Reply to reviewer 2

In the following, we address all reviewer comments point-by-point. The reviewer comments are shown in black, the author responses are shown in green and changes to the manuscript are shown in orange.

The manuscript aims to investigate the variability of turbulent particle fluxes over three surface types using five weeks of continuous eddy covariance measurements in the High Arctic obtained during the Atmospheric Rivers and the Onset of Arctic Sea Ice Melt (ARTofMELT) campaign. The main conclusion of the study is that 'while net particle deposition is observed to dominate over the packed ice, both emission and deposition are equally observed over leads and open water, underlining the importance of surface heterogeneity and turbulence intensity for the exchange of fluxes in the High Arctic'. The manuscript is mostly well written but needs some additional editing work for better readability to the general reader (mostly pointed out by the other reviewer). The dataset presented could be a valuable resource for advancing the understanding of particle flux dynamics in the Arctic.

We would like to thank the reviewer for their time and effort, as well as for their constructive feedback. Below, we provide a response to the comments, which have helped us to improve the manuscript. In addition, we have also restructured the Methods section to provide a clearer separation between particle concentration data, turbulence data, particle flux calculations and quality control, surface characterization, and dry deposition modelling. The order of the individual sections was revised to provide a clearer and more coherent description of the data processing and analysis.

My major concern is related to the way surface characterization has been done. Since the main conclusion of the study depends upon the classification of surface types using onboard imagery, more clarity is needed in the manuscript regarding the number of images in a flux period from each camera, image quality, area selected, internal variability in surface type, image sampling, and uncertainty in classification of the surface types using the said algorithm. Further, a solid justification to choose the so-called WAKE algorithm in place of various well-documented and validated open-source image processing algorithms for sea surface identification is needed.

Considering the importance of this methodology for the interpretation of the results, we agree with the reviewer that the original description of the surface type classification may have been too brief. We have therefore expanded this section. The revised manuscript now provides a more detailed description of the image processing workflow. This includes the image sampling strategy, selection of the upwind region of interest, generation of the training data, training of separate classifiers for different camera perspectives and illumination conditions, and automated batch processing of the complete image dataset. We have also added a description of the manual quality control procedure, as well as the limitations associated with fog, water droplets, whitecaps, and periods of maneuvering or icebreaking. This clarifies the uncertainty of the surface classification. Finally, we justify our selection of the Trainable WEKA

Segmentation approach by comparing it with commonly used image segmentation methods and explaining why we chose a supervised random forest classifier.

Line 138-141: Hourly images of the ship's surroundings, which were used to classify the surface types, were captured using three Mobotix M24 IP cameras (Mobotix M24 IP, Langmeil, Germany). These were installed on the seventh deck of the Oden, facing the port side, starboard side and bow. For each surface classification, an image was selected from the camera facing the upwind fetch according to the relative wind direction averaged over the hour.

Line 286-310: The surrounding surface types were automatically evaluated using a random forest algorithm implemented in the Trainable WEKA Segmentation plugin (Waikato Environment for Knowledge Analysis) within the Fiji distribution of ImageJ (Schneider et al., 2012; Schindelin et al., 2012; Arganda-Carreras et al., 2017) and applied to an image of the surface taken every hour. Depending on the direction of the wind in relation to the ship's position, one of three image orientations was selected to define the surface type located upstream. For each hourly surface classification, a single image from the camera facing the upstream fetch was analyzed. The data on the relative wind direction was also averaged over a period of one hour. Image processing macros within Fiji were used for the surface type analysis and to tilt, crop and resize the images. The Trainable WEKA Segmentation plugin was chosen because it performs supervised, pixel based image classification. It uses manually labeled training data to train a classifier that can then be used to automatically classify the remaining images. Several commonly used image segmentation approaches (Minaee et al., 2022) were evaluated before selecting the final workflow. These included threshold based methods (Otsu, 1979), k-means clustering (Nameirakpam et al., 2015) and Trainable WEKA Segmentation (Arganda-Carreras et al., 2017). Threshold based methods are sensitive to image noise and variations in image intensity. In contrast, random forest classification has been shown to improve robustness against interference and reduce the need for manual intervention in complex sea ice images (Wang et al., 2024). Therefore, Trainable WEKA's supervised random forest classification was selected for this study. ImageJ macros were used to automate the workflow, enabling efficient and consistent batch processing of large image datasets. The images were cropped to a predefined region of interest representing the upwind area, excluding the ship structure and other irrelevant parts of the image. The training data for the WEKA classifier was generated by manually labeling representative pixels belonging to the different surface classes. WEKA on Fiji was subsequently employed to train different classifiers for image segmentation. Separate classifiers were trained for the various camera perspectives and lighting conditions experienced during the expedition. The trained classifiers were then applied to the full set of images using ImageJ macros. This approach enabled the complete image dataset to be processed automatically with consistent classification settings, while substantially reducing the amount of manual processing required. Finally, ImageJ was used to calculate the area ratio of the segmentation into closed ice surfaces, water surfaces, and mixed surfaces consisting of thin ice and brash ice (Fig. 4). The analysis was manually checked, as the algorithm sometimes misclassified surface types in images affected by fog, water droplets on the camera lens, or small waves. These images were analyzed manually. To avoid misclassification due to changing surface types, surface type data should be considered with caution for periods of maneuvering, icebreaking and/or when the speed over ground was larger than 1 knot. For the statistical evaluation of the surface type fraction, only periods during which Oden was drifting with a low speed over ground ≤ 1 knot were considered. Taking into account this criterion, approximately 75% of the dataset remained available for analysis.

Overall, I am satisfied with the scientific idea and analysis presented in the paper and recommend acceptance of the paper after the above clarification.

Again, we would like to thank the reviewer for their time and effort, as well as for their overall positive feedback. We are convinced that the revisions have improved the clarity of the manuscript.

References:

Arganda-Carreras, I., Kaynig, V., Rueden, C., Eliceiri, K. W., Schindelin, J., Cardona, A., and Sebastian Seung, H.: Trainable Weka Segmentation: a machine learning tool for microscopy pixel classification, Bioinformatics, 33, 2424–2426, https://doi.org/10.1093/bioinformatics/btx180, 2017.

Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., and Terzopoulos, D.: Image Segmentation Using Deep Learning: A Survey, IEEE transactions on pattern analysis and machine intelligence, 44, 3523–3542, https://doi.org/10.1109/TPAMI.2021.3059968, 2022.

Nameirakpam, D., Singh, K., and Chanu, J.: Image Segmentation Using K -means Clustering Algorithm and Subtractive Clustering Algorithm, Procedia Computer Science, 54, 764–771, https://doi.org/10.1016/j.procs.2015.06.090, 2015.

Otsu, N.: A Threshold Selection Method from Gray-Level Histograms, IEEE Transactions on Systems, Man, and Cybernetics, 9, 62–66, https://doi.org/10.1109/TSMC.1979.4310076, 1979.

Schindelin, J., Arganda-Carreras, I., Frise, E., Kaynig, V., Longair, M., Pietzsch, T., Preibisch, S., Rueden, C., Saalfeld, S., Schmid, B., Tinevez, J.-Y., White, D. J., Hartenstein, V., Eliceiri, K., Tomancak, P., and Cardona, A.: Fiji: an open-source platform for biologicalimage analysis, Nature Methods, 9, 676–682, https://doi.org/10.1038/nmeth.2019, 2012.

Schneider, C. A., Rasband, W. S., and Eliceiri, K. W.: NIH Image to ImageJ: 25 years of image analysis, Nature Methods, 9, 671–675, https://doi.org/10.1038/nmeth.2089, 2012.

Wang, A., Wei, B., Sui, J., Wang, J., Xu, N., and Hao, G.: Integrating a data-driven classifier and shape-modulated segmentation for sea-ice floe extraction, International Journal of Applied Earth Observation and Geoinformation, 128, 103 726, https://doi.org/10.1016/j.jag.2024.103726, 2024.