Response to Reviewer 1

In black: Reviewer’s comments.

In blue: Response to reviewer.

In red: Revised manuscript.

General comments:

Snow is a crucial component in the land surface energy balance and the water-carbon cycle. Our understanding of the mechanisms by which snowpacks influence ecosystem respiration remains limited. This is partly due to the difficulty in monitoring snowpack properties, and over-simplification of snow processes when investigating the impact of snow on the ecosystem carbon cycle. In this study, the authors investigated the relation between six snow properties and ecosystem respiration using remote sensing data. They identified snowpack depth, snowpack duration, and snowpack density as the most important snow property that influence winter soil respiration, and they suggest that snowpack-respiration relation was regulated by thermal conditions rather than water availability. While previous studies on winter ecosystem respiration have presented observational results, information on broad-scale understanding using remote sensing and modelling has been lacking, making this study significant. The manuscript includes all the essential components. However, I have outlined several methodological concerns, along with several detailed or technical points, that could be addressed to further enhance the overall rigor and presentation of the study.

We sincerely thank you for the thorough evaluation and constructive comments. Your feedback sharpened the study’s methodological rigor, diagnostic transparency, and interpretive clarity. In response, we (1) diagnosed and managed collinearity among snowpack indicators using pairwise correlation matrices and variance inflation factors, and interpreted model coefficients in light of these diagnostics; (2) clarified data handling by applying spatial aggregation and latitude-weighted averaging to prevent latitudinal over-representation, and re-estimated contributions under this scheme, noting the resulting shifts in the relative influence of snow indicators; and (3) expanded the Methods section and references to explicate the machine-learning framework of FLUXCOM and to justify our choice of PLSR over multiple linear regression given multicollinearity and dimension-reduction needs. These revisions materially strengthen the manuscript and directly address the concerns raised. The text and supporting materials have been revised accordingly. We believe these revisions and clarifications have strengthened our manuscript and addressed your concerns. Once again, we appreciate the valuable feedback and are confident that these revisions will strengthen the contributions of our study.

Major problems:

1) The metrics used for snowpack include snowpack depth and snowpack density, which are interrelated. Given the collinearity among variables, using partial correlation analysis and partial least squares regression models is certainly reasonable. Moreover, statistical approaches should be evaluated for simplifying analysis and enhancing understanding.

We understand the concern regarding collinearity of snowpack variables. Due to the inherent correlation of snow hydro-physical processes, these indicators naturally exhibit covariance. We used a combination of correlation coefficient matrix and variance inflation factor (VIF) to systematically diagnose the collinearity of various snowpack indicators. Correlation analysis (Figure S5) shows a strong correlation between snowpack onset date and snowpack end date, exhibiting a significant positive correlation in 29.82% of the study area, with an average correlation coefficient of 0.77; while snowpack onset date and snowpack duration show a negative correlation, with a correlation coefficient of –0.69, and a significant correlation in 34.39% of the study area. Snowpack depth and snowpack density show a strong positive correlation, exhibiting a significant positive correlation in

24.63% of the study area, with an average correlation coefficient of 0.56. This phenomenon may be related to the fact that both reflect the physical state of snowpack; however, previous studies (Fassnacht et al., 2013; Sturm et al., 2010) have pointed out that the variation range of snow depth and snow density differs significantly at regional and station scales, and their correlation needs to be viewed objectively.

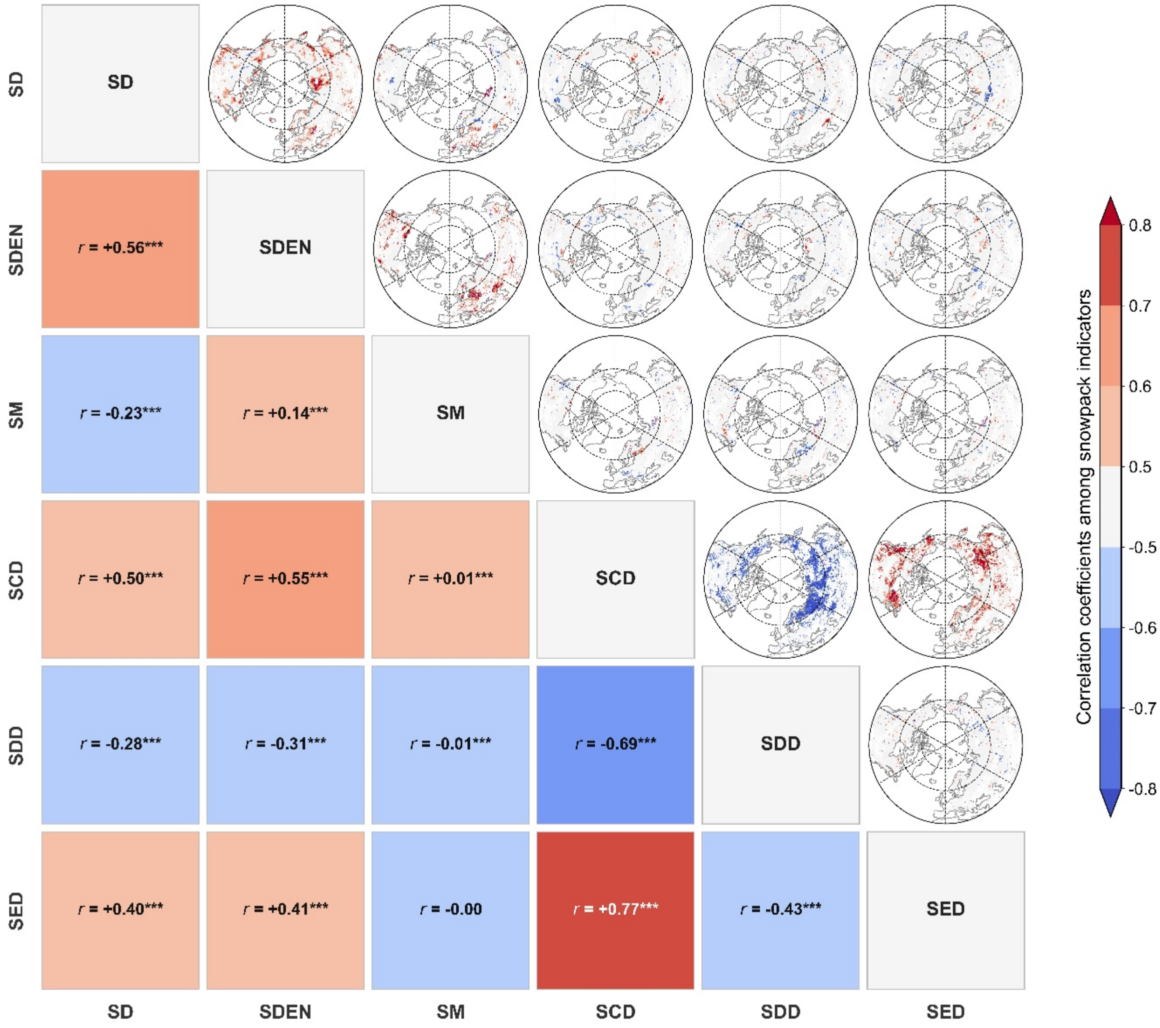

Figure S5. Correlation coefficients among snowpack indicators.

Snowmelt amount showed weak correlation with all other snowpack indicators (|r|<0.3), demonstrating strong independence.

The collinearity diagnosis (Table S4) showed that the VIF for snowpack onset date and snowpack end date were as high as 5.6 and 5.9, respectively, indicating severe collinearity problems for each. After comprehensive consideration, since the VIF for snowpack duration was only 2.1 and could more comprehensively reflect the temporal characteristics of snowpack, this study ultimately retained snowpack depth and snowpack density as the core indicators of static snowpack properties, selecting snowpack duration rather than snowpack end date to represent the temporal dimension of snowpack.

Table S4. Variance inflation factor of snowpack indicators.

Snowpack indicator	**VIF**
SD	4.2
SDEN	3.8
SM	1.3
SOD	5.6
SDD	2.1
SED	5.9

2) The author employs snowpack depth and snowpack density to characterize snow. A question arises as to why snowpack water equivalent is not used, considering it can describe both snowpack depth and snowpack density and is commonly utilized in snow-ecology studies (e.g., Wang et al. "Disentangling the mechanisms behind winter snow impact on vegetation activity in northern ecosystems." Global Change Biology 24.4 (2018): 1651-1662).

Thank you for your question regarding the selection of snowpack indicators. While snow water equivalent (SWE) can simultaneously characterize snowpack depth and snowpack density, it is defined as the depth of liquid water obtained upon complete melting of a snowpack of a given depth, and is used to quantify the actual water stored within the snowpack, thereby carrying greater hydrological significance. As the core finding of this study is that the impact of snowpack on $\mathrm{Reco}_{\mathrm{winter}}$ is modulated by thermal conditions, we sought to select indices more appropriate for characterizing the insulating properties of snowpack, and therefore chose to treat snowpack depth and snowpack density as separate variables. Furthermore, in snow ecology research, emphasis is typically placed on the post-melt effects of snowpack on ecosystem functioning during the growing season, and commonly adopts $\mathrm{SWE}_{\max}$ as the proxy for snowpack. $\mathrm{SWE}_{\max}$ is defined as the annual maximum snow water equivalent, which carries huge hydrological significance. In contrast, this study focuses on the effects of snowpack on the winter ecosystem, emphasizing the average winter conditions. Accordingly, all indicators (with the exception of snowmelt amount during winter) are represented as mean values rather than maximum values.

3) The datasets are described as having been interpolated to a 0.25-degree resolution. This characterization raises two related concerns: (1) The procedure appears to represent aggregation or downsampling rather than interpolation in the strict sense, and it would be important to clarify whether this step was implemented through spatial averaging. (2) If all available 0.25-degree grid cells were assigned equal weights in the statistical analyses, this would introduce a latitudinal bias, disproportionately emphasizing higher latitudes relative to lower ones (by approximately a factor of two). Although the maps visually resemble an equal-area projection or a comparable adjustment, clarification is needed as to whether and how differences in grid-cell area were taken into account in the analyses.

Thank you for the comment. Regarding issue 1, we strictly adhered to the spatial averaging method, using bilinear interpolation resampling to unify the spatial resolution of all datasets. Regarding issue 2, the original manuscript did indeed perform a pixel count for all 0.25-degree grid cells. We subsequently used a latitude-weighted averaging method to re-perform the area statistics, optimizing for differences in grid cell areas across different latitude ranges.

$$A_{i,j} = R^2 \cdot \cos(\varphi_i) \cdot \Delta\varphi \cdot \Delta\lambda$$

where $A_{i,j}$ is the actual area (km^2) of the pixel in the i-th row and j-th column; R is the average radius of the Earth (6371 km); φ_i is the latitude (rad) of the center of the pixel in the i-th row; $\Delta\varphi$ and $\Delta\lambda$ are the latitude and longitude resolution (rad) of the pixel, respectively.

We did notice a change in proportion counts, e.g, In Figure 1, the proportion that snowpack depth and FLUXCOM $Reco_{winter}$ are significantly correlated shifted from 20.45% to 23.32%. We did notice a decline in proportions that snowpack duration and FLUXCOM $Reco_{winter}$ are significantly correlated (from 12.54% to 10.95%), because the area they are correlated is mostly located in high latitudes. In Figure 2, the proportion that snowpack depth was the dominant factor influencing $Reco_{winter}$ variability, shifted from 13.85% to 14.84%, snowpack density from 7.75% to 8.55%, snowpack duration shifted from 8.83% to 8.31%, and the sum of three snow indicators shifted from 30.43% to 31.70%. Climate from 11.26% to 10.77%.

Minor problems:

Line 67: “average … of all nine machine learning methods.” This phrasing may be unclear to readers.

FLUXCOM employs multiple machine learning methods to produce ecosystem respiratory products, detailed in the paper (Jung et al., “Scaling carbon fluxes from eddy covariance sites to globe: synthesis and evaluation of the FLUXCOM approach”. Biogeosciences, 17.5 (2020): 1343-1365). The data we used is the mean of the respiratory products generated using nine machine learning methods.

Line 67: As FLUXCOM uses multiple methods to generate carbon flux data, we used the mean flux product derived from all nine machine learning methods.

Line 99: what is the difference between PLSR analysis and multiple linear regression?

The main difference between multiple linear regression (MLR) and partial least squares regression (PLSR) lies in the different methods they use to handle the relations between independent variables. MLR relies on the premise that the original variables are independent; however, it fails when multicollinearity exists among the independent variables. PLSR, on the other hand, decomposes both the independent and dependent variables into latent components, uses these components for regression, and calculates the explanatory power of each independent variable through its loadings on all latent components. Because multicollinearity may exist among ecological variables, this study employs PLSR.

Line 104: how was VIP calculated?

The calculation method of VIP is described in details in Supplement methods S1.5. For a partial linear regression model with m latent components where one seeks to predict y (n×1) from X (n×p), the VIP value for the j^{th} is defined as follows:

$$\mathrm{VIP}_j = \sqrt{\frac{p}{\sum_{h=1}^{m} R^2_{(y,t_h)}} \sum_{h=1}^{m} R^2_{(y,t_h)} w^2_{kj}}$$

where $R^2_{(y,t_h)}$ is the proportion of the y variance explained by t_h.

Line 223: what is the hypothesis that the regulation effect of snow should differ among vegetation types? The rationality of this analysis needs to be explained.

After discovering that the impact of snowpack on $\mathrm{Reco}_{\mathrm{winter}}$ is significantly sensitive to thermal conditions, we wanted to investigate whether this effect applies across different vegetation types, or whether it is a natural change resulting from vegetation succession under different thermal conditions. Therefore, we investigated whether there are differences in the impact of snowpack on $\mathrm{Reco}_{\mathrm{winter}}$ under different vegetation types. Figure 5 shows that the impact of snowpack on $\mathrm{Reco}_{\mathrm{winter}}$ is highly sensitive to thermal conditions, and this pattern is universal across different vegetation types. Therefore, we reject the hypothesis that the moderating effect of snowpack varies with vegetation type, concluding that the impact of snowpack on $\mathrm{Reco}_{\mathrm{winter}}$ is primarily influenced by thermal conditions.

References:

Fassnacht, S., Heath, J., and Musselman, K.: Small scale spatial variability of snow density and depth over complex alpine terrain: Implications for estimating snow water equivalent, Advances in Water Resources, 55, 40–52, https://doi.org/10.1016/j.advwatres.2012.08.010, 2013.

Sturm, M., Taras, B., Liston, G. E., Derksen, C., Jonas, T., and Lea, J.: Estimating snow water equivalent using snow depth data and climate classes, Journal of Hydrometeorology, 11, 1380–1394, https://doi.org/10.1175/2010jhm1202.1, 2010.