To editor:

We sincerely thank the reviewer for their valuable feedback and insightful comments. These have significantly improved the clarity, quality, and precision of our manuscript.

In response to the reviewers' comments, we have revised the manuscript and prepared a point-by-point response. For easy reference, the original comments are reproduced in blue, followed by our responses in black. All changes made to the manuscript text are highlighted in red.

The manuscript presented a detailed study on the impact of snow on the cropland gross primary productivity in northeast China, by using dataset retrieved from satellite remote sensing and reanalyzes and others. The topic is interesting, as the structure is clear together with the logic. However, a main problem of the current version is the absence of physical mechanisms because most explanations are based on statistical analysis. In addition, I have some specific comments as below, and hope the authors can still improve the manuscript accordingly.

Response: We deeply appreciate the reviewer's constructive and thoughtful feedback. The points raised have been instrumental in improving the manuscript, particularly in clarifying the physical mechanisms behind the observed relationships and in refining the structure and presentation. We made significant modifications, including: (1) removing the former results regarding paddy land, including method, figures, and context; (2) moving the former Discussion into Results and drafting a new Discussion. Below, we provide a detailed point-by-point response to each comment.

In the second paragraph of the introduction section, a summary on the previous studies on the impact of snow on GPP was presented. How about the associated study in the northeast China? I think the readers would wonder if there is any existed studies in the same area.

Response: Thank you for this helpful suggestion, and we add the comparison with previous work in the Introduction (Line 92-97) and Discussion (Line 504-509).

Previous work by Wang et al. (2024) shows that the relationship between snow cover and vegetation productivity in Northeast China varies by underlying surface type and is further modulated by local environmental conditions. A knowledge gap exists in previous work regarding how multi-metric snow characteristics interact with snow–vegetation productivity relationships simultaneously across agricultural regions in Northeast China. (Line 92-97)

Wang et al. (2024) showed that in this region, increases in SWE tend to favor GPP in dryland and grassland, while snow phenology metrics such as SCED and SCD are more influential in forests. Our results refine this picture by isolating cropland and demonstrating that (i) SWE dominates GPP variability in moisture-limited cultivated systems, (ii) SCD and SCED become critical where cold stress and drainage limitations are prominent, and (iii) the relative dominance of these metrics shifts systematically. (Line 504-509)

Reference:

Wang, Y. et al., 2024. Unraveling the effects of snow cover change on vegetation productivity: Insights from underlying surface types. Ecosphere, 15(5): e4855.

In figure 1, the six sub-regions in figure 1c is hard to clearly see. And in the context, only the climate features of northeast China was introduced, how about the six sub-regions? What do you mean "distinct climatic characteristics across these six sub-regions"? More explanations are necessary.

Response: We appreciate this comment and have revised both the figure and the text for clarity. In Figure 1c, we have enhanced the visual representation of the six sub-regions by adjusting the contrast and adding labels to improve readability. Additionally, we have expanded the text (Lines 121-129) to elaborate on the distinct climatic characteristics of these sub-regions, including differences in temperature, precipitation patterns, and snow cover duration, which influence GPP dynamics. The sub-regions were chosen based on these climatic differences to explore regional variations in snow cover's impact on GPP.

The region features a temperate monsoon climate characterized by winter snowfall (Xue et al., 2022), low evaporation rates, and high humidity. However, as shown in Table 1, there are pronounced climatic gradients across the six sub-regions. The effective accumulated temperature (≥10°C) ranges from 2320°C in the cooler Xing'an Mountain area to 3654°C in the warmer Liaohe Plain (Xu et al., 2023). Similarly, annual precipitation exhibits stark contrasts, from a mere 200–400 mm in the arid Western Sand Area to 800–1200 mm in the humid Changbai Mountain. These geographic and climatic differentiations are crucial for understanding regional ecosystem responses. (Lines 121-129)

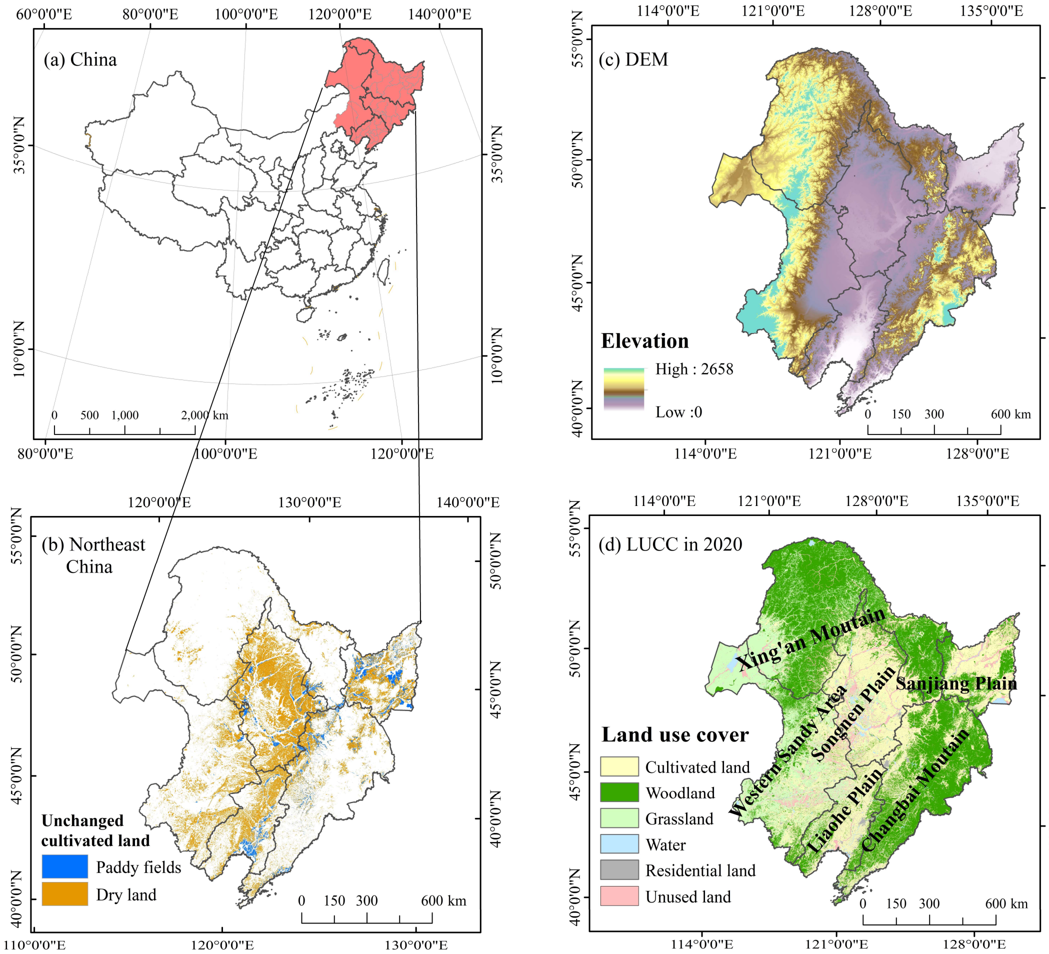

Figure 1 The overview of the study area: (a) China; (b) cultivated land in Northeast China; (c) digital elevation model (DEM) provided by SRTM; (d) land use types provided by LUCC

In the method section, I think it may be not necessary to present all statistical algorithms because some of them are widely-employed ones. Besides, the spatial and temporal resolutions of these data are different, how to interpolate them into the same grids? And will that interpolation introduce any associated uncertainty into the analysis?

Response: We agree with the reviewer's comment regarding the level of detail in the methods section. We have streamlined the presentation of statistical algorithms to focus on those that are critical to the analysis, while removing more widely used ones.

Besides, we fully acknowledge the importance of data preprocessing methods. All datasets were resampled to a consistent spatial resolution of 0.05°×0.05° using the nearest neighbor method to facilitate subsequent pixel-by-pixel analysis. We recognize that resampling introduces uncertainties; however, it is a necessary step for multi-source data fusion and pixel-by-pixel statistical analysis, which are discussed in the Discussion 4.2 (Line 549-552).

2.3.1 Trend analysis

The long-term trends in the annual time series of SCD, SWE, and GPP (2001-2020) were analyzed using the Theil-Sen slope method (Sen,1968). The statistical significance of these trends was evaluated with the Mann-Kendall test (Kendall, 1948; Mann, 1945).

2.3.2 Partial correlation

All datasets were resampled to a consistent spatial resolution of 0.05°×0.05° using the nearest neighbor method to facilitate subsequent pixel-by-pixel analysis. Then, a partial correlation analysis was employed to statistically quantify the relationship between two variables while controlling for the effects of one or more covariates (Gonzalez, 2003; Kashyap and Kuttippurath, 2024; Wei et al., 2022). Specifically, we applied pixel-wise partial correlation to examine the impacts of SCD, SWE, and SCED on GPP across various land-use types, while controlling for concurrent temperature, precipitation, and solar radiation to isolate the direct effects of snow cover.

2.3.3 Ridge regression

Given the potential multicollinearity among snow cover indicators, we used ridge regression rather than ordinary least squares to ensure stable coefficient estimates (Zhao et al., 2023). This approach was applied pixel-wise to quantify the relative contributions of SCD, SWE, and SCED to GPP across the study area. This method identified the dominant snow-cover indicators influencing GPP on cultivated land in each zone, providing valuable insights into the spatial heterogeneity of snow cover's effects on vegetation productivity.

2.3.4 Partial least squares structural equation model

To decipher the complex causal pathways through which snow affects GPP, we employed a Partial Least Squares Structural Equation Model (PLS-SEM). Two latent variables were created during model construction, including Snow and Climate. Snow included three snow cover indicators covering SCD, SWE, and SCED, whereas Climate included three meteorological indicators covering precipitation, temperature, and solar radiation. The PLS-SEM also included two soil parameter variables, covering SM, ST, and GPP data for different vegetation types. All variables were normalized before the analysis to facilitate comparison of path coefficients. The path coefficients in PLS-SEM analysis represent the magnitude and direction of direct effects between two variables. Positive and negative path coefficients correspond to the positive and negative impacts of the independent variable on the dependent variable, respectively, with their values quantifying the impact strength. The goodness-of-fit (GOF) index globally evaluates the quality of the path models and determines their validity. A GOF above 0.36 indicates applicable model results (Wetzels et al., 2009).

From section 3.1, spatiotemporal distribution of snow cover is more suitable for the manuscript than "snow cover dynamics" in the title, because the latter is within a small scale as I see.
Response: Thank you for this suggestion. We have revised the title of Section 3.1 to "Spatiotemporal Distribution of Snow Cover" to reflect the scope of the analysis more accurately. The focus of this section is indeed on the distribution patterns of snow cover over time and space, rather than on its dynamics at a small scale (Lines 244).

I do not like the titles of section 3.2 and 3.3. Both are in the style of the relationship between A and B. However, the logical relation between A and B is not clear. I mean who is the reason and who is the result. For example, “the relationship between snow cover and soil properties” is somewhat amazing. Snow cover is associated with climate and weather, but soil property is by land surface. Does A decide B? or B decide A? If we only give some statistical results between A and B rather than the physical mechanism between them, this is only a mathematical game.

Response: We thank the reviewer for this insightful comment. We agree that the original section titles were too vague and did not reflect the causal relationships investigated. Following the reviewer's suggestion, we have revised the titles to represent the scientific logic of our analysis better:

Section 3.2 has been changed from "The relationship between snow cover and soil properties" to "Effects of Snow Cover on Soil Properties". (Line 307)

Section 3.3 has been changed from "The relationship between GPP and snow cover" to "Influence of Snow Cover on GPP". (Line 370)

I suggest the authors can add a short paragraph between section 4 and 4.1 to tell why and what will you do in the discussion section, and what is the logic among the three sections below.

Response: We have added a brief introductory paragraph between Section 4 and 4.1 to provide context for the discussion. This paragraph outlines the logical flow of the discussion, explaining how the results will be interpreted in light of the physical mechanisms at play and how each of the subsequent sections will contribute to understanding the impact of snow cover on GPP (Lines 479-488).

This study aimed to elucidate the spatiotemporal variations in snow cover parameters (SWE, SCD, and SCED) and their heterogeneous impacts on gross primary productivity (GPP) of cultivated land across six subregions in Northeast China, while uncovering the underlying regulatory mechanisms through soil properties. By integrating long-term satellite and reanalysis products with partial correlation analyses and a PLS-SEM framework, we show that snow cover exerts strong but spatially heterogeneous controls on cropland GPP via its effects on spring soil temperature and moisture, with distinct response patterns between dryland and paddy systems and among key agricultural plains. These findings demonstrate that snow is not merely a passive climatic background factor but an active regulator of agricultural carbon uptake in a region that is both snow-dominated and critical for national food security.

I suppose to see more physics in the section 4.3, but it is a pity that there are still some mathematical analyses rather than physical explanations. For example, “In the Changbai Mountain agroecosystem, the snow cover-ST-GPP pathway exhibited a significant indirect effect (βsnow-ST × βST-GPP = –0.67 × 0.76 = –0.51), indicating that snow cover suppressed photosynthetic efficiency through thermal limitation mechanisms during the growing season." What I want to know is why and how the snow cover suppressed photosynthetic efficiency through some physical mechanisms.

Response: Thank you for raising this critical point. We have moved the former Discussion into Results, and added a new Discussion (Lines 478-579).

4 Discussion

This study aimed to elucidate the spatiotemporal variations in snow cover parameters (SWE, SCD, and SCED) and their heterogeneous impacts on gross primary productivity (GPP) of cultivated land across six subregions in Northeast China, while uncovering the underlying regulatory mechanisms through soil properties. By integrating long-term satellite and reanalysis products with partial correlation analyses and a PLS-SEM framework, we show that snow cover exerts strong but spatially heterogeneous controls on cropland GPP via its effects on spring soil temperature and moisture, with distinct response patterns between dryland and paddy systems and among key agricultural plains. These findings demonstrate that snow is not merely a passive climatic background factor but an active regulator of agricultural carbon uptake in a region that is both snow-dominated and critical for national food security.

4.1 Changes in snow cover and GPP

The principal findings demonstrate a 63% decrease in SWE across cultivated lands, contrasted by a 54% increase in SCD and delayed SCED in 61% of areas, which collectively correlated with significant GPP enhancements in 74% of regions, underscoring snow cover's pivotal role in modulating agricultural carbon assimilation under climatic shifts. Our results are broadly consistent with recent large-scale assessments showing that snow cover changes exert strong and spatially heterogeneous influences on vegetation productivity across the Northern Hemisphere (Liu et al., 2023; Mudryk et al., 2020). Similar to Liu et al. (2023), we find that both the direction and magnitude of snow–GPP relationships depend on background climate, and that failing to consider lagged hydrothermal pathways can underestimate the true influence of snow on growing-season productivity. However, whereas Liu et al. (2023) emphasized lagged snow effects in natural ecosystems, our study focuses specifically on cultivated land, where management practices and soil manipulation modulate snow–soil–GPP linkages.

Within Northeast China, our findings complement and extend previous analyses that examined snow–vegetation interactions across all underlying surface types. Wang et al. (2024) showed that in this region, increases in SWE tend to favor GPP in dryland and grassland, while snow phenology metrics such as SCED and SCD are more influential in forests. Our results refine this picture by isolating cropland and demonstrating that (i) SWE dominates GPP variability in moisture-limited cultivated systems, (ii) SCD and SCED become critical where cold stress and drainage limitations are prominent, and (iii) the relative dominance of these metrics shifts systematically.

4.2. Linkages of snow, soil, and GPP

The spatial patterns of SWE, SCD, and SCED reveal a clear north–south and east–west organization of snow regimes over cultivated land. Areas with deeper snowpacks and longer snow duration are concentrated at higher latitudes and elevations, while low-lying southern and coastal croplands experience shallower and shorter-lasting snow. Against this backdrop, our correlation analyses show that snow metrics affect GPP primarily through their modification of soil hydrothermal conditions, in line with the notion that vegetation responds to hydrothermal states rather than snow itself (Liu et al., 2023).

In cold, energy-limited subregions, thicker and more persistent snow tends to enhance GPP by moderating winter and early-spring stress. Increased SWE and longer SCD insulate the soil, maintaining higher near-surface temperatures and reducing freeze–thaw damage, which promotes higher early-season GPP through improved root activity and reduced winter mortality (Mudryk et al., 2020; Liu et al., 2023). In these areas, our PLS-SEM results indicate that the dominant pathway from snow to GPP is temperature-driven: SWE and SCD warm the soil profile, advance favorable thermal conditions for crop emergence, and indirectly raise GPP by shortening the period of severe cold stress.

By contrast, in relatively warm but moisture-limited croplands, SWE emerges as the primary control on interannual GPP variability. Here, snow acts as a critical seasonal water reservoir. Higher SWE increases spring soil moisture, which alleviates early-season water stress and supports more vigorous canopy development, consistent with prior work highlighting the role of snow-derived water for spring soil moisture and subsequent crop performance in Northeast China (Li et al., 2022; Wang et al., 2024). In these zones, the structural paths in the PLS-SEM are dominated by SWE, soil moisture, and GPP, underscoring a moisture-mediated mechanism akin to the broader link between water availability and global GPP.

4.2. Limitations and projections

Several limitations should be acknowledged when interpreting these findings. First, despite using recent high-quality products, uncertainties remain in the underlying datasets. The SWE fields used here, although tailored for China (Jiang et al., 2022), are derived from passive microwave retrievals and data assimilation, which can underestimate SWE in complex terrain and under deep, dense snow (Mihalevich et al., 2022). Similarly, ERA5-Land soil temperature and moisture fields, while widely validated (Muñoz-Sabater et al., 2021), inevitably smooth sub-grid heterogeneity associated with microtopography, tillage practices, and irrigation. MODIS GPP products also carry known uncertainties in cropland, especially under mixed pixel conditions and heterogeneous management. These uncertainties are unlikely to overturn the main regional patterns identified here, but they could affect estimates of effect magnitude, particularly in transition zones where snow–GPP relationships are weak or mixed. Besides, the spatial and temporal resolution of our analysis imposes constraints on generalizability. Aggregating to moderate-resolution grid cells inevitably mixes different soil types, management regimes, and microclimates, which may lead to conservative estimates of snow impacts where fields are strongly heterogeneous.

Furthermore, our analytical framework is observational and relies on correlation and PLS-SEM to infer dominant pathways rather than process-based simulation. Although PLS-SEM is designed to disentangle direct and indirect effects within complex variable networks, it cannot fully resolve causal mechanisms, and its results depend on the specified model structure and variable selection. For example, we did not explicitly represent snow metamorphism, subsurface runoff, or crop management practices, all of which can modulate how snow-induced hydrothermal changes translate into GPP responses (Bodner et al., 2015). We just discussed the dryland of cultivated land in this paper, and future work will consider the paddy land. Incorporating these factors in future structural models, or coupling our observational analysis with process-based land–surface or crop models, would help test the robustness of the inferred pathways.

In summary, this study demonstrates that multiple dimensions of snow cover—SWE, SCD, and SCED—jointly structure the soil hydrothermal environment and GPP of cultivated land in Northeast China, with the dominant control shifting from SWE in moisture-limited areas to SCD and SCED in colder or poorly drained regions. This research provides a process-based framework for understanding snow-vegetation coupling in cold-region agroecosystems, moving beyond simple correlative analyses. The novel application of ridge regression to identify the dominant snow indicator for GPP in each subregion offers a powerful tool for regional-scale assessment and prediction. From an application perspective, these findings can directly inform climate-adaptive agricultural management. For example, in the Western Sand Area, practices that enhance snow harvesting and retention could be prioritized to bolster spring soil moisture. In contrast, in the Changbai Mountain, selecting crop varieties with lower base temperatures for growth or developing strategies to accelerate snowmelt (where feasible) could mitigate the negative impacts of a delayed SCED.