Author's response to the review of:

Environmental drivers constraining the seasonal variability of satellite-observed methane at Northern high latitudes

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Response to Anonymous Referee #1

In the following, referees' comments are shown in blue, and the authors' responses are provided in black. Orange indicates text from the manuscript, including both original and revised sentences or paragraphs.

This study investigates how environmental variables influence the seasonal variability of methane (CH_4) at high latitudes in the Northern Hemisphere, utilizing satellite observations from TROPOMI along with meteorological datasets. The research provides a valuable contribution to understanding CH_4 variability, identifying key drivers such as snow cover, soil moisture, and soil temperature. Only minor revisions are recommended to enhance the clarity, interpretability, and completeness of the manuscript.

First, we would like to thank the referee for the positive feedback and valuable comments. We hope that our answers are sufficient, and we believe that the manuscript will be improved after the changes. Below, we address each comment in detail.

1. Lines 190-195 : How to determine the study area by testing? Can you explain it in detail?

We began identifying suitable high-latitude wetland regions by combining information from inversion results that indicated significant natural methane emissions (e.g., Erkkilä et al., 2023; Tsuruta et al., 2023) with wetland coverage data from the BAWLD (Olefeldt et al., 2021) dataset. Based on this preliminary analysis of potential case study areas, we selected four regions in Northern Eurasia and two in Canada. However, after collecting TROPOMI data for these regions, we found that the data coverage and amount over the Canadian areas did not allow reliable fitting of the seasonal cycles and, consequently, further analysis. Therefore, the Canadian areas were excluded. In contrast, the originally defined Southern Siberia case study area had a very good data coverage, which allowed us to divide it into two separate case study areas (Middle and Southern Siberia area on the paper).

We agree that the sentence
After testing, we decided to concentrate on five areas over Northern Eurasia.
in the manuscript was unclear and vague. In the revised manuscript, we will replace it with the following clarification:
We tested different case study areas over Canada and Eurasia based on inversion results of natural methane fluxes (e.g., Tsuruta et al., 2023; Erkkilä et al., 2023) and wetland coverage from the BAWLD dataset. We selected five areas in Northern Eurasia, where TROPOMI data coverage was good enough to constrain the fit for the XCH4 seasonal cycles and perform further analysis.

2. Lines 325-330: Did you validate the Random Forest model using cross-validation techniques (e.g., k-fold validation)? If so, how consistent were the importance rankings across different training-test splits?

We did not originally validate the Random Forest model using cross-validation techniques. Instead, we assessed the robustness of feature importances and rankings by performing repeated training–test splits, as described in lines 334–345, using 1 000 different random seeds and model iterations. However, based on the referee's suggestion, we additionally performed a 10-fold cross-validation to further assess the consistency of the feature importance rankings. The results showed that for PI the feature rankings were the same across all ten folds for each of the three XCH_4-related variables (seasonal cycle, daily median, and their difference). For RFFI, minor differences were observed: in the seasonal cycle analysis, the fourth and fifth variables occasionally changed order, and in the daily median case, the order of the fifth and sixth variable were different. However, in both cases, the actual importance values of these variables overlapped within the calculated uncertainty ranges, indicating that the observed differences were not significant.

The results confirm that the environmental variables identified as the most important in the PI and RFFI analysis were consistently ranked among the most important features across the folds, which supports the overall robustness of our findings.

To clarify the methodology, we will revise the following paragraph (lines 334–345) and include a note on the cross-validation procedure:

To evaluate the uncertainty of RFFI and PI we fitted the random forest model 1000 times using different random seeds. The final feature importance values that are presented in the results in Sect. 4.1 were calculated as the average of these 1000 fits and the uncertainties of the importance values were estimated by calculating the standard deviation of the sample.

and add the information from the cross-validation to the paragraph:

To evaluate the uncertainty of RFFI and PI, and to assess the robustness of the calculated feature importance values and rankings, we performed repeated training–test splits using 1000 different random seeds and Random Forest model iterations. The final feature importance values presented in the results in Sect. 4.1 were calculated as the average across these 1000 fits, and the uncertainties of the importance values were estimated by calculating their standard deviation. In addition, to assess the consistency of the importance rankings, we performed a 10-fold cross-validation, where feature importance values were calculated independently for each fold and compared. Cross-validation confirmed the stability of the most important environmental variables across folds. Differences in calculated importance rankings were observed only for RFFI, and only among environmental variables that had similar RFFI scores within their respective uncertainty ranges. For the seasonal cycle, the ranking of the fourth and fifth variables differed between the RFFI and k-fold results, and for daily medians, the difference was seen between the fifth and sixth variables.

3. Lines 345-350: Since multiple environmental variables (e.g., snow cover and soil freeze-thaw state) exhibit high correlations ($r > 0.85$), how do you ensure that feature importance rankings are not biased by collinearity in the Random Forest model?

We acknowledge that collinearity can influence the interpretation of feature importances in Random Forest models. To assess this, we performed repeated training–test splits using 1000 different random seeds, which allowed us to estimate the uncertainty of the feature importance values. As mentioned and clarified in point 2 above, the importances presented in the results in Sect. 4.1 are based on the mean values across these 1000 model iterations, and the standard deviations were used to assess the stability of the feature rankings.

Additionally, we applied both PI and RFFI to analyze the agreement between the two importance estimation methods. This comparison is relevant because RFFI is known to be more sensitive to multicollinearity, while PI tends to be more robust in the presence of correlated variables. While we recognize that these methods cannot fully eliminate potential bias introduced by correlated environmental variables, we note that the relationships between snow-related variables and the seasonal cycle of XCH_4, as presented in Sect. 4.2, are also evident in the original time series data, independently of the machine learning model. This provides qualitative support for the observed importance of the snow-related variables onto the seasonal cycle of XCH_4.

To reflect this limitation related to the correlated environmental variables, we will add a sentence to the Conclusions section (in the paragraph ending at line 595), to emphasize that feature importance rankings may be affected when using strongly correlated environmental variables:
Although we applied multiple techniques to assess the robustness of the Random Forest model and feature importance rankings, we acknowledge that strong correlations between environmental variables remain a potential source of bias in the results. Therefore, the connection between snow and the XCH_4 seasonal cycle was also examined more closely using time series analysis.

4. Lines 415-420: Have you considered the contribution of atmospheric transport processes to the observed seasonal variability of methane concentrations, particularly the potential influence from emission sources located outside your study regions?

Yes, we acknowledge that atmospheric transport processes may affect methane concentrations in the case study areas. During the manuscript analysis phase, we included wind direction at the 850 hPa pressure level from ERA5 as one of the environmental variables. However, its permutation importance was the lowest among all tested variables (less than 0.023 for both the seasonal cycle and daily medians), and it was therefore excluded from the final analysis. This suggests that the XCH4 variability is not (to a large extent) driven by atmospheric transport patterns.

As a result of this review comment, we conducted an additional test: wind direction was categorized into eight compass sectors (North: 337.5°–22.5°, North-East: 22.5°–67.5°, East: 67.5°–112.5°, etc.), and the resulting categorical variable was used as an input to the Random Forest model to assess its importance. This was done to investigate whether the wind direction in degrees was too noisy or variable for the model to detect consistent patterns. However, the importance values of the categorized wind direction variable were even lower than those of the original wind direction in degrees.

These results suggest that, within the spatial and temporal scale of our study, atmospheric transport, at least as represented by 850 hPa wind direction, does not play a clear dominant role in explaining the observed seasonal variability of XCH_4.

5. Lines 450-455: Soil moisture is identified as a key driver of seasonal CH_4 However, why does it not have the same level of importance in daily variations? Could transient factors like precipitation events or drainage explain this discrepancy?
6. Lines 490-495: The ranking of OH as a CH_4 sink varies between the two feature importance methods (Permutation Importance and RFFI). Why do these differences arise?

Comments 5 and 6 both refer to the analysis presented in the original manuscript version. During the revision process, an error was identified in Fig. 4: the labels of the environmental variables on the y-axes of the subfigures were incorrectly ordered due to a manual mistake during the visualization process. As a result, the interpretation in Sect. 4.1 was based on an incorrect figure and it has been rewritten. We apologize for this minor error, and next point out the key differences in the interpretation of the corrected Fig. 4 with respect to the incorrect version that was submitted. The corrected figure and rewritten Section 4.1 can be found from the bottom of this document.

Based on the corrected figure, the role of soil moisture is only minor for the seasonal cycle of XCH_4, and the main driver of the seasonal cycle is OH and the second most important driver is SWE. The main driver for daily medians is the 2-meter air temperature, which is important for daily medians but not for the seasonal cycle. This finding is coherent and supports the overall interpretation of the seasonal and short-term variability.

The ranking of OH for daily medians still differs between PI and RFFI, although the discrepancy is smaller than in the original version of the manuscript. The largest variation in ranking between the importance methods is observed for soil temperature, which is likely due to its strong correlation with air temperature. The remaining variation in OH ranking may be linked to the relatively low explanatory power of the Random Forest model for daily medians: the coefficient of determination is only 0.32, indicating that the model explains approximately one third of the observed daily variability.

These updated results will be more clearly presented and thoroughly explained in the corrected version of Sect. 4.1.

7. Lines 580-585: Does the observation that seasonal CH_4 maxima and minima closely align with the timing of complete snowmelt imply that snow cover primarily controls the seasonal variability through its effects on soil temperature and moisture? Could you further discuss this controlling mechanism?

Yes, we assume that snow cover influences methane emissions through two main processes: (1) by acting as an insulating layer, and (2) by contributing to soil thawing and moisture dynamics. As an insulating layer, snow affects soil freezing and thawing dynamics, which in turn influence soil temperature, and thus methane emissions. Additionally, snow slows down methane transport from the soil to the atmosphere. When snow melts, it contributes to soil thawing by releasing meltwater, which warms the upper soil layers and increases soil moisture.

However, these mechanisms have not yet been conclusively confirmed by in-situ studies, and therefore we did not elaborate on them further in the manuscript than what is discussed above. Currently, FMI is conducting an in-situ multi-year winter campaign in Sodankylä (Finland), where these processes are being investigated in detail using methane flux and concentration measurements combined with microwave-based snow observations over wetland areas. We hope that future results from this campaign will provide further insights into the role of snow in seasonal methane dynamics.

Olefeldt et al., Earth Syst. Sci. Data, 13, 5127–5149, 2021 https://doi.org/10.5194/essd-13-5127-2021
Erkkilä et al., Remote Sens. 2023, *15*(24), 5719; https://doi.org/10.3390/rs15245719
Tsuruta et al., Remote Sens. 2023, *15*(6), 1620; https://doi.org/10.3390/rs15061620

May 20, 2025

Response to Anonymous Referee #2

In the following, the reviewer's comments are in blue and responses in black. As instructed by the Editor, we have not yet carried out major changes to the manuscript; however, our intentions are detailed here for the Editor's and Reviewer's evaluation.

In addition, we discovered a minor error in Fig. 4 of the manuscript. Specifically, the labels of the environmental variables on the y-axes of the subfigures were incorrectly ordered due to a manual error in the visualisation step, which affected the interpretation of the results in Sect 4.1. The revised Sect. 4.1 can be found from the bottom of this document.

The present study focuses on environmental drives affecting observations of methane total columns in Northern boreal regions. The manuscript is very well written, well detailed and balanced. Direct analysis of satellite observations are valuable, even before inversion or modelling study, as they allow to get coarse insights on how regional environments react to external drivers, especially in Northern Boreal regions where observational data are very scarse. The present study can be considered for publication but needs a redefinition of its scope as it is too narrow at the moment.

We would like to thank the referee for the positive feedback on the structure, language, and balance of the manuscript. We understand the reviewer's concern about the narrow scope of the manuscript, and after internal discussions among the co-authors about widening the scope, we have carefully considered the options presented by the reviewer. In general, all three options are well-justified, invoke our curiosity, and likely their results would further point to new research questions for the future. Because our aim with this paper is to study the insights of the correlations between environmental drivers and total column methane, we consider Option 3 presented by the Reviewer as the most interesting and yet straightforward avenue to broaden the scope of the present study. In what follows, we will consider each option in more detail, from the perspectives of their added value to the present study and yet keeping the scope of the study somewhat focused. The purpose of this research is also to contribute to the ESA-NASA Arctic Methane and Permafrost Challenge (AMPAC), where the aim is to explore the insights given by current EO datasets but also to benchmark existing model systems and address their discrepancies to observations. Our preference towards expanding in the direction of Option 3 is therefore also driven by our desire to further contribute to the AMPAC-relevant discussion and initialize the benchmarking of total column methane.

I recommend exploring the following axes to justify publication:

1. Impact of TROPOMI product on conclusions
   The authors chose the WFMD product to conduct their study. This seems reasonable with latest versions of WFMD. Still, other products (operational and SRON research product, as well as Balasus BLENDED product) can show different patterns and may lead to different conclusions

We appreciate the referee's suggestion to explore the potential impact of different TROPOMI XCH_4 products on our conclusions. We agree that the choice of the satellite product (as well as its sampling, temporal time span, area selection etc.) can affect the observed patterns and may lead to different conclusions. Based on our previous research, we have already gained some insight on the differences between the operational, the SRON scientific product and our choice for this study, the WFMD product.

In this study, we selected the updated WFMD product primarily because our recent evaluations (Lindqvist et al., 2024) show that it outperforms other TROPOMI products (SRON scientific and operational products) in terms of substantially reduced seasonal biases at high northern latitudes (for the seasonal bias in the SRON product, see also Lorente et al., 2022). These residual seasonal biases may severely hamper the reliable interpretation of seasonal variability. While we acknowledge the added value of the operational and SRON research products, and generally always prefer to analyze multiple products for a better understanding of a given phenomenon, we are concerned that the spatial and seasonal biases quantified in the Arctic and sub-Arctic regions may significantly influence the results derived from those datasets.

The BLENDED product by Balasus et al. (2023) presents another interesting and promising approach. However, their evaluation was primarily based on mean biases against TCCON stations, and it remains unclear whether high-latitude seasonal biases have been in more detail addressed in that product. Therefore, we considered that it was methodologically more robust to base the present analysis on the WFMD dataset, which has been specifically evaluated for its seasonal performance at high latitudes.

2. Added value of satellite products
   TROPOMI offers a valuable data sets in Northern latitudes, independent from local countries that can limit data access. Still, there exists long-term time series, both atmospheric and flux data in the Arctic, that could offer similar conclusions than the same paper. The authors are encouraged to compare their results to what would be achieved with local data, in order to really assess the added value of TROPOMI (and future missions)

The in-situ flux and concentration studies cited in the manuscript have shown that local-scale environmental conditions can significantly affect fluxes and concentrations even within short distances (e.g., soil moisture; Kittler et al., 2017; lines 450–455 in the manuscript). This implies that within a single TROPOMI pixel, which covers a large area, there can be various different surface types and environmental states. In addition, the environmental variables used in our analysis describe the state of environment over similarly large areas, usually even larger than the TROPOMI satellite pixel size (for example SMOS F/T product, where a single pixel is 25 km x 25 km).

Therefore, we think that the spatial mismatch between satellite observations and in-situ measurements would introduce large uncertainties in a direct comparison, and upscaling methods as well as measurements from multiple locations within the satellite pixels would be required for a fair one-to-one comparison. Furthermore, our analysis focuses on seasonal and daily changes**,** and to enable the Random Forest analysis, we needed to combine data from all case study areas into a single model (lines 317–320). We assume that this would not be an appropriate approach for data from multiple in-situ sites with varying local-scale environments. For this reason, we consider that a similar type of analysis studying the link between environmental drivers and CH_4 variability using in-situ data, should be conducted at first independently, based solely on ground-based measurements of both CH_4 and environmental variables, and ideally by researchers with specific expertise in those datasets and observational methods. In addition, as CH_4 fluxes are not affected by the OH sink, the contribution of OH to surface-level CH_4 concentrations is likely less relevant than for total-column concentrations, and thus this could complicate the comparability of results.

Furthermore, the connections between snow and methane have not yet been conclusively confirmed by in-situ studies, and therefore we do not have relevant references to support these observations. Currently, FMI is conducting a multi-year in-situ winter campaign in Sodankylä (Finland), where these processes are being investigated in detail using methane flux and concentration measurements combined with microwave-based snow observations over wetland areas. We hope that future results from this campaign will provide further insights into the role of snow in seasonal methane dynamics.

3. Link to wetland and peatland models
   The method used in the manuscript merely deduce correlations between concentrations and environmental factors. The ML methods are very powerful in finding features and patterns,

> but often do not bring valuable insight on underlying processes. The team behind the manuscript run their own process-based model to simulate methane emissions. Analyzing the links between direct conclusions from the present work and what a process-based model manages to simulate would bring valuable conclusions on what should be improved in models to better represent Northern methane emissions.

We decided that to address the referee's suggestion and to broaden the scope of the manuscript, we will perform and include an additional analysis using modelled XCH_4 concentrations. This will help us establish a connection between XCH4, environmental variables, and the process-based model, JSBACH-HIMMELI in Finland and LPX-Bern DYPTOP in Russia, that is the origin of the prior wetland fluxes in the model system. Both JSBACH and LPX-Bern DYPTOP are global land surface models and include a multilayer hydrology model and representation of vegetation, soil carbon and methane emissions by specific submodels (Reick et al., 2013, Tyystjärvi et al., 2024, Lienert and Joos et al., 2018). The models for peatland methane emissions (Raivonen et al., 2017, Spahni et al., 2011) include methane production, oxidation, diffusion, plant transport and ebullition processes in a multi-layer wetland scheme. Methane fluxes in mineral lands are driven by soil moisture in both models. The wet mineral soil emissions depend on the soil moisture (above a critical treshold) and the soil heterotrophic respiration (Spahni et al., 2011). Soil sink for methane is calculated using a model for methane diffusion and oxidation in dry soils Curry et al. (2007).

We will further use our independent, satellite-based analysis to better understand the process-based model and evaluate how well the model system reproduces the satellite-based patterns and potentially identify environmental processes that should be improved to better represent methane emissions from Northern high latitudes. Our plan is to co-locate modelled XCH_4 concentrations from two different model setups with the TROPOMI observations, while also taking the averaging kernels into account:
1) A forward simulation using prior (non-optimized) fluxes.
2) An inversion simulation, where fluxes have been optimized using in-situ atmospheric observations.

The forward model to be used is TM5, and the inversion model is CarbonTracker Europe – CH_4 (CTE-CH_4; Tsuruta et al., 2017). The CTE-CH_4 simulation will be run with a similar configuration as in Tenkanen et al. (2025) but using updated prior fluxes and atmospheric in-situ observation datasets. We will apply both the feature importance analysis with environmental variables (as presented in Sect. 4.1) and the seasonal timing analysis (as presented in Sect. 4.2) to the modelled concentrations, similarly to how we did for the TROPOMI observations. Spatial and temporal co-location of the model and satellite concentrations will allow direct comparison of the derived patterns, as our preliminary analysis for the manuscript showed that the temporal coverage of satellite and environmental data sets strongly affects the importance analysis. Co-locating modelled concentrations with the same temporal sampling that the satellite observations have, will allow us to assess the same features and patterns with the modeled concentrations as with the satellite observations. We believe that by comparing the satellite-based and model-based results and especially by analyzing the differences between the prior and posterior concentrations, we will provide both more information on the added value of satellite observations, and insights into how the studied environmental variables affect the modeled seasonal cycle, and potentially the environmental processes that should be improved in the model could be recognized.

We appreciate the referee's suggestion on widening the scope of the manuscript and believe this analysis will strengthen the manuscript and increase its relevance and novelty to the research community, especially for the AMPAC community as well as space agencies and mission Science Teams.

Lindqvist et al., Remote Sens. 2024, 16(16), 2979; https://doi.org/10.3390/rs16162979
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Tyystjärvi et al., Biogeosci., 21, 5745–5771, https://doi.org/10.5194/bg-21-5745-2024, 2024.
Tsuruta et al., Geosci. Model Dev., 10, 1261–1289, 2017; https://doi.org/10.5194/gmd-10-1261-2017
Tenkanen et al., Atmos. Chem. Phys., 25, 2181–2206, 2025; https://doi.org/10.5194/acp-25-2181-2025

Appendix: Corrected Section 4.1

The main changes in interpretation are:

1. The main drivers of the seasonal cycle of XCH_4 are OH and SWE, instead of soil moisture and SWE.
2. For daily medians, the most important environmental variable is air temperature, instead of soil temperature.

Paragraphs that include any changes based on the correction to Figure 4 are marked in blue.

4.1 Links between environmental variables and XCH4

Our aim is to study the links between environmental variables and the seasonal variability of XCH4 and to estimate the potentially different drivers for the variability in different time scales. The time scales we consider include the fitted seasonal cycle, which captures the seasonal changes but cannot detect short-term variations or extremes, and day-to-day variability, which is more sensitive to small-scale atmospheric changes and can exhibit larger fluctuations than the seasonal cycle. In addition, we study the daily median – seasonal cycle difference, which describes the daily value's anomaly with respect to the seasonal value. The methane XCH4 data used in this study (WFMD v.1.8) performs well in comparisons to reference data sets across all seasons (Lindqvist et al., 2024), indicating its reliability in capturing both seasonal and daily variability. The mean daily median – seasonal cycle difference varied between the case study areas, ranging from 2.0 ppb to 3.9 ppb. This difference is generally highest during spring, when day-to-day variability peaks, with methane concentrations showing notably lower values on individual days (for example, Fig. 2 for the year 2018), and, additionally, the concentration drops sharply from the winter maximum to the winter minimum (for example, Fig. 2 for the year 2022).

The analysis is performed by applying random forest regression method using RFFI and PI importance metrics. Figure 4 shows PI and RFFI of each studied environmental variable on the detrended XCH4 daily medians ((a) and (b)), fitted XCH4 seasonal cycle ((c) and (d)) and for daily median – seasonal cycle difference ((e) and (f)). The environmental variables are ordered in the y-axis based on their PI rankings. Black line shows the uncertainty of the importance. Figure 5 shows the ranking of environmental variables based on their importance to different XCH4 components; the higher bar signifying higher significance. Each colour represents each XCH_4 component and the shade of the colour is based on the used importance method.

Based on Figs. 4 and 5, both PI and RFFI indicate that OH and SWE are the most important environmental variables in explaining XCH4 seasonal variability. The order of importance for the other environmental variables (snow cover, soil freeze-thaw state, soil temperature, soil moisture and air temperature) varies slightly between PI and RFFI but all of these variables are less significant than OH and SWE according to both methods. For the XCH_4 daily medians and the difference between daily medians and the seasonal cycle, PI and RFFI show somewhat similar results: according to both methods, air temperature is the most important environmental variable for both XCH_4 variables. For PI, this is clearer than for RFFI, and the order of importance for other environmental variables differs between the methods. Based on RFFI, soil temperature is the second most important for XCH_4 daily medians, while based on PI, it is OH. According to PI, the importance of the other environmental variables than air temperature and OH are minimal, while based on RFFI, each environmental variable has some effect. For the daily median - seasonal cycle difference, air temperature is the most important variable based on both RFFI and PI. This is expected, as air temperature was not significant for the XCH_4 seasonal cycle, but was for the daily medians, and OH was important for both. Interestingly, for the difference, the SWE, which was a significant factor in the seasonal cycle, does not appear as an important variable for the daily median - seasonal cycle difference.

The difference between the PI and RFFI results may result from correlated environmental variables. As noted in Sect. 3.4, the correlation between environmental variables can affect their relative importance, especially when considering RFFI, making it difficult to distinguish the individual contributions of the drivers. This issue is particularly evident, for example, in the XCH_4 daily median results, where RFFI suggests that soil temperature is the second most important variable, with an importance value very close to that of air temperature (Fig. 4 (d)). Soil temperature and air temperature are highly correlated ($r = 0.93$) which leads to challenges in distinguishing their individual importance in the RFFI results. In addition, PI ranks OH as the second most important and in RFFI it is ranked as the sixth. According to correlation analysis, OH and soil temperature are also highly correlated ($r = 0.87$), which might in addition explain the high ranking of soil temperature in the RFFI analysis. Given these concerns and considering the challenges RFFI faces when the features are correlated, we focus on the PI results and use RFFI results as supporting information for variables that are not as strongly correlated. It should also be noted that due to the high correlation of the variables, the PI values could still be affected to some (but to a much lesser) extent by the issue of shared information between features (see Sect. 3.4)

The similarities and discrepancies between PI and RFFI scores suggest that, for XCH_4 seasonal cycle, the random forest model performs relatively steadily, with OH and SWE being the main drivers of the seasonal cycle's phase. The stability of the results is in addition supported by the high explanatory power of the model, as indicated by the coefficient of determination for the seasonal cycle ($R^2 = 0.85$), which shows that the model captures most of the variability in the seasonal signal. However, for the short-term XCH_4 variability, the model is less stable, indicating that the mechanisms explaining daily variability are more complex and that short-term environmental variability has little systematic impact in the total column, which is reasonable. This is supported by the lower model's coefficient of determination ($R^2 = 0.32$). Nonetheless, air temperature plays clearly a role in short-term variability.

The driving factors and conditions of the seasonal variability of methane emissions from different land and vegetation types have been previously widely studied with in situ measurements and modelled CH_4 fluxes and concentrations. As stated in the introduction, the seasonal variability of the column-averaged dry-air mole fraction of methane is a combination of the seasonality of CH_4 emissions and sinks, and transport patterns. Therefore, the results from local flux studies cannot be directly compared to our findings, although fluxes influence the XCH4 concentrations. Next, we will compare our results with previous findings from in situ and model studies and examine how the dependencies of methane on environmental variables identified in those studies are reflected in our results.

East et al. (2024) studied the hemispheric differences and the drivers of the seasonality of methane concentrations based on model simulations. They showed that in the Southern Hemisphere the seasonal cycle is smooth and driven by the OH sink but the seasonal cycle in the Northern Hemisphere is asymmetric and has a sharp increase during summer. Based on their results with chemical transport model, they found that the magnitude, latitudinal distribution and seasonality of wetland emissions are critical for the seasonality of methane in the Northern Hemisphere as they determine the timing and magnitude of the summer increase. Our findings support and specify those of East et al. (2024) as our results point out the importance of OH, and in addition SWE and air temperature. SWE and air temperature are important factors for methane production in high latitude wetlands, either directly or indirectly, by influencing the soil water cycle and temperature.

Hydroxide OH was found to be the most significant factor for the XCH_4 seasonal cycle based on both the PI and RFFI scores. This result is consistent with East et al. (2024) and demonstrates that for total-column methane, the atmospheric CH_4 loss is an important factor controlling the seasonal cycle of XCH_4. For daily medians, OH was ranked as the second most important factor according to PI, while it ranked sixth based on RFFI. As discussed earlier, this difference in RFFI results may be due to the high correlation between OH and soil temperature (r = 0.87). It should be noted that to describe the effectiveness of the OH sink, we used monthly zonal mean CH_4 loss values from TM5, calculated for the latitude band 57°N–70°N (see Sect. 2.6). This method is a simplification; we assumed that large-scale OH loss is sufficient to examine the variability of XCH_4 in this study. This is based on the assumption that OH loss does not vary significantly between the study areas at monthly resolution. However, this assumption does not account for the fact that OH concentrations depend on factors such as UV radiation and humidity (Lelieveld et al., 2016; Zhao et al., 2019) and thus exhibit shorter-term and interannual variability. As we focus on northern high latitudes, we are dealing with surfaces that are both spectrally and seasonally variable, particularly due to snow cover, which can influence OH levels via changing UV reflectivity. For instance, Prinn et al. (2001) showed that during El Niño–Southern Oscillation (ENSO) events, increased cloud cover corresponds to reduced OH concentrations, likely due to decreased near-surface UV radiation. Consequently, snow cover may impact not only methane fluxes but also the atmospheric methane sink indirectly. This simplification might be also one reason behind the varying ranking of OH for daily medians as the monthly values do not have short-term variability and it did not vary between the case study regions. Studying the effectiveness of the OH sink in more detail would require more accurate OH estimates or the use of new proxies that can capture small-scale spatiotemporal variability. Given that the lifetime of OH is extremely short (typically around one second), and that it is highly sensitive to perturbations in both its sources and sinks (Glenn et al., 2019), it is challenging to measure OH directly or to model its spatial variability reliably. Until now, atmospheric methyl chloroform concentrations have often been used as a proxy for OH; however, this approach is becoming increasingly difficult as methyl chloroform levels decline (Zhang et al., 2018).

Snow and frost require similar conditions, specifically temperatures below zero degrees Celsius. Moreover, they are closely interconnected: snow acts as an insulating layer, influencing soil freezing and thawing. For methane emissions, snow plays an important role as it slows down methane from entering the atmosphere from the soil. Snow also contributes to soil thawing, as water from melted snow thaws the soil from above and increases the soil water volume. Studies that have carried out measurements outside the growing season have mainly focused on quantifying fluxes during the cold season and comparing them to annual emissions. However, only few studies have directly studied the relationship between snow and methane fluxes, partly due to the difficulty in accessing in situ observation sites during the winter months. The cold season emissions can cover a major part of the annual emissions, despite snow and soil frost (e.g, Zona et al., 2015; Rossger et al. 2022). The emissions during the cold season are relatively stable, with a monthly distribution accounting 4-8% of the annual emissions (Rossger et al., 2022}. However, since the cold season lasts in some parts of high latitudes from early October to early May, a significant amount of emissions is accumulated over this time period and therefore the cold season emissions are important to the annual methane budget in these areas. As mentioned in Sect. 2.4 the quality of SMOS F/T product data near Russia is affected by RFI interference. However, it was observed that in our case, the interference significantly impacted the data quality only for the year 2023. Our earlier results, which did not yet include data from 2023, were consistent with the current findings. This consistency suggests that the interference has not impacted our results, which is logical given the relatively low importance of soil freezing (Fig. 4).

From the studies that have been directly investigating the connections between snow and methane, Mastepanov et al. (2013) found that the springtime increase in CH_4 flux was strongly correlated with the timing of snowmelt. Additionally, Rossger et al. (2022) reported that earlier snowmelt and higher early summer temperatures in June has increased the early summer CH_4 fluxes in Siberian Tundra. Both Zona et al. (2015) and Rossger et al. (2022) showed a significant rise in methane emissions over a wetland following the spring thaw, and then strong monthly emissions that lasted over the thaw season. They both defined the seasons based on temperatures, either air or soil. Our results show that for the XCH_4 seasonal cycle, snow is a more determining factor than for XCH_4 daily medians; the amount and coverage of snow determines the phase of the XCH_4 seasonal cycle together with OH. However, Mastepanov et al. (2013) and Rossger et al. (2022) examined the effects of snow on small, well-defined land cover types, whereas in our study, the SWE data resolution is 5 km, approximately the same as the TROPOMI pixel size. Despite this relatively small grid size, it still encompasses a mixture of land cover types with differing melting timings. Additionally, when averaging across the entire case study area, further variability arises due to the diverse land cover types present. As shown in Sect. 3.1 in Table 1, none of the areas had a total wetland fraction exceeding 50\%, indicating that more than half of the area consists of non-wetland types. In Sect. 4.2 we further address this uncertainty by calculating case-study-area-specific uncertainties.

Based on flux studies, it can be stated that during the growing season, there is a positive correlation between methane flux and soil temperature (e.g., Mastepanov et al., 2013; Howard et al., 2020; Kittler et al., 2017}. This relationship is linked to microbiological activity, which is enhanced by higher soil temperatures, leading to increased methane emissions from wetlands. According to both PI and RFFI scores, air temperature is the most important factor influencing the detrended XCH_4 daily medians, although for PI, the uncertainty range is high. Nevertheless, air temperature remains the most important within this range. Zona et al. (2015) showed that when the soil temperature is below zero, CH_4 emissions are small, but as the soil temperature increases toward zero and above, methane emissions begin to rise, with the highest emissions occurring during July and August. Similarly, Kittler et al. (2017) showed that emissions peak during July and August and follow the soil temperature. We examined the correlation between air and soil temperature and the detrended XCH_4 daily median for each month separately and found that, during the period from May to August, the correlation between the daily mean air temperature and the detrended XCH_4 daily median was moderate, with Pearson correlation coefficients of 0.40, 0.41, 0.47, and 0.31, respectively. For daily mean soil temperature and the detrended XCH_4 daily median the correlation coefficients were 0.34, 0.39, 0.48, and 0.32, respectively. For air temperature the correlation in April was 0.37, during the other months the correlation was not larger than 0.3 for both air and soil temperature. Our results are consistent with in-situ studies in demonstrating the importance of temperature for daily methane variability. However, as air temperature appears more strongly expressed than soil temperature in our results, and as the explanatory power of the Random Forest model for daily medians was relatively low ($R^2 = 0.32$), we cannot conclude that daily variability in total-column methane is dependent on temperature alone.

The effect of soil moisture on methane emissions is complex, and the process is significantly influenced by factors such as wetland type or the time period (month, season, year) being studied. For example, Kittler et al. (2017) compared methane emissions from a drained area to a moister control area at moist tussock tundra that is located on Siberian permafrost area. They showed that the annual amount of methane emissions is correlated with soil moisture; in the drained area, annual methane emissions were lower than in the moister control areas. On the other hand, Zona et al. (2015) studied emissions from the Alaskan tundra and showed that, at the driest sites, cold-season emissions dominated the annual emissions. Our results do not indicate a systematic impact of soil moisture on XCH_4 variability as the ranking of soil water volume is varies from third (RFFI and XCH_4 daily medians) to seventh (RFFI and XCH_4 seasonal cycle). The lack of systematic response may arise from relatively strong day-to-day variability in soil moisture during the summer, as well as significant local variations, such as differences in soil types (e.g., Kittler et al., 2017, and their comparison between two adjacent areas). Since the environmental variables used in this study are relatively sparse in spatial grid resolution and are then averaged over larger areas, there are inevitably many different land cover and wetland types within each grid cell and within the case study area. To study the effect of soil moisture on XCH_4 at a more detailed level, it would likely be necessary to consider different soil types individually, permafrost areas, and the relationship between soil moisture and individual XCH_4 satellite observations. We tested the analysis using satellite-based soil moisture data (Dorigo et al., 2017) but the main issue was that it is not daily data, and there were significant data gaps during springtime. This prevented a comprehensive satellite-based analysis and was the reason to use ERA5 soil water volume instead.

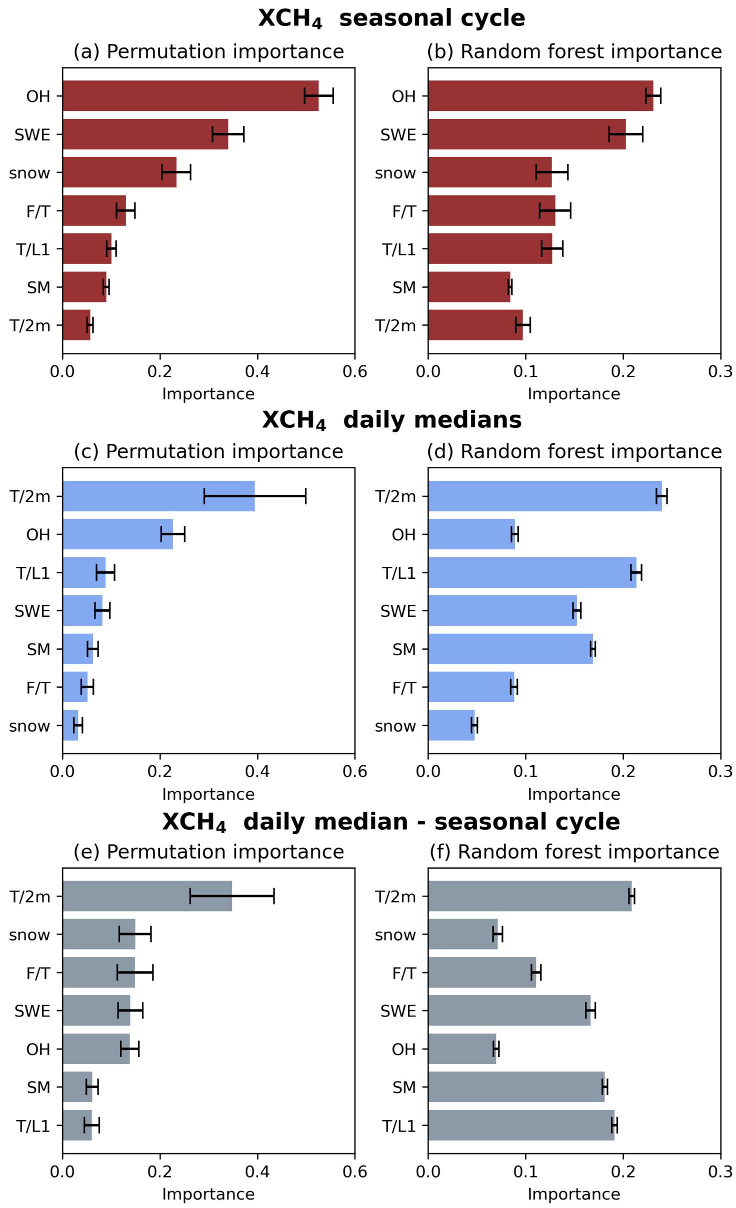

Figure 4. Permutation and random forest feature importance metrics for XCH4 seasonal cycle ((a) and (b)), XCH4 daily median ((c) and (d)), and XCH4 daily median – seasonal cycle difference ((e) and (f)). The importances are ordered based on the permutation importance, the most important being the uppermost and the lowest being the least important. The importances are calculated as an average from 1000 random forest fits and the uncertainties (black lines) are the standard deviations of those fits.

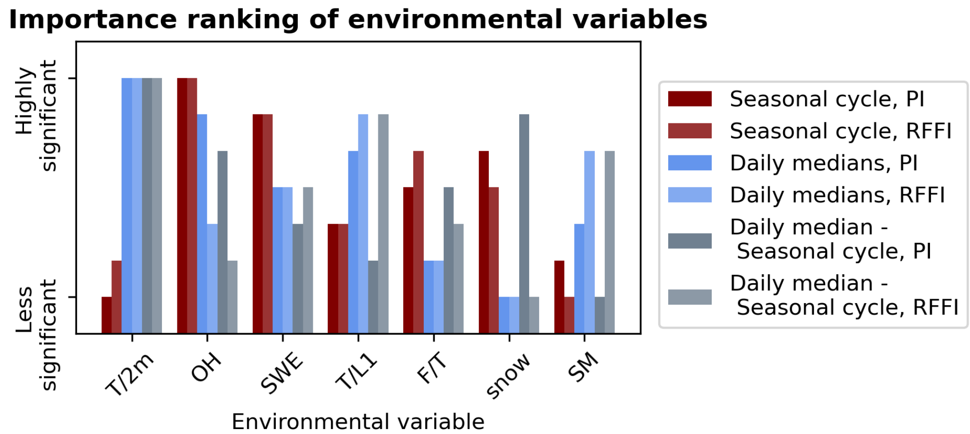

Figure 5. The ranking of environmental variables based on their importance to XCH4 variability. The height of each bar represents the variable's rank: a higher bar indicates greater importance. Each colour indicates different XCH4 component (blue: daily median; red: fitted seasonal cycle; grey: daily median – seasonal cycle difference) and the shade of the colour the used importance method (darker: PI; lighter: RFFI).