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 #1

The sensitivity of crop yields to soil moisture is an important topic because of its relevance to global food security. This study investigates how reduced snowpack affects this sensitivity in the Northern Hemisphere using the ERA5-Land reanalysis dataset and gridded annual crop-yield datasets. Partial correlation analysis and a separate dynamic linear model are applied at each pixel to demonstrate how diminishing snowpack intensifies crop-yield sensitivity to soil moisture. I have two major concerns regarding the quality of the crop-yield dataset and the reliability of the statistical model.

We sincerely appreciate your careful evaluation of our manuscript and your recognition of the importance of understanding crop-yield sensitivity to soil moisture in the context of global food security. We also thank you for raising the two important concerns regarding the quality of the crop-yield dataset and the reliability of the statistical model. We agree that these are critical aspects of the study that deserve careful consideration. Your comments have been very helpful in prompting us to further examine the robustness of our analyses and clarify the methodological choices underlying our findings. We have carefully considered each of your concerns and conducted additional analyses and made corresponding revisions to strengthen the reliability and clarity of our study. We believe these efforts have further improved the scientific rigor of our manuscript. Our detailed responses to your comments and the corresponding revisions are provided below.

Specific Comments:

[Comment 1] The crop-yield dataset used in this study does not appear to be a commonly used or well-established dataset. Although the authors mention that it was validated against 2,823 administrative units across 43 countries and showed good accuracy, they provide only a link to the dataset, without citing a relevant peer-reviewed paper presenting the validation results. Therefore, the reliability of the crop-yield dataset cannot be adequately assessed.

Thank you for your comment regarding the reliability of the crop-yield dataset. We agree that it is important to provide sufficient information on the scientific basis, development methodology, and validation results of the dataset for assessing its suitability.

Our study required crop-yield data covering the period 2000–2022 at a 5-km resolution. We therefore selected the global gridded crop-yield dataset developed by Qin et al. (2024). This dataset is based on GAEZ+ 2015, which has a well-established scientific basis. GAEZ+ 2015 integrates global agricultural statistics and spatial crop information, and its development methodology was published in the peer-reviewed journal Scientific Data (Grogan et al., 2022). Building on this dataset, Qin et al. (2024) further integrated multisource remote sensing observations and environmental data and improved the spatial estimation of crop production using machine learning models. The research team then developed a 5-km data product using this approach. The reported correlation coefficients between estimated crop yields and agricultural statistics were 0.92, 0.94, and 0.98 for maize, wheat, and soybean, respectively. These results indicate good agreement with agricultural statistics at the subnational scale, particularly in major crop-producing regions. Considering its scientific basis, documented methodology, reported validation results, and temporal and spatial coverage, we selected this dataset for our analysis. We have added the relevant peer-reviewed references and

provided a more detailed description of the selected dataset in the revised manuscript. In the revised manuscript we revised this part as follows:

"We used gridded crop yield data for maize, wheat, and soybean from 2000 to 2022, with a resolution of 5km×5km (Qin et al., 2024). The dataset was developed based on the GAEZ+ 2015 dataset (Grogan et al., 2022) that has been widely used in agricultural research (Hua et al., 2025; Wang et al., 2023). It provides spatially detailed estimates of major crop types across the globe. Validation against agricultural statistics from 2,823 administrative units across 43 countries showed strong correlations between estimated crop yields and reported statistics, with correlation coefficients of 0.92, 0.94, and 0.98 for maize, wheat, and soybean, respectively (Qin et al., 2024)."

These changes can be found in **LN 137–144.**

[Comment 2] I did not find any results regarding model evaluation or uncertainty quantification for the statistical model used in this study. Although Figure S3 presents the regression coefficients, the authors do not explain how the model performance was evaluated. In addition, "R" is used in the caption of Figure S3, whereas the legend refers to the "regression coefficient." The statistical model is also developed separately for each pixel using only 23 annual observations, which may introduce substantial uncertainty. Collinearity also warrants further investigation because the model includes five strongly interrelated snow variables. I therefore suggest carefully describing how the statistical model was evaluated, how collinearity was accounted for, and how uncertainty was quantified.

Thank you for this important comment. We agree that the original manuscript did not provide enough details on the evaluation of the statistical models and their performance, which may have made it difficult for readers to assess the reliability of the model fits.

In the original manuscript, model performance was mainly evaluated by examining the correlation between fitted and observed values, as shown in Fig. S3. Specifically, we calculated the correlation coefficient between fitted and observed values at each pixel to assess how well the models reproduced interannual variations in crop yield. However, correlation coefficients alone do not fully capture the agreement between fitted and observed values. We have therefore added scatter plots comparing observed and fitted values for the three crops, together with 1:1 reference lines and coefficients of determination, to provide a clearer and more quantitative assessment of model performance in the revised manuscript. The determination 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. The scatter plots and corresponding statistics are now presented in Fig. S4 of the revised manuscript.

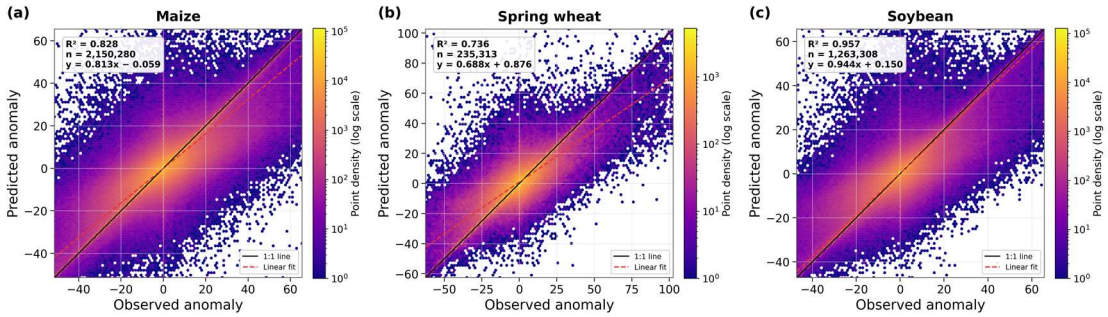

Figure S4. Validation of the DLM models. (a–c) indicate the coefficients of determination of crop yield anomaly predictions against observations for maize, spring wheat, and soybean.

We also thank you for pointing out the inconsistent terminology in the caption and legend of the original Fig. S3. The values shown in Fig. S3 represent the correlation coefficients between fitted and observed values, rather than the regression coefficients of individual explanatory variables. The term “regression coefficient” in the original legend was incorrect. We have replaced it with “correlation coefficient” and revised the corresponding descriptions in both the caption and legend to avoid ambiguity.

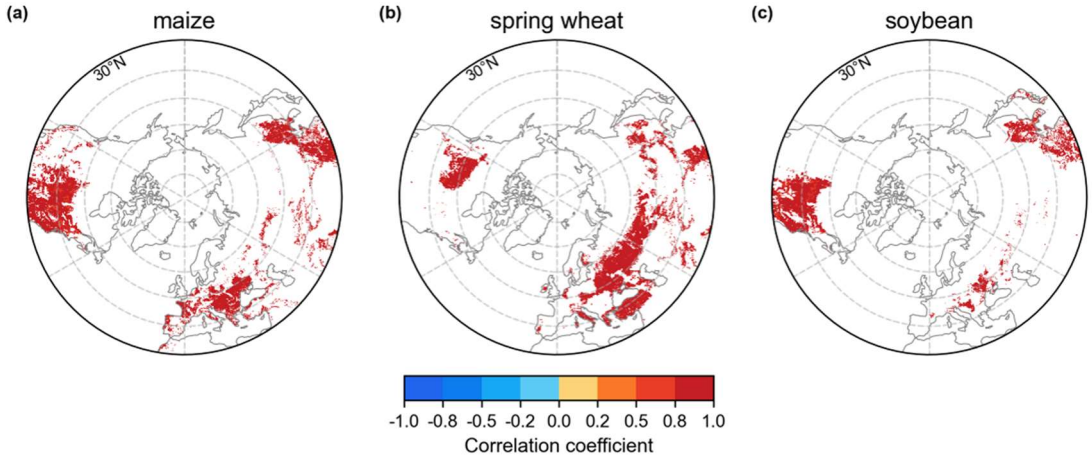

Figure S3. Performance of the DLM models. (a–c) indicate the correlation coefficient (R) between crop yield anomalies and predictions.

We thank you for the attention to the selection of the snowpack indicators. We addressed the potential redundancy among the five interrelated snowpack variables by applying 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. We used stepwise regression to identify the snowpack indicators that had the greatest influence on crop-yield sensitivity to soil moisture. As described in the manuscript, this method enables the selection of significant predictors from a pool of candidates and constructs an optimal model for each crop type. A bidirectional elimination strategy, combining

forward selection and backward elimination, was used to iteratively add or remove variables. The F-test was used to determine the significance of variable entry or removal, with the significance level set at $\alpha = 0.1$. Specifically, we applied bidirectional stepwise ordinary least squares (OLS) regression at the pixel level to reduce redundancy among five interrelated snowpack variables (SWE, SCED, Melt_03, Melt_04, and Melt_05). All predictor and response variables were standardized at each pixel. A variable was included in the model when its p-value was below 0.10 and removed when its p-value exceeded 0.10. This procedure was repeated until the set of selected variables remained unchanged, yielding the final set of explanatory variables for each pixel. This procedure was used to maintain 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 model-fitting results of the stepwise regression are also presented in the Supplementary Materials.

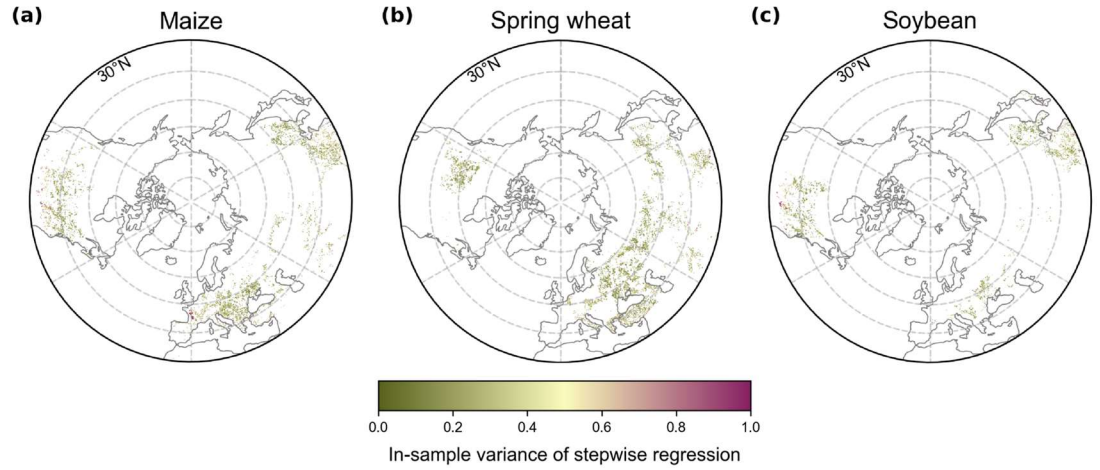

Figure S5. Validation of the stepwise regression models. (a–c) report the variance (σ^2) in sensitivity explained by snowpack indicators.

[Comment 3] A relatively permissive threshold of $p < 0.1$ is used in this study. Would the main results and conclusions remain robust if the more conventional threshold of $p < 0.05$ were used?

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 permissive threshold compared with stricter 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. The results obtained at $p < 0.05$ have also been included in the Supplementary Materials of the revised manuscript to provide further support for our main findings.

In the revised Supplementary Materials, we revised this part as follows:

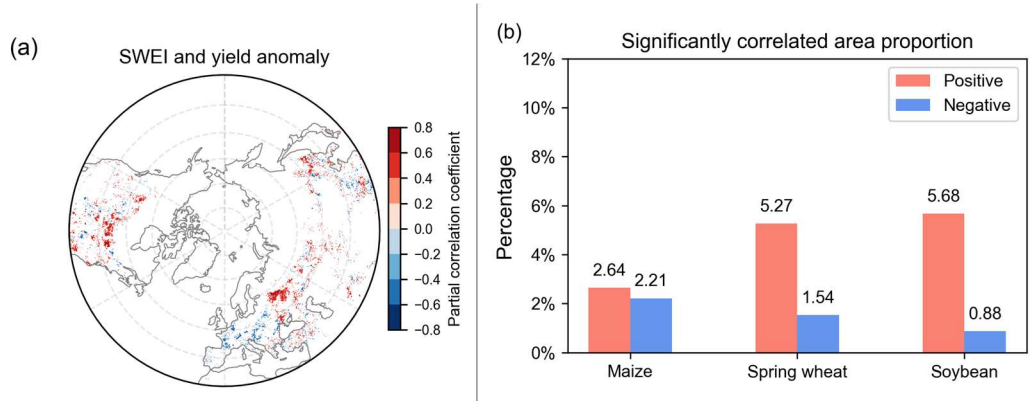

Figure S6. Partial correlations between SWEI and yield anomaly of maize, soybean, and spring wheat ($p < 0.05$) from 2000–2022 in the Northern Hemisphere. (a) Spatial distribution of significantly correlated pixels ($p < 0.05$) between SWEI and yield anomaly aggregated across maize, spring wheat, and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

[Comment 4] Title: It might be better to use "crop-yield sensitivity", and "Northern Hemisphere" should be capitalised.

Thank you for your helpful suggestion. We have revised the title by using "crop-yield sensitivity" and capitalizing "Northern Hemisphere" as recommended. In addition, we have revised the relevant expressions throughout the manuscript to ensure consistency.

[Comment 5] Lines 20 and 185-190: The percentages 52.99%, 72.75%, and 82.66% appear to represent the proportion of positively correlated pixels among pixels with statistically significant correlations, rather than the proportion of the entire crop area. Figure 1 indicates that only approximately 5.32%, 9.00%, and 10.07% of the respective crop areas have significant positive correlations. The denominator must be stated explicitly; otherwise, the abstract substantially overstates the spatial extent of the relationship.

We thank you for pointing out this issue. We agree that the original statement could be misinterpreted as referring to the proportion of the entire study area showing significant positive correlations. In fact, these percentages represent the proportion of positive correlations among significantly correlated pixels, rather than the proportion of the respective crop area. We have revised the statement accordingly:

"Our analysis reveals positive associations between crop yields and variations in snowpack. Among significantly correlated pixels, approximately 52.99% for maize, 72.75% for spring wheat, and

82.66% for soybean show positive correlations."

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

[Comment 6] Although Text S1 in the Supplementary Material describes how the snowpack metrics were calculated, the main manuscript does not direct readers to it. It would be helpful to add a statement such as "Detailed calculations are provided in Supplementary Text S1."

Thank you for the important suggestion. We have added a reference to Supplementary Text S1 in the revised manuscript to direct readers to the detailed calculations of the snowpack metrics:

"We used snow water equivalent (SWE) variables in this dataset to characterize the snowpack indicators including standardized snow water equivalent index (SWEI), maximum SWE (SWEmax), snow cover end date (SCED), and spring snowmelt (Calculation see in Supplementary Text S1)."

These changes can be found in **LN 124–127.**

[Comment 7] Growing-season definition: A fixed June–September growing season and February–May cold season are applied across all crops and Northern Hemisphere locations. This overlooks large spatial and crop-specific differences in planting, emergence, and harvest dates. It also conflicts with the later interpretation that soybeans respond differently because it is sown later. The analysis should use crop- and location-specific calendars or, at minimum, provide sensitivity tests using alternative seasonal windows.

We thank you for their 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 area 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.

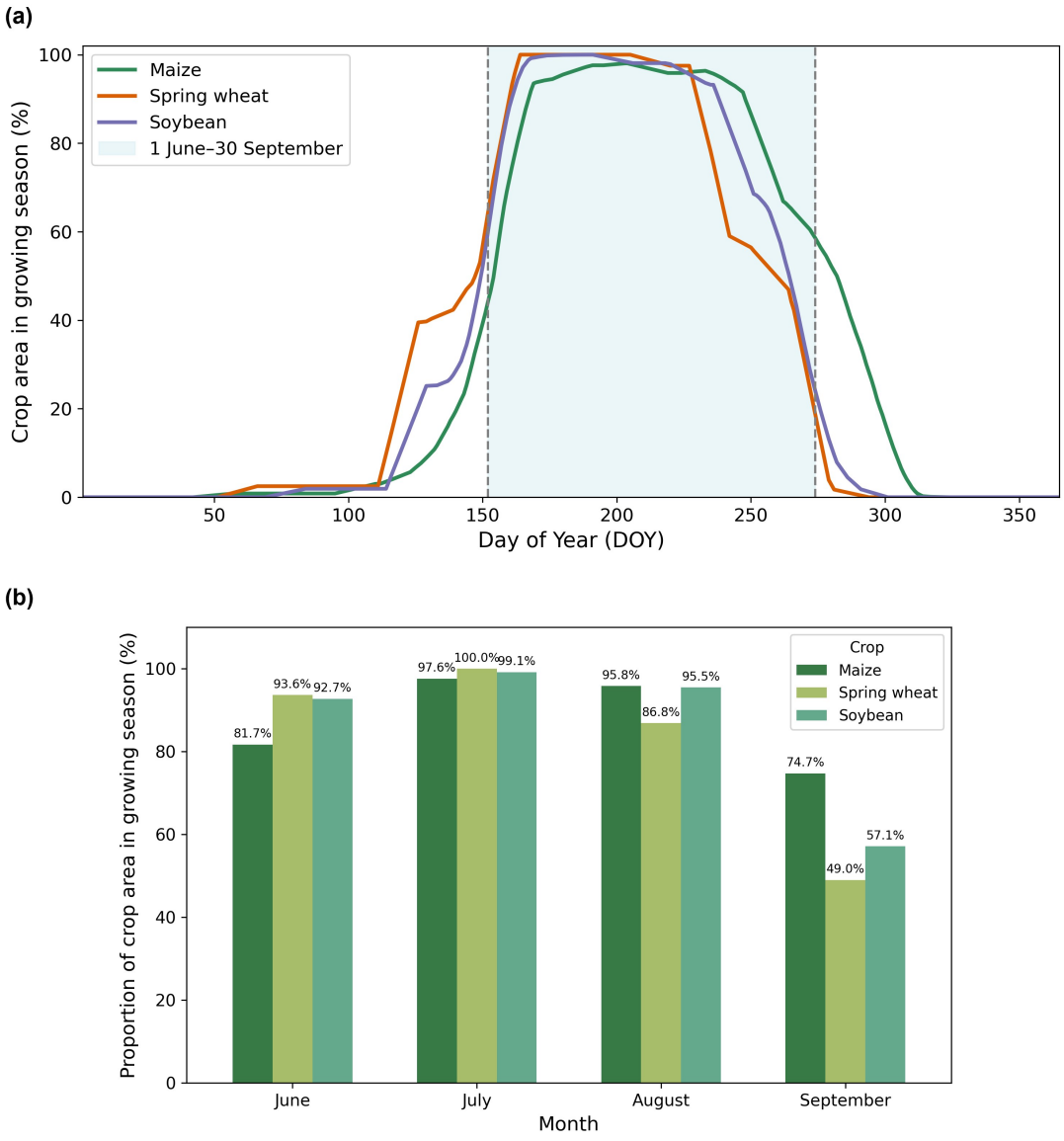

Figure S7. Distribution of planting and harvesting dates and the proportion of crop area within the core growing season for maize, spring wheat, and soybean across the study area.

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 8] Line 159-162 and Figure 2: The bin boundaries or centres, binning method, sample sizes, error-bar definition, and sensitivity units are missing.

Thank you for this valuable comment. We agree that the binning procedure and the statistical information in Figure 2 should be more clearly described.

Following the bin-based analysis approach of Wang et al. (2018), we grouped pixels according to three categories of snow-related variables to examine the relation between snow conditions and crop drought sensitivity. The binning ranges were determined based on the valid values of each snow variable during 2000–2022. Specifically, for maximum snow water equivalent (SWEmax), the ranges were 0–160 mm for maize and soybean and 0–190 mm for spring wheat. For snow-cover end date (SCED), the ranges were 0–140, 0–145, and 0–150 DOY for maize, spring wheat, and soybean, respectively. For spring snowmelt, the ranges were 0–160 mm for maize and soybean and 0–190 mm for spring wheat. We applied an equal-width binning method, dividing the range of each snow variable into five equally spaced intervals to characterize the variation in drought sensitivity along snow-condition gradients. The analysis included 93,490, 10,231, and 54,926 valid pixels for maize, spring wheat, and soybean, respectively. Within each bin, the mean drought sensitivity was calculated, and the error bars represent 95% confidence intervals (95% CI), calculated as ±1.96 times the standard error of the mean. Drought sensitivity was quantified using the soil moisture regression coefficient derived from Equation (1). Since the variables were standardized prior to regression, the resulting sensitivity coefficient is dimensionless.

We have revised the caption of Figure 2 and Section 2.3 to clarify the binning ranges and

method, sample sizes, error-bar definition, and units of drought sensitivity, thereby improving the transparency and interpretability of the results.

In the revised manuscript we revised this part as follows:

"2.3 Statistical analysis We conducted a bin-wise analysis of crop-yield sensitivity to soil moisture under varying levels of SWEmax, SCED, and spring melt during the cold season (Wang et al., 2018). For each of the three snowpack-metrics, we defined five discrete intervals using an equal-width binning method based on the valid data ranges from 2000 to 2022. For SWEmax, the ranges were 0–160 mm for maize and soybean and 0–190 mm for spring wheat. For SCED, the ranges were 0–140, 0–145, and 0–150 DOY for maize, spring wheat, and soybean, respectively. For spring melt, the ranges were 0–160 mm for maize and soybean and 0–190 mm for spring wheat. We quantified the sensitivity of crop yields to soil moisture within each interval based on pixel-level statistics, using 93,490, 10,231, and 54,926 valid pixels for maize, spring wheat, and soybean, respectively."

These changes can be found in **LN 217–226.**

"Figure 2. Sensitivity of maize, spring wheat, and soybean yields to soil moisture under different intervals of snowpack-metrics, including SWEmax, SCED, and spring melt with all samples divided into five groups. (a-c), (d-f), and (g-i) represent maize, spring wheat and soybean sensitivity to soil moisture under different snowpack-metrics respectively. Bars show mean sensitivity, with error bars indicating approximate 95% confidence intervals. Sensitivity is expressed as a dimensionless standardized regression coefficient. The right panel shows the histogram of snowpack metrics with the vertical red line indicating the mean of all samples."

These changes can be found in **LN 301–307.**

[Comment 9] Figure 3: How are the "dominant snowpack indicators" defined and identified? An explicit definition is needed.

Thank you for this helpful comment. We agree that a clearer definition of the dominant snowpack indicators is necessary to better explain the results presented in Figure 3. In this study, the dominant snowpack indicators were identified based on the results of backward stepwise regression and their spatial proportions across the study area.

Specifically, we first applied backward stepwise regression at each grid cell, using five candidate snowpack indicators, including SWEmax, SCED, and snowmelt in March, April, and May, to explain changes in crop-yield sensitivity to soil moisture. The regression procedure was used to select the explanatory variables retained in the final model at each grid cell. We then calculated the proportion of grid cells associated with each selected snowpack indicator for maize, spring wheat, and soybean, respectively. The indicator accounting for the largest proportion of the study area was identified as the dominant snowpack indicator for each crop. Furthermore, the direction of the associations was determined based on the signs of the corresponding regression coefficients. By comparing the proportions of grid cells with positive and negative coefficients, we further characterized the overall direction of the associations between snowpack indicators and changes in crop-yield sensitivity to soil moisture. We have clarified the definition and identification procedure of the dominant snowpack indicators in the Methods section. We believe these revisions provide a

clearer explanation of how the dominant indicators and their associated effects were identified.

In the revised manuscript we revised this part as follows:

"We employed a stepwise regression model to further clarify the role of snowpack in yield soil moisture sensitivity. We identified which of the three aspects, snow accumulation, duration, or snowmelt water amount, plays the dominant role in explaining yield sensitivity to soil moisture. This method enables the selection of significant predictors from a pool of candidates and constructs an optimal model for each crop type. A bidirectional elimination strategy, which integrates forward selection and backward elimination, was used to iteratively add or remove variables. The F-test was used to determine the significance of variable entry or removal, and the significance level was set to $\alpha = 0.1$. We identified the most influential explanatory factor at each grid cell with this approach. We then calculated the proportion of grid cells in which each indicator was identified as the most influential explanatory factor for each crop. The indicator with the largest proportion was defined as the dominant snowpack indicator for that crop."

These changes can be found in **LN 229–239.**

[Comment 10] The reference list requires careful checking, and the literature review could be improved. For example, the references in lines 532–534 and 478–480 appear to be duplicates, and the capitalisation of journal titles is inconsistent. The reference attributed to Fuyou et al. (2024) appears to concern agricultural-field segmentation rather than the gridded crop-yield dataset described in the Methods and should therefore be verified. It would also be helpful to review recent publications on snow, crop yield, and food security to ensure that important relevant studies have not been overlooked.

Thank you for these useful suggestions. We have checked the reference list, removed the duplicate entries, and standardized the capitalization of journal titles.

We also verified the citation for the gridded crop-yield dataset. The reference to Fuyou et al. (2024) has been replaced with the dataset citation： Qin, X., Wu, B., Zeng, H., Zhang, M., & Tian, F. (2024). *Global gridded crop production dataset at 5 km resolution from 2000 to 2022* [Data set]. Aerospace Information Research Institute, Chinese Academy of Sciences. https://doi.org/10.11878/db.202412.017258. The in-text citation has been updated to "We used gridded crop yield data for maize, wheat, and soybean from 2000 to 2022, with a resolution of 5km×5km (Qin et al., 2024)."

We agree that incorporating recent studies on snowpack, crop yields, and food security would help strengthen the scientific background and contextualize the significance of our study. We have further reviewed recent studies on snowpack changes, crop productivity, and food security, and added the following relevant references to the revised manuscript. These studies highlight the impacts of climate change on global crop production and food security (Hultgren et al., 2025), the role of snow cover in regulating soil conditions and vegetation productivity (Xu et al., 2024), and the effects of changing snowmelt dynamics on spring agricultural drought (Yao & Shinde, 2026), collectively underscoring the importance of snowpack for agricultural production and food security. In addition, Baah-Kumi et al. (2024) examined the role of irrigation water management in

agricultural responses to snowpack changes, providing useful insights for future research directions. Overall, these additional references strengthen the scientific background of our study and provide a broader context for interpreting our findings.

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 study. Thank you again for all your work.

References:

Ahmed, M. A., Passioura, J., & Carminati, A. (2018). Hydraulic processes in roots and the rhizosphere pertinent to increasing yield of water-limited grain crops: A critical review. *Journal of Experimental Botany*, *69*(13), 3255–3265. https://doi.org/10.1093/jxb/ery183

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