Revision Notes

Dear Editor,

Thank you very much for your letter, and I am very grateful for your timely and efficient review of our manuscript entitled "Diminishing Snowpack Intensifies Crop-Yield Sensitivity to Soil Moisture in the Northern Hemisphere ".

I also would like to express my sincere appreciation to the reviewers for their careful reading and helpful comments. The comments are all valuable and are very helpful for revising and improving our manuscript as well as describing the significance of our study. We have carefully reviewed the comments and have made corrections that we hope will be met with approval. The main corrections in the manuscript and the responses to the reviewers' comments are provided below.

Please noted that "LN" in these revision notes indicates the line number of the manuscript. These numbers are different from the line numbers of the PDF file generated by the submission system.

Responses to Reviewer #2

This manuscript addresses an important and timely topic: the sensitivity of crop yields to snowpack-modulated soil moisture across the Northern Hemisphere. Integrating snowpack, climate, soil moisture, and crop yield datasets for maize, spring wheat, and soybean over 2000–2022 carries potential value. The research question is highly relevant to food security under climate change, and the multi-crop, spatially explicit analytical framework is, in principle, appropriate. Nevertheless, the manuscript has weaknesses in statistical inference, causal interpretation, and methodological transparency. Several key conclusions appear overstated relative to the supporting analyses.

We sincerely appreciate your careful evaluation of our manuscript and your recognition of the importance of understanding the role of snowpack in crop-yield sensitivity to soil moisture under climate change. We also thank you for your thoughtful and constructive comments regarding statistical inference, causal interpretation, and methodological transparency. We agree that these aspects are essential for ensuring the scientific rigor and reliability of our findings. Your comments have been very helpful in prompting us to further examine the robustness of our analyses, clarify the methodological procedures, and refine the interpretation of our results. We have clarified the spatial extent and relative proportions of significant positive and negative correlations and refined the interpretation of the correlation results to avoid overstatement. We have also revised the description of Figure 2 to provide a clearer and more quantitative interpretation of the results. In addition, we have provided further assessments of model-fitting performance and expanded the discussion of uncertainties and limitations associated with our statistical methods and datasets. These revisions aim to avoid unsupported causal interpretations and ensure that our conclusions remain consistent with the evidence provided by our analyses. We believe these revisions have further strengthened the rigor and clarity of our manuscript. Our detailed responses to each comment and the corresponding revisions are provided below.

Specific comments:

[Comment 1] My primary concern lies with the statistical method used to quantify sensitivity, given the difficulty of confounding control. The authors first estimate pixel-level yield sensitivity to soil moisture, then use this estimated sensitivity as a response variable in a second-stage regression with snowpack metrics. This creates a generated regressor problem: first-stage coefficient estimates contain measurement error, and ignoring this uncertainty in the second stage can produce biased estimates and inflated significance.

In addition, snowpack metrics such as SWEmax, SCED, and spring snowmelt are likely highly collinear. Comparisons identifying their “dominant” roles are therefore unstable. I suggest testing whether the identity of the dominant indicator remains robust across regions and crop types.

We thank you for raising concerns about the reliability of the two-stage statistical framework. We evaluated the model-fitting performance at both stages, and the results showed that both models achieved reasonable fits. Nevertheless, we acknowledge that uncertainty in the first-stage sensitivity estimates may still propagate into the second-stage regression. We will further quantify collinearity among the snowpack indicators using correlation matrices and variance inflation factors (VIFs), and

provide maps of dominant indicator selection frequencies across crop types and regions to assess the stability of indicator selection.

In the first-stage analysis, we used a dynamic linear model (DLM) to estimate crop-yield sensitivity to soil moisture. DLMs are well suited to time-series analysis and have been widely applied in geoscience and environmental studies (Prado et al., 2021; West & Harrison, 1997). Based on Bayesian principles, the model recursively updates its parameters through Kalman filtering, producing time-varying estimates of crop-yield sensitivity. We evaluated model performance by comparing observed and fitted crop yields. The corresponding scatter plots, together with 1:1 reference lines and coefficients of determination (Figure S4). The determination values for maize, spring wheat, and soybean were 0.828, 0.736, and 0.957, respectively, indicating that the models reproduced the observed yield variations reasonably well. In the second-stage analysis, we applied bidirectional stepwise ordinary least squares (OLS) regression at the pixel level to identify the snowpack indicators associated with crop-yield sensitivity to soil moisture. The five candidate predictors were SWE, SCED, Melt_03, Melt_04, and Melt_05. The final selected models had in-sample σ^2 values ranging from 0.12 to 0.90 (Figure S5), and their fitting results are also presented in the Supplementary Materials. These results demonstrate the explanatory performance of the second-stage models in capturing spatial variations in crop-yield sensitivity to soil moisture.

We acknowledge that, although both stages showed reasonable model-fitting performance, uncertainty in the first-stage sensitivity estimates may still propagate into the second-stage regression and affect the precision and statistical significance of its estimates. As this uncertainty propagation was not explicitly quantified in our analysis, we have added this issue to the limitations discussed in the revised manuscript:

"Our results identify the major snowpack indicators associated with crop-yield sensitivity to soil moisture through stepwise regression. Although both stages achieve reasonable model-fitting performance, some uncertainty in the first-stage sensitivity estimates may remain and could potentially influence the precision and statistical significance of the second-stage results."

These changes can be found in **LN 480–483.**

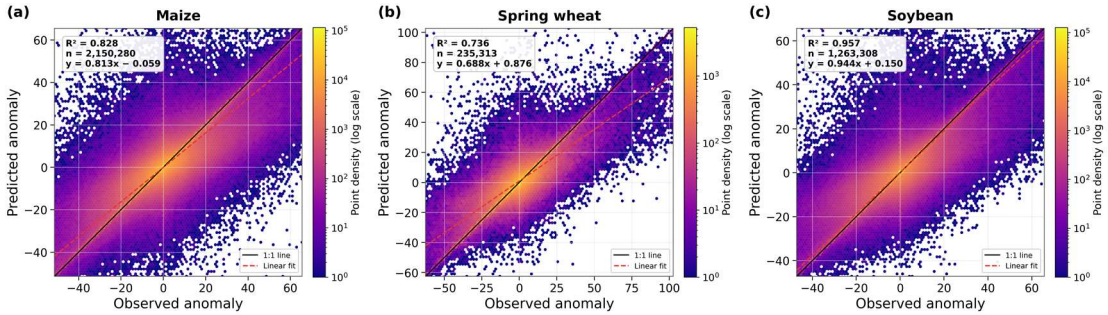

Figure S4. Validation of the DLM models. (a–c) indicate the coefficients of determination of crop yield anomaly predictions against observations for maize, spring wheat, and soybean.

We thank the reviewer for raising the concern about collinearity among snowpack indicators and the stability of the identified dominant indicators. The results presented in our manuscript were already derived from crop-specific, pixel-wise bidirectional stepwise OLS regression, allowing the

selected indicators to vary across different geographical locations and crop types.

Specifically, we applied bidirectional stepwise ordinary least squares (OLS) regression at the pixel level. This approach allowed us to select a subset of explanatory variables based on their statistical contributions, rather than including all five snowpack indicators in every model. Regression was performed separately for each pixel, with SWE, SCED, Melt_03, Melt_04, and Melt_05 as candidate predictors. All predictor and response variables were standardized at each pixel. The selection procedure combined forward selection and backward elimination, using F-tests with a significance threshold of $\alpha = 0.1$. Variables were included when their p-values were below 0.10 and removed when their p-values exceeded 0.10. This process was repeated until the set of selected variables remained unchanged, determining the final set of explanatory variables for each pixel. The selection procedure was performed separately for each crop at the pixel level, allowing the identification of dominant snowpack indicators to account for differences across regions and crop types. This approach was used to ensure model fitting accuracy while identifying the most influential explanatory variables. We assessed model goodness of fit using the in-sample variance (σ^2) of the final selected models, which ranged from 0.12 to 0.90. The corresponding model-fitting results are also provided in the Supplementary Materials of the revised manuscript.

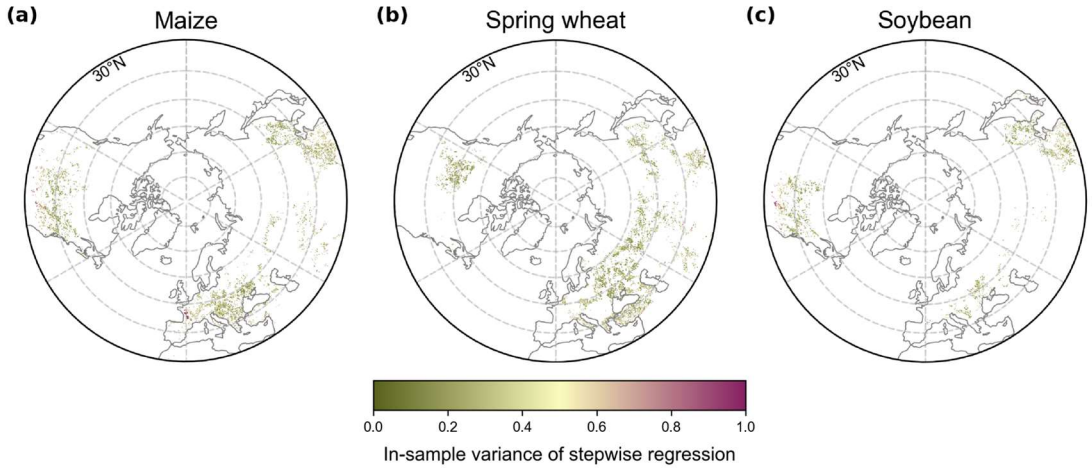

Figure S5. Validation of the stepwise regression models. (a–c) report the variance (σ^2) in sensitivity explained by snowpack indicators.

[Comment 2] The manuscript relies heavily on pixel-wise correlation and regression analyses, adopting a significance threshold of $p<0.1$. This threshold is relatively lenient, and the authors do not state whether multiple testing correction was implemented. Gridded datasets typically exhibit strong spatial autocorrelation, which can severely inflate the effective sample size and produce overly optimistic p-values.

We thank you for the attention to the choice of significance threshold and the reliability of pixel-level statistical inference. We agree that $p < 0.1$ is a relatively lenient threshold compared with more stringent significance levels. We therefore conducted an additional sensitivity analysis using a stricter threshold of $p < 0.05$ to examine whether the choice of significance threshold affected our results. Although the number of significantly correlated pixels decreased, the spatial patterns and

main findings remained consistent with those obtained at $p < 0.1$. For maize, 2.64% of the study area exhibited a significant positive correlation with SWEI, slightly exceeding the area showing a significant negative correlation (2.21%). Similarly, spring wheat yields were significantly positively correlated with SWEI in 5.27% of the study area, compared to1.57% with significant negative correlation, respectively. For soybean, 5.68% of the study area showed significant positive correlations with SWEI, far exceeding the 0.88% of area with significant negative correlations. Among all significant areas, the proportions of positive correlations for the three crops were 52.99%, 72.75%, and 82.66%, respectively. In this study, partial correlation analysis was primarily used to examine the spatial correlation between snowpack and crop-yield responses, rather than serving as the sole basis for subsequent analyses and conclusions. We further used a distributed lag model (DLM) to quantify the relationships between snowpack indicators and crop-yield responses. The model-fitting results (Figure S4), including scatter plots comparing predicted and observed values, are presented to assess model performance. The R^2 values for maize, spring wheat, and soybean were 0.828, 0.736, and 0.957, respectively. These results indicate that the models explain part of the interannual variability in crop yield and reproduce the overall patterns observed in the data reasonably well, providing support for the reliability of our subsequent analyses.

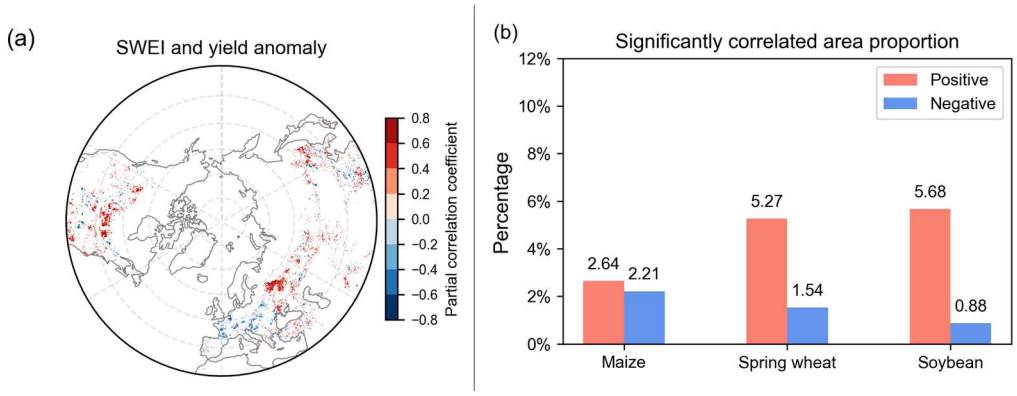

Figure S6. Partial correlations between SWEI and yield anomaly of maize, soybean, and spring wheat from 2000–2022 in the Northern Hemisphere. (a) Spatial distribution of significantly correlated pixels ($p < 0.05$) between SWEI and yield anomaly aggregated across maize, spring wheat, and soybean. (b) Proportion of pixels showing significant positive and negative correlations ($p < 0.05$) between SWEI and yield anomaly of maize, spring wheat, and soybean.

We thank you for the concern about spatial autocorrelation in gridded datasets. Our partial correlation analysis was conducted separately for each pixel using annual observations from 2000 to 2022. The significance test at each pixel was based on its own time-series observations rather than treating neighboring pixels as independent samples. In this pixel-wise framework, each significance test is based on the annual observations at the corresponding pixel, rather than on the number of neighboring pixels. We also compared the results obtained at $p < 0.1$ and $p < 0.05$. Although the number of significantly correlated pixels decreased under the stricter threshold, the main spatial patterns and findings remained consistent. We acknowledge that spatial dependence may still affect the interpretation of the overall spatial patterns of statistical significance.

[Comment 3] There is a inconsistency between the abstract and the results. The abstract states that

"the area showing significant positive correlation accounting for 52.99% for maize, 72.75% for spring wheat, and 82.66% for soybean." However, the results indicate that these percentages refer to the proportion of positive correlations among significantly correlated pixels, not the proportion of the entire study area.

We thank you for pointing out the inconsistency between the abstract and the Results section. We agree that describing these percentages as the "proportion of the area showing significant positive correlations" could lead readers to assume that they were calculated relative to the entire study area. In fact, the values of 52.99%, 72.75%, and 82.66% represent the proportions of pixels showing significant positive correlations among all pixels with significant correlations between crop yield and snowpack changes for each crop. We have revised the abstract to make this distinction clear and ensure consistency with the Results section. In the revised manuscript we revised this part as follows:

"Among pixels where crop yields were significantly correlated with snowpack variations, 52.99% for maize, 72.75% for spring wheat, and 82.66% for soybean showed positive correlations."

These changes can be found in **LN 35–37.**

[Comment 4] The actual significant positive area proportions are much smaller: 5.32% for maize, 9.00% for spring wheat, and 10.07% for soybean. For maize, the significant positive area is only slightly larger than the significant negative area (4.72%). This weakens the claim that snowpack has a consistently dominant positive effect on maize yields.

We thank you for the attention to the proportions of significantly positive correlations and the results for maize. We agree that significantly positive correlations accounted for only 5.32%, 9.00%, and 10.07% of the study area for maize, spring wheat, and soybean, respectively. For maize, the area showing significant negative correlations accounted for 4.72%, which was close to the proportion showing significant positive correlations. This relatively balanced distribution of positive and negative correlations indicates considerable spatial heterogeneity in the relation between snowpack and maize yield. In contrast, positive correlations were more prevalent among significantly correlated areas for spring wheat and soybean. We acknowledge that the original manuscript should have described these differences more cautiously, particularly the small difference between positive and negative correlations for maize.

Our partial correlation analysis primarily aimed to characterize the spatial relation between snowpack and crop yield across the Northern Hemisphere, providing a basis for our subsequent investigation of crop-yield sensitivity to soil moisture. Our main conclusions therefore do not rely solely on the results of the partial correlation analysis. Specially, we selected the snow water equivalent index (SWEI) as a proxy for snow drought because it reflects snow water supply and soil moisture conditions and can help assess vulnerabilities related to agriculture, water resources, and food security. These findings led us to further consider how changes in snowpack may affect agricultural productivity and ecosystem functioning through changes in snowmelt water supply and soil moisture balance. We therefore further examined the relation between snowpack conditions and crop-yield sensitivity to soil moisture. Our subsequent analysis showed that maize yield sensitivity to soil moisture decreased when SWEmax exceeded 96 mm, SCED was later than 84 days, and total

spring snowmelt exceeded 64 mm. We also used stepwise regression to compare the explanatory contributions of different snowpack indicators. The regression coefficients of the snowpack indicators were predominantly negative, and April snowmelt (Melt_04) was identified as the dominant explanatory variable over the largest proportion of the study area (28%). These findings provide further evidence of the relation between snowpack conditions and crop-yield sensitivity to soil moisture, supporting the main conclusions of our study.

In the revised manuscript we revised this part as follows:

"Overall, the partial correlation results indicate the positive effects of snowpack on crop yield outweigh the negative effects and it is consistent across all three crop types."

These changes can be found in **LN 269–271;**

"4.1 Importance of snowpack on soil moisture sensitivity of crop yield Our study demonstrates that snowpack exerts a generally positive influence on crop yields, with positive correlation pixels dominating among all three crop types. For spring wheat and soybean, positive correlations accounted for a substantially larger proportion of significantly correlated areas. The proportion was only slightly higher than that of negative correlations for maize, with the relation primarily characterized by spatial heterogeneity."

These changes can be found in **LN 376–379.**

[Comment 5] The study defines June–September as the average growing season for spring crops and February–May as the snow accumulation and melt period. However, maize, spring wheat, and soybean have very different sowing dates, growth stages, and peak water demand periods. These also vary strongly across the Northern Hemisphere.

We thank you for the attention to the definition of the seasonal windows. When defining the growing-season window, we have considered the spatial differences in crop calendars across the study area. The June–September period was selected based on the planting and harvesting calendars of maize, spring wheat, and soybean within our study region to represent the common growing period. However, this procedure was not clearly explained in the original manuscript, which may have caused confusion.

We have now included the distributions of planting and harvesting dates for the three crops across the study area in the Supplementary Materials (Fig. S7). The results show that more than 50% of the total crop area had been planted by June 1, while more than 50% had been harvested by September 30. The proportions of the growing crop area for all three crops were relatively high during this period. Figure S7(b) further shows that the proportions of crop area within the growing season reached 81.7%, 93.6%, and 92.7% in June for maize, spring wheat, and soybean, respectively, and increased to 97.6%, 100.0%, and 99.1% in July. These proportions remained high in August (95.8%, 86.8%, and 95.5%, respectively) before declining to 74.7%, 49.0%, and 57.1% in September. These results show that June–September represents the main period of overlap. We also examined regional differences in the growing-season coverage (Table S1). The proportions for maize, spring wheat, and soybean were 92.90%, 90.24%, and 91.27% in North America, 93.95%, 93.66%, and 100.00% in Europe, and 73.20%, 70.08%, and 72.27% in Asia, respectively. These

results further support the selection of a common growing-season window while showing regional differences in crop phenology.

We therefore selected June–September as a core growing-season to compare crop responses across regions and crop types on a consistent temporal basis. We also recognize that the term "average growing season" used in the original manuscript was ambiguous. The selected period is more appropriately described as a "core growing season." We have revised the terminology accordingly and clarified that this window represents the main period of overlap among the growing seasons of the three crops across the study area.

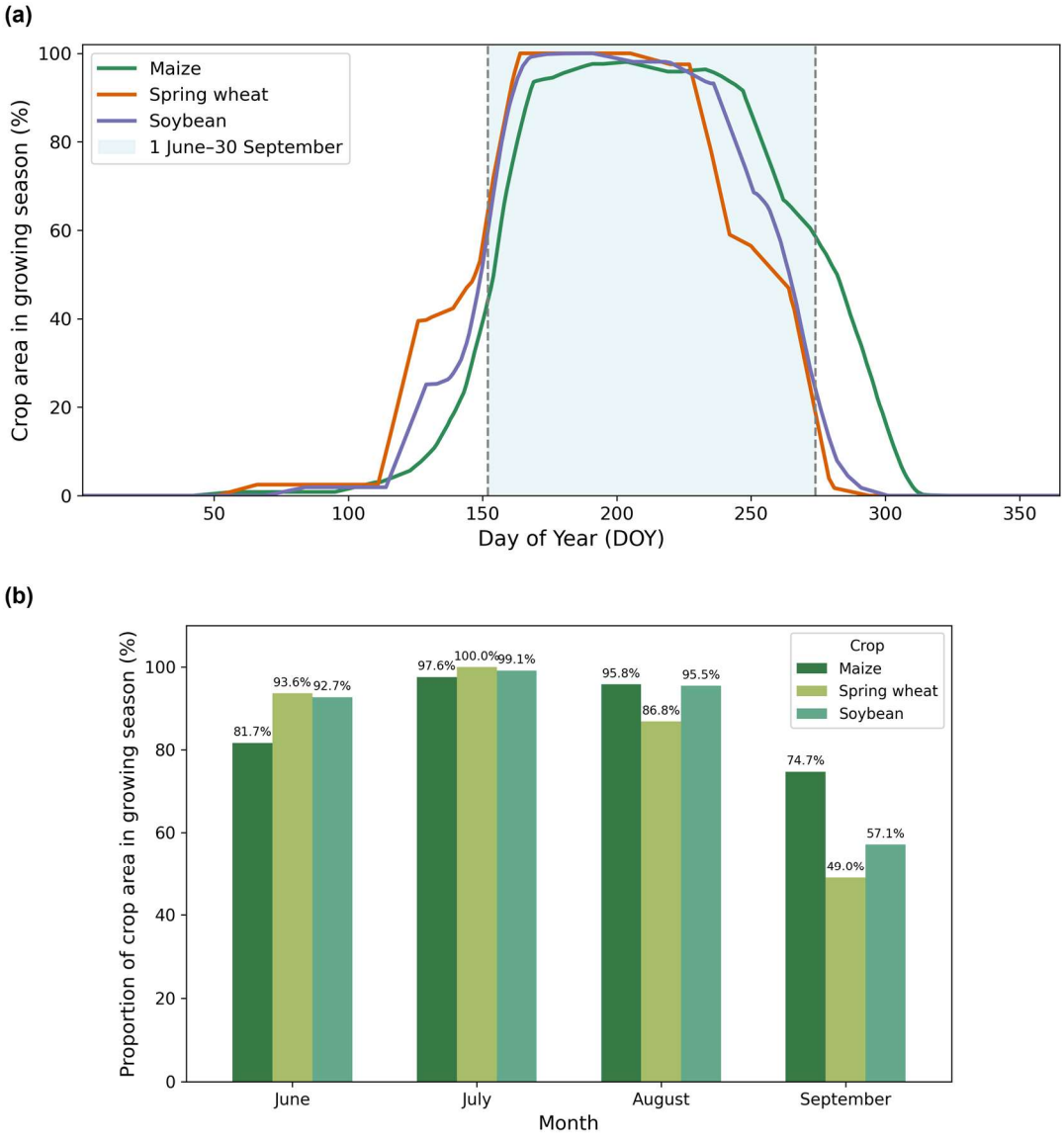

Figure S7. Distribution of planting and harvesting dates and the proportion of crop area within the core growing season for maize, spring wheat, and soybean across the study area.

Table S1. Regional proportions of crop in the growing-season during June–September

Region	Maize	Spring wheat	Soybean
North America	92.90	90.24	91.27
Europe	93.95	93.66	100.00
Asia	73.20	70.08	72.27

In the revised manuscript we revised this part as follows:

"Given the temporal mismatch between snow cover and crop growth, we defined June to September as the core growing season based on crop calendars for spring crops, because more than 50% of the crop area had been planted by June 1 and harvested by September 30, with relatively high proportions of all three crops in their growing seasons during this period (Figure S7a). We also analyzed the planting and harvesting dates, monthly proportions of crop area within the growing season, and regional differences for maize, spring wheat, and soybean. The results showed that June–September covered the main growing period of all three crops across the study area, despite some regional and crop-specific variations (Figure S7b; Table S1)."

These changes can be found in **LN 168–179.**

[Comment 6] The study defines rainfed grid cells as those with irrigated area fraction less than 30%. This threshold is quite high and may include substantial irrigated agriculture. I recommend using a stricter threshold, such as <10%, for the main analysis, and testing sensitivity to <10%, and <20%.

Thank you for this valuable suggestion. We agree that the selection of the irrigation threshold is an important consideration when identifying rainfed croplands. To assess the robustness of our findings to the choice of irrigation threshold, we conducted additional sensitivity analyses using stricter thresholds of 10% and 20%. The results obtained using the 20% threshold showed a high degree of consistency with those reported in the original manuscript. Although applying the stricter 10% threshold further restricted the study area, the main patterns and conclusions remained consistent with our original findings.

Specifically, under the 10% threshold, April snowmelt remained the dominant explanatory factor for changes in soil moisture sensitivity in maize and spring wheat, accounting for 28% and 25% of their respective study areas (Figure 3). For soybean, May snowmelt remained the most influential predictor, accounting for approximately 25% of the study area. Furthermore, the stepwise regression coefficients consistently indicated that, across all three crops and the examined snowpack indicators, the proportion of areas exhibiting negative effects exceeded that showing positive effects. These findings are consistent with the main results presented in the original manuscript. Overall, the sensitivity analyses demonstrate that although the irrigation threshold influences the spatial extent of the selected rainfed croplands, the dominant explanatory factors and the overall direction of their effects remain largely unchanged. This suggests that our main conclusions are relatively

robust to the choice of irrigation threshold.

We have incorporated these sensitivity analyses into the revised Supplementary Materials to clarify the influence of irrigation threshold selection on our findings.

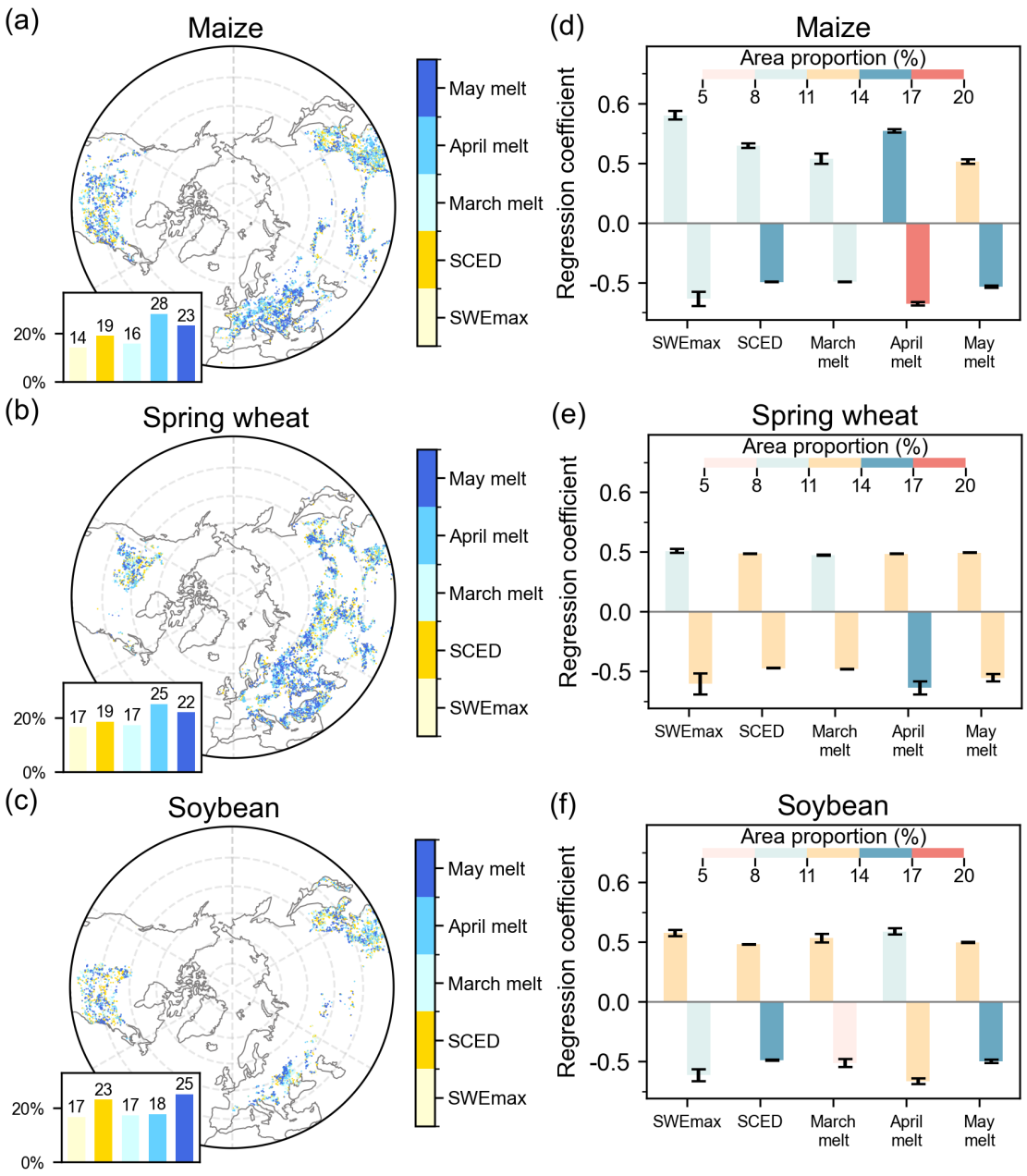

Figure S8. Sensitivity analysis of dominant snowpack indicators influencing crop-yield sensitivity to soil moisture in irrigation threshold < 10%.

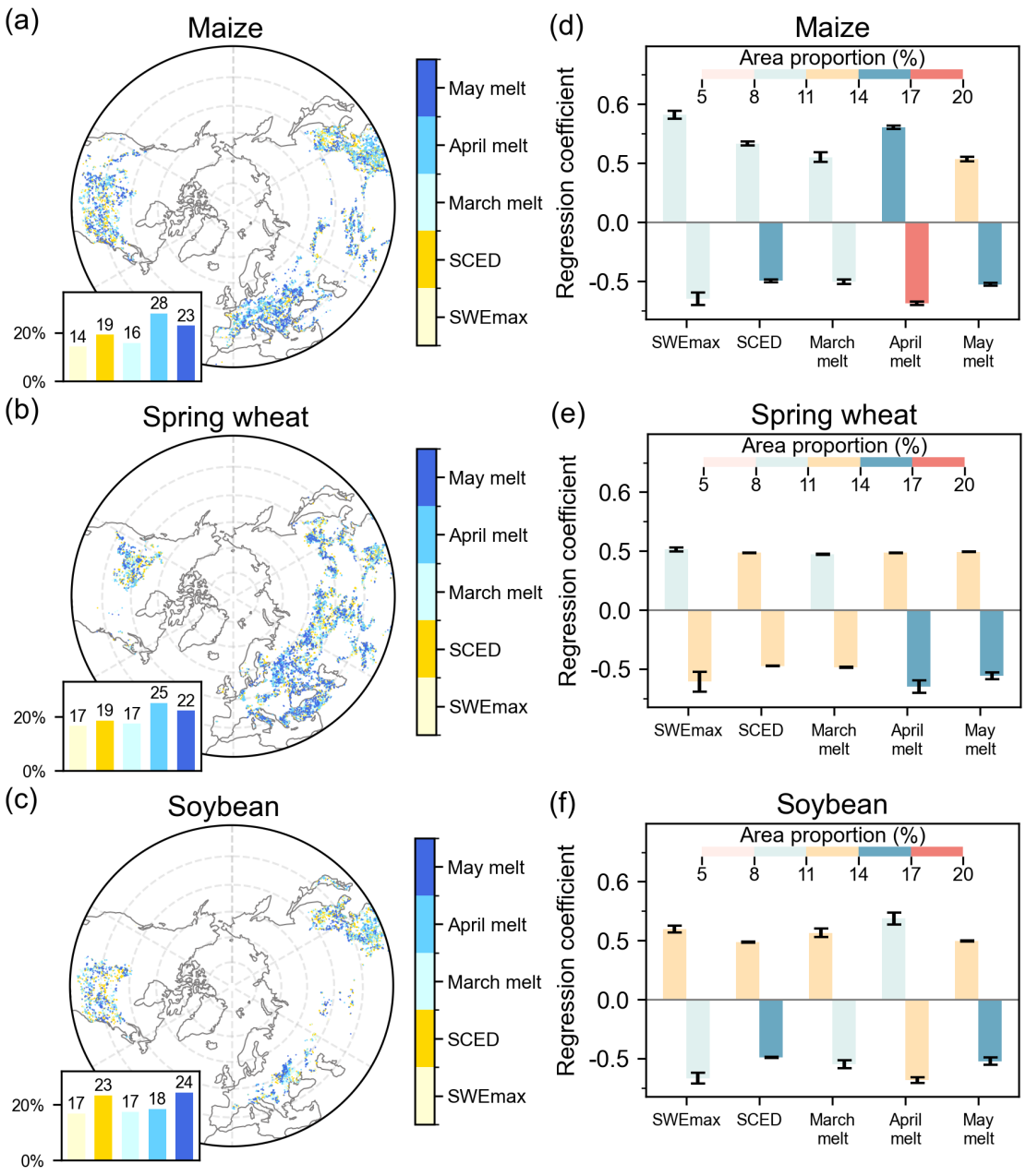

Figure S9. Sensitivity analysis of dominant snowpack indicators influencing crop-yield sensitivity to soil moisture in irrigation threshold < 20%.

In the revised manuscript we revised this part as follows:

"We conducted the analysis using a stricter threshold of less than 20% and 10% irrigated area to assess the sensitivity of our results to the irrigation threshold. The resulting spatial patterns and overall findings were consistent with those obtained using the 30% threshold, supporting the robustness of our results (Figure S8&S9)."

These changes can be found in **LN 158–161.**

[Comment 7] Moreover, the Global Map of Irrigation Areas v5 represents conditions circa 2005,

while the study period is 2000–2022. Irrigation expansion over this period could bias the results. This limitation should be explicitly discussed, and dynamic irrigation data should be used if possible.

Thank you for this important comment. We agree that the temporal representativeness of irrigation data is an important consideration, particularly given the potential changes in irrigation extent over the study period. In this study, the Global Map of Irrigation Areas (GMIA) v5 was used to identify predominantly rain-fed croplands and minimize the influence of irrigation on the analysis. However, as this dataset represents irrigation conditions around 2005, it may not fully reflect potential changes in irrigation extent over the study period (2000–2022). We recognize this limitation and have further clarified it in the revised manuscript. In particular, irrigation expansion or changes in irrigation practices over the study period may lead to discrepancies between the irrigation conditions represented by GMIA v5 and the actual irrigation conditions in individual years. Consequently, some grid cells classified as predominantly rainfed may have experienced changes in irrigation influence over time. Due to limitations in data availability, we were unable to incorporate temporally explicit irrigation data covering the study area and period with sufficient spatial and temporal consistency. We have therefore expanded the discussion of this limitation in the revised manuscript and highlighted the potential value of incorporating temporally explicit irrigation datasets in future studies to better distinguish rainfed and irrigated croplands and further reduce uncertainties associated with changes in irrigation extent.

In the revised manuscript we revised this part as follows:

"Due to limitations in data availability, the GMIA v5 dataset used in this study primarily represents irrigation conditions around 2005 and may not fully reflect irrigation expansion or changes in irrigation extent during the study period. Future studies could incorporate temporally explicit irrigation datasets to better account for changes in irrigation extent and improve the accuracy of rain-fed cropland identification."

These changes can be found in **LN 480–484.**

[Comment 8] There are inconsistencies in how "sensitivity" is discussed. Figure 2 suggests that spring wheat has numerically higher soil moisture sensitivity than maize and soybean. Yet the abstract states that "maize and soybean exhibit the strongest sensitivity to snowpack changes." These are different concepts: sensitivity to soil moisture versus sensitivity to snowpack. The manuscript must define these terms clearly and use them consistently.

Thank you for this insightful comment. We agree that clearly distinguishing between crop-yield sensitivity to soil moisture and sensitivity to snowpack changes is important for accurately understanding our findings. In the original manuscript, particularly in the Abstract, our explanation was not sufficiently clear, which may have caused confusion in interpreting the results.

The primary objective of our study is to investigate how changes in snowpack conditions affect crop-yield sensitivity to soil moisture. Changes in snowpack conditions may make crops that are already highly sensitive to soil moisture more vulnerable to risks and challenges, thereby further exacerbating their sensitivity to soil moisture. Therefore, in the Abstract, we primarily intended to convey that maize and soybean are the two crops most susceptible to the impacts of snowpack

changes. We recognize that the original wording in the Abstract did not accurately convey this information. We have revised the relevant statements in the Abstract to explicitly emphasize the influence of snowpack changes on crop-yield sensitivity to soil moisture. In addition, we have carefully reviewed the entire manuscript and refined the relevant terminology to ensure consistency and avoid similar ambiguities. We believe that these revisions will help readers better understand our findings and more clearly reflect the central objective of our study.

In the revised manuscript we revised this part as follows:

"Among different crops, the soil moisture sensitivity of maize and soybean is most strongly affected by changes in snowpack."

These changes can be found in **LN 42–43.**

[Comment 9] Furthermore, the relationships in Figure 2 are not consistently monotonic. Some intervals have large error bars, and the pattern varies by crop and snowpack metric. The statement that sensitivity "declines with higher SWEmax, later SCED, and greater spring snowmelt volume" is therefore too general and should be qualified.

We thank you for the comments on the interpretation of Figure 2. We agree that crop responses to snowpack changes can vary among crop types. Differences in the timing of water use and root water uptake processes may contribute to these variations (Ahmed et al., 2018), making crop-specific responses reasonable.

We had considered these differences in the original manuscript and discussed the specific response patterns of maize, spring wheat, and soybean following the description of the overall trend. Our results suggest that crop-yield sensitivity to soil moisture generally tends to decrease with increasing SWEmax, later SCED, and greater spring snowmelt, although the patterns and magnitudes of these relationships vary across crop types and snowpack indicators. We acknowledge that the original statement was too general and could imply a monotonic relation across all crops and snowpack indicators. Figure 2 mainly illustrates the overall patterns of crop-yield sensitivity to soil moisture under different snowpack conditions, rather than a strictly monotonic decline. In the revised manuscript we revised this part as follows:

"Crop-yield sensitivity to soil moisture generally tends to decrease with increasing SWEmax, later SCED, and greater spring snowmelt, although the patterns and magnitudes of these relations vary across crop types and snowpack indicators. Specifically, for maize, areas with SWEmax above 96 mm, SCED delayed beyond 84 days, and total spring snowmelt exceeding 64 mm show reduced sensitivity. For spring wheat, lower sensitivity is associated with SWEmax greater than 76 mm, SCED delayed beyond 90 days and spring snowmelt exceeding 76 mm. For soybean, regions with SWEmax above 96 mm, SCED later than 87 DOY, and spring snowmelt greater than 96 mm display weaker sensitivity to soil moisture. The regions where crop yield losses from soil moisture stress are relatively low are generally characterized by higher snowpack metrics values during the cold season."

These changes can be found in **LN 290–299.**

[Comment 10] The title and abstract contain grammatical errors: “crop yields sensitivity” should be “crop yield sensitivity”; “crop yields responses” should be “crop yield responses.”

Thank you for your careful reading and for pointing out these grammatical errors. We apologize for these oversights. We have corrected “crop yields sensitivity” to “crop yield sensitivity” and “crop yields responses” to “crop yield responses” in the title and abstract. In addition, we have carefully checked the entire manuscript and corrected all occurrences of these grammatical errors to ensure consistency and accuracy throughout the text.

[Comment 11] “accounted by climate change” should be “attributed to climate change.”

Thank you for pointing out this wording issue. We have changed “accounted by climate change” to “attributed to climate change” and revised similar expressions throughout the manuscript.

[Comment 12] The statement “significant decline in SWEmax (7.66%)” is ambiguous. Is this an area proportion or a decline magnitude? If it is an area proportion, write “7.66% of the study area.”

We appreciate your comment and agree that the original statement was ambiguous. The percentages reported here represent the proportion of the study area showing significant changes in SWEmax and SCED, rather than the magnitude of the changes themselves. We have revised the sentence accordingly to clarify this point:

“Unfortunately, our analysis also shows significant declines in SWEmax across 7.66% of the study area and that 10.26% of the study area exhibits a significant advance in SCED.”

These changes can be found in **LN 420–422.**

[Comment 13] Reference formatting is not fully consistent. Some entries lack journal names, volume/issue numbers, or DOIs.

Thank you for your comment. We have carefully reviewed and standardized the reference list. Missing DOIs, volume and issue numbers, and page ranges have been added where applicable. For reports, books, book chapters, and webpages that do not have journal volume or issue numbers or an assigned DOI, we have provided the appropriate publication details and available stable links. We have also checked that the in-text citations match the revised references.

Finally, I would like to express my gratitude for all your comments, which have been very helpful. We admire your professionalism in this matter and it has sparked a lot of thought for our future work. Thank you again for all your work.

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