https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Diminishing snowpack intensifies crop yields sensitivity to soil moisture in the northern hemisphere

Han Liu[1], Pengfeng Xiao[1, 2, *], Xueliang Zhang[1], Jingyu Wen[1], Yantao Liu[1], Hao Liu[3], Haikun Wang[4]

[1]Jiangsu Provincial Key Laboratory for Advanced Remote Sensing and Geographic Information Technology, Key Laboratory for Land Satellite Remote Sensing Applications of Ministry of Natural Resources, School of Geography and Ocean Science, Nanjing University, Nanjing, Jiangsu 210023, China

[2]Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing, Jiangsu 210023, China

[3]College of Meteorology and Oceanography, National University of Defense Technology, Changsha 410073, China

[4]Joint International Research Laboratory of Atmospheric and Earth System Sciences, School of Atmospheric Sciences, Nanjing University, Nanjing, Jiangsu 210023, China

Correspondence to: Pengfeng Xiao (xiaopf@nju.edu.cn)

Abstract. Crops face increasing threats from drought due to global warming, causing declines in yield. Snowpack, as a distinct seasonal water resource, contributes to soil moisture that can supply additional water during the growing season, thereby reducing exposure to soil moisture deficit and stabilizing yield. However, the response of crop yield to snowpack, and the degree to which snowpack influence crop yield sensitivity to soil moisture, remain insufficiently understood. In this study, we combined snowpack, climate, soil, and crop yield datasets in the Northern Hemisphere from 2000 to 2022 to assess how snowpack affects the relation between soil moisture and yield of maize, spring wheat, and soybean. Our analysis reveals that crop yields respond positively to variations in snowpack, with the area showing significant positive correlation accounting for 52.99% for maize, 72.75% for spring wheat, and 82.66% for soybean. Snowpack plays a predominantly negative regulatory role, with greater snowpack exerting a stronger buffering effect against drought impacts. In particular,

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

late-spring snowmelt is the most influential contributor to this buffering effect. Moreover, an earlier shift of snowmelt peaks from April to March intensifies the temporal mismatch between water availability and water demand of crops, aggravating yield reductions. Among different crops, maize and soybean exhibit the strongest sensitivity to snowpack changes. These findings highlight the crucial role of snowpack in regulating soil moisture-yield relation, informing strategies to safeguard food production under climate change.

1 Introduction

Rain-fed agriculture contributes approximately 60% of global crop production (Alexandratos & Bruinsma, 2012; WWAP, 2019), and one-third of global yield variability is attributed by climate change (Ray et al., 2015). Climate change has likely caused a 1% annual decline in consumable food calories from major crops (Ray et al., 2019), and recent estimates indicate that over 295 million people still faced acute food insecurity (GNAFC, 2025). The Intergovernmental Panel on Climate Change (IPCC) reports that current extreme weather events pose considerable risks to crop yield by altering agricultural growing conditions and exacerbating water scarcity (Ben-Ari et al., 2018; Field et al., 2014; Lobell et al., 2011; Schillerberg & Tian, 2023), which challenges the achievement of Sustainable Development Goal (SDG) 2 (Martin, 2015). Agricultural drought, proxy by soil moisture (SM), has become a major obstacle to global food security (AghaKouchak et al., 2023; Lesk et al., 2016; van Dijk et al., 2013). The contribution of growing-season precipitation to soil moisture is widely recognized; however, recent studies increasingly demonstrate that cold-season hydrological processes play a critical role in the water–yield relation (Harder et al., 2025; Li et al., 2025) and are essential for predicting the impacts of climate change on agriculture.

Cold-season snowpack plays a key role in sustaining soil moisture in the early growing season. The importance of antecedent soil moisture for crops is inversely proportional to growing-season precipitation (Harder et al., 2025). In a 3 °C warmer climate, only 60 million hectares of cropland would avoid exposure to green water scarcity, the shortage of precipitation-derived soil moisture available for crop growth (Rosa et al., 2020). Given these circumstances, it is reasonable to account for the role of snowpack on crop yield. Many studies investigated drought threats to agroecosystems only from the perspective of growing-season precipitation (Hendrawan et al., 2022; Kim et al., 2019; Meza et al., 2020). This

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

precipitation-focused view may overlooks the role of cold-season snowpack, helping to buffer crops against water stress and support yields (Huning & AghaKouchak, 2020; Yeşilköy et al., 2024). Moreover, snowpack has undergone substantial changes under climate change, widespread negative trends including declining snow cover extent, reduced snow water equivalent, and earlier onset of snowmelt have been observed across much of the Northern Hemisphere, particularly in North America and Eurasia (Hale et al., 2023; Pulliainen et al., 2020). Several regions, including the western United States and Afghanistan, have already experienced crop failures linked to snowpack anomalies (Howitt et al., 2018). In Northeast China, the absence of snowpack from February to May has been shown to reduce soil moisture by at least 20%, and cropland area suffers more than surrounding areas (Qi et al., 2020). These cases demonstrate that the dependence of food security on snowpack has become a key climate change risk. Therefore, the classic precipitation deficit in rain-fed crop production under global warming are expected to increase the importance of snowpack role in maintaining soil moisture and sustaining crop yields.

Snowpack remains a special water resource for crops (Lu et al., 2021; Potopová et al., 2016) and it affects yields response to soil moisture. The contribution of cold-season snowpack to soil moisture serves as an indicator of the baseline soil water available to crops, although the processes of snowpack accumulation and melting occur before the growing season. The antecedent moisture status plays a crucial role in determining crop exposure to subsequent drought. In regions with abundant snowpack, a slight decrease in soil moisture at the beginning of the growing season due to reduced precipitation is unlikely to result in significant drought stress later in the season (Lu et al., 2021). Consequently, the amount of snowpack largely determines the degree to which crop yield depends on additional soil moisture during the growing season, reflecting the vulnerability of crops to soil moisture deficit. Moreover, variations in snowpack amount and duration may influence soil microbial activity and nutrient dynamics (Berdanier & Klein, 2011), which form the environmental basis for crop growth and also affect crop responses to drought. Several studies have shown that snow-deficient seasons can further intensify agricultural drought conditions in the following growing season (Li & Wang, 2022; Nicholson et al., 2018; Potopová et al., 2016). Findings from field experiments in northeastern China focused on spring wheat and potato tubers have shown that the retention of snowpack increases soil moisture, which in turn improves crop yields (Jia et al., 2017; Wei et al., 2022). At broader spatial scales, most existing studies relied on vegetation-based indicators to infer the role of snowpack, and by

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

extension suggested potential implications for crops (Li et al., 2025; Potopová et al., 2016), yet without directly evaluating yield-level impacts. The interactions between the ability of snowpack to influence soil moisture sensitivity of crop yields have not been observed and quantified across large spatial extents. As a result, the role of snowpack on yield sensitivity to soil moisture across the Northern Hemisphere remains unclear. This knowledge gap may lead to underestimations of yield responses to agricultural drought, limiting the capacity to monitor food production dynamics accurately.

In this study, we aim to investigate whether snowpack variations in the Northern Hemisphere have affected the soil moisture sensitivity of three rain-fed crops, namely maize, spring wheat, and soybean, thereby exacerbating vulnerability to drought and ultimately affecting crop yields. Specifically, the study addresses the following three questions over the past two decades: (1) What are crop yields responses to snowpack changes in the Northern Hemisphere? (2) Does snowpack, via its moisture effect, buffer the negative influence of agricultural water stress on crop yield? (3) Which regions and crop types are most sensitive to snowpack reduction under global warming? These results will enhance our understanding of the interaction between snowpack and crop yield sensitivity to soil moisture and provide new insights for addressing food security under climate change.

2 Data and Method

2.1 Data

The datasets in this study include snowpack, crop yield, crop calendar, irrigation map, climate, and soil moisture data. Snowpack data were acquired from the ERA5-Land dataset with a 0.1°×0.1°grid, which is widely used in climate change studies and represents a state-of-the-art reanalysis dataset (Muñoz-Sabater et al., 2021). 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. SWEI is a proxy of snow drought. It describes snow water supply and soil moisture balance, and can effectively estimate vulnerabilities related to agriculture, water resources, and food security (Huning & AghaKouchak, 2020). SWEmax is the maximum value of SWE in a hydrological year (from September 1 to August 31 of the following year). SCED is defined as the final day of the last five

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

consecutive days of snowpack presence within each hydrological year (Wang et al., 2019). Monthly snowmelt is calculated as the difference between the SWE of the preceding month and that of the target month (Li et al., 2025). For instance, March melt was derived by subtracting March SWE from February SWE. A positive value was interpreted as actual snowmelt for that month, whereas negative values were treated as an absence of snowmelt. Spring snowmelt is calculated by aggregating the monthly snowmelt for March, April, and May.

We used gridded crop yield data for maize, wheat, and soybean from 2000 to 2022, with a resolution of 5km×5km (Fuyou et al., 2024). The dataset provides spatially detailed estimates of major crop types including maize, soybean, rice, and wheat across the globe, with validation against 2,823 administrative units across 43 countries showing good accuracy, particularly for soybean and wheat, followed by maize. Our study focused on rain-fed crop systems, and because rice is mostly distributed in areas with abundant water sources and guaranteed irrigation, we only used yield data for maize, soybean, and wheat. Although the yield dataset does not explicitly distinguish between winter and spring wheat, our study focused on the hydrological influence of snowpack on spring crops. Therefore, we used the crop calendar dataset (Sacks et al., 2010) to separate them to eliminate the thermal insulation effect of snowpack on winter wheat. The crop calendar dataset provides the spatial distribution of average planting and harvesting dates for winter and spring wheat worldwide. We retained only the yield data for pixels where spring wheat is exclusively cultivated. The Global Map of Irrigation Areas v5 (Siebert et al., 2013) was employed in this study for rain-fed crop yield, which was developed by Food and Agriculture Organization of the United Nations (FAO) and the University of Bonn. It provides global gridded data (5 arc-min resolution) on the percentage of area equipped for irrigation, representing conditions circa 2005. The dataset includes separate layers for surface water, groundwater, and non-conventional water sources. We classified a grid cell as rain-fed if the irrigated area fraction was less than 30%, and retained only those pixels for further analysis (Sharma et al., 2010).

Climatic and soil moisture data were acquired from the ERA5-Land reanalysis dataset with a 0.1°×0.1°grid. Four variables were chosen from this dataset: air temperature, precipitation, solar radiation, and volumetric soil water. The first three variables were used as control factors in the partial correlation analysis, while volumetric soil water was used to compute soil moisture sensitivity.

Due to crop yield data is only available from 2000 to 2022, the study period was restricted to 2000–2022, even though the temporal coverage of the other datasets exceeds this period. Additionally, all datasets were resampled to a geographic resolution of 0.1° using the nearest neighbor method to match the resolution of the climatic and snowpack data. It is noted that only seasonal snowpack dominated regions (>30° N) were analyzed. Given the temporal mismatch between snow cover and crop growth, we defined June to September as the average growing season for spring crops, and February to May as the period of snow accumulation and melt, based on crop calendars.

2.2 Calculation of crop yield sensitivity to soil moisture

We quantified yield sensitivity to soil moisture as the regression coefficient of yield anomalies with respect to soil moisture during the growing season (Lobell et al., 2020). Regions exhibiting higher yield sensitivity to soil moisture are expected to experience larger yield losses when soil moisture deficits occur, indicating greater vulnerability to agricultural drought. Crop yield anomaly was calculated for each grid cell to represents crop yield variations. Locally weighted regression model (LOWESS), a well-known de-trending methods for studying crop yields (Jägermeyr et al., 2021; Troy et al., 2015), was used to exclude the overall yield increase resulting from technological advances in each grid (Hendrawan et al., 2022). Crop yield anomaly we calculated was assumed to that mainly influenced by climate disruptions. We regulated the influence of climatic variables, including temperature, precipitation, and solar radiation, to isolate the effect of soil moisture on crop yield. Based on this, we constructed the following regression model to estimate yield sensitivity to soil moisture (Lobell et al., 2020; Zhu et al., 2022):

$$Y = \theta_{SM} SM + \theta_{temp} Temp + \theta_{prec} Prec + \theta_{rad} Rad + \epsilon \tag{1}$$

where Y, SM, $Temp$, $Prec$, and Rad represent yield anomaly, soil moisture, temperature, precipitation, and radiation, respectively. θ_{SM} represents a one-unit increase in the soil water component attributable to cold-season snowmelt and antecedent storage is associated with a θ-percentage-point change in the yield anomaly when holding same year precipitation constant. ϵ is the error term for the model. All variables were detrended to eliminate the influence of long-term trends and seasonal variations.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

We employed a Dynamic Linear Model (DLM) to estimate the sensitivities. DLMs account for multiple contributing factors and are well-suited for time series data, which have been increasingly adopted in geoscience and environmental studies (Prado et al., 2021; West & Harrison, 1997). DLM is built on Bayesian principles, where parameters are recursively updated over time using Kalman filtering, resulting in a time series of estimated coefficients. This enables us to characterize the temporal evolution of sensitivity. For each pixel, a separate DLM was constructed to account for the effects of soil moisture and climatic variables on crop yield.

2.3 Statistical analysis

We first conducted a pixel-wise partial correlation analysis between SWEI and yield anomaly of maize, spring wheat, and soybean, respectively, while controlling the influence of climatic factors, including temperature, precipitation, and solar radiation. It can help us understand the primary relations between snowpack and the yields of the three major crops in terms of both spatial distribution and effect intensity across the Northern Hemisphere.

We refined snowpack indicators into three metrics, i.e. SWEmax, SCED, and monthly snowmelt in March, April, and May, to clarify whether the condition of snowpack influences the response of crop yields to soil moisture. These metrics were used in subsequent analyses to refine the character of snowpack in terms of its physical properties, temporal dynamics, and hydrological contribution through meltwater supply. We then applied the Theil-Sen method to quantify the temporal and spatial trends of snowpack metrics across agricultural regions during 2000–2022. The significance of the trend was assessed using the Mann-Kendall test, a non-parametric method for detecting monotonic increasing or decreasing trends in time series (Gutierrez-Villanueva et al., 2023). A trend was considered significant when the p-value was less than 0.1. Then, we statistically calculated the soil moisture sensitivity of three crop yield. 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. For each of the three snowpack-metrics, we defined five discrete intervals and quantified the sensitivity of crop yields to soil moisture within each interval based on pixel-level statistics. This allows us to link cold-season snowpack conditions with spring crop yields and to examine whether varying crop responses to soil moisture correspond to different cold-season snowpack states.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

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 $\alpha = 0.1$.

Finally, we classified four types of regions affected by snowpack based on the sign combinations of the trend in yield soil moisture sensitivity and the snowpack influence on soil moisture sensitivity. An increasing trend of soil moisture sensitivity indicates that crop becomes more dependent on water availability, and thus more vulnerable to yield loss if under soil moisture stress. The magnitude of the snowpack buffering effect represents the degree to which snowpack regulates yield sensitivity to soil moisture. Negative values indicate that the capacity of snowpack to buffer soil moisture deficit risk weakens as snowpack decreases. In contrast, positive values suggest that snowpack no longer plays a buffer role when crops experience soil moisture stress, and crop yields are instead constrained by energy regulation or altered by human activities. Four categories are defined as high-sensitive zone, adaptive zone, vulnerable zone, and the managed zone, based on the characteristics of these indicators (+/−, −/+, +/+, and −/−). This integrative analysis allowed us to pinpoint risk hotspots and determine the crop types most sensitive to snowpack changes under global warming.

3 Results

3.1 Influence of snowpack on crop yields in the Northern Hemisphere

We found that anomalies in the yields of all three crops were generally positively correlated with SWEI ($p < 0.1$), with a mean magnitude of 0.47/–0.46. The significant positive correlation regions are mainly located in mid- to high-latitude regions of North America, Eastern Europe, and Northeast Asia, whereas negative correlations were observed in Western Europe and the central United States (Figure 1). For maize, 5.32% of the study area exhibited a significant positive correlation with SWEI, slightly exceeding the area showing a significant negative correlation (4.72%). The corresponding

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

mean correlation coefficients were 0.45 and –0.46, respectively. For soybean, 10.07% of the study area showed significant positive correlations with SWEI, far exceeding the 2.11% of area with significant negative correlations. The average magnitudes of these significant correlations were 0.47 and –0.46, respectively. Similarly, spring wheat yields were significantly positively correlated with SWEI in 9.00% of the study area, compared to 3.37% with significant negative correlation and mean correlation coefficients were 0.47 and –0.45, respectively. Among all significant areas, the proportions of positive correlations for the three crops were 52.99%, 72.75%, and 82.66%, respectively. 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.

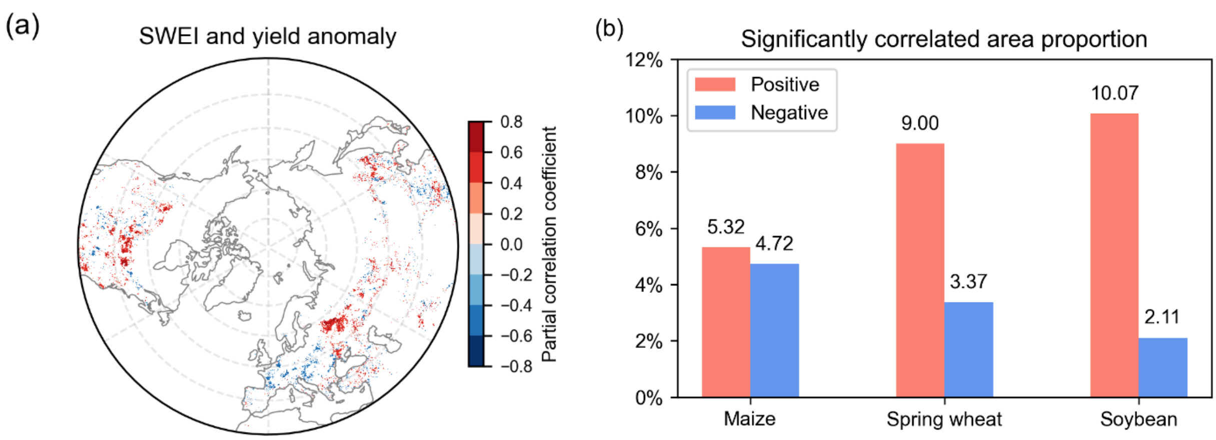

Figure 1. Partial correlations between SWEI and yield anomaly of maize, soybean, and spring wheat from 2000–2022 in the Northern Hemisphere. (a) Spatial distribution of significantly correlated pixels ($p < 0.1$) between SWEI and yield anomaly aggregated across maize, spring wheat, and soybean. (b) Proportion of pixels showing significant positive and negative correlations ($p < 0.1$) between SWEI and yield anomaly of maize, spring wheat, and soybean.

3.2 Sensitivity of crop yield to soil moisture under different snowpack conditions

Sensitivity of crop yields to soil moisture represents the propensity of yield loss when experiencing soil moisture deficit, and 43-65% of maize, soybean, and spring wheat cropland exhibited the expected positive effect of soil moisture on yields. The effects of soil moisture were spatially heterogeneous across the Northern Hemisphere. The positive effects were mainly

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

concentrated in western and central Siberia, the central United States, and northeastern China and adjacent regions of East Asia (Figure S2). Overall, the results are broadly consistent with current evidence that crop yield is dependent on soil moisture. Under different snowpack conditions, yield sensitivity to soil moisture is positive, with the exception that soybean shows a negative mean sensitivity in the highest spring melt interval (Figure 2). Despite the temporal mismatch between snowpack accumulation or melt processes and crop growth, we found a consistent moderation across the three crops: yield sensitivity to soil moisture declines with higher SWEmax, later SCED, and greater spring snowmelt volume. 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.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

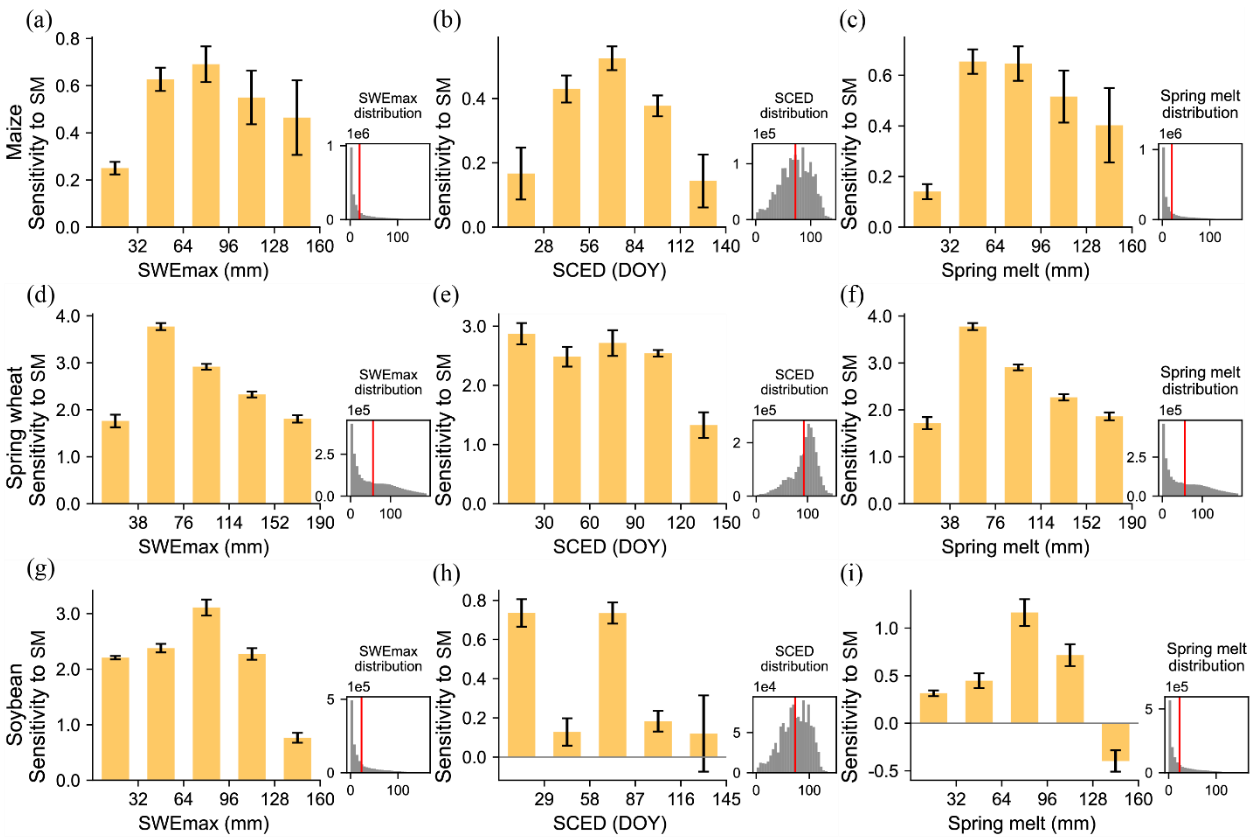

Figure 2. Sensitivity of maize, spring wheat, and soybean yields to soil moisture under different intervals of snowpack-metrics. (a-c), (d-f), and (g-i) represent maize, spring wheat and soybean sensitivity to soil moisture under different snowpack-metrics, including SWEmax, SCED, and spring melt with all samples divided into five groups. The right panel shows the histogram of snowpack metrics with the vertical red line indicating the mean of all samples.

3.3 Dominant snowpack indicators modulating crop yields sensitivity to soil moisture

The physical properties, temporal dynamics, and hydrological contribution of snowpack matters differently in modulating crop yields sensitivity to soil moisture. For maize and spring wheat, April melt emerged as the dominant explanatory factor for soil moisture sensitivity changes in 28% and 25% of the study area, respectively (Figure 3). For soybean, which is typically sown later than the other two crops, May melt was the most influential predictor of soil moisture sensitivity, accounting for approximately 24% of the area. In contrast, March snowmelt played a primary role in a smaller proportion of

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

study area: 16%, 17%, and 17% for maize, spring wheat, and soybean, respectively. These results suggest that, across all three crops, snowmelt occurring closer to the sowing period has a greater capacity to explain variations in yield sensitivity to soil moisture. According to stepwise regression coefficient, results further indicate that the proportion of area showing negative effects of snowpack indicators exceeds that of positive ones. This implies that snowpack variables generally exert a negative influence on soil moisture sensitivity, consistent with the findings from the statistical correlation analysis. Among all indicators, SWEmax and April melt contributed the most to explaining soil moisture sensitivity, with the highest absolute average regression coefficients across the three crops. For maize, the average coefficients were −0.27 (SWEmax) and −0.29 (April melt); for soybean, −0.22 and −0.30; and for spring wheat, −0.29 and −0.22, respectively. This indicates that greater snow accumulation and snowmelt occurring closer to the sowing period are associated with reduced crop dependence on soil moisture during the growing season. This in turn lower the risk of yield loss under agricultural drought stress.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

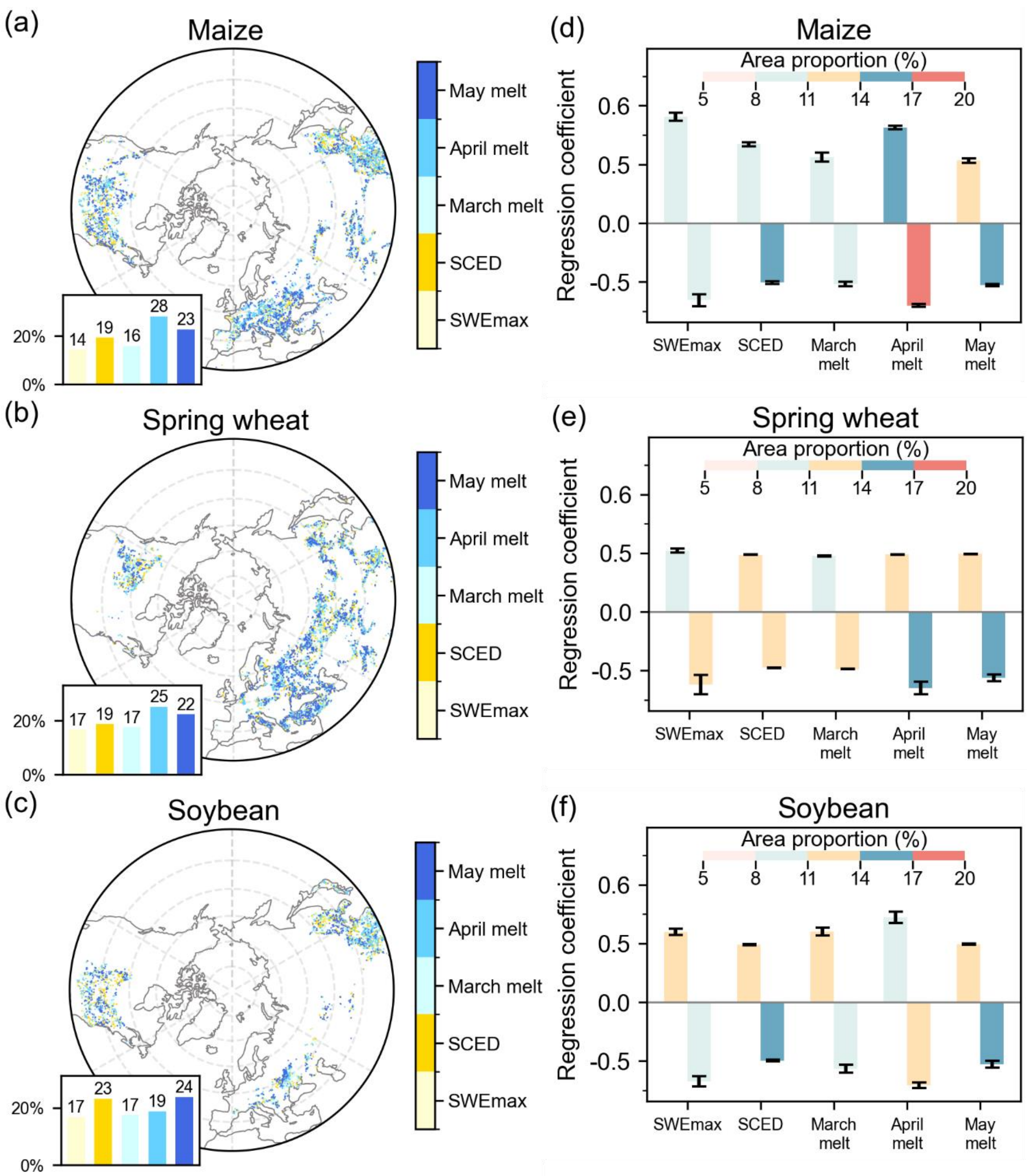

Figure 3. Dominant snowpack indicators influencing crop yields sensitivity to soil moisture. (a–c) Spatial distribution of the dominant snowpack indicators influencing crop yields sensitivity to soil moisture. The inset bar plots display the percentage of pixels where each indicator is dominant. (d–f) Average positive and negative contributions of each snowpack indicator to soil moisture sensitivity across the three crops.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

3.4 Key regions of crop sensitive to soil moisture deficit under snowpack decreasing

The soil moisture sensitivity of the three crops yield and their responses to declining snowpack exhibit pronounced differences and strong spatial heterogeneity across the Northern Hemisphere. Four categories are identified based on the four sign combinations of these two indicators (+/−, −/+, +/+, and −/−), namely the high-sensitive zone, adaptive zone, vulnerable zone, and managed zone (Figure 4). The high-sensitive zone represents key hotspots where the buffering effect of snowpack on soil moisture sensitivity is weakening, while crops become more sensitive to soil moisture deficits. The result reveals that 44%, 30%, and 32% of the study area for maize, spring wheat, and soybean, respectively, fall within this region. The adaptive zone refers to areas with relatively low risk. Despite the weakening of snowpack buffering, crop yield is not strongly dependent on soil moisture. It comprises 12% of maize, 21% of spring wheat, and 16% of soybean areas. For vulnerable zone, about 18% of maize, 14% of spring wheat, and 21% of soybean fall into this category. These regions are no longer primarily influenced by snowpack processes but still face increasing soil moisture deficit exposure and should be given attention for drought risk management. In contrast, managed zones occupy 25% of maize, 35% of spring wheat, and 31% of soybean areas. In these zones, the reduction in snowpack has little impact on crop yield. The crop yield is not strongly dependent on soil moisture but is influenced by other factors, such as energy availability or human management practices. The spatial distribution of high-sensitive zone also varied among the three crops. For maize, the high-sensitive areas are primarily located in the central United States, Central Europe, and the North China Plain. For spring wheat, the most affected regions include southern Canada, southern West Siberia, and the southwestern edge of the Eurasian continent. The soybean sensitive zones are concentrated in eastern North America and northeastern China. Maize and soybean are the two crops most affected by snowpack decline, with a greater proportion of pixels falling within the high-sensitive zone (44%/32%) compared to spring wheat (30%).

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

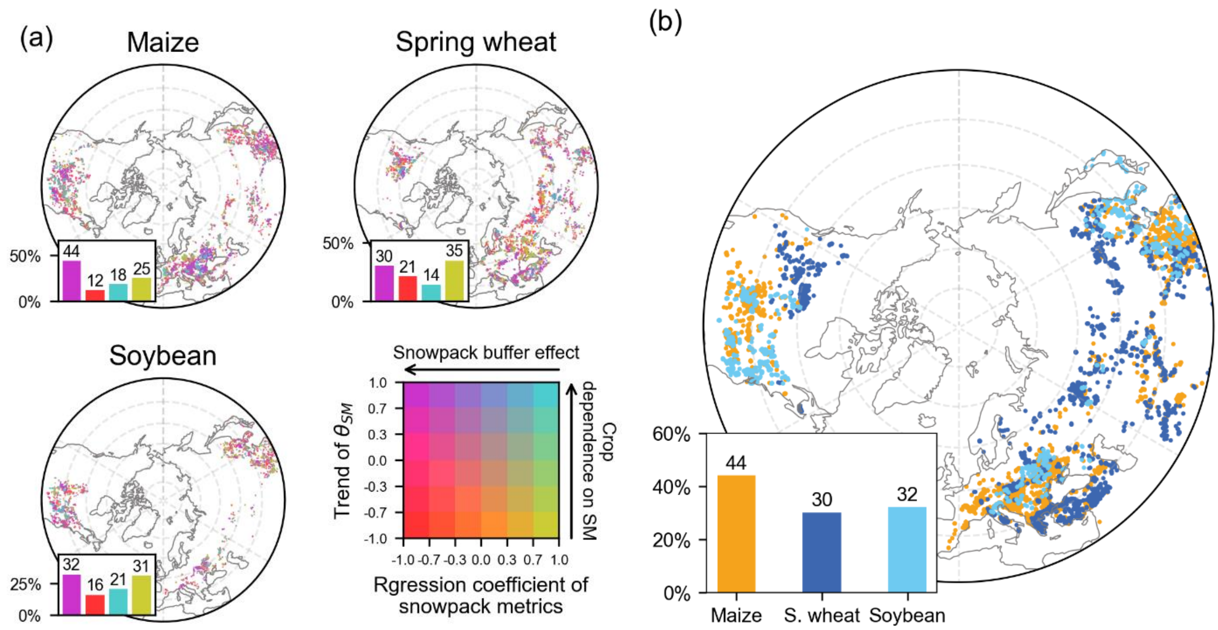

Figure 4. Modulating impacts of snowpack on the soil moisture sensitivity of crop yield across three major crops. (a) Spatial distribution of areas where the yield of three crop types currently influenced by the snowpack changes. In the inset at the lower right, the horizontal axis represents the buffer effect of snowpack, with the strength of this buffering increasing along the direction of the arrow. The vertical axis represents the dependence of crop yield on soil moisture, with greater dependence indicated along the arrow direction. The inset bar plot shows the proportion of areas classified into these four categories: high-sensitive zone, adaptive zone, vulnerable zone, and managed zone. (b) Combined spatial pattern of regions where declining snowpack intensifies yield losses across all three crop types. Here, S. wheat denotes Spring wheat.

4 Discussions

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. Nevertheless, a smaller proportion of regions exhibited negative correlation suggesting a dual effect in the interaction between snowpack and cropping systems. In high-latitude regions, crop growth is

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

more constrained by energy availability (Wang et al., 2018). Excessive snow accumulation and delayed snowmelt expose crops to colder and overly wet growing conditions, which hinder germination, reduce photosynthetic rates (Wipf & Rixen, 2010). Moreover, excessive snowpack can restrict the effective respiration of roots and soil microorganisms beneath the snow (Kim, 2014). It leads to reduced nutrient absorption efficiency, ultimately lowering productivity (Cooper et al., 2011) and leading to yield reductions.

Our study found that crops with lower soil moisture sensitivity during the growing season generally experienced richer snowpack (higher SWEmax, later SCED, and greater spring snowmelt) during the cold season. As a distinct form of water resource, snowpack indirectly influences crop yield by regulating soil moisture, even though the timing of snow accumulation and melt does not coincide directly with the crop growing season. Snowmelt makes an important contribution to soil moisture in spring and summer (Peng et al., 2010), and richer snowpack conditions during the cold season raise the baseline of growing-season soil moisture. Specifically, since the contribution of snowpack to soil moisture exhibits a lag effect (Wang et al., 2018), residual soil moisture and winter snowpack prior to the growing season can compensate for spring precipitation deficits (Věra Potopová et al., 2016). Therefore, the moisture contribution of snowpack can buffer crops against drought stress during the growing season by maintaining sufficient soil moisture. This prevents water limitations on photosynthesis (Wellstein et al., 2017) and sustaining stable crop yield. The buffering effect of snowpack on soil moisture deficit manifests through protecting crops from summer droughts and preventing premature leaf senescence (Khorsand Rosa et al., 2015). Drought can reduce crop yield by suppressing soil microbial activity (Sardans et al., 2008), whereas snowpack can improve soil nutrient availability, as soil microorganisms release nutrients at higher concentrations during snowmelt (Yano et al., 2015). These beneficial effects of cold-season snowpack help mitigate drought-induced yield losses. However, the interaction between snowpack and yield sensitivity to soil moisture shows strong spatial heterogeneity. In some regions, snowpack does not exhibit a pronounced buffering effect. This may be due to frozen soil, which prevents meltwater infiltration into the root zone for later crop use. Additionally, substantial changes in ozone concentration suppress crop responses to improved moisture availability (Mills et al., 2018). Soil erosion can also reduce soil water-holding capacity (Quinton et al., 2010), causing the beneficial effects of cold-season snowpack to diminish before crops reach their peak water demand.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

4.2 Agricultural consequences of snowpack changes and implications for sustainable crop yield

Two major strategies for increasing global food production are cropland expansion and the expansion of irrigation in dryland regions (Rosa et al., 2020). The former poses substantial risks to global biodiversity and carbon emissions, rendering it largely unsustainable, and the latter focuses on yield improvement, for which soil moisture is a key determinant (Rigden et al., 2020). Global warming has led to increased hydroclimatic stress on dryland agriculture. Our study revealed that snowpack can buffer crop responses to soil moisture deficit. Unfortunately, our analysis also shows a significant decline in SWEmax (7.66%) and that 10.26% of the study area exhibits a significant advance in SCED (Figure S4). Regression analysis further demonstrates that the buffering effect of snowpack on yield sensitivity to soil moisture is predominantly negative, suggesting that the buffering capacity of snowpack is being weakened under global warming. As a result, crops are increasingly exposed to drought risks, leading to potential yield losses.

In addition, the timing of water availability relative to crop growth stages is also of critical importance (Qin et al., 2020). Attribution analysis of soil moisture sensitivity of crop yields reveals that April melt is the most influential factor for the soil moisture sensitivity of maize and spring wheat yields, while May melt dominates for soybean, that is because soybean is typically sown later than the other two crops. Thus, snowmelt that occurs closer to its sowing period becomes the primary driver of its soil moisture sensitivity. However, in the trend analysis of spring snowmelt over study areas, we found that the proportion of March melt showed a significant increasing trend at a rate of 1.54% per year, while April snowmelt proportion decreased significantly at a rate of 1.26%·yr-1 (Figure S4). This indicates a seasonal shift in peak snowmelt toward earlier in the year, which may further widen the temporal gap between water supply from snowmelt and crop water demand. On the one hand, crops may fail to convert the available water into biomass, leading to reduced water use efficiency (Wang et al., 2020). On the other hand, meeting crop water requirements may necessitate the use of alternative water sources (Qin et al., 2020), which could further exacerbate water scarcity. Under continued warming, the declining and earlier snowmelt is likely to weaken the buffering effect of snowpack on drought stress, thereby reducing crop drought tolerance and exacerbating agricultural risk. Among the crop types analyzed, maize and soybean appear to be the most sensitive when experience soil moisture deficit under snowpack decreasing. Both of them are highly dependent on timely water availability and particularly vulnerable to the increasing mismatch between snowmelt timing and drought occurrence.

4.3 Agricultural management under snowpack variations

Our study distinguishes four types of yield responses, i.e., high-sensitive zone, adaptive zone, vulnerable zone, and managed zone, reflecting the diverse adjustment mechanisms of agricultural systems under snowpack reduction and changes in water availability. From the perspective of agricultural development, these results provide new insights for drought management. In high-sensitive zone, the buffering effect of snowpack is gradually weakening, while crop yield shows increasing dependence on soil moisture availability. Thus, yield stability in these areas increasingly depends on artificial water supplementation, such as groundwater use, irrigation, and improved soil water retention (Rockström et al., 2017). In vulnerable zone, snowpack plays a limited hydrological role, and crop growth is primarily energy limited and highly dependent on soil moisture, making them important areas for drought risk monitoring and long-term adaptation planning. In contrast, adaptive and managed zones likely reflect regions where adjustments in cropping structure, water resource management, and precision irrigation have already been implemented. These measures effectively mitigate the negative impacts of snowpack reduction but also reveal an increasing dependence of agricultural systems on human-managed water sources. As snowpack continues to decline, maintaining food production and food security will increasingly depend on sustainable water management (Qin et al., 2020). The weakening of snowpack buffering means that future yield will rely more heavily on human-regulated water supplies, emphasizing the importance of rational allocation and conservation of water resources. While ensuring stable crop yield remains the primary goal, overexploitation of groundwater or inefficient irrigation could undermine long-term sustainability (Sneed et al., 2013). Therefore, balancing agricultural productivity with responsible water use is essential to achieve both food security and resource resilience in under global warming.

4.4 Limitations and future perspective

This study reveals the influence of snowpack on the yields of three major crops in the Northern Hemisphere, with a focus on the moisture effect of snowpack in modulating crop soil moisture sensitivity. However, several sources of uncertainty warrant further discussion. In addition to its moisture effect, snowpack can also affect crop growth and yield by altering soil nutrient dynamics (Smull et al., 2019) and modifying the coupling between moisture and energy availability (Lesk et al., 2021). However, due to the limited availability of relevant datasets, these factors were not explicitly incorporated into our

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

analysis, which may lead to potential inconsistencies in the results. The development of more comprehensive and integrated datasets would facilitate further exploration of how snowpack dynamics influence crop yields. Future studies could evaluate the broader agricultural impacts of snowpack by integrating these multiple functional pathways. Although this study concentrates on rain-fed agriculture, it is worth noting that snowmelt also plays a crucial role in irrigated systems. Changes in snowmelt runoff can influence the availability of water to meet crop demands (Lutz et al., 2022; Qin et al., 2020). Furthermore, during crop growth, extreme weather events (Trnka et al., 2014), pest and disease (Smull et al., 2019), and anthropogenic interventions may occur and interfere with yield responses. These factors were not accounted for in our analysis but could influence or modulate crop responses to drought, potentially helping explain some of the regional disparities observed.

5 Conclusion

This study reveals the influence of snowpack on crop yield in Northern Hemisphere based on long-term observations. Our results demonstrate a positive correlation between the SWEI and three types of crop yield, suggesting that snowpack may impact agricultural productivity and ecosystem functioning by reducing snowmelt water supply and altering the soil moisture balance. A greater accumulation of snow during the cold season enhances soil moisture reserves in the subsequent growing season, thereby improving crop drought tolerance and reducing the risk of yield losses under soil moisture stress. Snowpack plays a predominantly negative regulatory role in yield sensitivity to soil moisture, with greater snowpack exerting a stronger buffering effect against drought impacts. Among the snowpack metrics examined, late-spring snowmelt is the most influential factor in explaining variations in soil moisture sensitivity. However, the observed shift in snowmelt peak toward earlier months may exacerbate the temporal mismatch between water availability and crop water demand, weakening the buffering capacity of snowpack. Maize and soybean appear particularly vulnerable to intensified drought stress under ongoing snowpack reduction. Overall, this study expands our understanding of snowpack dynamics affect crop yields and offers a new perspective on the interconnected roles of snowpack, agricultural drought, and crop productivity, with important implications for ensuring food security under climate change.

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Data availability

The daily snow water equivalent product, air temperature, precipitation, shortwave radiation, and soil moisture data are available from https://doi.org/10.24381/cds.68d2bb30. The crop yield data is available from https://doi.org/10.11878/db.202412.017258. The Global Map of Irrigation Areas v5 is available from https://storage.googleapis.com/fao-maps-catalog-data/geonetwork/aquamaps/gmia_v5_aei_pct_asc.zip. Global crop calendar dataset is available from https://sage.nelson.wisc.edu/data-and-models/datasets/crop-calendar-dataset/.

Author contributions

HL and PFX conceptualized this project. PFX and XLZ acquired the funding and supervised the project. HL performed the formal analyses and prepared the paper. PFX, XLZ, WJY, YTL, HL and HKW reviewed and edited the paper.

Competing interests

The authors declare no conflict of interest.

Acknowledgements

This work was funded by the National Natural Science Foundation of China (Grant Nos. 42571382 and 42471410). We are grateful to the High-Performance Computing Center, Nanjing University, for computational support.

References

AghaKouchak, A., Huning, L. S., Sadegh, M., Qin, Y., Markonis, Y., Vahedifard, F., Love, C. A., Mishra, A., Mehran, A., Obringer, R., Hjelmstad, A., Pallickara, S., Jiwa, S., Hanel, M., Zhao, Y., Pendergrass, A. G., Arabi, M., Davis, S. J., Ward, P. J., … Kreibich, H. (2023). Toward impact-based monitoring of drought and its cascading hazards. Nature Reviews Earth & Environment, 4(8), 582–595. https://doi.org/10.1038/s43017-023-00457-2

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Alexandratos, N., & Bruinsma, J. (2012). World agriculture towards 2030/2050: The 2012 revision (ESA Working Papers 12-03). https://doi.org/10.22004/ag.econ.288998

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., Van der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. Nature Communications, 9(1), 1627. https://doi.org/10.1038/s41467-018-04087-x

Berdanier, A. B., & Klein, J. A. (2011). Growing Season Length and Soil Moisture Interactively Constrain High Elevation Aboveground Net Primary Production. Ecosystems, 14(6), 963–974. https://doi.org/10.1007/s10021-011-9459-1

Cooper, E. J., Dullinger, S., & Semenchuk, P. (2011). Late snowmelt delays plant development and results in lower reproductive success in the High Arctic. Plant Science, 180(1), 157–167. https://doi.org/10.1016/j.plantsci.2010.09.005

Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea, M. D., Bilir, T. E., Chatterjee, M., Ebi, K. L., Estrada, Y. O., Genova, R. C., Girma, B., Kissel, E. S., Levy, A. N., MacCracken, S., Mastrandrea, P. R., White, L. L., & Intergovernmental Panel on Climate Change (Eds). (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability ; Summaries, Frequently Asked Questions, and Cross-Chapter Boxes ; A Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change.

Fuyou T., Yupei C. A. O., Hang Z., Bingfang W. U., Hongwei Z., Yazhou L. I. U., Xingli Q. I. N., Miao Z., Liang Z. H. U., & Weiwei Z. H. U. (2024). Agricultural field segmentation using spatial attention mechanism and multi-task learning strategy. [dataset] National Remote Sensing Bulletin, 28(11), 2850–2864. https://doi.org/10.11834/jrs.20243191

Gutierrez-Villanueva, M. O., Chereskin, T. K., & Sprintall, J. (2023). Compensating transport trends in the Drake Passage frontal regions yield no acceleration in net transport. Nature Communications, 14(1). https://doi.org/10.1038/s41467-023-43499-2

Harder, P., Helgason, W. D., Johnson, B., & Pomeroy, J. W. (2025). Observations and management implications of crop and water interactions in cold water-limited regions. Journal of Hydrology, 647, 132359. https://doi.org/10.1016/j.jhydrol.2024.132359

Hendrawan, V. S. A., Kim, W., Touge, Y., Ke, S., & Komori, D. (2022). A global-scale relationship between crop yield anomaly and multiscalar drought index based on multiple precipitation data. Environmental Research Letters, 17(1), 014037. https://doi.org/10.1088/1748-9326/ac45b4

Howitt, R. E., Medellín-Azuara, J., MacEwan, D., Lund, J. R., & Sumner, D. A. (2018). Economic Impact of the 2015 Drought on Farm Revenue and Employment.

Huning, L. S., & AghaKouchak, A. (2020). Global snow drought hot spots and characteristics. Proceedings of the National Academy of Sciences, 117(33), 19753–19759. https://doi.org/10.1073/pnas.1915921117

Jägermeyr, J., Müller, C., Ruane, A. C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., Foster, I., Folberth, C., Franke, J. A., Fuchs, K., Guarin, J. R., Heinke, J., Hoogenboom, G., Iizumi, T., Jain, A. K., Kelly, D., Khabarov, N., Lange, S., … Rosenzweig, C. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nature Food, 2(11), 873–885. https://doi.org/10.1038/s43016-021-00400-y

Jia, H., Zhang, Y., Tian, S., Emon, R. M., Yang, X., Yan, H., Wu, T., Lu, W., Siddique, K. H. M., & Han, T. (2017). Reserving winter snow for the relief of spring drought by film mulching in northeast China. Field Crops Research, 209, 58–64. https://doi.org/10.1016/j.fcr.2017.04.011

Khorsand Rosa, R., Oberbauer, S. F., Starr, G., Parker La Puma, I., Pop, E., Ahlquist, L., & Baldwin, T. (2015). Plant phenological responses to a long-term experimental extension of growing season and soil warming in the tussock tundra of Alaska. Global Change Biology, 21(12), 4520–4532. https://doi.org/10.1111/gcb.13040

Kim, W., Iizumi, T., & Nishimori, M. (2019). Global Patterns of Crop Production Losses Associated with Droughts from 1983 to 2009. https://doi.org/10.1175/JAMC-D-18-0174.1

Kim, Y. (2014). Effect of ablation rings and soil temperature on 3-year spring CO2 efflux along the Dalton Highway, Alaska. Biogeosciences, 11(23), 6539–6552. https://doi.org/10.5194/bg-11-6539-2014

Lesk, C., Coffel, E., Winter, J., Ray, D., Zscheischler, J., Seneviratne, S. I., & Horton, R. (2021). Stronger temperature–moisture couplings exacerbate the impact of climate warming on global crop yields. Nature Food, 2(9), Article 9. https://doi.org/10.1038/s43016-021-00341-6

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. Nature, 529(7584), 84–87. https://doi.org/10.1038/nature16467

Li D., Ouyang W., Wang L., Chen J., Zhang H., Sharkhuu A., Tseren-Ochir S.-E., & Yang Y. (2025). Revisiting snowmelt dynamics and its impact on soil moisture and vegetation in mid-high latitude watershed over four decades. Agricultural and Forest Meteorology, 362, 110353. https://doi.org/10.1016/j.agrformet.2024.110353

Li, X., & Wang, S. (2022). Recent Increase in the Occurrence of Snow Droughts Followed by Extreme Heatwaves in a Warmer World. Geophysical Research Letters, 49(13), e2022GL099925. https://doi.org/10.1029/2022GL099925

Lobell, D. B., Deines, J. M., & Tommaso, S. D. (2020). Changes in the drought sensitivity of US maize yields. Nature Food, 1(11), 729–735. https://doi.org/10.1038/s43016-020-00165-w

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. Science, 333(6042), 616–620. https://doi.org/10.1126/science.1204531

Lu, Z., Peng, S., Slette, I., Cheng, G., Li, X., & Chen, A. (2021). Soil moisture seasonality alters vegetation response to drought in the Mongolian Plateau. Environmental Research Letters, 16(1), 014050. https://doi.org/10.1088/1748-9326/abd1a2

Lutz, A. F., Immerzeel, W. W., Siderius, C., Wijngaard, R. R., Nepal, S., Shrestha, A. B., Wester, P., & Biemans, H. (2022). South Asian agriculture increasingly dependent on meltwater and groundwater. Nature Climate Change, 12(6), 566–573. https://doi.org/10.1038/s41558-022-01355-z

Martin. (2015). Goal 2: Zero Hunger. United Nations Sustainable Development. https://www.un.org/sustainabledevelopment/hunger/

Meza, I., Siebert, S., Döll, P., Kusche, J., Herbert, C., Eyshi Rezaei, E., Nouri, H., Gerdener, H., Popat, E., Frischen, J., Naumann, G., Vogt, J. V., Walz, Y., Sebesvari, Z., & Hagenlocher, M. (2020). Global-scale drought risk assessment for agricultural systems. Natural Hazards and Earth System Sciences, 20(2), 695–712. https://doi.org/10.5194/nhess-20-695-2020

Mills, G., Sharps, K., Simpson, D., Pleijel, H., Broberg, M., Uddling, J., Jaramillo, F., Davies, W. J., Dentener, F., Van den Berg, M., Agrawal, M., Agrawal, S. B., Ainsworth, E. A., Büker, P., Emberson, L., Feng, Z., Harmens, H., Hayes, F., Kobayashi, K., … Van Dingenen, R. (2018). Ozone pollution will compromise efforts to increase global wheat production. Global Change Biology, 24(8), 3560–3574. https://doi.org/10.1111/gcb.14157

Muñoz Sabater, J. (2019). ERA5-Land monthly averaged data from 1950 to present [Data set]. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/CDS.68D2BB30

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. Earth System Science Data, 13(9), 4349–4383. https://doi.org/10.5194/essd-13-4349-2021

Nicholson, C., Shinker, J. J., Hanway, V. M., & Zavala, S. (2018). The Influence of Atmospheric Circulation on Abnormal Snowpack Melt-Out Events and Drought in Wyoming. JAWRA Journal of the American Water Resources Association, 54(6), 1355–1371. https://doi.org/10.1111/1752-1688.12697

Peng, S., Piao, S., Ciais, P., Fang, J., & Wang, X. (2010). Change in winter snow depth and its impacts on vegetation in China. Global Change Biology, 16(11), 3004–3013. https://doi.org/10.1111/j.1365-2486.2010.02210.x

Potopová, V., Boroneanţ, C., Možný, M., & Soukup, J. (2016). Driving role of snow cover on soil moisture and drought development during the growing season in the Czech Republic. International Journal of Climatology, 36(11), 3741–3758. https://doi.org/10.1002/joc.4588

Prado, R., Ferreira, M. A. R., & West, M. (2021). Time Series: Modeling, Computation, and Inference, Second Edition (2nd edn). Chapman and Hall/CRC. https://doi.org/10.1201/9781351259422

Qi, W., Feng, L., Liu, J., & Yang, H. (2020). Snow as an Important Natural Reservoir for Runoff and Soil Moisture in Northeast China. Journal of Geophysical Research: Atmospheres, 125(22), e2020JD033086. https://doi.org/10.1029/2020JD033086

Qin, Y., Abatzoglou, J. T., Siebert, S., Huning, L. S., AghaKouchak, A., Mankin, J. S., Hong, C., Tong, D., Davis, S. J., & Mueller, N. D. (2020). Agricultural risks from changing snowmelt. NATURE CLIMATE CHANGE, 10(5), 459-+. https://doi.org/10.1038/s41558-020-0746-8

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Quinton, J. N., Govers, G., Van Oost, K., & Bardgett, R. D. (2010). The impact of agricultural soil erosion on biogeochemical cycling. Nature Geoscience, 3(5), 311–314. https://doi.org/10.1038/ngeo838

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. NATURE COMMUNICATIONS, 6, 5989. https://doi.org/10.1038/ncomms6989

Rigden, A. J., Mueller, N. D., Holbrook, N. M., Pillai, N., & Huybers, P. (2020). Combined influence of soil moisture and atmospheric evaporative demand is important for accurately predicting US maize yields. Nature Food, 1(2), 127–133. https://doi.org/10.1038/s43016-020-0028-7

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., & Smith, J. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio, 46(1), 4–17. https://doi.org/10.1007/s13280-016-0793-6

Rosa, L., Chiarelli, D. D., Sangiorgio, M., Beltran-Peña, A. A., Rulli, M. C., D'Odorico, P., & Fung, I. (2020). Potential for sustainable irrigation expansion in a 3 °C warmer climate. Proceedings of the National Academy of Sciences, 117(47), 29526–29534. https://doi.org/10.1073/pnas.2017796117

Sacks, W. J., Deryng, D., Foley, J. A., & Ramankutty, N. (2010). Crop planting dates: An analysis of global patterns. Global Ecology and Biogeography, 19(5), 607–620. https://doi.org/10.1111/j.1466-8238.2010.00551.x

Sardans, J., Peñuuelas, J., Estiarte, M., & Prieto, P. (2008). Warming and drought alter C and N concentration, allocation and accumulation in a Mediterranean shrubland. Global Change Biology, 14(10), 2304–2316. https://doi.org/10.1111/j.1365-2486.2008.01656.x

Schillerberg, T., & Tian, D. (2023). Changes in crop failures and their predictions with agroclimatic conditions: Analysis based on earth observations and machine learning over global croplands. Agricultural and Forest Meteorology, 340, 109620. https://doi.org/10.1016/j.agrformet.2023.109620

Sharma, B. R., Rao, K. V., Vittal, K. P. R., Ramakrishna, Y. S., & Amarasinghe, U. (2010). Estimating the potential of rainfed agriculture in India: Prospects for water productivity improvements. Agricultural Water Management, 97(1), 23–30. https://doi.org/10.1016/j.agwat.2009.08.002

Siebert, S., Döll, P., Hoogeveen, J., Faures, J.-M., Frenken, K., & Feick, S. (2005). Development and validation of the global map of irrigation areas. Hydrology and Earth System Sciences, 9(5), 535–547. https://doi.org/10.5194/hess-9-535-2005

Siebert, S., Henrich, V., Frenken, K., & Burke, J. (2013). Update of the Digital Global Map of Irrigation Areas to Version 5.

Smull, D. M., Pendleton, N., Kleinhesselink, A. R., & Adler, P. B. (2019). Climate change, snow mold and the Bromus tectorum invasion: Mixed evidence for release from cold weather pathogens. https://dx.doi.org/10.1093/aobpla/plz043

Sneed, M., Brandt, J. T., & Solt, M. (2013). Land subsidence along the Delta-Mendota Canal in the northern part of the San Joaquin Valley, California, 2003-10. In Scientific Investigations Report (Nos 2013–5142). U.S. Geological Survey. https://doi.org/10.3133/sir20135142

The United Nations world water development report 2019: Leaving no one behind (The United Nations World Water Development Report 2019). (2019). UNESCO. https://digitallibrary.un.org/record/3837335

Trnka, M., Rötter, R. P., Ruiz-Ramos, M., Kersebaum, K. C., Olesen, J. E., Žalud, Z., & Semenov, M. A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. Nature Climate Change, 4(7), 637–643. https://doi.org/10.1038/nclimate2242

Troy, T. J., Kipgen, C., & Pal, I. (2015). The impact of climate extremes and irrigation on US crop yields. Environmental Research Letters, 10(5), 054013. https://doi.org/10.1088/1748-9326/10/5/054013

van Dijk, A. I. J. M., Beck, H. E., Crosbie, R. S., de Jeu, R. A. M., Liu, Y. Y., Podger, G. M., Timbal, B., & Viney, N. R. (2013). The Millennium Drought in southeast Australia (2001–2009): Natural and human causes and implications for water resources, ecosystems, economy, and society. Water Resources Research, 49(2), 1040–1057. https://doi.org/10.1002/wrcr.20123

Věra Potopová, Potopová, V., C. Boroneanț, Boroneanţ, C., Martin Možný, Možný, M., Josef Soukup, & Soukup, J. (2016). Driving role of snow cover on soil moisture and drought development during the growing season in the Czech Republic. International Journal of Climatology, 36(11), 3741–3758. https://doi.org/10.1002/joc.4588

Wang, W., Wang, J., & Cao, X. (2020). Water Use Efficiency and Sensitivity Assessment for Agricultural Production System from the Water Footprint Perspective. Sustainability, 12(22), 9665. https://doi.org/10.3390/su12229665

Wang X., Wang T., Guo H., Liu D., Zhao Y., Zhang T., Liu Q., & Piao S. (2018). Disentangling the mechanisms behind winter snow impact on vegetation activity in northern ecosystems. Global Change Biology, 24(4), 1651–1662. https://doi.org/10.1111/gcb.13930

Wang X., Xiao J., Li X., Cheng G., Ma M., Zhu G., Altaf Arain M., Andrew Black T., & Jassal R. S. (2019). No trends in spring and autumn phenology during the global warming hiatus. Nature Communications, 10(1), 2389. https://doi.org/10.1038/s41467-019-10235-8

Wei F. U., Jian R. E. N., Yifan L. I., Xiaorong W. E. I., Shuhui Y. U., Yongxiang H. U., & Guofei S. (2022). Response of spring wheat yield to snow cover in the black soil region: A perspective from the regulation of freezing and thawing processes of seasonally frozen soil. Chinese Journal of Eco-Agriculture, 30(10), 1601–1609. https://doi.org/10.12357/cjea.20220006

Wellstein, C., Poschlod, P., Gohlke, A., Chelli, S., Campetella, G., Rosbakh, S., Canullo, R., Kreyling, J., Jentsch, A., & Beierkuhnlein, C. (2017). Effects of extreme drought on specific leaf area of grassland species: A meta-analysis of experimental studies in temperate and sub-Mediterranean systems. Global Change Biology, 23(6), 2473–2481. https://doi.org/10.1111/gcb.13662

West, M., & Harrison, J. (Eds). (1997). Introduction. In Bayesian Forecasting and Dynamic Models (pp. 1–31). Springer. https://doi.org/10.1007/0-387-22777-6_1

Wipf, S., & Rixen, C. (2010). A review of snow manipulation experiments in Arctic and alpine tundra ecosystems. Polar Research, 29(1), 95–109. https://doi.org/10.1111/j.1751-8369.2010.00153.x

Yano, Y., Brookshire, E. N. J., Holsinger, J., & Weaver, T. (2015). Long-term snowpack manipulation promotes large loss of bioavailable nitrogen and phosphorus in a subalpine grassland. Biogeochemistry, 124(1), 319–333. https://doi.org/10.1007/s10533-015-0100-9

Yeşilköy, S., Baydaroğlu, Ö., & Demir, I. (2024). Is snow drought a messenger for the upcoming severe drought period? A case study in the Upper Mississippi River Basin. Atmospheric Research, 309, 107553. https://doi.org/10.1016/j.atmosres.2024.107553

https://doi.org/10.5194/egusphere-2026-617
Preprint. Discussion started: 15 April 2026

Zhu, P., Kim, T., Jin, Z., Lin, C., Wang, X., Ciais, P., Mueller, N. D., Aghakouchak, A., Huang, J., Mulla, D., & Makowski, D. (2022). The critical benefits of snowpack insulation and snowmelt for winter wheat productivity. NATURE CLIMATE CHANGE, 12(5), 485-+. https://doi.org/10.1038/s41558-022-01327-3