



Local Emission Estimates of Methane in Northern Sweden with the MAGIC2021 Dataset and Lagrangian Transport Modelling

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Abstract. Wetland methane emissions at high latitudes are central to the present and future global methane budget, yet remain poorly constrained by observations. Here we combine airborne in-situ measurements from the MAGIC2021 campaign with Lagrangian transport modelling to estimate local wetland methane emissions near Kiruna, Sweden, and test whether current bottom-up wetland models reproduce the emission field that generates the observed atmospheric signal. We find no significant difference in performance between the assessed models, WetCHARTs and JSBACH-HIMMELI, and mean emissions that agree with the observation-based estimates over the targeted plumes. Emission variability, however, is underestimated by every product, with simulated standard deviations below a quarter of the observed value for half of them. Because our footprints integrate over areas larger than the model grid cells, variability misrepresentation is attributed to emissions varying on timescales shorter than model time steps, rather than to finer spatial sampling, which the method cannot test. This explains earlier findings from the same campaign, where model emissions appeared overestimated when sampling a generic atmosphere rather than plumes alone. In WetCHARTs, rescaling to a prescribed global total causes the high latitude flux to fall as the assumed temperature sensitivity rises, so the boreal contribution is set in part by a parametrisation chosen for the tropics. Agreement over emission hotspots is therefore not evidence that the regional emission field is correct, and the apparent bias of a wetland model depends on how the atmosphere is sampled, a caveat applying to tower networks, airborne campaigns and satellite retrievals alike.

1 Introduction

To understand and quantify emissions of methane at high latitudes represents a crucial challenge for reducing uncertainties in the global budget of methane, a greenhouse gas 28 times more potent than carbon dioxide over a 100-year period (Myhre et al., 2013). 4% of global CH₄ emissions are attributed to high latitudes (>60°N) (Saunio et al., 2025), a share that has the potential to dramatically increase in the future due to the large share of global carbon stored in circumpolar regions (Kasischke, 2000; Hugelius et al., 2014) and identified physical (Arctic amplification, increased wildfires frequency, Rantanen et al. (2022);



Box et al. (2019)) and biogeochemical (wetland-methane feedback, permafrost thaw, Zhang et al. (2023); Yuan et al. (2024); Ward et al. (2024)) mechanisms that could release large amounts of this stored carbon as methane. High latitudes methane emissions are dominated by wetlands (mostly peatland, Gorham (1991)), which include many diverse and complex ecosystems that are difficult to monitor and model (Bloom et al., 2017). Two main approaches have been used so far to compute continuous estimates of these emissions. The first is called the bottom-up approach and uses either models (relying on the parametrisation of physical and biochemical processes, Bloom et al. (2017); Raivonen et al. (2017)), inventories (compilation of emissions calculated from activity data and emission factors, providing an accounting of emissions, Janssens-Maenhout et al. (2014)) or data-driven approaches (based on the upscaling of surface flux measurements through e.g. flux chambers or eddy covariance Bernard et al. (2025)) (Saunois et al., 2025). Today, direct flux measurements are common and easily available with a larger amount targeting high latitudes sources (Delwiche et al., 2021; Bernard et al., 2025). However, they typically cover a very small spatial (100m - 2km) domain that often targets a specific source, and are strongly influenced by transport and footprint representativeness, which can lead to biases when trying to extrapolate emissions (Chu et al., 2021; Mekonnen et al., 2016). As such, bottom-up emissions rely much on theoretical/accounting inputs rather than observational constraints (Saunois et al., 2025). The other main method to estimate methane emissions is called the top-down approach and uses atmospheric measurements to infer surface fluxes, or FCH₄ (Saunois et al., 2025). This approach, based on inverse modelling, uses atmospheric transport models to link observed concentrations to emissions. It can be used at various scales, to study emissions from large regions such as the Arctic as a whole (Berchet et al., 2015; Thompson et al., 2017; Tsuruta et al., 2023; Wittig et al., 2023) or at the scale of a country, with higher resolutions (Tsuruta et al., 2019). Inversion techniques can leverage data collected from mobile measurements to constrain emissions by bottom-up models, which provide better spatial constraints (Karion et al., 2015; Lauvaux et al., 2016). This method is particularly useful for regions where tower measurements are scarce, as at high latitudes. However due to their cost, mobile measurements are typically performed over short periods of time and cover limited areas (Paris et al., 2010; Davis et al., 2017; Hartery et al., 2018; Berchet et al., 2020; Paris et al., 2008; Narbaud et al., 2023). Full inversion systems are also computationally expensive and require a long time to build properly. Thus, studies have estimated emissions from aircraft measurements using simpler approaches, such as the mass balance method (Karion et al., 2015; Pühl et al., 2024), which allows to estimate emissions from a specific area by measuring the concentration of a gas of interest up- and downwind from the source. Other methods based on space-borne estimates of atmospheric composition discriminate emission plumes from point sources against surrounding background, and estimate emissions combining observed enhancements with atmospheric transport modelling techniques such as Gaussian plume models (e.g. Nassar et al. (2017)). This method works particularly well when studying strong, spatially compact sources, such as cities or power plants, but are less applicable to more diffuse sources like wetlands, because the signal strength is typically too weak to be distinguishable through the whole atmospheric column. As such, there is still a lack of methods to quantify methane emissions from circumpolar wetlands at regional scale, which contributes to the persisting large uncertainties on their contribution to the global methane budget (Saunois et al., 2025).

A further difficulty is that wetland emissions vary strongly in time, responding to soil temperature at sub-daily to synoptic scales (Rinne et al., 2018) and, more broadly, to water table position and vegetation composition (Olefeldt et al., 2013). While



the seasonal cycle of these emissions has been evaluated extensively (Delwiche et al., 2021), their variability at shorter scales remains little tested against atmospheric measurements.

This applies to the Fennoscandian region, where the *Monitoring Atmospheric composition and Greenhouse gases through multi-Instruments Campaigns* (MAGIC) campaign took place in 2021 (Crevoisier, 2021). MAGIC2021 aimed at studying methane emissions in the region of Kiruna, Sweden, combining both airborne and ground-based in-situ measurements at high resolution. The campaign was conducted from 17 to 26 August 2021, when boreal wetland activity is typically at its peak (Barlow et al., 2016). Langot et al. (2025) have used data acquired by MAGIC2021 balloons and aircraft flights to evaluate the performance of several atmospheric transport models in reproducing meteorological variables as well as atmospheric CH₄ content at high latitudes. They notably found an excess of CH₄ in the boundary layer of WRF-Chem regional simulations that used certain bottom-up models as input surface emissions, which indicated that these emissions could be overestimated.

In this study, we focus on MAGIC2021 data acquired by the Cessna aircraft that was operated by the German Aerospace Center (*Deutsches Zentrum für Luft- und Raumfahrt* - DLR). It was equipped with a spectrometer that measured methane mixing ratios in the atmospheric boundary layer (ABL). The majority of flight paths was designed according to flux estimation strategies like mass balance, eddy covariance and Lagrangian estimation. We applied Lagrangian modelling to infer surface influence on CH₄ enhancements detected during campaign flights, leading to local wetland emission estimates. Results from this approach were then compared to emissions from bottom-up models in order to evaluate the performances of various methane emission parameterisations.

We first start by detailing our flux estimation method in Section 2. Then, Section 3 presents emission estimates from MAGIC2021 data and compares them to existing wetland models (bottom-up emissions models). Finally, we discuss the performance of different wetland models in reproducing the observed methane signals and provide insights into Fennoscandian wetland methane emission mechanisms.

2 Methods

2.1 In-situ data description

During MAGIC2021, the Cessna aircraft was equipped with a G1301-m Cavity Ring-Down Spectroscopy (CRDS) analyser from Picarro™ (Rella et al., 2013), which measured CH₄ mixing ratios along the flight track. CRDS is a time-based method that uses near-infrared laser technology to detect the spectral signature of gas sample molecules. The aircraft performed 12 flights over the region, mostly within the ABL and with a focus on wetland areas. Four flights with a raster-like pattern were selected for further analyses, because they captured distinct plumes of enhanced methane mixing ratios, embedded in background air. Our flux estimation technique requires a clear contrast between potential wetland CH₄ plumes and the background, with both airmasses spatially and temporally close to each other. Three of the selected flights were performed above a wetland region North East of Kiruna, while the 4th flight was performed over another wetland region South of Kiruna. The 4 flights were performed on the 22nd, 23rd and 26th August 2021, with 2 flights on the 26th. In the following, these flights are denoted: 22a,



23a, 26a and 26b, respectively. Figure 1 shows the flight paths plotted over the Corine2018 land cover (European Environment Agency, 2019).

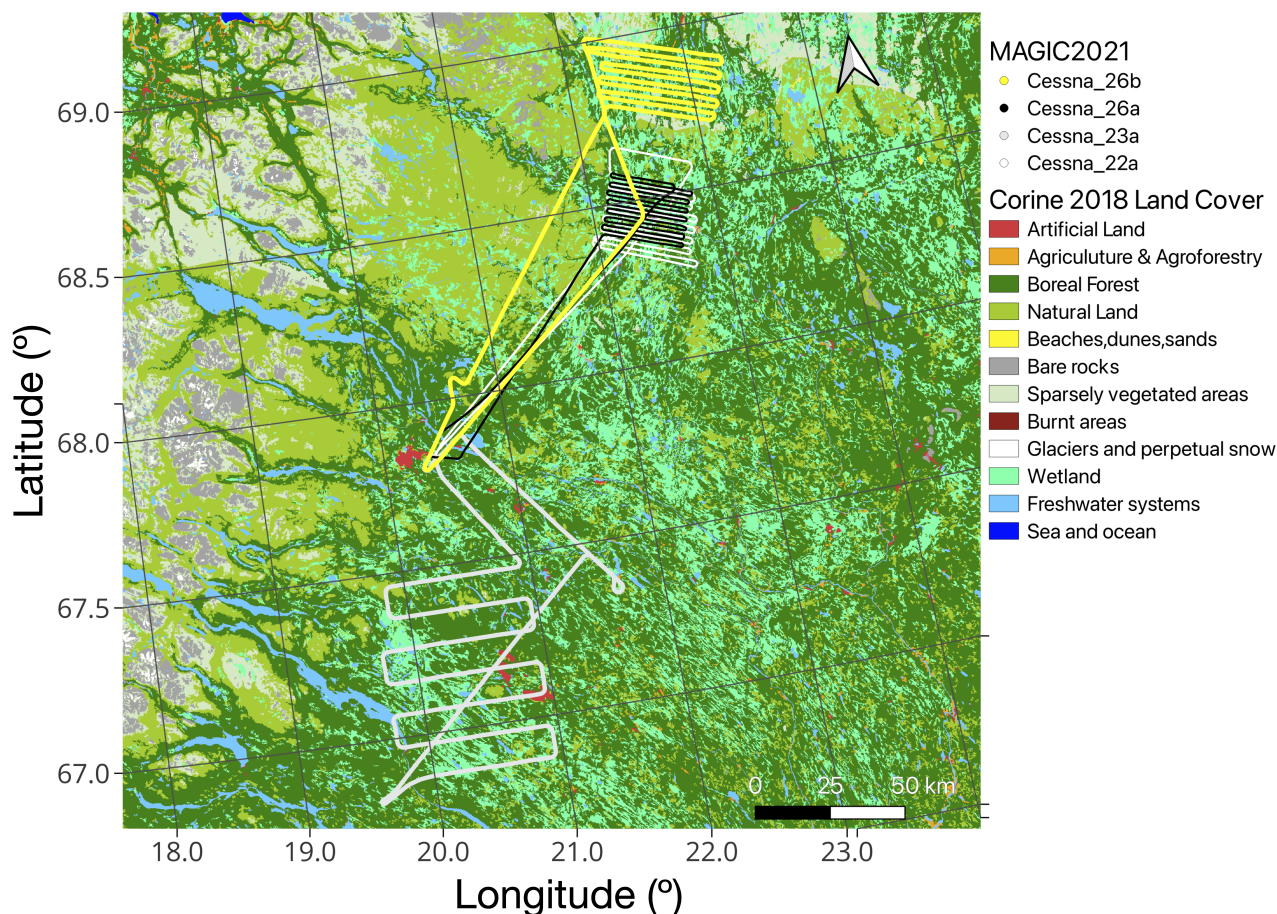


Figure 1. Flight paths of the 4 selected Cessna flights from MAGIC2021 over the Corine2018 land cover map (European Environment Agency, 2019).

- 90 CH_4 mixing ratios were measured in near real time during the flights using the G1301-m. The G1301-m is equipped with temperature and pressure control systems, allowing accurate long-term measurements with minimal reliance on calibration gases. Additionally, it includes pressure monitoring capabilities that adjust for the significant pressure variations experienced during flights, particularly vertical profilings. The system has undergone extensive vibration testing to withstand the demands of use on mobile platforms such as the Cessna aircraft. It has a precision ($1-\sigma$, 30 s) < 1.5 ppb for CH_4 (Roiger et al., 2023).
- 95 Figure 2 shows mixing ratios recorded along the flight paths of the 4 selected flights, once the Cessna reached the area of interest. Coloured data shows enhancements in CH_4 mixing ratios of varying magnitudes. Flights 22a, 26a and 26b were designed to be Lagrangian, i.e. follow the wind: A series of parallel legs perpendicular to prevailing winds, with the ratio between leg length and spacing between the legs allowing the aircraft to stay within the same airmass. The raster pattern of

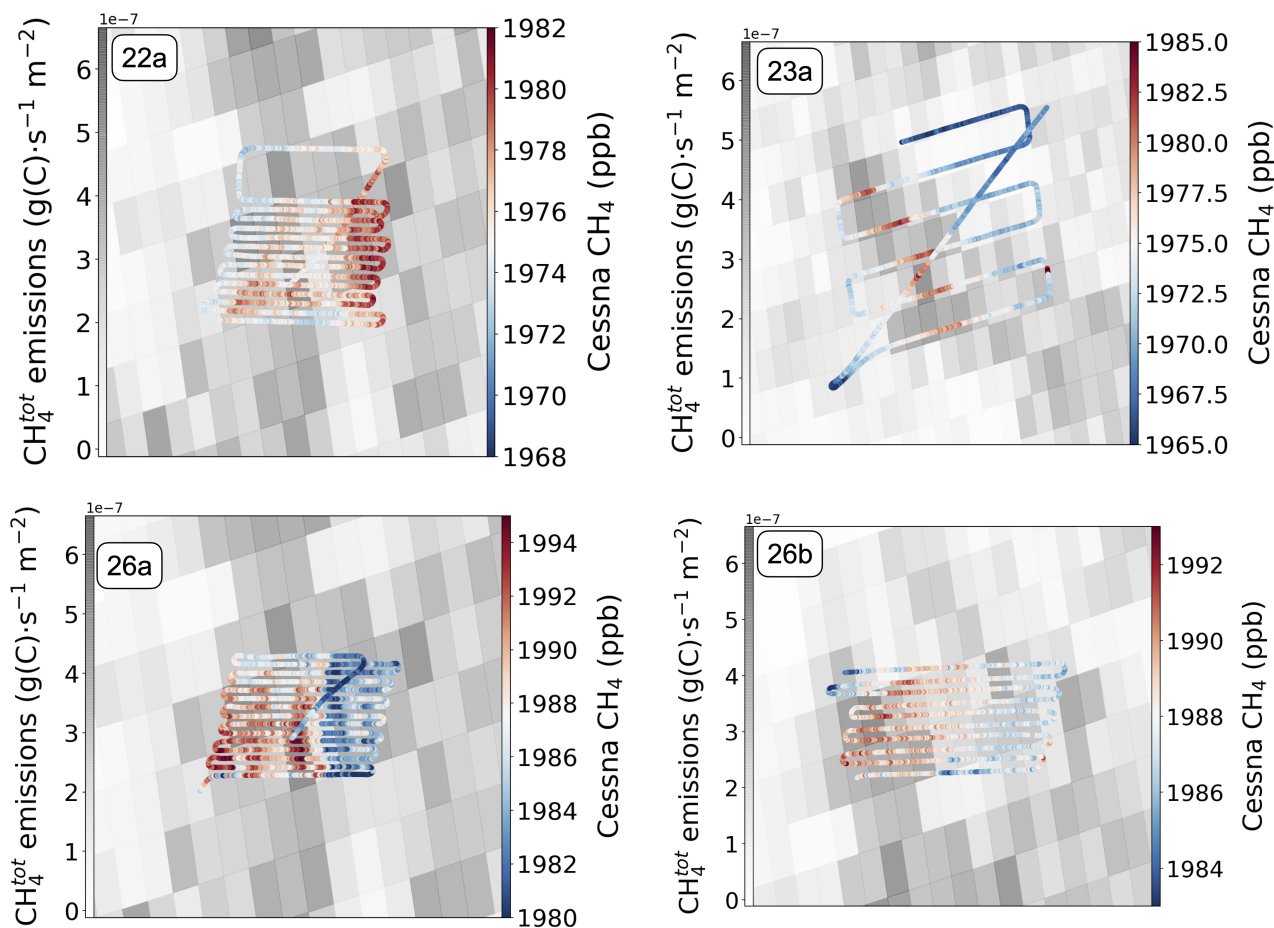


Figure 2. CH₄ mixing ratios measured along the flight paths of 4 selected Cessna flights from MAGIC2021 over the Kiruna region. Background tiles show JSB-HIM CH₄ emissions at 0.1°×0.1° resolution (details in Section 2.2.1).

flight 23a was coordinated with other platforms, to allow for complementary measurements and intercomparisons which are not discussed in this study.

Flight 22a covered its area of interest between 12:00 and 13:30 local time (LT) at an altitude of 630<z<800m. This flight is characterised by a 8-10 ppb enhancement on the east side of the raster compared to the background surrounding measurements. Flight 23a was performed in the morning and flew over the targeted area between 9:20 and 10:20 at z = 800m. Recorded mixing ratios show a slightly higher enhancement of ~15 ppb along a diagonal from the north-western to southern side of the measurements. Flight 26a was performed in the morning between 8:30 and 10:00 at 650<z<1000m, and measured enhancements of ~10 ppb. Flight 26b was performed in the afternoon, with targeted measurements realised between 13:00 and 14:30 at 800<z<1500m, and showed smaller enhancements of ~5-10 ppb. This was expected as the flight was performed at higher altitudes and over land with less wetland coverage (Figure 1).



2.2 Wetland emission models and WRF-Chem simulations

110 2.2.1 JSBACH-HIMMELI

Simulations from the coupled model JSBACH-HIMMELI (JSB-HIM) were performed at the Finnish Meteorological Institute (FMI) within the European VERIFY project and its follow-up EYE-CLIMA, under which most of the fields used here were prepared. The modelling framework is described in detail by Aalto et al. (2025). It couples the land component of the Max Planck Institute Earth System Model (MPI-ESM) process model JSBACH version 3.2 (Ekici et al., 2014) with the HIMMELI methane module version 1.0 (Raivonen et al., 2017). JSBACH includes a multilayer hydrology model and uses the YASSO model for representing soil carbon dynamics. HIMMELI is a methane emissions model for peatland ecosystems which details physical and chemical processes that control methane production and transport in peatlands. Thus HIMMELI takes as input the rate of anoxic soil respiration provided by JSBACH and simulates surface methane emissions.

Simulations were run over Europe, from which the Fennoscandian domain was extracted for the present study. They used land cover from EU-CORINE 2012, interpreting bogs and inland freshwater marshes as peatlands. Other types of land were considered as mineral soils. Outputs from JSB-HIM give emissions at a $0.1^\circ \times 0.1^\circ$ resolution and at a daily time step. The model provides 4 different components of wetland emissions: peatland CH_4 emissions, mineral soil CH_4 emissions, mineral soil CH_4 uptake and inundated land CH_4 emissions. Emission and uptake from mineral soil were merged in our study to get the net flux. Three sets of simulations, produced successively by FMI, were assessed here. They differ in the meteorological forcing used to drive the model. The first was driven by the CRUERA forcing, in which ERA5-Land fields (Muñoz-Sabater et al., 2021) are adjusted at the monthly scale towards the gridded observational dataset CRU-TS (Harris et al., 2020), here using CRU-TS version 3. The second was driven by ERA5-Land without the CRU adjustment. The third repeated the CRUERA setup with CRU-TS version 4. The three simulations are labelled JSB-HIM(CRU), JSB-HIM(ERA5) and JSB-HIM(CRU4) respectively. These fields are archived on Zenodo Aalto et al. (2025); the two earlier simulations are superseded production versions obtained directly from FMI.

2.2.2 WetCHARTs

WetCHARTs (Bloom et al., 2017) computes monthly wetland CH_4 emissions from 2001 to 2019 using a process-based model. It simulates simplified biogeochemistry parameters that control methane emissions from natural wetlands. Wetland CH_4 emissions F are derived at time t and location x from the following equation:

$$135 \quad F(t, x) = s \cdot A(t, x) \cdot R(t, x) \cdot q_{10}^{\frac{T(t, x) - 10}{10}} \quad (1)$$

where s is a global scaling factor, A is the wetland extent fraction, R is the C heterotrophic respiration per unit area at time t and $q_{10}^{\frac{T(t, x) - 10}{10}}$ is the temperature dependence of the ratio of C respired as CH_4 (where q_{10} is the relative CH_4 :C respiration for a 10°C increase and $T(t, x)$ is the surface skin temperature). Each version of the WetCHARTs emissions is labelled by a 4-digit number, where each digit represents a different input value for the variables in (1). The 4 parameters are the global



Digit position	Parameter name	Description
1	Global scaling factor	1 = 124.5 Tg CH ₄ /yr 2 = 166 Tg CH ₄ /yr 3 = 207.5 Tg CH ₄ /yr
2	Heterotrophic respiration model	1–8 = MsTMIP models 9 = CARDAMOM
3	Temperature dependence	1 = CH ₄ :C q_{10} is 1 2 = CH ₄ :C q_{10} is 2 3 = CH ₄ :C q_{10} is 3
4	Extent parametrisation	1 = SWAMPS & GLWD 2 = SWAMPS & GLOBCOVER 3 = PREC & GLWD 4 = PREC & GLOBCOVER

Table 1. Available WetCHARTs emissions parametrisations, where GSF is the global scaling factor, HRM is the heterotrophic respiration model, TD is the temperature dependence model and EP is the extent parametrisation used. For example product 2913 is an emission product from WetCHARTs which uses a global scaling factor of 166 Tg CH₄/yr, CARDAMOM as the heterotrophic respiration model, CH₄:C q_{10} = 1, PREC as the meteorological forcing and GLWD as the extent parametrisation. From Bloom et al. (2017).

140 scaling factor, heterotrophic respiration model, temperature dependence model and wetland extent parametrisation, which are respectively represented by the 1st, 2nd, 3rd and 4th digit of the label and can take different values as shown in Table 1.

18 versions of the emissions were available at the time of our study. Publicly downloadable products included results from simulations done with CARDAMOM as the heterotrophic respiration model and ERA5 monthly precipitation from the European Centre for Medium-Range Weather Forecasts reanalysis (ECMWF) coupled with GLWD and GLOBCOVER as the extent parametrisation (PREC & GLWD and PREC & GLOBCOVER respectively). Our study further trimmed down the WetCHARTs product to 8 versions to focus on the impact of temperature and wetland extent parameters which are among the main uncertainty sources regarding wetland methane emissions (Saunois et al., 2025; Zhang et al., 2023). The final selection included product number 1913, 2913, 2914, 2923, 2924, 2934, 3913, 3933. Because WetCHARTs estimates stop in 2019, emissions for the MAGIC2021 period were estimated by computing a climatology of August emissions of years 2016, 2017 and 2018.

2.2.3 WRF-Chem simulations

The Weather Research and Forecasting coupled with Chemistry (WRF-Chem) model was employed to simulate meteorological conditions and greenhouse gas concentrations during the MAGIC2021 campaign on a regional scale. The model configuration consisted of two domains: a parent domain (d01) encompassing Fennoscandia, Denmark, western Russia, and most Baltic



155 countries at 9km resolution, and a nested domain (d02) at 3km resolution covering northern Finland, Sweden, and Norway where MAGIC2021 measurements were conducted. Domain boundaries were carefully selected to avoid strong emissions and high topography near boundaries. Physical parametrisations are described in Langot et al. (2025).

Methane was modelled using passive tracers transported online alongside the meteorological variables. Distinct tracers were assigned to each emission sector. Independent tracers were specifically allocated to each wetland bottom-up products to allow
160 for parallel assessment, following the configuration detailed in Langot et al. (2025). Emissions were injected into the lowest model layer at each time step, where the tracers were subsequently subject to advection, boundary layer mixing, and convection.

Initial conditions were set using ERA5 reanalysis meteorology at $0.5^\circ \times 0.5^\circ \times 137$ levels resolution, with boundary meteorological conditions updated every 3 hours. Methane boundary conditions were provided by the inversion-optimised CAMS product v21r1 at $3^\circ \times 2^\circ \times 34$ levels resolution every 6 hours. Emissions within the simulation domains were represented by different tracers depending on source types, including anthropogenic (Olivier and Janssens-Maenhout, 2012), fire (Kaiser et al.,
165 2012), oceanic (Weber et al., 2019), wetland (Aalto, 2019; Bloom et al., 2017), and lake emissions (Johnson et al., 2022), each with specific spatial and temporal resolutions detailed in Langot et al. (2025).

The simulations were run from the 1st to the 31st of August 2021, allowing for a 15-day spin-up period to ensure realistic concentrations throughout the domain. This comprehensive setup enabled the construction of various atmospheric methane mixing
170 ratios products, notably using different wetland emissions, so wetland models could be assessed against the MAGIC2021 campaign.

2.3 Flux estimation method

2.3.1 Plume detection

To estimate fluxes, we employ an approach based on CH₄ plume detection, hereafter referred to as the “plume approach”.
175 This method of signal detection is similar to the one used with satellite observations to detect signals from known sources at different scales, notably cities or power plants (Nassar et al., 2017; Kuhlmann et al., 2020; Danjou, 2022), in that it considers as background and signal a series of measurements closely located in space and time that display significant differences in measured mixing ratios. We first select the raster portion of each flight and consider the bottom 50% of measured mixing ratios as background b . We then make 3 selections for labelling plume data p : the top 5%, 10% and 15% of recorded mixing ratios
180 are considered as methane enhancement from local wetlands. These 3 sets of data labelled as a signal allow to account for transport and footprint uncertainty. In practice, this meant that only portions of selected flights were used for the flux study. The 4 chosen flights from MAGIC2021 are shown in Figure 3 with the flight portion selected for flux estimates. Plume and background selections are also shown. The wetland signal ΔQ_i^p , i.e. the part of a mixing ratio measurement i due to wetland emissions is computed as follows:

$$185 \quad \Delta Q_i^p = Q_i^p - \bar{Q}^b, \quad (2)$$



where Q_i^p represents an individual mixing ratio of CH_4 measured in an identified plume along the plane flight path, and $\bar{Q}^b$ is the mean of background concentrations of the flight. Our assumption that the signal ΔQ_i^p is only due to local wetland emissions relies strongly on the fact that the plane flies at low altitudes in the ABL, but also on the flight locations picked, which were planned to specifically investigate those signals.

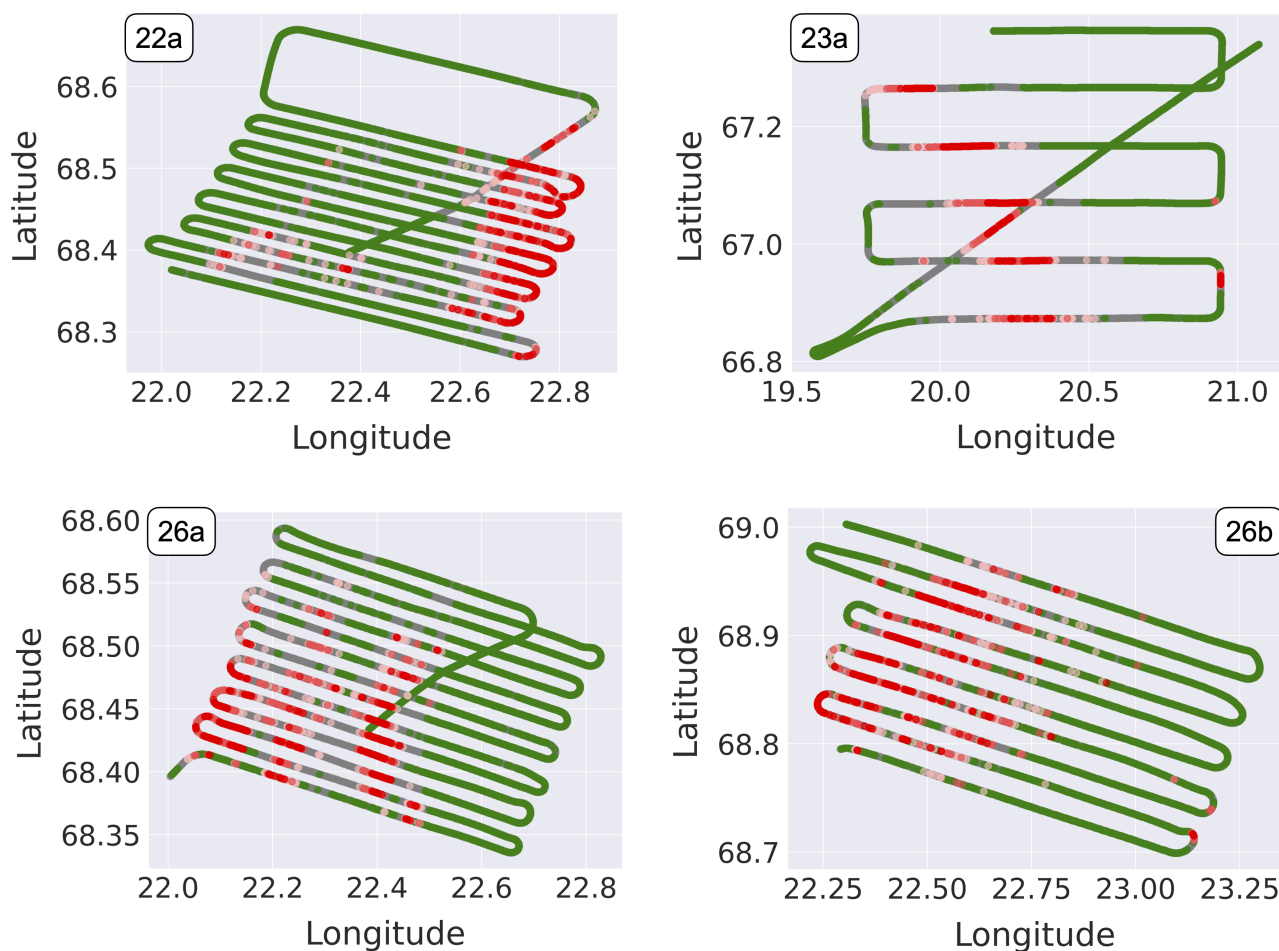


Figure 3. Portions of flights selected for flux estimation using the plume approach. Each panel shows the plume (beige-pink-red) and background (green) masks used to calculate the wetland signal ΔQ_i^p . Three plume masks were employed: red data shows the 5% highest concentrations, pink data shows the 5-10% highest concentrations and beige data shows the 10-15% highest concentrations. The green background mask shows the 50% lowest concentrations.



190 2.3.2 Lagrangian transport

The Lagrangian approach to transport tracks individual air parcels as they move through the wind field (Lauvaux, 2008). Crucially, Lagrangian transport is easily reversible in time, enabling a receptor-oriented framework, as for flux inversions: observations at a given receptor location can be linked backward in time to identify the surface regions that influenced these measurements. This computationally efficient approach forms the basis of our methodology, where atmospheric measurements
195 are used to constrain surface flux estimates.

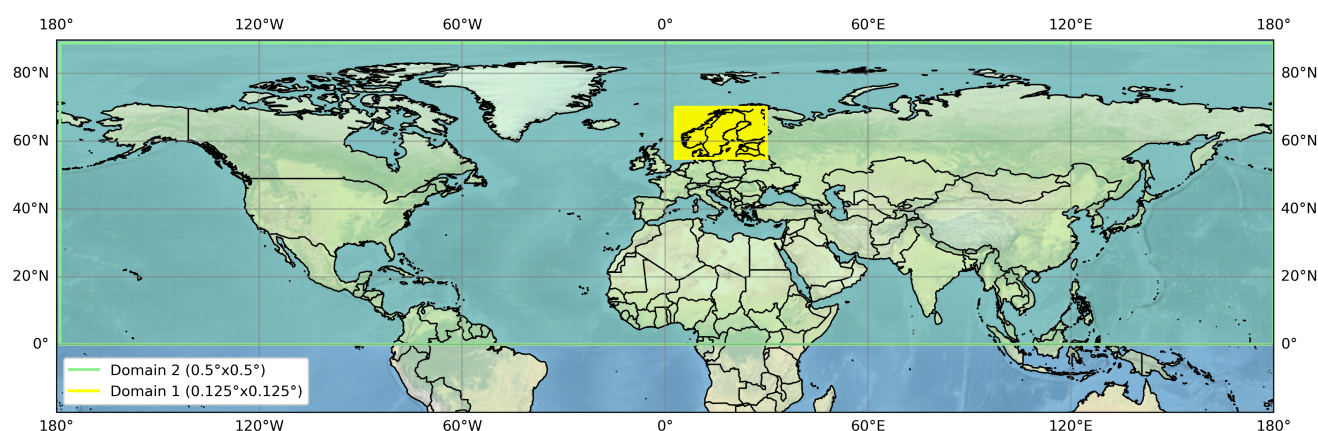


Figure 4. FLEXPART domains used for the MAGIC2021 campaign. This study uses only the smaller domain, shown in yellow, for local flux estimates.

The Lagrangian model that was used is called FLEXPART Stohl et al. (1998) version 10.4 described in Pissot et al. (2019). As shown in Figure 4, two nested domains were set up, the first being the whole northern hemisphere at a $0.5^\circ \times 0.5^\circ$ resolution. Transport in that domain was driven by ECMWF meteorological fields at a resolution of $1^\circ \times 1^\circ \times 137\eta \times 6h$ that were retrieved using the `flex_extract` toolbox (Tipka et al., 2020). The second (or nested) domain was centred around the Kiruna region, i.e. between $55^\circ N$ and $70^\circ N$ in latitudes and between $3^\circ E$ and $30^\circ E$ in longitude, with a resolution of $0.125^\circ \times 0.125^\circ$.
200 In this smaller domain the driving meteorological data was spatially better resolved, using ECMWF operational forecast at $0.1^\circ \times 0.1^\circ \times 137\eta \times 1h$ resolution. This was the domain used for local flux estimates, with an hourly particle release rate. Transport in the ABL is parametrised according to the Langevin equations for particle velocity components Stohl et al. (2005) and stochastic differential equations from Thomson (1987) well-mixed criteria Pissot et al. (2019). This takes into account the randomness characteristic of transport near the surface (turbulence) to better model particles trajectory during parts of their path
205 that are close to the surface, which is a crucial one for flux estimates. As a particle dispersion model, FLEXPART allows for the calculation of footprints or influence functions, which quantify the influence of emissions from a surface area on concentrations measured at any observation coordinates. FLEXPART computations, pre- and post-processing were driven by Berchet et al. (2023) and footprints were calculated according to eq. (2) (Lin, 2003; Karion et al., 2019):



$$210 \quad \mathcal{F}_{i,j} = \frac{m_{\text{air}}}{h\rho} \cdot \frac{1}{N_{\text{tot}}} \cdot \sum_{p=1}^{N_{\text{tot}}} \Delta t_{p,j} \quad , \quad (3)$$

where $\mathcal{F}_{i,j}$ is the footprint value of an individual observation i over an individual model grid cell j ($\mathcal{F}_i$ is a footprint vector including all individual footprint values for a given observation). The footprint is a function of the residence time of a given particle p over a grid cell j below height h , $\Delta t_{p,j}$. Here, N_{tot} is the number of released particles, m_{air} is the molar mass of air and ρ is the average air density below h . $\mathcal{F}_{i,j}$ is given in units of mixing ratio over flux, e.g. $\frac{ppb}{g \cdot m^{-2} \cdot s^{-1}}$ so that multiplying a
215 footprint by a surface flux at a location j gives the concentration due to emissions at j .

2.3.3 Flux computation

Using both wetland signals ΔQ and footprints $\mathcal{F}$, we can estimate the fluxes from a given area spanned by an i,j grid as follows:

$$F_k^p = \frac{\Delta Q_k^p}{\sum_{i,j} \mathcal{F}_{i,j}^k} \quad , \quad (4)$$

220 where F_k^p is the flux estimated from an observation k in the plume, ΔQ_k^p is the signal measured at k and $\mathcal{F}_{i,j}^k$ is the footprint value of observation k over the footprint grid i,j . This equation is applied to all observations in a plume to obtain an estimate of the total regional wetland methane flux causing excess of methane recorded at flight location. Next, we compare this plume approach to bottom-up emissions by transporting wetland model emissions to measurement locations with our Lagrangian transport:

$$225 \quad \Delta Q_k^{\text{mod}} = \sum_{i,j} \mathcal{F}_{i,j}^k \cdot e_{i,j} \quad , \quad (5)$$

where ΔQ_k^{mod} is the modelled signal at observation k and $e_{i,j}$ is the wetland emissions at grid cell i,j . This effectively means multiplying the footprint from each release location along the aircraft path by the wetland model emissions at each grid cell of that particular footprint. This requires regridding footprint outputs to bottom-up models spatial resolution. We therefore obtain the wetland signal transported by FLEXPART from the surface (bottom-up emissions) to our plane measurement locations. This
230 quantity is the equivalent of a ΔQ_k^p but as simulated by transporting surface emissions from wetland models with FLEXPART instead of determining it from measurements. We compute the regional flux associated with this modelled wetland signal as follows:

$$F_k^{\text{mod}} = \frac{\Delta Q_k^{\text{mod}}}{\sum_{i,j} \mathcal{F}_{i,j}^k} \quad , \quad (6)$$

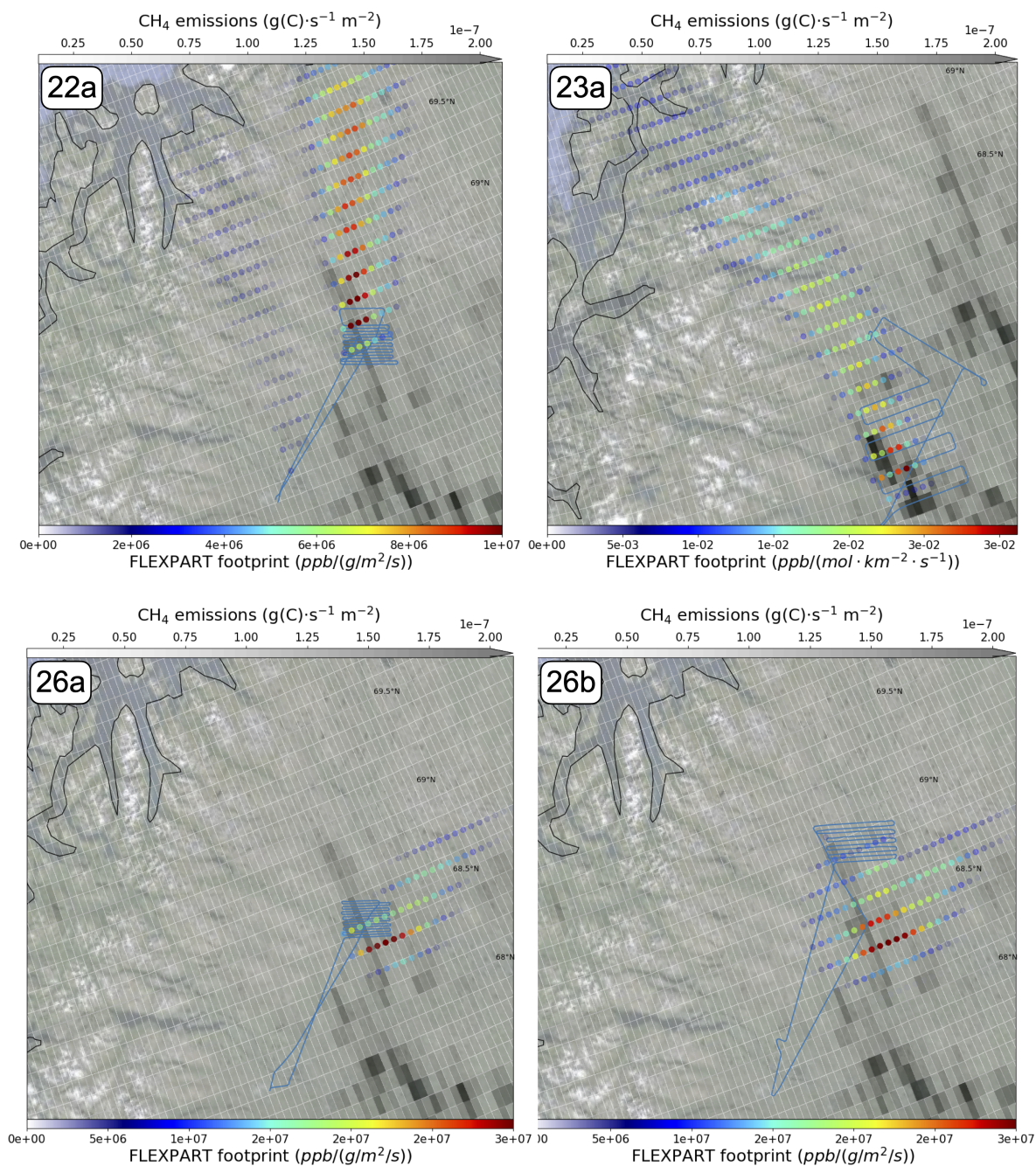


Figure 5. FLEXPART footprints of detected wetland plumes in Cessna measurements from 4 flights that performed raster-like trajectories over the Kiruna region (rainbow color). Background greyscale tiles show JSB-HIM emissions at $0.1^\circ \times 0.1^\circ$ resolution.



where, similarly as in equation (4), F_k^{mod} is the modelled flux at observation k . This allows us to compare observation
235 based (or top-down) estimates, F_k^p , with simulated wetland model (or bottom-up) emissions, F_k^{mod} , using the same transport
by FLEXPART.

3 Results and Discussion

3.1 Comparative analysis of flux estimates

Figure 6 shows F_k^p and F_k^{mod} values obtained from equations (4) and (6) for the four MAGIC2021 Cessna flights detailed
240 in Figure 2. The x -axis corresponds to FLEXPART release IDs, which index the spatiotemporal locations where Lagrangian
particles were released along the flight path. Release IDs are ordered sequentially to preserve the flight trajectory structure.

Across all four flights, both JSB-HIM and WetCHARTs fluxes span a wide range in magnitude, with differences of typically
a factor of 3-4 between the lowest and highest emissions. Within the WetCHARTs ensemble (blue curves), the lightest blue
members (2913) consistently lie at the top of the distribution, whereas darker blue members (e.g. 1913, 3913) give smaller
245 emissions. The three JSB-HIM configurations (green curves) also yield clearly separated mean levels and plume-averaged
values, highlighting simulations sensitivity to the choice of meteorological input data.

This figure shows that plumes detected in the observational data do not systematically coincide with higher fluxes from
bottom-up models. This is expected for WetCHARTs, whose values represent monthly climatologies, but Figure 6 also shows
that the daily JSB-HIM emissions exhibit a similarly weak temporal correspondence with the observed plume occurrences,
250 despite their higher temporal resolution. Overall, emissions from WetCHARTs and JSB-HIM are not clearly distinguishable in
their ability to reproduce emissions derived from the MAGIC2021 Cessna measurements.

Important flight-to-flight differences are also visible in top-down relative to bottom-up emissions. For example, fluxes from
the 23a flight were relatively higher, whilst those from 26b were lower. Flight times of our sample data (22a: 11:30-14:30,
23a: 8:30-11:15, 26a: 08:00-10:30, 26b: 12:30-15:20) seem to rule out a diurnal emission cycle as the driver of this variability.
255 Whilst sub-daily emission variations have been documented in wetlands (Zona et al., 2016; Rinne et al., 2018), the observed
differences here point instead to meteorological or hydrological controls.

The overall similar performance between JSB-HIM and WetCHARTs was initially unexpected, given that JSB-HIM emis-
sions are daily flux estimates at $0.1^\circ \times 0.1^\circ$ resolution, whereas WetCHARTs products are monthly climatologies at $0.5^\circ \times 0.5^\circ$
resolution. This suggests that processes controlling the observed wetland FCH₄ variability operate at scales that are not effec-
260 tively resolved even by JSB-HIM, so that increasing model resolution within the current model set-up does not substantially
improve agreement with the aircraft-derived fluxes. The underlying scale mismatch between modelled and observed emission
heterogeneity is explored more quantitatively in Section 3.4.

Average emission estimates for each flight are gathered in Figure 7. Adding plume selection and associated transport uncer-
tainty to the standard deviation of fluxes over each flight is shown to increase uncertainty by only 10%, which means that, first,
265 FLEXPART backward transport stays consistent with small changes in plume extents and, second, less significant methane
enhancements added as part of the plume when broadening data selection does not significantly affect flux estimates.

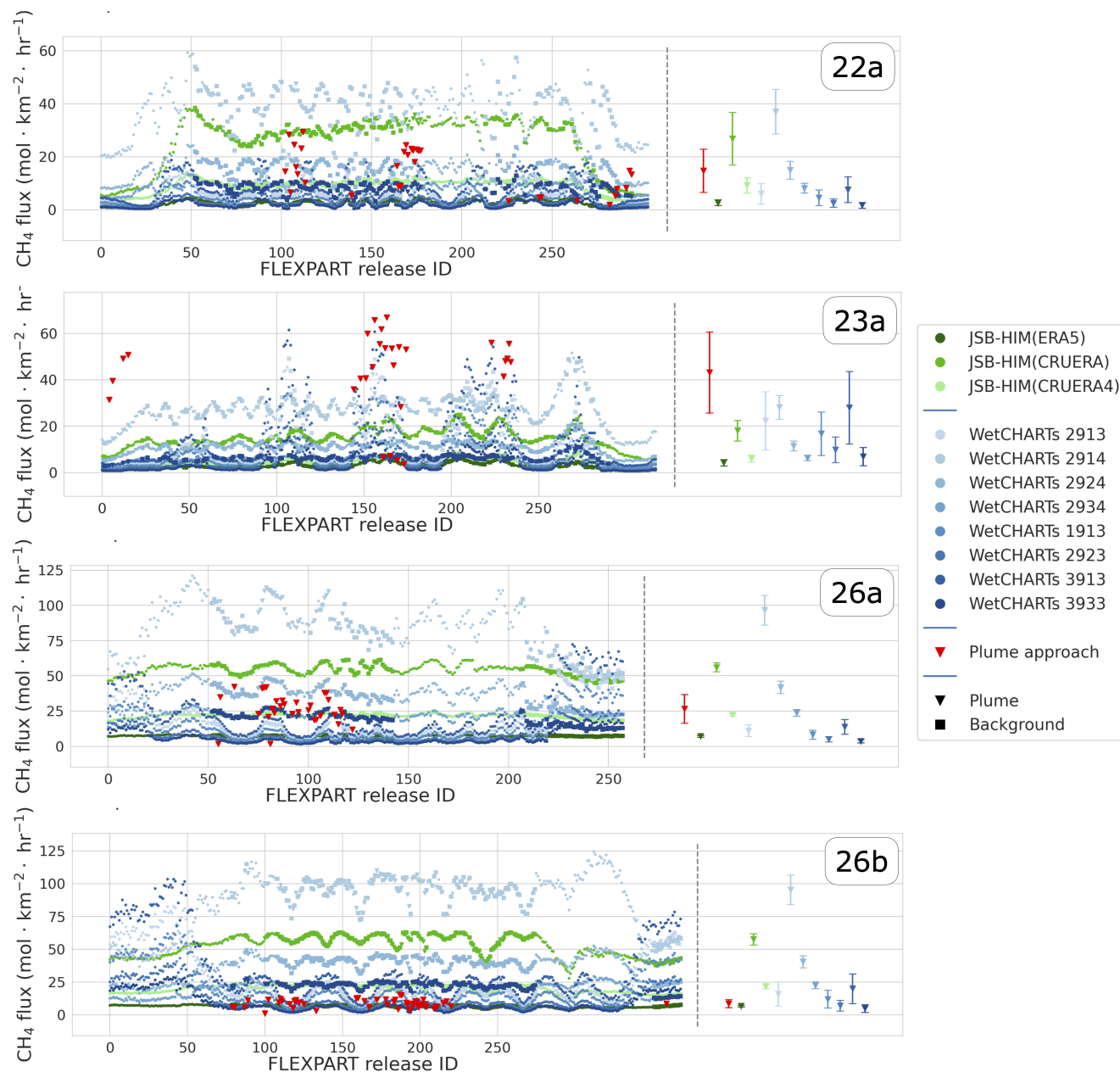


Figure 6. Wetland methane fluxes estimated from the MAGIC2021 Cessna flights using the plume approach (top-down, red). Green scatter data corresponds to JSB-HIM emissions and blue scatter to WetCHARTs emissions (bottom-up, see Table 1 for more detail). The x -axis represents the count of sequentially ordered FLEXPART particle releases along the flight path. On the left hand side of each plot, upside-down triangles show flux values estimated using the footprint from methane enhancements detected in Cessna in-situ data using the top 10% criterium. Squares show flux values corresponding to methane background mixing ratios. The right hand side of each plot shows the mean and standard deviation of derived fluxes using the part of flights where plumes were detected.

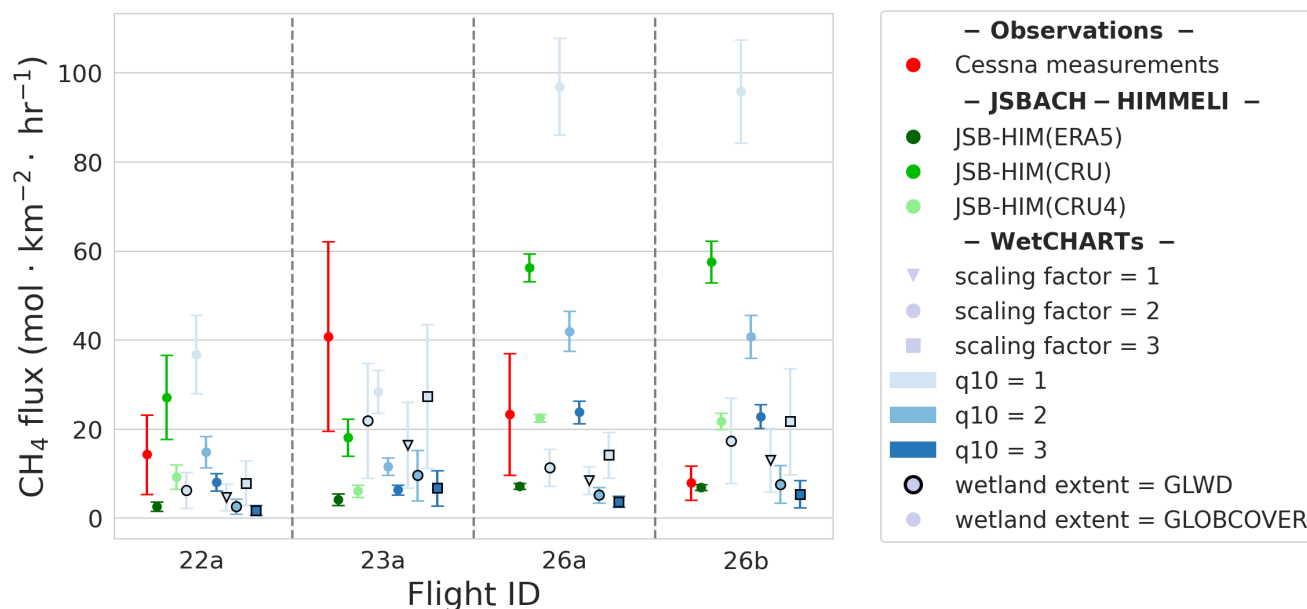


Figure 7. Mean wetland methane emissions per flight, estimated from FLEXPART and both the MAGIC2021 dataset using the plume approach (red) and wetland model emissions (green and blue). Uncertainty shown here combines the standard deviation of fluxes over each flight and uncertainty on footprints provided by the three plume selection methods (5%, 10% and 15% of highest recorded mixing ratios).

3.2 JSB-HIM parametrisation analysis

JSB-HIM fluxes vary in both magnitude and variability with driving meteorology. Emissions by JSB-HIM(CRU) are higher than top-down estimates in 3 out of the 4 flights analysed, while JSB-HIM(ERA5) emissions are systematically lower. JSB-HIM(CRU4) emissions lie between the other two versions. This stems from the fact that ERA5 was the driest meteorological dataset, followed by CRU4. Within each flight, variability is visibly correlated with mean emissions: higher emissions also display stronger variation amplitudes. This behaviour comes from sampling spatially intermittent sources, as flights over emission-rich regions encounter more frequent transitions between methane plumes and background air masses. This is consistent with the standard expectation that both observed variability and estimation uncertainty increase with flux magnitude in intermittent-source regimes (Jung et al., 2020). Top-down estimates typically vary more strongly than bottom-up emissions, so higher mean emission from wetland models show variations closer to those derived from observations. For JSB-HIM products, modifying input precipitation therefore does not significantly affect the overall model performance in reproducing the observed methane signals. It consists mainly in a trade-off between reproducing emissions mean or variability.

3.3 WetCHARTs parametrisation analysis

WetCHARTs estimates are categorised according to 3 varying parameters: scaling factor, temperature dependence (q_{10}) and wetland extent. In terms of wetland extent, the GLOBCOVER parametrisation leads to higher flux estimates. This can be seen



by comparing product 2913 (light blue circle with black edge) to 2914 (same colour without the black edge), which only differ by their wetland extent parameter. Estimates from 2913 are relatively close to estimates from Cessna measurements while 2914 emissions are overestimated in 3 out of 4 flights with particularly large overestimates for the 2 flights on 26/08 with $FCH_4^{2914} \approx 95 \text{ mol} \cdot \text{km}^{-2} \cdot \text{hr}^{-1}$ whereas $FCH_4 < 25 \text{ mol} \cdot \text{km}^{-2} \cdot \text{hr}^{-1}$ for both observation derived fluxes and 2913 product. In general GLWD estimates are shown to be lower, with moderately/slightly underestimated emissions in 3 out of the 4 flights ($< 10 \text{ mol} \cdot \text{km}^{-2} \cdot \text{hr}^{-1}$ difference). GLWD is an older product (Lehner and Döll, 2004) compared to GLOBCOVER (Bontemps et al., 2011) but it still appears to show better performance mapping Fennoscandian wetlands in the region of Kiruna. The spatial resolution of wetland extent mapping is an important parameter (Hashemi et al., 2025), which could partly explain the observed discrepancy. Indeed, GLWD has a $\sim 800\text{m}$ spatial resolution and while GLOBCOVER has a resolution of 300m . Hashemi et al. (2025) showed that more resolved land cover maps tend to output higher FCH_4 as they better capture small water bodies and wetlands that coarser maps miss. Higher FCH_4 from simulations using GLOBCOVER could also stem from issues encountered when classifying land covers in GLOBCOVER. This classification was done by experts who used data from the satellite MERIS, that misses a SWIR channel thus making it difficult to identify surfaces such as wetlands. More particularly, it made it hard to distinguish them from other ecosystems such as shrublands or grasslands (Bontemps et al., 2011), which could have potentially led to an overestimation of their extent in Fennoscandia. Other factors, such as thematic detail (differentiation between wetland types, have also been identified as an important factor in the amount of emissions from wetlands (Kuhn et al., 2021; Hashemi et al., 2025). Extent parameterisations do not differentiate between wetland types in WetCHARTs, as the model aggregates all types of wetlands from GLOBCOVER or GLWD when computing the extent from which emissions are estimated (Bloom et al., 2017) so that could lead to errors in output emissions.

Increasing temperature dependence appears to lower FCH_4 , which goes against previous studies on the temperature dependence of wetland emissions (Johnston et al., 2021; Ward et al., 2024). This can be seen by comparing data with same symbol and edge color but varying fill color, e.g. 2913 and 2923 which use $q_{10} = 1$ and $q_{10} = 2$ respectively, or 3913 and 3933 which use $q_{10} = 1$ and $q_{10} = 3$ respectively. For these 2 cases the higher q_{10} values lead to lower flux estimates in every flight. The setting of $q_{10} = 1$ essentially sets the ratio of carbon emitted as methane independent of temperature. However equation (1) suggests that as temperature increases, more carbon should be emitted as methane. This issue arises because each WetCHARTs realisation is rescaled to match a prescribed global CH_4 total. Without this scaling, increasing the temperature dependence makes tropical emissions grow much faster than boreal emissions. When the global scaling factor is then applied, simulations with low q_{10} (which have lower global emissions and a smaller tropical-boreal contrast) are scaled up, boosting high-latitude emissions. In contrast, simulations with high q_{10} (which strongly amplify tropical emissions) are scaled down everywhere, so their boreal emissions are reduced despite their stronger intrinsic temperature sensitivity. Scaling is necessary to ensure that the total emissions from WetCHARTs are consistent with the global methane budget, but this means that improvements on other model parameters such as emissions temperature dependence need to be done so that the governing emissions equation is physically consistent throughout the simulations ensemble (A. Bloom, pers. comm., 19/09/2024).

Taken together, these results suggest that several, potentially compensating, biases may be present in WetCHARTs for the Kiruna region (in wetland extent, temperature dependence and global scaling, and the treatment of wetland types). It is



therefore possible that the apparently better performance of some specific parametrisations (e.g. using GLWD rather than GLOBCOVER) in our experiment partly reflects fortuitous cancellations of errors, rather than an unequivocally more realistic configuration.

3.4 Comparison with WRF-Chem Eulerian simulations

Figure 8 shows a four-metric assessment comparing the performance of WetCHARTs and JSB-HIM wetland emission models using two independent evaluation methods. The top panel reproduces results from Langot et al. (2025), where high-resolution WRF-Chem (d02) simulated ABL mixing ratios, driven by WetCHARTs and JSB-HIM as *a priori* emissions, were evaluated against MAGIC2021 in-situ airborne measurements. The bottom panel shows our assessment of the same wetland models, this time directly in terms of emissions: comparing *a priori* estimates against observation-derived emissions from FLEXPART (see Section 2). Although these quantities cannot be compared at face value, as they are not related to the same physical variable, they provide complementary perspectives on wetland models performance.

In Langot et al. (2025), in-situ data consisted of compiled airborne data from all balloon (AirCore, Karion et al., 2010; Membrive et al., 2017) and aircraft (Cessna and ATR42) campaign flights. Mixing ratios from WRF-Chem were found to overestimate ABL methane content compared to MAGIC2021 measurements, with a positive bias in the ABL as high as $\bar{\Delta} = 60$ ppb. This was associated with high RMSE values. Mixing ratio variability was also overestimated, which meant that recorded amounts of atmospheric methane were correlated with its variability, as was found here for surface emissions. Correlation was weak ($0.4 < \rho < 0.6$) between simulated and measured ABL mixing ratios. An overestimate of this kind is most directly read as emissions that are too high, though it could in principle reflect boundary-layer mixing that is too weak. The latter is constrained by the meteorological evaluation of Langot et al. (2025), in which the modelled temperature profiles reproduced the MAGIC2021 soundings through the boundary layer at the model vertical resolution and without substantial bias; the emission interpretation is developed first below, and the mixing alternative is then revisited with independent evidence from the present Lagrangian framework.

The bottom panel of Figure 8 shows an assessment of the same wetland models, this time comparing directly emission estimates as described in Section 2, instead of mixing ratios. Here, the assessment uses a selected sample of boundary-layer Cessna flights specifically targeting methane emissions above wetland areas, rather than the campaign-wide multi-platform dataset used in the top panel. First, FCH_4 from wetland models is not systematically overestimated with respect to the plume-approach estimates. This is the opposite of what might have been inferred from the mixing-ratio-based evaluation alone. Three wetland model products display higher emissions on average over the four studied flights than those derived using observations, with $\Delta < 20 \text{ mol}\cdot\text{km}^{-2}\cdot\text{hr}^{-1}$ for two of them. Other simulations underestimate emissions over the four flights, with $\Delta < 20 \text{ mol}\cdot\text{km}^{-2}\cdot\text{hr}^{-1}$. Second, emission variability is underestimated by all wetland models: $\sigma_N < 1 \cdot \sigma_{\text{REF}}$ for all products and $\sigma_N < 0.24 \cdot \sigma_{\text{REF}}$ for four of them. This could be expected to an extent, as emission variability is correlated with emission amplitude and the coarse resolution of wetland models tends to smooth out emissions heterogeneity, as suggested earlier when discussing individual flight analyses.

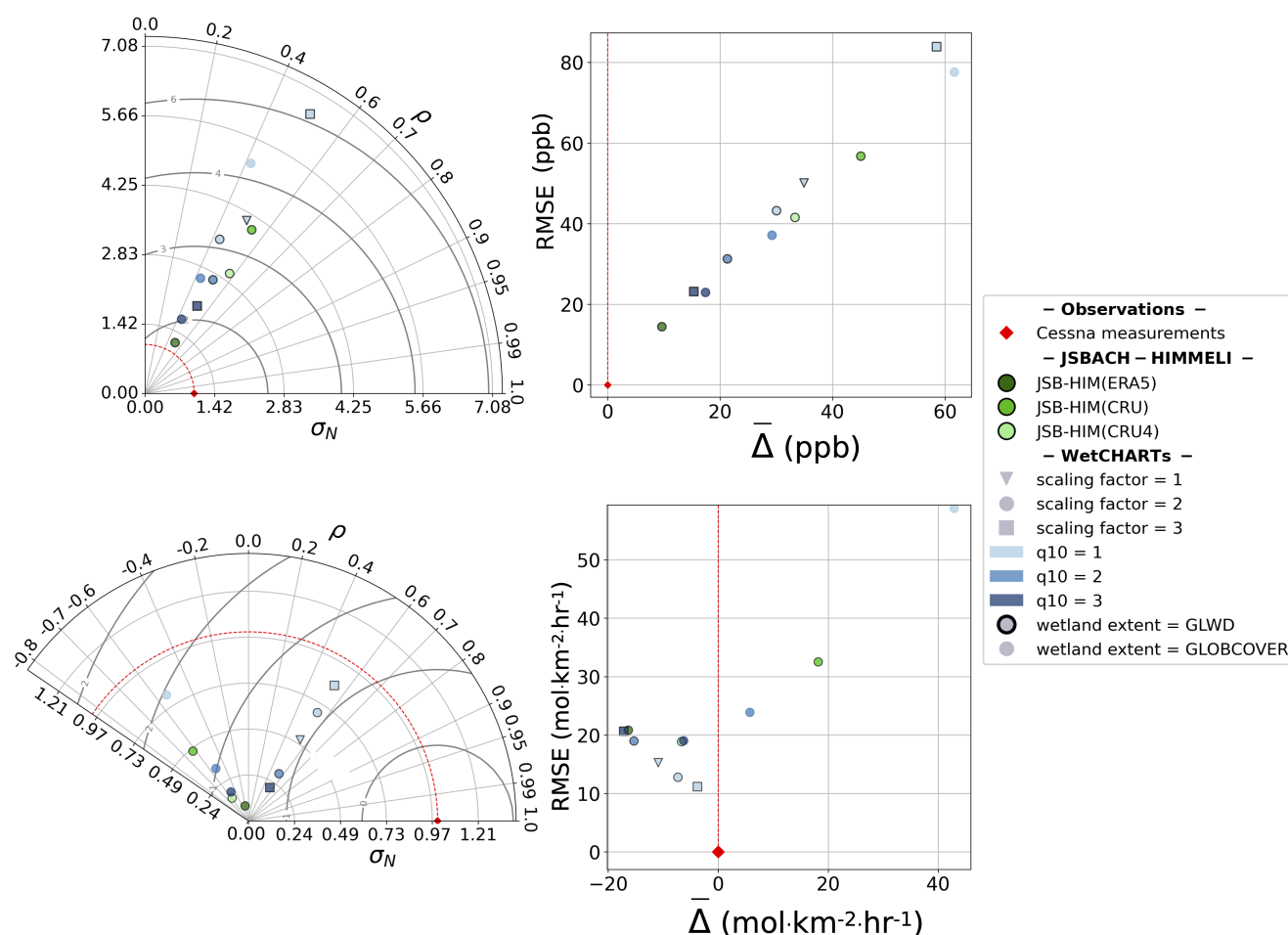


Figure 8. Taylor diagram showing correlation ρ versus normalised standard deviation σ_N (left) and RMSE vs bias ($\bar{\Delta}$) (right) diagrams of **top:** ABL CH₄ mixing ratios as modelled by WRF-Chem d02 assessed against MAGIC2021 in-situ measurements from Langot et al. (2025) and **bottom:** Emissions from wetland models assessed against emissions derived from MAGIC2021 data and FLEXPART. The red symbol represents the reference data from MAGIC2021 Cessna flights. Green coloured symbols represent JSB-HIM emissions and blue coloured symbols represent WetCHARTs emissions. Different shades of blue are used for different temperature dependences in WetCHARTs products, while different shades of green are used for different meteorological forcings in JSB-HIM products. Symbols' shape and edge colour represent different scaling factors and wetland extent parametrisations in WetCHARTs products.



350 Taken together, the ABL mixing ratio evaluation from Langot et al. (2025) and the top-down versus bottom-up FCH₄ comparison presented here clarify the nature of the model-observation mismatch. ABL mixing ratio comparisons, which did not specifically target wetland emissions, showed that mean model emissions were positively biased. By contrast, when focusing on wetland plumes along the Cessna tracks, mean FCH₄ appears approximately unbiased, but emission variability is too low for all products. Looking at equations (4) and (6), emission variability could in principle arise either from the numerator (i.e. the wetland signal ΔQ term) or the denominator (i.e. the surface influence term $\sum \mathcal{F}$). However, the surface influence term is identical in both equations, so it cancels and the comparison is insensitive to errors in the transport operator itself. The difference in variability between top-down estimates and bottom-up emissions must therefore come from the wetland signal. In other words, for equally strong surface influence on a measurement, Cessna methane signals vary more strongly than those simulated by wetland models. At the resolutions considered here, bottom-up simulations therefore produce emissions that are too homogeneous compared to what is seen in the observations.

This behaviour is consistent with a fundamental mismatch between the scale at which wetland emission is generated and the scale at which bottom-up models represent it, as already hypothesised in our discussion of flight-by-flight results (see Section 3.1). Although areas flown over are usually treated as spatially diffuse and temporally smooth sources, signals recorded above them fluctuate far more than modelled ones at equal surface influence. As shown below, this excess variability cannot be ascribed to the spatial dimension, which our footprints average out, and is therefore attributed to emissions varying on timescales shorter than the model time step, coherently enough over a footprint that variations are not averaged out either. This points towards controls acting in phase over areas comparable to a footprint, namely soil temperature (Rinne et al., 2018) and water table position (Olefeldt et al., 2013). Wetland emissions are also expected to be spatially patchy at scales well below model grids (Sachs et al., 2010; Hashemi et al., 2025; Yazbeck et al., 2025), and both forms of heterogeneity likely arise from the same wetland features, but only the temporal one can be assessed here. Bottom-up models hold emissions of a grid cell constant over a time step, so when transported by FLEXPART they cannot fluctuate as observed ones do. To reproduce the sharp variability observed during aircraft transects across emission hotspots, models require either unrealistically elevated mean emissions (to recreate comparable plume signals) or explicit representation of sub-grid heterogeneity, which current wetland models lack (Smith et al., 2022). Our results indicate that JSB-HIM(CRU), with higher mean fluxes, partially compensates for this smoothing by generating larger absolute variations, but the underlying emission intermittency remains unresolved.

Thus, our study confirms previous findings showing that if emission models are calibrated to reproduce the strongest emissions but fail to capture their variability, they will exhibit a positive bias by continuously attributing high emissions to wetland areas that, in reality, emit only intermittently (Bohn and Lettenmaier, 2010; Bansal et al., 2023; Chen et al., 2024; Hashemi et al., 2025). The lack of a significant increase in performance from WetCHARTs to JSB-HIM products, despite the higher spatial and temporal resolution of JSB-HIM, supports this view: simply refining the grid and using daily instead of monthly emissions does not resolve the processes that drive the observed variability. This indicates that key mechanisms influencing our measurements occur at sub-daily scales and/or at spatial scales smaller than $0.1^\circ \times 0.1^\circ$. Wetland methane emissions have been shown to exhibit sub-daily variations (Rinne et al., 2018) and spatial variability at fine scale (Hashemi et al., 2025). Rinne et al. (2018) further showed that temporal variations are irregular throughout the day. Improving wetland models skill therefore re-



385 requires not only better meteorological forcing but, more fundamentally, advances in representing spatial and temporal emission heterogeneity at scales currently unresolved by global bottom-up models.

This attribution to the emissions themselves rests on setting aside two transport-side explanations. The first concerns spatial resolution. While spatial heterogeneity at <100 m scales is known to be an important driver of wetland F_{CH_4} (Sweeney et al., 2022; Hashemi et al., 2025), our observational footprints ($1\text{--}5^\circ \times 1\text{--}5^\circ$) integrate over larger areas than the wetland model grids
390 ($0.1\text{--}0.5^\circ \times 0.1\text{--}0.5^\circ$), so the reduced variability in bottom-up estimates cannot be attributed to insufficient spatial resolution. Spatial structure below the footprint scale is averaged out of F_k^p as well, so the present framework cannot test whether the emission field is spatially patchy, only whether it varies in time faster than the models allow. The second explanation is that the positive boundary-layer bias of Langot et al. (2025) reflects mixing that is too weak in WRF-Chem rather than emissions that are too high. For a surface-emitted tracer accumulating in a well-mixed layer of depth h , the enhancement scales as
395 $\Delta C \approx Ft/(\rho h)$, so a near-surface bias can be produced either by raising F or by lowering h . This confound is documented in mesoscale tracer transport (Gerbig et al., 2008). Two elements argue against it here. The temperature profiles simulated through the boundary layer reproduced the MAGIC2021 soundings at the model vertical resolution without substantial bias (Langot et al., 2025). Since mixed-layer depth is governed by this thermal structure, reproducing a bias as large as $\bar{\Delta} = 60$ ppb through mixing alone would require a mixed-layer several times shallower than this structure permits, which the temperature
400 comparison excludes. The underestimation of emission variability is moreover obtained with FLEXPART, whose turbulence parametrisation is independent of the WRF-Chem boundary-layer scheme, so the excess homogeneity of the inventories is not the artefact of a single mixing parametrisation. A mixing error of the size required is therefore excluded, though exact representation of mixing is not claimed here.

Reproducing fluxes derived from MAGIC2021 high resolution data is therefore not currently possible with current wetland
405 models, as bottom-up emissions would need to be estimated at a sub-daily resolution to accurately represent wetland emissions during summer months. With the current type of wetland models, our study suggests that a choice has to be made between accurately representing emissions to match long term observations over larger spatial and temporal scales, or to represent well individual plumes that can be probed by high resolution measurements such as the one performed during MAGIC2021. As currently constructed, bottom-up models were found to match mean emissions from local hotspots whilst failing to represent the
410 natural variability of wetland CH_4 emissions, leading to large overestimates when sampling representative regional conditions. Results are however limited by our experimental set-up, notably the short period of time over which the flights were performed.

4 Conclusions and perspectives

We estimated local wetland emissions using the so-called plume approach, combining MAGIC2021 ABL measurements with Lagrangian modelling. ABL measurements were performed by flying a Cessna aircraft at low altitudes for several hours over
415 specific areas identified as potential emission hotspots. Top-down emission estimates were then used to assess existing wetland emissions models. These high resolution measurements captured the sub-daily variability of emissions that are not modelled by current bottom-up estimates. Under these settings, wetland model emissions transported by FLEXPART matched CH_4 signals



detected in the ABL, but underestimated emissions variability. This led to significant overestimates of emissions (and ABL mixing ratios) when considering measurements on regional scales that do not specifically target emission hotspots (Langot et al., 2025). Footprints of Cessna measurements integrate over areas larger than model grid cells, which averages out spatial structures from both observation-derived and model-derived estimates. The larger variability of observation-derived estimates therefore reflects emissions varying on timescales shorter than the model time step. Whether emissions are also spatially structured below the footprint scale cannot be tested here. Boreal wetland emissions are therefore episodic rather than temporally persistent, a behaviour bottom-up models cannot produce as they hold emissions of a grid cell constant over their time step. This diagnosis was made for both WetCHARTs and JSB-HIM products, even though the latter has higher spatial and temporal resolutions. The positive ABL bias is attributed to this lack of variability rather than to deficient boundary-layer mixing, since the modelled temperature profiles reproduced the soundings through the boundary layer without substantial bias (Langot et al., 2025) and the diagnosis is reproduced with an independent Lagrangian transport model.

Changing the meteorological forcings of JSB-HIM simulations did not significantly impact overall model performance in reproducing the observed signals. More precipitation led to better variability representation but worse agreement with hotspot mean emissions, so that the choice of forcing amounts to a trade-off rather than to an improvement. On the other hand, rudimentary sensitivity analysis of WetCHARTs products showed that both wetland extent parametrisation and temperature dependence were important factors in determining model performance. The GLOBCOVER extent parametrisation was found to overestimate emissions in the Kiruna region compared to the GLWD parametrisation, possibly due to known wetland classification issues which could lead to overestimation of wetland extent in Fennoscandia (Bontemps et al., 2011). Overall, our study confirms that current wetland models lack the ability to reproduce emissions variability caused by sub-grid scale processes as observed with high resolution measurements, such as those from MAGIC2021, consistent with the FLUXNET-CH₄ synthesis showing that tower-scale CH₄ seasonality cannot be explained by temperature or GPP alone (Delwiche et al., 2021). Tiling (Yazbeck et al., 2025) and innovative use of flux tower measurements (Ying et al., 2025; Kallingal et al., 2025) offer practical avenues to incorporate these processes.

Temperature dependence of emissions exhibited a peculiar behaviour at high latitudes, with higher q_{10} values leading to lower flux estimates, and the best performing WetCHARTs products all had $q_{10} = 1$. This follows from the scaling applied to keep total WetCHARTs emissions consistent with the global methane budget: for a fixed global total, raising the assumed temperature sensitivity increases the tropical share and necessarily reduces the high latitude one, so the boreal allocation responds to a parameter that describes emissions elsewhere. The boreal share of the bottom-up budget is therefore set in part by a parametrisation choice made for the tropics rather than by boreal physics, and the resulting high latitude temperature response is physically inconsistent. Since the sensitivity of high latitude wetlands to warming is the principal reason for interest in this region (Koffi et al., 2020), this places a structural limit on what globally rescaled bottom-up products can say about the future evolution of the methane budget, independently of how well they reproduce present day means.

Several limitations bound these conclusions. The plume approach used here was applied to four selected flights; extending the flux estimation framework using column enhancements (Hartery et al., 2018; Sweeney et al., 2022) could enable use of additional MAGIC2021 data. Transport modelling relies on a single model (FLEXPART), and robustness of flux estimates



would benefit from intercomparison with alternative transport models (e.g., WRF-LPDM, Lauvaux et al. (2016)) to more thoroughly assess transport uncertainty, as demonstrated by Karion et al. (2019). The two-week duration of MAGIC2021 in August 2021 provides a snapshot of wetland model performance during the peak emission period but cannot assess seasonal or interannual variability, a gap that reflects the broader absence of sustained multi-season observational networks at high latitudes (Ying et al., 2025). The campaign period coincides with the most dynamic and least predictable emission regime of the year, but misses the seasonal transitions that are critical for understanding annual budgets (Zona et al., 2016; Ward et al., 2024), so extending temporal coverage through longer-term and less intensive campaigns would complement high-resolution intensive campaigns like MAGIC2021.

The consequence of matching hotspot emissions in the mean while missing their variability may extend beyond model scoring, although this is not tested here. A prior flux field with too little temporal variance produces boundary layer signals that are too smooth, and in an inversion this would enter through the prior error covariance: if the assumed error structure does not admit sub-daily variability, the system cannot concentrate flux into the short intervals that produced an observed enhancement, and the residual is absorbed into the mean flux or into the observation and transport error terms. Tenkanen et al. (2025) found optimised Finnish CH₄ emissions to depend strongly on the prior used, the min-to-max spread reaching 71% of the mean national total across their priors and remaining 58% after optimisation, and reported that deriving natural prior uncertainties from a process-based model ensemble improved agreement with observations at their southern sites compared to the standard assumption of 80% of the prior emissions. The variance deficit diagnosed in this study could be one candidate contribution to such prior dependence, and reducing it at high latitudes may require prior error structures that admit sub-daily variability rather than improved mean fluxes alone. The same argument applies to the interpretation of satellite retrievals, which exhibit systematic high latitude biases (Lindqvist et al., 2024). Airborne measurements coupled with high-resolution transport modelling can bridge the gap between local process studies and satellite-scale inversions. Future missions including MERLIN (active LIDAR, Pierangelo et al. (2016); Ehret et al. (2017)), Sentinel-5 and IASI-NG (thermal infrared, Crevoisier et al. (2014)) promise improved high latitude coverage, but their validation will require sustained field programs beyond single campaigns.

More broadly, the apparent bias of a wetland model at high latitudes is a property of the model and of the sampling taken together, not of the model alone. Tower networks, airborne campaigns and satellite retrievals each sample the boreal atmosphere non-uniformly with respect to emission hotspots, so a product that appears unbiased against one could appear biased against another, as obtained here between plume-targeted and generic sampling of the same dataset. Comparisons of bottom-up estimates against atmospheric data at these latitudes should therefore state the sampling geometry alongside the bias.

These results carry a practical consequence for how future boreal emissions are modelled and tracked. Our measurements indicate that emissions vary faster than current bottom-up products resolve. These products are able to match mean emissions from local hotspots, but spread them homogeneously and persistently over their grid cell and time step. A similar analysis could be carried in spatial dimensions, though footprint integration applied here cannot establish whether emissions are as heterogeneous in space as they are in time. A model carrying no representation of this unresolved variability has no mechanism to express a change in variability itself, and can only express it as a change in its smooth mean. Whether a change of that



kind would be visible in the atmosphere depends in turn on how the atmosphere is sampled, and the present study shows that the same campaign appears to support differing conclusions under plume-targeted and under generic sampling. Sparse tower
490 networks and coarse satellite pixels both sample the boreal atmosphere unevenly with respect to emission hotspots, and Wittig et al. (2024) estimated that the existing in-situ network would need 10 to 30 years to detect a large and sustained Arctic methane release in sparsely covered regions. Airborne campaigns resolving individual plumes over large areas, such as MAGIC2021, therefore provide access to the emission structure that bottom-up products and monitoring networks currently miss. The diagnosis presented here rests on four flights over two weeks near Kiruna and cannot be extrapolated to the circumpolar domain
495 or to other seasons, but the mechanism is not specific to this region: it follows from the mismatch between the scale at which wetland emission is generated and the scale at which it is modelled, and should be expected wherever that mismatch persists.

Data availability. The MAGIC2021 Cessna CH₄ measurements used in this study are archived at <https://doi.org/10.25326/915>.

WetCHARTs wetland emissions (v1.3.1) are available from the ORNL DAAC at <https://doi.org/10.3334/ORNLDAAAC/1915>. The WetCHARTs model is described in Bloom et al. (2017).

500 JSBACH-HIMMELI wetland emissions were produced at FMI within the VERIFY and EYE-CLIMA projects. Simulation fields are archived on Zenodo at <https://doi.org/10.5281/zenodo.11635335> (Leppänen et al., 2025). The modelling framework is described in Aalto et al. (2025), the HIMMELI methane module in Raivonen et al. (2017) and the JSBACH land model in Ekici et al. (2014).

The FLEXPART Lagrangian particle dispersion model version 10.4 is archived on Zenodo at <https://doi.org/10.5281/zenodo.3542278> and described in Pisso et al. (2019). The FLEXPART pre- and post-processing toolbox is archived at <https://doi.org/10.5281/zenodo.7766372>
505 (Berchet et al., 2023). ECMWF meteorological fields were retrieved and prepared using `flex_extract` v7.1.2 (Tipka et al., 2020).

The WRF-Chem model version 4.3 employed for the regional simulations is described in Skamarock et al. (2019) and available at <https://doi.org/10.5065/D6MK6B4K>. Model output was extracted at the measurement locations for the analysis; the full simulation output (approximately 200 GB) is archived at LMD and available from the authors on request.

ERA5 reanalysis is available from the Copernicus Climate Data Store (<https://doi.org/10.24381/cds.adbb2d47>), and the CAMS v21r1
510 inversion-optimised CH₄ product from the Copernicus Atmosphere Monitoring Service (<https://doi.org/10.24381/ed2851d2>).

Carbon footprint

The full carbon footprint of the MAGIC2021 campaign is still being estimated. For this study, we compute an approximate value based on the highest emitters: aircraft flights. The Cessna from DLR has a 675HP turbine engine and flew for 27h22min, which according to LabosIpoint5 data equates to an emissions of 13 ± 1 tCO₂. The carbon footprint of the campaign as a
515 whole will be higher still, as it includes provided meals, travels to Kiruna for every team involved and additional airborne measurements that were not used in this paper. Also neglected here is the footprint of the data analysis and model simulations post-campaign, which are run using high performance computing facilities. Carbon footprint numbers given here are therefore not representative of the whole campaign footprint and should be considered as a lower bound for the footprint of this paper only.



- 520 *Author contributions.* - FL, CC & TL designed the study
- FL performed the derivation of fluxes from observations and lagrangian simulations with help from TL, CA and AB
 - FLEXPART simulations were performed by AB & SW
 - WRF-Chem simulations were designed and run by FL with support from TL and CA
 - Cessna data were acquired and provided by AF, K-DG, AR as well as Heidi Huntrieser, Vladyslav Nenakhov and Magdalena Pühl
- 525 - Cessna CH₄ data was produced by AF
- Analysis of results and writing of the manuscript was done by FL with support from all co-authors

Competing interests. The authors declare that they have no conflict of interest.

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