RC2: 'Comment on egusphere-2025-3236', Anonymous Referee #2, 01 Sep 2025

Comment 2.1

The manuscript by Du et al. investigates active layer thickness (ALT) in the North Slope of Alaska using a combination of machine learning, intensive field sampling, and multi-source remote sensing data. The authors address ALT variability across multiple spatial scales. The main findings highlight the drivers of ALT at different scales. Additionally, the study quantifies scale-dependent uncertainties in ALT mapping and identifies functional relationships describing how these uncertainties change with spatial resolution. The paper is well-written and addresses an important topic in permafrost research. There are, however, some points that could be further discussed and a number of comments that should be addressed.

Response 2.1: Thanks for the careful review and insights into the study! We revised our manuscript accordingly. Please check our point-by-point responses below. All revisions were marked in blue.

Comment 2.2

The parameter importance at different resolutions is reported and supported by previous studies in the discussion section (L292-302). The discussion could be extended to provide more in-depth interpretation of the underlying mechanisms and implications.

Response 2.2: Thanks for the suggestion. We extended the discussion for more in-depth interpretation of the mechanisms underlying the ALT patterns described by in-situ observations and RF model predictions. The revisions are also presented below.

"Consistent with previous studies, our field observations and RF estimates (section 4.1.1) confirmed that greater ALT is most common in areas with standing water or adjacent to creeks (e.g., Plot 5; Fig. 4g, 4h, 4i), where wet conditions enhance soil thermal conductivity in foothills tundra (Grant et al., 2017; Clayton et al., 2021) despite increased latent heat required for thawing. Relatively larger ALT was also found in the vicinity of subsurface rocks (e.g., within 1-m distance) (e.g., Plot 6; Fig. 5j, 5k, 5l), whose high thermal conductivities facilitate heat propagation and summer thawing (Bonnaventure et al., 2013). Relatively lower ALT was recorded under shrubs, which likely cool the ground in summer through canopy shading (Lawrence and Swenson, 2011) and in winter through the thermal bridging effect (Domine et al., 2022). However, shrubs can also have a counteracting influence on ALT by promoting snow accumulation; whereby, the deeper snow layer insulates the ground, leading to warmer winter soil temperatures (e.g., Palmer et al., 2012; Morse et al., 2012; Kropp et al., 2020) which can result in a deeper active layer when this winter warming effect outweighs the summer shading effect of the shrubs (Way and Lapalme, 2021). A thick moss layer may also slow active layer thaw through its insulating capacity (Schuuring et al., 2024), though no specific descriptions of the moss layer were made in our sampling.

In the Imnavait Creek area, the thickness of the organic layer increases from hill crests to foot slopes. The thicker organic layer provides enhanced thermal insulation, leading to a shallower active layer downhill (Walker and Walker, 1996). Accordingly, Plots 3 and 4 on west-facing downhill slopes and Plot 5 in the valley bottom exhibited overall high soil organic matter content (~75%) and relatively low ALT (~44 cm). In contrast, the higher-elevation Plot 6 had lower organic matter (~46%) and a higher ALT (~58 cm). Besides terrain-controlled organic matter distribution, topography also affects ALT through its impacts on runoff and drainage, soil temperature, snow properties, and vegetation types (Walker and Walker, 1996, Li et al., 2017). Accordingly, topography information including slope (17.40%) and aspect (13.44%) are among the most important factors shaping ALT variations in the ML- and drone-based analysis, while surface features including vegetation, water bodies, and soil properties determined from the multi-spectral reflectance and optical-NIR indices, all showed important contributions to the 5-m ALT predictions over the sampling plots (7.24% to 14.05%; section 4.1.1).

It is noted that additional radar (L-band 1.26 GHz) observations from UAVSAR helped to enhance the performance of the first RF model (e.g., R increased from 0.78 to 0.81), but were not used in the subsequent scaling analysis (section 3.1.2). For the features selected for radar-based ALT predictions, red-edge reflectance (16.67%), HV-polarized radar backscatter (16.04%), aspect (15.33%), and HH-polarized radar backscatter (15.04%) contributed most to the predictions, while the red band (13.34%), slope (11.99%), and green band (11.57%) observations were relatively less important. The sensitivity of radar backscatter to vegetation biomass, surface water bodies, and soil wetness likely enhanced the ALT estimation.

For the ML- and satellite-based analysis, terrain factors (elevation, slope, and aspect) collectively dominate the ALT predictions (64.89% contribution) at 10-m resolution. The broad ALT patterns over the surrounding region (Fig. 5a) largely align with terrain-driven variability (section 4.1.2), as also observed in a previous study (Hinkel and Nelson, 2003). In general, south-facing slopes in the Northern Hemisphere receive more solar radiation than north-facing slopes, leading to warmer soil and larger ALT. However, the study region is characterized by gentle terrain slopes and west facing aspects (Fig. 5). Besides the terrain-controlled organic matter distribution observed over the Imnavait Creek area, direct solar radiation loading is higher around the hill tops and lower in downslope areas (Hinkel and Nelson, 2003), thus promoting larger ALT conditions in the uplands (Fig. 5). Topography therefore exerts a direct influence on the general thaw pattern as shown in the regional ML analysis".

Added reference:

Walker, D. A. and Walker, M. D.: Terrain and vegetation of the Imnavait Creek watershed, Landscape function and disturbance in Arctic Tundra, pp. 73-108, Berlin, Heidelberg: Springer Berlin Heidelberg, 1996.

Li, A., Tan, X., Wu, W., Liu, H. and Zhu, J.: Predicting active-layer soil thickness using topographic variables at a small watershed scale, Plos one, 12(9), p.e0183742, 2017.

Comment 2.3

Using the 0.1 m results as a benchmark raises some questions. In Figure 4 (especially panel f), these values appear to differ from both in situ measurements and the 5 m results, which could be further discussed. Since the 0.1 m data are synthetically generated for the scaling effects analysis, it would be helpful if the authors could comment on any potential influence on the results.

Response 2.3: Thanks for the comment. We first specified the differences of the ML-results in different resolutions in Section 4.1.1 as follows:

"The resulting 5-m and 0.1-m ALT maps were compared with the field measurements (Fig. 4). The 5-m ALT maps (Fig.4b, 4e, 4h, 4k) captured the primary ALT patterns observed from the field measurements (Fig. 4a, 4d, 4g, 4j) including elevated ALT along the perimeter of Plot 3, consistently low ALT throughout Plot 4, high ALT values following the water tracks in Plot 5, and generally deep ALT in Plot 6. The 0.1-m results revealed significantly finer variations (Fig. 4c, 4f, 4i, and 4l) …. Specifically, higher ALT values are visible along Imnavait Creek within Plot 5, as shown by the red pixels in the field measurements (Fig. 4g), 5-m ML predictions (Fig. 4h), and 0.1-m ML results (Fig. 4i). However, field sampling revealed substantial ALT variation within individual 5-m grid cells, with a standard deviation of up to 32 cm as distance from the watercourse increases. These meter- to sub-meter variations are only resolved in the 0.1-m results (Fig. 4i), which distinguish the high ALT values along the creek (red pixels) from the lower values in adjacent areas (blue pixels). Similarly, the stripe patterns of ALT in Plot 4 associated with alternating bands of dwarf willow, grasses, and tussocks (Fig. 1; Section 2) are clearly defined in the 0.1-m predictions (Fig. 4c) but are not discernible in the 5-m results (Fig. 4b). For Plot 6 where overall high ALT is observed (Fig.4 j, 4k, and 4i), heterogeneity is only captured by the 0.1-m results (Fig. 4l). The pattern of interspersed lower-ALT (non-red) pixels within high ALT areas (Fig. 4l) is likely associated with widespread clusters of underlying rocks and complex vegetation cover observed in the field (Fig. 1; Section 2)".

We then added the following in section 4.1.1 for clarifying the model performance and uncertainties.

"Considering the larger ALT variability and more diversified surface conditions at 0.1-m resolution relative to the 5-m resolution, the RF model trained using limited 5-m data set may not be able to fully capture the 0.1-m ALT variations, leading to inconsistency of the overall ALT patterns between the 5-m and 0.1-m results (e.g., Plot 4; Fig. 4d, 4e, 4f) and additional uncertainties in the multi-resolution analysis. In addition, the RF predictions tended to be centralized, which may underestimate larger ALT values (e.g., fewer dark red pixels with ALT higher than 65 cm in Fig. 4h and 4i than the measurements in Fig. 4g) and overestimate smaller ones relative to the measurements (e.g., dark blue pixels with measured ALT smaller than 35 cm in Fig. 4g but not in the ML predictions in Fig. 4h and 4i)".

Comment 2.4

Furthermore, the set of predictors chosen for the 5 m and 10 m models are not the same, with many variables omitted from the 10 m model. Could the authors clarify the rationale behind this choice? Since red-edge reflectance has relatively high importance at 5 m, it could have been valuable to investigate the 10 m red-edge from Sentinel-2 by performing super-resolution on the 20 m red-edge band. Additionally, elevation, which appears to have the highest importance for the 10 m model, was not included for the higher-resolution 5 m model. Could the authors comment on these choices and their potential implications?

Response 2.4: Thanks for the comment. The predictors were selected based on the "leave one feature out" (LOFO) approach (Liu et al., 2013). If removing a feature led to improved or unchanged RF performance, the feature was not selected since it was less important or redundant. For example, for the 5-m RF model, removing elevation feature led to essentially no performance change (R change less than 0.01; RMSE change less than 0.25 cm). This indicates that terrain control on 5-m ALT distributions over the sampling plots can be represented by aspect and slope. Similarly, the removing of Sentinel-2 red-edge bands reflectance led to negligible performance change for the 10-m RF model, which is likely due to the dominant control from terrain factors on the ALT distributions at 10-m resolution.

Reference:

Liu, J., Danait, N., Hu, S. and Sengupta, S., 2013, December. A leave-one-feature-out wrapper method for feature selection in data classification. In 2013 6th International Conference on Biomedical Engineering and Informatics (pp. 656-660). IEEE.

Comment 2.5

For the machine learning predictors at 5 m resolution, the DEM derived from RGB imagery was used. Were any differences investigated between this DEM and the ArcticDEM aggregated to the same 5 m resolution? Could the authors discuss any potential consequences of using the RGB-derived DEM compared to ArcticDEM?

Response 2.5: As suggested, we compared the two DEM data sets at the same 5-m resolution. The two DEMs were highly correlated (R = 0.99) across the four plots, though ArcticDEM is consistently higher in elevation for approximately 5.1 m than the drone-based DEM. After removing the bias, the RMSE between the two DEMs is 0.47m. The associated 5-m ALT predictions using ArcticDEM performed nearly as well as those from the drone-based DEM, with RMSE increasing from 6.53 cm to 7.24 cm and correlation declining slightly from 0.78 to 0.72.

Accordingly, we added the following discussion in Section 5.1

"To assess the impact of DEM choice on 5-m ALT predictions, we compared drone-based DEM and ArcticDEM across the four plots. The two DEMs were highly correlated (R = 0.99), though ArcticDEM showed a positive bias of approximately 5.1 m. Nevertheless, ALT predictions derived from ArcticDEM performed nearly as well as the drone-based benchmark, with RMSE increasing slightly from 6.53 cm to 7.24 cm, and correlation decreasing from 0.78 to 0.72".

Comment 2.6

The study focuses on a specific region. Could you comment on the transferability of the model to other regions? Would additional in situ training data be required for applying the approach elsewhere? Are similar parameter importances and scaling effects to be expected in other regions, and how representative is the study area for the broader Arctic context?

Response 2.6: Thanks for the comments!

Based on the Circumpolar Arctic Vegetation Map (CAVM) (Raynolds et al., 2019), plot 3 and 4 belong to vegetation type G3 (Non-tussock sedge, dwarf-shrub, moss tundra) while plot 5 and 6 belong to vegetation type S1 (Erect dwarf-shrub, moss tundra), where G3 and S1 together represent 29.8% area of the Arctic (excluding glacier and water bodies). The Arctic here was defined as the "area of the Earth with tundra vegetation, an arctic climate and arctic flora, with the tree line defining the southern limit" (Raynolds et al., 2019). Accordingly, the model, parameter importance and scaling effects are more suitable for representing the Arctic G3 and S1 areas relative to other regions. However, the study area is also unique in its abundance of glacier deposits and low rolling terrain, and the in-situ measurements were only from one season. For a more rigorous assessment of the applicability or transferability of the data-driven model for other regions, multiple-season measurements over a few spatially-distributed regions within the Arctic would be necessary.

Accordingly, we added the following in the discussion:

"Based on the Circumpolar Arctic Vegetation Map (CAVM) (Raynolds et al., 2019), plot 3 and 4 belong to vegetation type G3 (Non-tussock sedge, dwarf-shrub, moss tundra) while plot 5 and 6 belong to vegetation type S1 (Erect dwarf-shrub, moss tundra), where G3 and S1 together represent 29.8% area of the Arctic (excluding glacier and water bodies). The Arctic here was defined as the "area of the Earth with tundra vegetation, an arctic climate and arctic flora, with the tree line defining the southern limit" (Raynolds et al., 2019). Accordingly, the model, parameter importance and scaling effects are more suitable for representing the Arctic G3 and S1 areas relative to other regions. However, the study area is also unique in its abundance of glacier deposits and low rolling terrain. For a more rigorous assessment of the applicability or transferability of the data-driven model for other regions, in-situ measurements over a few spatially-distributed regions within the Arctic would be necessary.

In addition, the ALT inter-annual variations are affected by many dynamic factors (e.g., air temperature, snow cover properties, and disturbances), which are not explicitly accounted for by the current model. Multi-season ALT measurements and inclusion of temporally variant predictors in the data-driven model would help extend the current approach and better capture the ALT inter-annual dynamics".

Added reference:

Raynolds, M. K., Walker, D. A., Balser, A., Bay, C., Campbell, M., Cherosov, M. M., Daniëls, F. J., Eidesen, P. B., Ermokhina, K. A., Frost, G. V. and Jedrzejek, B.: A raster version of the Circumpolar Arctic Vegetation Map (CAVM), Remote Sensing of Environment, 232, p.111297, https://doi.org/10.1016/j.rse.2019.111297, 2019.

Comment 2.7

You are mentioning the importance of not only ALT spatial distributions but also temporal dynamics (L44). Could you maybe comment on the feasibility of resolving ALT temporal dynamics with the current approach? For instance, what is the potential for detecting interannual variations in ALT with the presented approach? In addition, since the Sentinel-2 data originate from multiple summer months (L151), could the authors comment on how intra-seasonal variability might influence the results?

Response 2.7: Thanks for the comment! The ALT inter-annual variations are affected by many dynamic factors (e.g., air temperature, snow cover properties, and disturbances), which are not explicitly accounted for by the current model. Multi-season ALT measurements and inclusion of temporally variant predictors in the data-driven model would help better capture the ALT inter-annual dynamics. Accordingly, we added the following in the discussion:

"Based on the Circumpolar Arctic Vegetation Map (CAVM) (Raynolds et al., 2019), plot 3 and 4 belong to vegetation type G3 (Non-tussock sedge, dwarf-shrub, moss tundra) while plot 5 and 6 belong to vegetation type S1 (Erect dwarf-shrub, moss tundra), where G3 and S1 together represent 29.8% area of the Arctic (excluding glacier and water bodies). The Arctic here was defined as the "area of the Earth with tundra vegetation, an arctic climate and arctic flora, with the tree line defining the southern limit" (Raynolds et al., 2019). Accordingly, the model, parameter importance and scaling effects are more suitable for representing the Arctic G3 and S1 areas relative to other regions. However, the study area is also unique in its abundance of glacier deposits and low rolling terrain. For a more rigorous assessment of the applicability or transferability of the data-driven model for other regions, in-situ measurements over a few spatially-distributed regions within the Arctic would be necessary.

In addition, the ALT inter-annual variations are affected by many dynamic factors (e.g., air temperature, snow cover properties, and disturbances), which are not explicitly accounted for by the current model. Multi-season ALT measurements and inclusion of temporally variant predictors in the data-driven model would help extend the current approach and better capture the ALT inter-annual dynamics".

For examining the impacts of intra-seasonal variability of Sentinel-2 data on our study, we replaced the original Sentinel-2 summer composite (June to August) by the July composite. For our study, the impact of Sentinel-2 intra-seasonal variability is relatively small, and the ALT results are highly consistent in their spatial patterns (R 0.91; RMSE 2.0 cm; Bias -0.57 cm; figure R1 below).

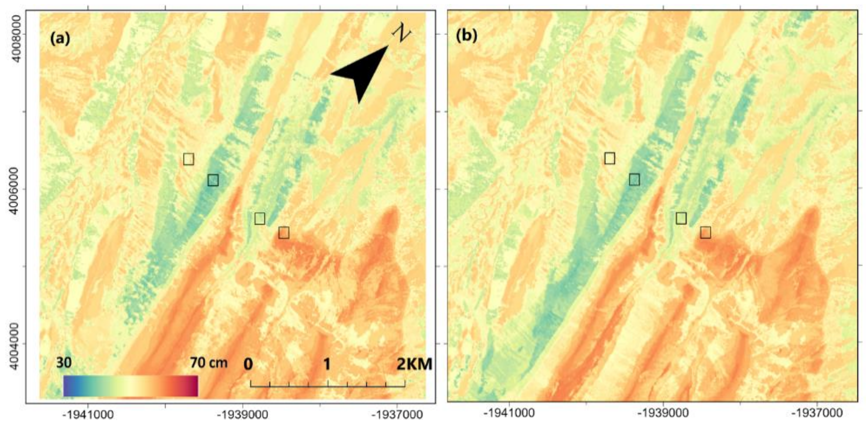

Fig R1. Comparisons between model predictions using Sentinel-2 summer composite (June to August; a) and July composite (b).

Comment 2.8

Further comments:

The capitalization in the section titles is not consistent.

Response 2.8: Thanks for the careful check. All section titles were formatted in the revision to ensure consistency in capitalization style.

Comment 2.9

L22: North Slope not Northern Slope

Response 2.9: Corrected as below.

"…within the North Slope of Alaska"

Comment 2.10

L62-63: You mention ALT derivation from LiDAR and from InSAR deformation signals driven by soil freeze–thaw. This connection needs further explanation as ground deformations do not directly translate to active layer thickness estimates without additional assumptions.

Response 2.10: As suggested, we added the following to further explain the connections between ALT estimation and measurements from LiDAR and InSAR.

"…more indirect measures of surface topographic features from Light Detection and Ranging (LiDAR) (Gangodagamage et al., 2014) and soil freeze-thaw (FT) driven land surface deformations from Interferometric synthetic aperture radar (InSAR) measures (Schaefer et al., 2015). The distribution of ALT over ice-wedge polygon landscapes was empirically inferred using relevant topographic features quantified from LiDAR surface elevation measurements and data fusion approaches (Gangodagamage et al., 2014). In addition, the active layer heaves when frozen and subsides when thawed due to denser liquid water than ice. The seasonal vertical ground movement measured using InSAR is thus related to the ALT and ice/water content (Schaefer et al., 2015)".

Comment 2.11

L64ff: You state that low-frequency microwave measurements show strong potential for mapping ALT. However, the connection to active layer thickness is not entirely clear, since ALT cannot be directly measured with these observations. Could the authors elaborate on the underlying mechanism or clarify how these measurements can be translated into ALT estimates?

Response 2.11: As suggested, we elaborated the underlying mechanisms for using microwave to estimate ALT as below.

"Low-frequency (e.g., L- and P-band) microwave measurements are capable of penetrating through vegetation and soil layers and show strong potential for mapping active layer properties, including soil moisture and FT dynamics, organic matter content, and ALT (Tabatabaeenejad et al., 2014; Bakian-Dogaheh et al., 2025). This is due to the strong microwave sensitivity to the changes of soil dielectric properties, which are affected by soil moisture, texture, and freeze/thaw state (Kneisel et al., 2008; Du et al., 2019). In particular, the contrast in dielectric permittivity at the interface between thawed and frozen soil layers may lead to measurable microwave backscattering or reflection signals for estimating ALT (Kneisel et al., 2008)".

Comment 2.12

L75: The manuscript mentions "direct microwave sensing of soil profiles" for ALT. However, this is somewhat misleading, as ALT is not directly measurable from microwave observations.

Response 2.12: To be more rigorous, we deleted the words “Besides direct microwave sensing of soil profiles”.

Comment 2.13

L92: Could you please provide information on the method on which the regional records are based?

Response 2.13: The sentence was expanded for providing more detailed description of the regional records as below.

“…and regional ALT records at 1-km resolution, which were generated using machine learning by combining in situ ALT observations with a suite of observational biophysical variables (Liu et al., 2024)”.

Comment 2.14

L94: The numbering of the study plots starts at Plot 3 rather than Plot 1. Could you clarify why Plots 1 and 2 are not included or why the numbering begins at 3?

Response 2.14: Besides ALT measurements, our field experiment was also designed to conduct soil coring, soil moisture sampling, and surface roughness measurements over six plots (labeled 1 to 6). Intensive ALT sampling analyzed in this study was only performed on Plots 3, 4, 5, and 6. Here we used the same naming convention as our field experiment and the associated data archive.

Comment 2.15

L100: Is there a specific reason why the Canada Albers Equal Area Conic projection was chosen for Alaska? This projection results in scenes that are not north-oriented, with north arrows appearing consistently tilted. Could the authors clarify the rationale behind this choice?

Response 2.15: This study and field work are part of the larger NASA ABoVE campaign, which adopts the Canada Albers Equal Area projection for use and archiving of geospatial data products (https://above.nasa.gov/implementation_plan/standard_projection.html). Accordingly, we used the ABoVE standard projection for defining the sampling plots and performing the following analysis.

Accordingly, we added the following in Section 2 of the revised manuscript:

"As part of the NASA Arctic Boreal Vulnerability (ABoVE) field campaign, our study used ABoVE standard projection, which is Canada Albers Equal Area projection, for data visualization and analysis (https://above.nasa.gov/implementation_plan/standard_projection.html)".

Comment 2.16

Figure 1: It is unclear whether the black rectangles represent the actual footprints of the RGB images, as the displayed RGB images appear to be rotated relative to these rectangles.

Response 2.16: Thanks for the comment. In the revised Figure 1, the drone RGB images were clipped for showing the plot areas (black rectangles) only.

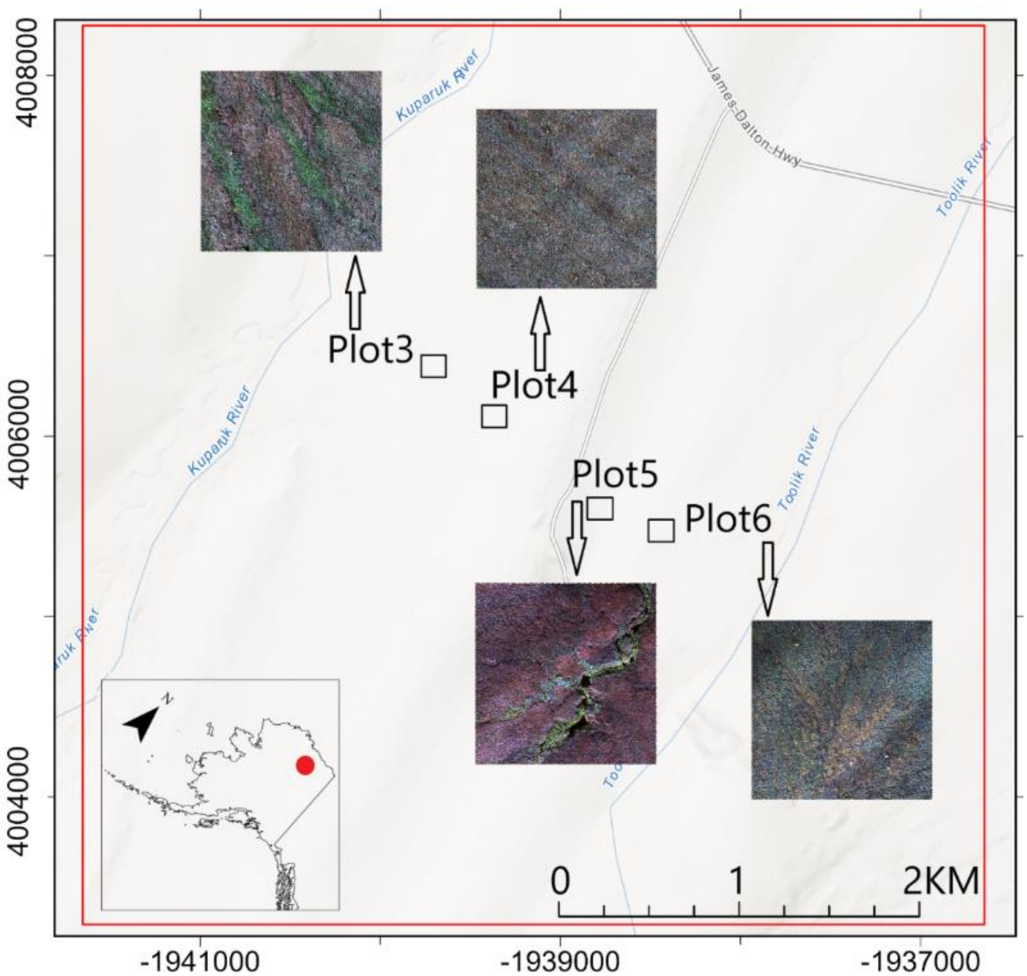

Figure 1: The study region encompasses an Arctic tundra area (68.6167°, -149.3167°; red dot in the inset) in the northern foothills of the Brooks Range, Alaska. The region consists of four intensively sampled plots (Plot 3, Plot 4, Plot 5, and Plot 6; 90 m x 90 m each) with their corresponding true-color RGB (red-green-blue) drone images displayed alongside for visual inspection only, and surrounded by a larger 5 km by 5 km study region (red rectangle) used for

analyzing ALT scaling effects. The map was plotted using Canada Albers Equal Area Conic projection.

Comment 2.17

L146: The method chosen to aggregate the data is not specified and should be clarified.

Response 2.17: To be more clear, the sentence was revised as "The drone-based optical images and products were aggregated to both 0.1 m and 5 m resolutions through pixel averaging…"

Comment 2.18

L163: re-constucting or reconstructing

Response 2.18: We corrected the typo and used "…trained to reconstruct ALT patterns" in the revision.

Comment 2.19

L163-165: I find this sentence and Figure 3 somewhat misleading and suggest revisions to avoid confusion. In Figure 3, the arrow from the '0.1 m predictors' to the model could incorrectly suggest that the model was trained at 0.1 m, whereas it was actually applied at that resolution. This should be represented in a way that clearly distinguishes training from application/prediction to avoid any confusion. Additionally, the arrows from 'Aggregated to 10 m ALT' and 'Field ALT sampling' connect to the predictors, which does not seem correct and should rather lead into the models. Additionally, ‚Scaling analysis' should be capitalized for consistency.

Response 2.19:

Thanks for the comment! The text and flowchart (Figure 3) were revised accordingly to avoid confusion. We also capitalized "Scaling analysis" for ensuring consistency. The revisions are also presented below:

"A data-driven Random Forest (RF) model was first trained to reconstruct ALT patterns at a 5-m resolution over the intensively sampled plots. This model was also used with 0.1-m predictors to generate the ALT maps at 0.1 m resolution. The 5-m ALT results were subsequently aggregated to 10-m resolution to train a second RF model, which was used to produce the 10-m ALT map over the surrounding region (Figure 3)".

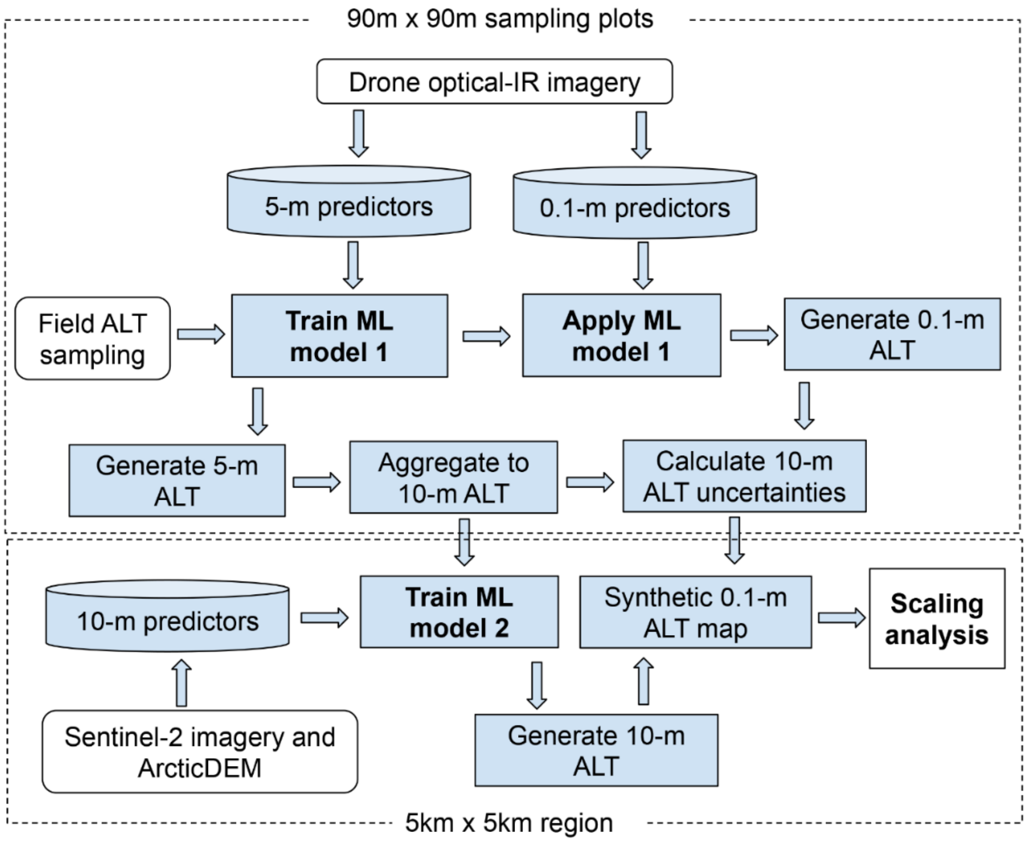

Figure 3: An overall flowchart of the machine learning (ML) based active layer thickness (ALT) mapping and analysis.

Comment 2.20

Table 1: aspect (on the right side) should be capitalized for consistency

Response 2.20: Thanks for pointing out the inconsistency. "Aspect" was used in the revision.

Comment 2.21

Figure 4: The coordinate labels are difficult to read and should be enlarged for better readability.

Response 2.21: Figure 4 was re-plotted to ensure ALT measurements and predictions were only mapped over their overlapping areas for easier comparisons. The labels were also enlarged for better readability as suggested.

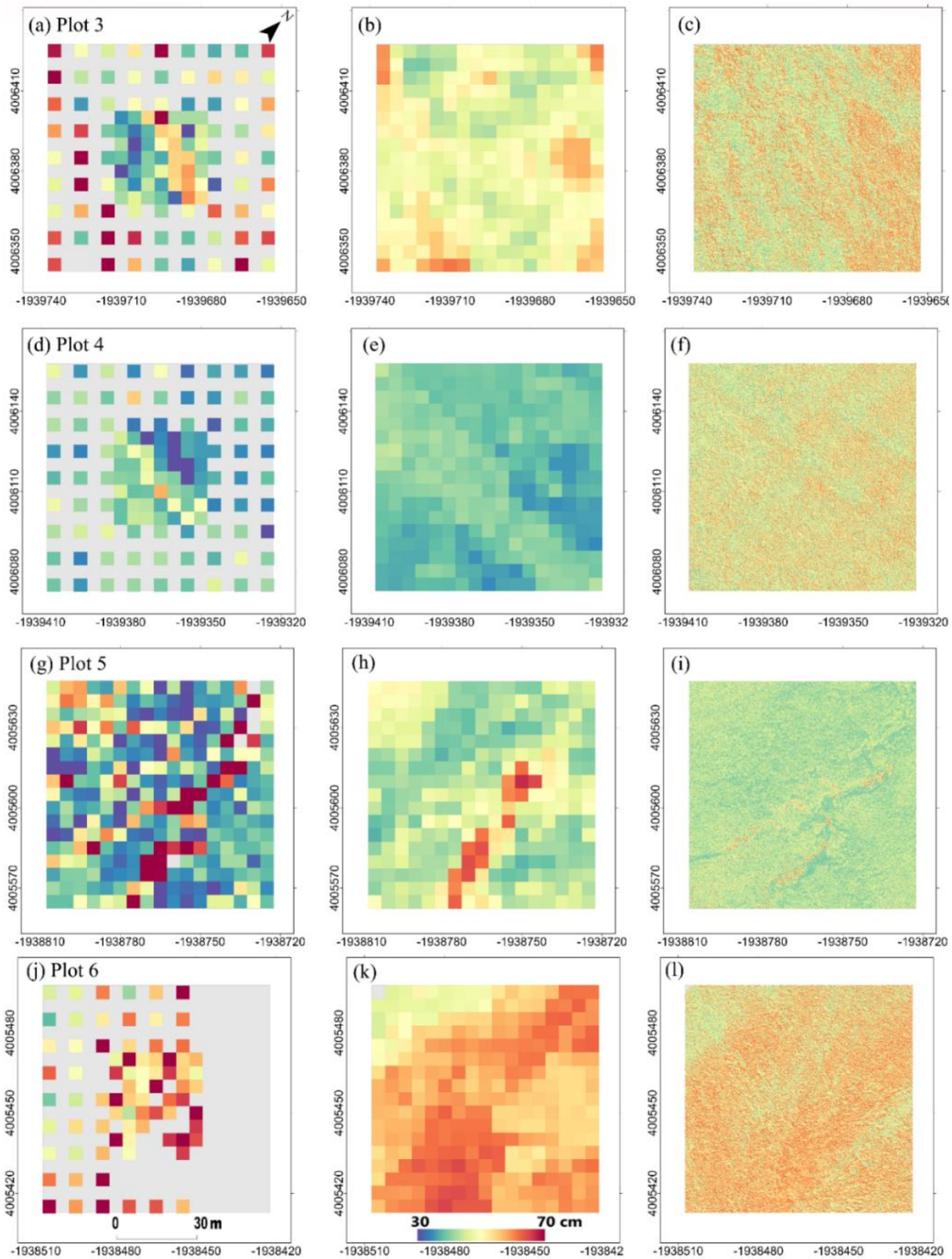

Figure 4. Comparisons of ALT spatial patterns derived from field measurements (a, d, g, j), 5-m machine learning outputs (b, e, h, k), and 0.1-m machine learning estimates (c, f, i, l) for the intensively sampled plots (grey shading indicates areas without sampling). The map was plotted using Canada Albers Equal Area Conic projection.

Comment 2.22

L247-249: This statement may be misleading, since NDVI (19.85%) is more important than aspect (17.85%) or slope (17.16%).

Response 2.22: The sentence was revised to be more rigorous as below.

"Terrain factors collectively form the most important control on the ALT distributions at 10-m resolution (elevation 29.88%, aspect 17.85%, slope 17.16%), while vegetation (NDVI 19.85%) and surface wetness (15.26%) conditions are relatively less important".

Comment 2.23

Figure 5: It would be helpful to also include elevation, since it is reported as the most important factor.

Response 2.23: As suggested elevation map was added to Figure 5 as shown below.

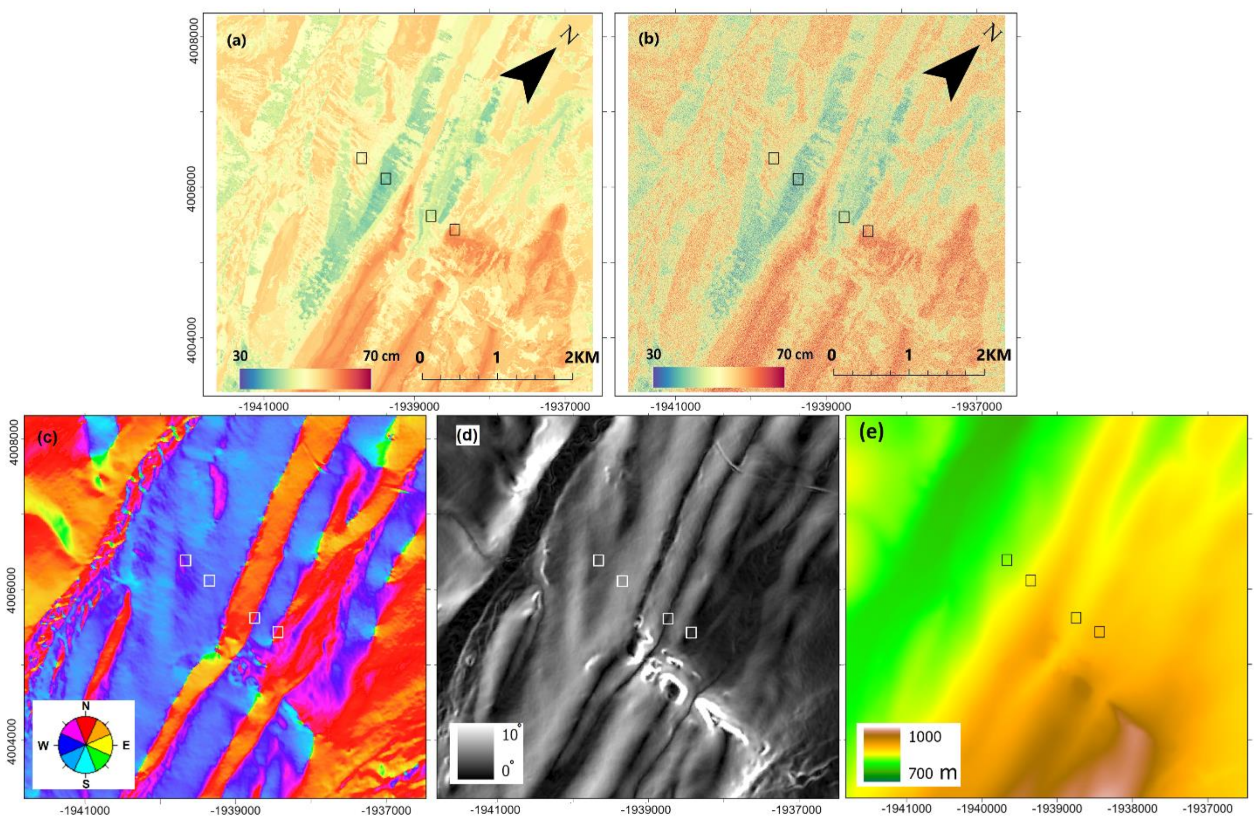

Figure 5: Comparisons between ALT distributions at 10-m resolution derived from machine learning (a), the synthetic ALT map at 0.1-m resolution (b), terrain aspect (c), slope (d), and elevation (e) over a larger 5 km x 5 km area surrounding the sampling plots (black/white rectangles). The map was plotted using Canada Albers Equal Area Conic projection.

Comment 2.24

L296-298: Only the change in R is reported for radar-based observations; it would be helpful to also show their importance relative to other predictors.

Response:

As suggested, feature importance information in radar-based ALT predictions was added as below.

"It is noted that additional radar (L-band 1.26 GHz) observations from UAVSAR helped to enhance the performance of the first RF model (e.g., R increased from 0.78 to 0.81), but were not used in the subsequent scaling analysis (section 3.1.2). For the features selected for radar-based ALT predictions, red-edge reflectance (16.67%), HV-polarized radar backscatter (16.04%), aspect (15.33%), and HH-polarized radar backscatter (15.04%) contributed most to the predictions, while the red band (13.34%), slope (11.99%), and green band (11.57%) observations were relatively less important. The sensitivity of radar backscatter to vegetation biomass, surface water bodies, and soil wetness likely enhanced the ALT estimation".