and to validate satellite-derived carbon cycle data products (e.g. Sun et al., 2017; Zhang et al., 2017a).

In this study, we synthesized EC CH₄ flux data from 25 EC CH₄ flux sites and developed an observation-based monthly gridded data product of northern wetland CH₄ emissions. We focus on northern wetlands (north of 45 °N) due to their significance in the global CH₄ budget and relatively good data coverage and process understanding, at least compared to tropical systems (Knox et al., in review). ~~The Arctic is~~ High latitude regions are projected to warm during the next century at a faster rate than any other region, which will likely significantly impact the carbon cycling of wetland ecosystems (Tarnocai, 2009; Zhang et al., 2017b) and permafrost areas of the Arctic-Boreal Region (Schuur et al., 2015). To date, CH₄ emission estimates for northern wetlands are typically based on process models (Bohn et al., 2015; Bloom et al., 2017a; Chen et al., 2015; Melton et al., 2013; Stocker et al., 2013; Wania et al., 2010; Watts et al., 2014; Zhang et al., 2016) or inversion modelling (Bohn et al., 2015; Bruhwiler et al., 2014; Spahni et al., 2011; Thompson et al., 2017; Thonat et al., 2017; Warwick et al., 2016), yet scaling of existing chamber measurements to the northern wetland area has also been published (Zhu et al., 2013). However, CH₄ emission estimates obtained with the former ~~the first~~ two approaches are not ~~completely~~ independent since the attribution of CH₄ emissions derived using inversion models to different emission sources (e.g. wetlands) depends largely on ~~the~~ a priori estimates of these emissions (i.e. process models for wetland emissions), highlighting the tight coupling between these two approaches (Bergamaschi et al., 2013, Spahni et al., 2011). Hence, the main objective of this study is to produce an independent data-driven estimate of northern wetland CH₄ emissions. This product could be used as an additional constraint for the wetland emissions and hence aid in process model refinement and development. Additionally, the drivers causing CH₄ flux variability at the ecosystem scale are also evaluated and methodological issues are discussed which will support future CH₄ wetland flux upscaling studies.

2 Materials and Methods

Data from flux measurement sites (Fig. 1) were acquired and used together with forcing data to estimate CH₄ emissions from northern wetlands with monthly time resolution using a random forest (RF) modelling approach. Both in-situ measurements and remote sensing are utilized in this study. In this section, the RF approach is briefly introduced (Sect. 2.1) and data selection, quality filtering, gap filling and aggregation to monthly values are described (Sect. 2.3). ~~We identified~~After this procedure, 40.7 site-years ~~were~~ available for ~~the~~ analysis, measured between years 2005 and 2016. To perform upscaling to all wetlands north of 45 °N, gridded data products of the flux drivers ~~and were needed, as well as~~ wetland distribution maps were needed. These products are presented in Sect. 2.4 and 2.5, respectively. Finally, the upscaled wetland CH₄ emissions are compared against process model outputs, with the models briefly described in Sect. 2.6.

Here, wetlands are defined as terrestrial ecosystems with water table positions near the land surface and with plants that have adapted to these water-logged conditions. We exclude lakes, reservoirs and rivers from the study, in addition to ecosystems with significant human influence (e.g. drainage, rewetting). We consider peat forming wetlands (i.e. mires), which can be further classified as fens and bogs based on hydrology, as well as wetlands with hydric mineral soils. Tundra wetlands may have only a shallow peat layer, or none at all. Unified classifications for wetlands are still lacking, and typically different countries follow their own classification scheme, albeit some joint classification schema have been developed (e.g. Ramsar Classification System for Wetland Type).

2.1 Random forest algorithm

Random forest (RF) is a machine-learning algorithm that can be used for classification or regression analyses (Breiman, 2001). ~~and I~~ in this study the RF models consists of a large ensemble of regression trees. Each individual regression tree is built by training it with a random subset of training data and the trees are trained independently of each other. The RF model output is then the average of all the predictions made by individual regression trees in the forest. Hence the RF algorithm applies the bootstrap aggregation (bagging) algorithm and takes full advantage of the fact that ensemble averaging decreases the noise of the prediction. In addition to random selection of training data, the predictor variables used in split nodes are also selected from a random sample of all predictors which minimizes the possible correlation between trees in the forest (Breiman, 2001) and decreases the possibility of overfitting. The predictor variables can be either categorical or continuous. The variables are then used in the split nodes to divide the data into two (e.g. categorical variable true or false or continuous variable such as e.g. temperature above or below 5 °C).

Performance of RF algorithms to predict CO₂ and energy fluxes across FLUXNET sites ~~were~~have been compared against other machine-learning algorithms such as artificial neural networks and multivariate regression splines by Tramontana et al. (2016) who showed that differences between methods were negligible. We anticipate a similarly negligible effect of machine-learning algorithm choice for CH₄ fluxes. ~~These results are also likely to apply for CH₄ fluxes.~~ For a thorough description of the RF algorithm for flux upscaling purposes, the reader is referred to Bodesheim et al. (2018) (and references therein).

In this study, the RF models were developed using the MATLAB 9.4.0 (R2018a) TreeBagger function with default values similarly to Bodesheim et al. (2018). These settings included a minimum of five samples in a leaf node and used mean squared error (MSE) as a metric for deciding the split criterion in split nodes. Each trained forest consisted of 300 randomized regressions trees.

2.1.1 RF model development for CH₄ flux gapfilling

Our RF algorithm was used for gapfilling the daily CH₄ flux time series ~~at a daily time step, T~~ and the performance of the RF model was evaluated against ~~so-called~~ 'out-of-bag' (OOB) data (approximately 1/3 of data for each tree). Since each individual tree in the RF model was trained using a subset of training data, the rest of the data (i.e. OOB data) can be used as independent validation data to evaluate the prediction performance of that particular regression tree and hence the whole forest (Breiman, 2001). Only the five most important predictors were retained for the gapfilling models for each site. The relative importance of predictors (e.g. air temperature ~~and the others~~) was evaluated by randomly shuffling the predictor data and then estimating the increase in ~~mean squared error (MSE)~~ when model output is compared against OOB data (Breiman, 2001). For important predictors, MSE will increase significantly due to shuffling, whereas the effect of shuffling on MSE is minor for the less important predictors ~~on MSE is minor~~. Note that this procedure was executed separately for each site and thus different predictors may have been used for different sites for gapfilling.

2.1.2 RF model development for CH₄ flux upscaling

For upscaling purposes, one RF model was developed using all the available data in order to maximize the information content ~~derived from the available data~~ for the upscaled global (>45 °N) CH₄ flux map. The model performance or uncertainty, however, was evaluated using two approaches: by using the data in two ways. 1) The predictive performance of the model was assessed using the widely used 'leave-one-site-out' cross-validation scheme (e.g. Jung et al., 2011). In order to avoid correlation between training data and validation data, sites ~~were excluded from the training data when a site~~ located nearby (closer than 100 km) ~~was used as a validation site~~ were excluded from the training data (Roberts et al., 2016). 2) ~~T~~In turn, the uncertainty of the upscaled fluxes was estimated by bootstrapping. 200 independent RF models were trained using a bootstrap sample of the available data. This yielded 200 predictions for each pixelgrid cell and time step in the upscaled CH₄ flux map. ~~T~~and the variability over this prediction ensemble was used as an uncertainty measure following. ~~This follows the methodology used~~ e.g. by Aalto et al. (2018) and Zhu et al. (2013). ~~One should note that~~ this uncertainty estimate reflects the ability of the RF model to capture the dependence of CH₄ flux on the used predictors in the available data. H, however, it does not have any reference to actual in-situ CH₄ fluxes unlike the model predictive performance estimated with cross-validation. Predictors for the RF model used in the upscaling were determined following Moffat et al. (2010). First, the RF models were trained for each site using one predictor at a time (see all the predictors in Table 1). The single predictor which yielded the best match against validation data (leave-one-site-out scheme) was selected as the primary driver. Then, the RF models were trained again with the primary driver plus each of the other predictors in turn as secondary drivers. Then the RF model

performance was again evaluated, and the best predictor pair selected for the next round. This procedure was continued until all the predictors were included in the RF model. The smallest set of predictors capable of producing adequate-optimal RF model performance was used for flux upscaling.

2.2 Metrics for model performance evaluation

The RF model performance was evaluated against independent validation data using a set of statistical metrics, which were related to different aspects of model performance. During the RF model training ~~the mean-squared-error~~ (MSE) was optimized:

$$MSE = \overline{(o - p)^2}, \quad (1)$$

where o and p are vectors containing the observed and predicted values, respectively, and the overbar denotes averaging.

The Nash-Sutcliffe model efficiency (NSE; Nash and Sutcliffe, 1970) ~~(NSE) can be~~ was used to evaluate how well the model was able to predict validation data when compared against a reference (typically the mean of the validation data):

$$NSE = 1 - \frac{\sum_{i=1}^n (o_i - p_i)^2}{\sum_{i=1}^n (o_i - \bar{o})^2}, \quad (2)$$

where i is index running over all the n values in the o and p vectors. When NSE is equal to 1, there is a perfect match between prediction and observations. Values above 0 imply that the model predicts the observations better than the mean of observations and values below 0 indicate that the predictive capacity of the model is worse than the mean of validation data. Note that NSE calculated with Eq. (2) above is equivalent to the coefficient of determination calculated using residual sum of squares and total sum of squares. However, following the approach used in previous upscaling studies (e.g. Bodesheim et al., 2018; Tramontana et al., 2016), we opted to call this metric NSE. Instead, the coefficient of determination (R^2) was estimated as the squared Pearson correlation coefficient. Note that R^2 and NSE are equal when there is no bias between o and p and the residuals follow Gaussian distribution. ~~In the Results section~~ Pearson correlation coefficients obtained with different model runs are compared using Fisher's r to z transformation.

The standard deviation (σ) of the model residuals was used to evaluate the spread of model residual values (RE):

$$RE = \sigma(o - p), \quad (3)$$

whereas bias between model predictions and validation data were used to estimate the systematic uncertainty in the upscaled fluxes (BE):

$$BE = \bar{o} - \bar{p}. \quad (4)$$

Note that RE equals RMSE when there is no systematic difference between the model predictions and observations (i.e. when BE equals zero).

2.3 Data

2.3.1 Data from eddy covariance flux measurement sites

Data were acquired from 25 sites that 1) measure CH_4 fluxes with the EC technique, 2) are located north of 45 °N and 3) are wetlands as defined above and without substantial human influence on ecosystem functioning (see the site locations in Fig. 1

and the site list in Appendix A). The sites were evenly distributed among wetland types: fens (~~n=9 sites~~), bogs (7) and wet tundra (9) ~~ecosystems across as well as biomes~~: tundra (11), boreal (8) and temperate (6) ~~biomes~~, as defined in Olson et al., (2001). At 15 of the 25 sites, sedges (e.g., *Rhynchospora alba*, *Eriophorum vaginatum*, *Carex limosa*) were the dominant vascular plant functional type in the flux measurement source area. Most of the sites (18 out of 25) were located north of 60 °N and the highest density of sites were in Fennoscandia and Alaska (Fig. 1). The magnitude of monthly CH₄ flux data varied between sites and the median time series length was 14.5 months of CH₄ flux data per site. Overall, the dataset spanned between years 2005 and 2016. The sites represent northern wetlands sufficiently well to create an first upscaled CH₄ flux product based on EC data. ~~S In the Results section,~~ sites are referred to with their FLUXNET IDs and if not available, new temporary site IDs were generated for ~~the usage in~~ this study (see Appendix A).

Site PIs provided CH₄ fluxes and their potential drivers (air temperature and pressure, precipitation, wind speed and direction, friction velocity, net ecosystem exchange of CO₂ and its components (canopy photosynthesis and ecosystem respiration), photosynthetically active radiation, water table depth, soil temperature) ~~and a description of each site~~. However, out of the in-situ measurements only air temperature and precipitation were used for developing the RF model for flux upscaling since gridded data products of the other potentially important drivers were not readily available and/or the data for the other drivers were missing from several sites.

Thirty-minute-averaged flux data were acquired from 21 sites and daily data were provided for four sites. The flux time series were quality filtered by removing fluxes with the worst quality flag (based on 0,1,2-~~flagging~~ scheme, Mauder et al., 2013) and ~~with when~~ friction velocity below a filtered using site-specific threshold ~~(if it was typically done at the flux site and~~ friction velocity and threshold data were available for the site). After filtering, daily medians were calculated if the daily data coverage was above 29 out of 48 half-hourly data points (daily data coverage at minimum 10 data points for sites without diel pattern in CH₄ flux) and no gap-filling was done to the time series prior to calculation of daily values. While this may cause slight systematic bias in the daily flux values, this bias is unlikely to be significant because the magnitude of diel patterns in CH₄ fluxes is typically moderate (e.g. Long et al., 2010) or negligible (e.g. Rinne et al., 2018), although at sites with *Phragmites* cover a relatively strong diurnal cycle can be observed (e.g. Kim et al., 1999; Kowalska et al., 2013).

Unlike the CH₄ flux data, the other in-situ data from the sites were gap-filled prior to the calculation of daily values. The gapfilling was done only if the daily data coverage was above 60 % ~~and F~~ for the days with lower data coverage, no daily values ~~were not~~ calculated. Shorter gaps (<2 hours) were filled with linear interpolation, whereas longer gaps (between 2 to 14.5 hours) were replaced with mean diurnal variation within a 30-day moving window. However, for precipitation, daily sums were calculated without any gapfilling. Besides the measurements at the sites, potential solar radiation (R_{pot}) and its time derivative ($der(R_{pot})$) were calculated based on latitude and time of measurement. In order to remove the R_{pot} latitudinal dependence it was normalized to be between 0 and 1 before usage.

CH₄ flux drivers measured in-situ, in addition to the remote sensing data (Sect. 2.3.2), were used for the gapfilling of CH₄ time series with the RF algorithm (Sect. 2.1.1). For each site the gapfilling models generally agreed well with the independent

validation data (mean NSE=0.74 and mean RMSE = 9 nmol m⁻² s⁻¹). After gapfilling, the CH₄ flux time series were aggregated to monthly values if the monthly data coverage prior to gapfilling was at least 20 %.

The daily time series of air temperature and precipitation measured at the sites were gapfilled using the ~~WFDEI~~ (WATCH Forcing Data methodology applied to ERA-Interim (~~WFDEI-data~~) data (Weedon et al., 2014). Prior to using the WFDEI data for gapfilling, the data were bias corrected for each site as is typically done for climate or weather reanalysis data (e.g. Räisänen & Rätty, 2013; Rätty et al., 2014). For precipitation, the mean of WFDEI data were simply adjusted to match site mean precipitation. For air temperature the bias correction was done for each month separately using quantile mapping with smoothing within a moving seven-month window. Quantile mapping compares the cumulative distribution functions (CDFs) of WFDEI and site measurements against each other and adjusts the WFDEI data so that after adjustment its CDF matches with the CDF of the site measurements (~~See more details about the bias correction procedures e.g. in~~ Räisänen & Rätty, 2013). After gapfilling the daily time series with WFDEI data, monthly and annual precipitation were calculated, in addition to monthly mean air temperature.

2.3.2 Remote sensing data

~~Several~~ Data products from the Moderate Resolution Imaging Spectrometer (MODIS) were used in this study to derive various driving variables. For RF model development the following data products at 500 m or 1000 m spatial resolution were used: MOD10A1 snow cover (Hall and Rigs, 2016), MOD11A2 daytime and night-time land surface temperature (LSTd and LSTn, Wan et al., 2015), MOD13A3 enhanced vegetation index (EVI, Didan, 2015) and MOD09A1 surface reflectance (Vermote, 2015). More elaborate data ~~satellite~~ products estimating ecosystem gross primary productivity (GPP) and net primary productivity (NPP; MOD17) were not included here for two reasons: 1) many of the sites included here were misclassified in the land cover map used in MOD17 (e.g. as woody savanna), hence severely influencing the estimated GPP and NPP (Zhao et al., 2005), and 2) sites that were correctly classified as permanent wetlands were in fact assigned a fill value and removed from the product since the product is not strictly valid for these areas (Lees et al., 2018). All the remote sensing data products were quality filtered using the quality flags provided along with the data.

The MODIS snow cover ranged from 0 (no snow) to 100 (full snow cover) and was converted to a simple snow cover flag (SC) consisting of 0 and 1 depending whether the snow cover data were below or above 50, respectively. A vector containing days since snow melt (DSSM) was calculated using the snow cover flag and normalized to 0 (beginning) and 1 (end) for each growing season (Mastepanov et al., 2013). The MOD09A1 surface reflectance at bands 2 (841-876 nm) and 5 (1230-1250 nm) were used to calculate the simple ratio water index (SRWI=band 2/band 5) following Zarco-Tejada & Ustin (2001). SRWI showed spurious values when there was snow cover and hence these points were replaced with the mean SRWI observed at each site when there was no snow. Meingast et al. (2014) showed that SRWI can be used as a proxy for wetland water table depth, although their results were affected by changes in vegetation cover, which might hinder across-site comparability in this study. Additionally, following the temperature and greenness modelling approach (Sims et al., 2008), a product of EVI and LSTd was included in the analysis as a proxy for gross primary productivity (GPP), following a previous peatland study

(Schubert et al., 2010). The remote sensing data were provided with daily (MOD10A1), 8-day (MOD09A1, MOD11A2) or monthly (MOD13A3) time resolution and the data were aggregated to monthly means prior to usage.

2.3.3 Additional categorical variables

The sites were also classified based on the presence of permafrost in the source area (present or absent) and according to biome type. Biome types (temperate, boreal, tundra) were determined from Olson et al. (2001) and the information about the permafrost was provided by the site PIs. Furthermore, the data were categorized based on wetland type and sedge cover as in Treat et al. (2018) and Turetsky et al. (2014). However, such information is not available in the gridded format needed for upscaling, nevertheless inclusion of these variables can be used to assess how much they increase the predictive performance of the model. ~~Biome types (temperate, boreal, tundra) were determined from Olson et al. (2001).~~

2.4 Gridded data sets used in flux upscaling

For upscaling CH₄ fluxes using the developed RF model, the LST data were acquired from the aggregated product MOD11C3 (Wan et al., 2015), and snow cover data from MOD10CM (Hall and Riggs, 2018). Distribution of permafrost in the northern latitudes were estimated using the circum-Arctic map of permafrost derived by National Snow and Ice Data Center (Brown et al., 2002). The resolution of the gridded data was adjusted to match the resolution of the wetland maps using bilinear interpolation if needed. Additionally, land and ocean masks (Jet Propulsion Laboratory, 2013) were utilized when processing the gridded data sets.

2.5 Wetland maps

Upscaled fluxes were initially estimated in flux densities per wetland area, that is (amount of CH₄) per (area of wetland) per (unit of time). To create a gridded product of CH₄ emissions from the northern wetlands, these upscaled flux densities were converted into (amount of CH₄) per (grid cell area) per (unit of time) using different wetland maps. Wetland mapping is an ongoing field of research and the usage of different wetland maps contributes to the uncertainty of global wetland CH₄ emission estimates (e.g. Bloom et al., 2017a; Zhang et al., 2017b). Hence, three different wetland maps (PEATMAP, DYPTOP and GLWD) were used in this study to evaluate how much they affect the overall estimates of northern high latitude wetland CH₄ emissions.

The recently developed static wetland map PEATMAP (Xu et al., 2018) combines detailed geospatial information from various sources to produce a global map of wetland extent. ~~Here Within the presented study,~~ the polygons in PEATMAP were converted to fractions of wetland in 0.5° grid cells. While PEATMAP is focused on mapping peatlands, marshes and swamps (typically on mineral soil) are included in the product for certain areas in the northern latitudes. However, most of the wetlands in the northern latitudes are peatlands and thus PEATMAP is suitable for our upscaling purposes. The dynamic wetland map estimated by the DYPTOP model (Stocker et al., 2014) was used by aggregating peat and inundated areas to form one dynamic wetland map with 1° resolution. The widely used Global Lakes and Wetlands Database (GLWD, Lehner and Döll, 2004) is a

static wetland map with 30 arc second resolution and ~~since it has been widely used was used in this study here it provided as~~ a point of reference for the other two maps. The map was aggregated to 0.5° resolution and lakes, reservoirs and rivers were excluded from the aggregated map.

2.6 Process models

The upscaled CH₄ fluxes were compared against ~~the output from~~ two process models: LPX-Bern (Spahni et al., 2013; Stocker et al., 2013; Zürcher et al., 2013) and the model ensemble WetCHARTs version 1.0 (Bloom et al., 2017a, 2017b). LPX-Bern is a dynamic global vegetation model which models carbon and nitrogen cycling in terrestrial ecosystems. The model has a separate peatland module with peatland-specific plant functional types (see more details in Spahni et al., 2013). The wetland extent in LPX-Bern was dynamically estimated using the DYPTOP approach with 1° resolution (Stocker et al., 2014). WetCHARTs combines several prescribed wetland maps with different gridded products for heterotrophic respiration and temperature sensitivity (Q_{10})-parameterizations for CH₄ production to form a model ensemble of wetland CH₄ emissions (Bloom et al., 2017b). Here we used the extended ensemble of WetCHARTs.

3 Results

3.1 Selecting the predictors for the RF model

The predictors in Table 1 were selected one-by-one using the procedure described in Sect. 2.1.2. The order in which the predictors were selected is shown in Fig. 2. LSTn alone gave NSE=0.29. After including the category ~~permafrost presence/absence or absence of permafrost~~, R_{pot} , SC and biome class increased NSE to 0.47. ~~However, albeit~~ the influence of SC and biome class on the model performance was marginal ~~based on the small increase in NSE~~. Additional predictors did not increase the model performance further because 1) they were strongly correlated with a predictor already included in the model (e.g. T_{air} is correlated with LSTn) ~~and hence they did not add any new information to the system~~, or 2) the predictors did not contain any information about CH₄ flux variability. The model response to ~~other~~ predictors ~~other~~ than biome category was physically reasonable (e.g. permafrost and snow cover decrease fluxes, close to exponential dependence on LSTn), whereas the response to biome category was contrary to expectations. The RF model estimated the CH₄ flux magnitude from the different biomes to be in the order tundra<temperate<boreal, whereas in prior studies it has been shown to be in the order tundra<boreal<temperate (Knox et al., in review; Treat et al., 2018; Turetsky et al., 2014). This discrepancy may be due to the limited number of measurement sites and related sampling bias problems. Hence in order not to upscale an incorrect pattern of decreasing CH₄ emissions when moving from boreal to temperate regions, the biome class was omitted from upscaling. In the subsequent analysis and flux upscaling only the four first predictors (LSTn, permafrost category, R_{pot} and SC) are utilized. We further tested whether information about wetland type or sedge cover would improve the model performance ~~even though, although~~ these ~~categorical~~ variables were not available in gridded format and hence were not usable for upscaling. Including the sedge flag increased the NSE to 0.53, although the increase in Pearson correlation was not statistically significant ($p>0.05$,

comparison of correlation coefficients using Fisher's r to z transformation). Also, wetland type did not have a statistically significant influence on the model performance ($p > 0.05$ and $NSE = 0.49$ if type included). Using too many categorical variables in a RF model may be problematic because each site may end up with a unique combination of categorical variables.

The most important predictor for the model was temperature, similar to numerous studies showing that wetland CH_4 emissions are strongly correlated to soil temperature (Christensen et al., 2003; Helbig et al., 2017; Jackowicz-Korczyński et al., 2010; Rinne et al., 2018; Yvon-Durocher et al., 2014; Knox et al., in review). Selection of LSTn as the primary driver instead of the other temperature variables was likely an outcome of the available data and the used algorithm to select the drivers. With slightly different data set (more sites) other temperature variables (e.g. T_{air}) might have been more important drivers for the CH_4 flux variability. Estimating apparent Q_{10} from the RF model LSTn dependence yielded a value of 1.90 ± 0.03 and for validation data it was slightly higher (1.97 ± 0.06) (Fig. 3). These values are comparable to the ones reported in Turetsky et al. (2014) for CH_4 chamber measurements at bog and fen sites. The temperature dependence of CH_4 production is modelled in many process models with the parameter Q_{10} value close to 2 (Xu et al., 2016b), which agrees with the CH_4 emission temperature dependence shown here. However, one should note that also CH_4 oxidation depends on temperature and the derived apparent Q_{10} value describes the temperature dependence of surface CH_4 emission, which is always a combination of CH_4 production and oxidation.

3.2 Model agreement with validation data

The overall systematic bias (BE) between the RF predictions and validation data was negligible (Fig. 4), whereas the spread of the data (RE) was more pronounced (Fig. 4). RE is evident in Fig. 4 also as significant scatter around the 1:1 line. Following Moffat et al. (2010), RE was analysed further by binning the data based on CH_4 flux magnitude and calculating RE for each bin. RE clearly correlated with flux magnitude ($RE = (0.52 \pm 0.06)FCH_4 + (3.3 \pm 2.0) \text{ nmol m}^{-2} \text{ s}^{-1}$, where FCH_4 denotes CH_4 flux) indicating that the relative random error of the RF model prediction was nearly constant and approximately 50 % for high fluxes. The systematic error BE did not show a clear dependence on flux magnitude. The RF model performance was worse on site mean level than with monthly data. When comparing site means, NSE and R^2 were both 0.25 and RE and BE were $27.0 \text{ nmol m}^{-2} \text{ s}^{-1}$ and $1.5 \text{ nmol m}^{-2} \text{ s}^{-1}$, respectively. Possible drivers causing the remaining CH_4 flux variability not captured by the RF model (i.e. the scatter in Fig. 4) are discussed in Sect. 4.2.1.

When considering the model performance for each site separately, the agreement shows different characteristics (see Fig. 5 for four examples). For individual sites the magnitude of BE is typically somewhat higher (median of absolute value of BE approximately $11 \text{ nmol m}^{-2} \text{ s}^{-1}$), whereas RE is lower than for the overall agreement (median RE approximately $10 \text{ nmol m}^{-2} \text{ s}^{-1}$). These results indicate that the upscaled CH_4 fluxes have in general relatively low bias and high random error, whereas individual pixels in the upscaled CH_4 map may have higher bias, but lower random error.

The mean annual cycle of CH_4 emission predicted by the RF model agrees well with the mean annual cycle calculated from the validation data (not shown). During the nongrowing season the RF model slightly overestimates the fluxes (15 % overestimation) but such differences were negligible. Difference between, but during rest of the year the differences are

negligible (<1 %). However, for individual sites ~~CH₄ emission seasonality~~ the agrees ~~less~~ ~~ment is not as good~~. For instance, at US-Los (~~located in Wisconsin, US~~) the modelled CH₄ emissions start to increase one month ~~earlier too early~~ in the spring (Fig. 5b). ~~T~~and the nongrowing season fluxes are overestimated at ~~all~~ four example sites (FI-Sii, US-Los, US-Atq and RU-Ch2; Fig. 5). ~~T~~Out of the example sites, the mean flux magnitude is modelled well at FI-Sii (Fig. 5a), whereas at US-Los (Fig. 5b) and US-Atq (Fig. 5c) the RF model overestimates and at RU-Ch2 (Fig. 5d) underestimates the CH₄ emissions. The flux bias had a relatively large impact on site-specific NSE. For example, for US-Atq NSE was -1.85, meaning that the ~~mean of~~ observation ~~means~~ would be a better predictor for this site than the RF model (see the NSE definition in Sect. 2.2). The RF model is not able to replicate the ~~between-year differences~~ ~~interannual variability~~ in CH₄ emissions at the example sites. ~~Capturing and explaining the~~ interannual variability has been difficult also in previous upscaling studies of CO₂ and energy fluxes (e.g. Tramontana et al., 2016).

In general, the RF model performance was better for ~~permafrost-free~~ sites ~~without~~ than ~~for sites~~ with permafrost ($r = 0.66$ and $r = 0.51$, respectively; $p < 0.05$), which is likely related to the fact that at sites with permafrost the MODIS LSTn is not as directly related to the soil temperature than at sites without permafrost. Hence, LSTn is not as good proxy for the temperature which is controlling both CH₄ production and consumption and this results in a worse performance than at sites without permafrost.

3.3 Upscaled CH₄ fluxes

The RF model ~~developed in this study~~ was used together with the gridded input datasets (Sect. 2.4) and wetland ~~distribution~~ maps (Sect. 2.5) to estimate CH₄ emissions from northern wetlands ~~induring years~~ 2013 and 2014. The mean CH₄ emissions of the two years from the RF model are plotted in Fig. 6 together with CH₄ wetland emission maps from ~~the~~ process model LPX-Bern and model ensemble WetCHARTs. Differences between the process model estimations and upscaled fluxes are shown in Fig. 7. In general, the spatial patterns ~~are similar among~~ ~~look similar in all~~ emission maps, which is ~~not surprising given that understandable since~~ the spatial variability is largely controlled by the underlying wetland distributions. One noteworthy difference is that WetCHARTs, RF-PEATMAP (i.e. RF modelling with PEATMAP) and RF-GLWD show higher emissions from western Canada than LPX-Bern or the upscaled fluxes using the wetland map from that process model (RF-DYPTOP). The other difference is ~~that~~ RF-GLWD show negligible emissions from Fennoscandia (Fig. 6c). These differences are related to differences in the underlying wetland maps. ~~While the wetland maps differ, there is no consensus on which is more accurate, so comparisons indicate the uncertainty in upscaling emanating from uncertainties in wetland distribution.~~ ~~Three statistical metrics (NSE, R² and RE) were calculated between RF-DYPTOP and LPX-Bern for each grid cell (Fig. 8). The figure illustrates how well the temporal variability of CH₄ emissions estimated by RF-DYPTOP and LPX-Bern agree in each grid cell. NSE values are low in areas where the systematic difference between RF-DYPTOP and LPX-Bern was high (compare Figs. 8a and 7a) since the bias strongly penalises NSE. The R² values are high throughout the study domain, likely due to the fact that the seasonal cycle of CH₄ emissions dominated the temporal variability in most of the grid cells and the seasonal cycles were in phase between RF-DYPTOP and LPX-Bern. RE values calculated between RF-DYPTOP and LPX-~~

Bern were high in areas where also the emissions estimated by RF-DYPTOP were high (compare Figs. 8c and 6a). This is likely due to the fact that, even though the seasonal cycles were in phase, their amplitudes were different which increased the variability between LPX-Bern and RF-DYPTOP (i.e. increase in RE).

The uncertainties of the upscaled fluxes were estimated from the spread of predictions made with the ensemble of 200 RF models (~~(Seet. 2.1.2) and are shown in~~ Fig. 89). The uncertainty mostly scales with the flux magnitude (compare Fig. 6 a)-c) with Fig. 8-9 a)-c)), meaning that grid cells with high fluxes tend to have also high uncertainties. However, the relative flux uncertainty does have some geographical variation (Fig. 8-9 d)-f)). The highest relative uncertainties are typically at the highest and lowest latitudes of the study domain. In these locations the dependencies between the predictors and the CH₄ flux are not as well-defined as in the locations with lower uncertainties leading to larger spread in the ensemble of RF model prediction. For instance, at low latitudes LST_n may go beyond the range of LST_n values in the training data (see the range in Fig. 3) and hence the RF model predictions are not well-constrained in these situations. On the other hand, lower relative uncertainties are typically obtained for locations close to the measurement sites incorporated in this study (compare Fig. 1 and 89), since the dependencies between the predictors and the CH₄ flux are better defined ~~better~~.

The seasonality ~~iesy~~ of the upscaled fluxes and CH₄ fluxes from process models are similar with highest CH₄ emissions in July-August and lowest in February ~~, and T~~ this seasonal pattern is ~~consistenteomparable~~ throughout the ~~whole~~ study domain (Fig. 910). Warwick et al. (2016) and Thonat et al. (2017) showed that the northern wetland CH₄ emissions should peak in August-September in order to explain correctly the seasonality of atmospheric CH₄ mixing ratios and isotopes measured across the Arctic. Hence the wetland CH₄ emissions presented here are peaking approximately one month too early to perfectly match with their findings. CH₄ flux magnitude agrees well between WetCHARTs and the upscaled flux during spring and midsummer (April-July), whereas LPX-Bern is estimating lower fluxes (0 % and 26 % difference, respectively). During late summer and autumn (August-October) both process models are estimating slightly lower fluxes than the upscaled estimate (17 % and 19 % difference, respectively). The upscaled fluxes show somewhat higher emissions also during the nongrowing season (November-March) than the two process models (27 % and 35 % difference, see Table 2) and the upscaled estimates of nongrowing season emissions are relatively close to ~~a~~ the recent model estimate (~~by~~ Treat et al. (2018)). This result promotes the recent notion that process models might be underestimating nongrowing season fluxes at high latitudes (e.g. Treat et al., 2018; Xu et al., 2016a; Zona et al., 2016).

Treat et al. (2018) adjusted WetCHARTs model output so that it matches with their estimates of nongrowing season CH₄ emissions and then estimated annual wetland CH₄ emissions north ~~offrom~~ 40 °N to be $37 \pm 7 \text{ Tg}(\text{CH}_4) \text{ yr}^{-1}$ using this adjusted model output. The estimates derived here for the annual emissions using the three wetland maps are similar (see Table 2), especially when considering ~~ourthat here we have~~ slightly smaller study domain (above 45 °N). The two process models included in this study estimated slightly lower mean annual emissions than the upscaled fluxes (11 % and 26 % difference between the mean upscaled estimate and WetCHARTs and LPX-Bern, respectively; see also Table 2). However, given the uncertainties in upscaling as well as in process models this can be regarded as relatively good agreement. Different process models may be driven with different climate forcing data and they may have discrepancies in the underlying wetland

distributions, in addition to the different parameterisations and descriptions of the processes behind the CH₄ emissions. These sources of uncertainty should be recognised when models are compared against each other or against upscaling products.

In order to further evaluate the agreement between the upscaled fluxes and process models we ~~focused on~~ concentrated on two specific regions: Hudson Bay Lowlands (HBL) and Western Siberian Lowlands (WSL) (see locations in Fig. 1). The upscaled fluxes ~~indicates how clearly~~ higher annual emissions for both subdomains compared to ~~than~~ the two process models; or ~~what has been~~ previously published ~~estimated in the literature~~ (Table 2). ~~F~~ Although for WSL the upscaled estimates are within the range of variability observed between process models and inversion modelling in WETCHIMP-WSL (Bohn et al., 2015) and close to Thompson et al. (2017). ~~T~~ Bohn et al. (2015) also notes that the upscaled estimates by Glagolev et al. (2011) ~~might is most likely an~~ underestimate ~~of the~~ CH₄ emissions from the WSL area (Bohn et al. ,2015). Furthermore, the process models in Bohn et al. (2015) are likely underestimating the nongrowing season CH₄ emissions which might partly explain the discrepancy to the upscaled estimates in this study. Hence, the upscaled CH₄ emission estimates for the WSL area, while large, are still in a reasonable range.

For HBL, the discrepancy between upscaled emission estimates and the estimates based on process models or previous studies is larger (Table 2). The upscaling results agree with Zhang et al. (2016) and Melton et al. (2013) but show over twice larger emissions from HBL than the other estimates (Table 2). This cannot be explained by wetland mapping since the difference holds also when DYP TOP wetland map is used in upscaling. There are only few ~~not many~~ long-term EC flux studies conducted in the HBL area and the only one found (Hanis et al., 2013) showed on average 6.9 g(CH₄) m⁻² annual emissions at a subarctic fen located in the HBL. If the upscaled CH₄ emissions are downscaled back to ecosystem level at the HBL area with wetland maps, we get on average 11.0 g(CH₄) m⁻² annual CH₄ emission for the HBL area based on the RF model output, which is 1.6 times larger than the estimate by Hanis et al. (2013). While Hanis et al. (2013) studied only one wetland during different years than here (years 2008-2011 in Hanis et al. (2013), here 2013-2014) it is still noteworthy that the relative difference between Hanis et al. (2013) and this study is similar to the discrepancy between this study and the inversion estimates (Pickett-Heaps et al. (2011); Thompson et al. (2017)) at the whole HBL scale. ~~All three studies (Hanis et al. (2013); Pickett-Heaps et al. (2011); and Thompson et al. (2017))~~ show near zero CH₄ emissions during October-April and onset of CH₄ emissions in mid-May or even June, largely dependent on when the ground was free of snow and unfrozen. This is somewhat surprising given the fact that only 32 % of wetlands in the area are underlain by permafrost (based on amalgam of PEATMAP and permafrost map) and hence the soils are likely not completely frozen and some non-growing season CH₄ emissions are likely to occur in such conditions (e.g. Treat et al., 2018). The upscaled nongrowing season CH₄ emissions show on average 1.1 Tg(CH₄) yr⁻¹ emissions ~~during these nongrowing season months~~ for the HBL area. This partly, but not completely, explains the discrepancy between the CH₄ emission estimates for the HBL area. All these results suggest that the upscaled product likely overestimates CH₄ emissions from the HBL area.

Discussion

4.1 Comparing the RF model predictive performance to previous studies

The RF model performance was worse when compared against independent validation data than what has been achieved in previous upscaling studies for GPP and energy fluxes ($R^2 > 0.7$), and ecosystem respiration (R_{eco} ; $R^2 > 0.6$) (e.g. Jung et al., 2010; Tramontana et al., 2016). However, whereas the RF model performance for monthly CH_4 emissions was comparable to for net ecosystem exchange of CO_2 (NEE) ~~was has been similar~~ ($R^2 < 0.5$) ~~as here for monthly CH_4 emissions~~ (e.g. Jung et al., 2010; Tramontana et al., 2016). Likely reasons for this finding include for instance that for other fluxes there is simply more data available from several sites spanning the globe. ~~For example, the La Thuile synthesis dataset used by Jung et al. (2010) and Tramontana et al. (2016) consists of 965 site-years of data from over 252 EC stations.~~ ~~Whereas here we have data from 25 sites with CH_4 fluxes.~~ Furthermore, the drivers (or proxies for the drivers) of e.g. GPP and energy fluxes are more easily available from remote sensing (e.g. MODIS) and weather forecasting re-analysis data sets (e.g. WFDEI). ~~In contrast, whereas CH_4 emissions are more related to belowground processes, thus taking place belowground thus and hence the~~ drivers for these processes are more difficult to measure remotely, ~~which is in practice needed for the upscaling.~~ Also, there are temporal lags between changes in drivers (e.g. LSTn) and CH_4 fluxes ~~in responses~~ to these changes. ~~Consequently, and hence~~ training a machine learning model such as RF ~~model~~ on such data is difficult since ~~the~~ RF model assumes ~~a instantaneous direct~~ relationship between the change and response. However, one should also note that GPP or R_{eco} are never directly measured with the EC technique, they are always at least partly derived products (Lasslop et al., 2009; Reichstein et al., 2005). Hence direct functional relationships between GPP and R_{eco} and ~~their~~ environmental drivers are inherently included in these flux estimates, whereas NEE and CH_4 emissions ~~are can be~~ directly measured without additional modelling. Also, both NEE and CH_4 emissions are ~~differences between component fluxes combinations of two counteracting processes~~ (NEE: GPP and R_{eco} ; CH_4 flux: production and oxidation). Therefore, GPP and R_{eco} upscaling algorithms show better correspondence with validation data than for NEE or CH_4 emissions and the results for NEE would be the correct point of reference for the RF model performance presented here.

While the RF model performance in this study was inferior to previous upscaling studies for other fluxes ~~when evaluated using different statistical metrics~~, it was still comparable to what has been shown before for several process models for CH_4 emission (McNorton et al., 2016; Wania et al., 2010; Zürcher et al., 2013; Zhu et al., 2014; Xu et al., 2016a). For instance, McNorton et al. (2016) validated the land-surface model JULES against CH_4 flux data from 13 sites and found $R^2 = 0.10$ between the validation data and the model. Wania et al. (2010) found on average $\text{RMSE} = 29 \text{ nmol m}^{-2} \text{ s}^{-1}$ and $\text{RMSE} = 42 \text{ nmol m}^{-2} \text{ s}^{-1}$ with and without tuning their model LPJ-WhyMe against CH_4 flux data from seven sites. Zürcher et al. (2013) found the time-integrated CH_4 flux to be well represented by LPX-Bern model across different sites. ~~A and a~~ tight correlation ($R^2 = 0.92$) is found between simulated and measured cumulative site emissions after calibrating the model against the measurements. While Xu et al. (2016a) did not explicitly show any statistical metrics, their model (CLM4.5) comparison against site level CH_4 flux data seemed to be somewhat better than in Wania et al. (2010) or McNorton et al. (2016). Xu et al. (2016a) emphasize the

importance of nongrowing season emissions and the fact that their model was clearly underestimating these emissions. Zhu et al. (2014a) calibrated their model (TRIPLEX-GHG) for each measurement site by changing e.g. the Q_{10} for CH_4 production and CH_4 to CO_2 release ratio to be site-specific and found on average $R^2=0.64$ when comparing the calibrated model against measurements at 17 CH_4 flux measurement sites. However, their findings are not directly comparable to the RF model agreement with validation data shown here due to their model calibration against data before comparison. Nevertheless, their results show that even after calibration, the process models are not fully able to capture the CH_4 flux variability in measurements. Miller et al. (2014) argued that the structure of some of the process models is so might-be-too-complex so that the their required forcing variables input information may not cannot be reliably provided at larger spatial scales. All of these five models (JULES, LPJ-WhyMe, LPX-Bern, CLM4.5 and TRIPLEX-GHG) are contributing to the global CH_4 budget estimation within the Global Methane Project (Saunois et al., 2016), highlighting that these results summarize the agreement between state-of-the-art process models and field measurements.

4.2 Methods to improve RF model predictive performance

4.2.1 Missing predictors

In this study a statistical model was developed using the RF algorithm, and the model was able to yield $R^2=0.47$ against monthly CH_4 flux validation data. Our upscaling using RF model focused on 2013-2014, as these were the years with the largest overlap of collected data. However, all data from all the years (2005-2016) were used to develop and validate the model. The incomplete match between the RF model and validation data is likely caused by the fact that not all the possible drivers causing inter- and intra-site within and across site variability into the CH_4 emissions were included in the analysis and hence all the variability could not be explained by the model.

Christensen et al. (2003) were able to explain practically all the variability ($R^2=0.92$) in annual CH_4 emissions in their multisite chamber study with only two predictors: temperature and the availability of substrates for CH_4 production. Also, Yvon-Durocher et al. (2014) speculate that the amount of substrates for microbial CH_4 production explains across site variability of CH_4 fluxes in their data. However, gridded data on spatially explicit substrate information nsueh are currently nonexistent. data about substrates is impossible to achieve in a gridded format, which is a strict requirement for upscaling. Hence proxies for the substrates available for methanogenesis are needed. The current paradigm on wetland CH_4 emissions is that most of the emitted CH_4 is produced from recently fixed carbon being used as precursors for the, since CH_4 producing *Archaea* favour fresh labile carbon (e.g. Chanton et al., 1995; Whiting and Chanton, 1993). Most of the process models are based on the premise that a certain fraction of ecosystem net primary productivity (NPP) is available and used for CH_4 production or alternatively a fraction of heterotrophic respiration is allocated to CH_4 emissions (e.g. Xu et al., 2016b). ThusHence, hypothetically ecosystem NPP (or GPP) could potentially also be included as a predictor here for the RF model and used as a proxy for the amount of substrates available for CH_4 production. However, the RF model performance in this study was not

enhanced if variables closely related to NPP (EVI and the product of EVI and LSTd) were included as predictors. Also, Knox et al. (in review) did not find GPP as an important predictor of CH₄ emission variability in their multi-site synthesis study.

Using ~~the ecosystem level~~ NPP (or proxies for it) for the RF model development might be an oversimplification~~overly simplified approach~~, since it has been shown that ~~it is~~ especially the deep-rooting sedges and their NPP ~~that~~ are important for CH₄ production (Joabsson and Christensen, 2002; Ström et al., 2003, 2012; Waddington et al., 1996). Hence, information about plant functional types (PFTs) would be needed to better explain the CH₄ flux variability (Davidson et al., 2017; Gray et al., 2013). Furthermore, the fraction of the fixed carbon allocated to the roots and released as root exudates (hence available for CH₄ production) varies between species and root age (Proctor and He, 2017; Ström et al., 2003), further complicating the connection between NPP and CH₄ emissions~~this issue~~. The sedges also act as conduits for CH₄ allowing the CH₄ produced below water level to rapidly escape to the atmosphere and bypass the oxic zone in which the CH₄ might have otherwise been oxidized (Waddington et al., 1996; Whiting and Chanton, 1992). Besides sedges, *Spaghnum* mosses are also important because methanotrophic bacteria that live in symbiosis with these mosses significantly decrease the CH₄ emissions to the atmosphere when they are present (Larmola et al., 2010; Liebner et al., 2011; Parmentier et al., 2011; Raghoebarsing et al., 2005; Sundh et al., 1995). In a modelling study, Li et al. (2016) showed that it was essential to consider the vegetation differences between sites when modelling CH₄ emissions from two northern peatlands. Hence, ideally one should have gridded information on wetland species composition and associated NPP~~in a gridded format together with their NPP~~ across the high latitudes to significantly improve the upscaling results ~~from the results shown here~~. Unfortunately~~Naturally~~ such information is not yet readily available and therefore ~~alternatively~~ modelled estimates could be used (e.g. LPX-Bern which includes several peatland-specific PFTs ~~which are~~ allowed to freely ~~to~~ evolve during the model run) (Spahni et al., 2013). However, in such case the upscaled CH₄ emission estimates would not be any more model independent and therefore less suitable for model validation. We also note that many process models have only one PFT per wetland.

Different variables related to water input to the ecosystem (i.e. P, P_{ann}) or surface moisture (SRWI) did not enhance the RF model predictive performance, recognizing~~reflecting~~ that water table depth (WTD) is not solely controlled by input of water via precipitation, but also evapotranspiration and lateral flows affect wetland WTD, data that were missing from our study. These findings are consistent with previous studies (e.g. Christensen et al. 2003, Rinne et al. 2018, Pugh et al. 2018 and Knox et al. (in review)) who showed only a modest CH₄ flux dependence on WTD in wetlands/peatlands, if any. In contrast, several chamber-based studies have shown a positive relationship between WTD and CH₄ fluxes (Granberg et al., 1997; Olefeldt et al., 2012; Treat et al., 2018; Turetsky et al., 2014). In general, chamber-based studies often show spatial dependency of CH₄ flux ~~dependency~~ on WTD whereas studies done at ecosystem scale with EC generally do not show temporal WTD dependency, albeit there are exceptions (e.g. Zona et al., 2009). This might indicate that WTD controls meter scale spatial heterogeneity of CH₄ flux between microtopographical features (e.g. Granberg et al., 1997) but not temporal variability on the ecosystem scale, provided that WTD stays relative close to the surface. Also, the chamber studies tend to observe spatial variation, which can be indirectly influenced by WTD via its influence to plant communities, whereas EC studies observe typically temporal variation in sub-annual timescales. However, the effect of WTD might be masked by a contradicting~~confounding~~ effect caused

by plant phenology, since vegetation biomass often peaks at the same time as the WTD is at its lowest. While the variables related to WTD did not increase the RF model performance, WTD might still play a role in controlling ecosystem scale CH₄ variability when it is exceptionally high or low. For instance, the year 2006 was exceptionally dry at the Siikaneva fen and hence CH₄ emissions during that year were lower than on average (cf. Fig. 5a). However, in order to accurately capture such dependencies with the machine learning techniques (such as RF), they should be frequent enough so that the model can learn these dependencies.

RF model performance was better at ~~non-permafrost-free~~ than at permafrost sites ~~which might indicate and this likely-related to the fact that the LSTn might not be is not an appropriate good~~ proxy for the temperature controlling the CH₄ production and oxidation rates at sites with permafrost. Also, ~~no~~ information ~~on the development of the seasonally unfrozen, and hydrologically and biogeochemically about~~ active layer ~~depth~~ was ~~not~~ included ~~in the RfF model~~here. Furthermore, Zona et al. (2016) showed strong hysteresis between soil temperatures and CH₄ emissions at their permafrost sites in Alaska, whereas ~~for instance~~ Rinne et al. (2018) show a synchronous exponential dependence between soil temperature and CH₄ emissions at a boreal fen without permafrost. The hysteresis observed in Zona et al. (2016) could be explained by the fact that part of the produced CH₄ at these permafrost sites is stored below-ground for several months before it is ~~being~~ emitted to the atmosphere causing a ~~long~~-temporal lag between soil temperature and ~~observed~~ surface flux ~~which would emerge as a hysteresis between soil temperature and CH₄ emission~~. In any case, more knowledge on soil processes (soil thawing and freezing, CH₄ production and storage) are needed before the CH₄ emissions from these permafrost ecosystems can be extrapolated to other areas with greater confidence.

It should be emphasized that the drivers causing across site variability in ecosystem scale CH₄ emissions are in general unknown since studies comparing EC CH₄ fluxes from multiple wetland sites have only recently been published (Baldocchi, 2014; Knox et al., in review; Petrescu et al., 2015). Most ~~previous CH₄ of the past~~ synthesis studies ~~were based have concentrated~~ on plot-scale measurements (Bartlett and Harriss, 1993; Olefeldt et al., 2012; Treat et al., 2018; Turetsky et al., 2014). ~~However,~~ the CH₄ flux responses to environmental drivers ~~and their relative importance~~ might be ~~somewhat~~ different at ecosystem scale since CH₄ fluxes typically show significant spatial variability ~~at on~~ sub-m scale (e.g. Sachs et al., 2010). Furthermore, the temporal coverage of plot-scale measurements with chambers is usually relatively poor, whereas EC measurements provide continuous data on ecosystem scale. This study and Knox et al. (in review) show that temperature is important when predicting CH₄ flux variability in a multisite CH₄ flux dataset, but significant fraction of CH₄ flux variability is still left unexplained. It remains a challenge for future EC CH₄ flux synthesis studies to discover the drivers explaining the rest of the variability.

4.2.2 Quality and representativeness of CH₄ flux data

The RF model performance may improve if instrumentation, measurement setup and the data processing are harmonized across sites, since these discrepancies between flux sites might have caused spurious differences in CH₄ fluxes. These differences would have created additional variability in the ~~synthesis whole~~ dataset which would in turn 1) influence the training of RF

model and 2) decrease e.g. NSE values obtained against validation data since there would be artificial variability in the validation data which is not related to the predictors. In this study, the site PIs processed the data themselves using different processing codes, albeit the gapfilling was done centrally in a standardized way.

While these issues mentioned above could impact the upscaling results shown here, prior studies have shown that the usage of different instruments or processing codes do not significantly impact CH₄ flux estimates. For instance, Mammarella et al. (2016) showed that the usage of different processing codes (EddyPro and EddyUH) resulted in general in 1 % difference in long-term CH₄ emissions. On the other hand, CH₄ instrument cross comparisons have shown small differences (typically less than 7 %) between the long term CH₄ emission estimates derived using different instruments (Goodrich et al., 2016; Peltola et al., 2013, 2014). While these studies show consistent CH₄ emissions they also stress that the data should be carefully processed to achieve such good agreement across processing codes and instruments. In addition, many issues related to e.g. friction velocity filtering and gapfilling of CH₄ fluxes are still unresolved, and the role of short-term emission bursts, which are common in methane flux time series, needs to be further investigated (e.g. Schaller et al., 2017). However, recently Nemitz et al. (2018) advanced these issues by proposing a methodological protocol for EC measurements of CH₄ fluxes used to standardize CH₄ flux measurements within the ICOS measurement network (Franz et al, 2018).

Twenty-five flux measurement sites were included in this study and they were distributed across the Arctic-Boreal region (see Fig. 1). The measurements were largely concentrated in ~~the~~ Fennoscandia and Alaska, whereas data from e.g. the HBL and WSL areas were missing. Long-term EC CH₄ flux measurements are largely missing from these vast wetland areas casting uncertainty on wetland CH₄ emissions from these areas. The location of a flux site is typically restricted by practical limitations related to e.g. ease of access and availability of grid power. Hence open-path instruments with low power requirements potentially open up new areas for flux measurements (McDermitt et al., 2010), yet they need continuous maintenance which is not necessarily easy in remote locations. However, one could argue that the geographical location of flux sites is not vital for upscaling, more important is that the available data represents well the full range of CH₄ fluxes across the northern latitudes and more importantly the CH₄ flux responses to the environmental drivers. Also, sites should ideally cover all different wetlands with varying plant species composition, whereas geographical representation is not necessarily as important. CH₄ flux site representativeness could be potentially assessed in the same vein as in previous studies for other measurement networks (Hargrove et al., 2003; Hoffman et al., 2013; Papale et al., 2015; Sulkava et al., 2011). However, before such analysis can be done, the main drivers causing across sites variability in ecosystem scale CH₄ fluxes should be better identified.

Most of the CH₄ flux data here and in the literature have been recorded during the growing season when the CH₄ fluxes are at maximum, whereas year-round continuous CH₄ flux measurements are not as common. This is likely due to the harsh conditions in the Arctic during winter which make continuous high-quality flux measurements very demanding (e.g. Goodrich et al., 2016; Kittler et al., 2017a), but also in part since the large-scale importance of nongrowing season emissions has just recently been recognized (Kittler et al., 2017b; Treat et al., 2018; Xu et al., 2016a; Zona et al., 2016). For upscaling year-round CH₄ emissions, continuous measurements are vital to accurately constrain also the non-growing season emissions and their drivers.

5 Data availability

The presented upscaled CH₄ flux maps (RF-DYPTOP, RF-PEATMAP and RF-GLWD), ~~and~~ their uncertainties and the underlying CH₄ flux densities are accessible via an open-data repository Zenodo (Peltola et al., 2019). The datasets are saved in netCDF-files and they are accompanied by a read-me file. The dataset can be downloaded from <https://doi.org/10.5281/zenodo.2560163> ~~10.5281/zenodo.2560164~~.

6 Conclusions

Methane (CH₄) emission data ~~consisting of~~ comprising over 40 site-years from 25 eddy covariance flux measurement sites across the Arctic-Boreal region were assembled and upscaled to estimate CH₄ emissions from northern (>45 °N) wetlands. The upscaling was done using the random forest (RF) algorithm. The performance of the RF model was evaluated against independent validation data utilizing the leave-one-site-out scheme which yielded value of 0.47 for both the Nash-Sutcliffe model efficiency and R². These results are similar to previous upscaling studies for the net ecosystem exchange of carbon dioxide (NEE) but are less good than for the individual components of NEE or energy fluxes (e.g. Jung et al., 2010; Tramontana et al., 2016). The performance is also comparable to studies where process models are compared against site CH₄ flux measurements (McNorton et al., 2016; Wania et al., 2010; Zürcher et al., 2013; Zhu et al., 2014; Xu et al., 2016a). Hence, despite the relatively high fraction of unexplained variability in the CH₄ flux data, the upscaling results are useful for comparing against models and could be used to evaluate model results. The three gridded CH₄ wetland flux estimates and their uncertainties are openly available for further usage (Peltola et al., 2019).

The upscaling to the regions > 45 °N resulted in mean annual CH₄ emissions comparable to prior studies on wetland CH₄ emissions from these areas (Bruhwiler et al., 2014; Chen et al., 2015; Spahni et al., 2011; Treat et al., 2018; Watts et al., 2014; Zhang et al., 2016; Zhu et al., 2013) and hence in general support the prior modelling results for the northern wetland CH₄ emissions. When compared to two validation areas, the upscaling likely overestimated CH₄ emissions from the Hudson Bay Lowlands, whereas emission estimates for the western Siberian lowlands were in a reasonable range. Future CH₄ flux upscaling studies would benefit from long-term continuous CH₄ flux measurements, centralized data processing and better incorporation of CH₄ flux drivers (e.g. wetland vegetation composition and carbon cycle) from remote sensing data needed for scaling the fluxes from the site level to the whole Arctic-boreal region.

Appendix A

Table A1. Description of eddy covariance sites included in this study.

Time resolution of data	Wetland type	Biomass based on Olson et al. (2011)	permafrost present (true/false)	sedges as dominant vegetation type (true/false)	Reference	Amount of monthly CH ₄ flux data available	Latitude, Longitude	Site PI	Site ID	Name
30 min	bog	temperate	false	false	Hommel et al. (2014)	2	47.8064, 11.3275	Janina Klatt, Hans Peter Schmid	DE-StN	Schechenfilz Nord
30 min	wet tundra	tundra	true	true	Parmetier et al. (2011)	5	70.8291, 147.4943	Albertus J. Dolman	RU-Cok	Chokurdakh
30 min	wet tundra	tundra	true	false	Marushchak et al. (2016)	5	67.0547, 62.9405	Thomas Friborg	RU-Vor	Vorkuta
30 min	fen	tundra	false	true	Jammet et al. (2017)	6	68.3542, 19.0503	Thomas Friborg	SE-St1	Stordalen
30 min	bog	tundra	true and false ^a	false		55	68.3560, 19.0452	Janne Rinne	SE-Sto	Stordalen (ICOS)*
30 min	fen	boreal	false	true	Rinne et al. (2018)	104	61.8327, 24.1928	Timo Vesala, Ivan Mammarella	FI-Sii	Siikaneva 1

30 min	bog	boreal	false	false	Korrensalo et al. (2018)	26	61.8 375, 24.1 699	Timo Vesala, Ivan Mammarella	FI-Si2	Siikaneva 2
30 min	fen	boreal	false	true	Aurela et al. (2009)	59	67.9 972, 24.2 092	Annalea Lohila	FI-Lom	Lompolojänkkä
daily	bog	boreal	false	false	Nadeau et al. (2013)	3	53.6 744, - 78.1 706	Daniel F. Nadeau	CA-JBL	James Bay lowlands
30 min	fen	temperate	false	false	Pugh et al. (2018)	30	46.0 827, - 89.9 792	Ankur R. Desai	US-Los	Lost Creek
30 min	wet tundra	tundra	true	true	Zona et al. (2016)	11	70.4 696, - 157. 4089	Donatella Zona	US-Atq	Atkasuk
30 min	wet tundra	tundra	true	true	Zona et al. (2016)	16	71.2 810, - 156. 6123	Donatella Zona	US-Beo	Barrow Environmental Observatory
30 min	wet tundra	tundra	true	true	Zona et al. (2016)	16	71.2 809, - 156. 5965	Donatella Zona	US-Bes	Biocomplexity Experiment South tower

30 min	wet tundra	tundra	true	true	Zona et al. (2016)	15	68.4 865, - 155. 7502	Donatella Zona	US-Ivo	Ivotuk
30 min	fen	temperate	false	false	Long et al. (2010)	5	54.9 538, - 112. 4670	Lawrence B. Flanagan	CA-WP1	Western peatland
daily	bog	temperate	false	false	Brown et al. (2014)	16	45.4 094, - 75.5 186	Elyn Humphreys	CA-Mer	Mer Bleue
daily	wet tundra	boreal	true	true	Kittler et al. (2017)	21	68.6 169, 161. 3509	Mathias Göckede	RU-Ch2	Cherchy reference
30 min	fen	temperate	false	true	Kowalska et al. (2013)	4	52.7 622, 16.3 094	Bogdan Chojnicki	PL-wet	Rzecin
30 min	fen	boreal	false	true	Nilsson et al. (2008)	22	64.1 820, 19.5 567	Mats B. Nilsson, Matthias Peichl	SE-Deg	Dege rö Stor myr
daily	fen	temperate	false	true	Pypker et al. (2013)	5	46.3 167, - 86.0 500	Thomas Pypker	US-Sen	Sene y
30 min	bog	boreal	false	false	Helbig et al. (2016)	14	61.3 000, - 121. 3000	Oliver Sonnentag	CA-SCC	Scotty Creek

30 min	wet tundra	tundra	true	true	Sachs et al. (2008)	11	72.3 667, 126. 5000	Torsten Sachs	RU-Sam	Sam oylov
30 min	wet tundra	tundra	true	true		7	68.6 060, - 149. 3110	Eugenie S. Euskirchen	US-ICH	Imnavait Creek
30 min	fen	boreal	false	true	Euskirchen et al. (2014)	16	64.7 040, - 1483 130	Eugenie S. Euskirchen	US-BCF	Bonaanza Creek, fen
30 min	bog	boreal	false	false	Euskirchen et al. (2014)	14	64.7 000, - 148. 3200	Eugenie S. Euskirchen	US-BCB	Bonaanza Creek, bog

^a Data from this site is divided into two since data from two wind directions differ from each other (with and without permafrost).

Author contribution

OP, TA and TV designed the study and YG contributed further ideas for the study. OP did the data processing and analysis, except OR prepared the PEATMAP map for the study. PA, MA, BC, ARD, AJD, ESE, TF, MG, MH, EH, GJ, JK, NK, LK, AL, IM, DFN, MBN, WCO, MP, TP, WQ, JR, TS, MS, HPS, OS, CW and DZ provided CH₄ fluxes and other in-situ data for the study. FJ and SL did the LPX-Bern model runs. OP wrote the first version of the manuscript and all ~~the~~ authors provided input, commented it and made modifications.

Competing interests

The authors declare that they have no conflict of interest.

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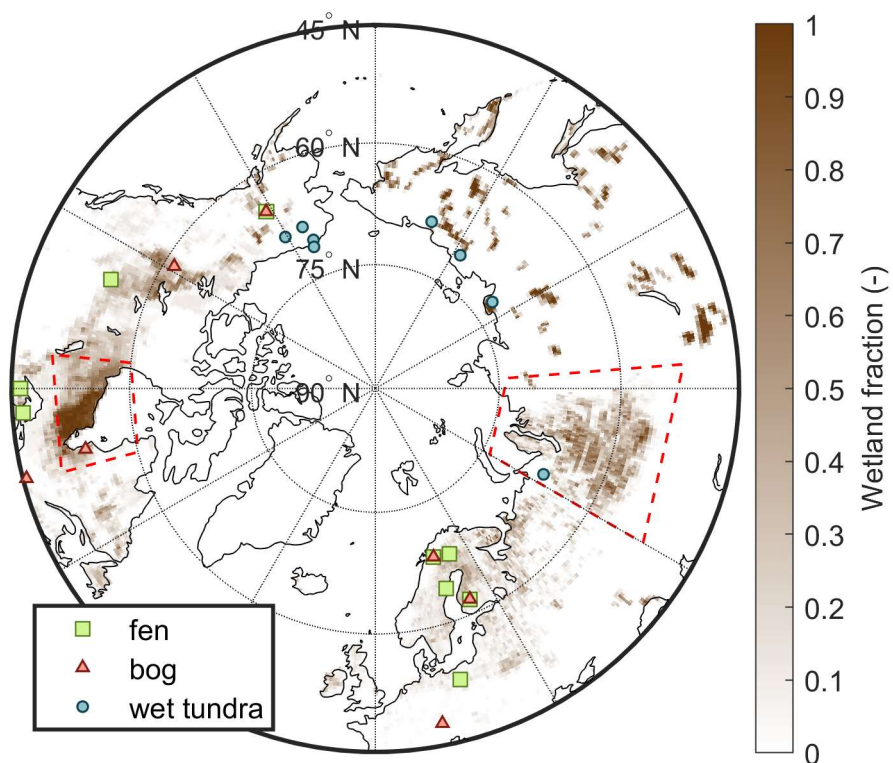


Figure 1: Map showing the locations of the EC measurements. The distribution of wetlands shown in the figure is based on Xu et al. (2018). Hudson Bay Lowlands (50°N-60°N, 75°W-96°W) and Western Siberian Lowlands (52°N-74°N, 60°E-94.5°E) are highlighted with red dashed lines.

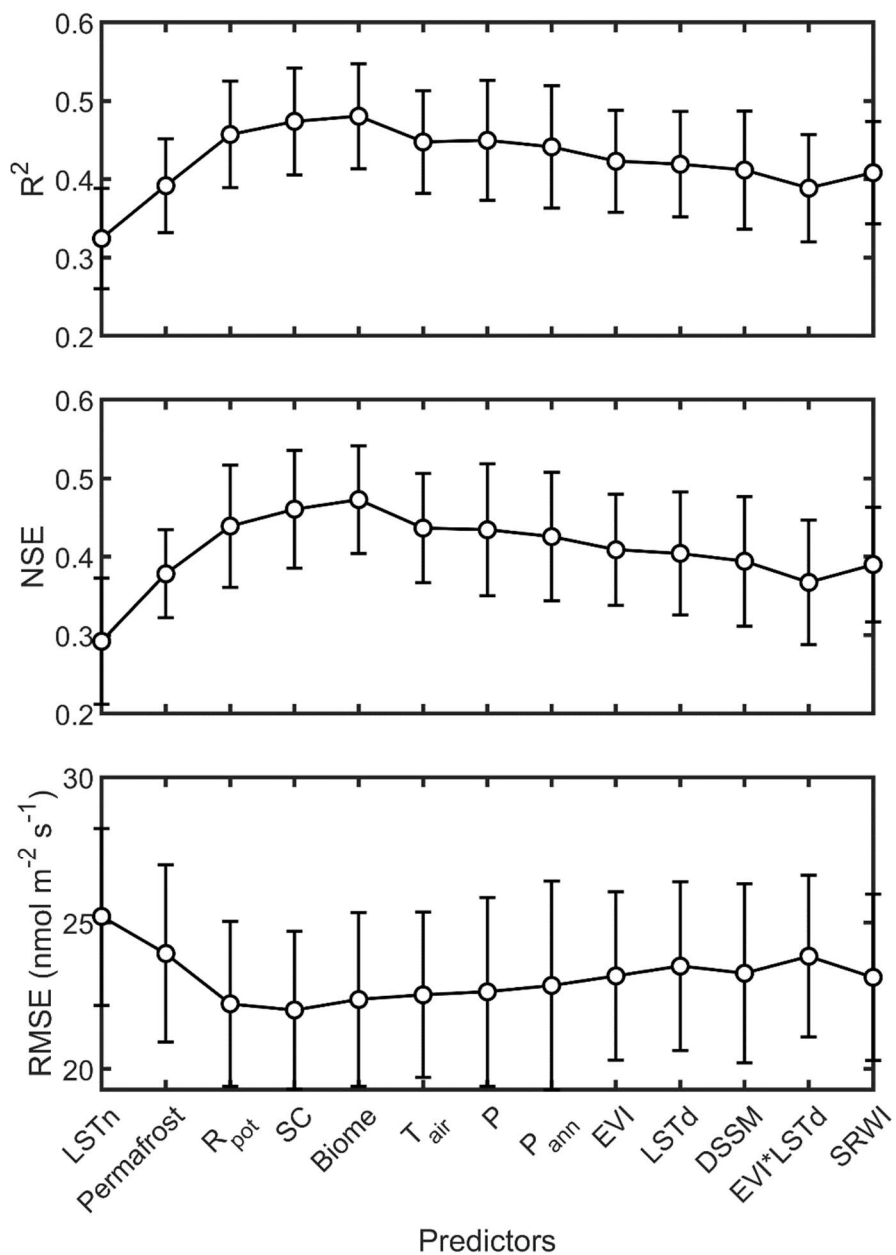


Figure 2. Evolution of statistical metrics during RF model development. Predictors were added to the RF model starting from the left of the figure and accumulate along the x-axis. For instance, the x-tick label “SC” shows the RF model performance when LSTn, Permafrost, R_{pot}, and SC were used as predictors in the model. See the x-tick label explanations in Table 1. The error bars denote 1-sigma uncertainty of the values estimated with bootstrapping.

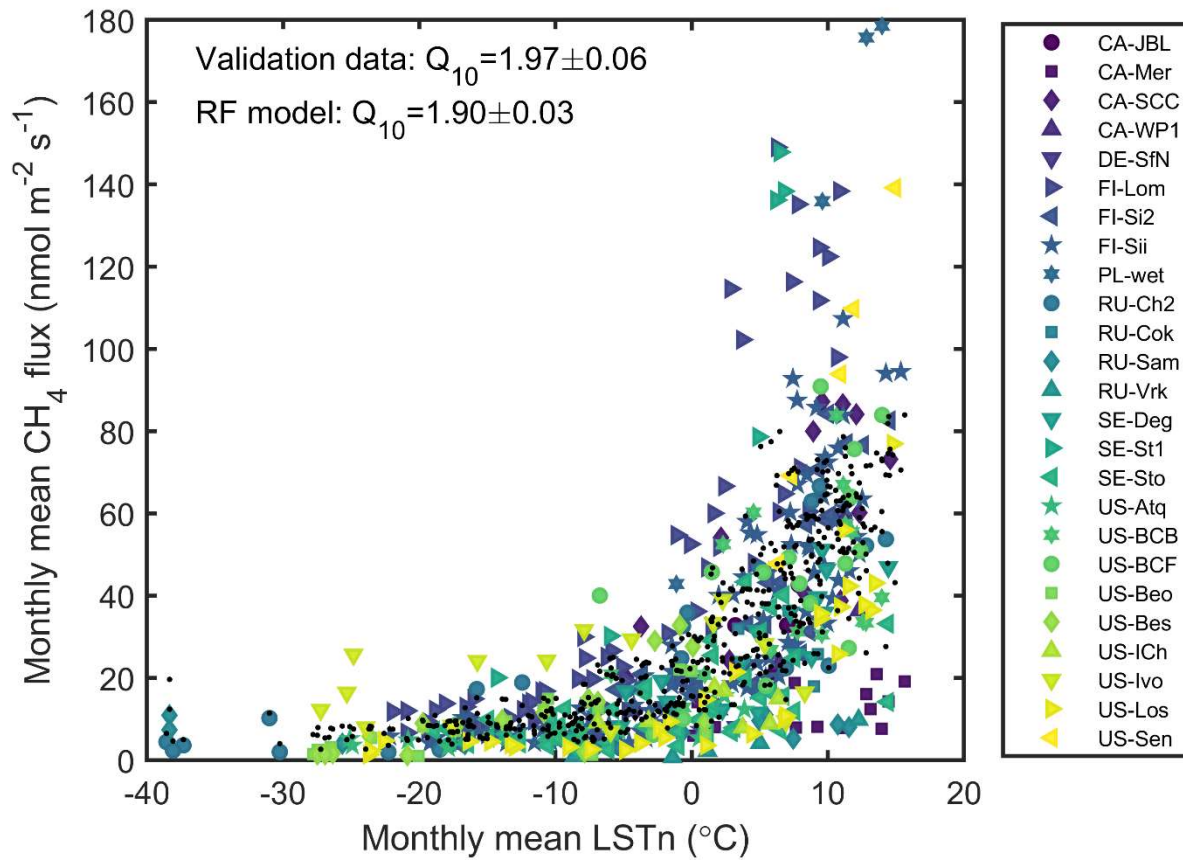


Figure 3. Dependence of monthly mean CH_4 emissions on monthly mean land surface temperature at night (LSTn) derived from MODIS data. Eddy covariance measurements are shown with filled markers (unique colour for each site) and random forests model predictions for each site are given with black dots.

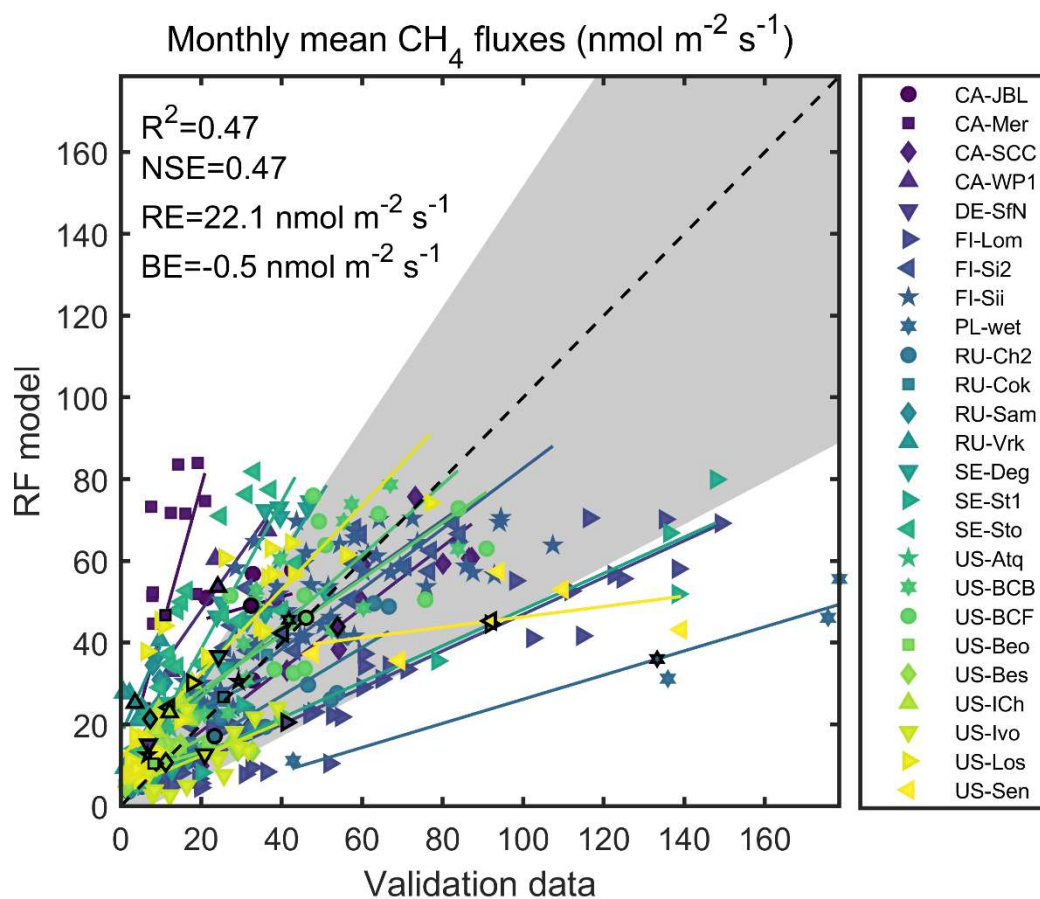


Figure 4. Relation between monthly mean CH₄ fluxes predicted by the RF model and independent validation data. Monthly average values from the same site are identified by unique colours and least squares linear fit to data from each site is also plotted using the same colour. Site means are shown with markers with black edges. The dashed line shows the 1:1 line. The shaded area shows the uncertainty range estimated from the RE CH₄ flux dependence (see text for further details). The statistics in the figure are calculated using the monthly data.

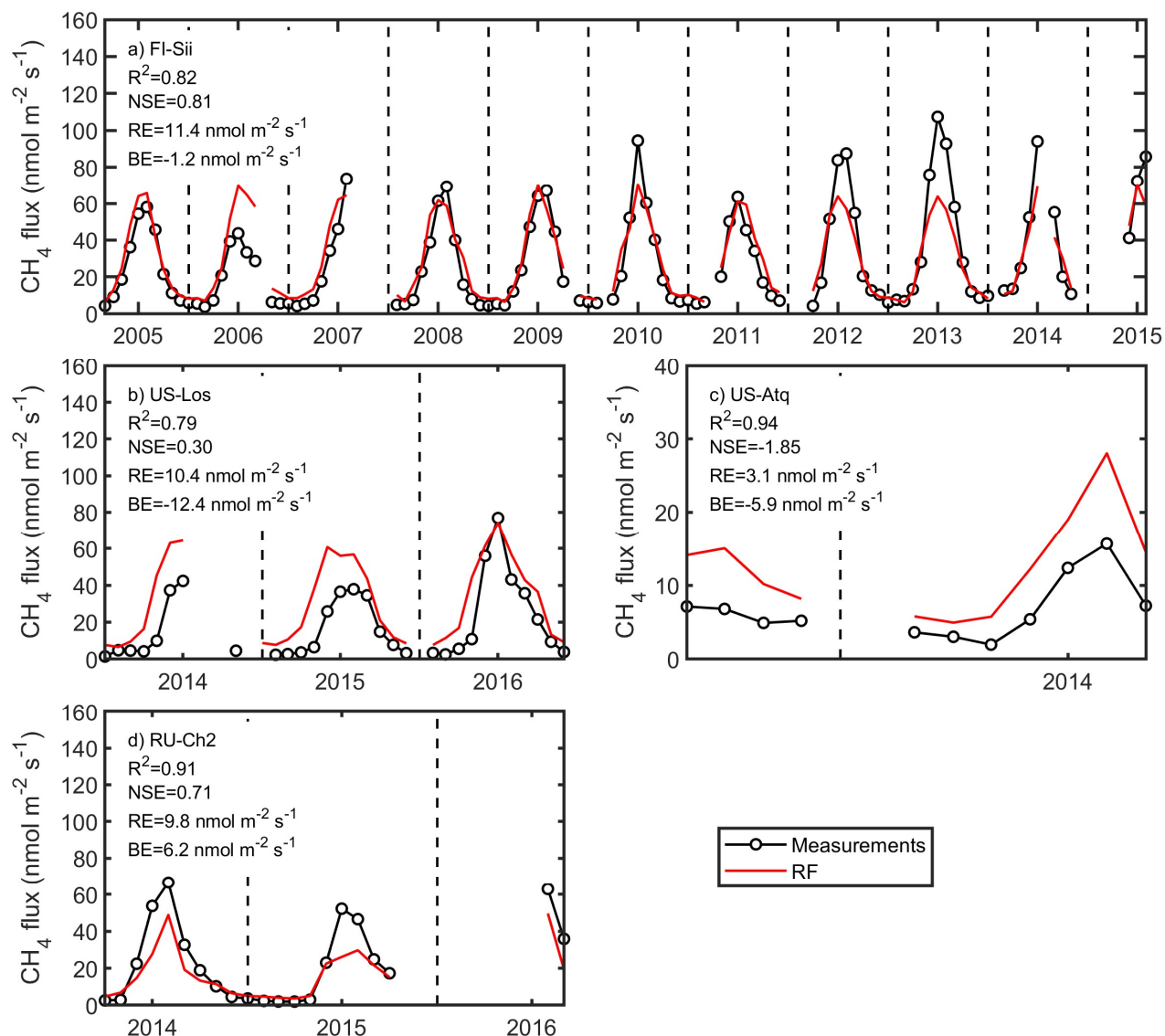


Figure 5. Time series of modelled CH_4 emissions (red lines) together with validation data (circles) at four example sites: a) Siikaneva oligotrophic fen in Finland, b) Lost Creek shrub fen in Wisconsin, US, c) Atkasuk wet tundra in Alaska, US and d) Chersky wet tundra in northeast Siberia, Russia. Vertical dashed lines denote a new year. Note the changes in y-axis scales. Site specific model performance metrics are also included.

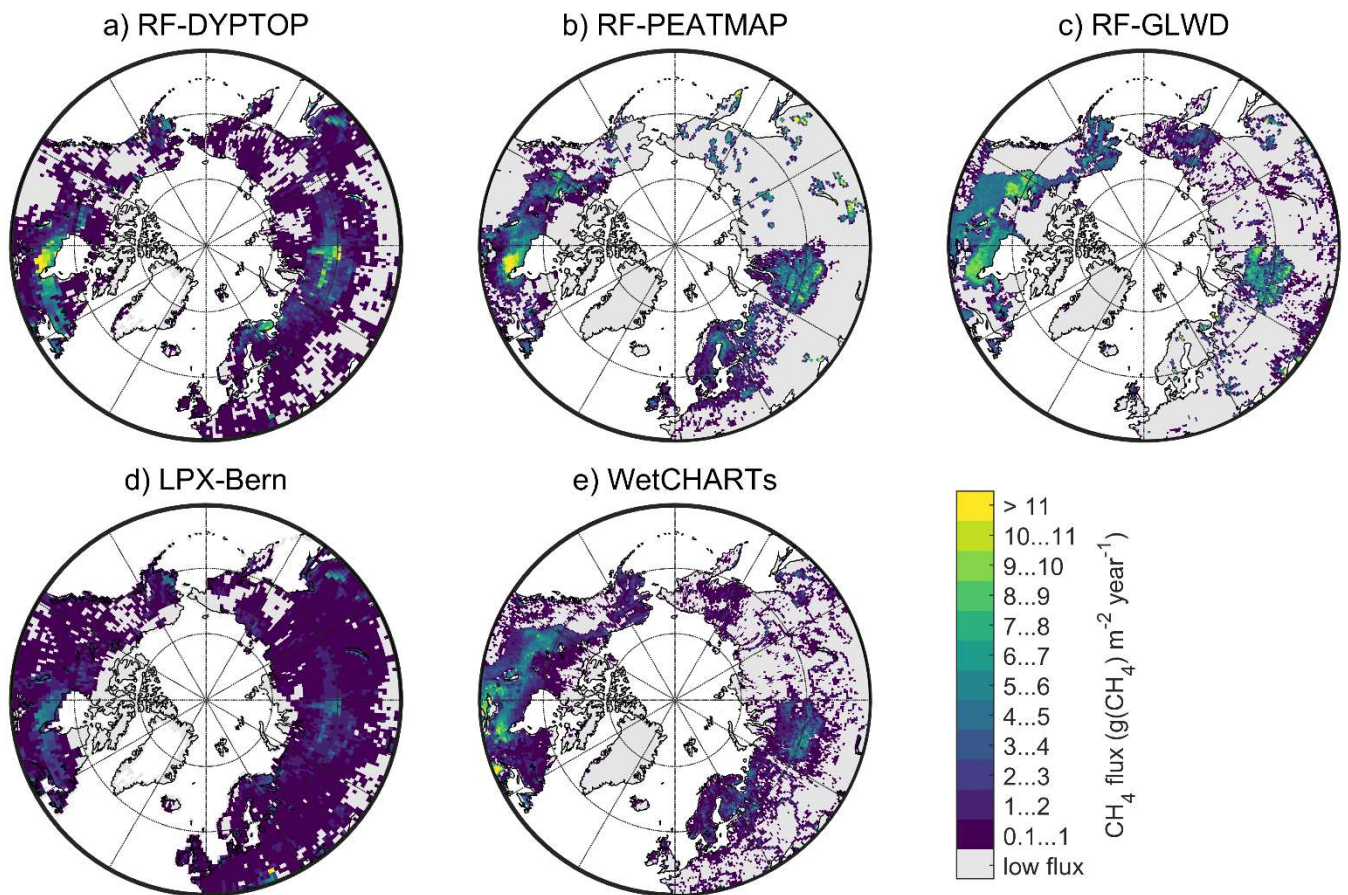


Figure 6. Mean annual CH_4 wetland emissions during years 2013-2014 estimated by upscaling EC data using the RF model and three wetland maps (top row) and process models (bottom row). Grid cells with low CH_4 wetland emissions (below $0.1 \text{ g}(\text{CH}_4) \text{ m}^{-2} \text{ year}^{-1}$) are shown with grey. The flux rates refer to total unit area in a grid cell.

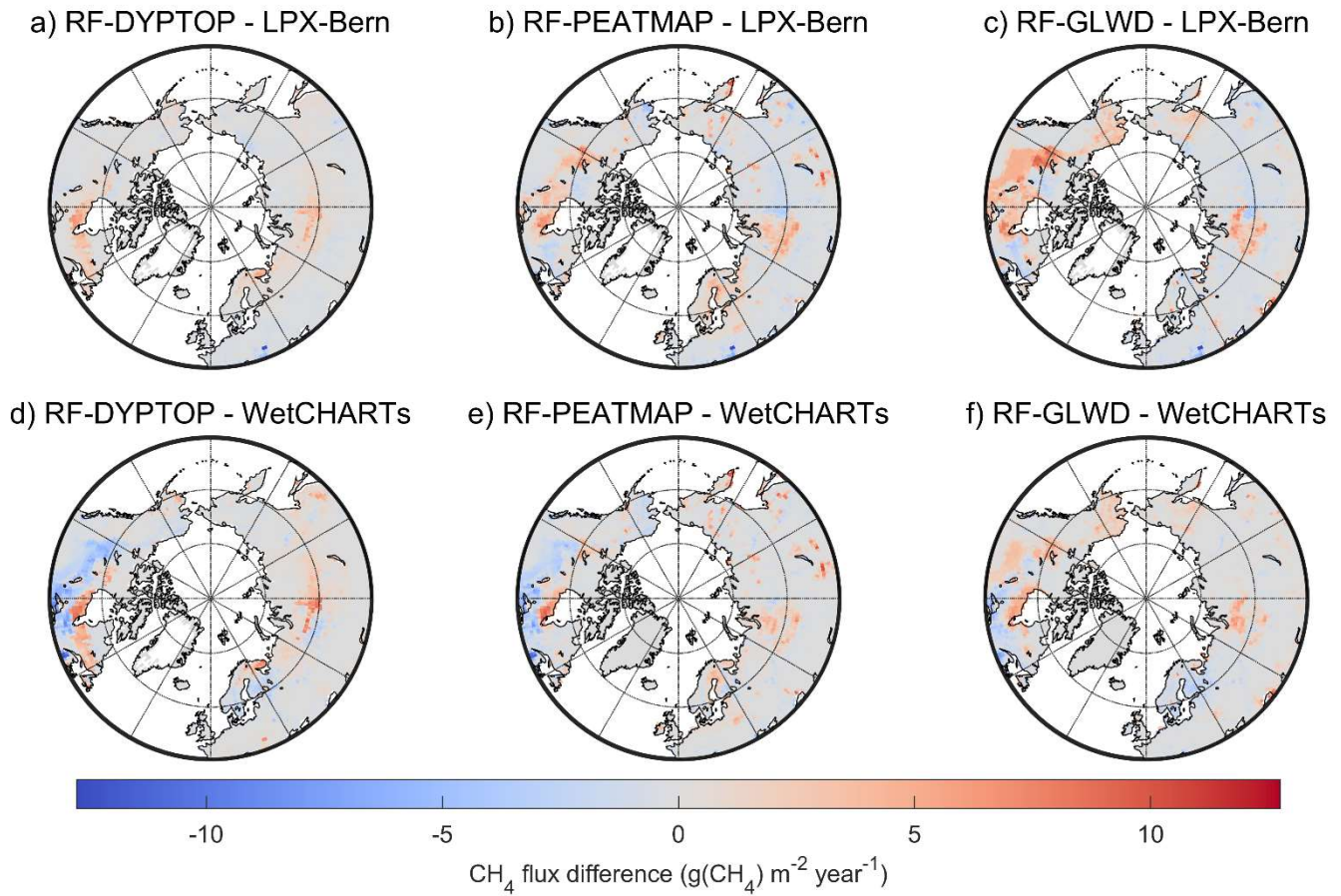


Figure 7. Difference in mean annual CH_4 wetland emissions during years 2013-2014 estimated by upscaling EC data using the RF model with different wetland maps and process models. All the CH_4 emission maps were aggregated to 1° resolution before comparison. The flux rates refer to total unit area in a grid cell.

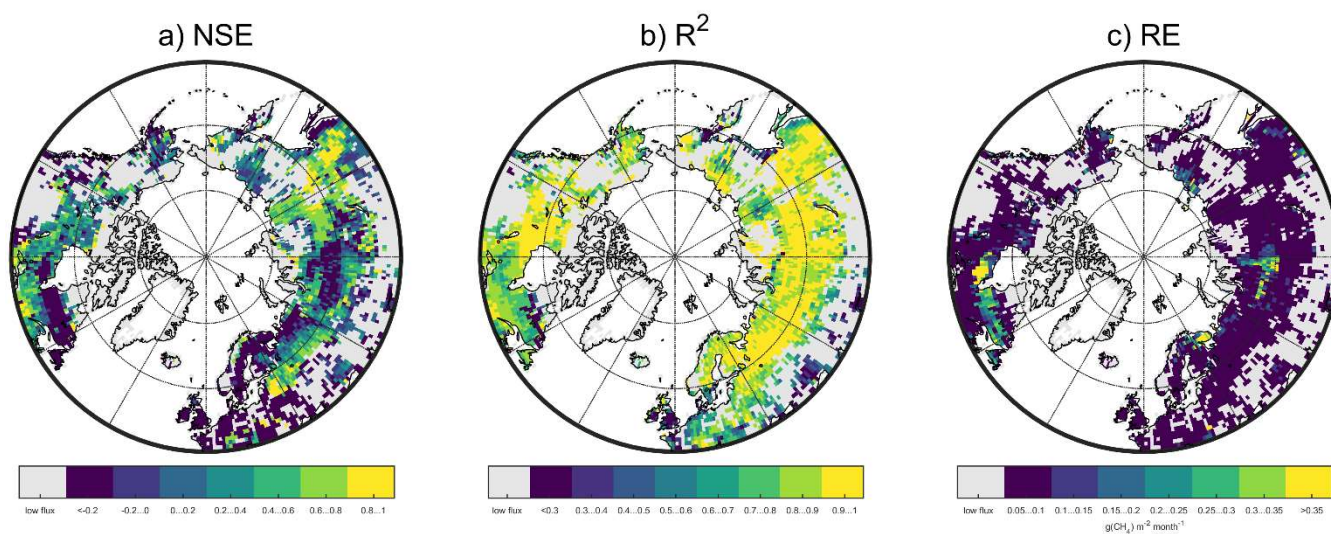


Figure 8. NSE, R^2 and RE calculated between RF-DYPTOP and LPX-Bern. Grid cells with low CH_4 wetland emissions (below $0.1 \text{ g}(\text{CH}_4) \text{m}^{-2} \text{year}^{-1}$) are shown with grey. RE values refer to total unit area in a grid cell.

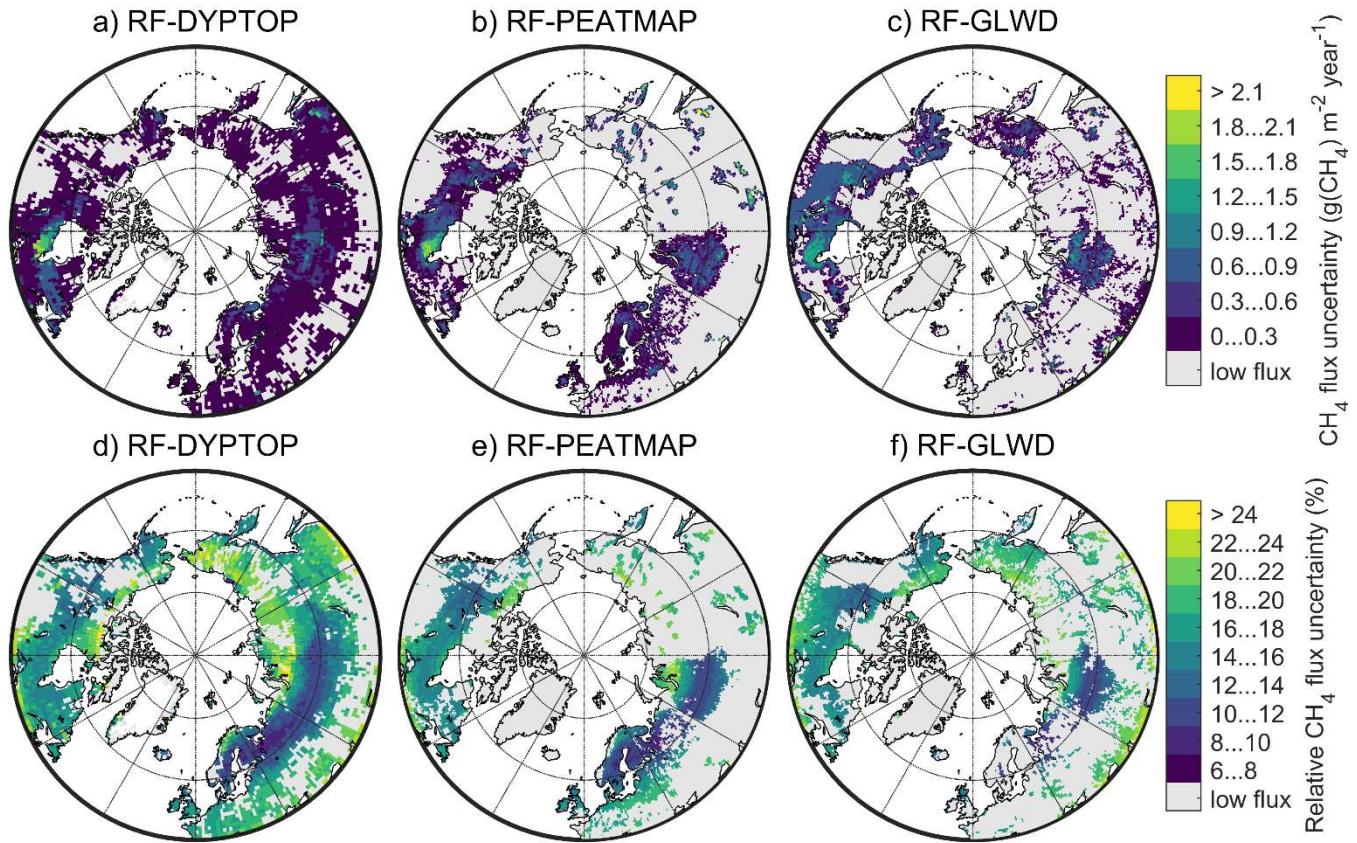


Figure 89. Absolute (subplots a-c)) and relative (subplots d-f)) uncertainties of the upscaled CH_4 fluxes using different wetland maps. Uncertainty is estimated as $1-\sigma$ variability of the predictions by 200 RF models developed by bootstrapping the training data (Sect. 2.1.2). Grid cells with low CH_4 wetland emissions (below $0.1 \text{ g}(\text{CH}_4) \text{ m}^{-2} \text{ year}^{-1}$) are shown with grey. The absolute uncertainties refer to total unit area in a grid cell.

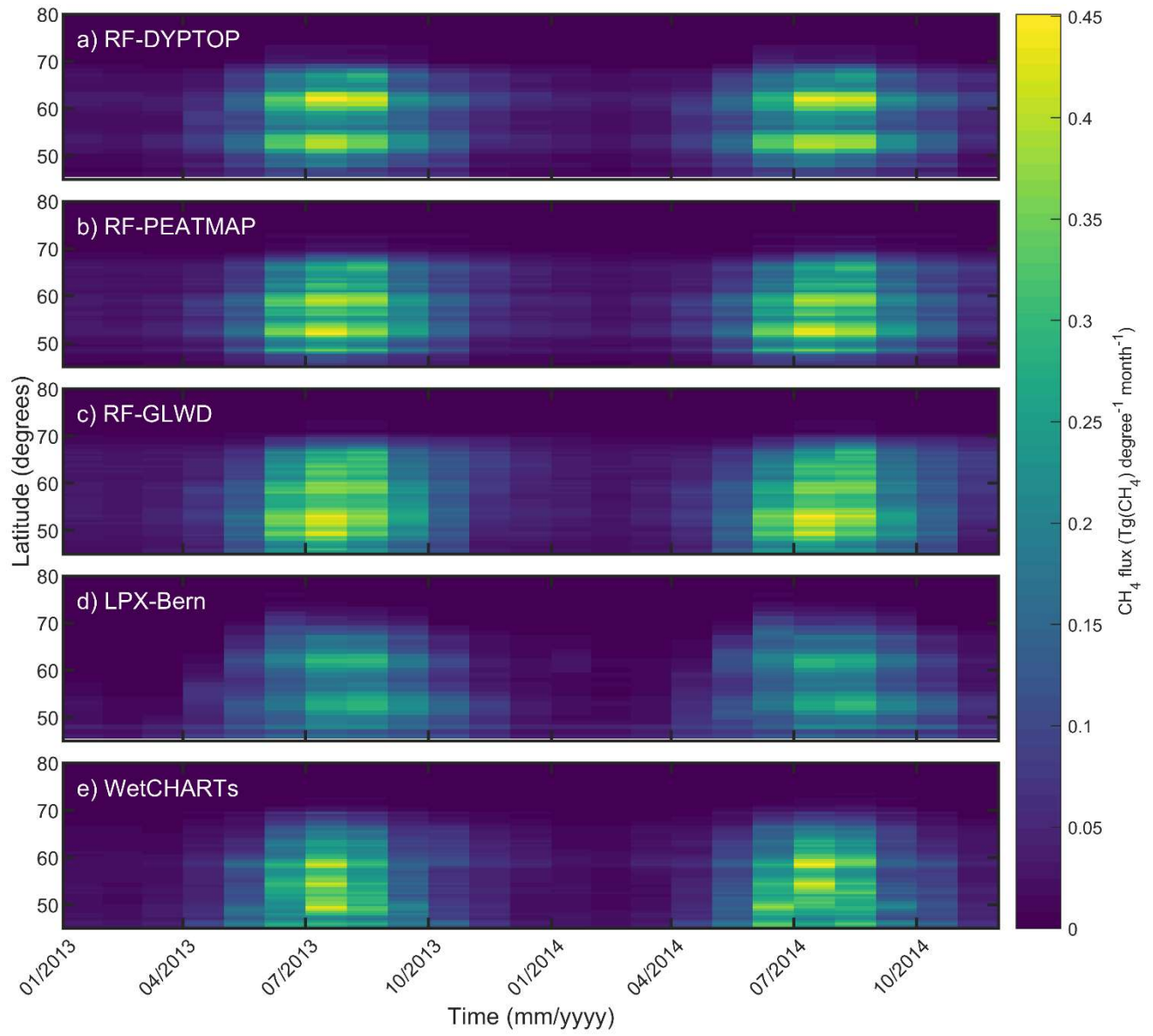


Figure 910. Monthly time series of zonal mean CH_4 fluxes. The upscaled fluxes with different wetland maps are shown in subplots a), b) and c) and wetland CH_4 emissions estimated with the two process models are given in subplots d) and e).

Table 1. Description of input variables for RF model development for upscaling. Data were aggregated to monthly values (see text) unless otherwise noted below.

	Name	Description	Data source	Available in gridded format
Site measurements	T_{air}	Mean air temperature	site PI & WFDEI	Yes
	P	Precipitation	site PI & WFDEI	Yes
	P_{ann}	Annual precipitation	site PI & WFDEI	Yes
Remote sensing	LST _n	Land surface temperature at night	MOD11A2	Yes
	LST _d	Land surface temperature at day	MOD11A2	Yes
	EVI	Enhanced vegetation index	MOD13A3	Yes
	SRWI	Simple ratio water index (SRWI = R_{858}/R_{1240})	MOD09A1	Yes
	SC	Snow cover flag	MOD10A1	Yes
	EVI* LST _d	Product of EVI and LST _d , a proxy for GPP (Schubert et al., 2010)	MOD13A3 & MOD11A2	Yes
Additional categorical variables	Permafrost	Flag for permafrost at site (true/false)	site PI	Yes
	Biome	Site classification based on biome (temperate, boreal and tundra)	Olson et al. (2001)	Yes
	type	Wetland type (fen, bog, tundra)	site PI	No
	sedge	flag for sedges as dominant vegetation type (true/false)	site PI	No
Other	R_{pot} & $\text{der}(R_{\text{pot}})$	Potential solar radiation at the top of atmosphere and its first time derivative	-	Yes
	DSSM	Days since snowmelt, derived from the snow cover flag	-	Yes

Table 2. Annual CH₄ wetland emissions in different subdomains (Hudson Bay lowlands and Western Siberian lowlands, see Fig. 1) and time periods. The values are given in Tg(CH₄) year⁻¹. Note that estimates from some reference studies are not for the same period as the one studied here (2013-2014). For WetCHARTs the mean of the model ensemble together with the range (in parentheses) are given, whereas for the upscaling results the 95 % confidence intervals for the estimated emissions are given.

	Reference	Hudson Bay lowlands	Western Siberian lowlands	Nongrowing season fluxes from northern wetlands (November...March)	Annual emissions north from 45 °N
Inversion models	Bohn et al. (2015), WETCHIMP-WSL		6.06 ± 1.22		
	Bruhwieler et al. (2014) ^a				23
	Kim et al. (2011)		2.9 ± 1.7 and 3.0 ± 1.4		
	Miller et al. (2014)	2.4 ± 0.3			
	Spahni et al. (2011)				28.2 ± 2.2
	Thompson et al. (2017)	2.7-3.4	6.9 ± 3.6		
Process models	Bohn et al. (2015), WETCHIMP-WSL		5.34 ± 0.54		
	Chen et al. (2015) ^b	3.11 ± 0.45			35.0 ± 6.7
	Melton et al. (2013), WETCHIMP ^c	5.4 ± 3.2			
	Pickett-Heaps et al. (2011) ^d	2.3 ± 0.3			
	Treat et al. (2018) ^e			6.1 ± 1.5	37 ± 7
	Watts et al. (2014)				53
	Zhang et al. (2016) ^f	5.5 ± 1.1	4.6 ± 0.6		30.3 ± 5.4
	This study, LPX-Bern	2.5	4.4	4.5	24.7
	This study, WetCHARTs	2.8 (0.5-8.7)	4.2 (1.6-9.4)	5.1 (0.6-17.0)	29.7 (8.7-74.0)
Flux measurement upscaling	Glagolev et al. (2011)		3.9 ± 1.3		
	Zhu et al. (2013)				44.0-53.7
	This study, RF-PEATMAP	4.8 (3.3-6.3)	6.6 (4.9-8.4)	6.7 (4.9-8.5)	31.7 (22.3-41.2)

	This study, RF-DYPTOP	4.6 (3.1-6.0)	7.0 (5.2-8.8)	6.2 (4.6-7.8)	30.6 (21.4-39.9)
	This study, RF-GLWD	4.9 (3.4-6.5)	6.8 (5.0-8.5)	8.0 (5.8-10.2)	37.6 (25.9-49.5)

a Approximately north from 47 °N

b Approximately north from 45 °N

c Mean annual CH₄ emissions from eight models \pm 1-sigma of interannual variation in the model estimates for the period 1993-2004.

d Process model tuned to match atmospheric observations

e North from 40 °N

f Mean \pm 1-sigma over LPJ-wsl model results using different wetland extends for the period 1980-2000.