

Article

Snowmelt Timing and Contrasting Vegetation Responses to Compound Dry–Hot Events in Northwest China’s Mountains

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Highlights

What are the main findings?

- Snowmelt timing separated short-term vegetation damage from cumulative growing-season loss.
- The initial post-snowmelt moisture surplus gradually shifted to a deficit, revealing a persistent hydrological legacy of snowmelt.

What are the implications of the main findings?

- Vegetation-risk assessments should track both event-period maxima and cumulative growing-season losses.
- Regional moisture backgrounds and local snow–topography settings provide complementary evidence for mountain monitoring.

Abstract

Seasonal snow regulates spring water supply and vegetation development, thereby shaping vegetation responses to summer compound dry–hot events. Whether snowmelt timing relative to event onset explains the contrast between peak damage and cumulative deficit remains unresolved. Regional observations from 2006 to 2025 were integrated with high-resolution satellite data across Northwest China to combine regional association analyses with local comparisons within the same events. Snowmelt completion timing, the snowmelt–event interval, antecedent root-zone moisture, and local snow–terrain conditions were evaluated. Earlier snowmelt was associated with lower peak damage but greater seasonal cumulative vegetation deficit. As the snowmelt–event interval increased from 56 to 148 days, cumulative deficit decreased by 9.30 z-observations. The mean standardized root-zone moisture residual declined from 0.12 during the initial post-snowmelt period to −0.43 in the last valid period. In local annual-baseline comparisons, late-snow candidates showed greater peak damage and cumulative deficit than matched controls. Under an event-preceding baseline, candidate pixels had 0.0489 lower cumulative EVI2 deficit than controls across 77 event-sensitive samples, and this direction persisted after sequentially excluding mountain systems. Future scenarios showed jointly high peak damage and cumulative deficit in the Altai under some climate combinations. These results provide evidence for incorporating snowmelt preconditioning into assessments of mountain vegetation risk that account for both event impacts and seasonal losses.

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Keywords: snowmelt preconditioning; compound dry–hot events; soil moisture memory; cumulative vegetation deficit; snow refugia

1. Introduction

Seasonal snow links cold-season water storage in mountain ecosystems with warm-season vegetation growth. Snowmelt timing determines when stored water enters the soil and affects the timing of both growth initiation and the seasonal soil-moisture peak [1]. Earlier snow disappearance advances water release and growth onset while extending the snow-free period; later disappearance delays meltwater supply and shortens the snow-free growth window. Years with reduced snow accumulation and shorter snow duration are more prone to subsequent warm-season compound dry–hot anomalies, and this association is strongest soon after snow disappearance and weakens thereafter [2]. From snowmelt completion to dry–hot event onset, soil-moisture replenishment, vegetation growth, and evapotranspiration continue to evolve. Event onset therefore occurs against a particular antecedent state of water availability and vegetation growth. How this temporal linkage relates to peak vegetation damage and seasonal cumulative deficit is central to understanding snowmelt preconditioning.

Soil moisture provides the cross-season storage pathway for snowmelt preconditioning. After meltwater enters the soil, the resulting moisture anomaly decays through the combined effects of precipitation inputs, soil storage, and vegetation water use; its persistence constitutes soil-moisture memory [3]. Snow phenology and vegetation development in the mountains of Northwest China vary strongly with elevation and region [4,5]. Vegetation types also differ in their sensitivity to snow onset, disappearance, and duration, so snowmelt timing has distinct ecological implications across hydroclimatic and ecological settings [6]. Soil water-holding capacity, post-melt precipitation, and vegetation water use further determine how long a snowmelt-related moisture signal is retained. These regional patterns have been documented for snow phenology and growing-season onset, but whether snowmelt-related moisture anomalies persist into compound dry–hot events and shape event-period vegetation responses remains directly untested.

The relationship between snowmelt preconditioning and vegetation response depends on the observation window. Snow variability can affect vegetation productivity over periods of weeks to months, and the association may change sign with lag length; a fixed window therefore cannot fully capture the process [7]. In dry environments, seasonal contrasts are especially pronounced: an early-season growth benefit associated with earlier snowmelt can be offset by subsequent water stress, resulting in late-season or annual productivity losses [8]. Conversely, peak annual biomass may remain stable across changes in snowmelt timing, even as summer drought alters biomass allocation and community composition [9]. A maximum anomaly at one time point and a seasonal cumulative response thus represent different processes. Peak event damage measures the largest departure from normal conditions, whereas cumulative deficit integrates both damage magnitude and duration. Treating them separately helps determine whether snowmelt preconditioning changes short-term damage intensity, seasonal loss, or both.

Regional snowmelt relationships cannot resolve the fine-scale environmental gradients within mountain systems. Wind redistribution, slope aspect, solar radiation, and terrain heterogeneity jointly shape snow cover, so adjacent patches can differ in snow persistence, melt date, and soil-moisture conditions. These fine-scale differences are also expressed in vegetation composition and growth patterns. Along an approximately 40-day snowmelt gradient in the Colorado Rockies, plant community composition, flowering phenology, physiological status, and peak cover changed markedly [10]. Incorporating

snow persistence into alpine plant-distribution models also improves spatial predictions, especially for snow-dependent species [11]. Community composition and species distributions record long-term vegetation responses to local snow environments, however, and do not directly indicate whether late-snow patches experience less damage during a particular compound dry-hot event. Detecting such event-period differences requires identifying candidate patches from snow and terrain conditions before vegetation damage is observed, then using high-resolution observations to compare them with neighboring vegetation exposed to the same event and climatic background.

Against this background, this study examined open natural vegetation in the mountains of Northwest China using regional observations from 2006 to 2025 together with recent high-resolution satellite data. At the regional scale, the associations of snow disappearance completion date, the snowmelt-event interval, and antecedent root-zone soil moisture with vegetation responses during soil-moisture-driven compound dry-hot events were examined, including how these associations varied with environmental conditions and event intensity. At the local scale, vegetation responses in late-snow-terrain patches were compared with those in neighboring vegetation during the same dry-hot events. This study links snowmelt-related antecedent conditions to vegetation damage during individual compound dry-hot events, combining regional temporal associations with local contrasts under shared climatic exposure to provide evidence across scales on how mountain vegetation responds to dry-hot stress under different antecedent snow-melt conditions.

2. Materials and Methods

2.1. Study Area

The study area lies in inland northwestern China and along the northern margin of the Tibetan Plateau. It spans 73.80–103.97°E and 33.67–49.18°N and covers the Chinese portions of the Altai, Tianshan, Qilian, and Kunlun Mountains (Figure 1). The Altai Mountains lie north of the Junggar Basin; the Tianshan Mountains traverse central Xinjiang and separate the Junggar and Tarim basins; the Kunlun Mountains extend along the southern margin of the Tarim Basin and the northern margin of the Tibetan Plateau; and the Qilian Mountains are situated along the northeastern margin of the Tibetan Plateau and south of the Hexi Corridor. These four mountain systems encompass contrasting snow, moisture, temperature and vegetation conditions across northwestern China. Regional studies have documented snow phenology-vegetation relationships in the Tianshan and Qilian Mountains [4,5]. Located deep within the Eurasian continent, the study region has pronounced continentality and an arid-semi-arid climate. Moisture supply in the Qilian Mountains is dominated by westerly circulation in most years, with occasional summer-monsoon incursions [12]. In the Tianshan Mountains, continental sources dominate precipitation moisture, while East and South Asian moisture also contributes to summer precipitation in the east [13].

The four mountain systems contain multiple headwater regions of inland rivers and serve as important mountain water sources and ecological barriers in the arid zone of northwestern China. They play a key role in maintaining downstream oasis water supply and ecological stability. Complex topography produces pronounced differences in elevation, aspect, and hydrothermal conditions, resulting in strong spatial heterogeneity in snow persistence, snow disappearance dates, and vegetation distribution. With increasing elevation, vegetation generally transitions from low-elevation desert steppe and mountain steppe, through mountain forest or forest-steppe belts at some middle elevations, to alpine meadow, alpine steppe, alpine desert, and permanent snow-and-ice belts; the specific zonation varies with mountain system and slope aspect. Across the four mountain

systems, these hydrothermal and ecological differences form a representative regional environmental gradient.

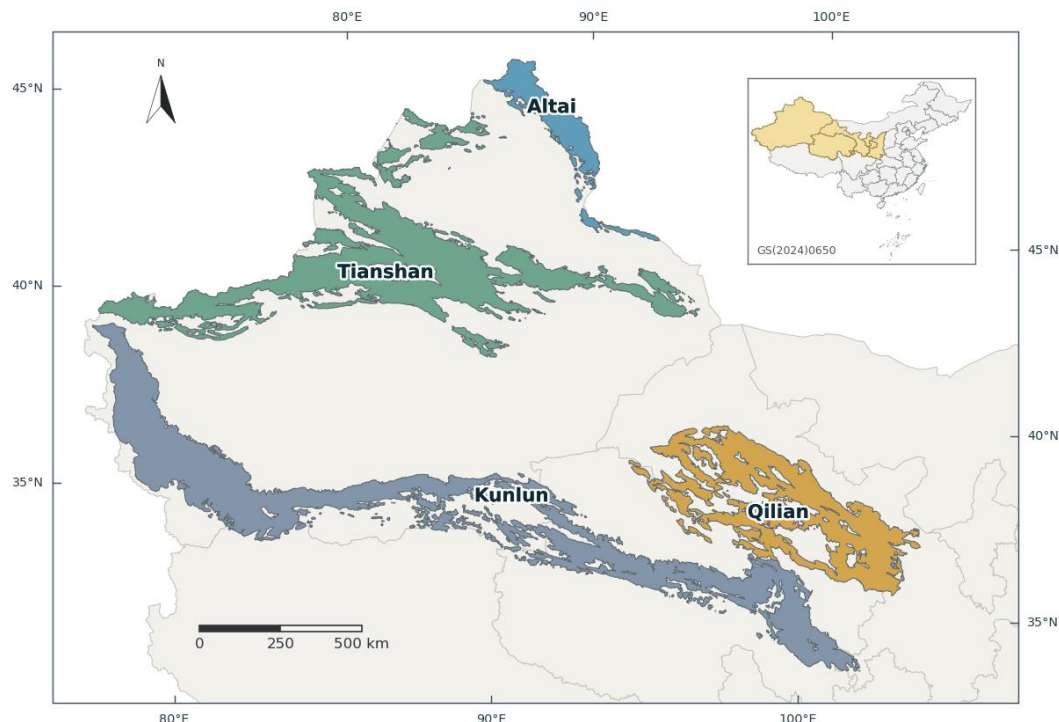


Figure 1. Location and coordinate framework of the study area. The map shows the four mountain systems in northwestern China and the regional analysis domain.

2.2. Data Sources

Daily ERA5-Land reanalysis data [14] from the European Center for Medium-Range Weather Forecasts provided near-surface air temperature, precipitation, surface solar radiation, and volumetric soil water content to identify compound dry–hot events, construct root-zone soil-moisture indicators, and characterize pre-event hydrothermal conditions. Future conditions were projected using CMIP6 simulations of ACCESS-ESM1-5 [15] and MPI-ESM1-2-HR [16] obtained from the Earth System Grid Federation (ESGF), covering historical experiments and the SSP2-4.5 and SSP5-8.5 scenarios [17]. The simulated variables included daily maximum and minimum air temperature, precipitation, downward shortwave radiation at the surface, snow water equivalent, and layered soil moisture, providing inputs for identifying model-internal snow disappearance dates and compound dry–hot events.

Regional snow and vegetation observations were obtained from MODIS Collection 6.1 products. MOD10A1 and MYD10A1 [18,19] were used to identify snow disappearance dates, MOD13Q1 and MYD13Q1 [20,21] to analyze vegetation responses, and MOD16A2GF [22,23] to analyze pre-event evapotranspiration; the PML-V2.2a MODIS product [24,25] was also included to compare evapotranspiration products. Local snow and vegetation observations were based on the harmonized Sentinel-2 MSI Level-2A surface-reflectance products [26,27], with spatial resolutions of 10 m for the visible and near-infrared bands and 20 m for the shortwave-infrared bands. Cloud Score+ V1 [28,29] supplied observation-quality information.

Land-cover data comprised the 500 m MCD12Q1 Collection 6.1 annual product [30,31] and the 10 m Dynamic World V1 product [32]. The former was used to identify regional natural vegetation and its cover stability; the latter used land-cover class proba-

bilities to identify local cropland, built-up land, and other cover types to support screening of natural-vegetation samples. Ecosystem stratification used the China 1:1,000,000 Vegetation Dataset and its attribute descriptions provided by the National Cryosphere Desert Data Center [33] to distinguish vegetation types. Topographic data came from the 30 m Copernicus DEM GLO-30 [34], providing elevation, slope, aspect, curvature, topographic wetness, and potential radiation as basic variables characterizing the topographic context of snow retention and vegetation responses. Figure 2 summarizes the workflow from data preparation and indicator construction to regional and local analyses and future scenario projections.

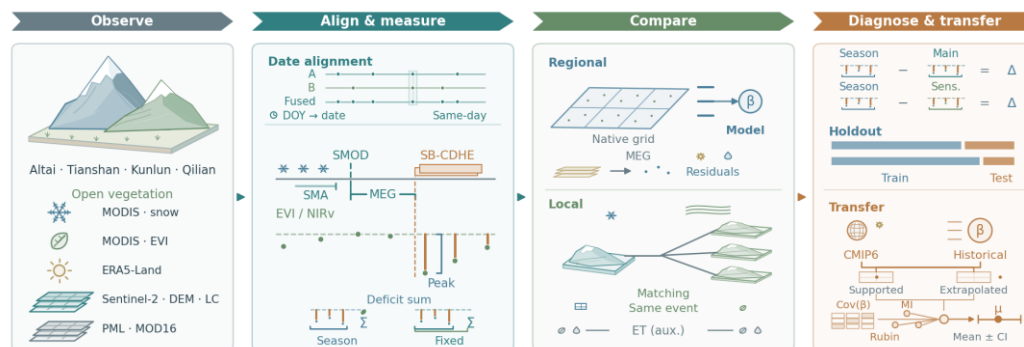


Figure 2. Overall methodological framework for investigating the relationship between snowmelt preconditioning and vegetation responses to compound dry-hot events in the mountains of north-western China.

2.3. Snow Disappearance Date, Compound Dry-Hot Events, and the Time Gap

Snow disappearance dates were identified from daily MODIS snow observations [18,19] for 2001–2025, using 2001–2005 to prepare pre-period states and 2006–2025 as the formal event-analysis period. The snow disappearance date (snowmelt date, SMOD) was defined as the last day with observed snow after seasonal retreat and before the onset of a stable snow-free period. Valid observations before and after snow disappearance and short-term snow reappearance were incorporated into quality control to represent the completion date of optically observable snow disappearance. SMOD was compared with Sentinel-2 snow-disappearance intervals defined by the last clear snow-covered and subsequent clear snow-free observations, using median interval bounds within MODIS footprints to evaluate date differences, interval widths and containment.

To characterize interannual differences in snow-disappearance timing, the day of year of the snow disappearance date was robustly standardized using its median and median absolute deviation [35], yielding the standardized snowmelt-date anomaly (SMA):

$$SMA_{p,y} = \frac{D_{p,y} - \tilde{D}_p}{1.4826MAD_p}, MAD_p = median_{y \in B_p} |D_{p,y} - \tilde{D}_p|.$$

Here, $D_{p,y}$ is the day of year of the snow disappearance date for pixel p in year y , and B_p is the set of valid years in the baseline period. $\tilde{D}_p$ and MAD_p are the corresponding median and median absolute deviation, respectively, and 1.4826 is the normal-consistency correction factor. SMA is dimensionless; negative values indicate earlier snow disappearance, whereas positive values indicate later disappearance. SMA was not calculated when the median absolute deviation was zero.

On the native climate grid, soil-moisture-based compound dry-hot events [36,37] were identified where anomalously high daily maximum air temperature coincided with anomalously low root-zone soil moisture and were matched to the corresponding snow disappearance dates. Percentiles were calculated for each cell from seasonally matched

reference-period data. Heatwaves required daily maximum temperature above the 90th percentile for at least three consecutive valid days [38]. Persistent root-zone drought was identified below the 20th percentile [39]. Heatwaves within the same continuous drought were grouped into one event cluster, with event independence assessed from the intervening interval and soil-moisture recovery. The snowmelt-to-event gap (MEG) was defined as the difference between the event start date and the snow disappearance date:

$$\text{MEG}_{i,e} = t_{c(i),e}^{\text{start}} - t_{i,y(e)}^{\text{SMOD}}.$$

Here, i denotes the regional analysis unit, $c(i)$ its corresponding climate grid cell, e a compound dry-hot event, and $y(e)$ the year in which the event occurred; $t_{c(i),e}^{\text{start}}$ is the event start date, and $t_{i,y(e)}^{\text{SMOD}}$ is the median snow disappearance date for that unit in the event year. MEG is expressed in days. The MEG regressions included compound dry-hot events that began after snow disappearance. The start and end of the growing season (SOS and EOS) were derived from single-season double-logistic curves [40] fitted to the EVI time series.

2.4. Vegetation Outcomes and Regional Estimation

Vegetation damage was represented by the standardized deficit of observed EVI [41] relative to its expected baseline trend. Based on valid baseline-period observations from the same within-year periods, expected EVI was estimated with a Theil–Sen trend estimator [42], and the residuals were standardized using their median absolute deviation after consistency correction [35]. Maximum damage and seasonal cumulative deficit were then calculated during the event period:

$$d_{i,t} = \frac{\hat{\text{EVI}}_{i,t} - \text{EVI}_{i,t}}{s_{i,t}}, D_{i,e} = \max_{t \in \mathcal{T}_{i,e}} [d_{i,t}]_+, C_{i,e} = \sum_{t \in \mathcal{S}_{i,e}} [d_{i,t}]_+.$$

Here, i , t , and e denote the analysis unit, observation date, and event, respectively; $\hat{\text{EVI}}$ is the baseline-trend expectation for the corresponding within-year period; s is the baseline residual scale; and $[d]_+ = \max(d, 0)$. $\mathcal{T}$ and $\mathcal{S}$ contain dates on which standardized deficits could be calculated during the event start–end period and from event onset to the end of the growing season, respectively. D is dimensionless maximum damage, whereas C is the cumulative deficit calculated as the equal-weight sum of the actual observations (z-observations).

Separate weighted regression models were fitted with D and C as response variables:

$$Y_{i,e} = \alpha_{m(i)} + \beta M_{i,e} + \boldsymbol{\gamma}^T \mathbf{X}_{i,e} + \varepsilon_{i,e}, \Delta_{\text{MEG}} = \beta \frac{Q_{0.75} - Q_{0.25}}{\sigma_{\text{MEG}}}.$$

Here, Y is the corresponding vegetation response; $\alpha_{m(i)}$ is the mountain-system intercept; M is MEG standardized by its weighted mean and standard deviation; β is the shared slope; $\mathbf{X}$ comprises the likewise standardized event intensity, spring temperature, spring precipitation, spring radiation, pre-event soil moisture, and elevation; $\boldsymbol{\gamma}$ contains the corresponding coefficients; and ε is the error term. All independent events had equal total weight. $Q_{0.75}$, $Q_{0.25}$, and σ_{MEG} are the upper and lower quartiles and the weighted standard deviation of the raw MEG values in the corresponding analysis sample, respectively; Δ_{MEG} denotes the predicted difference adjusted to the interquartile range. Confidence intervals were estimated using event-clustered uncertainty [43]. Sensitivity analyses used climate-grid clustering and a quadratic MEG term. Fixed-duration post-onset deficits were compared with seasonal deficits within common samples using the same covariates and weights, with accumulation duration and observation count examined in separate adjusted models.

2.5. Root-Zone Soil Moisture and Post-Snowmelt Moisture Dynamics

Layered volumetric soil water content from ERA5-Land was weighted by soil-layer thickness to derive root-zone soil moisture. The median for the corresponding within-year period during the baseline period was subtracted to obtain the soil-moisture anomaly. Within each climate grid cell, a ridge-regression model [44] was fitted using recent precipitation, temperature, and annual-cycle terms. The regularization parameter was selected by blocked cross-validation across consecutive years [45], and standardized residuals were calculated:

$$\theta'_{c,t} = \theta_{c,t}^{\text{RZ}} - \tilde{\theta}_{c,d(t)}^{\text{RZ}}, r_{c,t} = \frac{\theta'_{c,t} - \hat{\theta}'_{c,t} - \bar{\varepsilon}_c}{s_{\varepsilon,c}}.$$

Here, c and t denote the climate grid cell and date, respectively, and $d(t)$ is the calendar day of year. θ^{RZ} , $\tilde{\theta}^{\text{RZ}}$, and $\hat{\theta}'$ are root-zone soil moisture, the seasonal baseline median, and the predicted anomaly, respectively; $\bar{\varepsilon}_c$ and $s_{\varepsilon,c}$ are the mean and sample standard deviation of the training residuals. Soil-moisture anomalies are expressed in $\text{m}^3\cdot\text{m}^{-3}$, whereas the standardized residual r is dimensionless.

Starting from the snow disappearance date, mean soil-moisture residuals were calculated over successive periods within a fixed process window, and usable periods were screened based on the proportion of valid observations. The means of the first and last valid periods represented the initial and terminal states, respectively. The direction of change was described by the slope of a linear regression of period means against time, and the valid daily residuals within the window were accumulated to obtain the net cumulative quantity:

$$A_{r,c} = \sum_{t \in \mathcal{W}_c} r_{c,t} \Delta t.$$

Here, $\mathcal{W}_c$ is the set of dates with valid residuals for climate grid cell c following its corresponding snow disappearance date and within the fixed process window, and $\Delta t = 1\text{d}$. $A_{r,c}$ retains the net contribution of positive and negative residuals; the change slope and net cumulative quantity have units of d^{-1} and d , respectively.

2.6. Conditional Responses and Association Heterogeneity

Nonlinear models characterized how vegetation damage varied with the standardized snowmelt-date anomaly:

$$Y_{i,e} = \alpha_{c(i)} + \lambda_{y(e)} + f(\text{SMA}_{i,e}) + \boldsymbol{\beta}^T \mathbf{Z}_{i,e} + \varepsilon_{i,e}.$$

Here, i and e denote the analysis unit and event, respectively; Y is the corresponding vegetation-damage metric; $\alpha_{c(i)}$ and $\lambda_{y(e)}$ are climate-grid and year fixed effects, respectively; and f is a smooth response function. The baseline covariates $\mathbf{Z}$ comprised pre-snowmelt event burden and the vegetation anomaly during the preceding growing season, and $\boldsymbol{\beta}$ contains their coefficients; ε is the error term.

In the conditional-response model, the univariate smooth term was replaced by a response surface $g(\text{SMA}, I)$ containing the standardized snowmelt-date anomaly, compound dry-hot intensity I , and their interaction. The replacement covariates were spring precipitation, temperature, and radiation; green-up anomaly and date; pre-event evapotranspiration and soil moisture; and MEG, with the fixed effects unchanged. Both model types used low-rank thin-plate splines [46] and restricted maximum likelihood estimation [47]. A clustered bootstrap [48], with resampling by climate grid and event, was used to construct 95% simultaneous confidence intervals.

Samples were classified as above or not above the model-expected level according to the mean root-zone soil-moisture residual within a fixed window before event onset.

Weighted regressions compared vegetation damage between groups, adjusting for climate-grid and year fixed effects, pre-snowmelt event burden, and the preceding growing-season vegetation anomaly; uncertainty was estimated by independent-event clusters. Interactions between moisture status and MEG, compound dry-hot intensity, mountain system, and ecosystem type were also added to assess heterogeneity in the association. A control model based on pre-event hydrothermal and phenological conditions was also fitted to examine the association estimate under different covariate sets.

Sensitivity to event thresholds was evaluated by repeating the MEG–vegetation response analysis using temperature/soil-moisture percentile combinations of 95/20, 90/10 and 95/10. Event persistence, grouping and independence rules were retained. Linear and quadratic regressions were refitted using the same event-normalized weighting, and contrasts between the 75th and 25th percentiles of MEG were estimated with event- and climate-grid-clustered 95% confidence intervals.

2.7. High-Resolution Same-Event Matching and Stability Analysis

Using Sentinel-2 snow observations [49] and topographic information, snow–terrain exposure types were predefined at a common 20 m spatial scale on the basis of late-lying snow, aspect, curvature, topographic wetness, and potential radiation. Vegetation outcomes were not used to define the classification, thereby avoiding selection of candidate pixels by damage magnitude and defining groups for comparing local vegetation responses under the same compound dry-hot event.

The annual-baseline analysis used the median vegetation index for the same 16-day period in previously valid years as the reference. The maximum positive deficit and cumulative positive deficit of EVI2 [50] and NIRv [51] were calculated from event onset to the end of the growing season. Within the same event window and climate grid cell, exact matching by ecosystem type used 1:3 Mahalanobis-distance nearest-neighbor matching without replacement [52]. Matching covariates included pre-event EVI2 and NIRv, elevation, slope, observation support, and event phenology. Logistic regression using these covariates estimated propensity scores [53]. Within the common-support range, a propensity-score caliper of 0.20 times the within-group standard deviation of the propensity-score logit [54] constrained differences between candidates and controls, and balance was assessed using the pre- and post-matching standardized mean differences in the covariates. Caliper sensitivity was evaluated using multipliers of 0.10 and 0.30, with the remaining matching rules retained. Each matched set contained one candidate pixel and three control pixels, and their vegetation-outcome difference was:

$$\delta_k = Y_k^T - \frac{1}{3} \sum_{j=1}^3 Y_{kj}^C.$$

Here, k denotes a matched set, and Y_k^T and Y_{kj}^C are the vegetation outcomes for the candidate pixel and the j th control pixel, respectively. Each outcome was calculated separately, with the difference retaining the unit of the corresponding metric; negative values indicate lower damage or deficit for the candidate pixel. For the annual-baseline analysis, valid matched sets were aggregated with equal weights:

$$\hat{\Delta}_A = \frac{1}{K_A} \sum_{k=1}^{K_A} \delta_k^A.$$

Here, K_A is the number of valid matched sets, and superscript A denotes outcomes calculated using the annual reference. Confidence intervals were calculated using an event-window-clustered CR2 correction with Satterthwaite degrees of freedom [55].

The event-window analysis instead used pre-event vegetation level as the reference and performed 1:3 nearest-neighbor matching with replacement [52] within the same event window, climate grid cell, and ecosystem class. Controls were selected according to

pre-event EVI2, NIRv, elevation, slope, and the number of clear observations. Matching differences were averaged first within each event window, then with equal weights across windows of the same independent event, and finally with equal weights across independent events:

$$\hat{\Delta}_E = \frac{1}{N_E} \sum_{e=1}^{N_E} \left[\frac{1}{W_e} \sum_{w=1}^{W_e} \left(\frac{1}{K_{ew}} \sum_{k=1}^{K_{ew}} \delta_{ewk}^E \right) \right].$$

Here, N_E is the number of independent events, W_e is the number of event windows in event e , and K_{ew} is the number of valid matched sets in the corresponding event window; superscript E denotes outcomes referenced to pre-event vegetation level. Intervals were estimated using clustered-bootstrap resampling [48] at the climate-grid and event levels. Annual-baseline and event-window results were retained separately. The influence of sample composition was examined through sequential exclusion of each mountain system and modification of the land-cover stability-support criteria; estimates under the different reference and support conditions were reported separately.

2.8. Uncertainty, Sensitivity, and Scenario Analyses

Soil-moisture process metrics were summarized separately by snow–climate-grid association record and with equal weights across climate grid cells. The former was calculated as the mean of valid association records, whereas the latter first averaged within each climate grid cell and then averaged the grid-cell means with equal weights, thereby distinguishing the effects of association-record counts from those of spatial-unit composition on the summary. Uncertainty in the climate-grid–equal-weight means was estimated by resampling climate grid cells, and the resulting intervals were used to compare process metrics descriptively.

The soil-moisture-status association analysis retained valid observations and used grouped cross-validation by event and climate grid cell [45] for model selection and imputation of missing covariates and vegetation-damage metrics. Separate regressions were fitted to multiple imputed datasets, and estimates and their uncertainty were combined using Rubin's rules [56]; observed, predicted, and extrapolated sources were flagged. The pooled total variance was:

$$T = \theta + \left(1 + \frac{1}{m}\right) B.$$

Here, T is the pooled total variance, θ is the mean estimated variance across imputed datasets, B is the sample variance among the effect estimates, and m is the number of imputed datasets.

The evapotranspiration-product comparison paired pre-event cumulative positive anomalies from PML and MOD16 by event and calculated the mean and difference between the two products [57]:

$$a_i = \frac{P_i + M_i}{2}, d_i = P_i - M_i.$$

For each mountain system, the mean difference and descriptive difference limits were:

$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i, s_d = \sqrt{\frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}}, L_{\pm} = \bar{d} \pm 1.96s_d.$$

Here, P_i and M_i are the pre-event cumulative positive anomalies from PML and MOD16, respectively, for record i , each calculated against the same calendar-day baseline; n is the number of valid paired records for the mountain system; a_i and d_i are used as the horizontal and vertical coordinates, respectively; $\bar{d}$ is the mean difference; s_d

is the sample standard deviation of the differences; and $L_{\pm}$ are the descriptive difference limits.

Future scenario analysis was based on CMIP6 simulations. Compound dry-hot events occurring after snow disappearance were identified, and the regional response models established for the historical period were used to estimate the corresponding vegetation damage. To align climate simulations with observational data, prediction variables were standardized using the historical reference period for each model and scenario and mapped to the standardized coordinates of the observational models. Estimates within historical common support were distinguished from extrapolative estimates, with projections conditional on transfer of the historical response relationships. Results were reported separately by mountain system, model, scenario, and future period. The intervals incorporated shared coefficient covariance and uncertainty across imputed datasets. Temporal transferability was assessed by training on 2006–2020 and testing on 2021–2022 and by training on 2006–2022 and testing on 2023–2025, with both response specifications refitted within each training period. The resulting estimates represent conditional mean vegetation responses under the specified climate conditions; their intervals do not encompass all between-model differences or scale-transformation errors.

3. Results

3.1. Divergence Between Maximum Vegetation Damage and Seasonal Cumulative Deficit Along the Snowmelt-to-Event Interval

Among Sentinel-2 observations with strong support, higher-confidence MODIS dates more often fell within the snow-disappearance intervals. The associations of snowmelt timing and the snowmelt-to-event interval with maximum vegetation damage and seasonal cumulative deficit were examined. The vegetation response to snowmelt timing diverged between maximum damage and seasonal cumulative deficit, with a clearer decline in cumulative deficit as the snowmelt-to-event interval increased. Predicted maximum damage increased gradually with the interval: as MEG increased from 57 to 141 days, it increased from 4.12 to 4.76 z (Figure 3a). By contrast, seasonal cumulative deficit declined steadily as MEG increased, from 16.05 at 56 days to 6.74 z-observations at 148 days, a difference of −9.30 z-observations (Figure 3b). A longer snowmelt-to-event interval was therefore mainly associated with a smaller seasonal cumulative deficit, whereas maximum damage changed little. Seasonal estimates changed little within the common samples, while the fixed-window comparisons showed weaker evidence of an association. The seasonal association also diminished after separate adjustment for accumulation duration or observation count. Focusing only on maximum damage during the event may consequently overlook the association between snowmelt timing and cumulative vegetation deficit over the subsequent growing season.

Earlier snowmelt was associated with lower maximum damage but not with a smaller seasonal cumulative deficit. As SMA increased from negative to positive values, indicating a shift from earlier-than-usual to later-than-usual snowmelt, the predicted maximum damage increased from 2.42 to 7.60 z (Figure 3c), whereas the point prediction of seasonal cumulative deficit showed the opposite pattern, declining from 15.57 to 2.51 z-observations; the prediction interval was wider at the later-snowmelt end (Figure 3d). The predicted patterns indicate that earlier snowmelt combined relatively mild event-peak damage with a larger seasonal cumulative deficit, whereas later snowmelt showed the opposite combination. The vegetation-response difference associated with earlier snowmelt was therefore more pronounced in cumulative within-season deficit than in the peak of a single damage event. The comparison of MEG model results also showed that, when MEG increased from the 25th to the 75th percentile, the point-estimate differences in max-

imum damage were 0.64 and 0.98 z in the linear and quadratic models, respectively (Figure 3e), whereas seasonal cumulative deficit decreased by 9.30 and 9.51 z-observations, respectively (Figure 3f). MEG was negatively associated with seasonal cumulative deficit under both event-based and climate-grid clustering specifications and across the tested threshold combinations, with the estimated magnitude varying among threshold combinations.

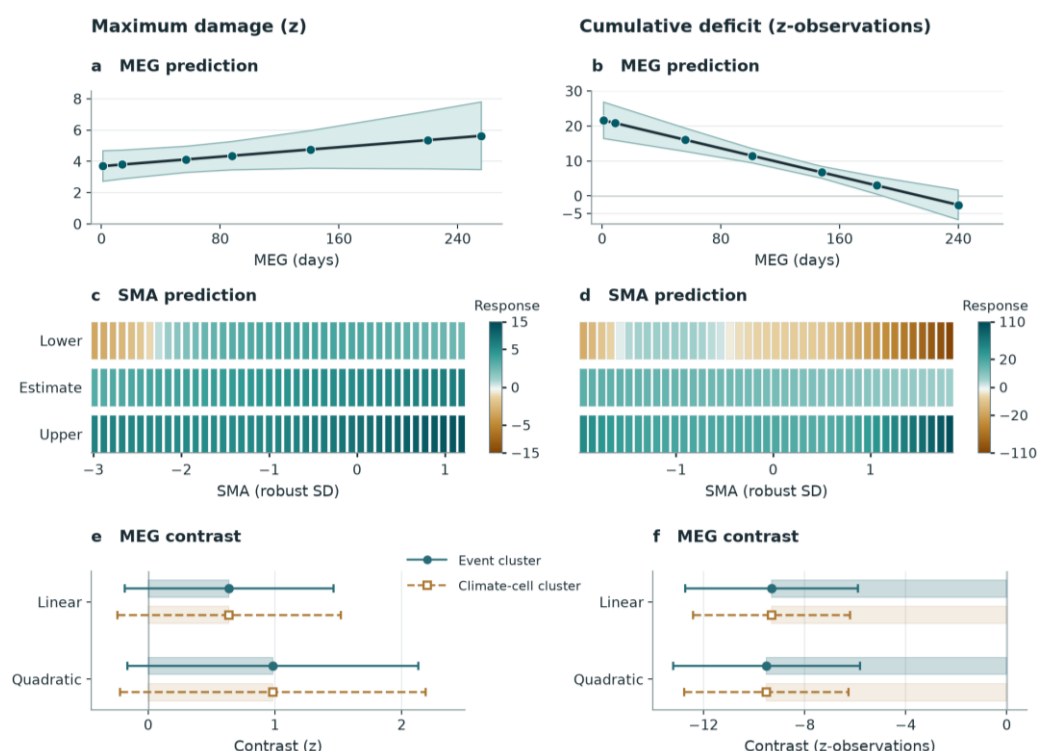


Figure 3. Divergent responses of maximum vegetation damage and seasonal cumulative deficit to snowmelt timing. (a,b) Predicted relationships with the snowmelt-to-event interval (MEG); (c,d) predicted relationships with the standardized anomaly of snowmelt date (SMA); (e,f) predicted differences between the 75th and 25th percentiles of MEG in the linear and quadratic models.

3.2. Event-Preceding Soil-Moisture Status and Post-Snowmelt Moisture Changes

The event-preceding root-zone soil-moisture anomalies and post-snowmelt moisture changes across mountain systems jointly characterized the antecedent moisture conditions under which vegetation experienced compound dry-hot events. Across 194 climate-grid cells and 348 events, event-preceding root-zone soil moisture was generally below the seasonal baseline, with a weighted mean anomaly of $-0.0070 \text{ m}^3\cdot\text{m}^{-3}$ and a 95% confidence interval of -0.0084 to $-0.0054 \text{ m}^3\cdot\text{m}^{-3}$ (Figure 4a). The contrast between the Tianshan and Qilian was particularly pronounced. The mean anomaly in the Tianshan was $-0.0135 \text{ m}^3\cdot\text{m}^{-3}$, and its confidence interval was entirely below those of the other three mountain systems, indicating a stronger antecedent moisture deficit. The Kunlun and Altai also showed negative anomalies, whereas the mean state in the Qilian was close to the seasonal baseline, with a less pronounced dry signal and greater uncertainty. These anomalies were calculated relative to the seasonal state of each mountain system, indicating a greater departure from normal conditions in the Tianshan before the events.

With equal weighting across climate-grid cells, the mean residual during the first 0–7 days after snow disappearance was 0.12 (Figure 4b). The initial Tianshan residual was sensitive to the aggregation weights: the snow-climate-grid-link mean was negative, whereas the climate-grid-equal-weighted mean was positive. By the last valid interval, the overall residual had declined to -0.43 , indicating a transition from slightly above the

model expectation initially to below the expectation at the end of the period (Figure 4c). The greatest changes in interval means occurred in the Kunlun and Qilian, which had the largest absolute negative and positive slopes, respectively (Figure 4d). Although the Altai showed a recovery trend, its net cumulative amount remained the most negative, indicating that an improvement in moisture state can coexist with a low cumulative value (Figure 4e). In the Tianshan, the net cumulative amounts were -29.31 d and -8.95 d for the link-weighted and climate-grid-equal-weighted means, respectively. Both weighting schemes indicated negative cumulative departures, although the magnitude of the cumulative departure differed substantially.

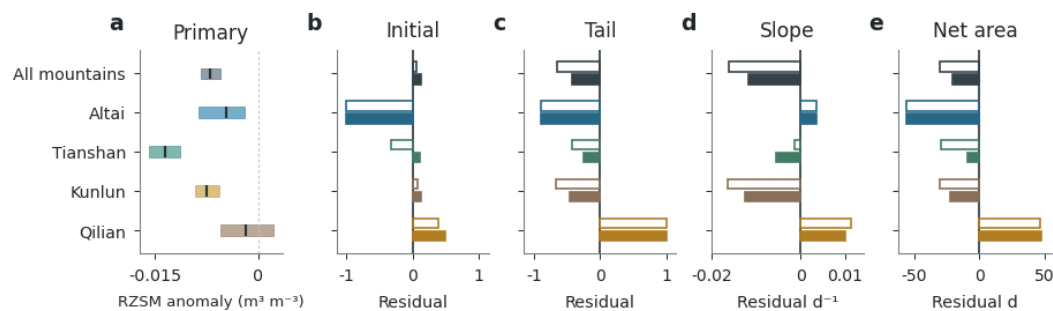


Figure 4. Event-preceding root-zone soil-moisture status and post-snowmelt moisture changes. (a) Event-preceding moisture anomalies; vertical lines and rectangles indicate weighted means and 95% bootstrap confidence intervals, respectively. (b–e): Initial values, terminal values, change slopes, and net cumulative amounts of standardized post-snowmelt moisture residuals; open and filled bars indicate the snow–climate-grid-link means and climate-grid-equal-weighted means, respectively.

3.3. Conditional Associations Between Moisture Status and Vegetation Damage

Event-preceding moisture status characterized the antecedent moisture background of compound dry–hot events, but whether it was associated with vegetation damage, and whether this association was modified by the snowmelt-to-event interval and event intensity, required further examination (Figure 5). In a sensitivity analysis using 50 sets of model-repaired data, the overall association distribution for maximum damage shifted from slightly negative values in the baseline model toward positive values, with the pooled coefficient changing from -0.71 to 0.30 . The two distributions for seasonal cumulative deficit overlapped substantially. The MEG interaction for maximum damage shifted in the opposite direction, with a more negative control-model distribution and the pooled coefficient declining from -0.60 to -1.75 , whereas the two distributions for seasonal cumulative deficit were similar in shape. For the event-intensity interaction, the two distributions for maximum damage largely overlapped, while the control-model distribution for seasonal cumulative deficit shifted slightly toward the positive side. Thus, the differences between models were reflected mainly in opposite shifts in the overall association and MEG interaction for maximum damage, whereas the corresponding distributions for seasonal cumulative deficit were comparatively consistent.

Columns represent the overall association, MEG interaction, and event-intensity interaction, respectively; rows represent maximum damage and seasonal cumulative deficit, respectively. Blue and orange indicate the baseline and control models, respectively. Histograms and the short marks at the bottom show the frequencies and values of the 50 model-repair estimates and do not represent confidence intervals.

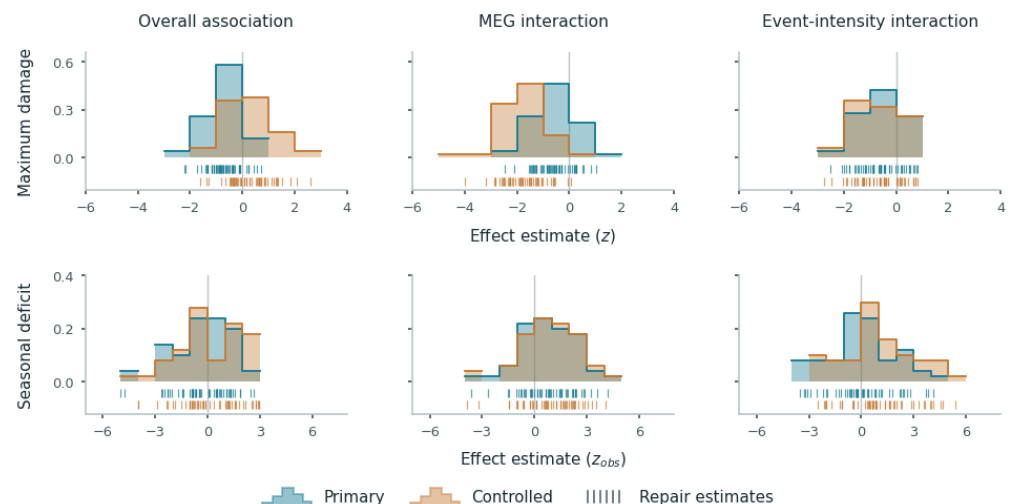


Figure 5. Distributions of estimated associations between moisture status and vegetation damage.

In the baseline model, the mountain-system contrast for maximum damage was most pronounced between the opposite distributions in the Tianshan and Qilian, with pooled coefficients of 3.29 and -3.31 , respectively (Figure 6). However, the estimated seasonal cumulative deficit in the Tianshan was shifted toward the negative side, indicating that the association of moisture status with peak damage and seasonal cumulative loss did not have the same direction. The Qilian was characterized by strong model sensitivity in seasonal cumulative deficit: the control-model distribution shifted markedly to the right, and the pooled coefficient changed from -0.90 to 2.99 . Across ecosystems, the maximum-damage estimates for alpine meadow were concentrated below zero, whereas seasonal cumulative deficit was shifted toward the positive side, forming an indicator combination opposite to that of the Tianshan. The main change in alpine steppe occurred in maximum damage, for which the control model shifted markedly toward the positive side relative to the baseline model, while the seasonal cumulative deficit distribution changed little. The seasonal cumulative deficit estimates for desert steppe were relatively high but broadly dispersed, indicating that larger association estimates coincided with greater variation among model-repair realizations.

The upper and lower groups represent mountain systems and ecosystems, respectively; within each group, maximum damage and seasonal cumulative deficit are shown in sequence.

3.4. High-Resolution Snow–Topography Context and Differences in Vegetation Damage

Regional-scale analyses cannot resolve continuous variation in snow and topography at fine scales within mountain systems. Late-snow and topographic candidate pixels were therefore compared with matched controls at a common 20 m scale and within the same compound dry–hot events. During 2019–2025, the median snow-disappearance date in high-resolution plots was consistently later in the Kunlun than in the other mountain systems (Figure 7a). The damage differences between all six candidate-pixel classes and their matched controls were positive, with late-snow candidates showing the largest difference, followed by compound candidates. This ordering occurred for both maximum damage and seasonal cumulative deficit in EVI2 and NIRv (Figure 7b). The annual-baseline late-snow comparison included 61,598 distinct candidate pixels and 173,092 distinct control pixels. Across 52 matched windows representing 50 independent events, the EVI2 maximum damage and seasonal cumulative deficit of late-snow pixels were 0.0124 and 0.0547 higher, respectively, than those of matched controls. The maximum absolute pooled standardized mean difference decreased from 0.360 before matching to 0.076 afterward,

and the EVI2 and NIRv contrasts remained positive at caliper multipliers of 0.10, 0.20 and 0.30. Among the single-feature topographic candidates, curvature had the smallest damage difference, whereas potential radiation had the largest. Among the 70 independent events covered by the main analysis, half had a cumulative compound intensity no greater than 12.34, whereas only four events exceeded 100, producing a pronounced right-hand tail (Figure 7c).

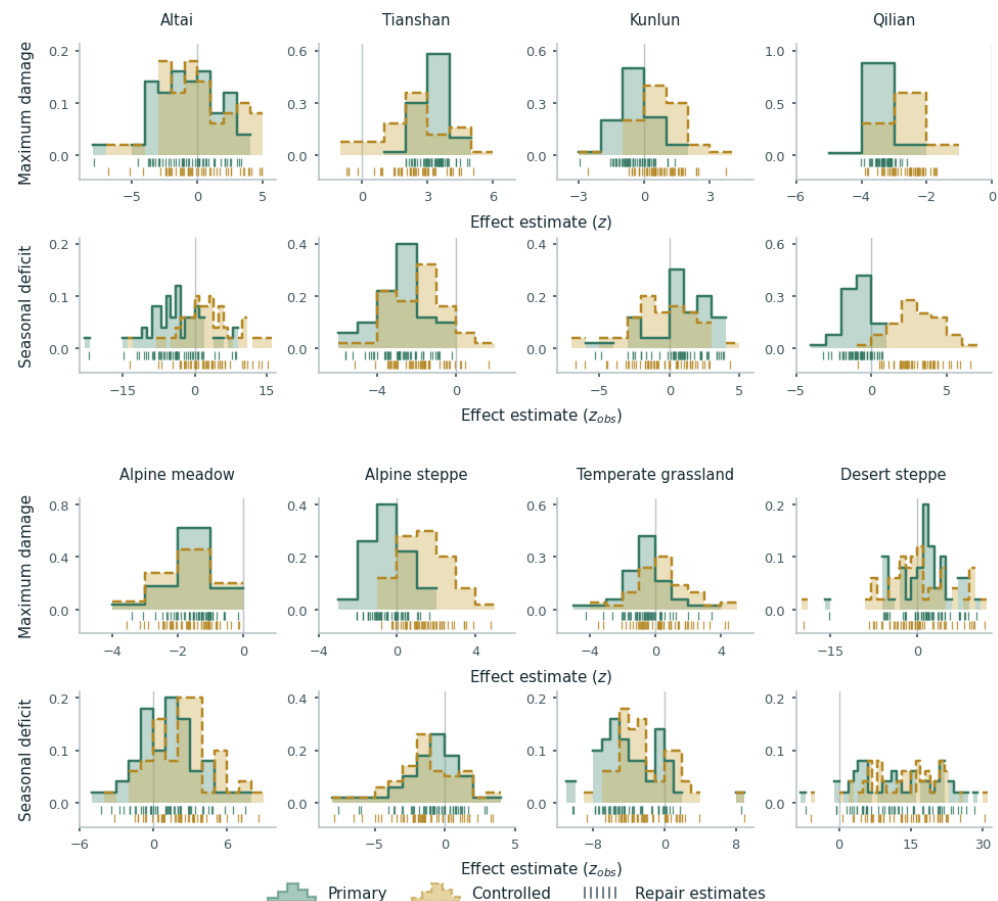


Figure 6. Estimated associations between moisture status and vegetation damage across mountain systems and ecosystems.

A single mountain system could dominate the overall matching differences. To address this possibility, each of the four mountain systems was sequentially excluded, and the stability of the maximum-damage differences and candidate ordering was tested (Figure 8a). After excluding the Tianshan, the EVI2 maximum-damage difference for late-snow candidates decreased slightly from 0.0124 to 0.0112, while that for compound candidates decreased from 0.0100 to 0.0048; the differences for the other four topographic candidate classes also became smaller. The late-snow candidate retained the highest point estimate, and its separation from the compound and individual topographic candidates also increased; the point estimates for curvature and the topographic wetness index changed from positive to slightly negative. Excluding the Qilian affected the late-snow candidate and the other candidates in opposite directions: the late-snow difference declined to 0.0088, whereas the compound and four individual topographic candidates all increased. The differences for the compound candidate and potential radiation reached 0.0124 and 0.0121, respectively, and the topographic wetness index also exceeded the late-snow candidate, moving the late-snow candidate from first place in the main analysis to fourth. By contrast, excluding the Altai or Kunlun caused only small changes in magnitude, and the ordering of all six candidates remained the same as in the main analysis.

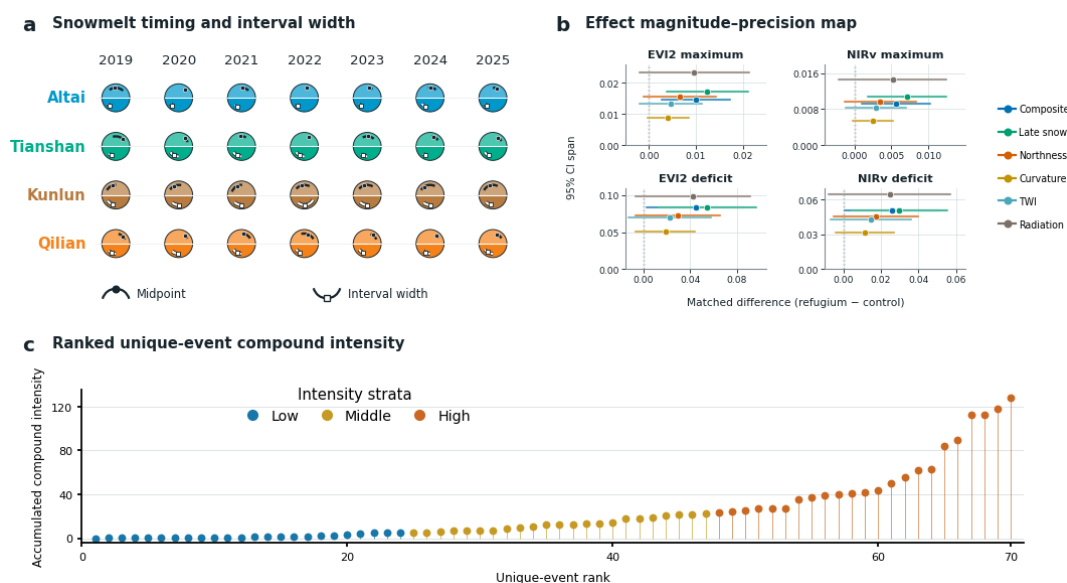


Figure 7. High-resolution snow timing, matched vegetation differences, and event intensity. **(a)** Midpoint of the snow-disappearance date and the width of the delineated interval during 2019–2025, including model-repaired values; arcs and markers indicate the interquartile range and median, respectively. **(b)** Matched differences between candidate pixels and controls, with 95% confidence intervals; the vertical axis represents interval width. **(c)** The 70 independent events ranked by cumulative compound intensity.

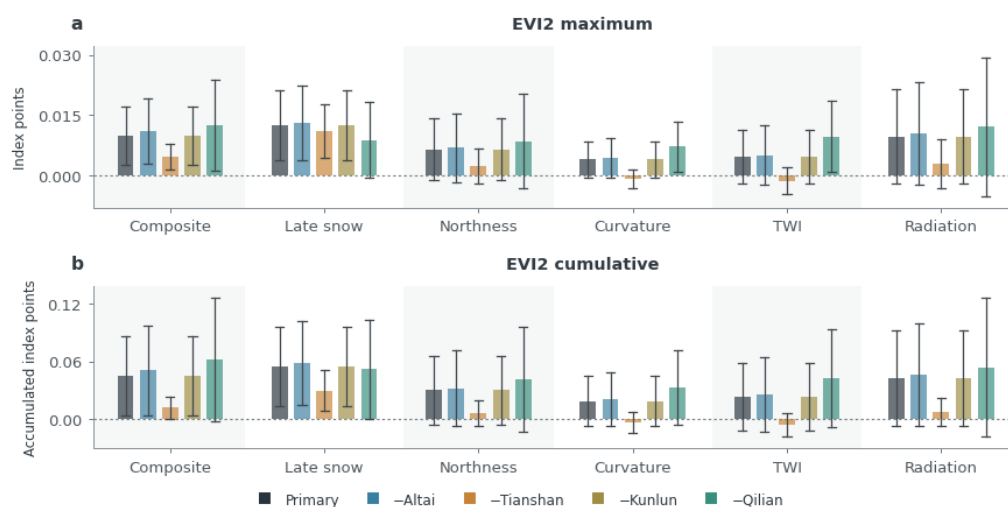


Figure 8. Matched vegetation differences after sequential exclusion of mountain systems. **(a,b)** EVI2 maximum damage and seasonal cumulative deficit, respectively, relative to the annual baseline. Bars and error bars indicate the differences between candidate pixels and matched controls and their 95% confidence intervals.

For seasonal cumulative deficit, the late-snow candidate remained higher than the matched controls in all four mountain-system exclusion tests, and the 95% confidence intervals supported this direction in all groups (Figure 8b). However, unlike the relatively small change in maximum damage after excluding the Tianshan, the cumulative-deficit difference for the late-snow candidate decreased from 0.0547 to 0.0297, indicating that peak-damage differences and seasonal cumulative differences responded differently to sample composition. The cumulative-deficit difference for the compound candidate decreased from 0.0447 to 0.0117, and that for potential radiation decreased from 0.0425 to 0.0070; curvature and the topographic wetness index both became slightly negative. After

excluding the Qilian, the cumulative-deficit difference for the late-snow candidate was 0.0518, close to the main-analysis estimate, whereas that for the compound candidate increased to 0.0615 and exceeded the late-snow candidate. Thus, this reversal in ordering was driven mainly by an increase in the compound-candidate estimate rather than by a substantial weakening of the cumulative-deficit estimate for the late-snow candidate. Across the two outcomes, the maximum-damage difference for the late-snow candidate was lowest when the Qilian was excluded, whereas its cumulative-deficit difference was lowest when the Tianshan was excluded (Figure 8a,b).

3.5. Matched Vegetation Differences and Stability Within the Event Window

The annual baseline reflects departures of vegetation from the corresponding period in previous years, whereas the event-preceding baseline focuses on changes after event onset. In a sensitivity sample with relaxed land-cover stability screening, the event-preceding vegetation level was used as the reference, and damage was compared between candidate pixels and matched controls across 77 independent events. The EVI2 seasonal cumulative deficit of candidate pixels was lower than that of controls, with a pooled difference of -0.0489 ; the confidence intervals from all four mountain-system exclusion tests supported this negative association (Figure 9a). After excluding the Tianshan and Altai, the differences narrowed to -0.0407 and -0.0426 , respectively; after excluding the Qilian, the difference widened to -0.0693 , whereas the estimate after excluding the Kunlun remained close to that for the complete sample. Changes in mountain-system composition altered the magnitude of the difference, but the direction of lower seasonal cumulative deficit for candidate pixels was retained throughout. Event-level results further showed that 52 of the 77 events had negative differences, and the distribution extended farther into the negative tail, with a minimum of -0.3611 , whereas the largest positive value was only 0.0526. The overall negative difference in cumulative deficit was therefore reflected both in the larger number of events with negative differences and in the longer negative tail.

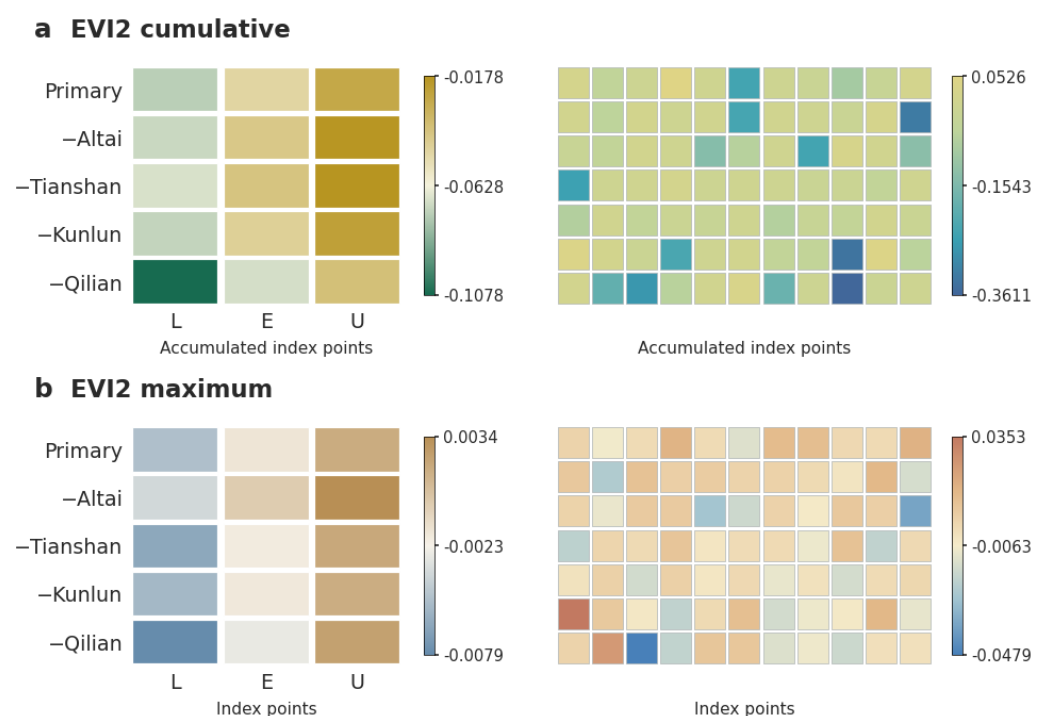


Figure 9. EVI2 matched differences for candidate late-snow-topographic pixels. (a) Seasonal cumulative deficit; (b) maximum decline.

The pooled difference in maximum decline was -0.0015 . The point estimates remained slightly negative in all mountain-system exclusion groups, but the direction was not clearly resolved (Figure 9b). Event-level comparisons showed that, in the 33 events in which candidate pixels had a lower maximum decline than controls, their seasonal cumulative deficit was also lower than that of controls. In addition, 19 events had a lower seasonal cumulative deficit but a higher maximum decline. The divergence between the two indicators was therefore concentrated in the latter group: reduced cumulative deficit was not accompanied by a simultaneous reduction in peak decline.

3.6. Cross-Product Consistency of Event-Preceding Evapotranspiration Anomalies

A single evapotranspiration product cannot reveal how sensitive estimates of event-preceding anomaly intensity are to product selection. Cumulative positive evapotranspiration anomalies from PML and MOD16 were therefore compared using the same sample and time window. Among 612 paired records, the Kunlun showed the clearest concentration along the 1:1 line: records with both low and relatively high values were close to the line, and the correlation coefficient reached 0.83 (Figure 10a). Tianshan records were much more widely dispersed on both sides of the 1:1 line. Some records showed a weak anomaly in MOD16 but a high value in PML, while the opposite pattern also occurred; the correlation coefficient was only 0.47. This bidirectional departure indicates that the difference between products in the Tianshan did not simply reflect an overall higher estimate from one product. The correlation coefficient in the Qilian was 0.65. Its point cloud generally extended toward the upper right as anomaly magnitude increased, but substantial vertical spread remained at similar MOD16 values, indicating a combination of common variation and amplitude dispersion.

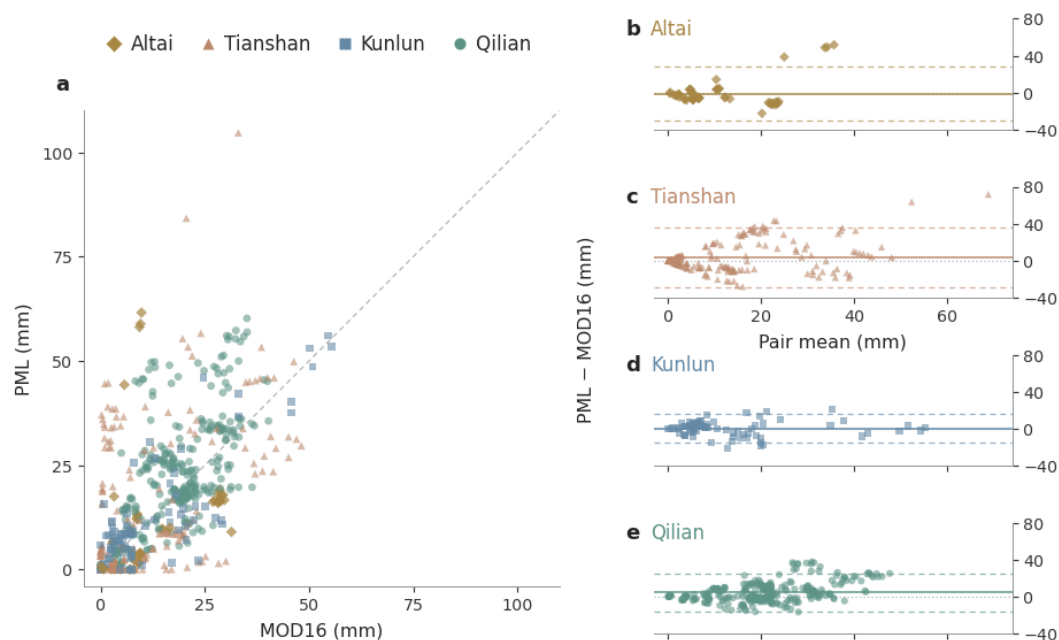


Figure 10. Cross-product comparison of event-preceding cumulative positive evapotranspiration anomalies. (a) Paired PML and MOD16 values; (b–e) product differences and paired means for the Altai, Tianshan, Kunlun, and Qilian, respectively. Solid and dashed lines indicate the mean difference and its ± 1.96 standard deviations, respectively; units are mm.

The mean product differences in the Qilian and Tianshan were similar, but the distribution of paired differences was substantially wider in the Tianshan (Figure 10c,e). In both regions, PML estimates were higher on average, but the Tianshan also contained larger positive and negative differences; a small number of records in the positive tail lay

far from the main distribution, and the standard deviation of the differences was 16.56 mm, higher than the 10.55 mm observed in the Qilian. Similar mean offsets therefore did not imply an equivalent record-level correspondence between the two regions; the Tianshan mean concealed greater bidirectional disagreement. The Kunlun showed both a mean difference close to zero and a relatively narrow difference distribution (Figure 10d), consistent with the concentration along the 1:1 line in the scatterplot. This indicates that its close cross-product correspondence involved both common variation and relatively similar anomaly magnitudes.

3.7. Vegetation Damage and Seasonal Deficit Under Future Climate Scenarios

When the response relationships established for the historical period were applied to future climate combinations, the analysis first identified the mountain systems in which high damage values were concentrated and examined whether this pattern changed with the response-model specification (Figure 11). Maximum damage showed two pronounced patterns among mountain systems. The Altai had the widest range of estimates, from 0.55 to 2.32 in the main analysis. Within this range, MPI-ESM1-2-HR under SSP5-8.5 during 2061–2080 produced the peak value of 2.32; the sensitivity analysis reached 2.61 under the same combination. The Tianshan showed persistent stratification by climate model: in the main analysis, estimates for MPI-ESM1-2-HR were concentrated between 1.27 and 1.49, overall higher than the 0.53–1.00 range for ACCESS-ESM1-5. This ordering persisted under the alternative response model.

Seasonal deficit further revealed the cumulative magnitude of damage over the fixed response window. The Altai remained the mountain system with the most pronounced cumulative deficit, with main-analysis estimates ranging from 1.68 to 6.08 and reaching their maximum under the same climate combination that produced the maximum-damage peak. Estimates for the Kunlun were concentrated between 0.69 and 1.58, while estimates for the Tianshan and Qilian lay between those for these two systems. The alternative response model increased seasonal deficit for nearly all combinations, with the Altai peak rising to 6.78. Across all combinations, seasonal deficit increased by an average of 0.87 z-observations, whereas maximum damage increased by an average of 0.20 prediction-RMS-standardized units, indicating that the response-model specification had a greater effect on cumulative damage magnitude. The correspondence between high-value combinations for the two indicators further showed that climate combinations with more serious event-period damage were generally also associated with larger seasonal cumulative deficits.

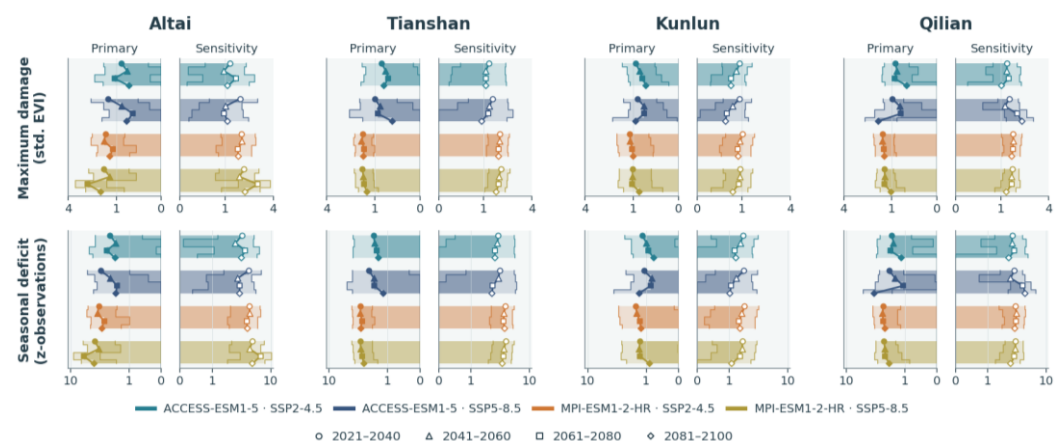


Figure 11. Maximum vegetation damage and seasonal deficit across four mountain systems under future climate scenarios.

4. Discussion

4.1. Divergence Between Peak Damage and Seasonal Cumulative Deficit Along the Snowmelt-to-Event Interval

Across the mountains of northwestern China, earlier snowmelt was associated with lower maximum vegetation damage but a larger seasonal cumulative deficit. This contrast shows that snowmelt timing can be linked to peak and cumulative responses in opposite directions. Maximum damage emphasizes the most severe departure during an event, whereas cumulative deficit retains the contribution of deficits at each observation date from event onset to the end of the growing season. A lower damage peak can therefore coexist with a greater seasonal burden, and a ranking based on the most severe event-period response can be reversed when cumulative loss is considered. A comparable trade-off between early-season gains and later-season losses has been reported for snowmelt-related carbon uptake: greater spring carbon uptake under earlier snowmelt can coexist with reduced summer productivity, reducing the contribution of early growth to annual carbon uptake [8].

The snowmelt-to-event interval was primarily associated with a smaller seasonal cumulative deficit, whereas maximum damage increased only slowly. The snowmelt-date anomaly indicates whether snow disappeared earlier or later than usual, while the snowmelt-to-event interval links that seasonal background to the timing of a compound dry-hot event. A longer interval can result from earlier snowmelt or a later event and therefore also reflects the position of the event within the seasonal trajectory. A later event shortens the period over which deficits can accumulate between event onset and the end of the growing season, so the cumulative metric depends on both the magnitude of vegetation departure and the time available for accumulation. Window diagnostics further support interpreting seasonal deficit as the total post-onset vegetation burden, alongside shorter-term responses measured over fixed windows. The anomaly relative to the usual snowmelt date and the snowmelt-to-event interval therefore carry distinct ecological meanings and should be interpreted together with event timing and the response window. In the local sensitivity analysis using pre-event vegetation level as the reference, peak decline and cumulative deficit also yielded opposite candidate-control orderings: 19 events had point estimates indicating a larger peak decline but a smaller cumulative deficit for candidate pixels.

4.2. Conditional Association Between Antecedent Moisture Status and Vegetation Damage

Root-zone soil moisture before compound dry-hot events was generally below the seasonal norm across the mountains of northwestern China, indicating that vegetation entered these events under already depleted moisture conditions. In the post-snowmelt process sample, moisture residuals also shifted from slightly above the model expectation initially to below expectation at the end. The former characterizes the antecedent deficit at event onset, whereas the latter shows that the relative moisture advantage shortly after snow disappearance did not persist through the observation window. Once meltwater enters the soil, its contribution during the subsequent growing period depends on retention and consumption within the soil profile. Snow-manipulation experiments likewise show that earlier snowmelt can maintain drying in shallow soil for several months while producing no clear response in deeper layers, indicating that the moisture response to snowmelt timing is constrained by soil depth [58].

In the baseline model, the point estimate linking antecedent moisture to maximum damage was positive in the Tianshan and negative in the Qilian; alpine meadow showed a negative association for peak damage but a positive association for seasonal cumulative deficit. These combinations are consistent with a role for moisture that depends on the

balance between water supply and vegetation water use. Transpiration cools vegetation through latent-heat exchange while consuming soil water, so the cooling benefit is accompanied by depletion of stored water. Simulations of vegetation greening show that cooling and drying effects of contemporaneous transpiration can offset one another, while enhanced early-season transpiration can intensify subsequent warm-season soil-moisture deficits [59]. This balance provides a process-based interpretation for the observed combinations of moisture status and damage: the benefit of wetter antecedent conditions depends on how much water remains available when the event arrives and whether subsequent inputs can sustain vegetation demand.

Event-preceding evapotranspiration anomalies provide additional information about antecedent water use. In the Kunlun, PML and MOD16 showed strong covariation and similar anomaly magnitudes, providing convergent product support for anomalous evapotranspiration activity in that region. Root-zone moisture anomalies describe the relative water-storage state at event onset, whereas cumulative positive evapotranspiration anomalies summarize water output above the seasonal baseline during the preceding period. The two indicators, therefore, represent complementary evidence: one describes state, and the other flux.

4.3. Local Ecological Meaning of Late-Snow and Terrain Candidates

The high-resolution matching analysis across the mountains of northwestern China compared candidate pixels with controls from the same event, climate grid cell, and ecosystem type. This design evaluated snow and terrain conditions under similar large-scale exposure. Candidate classes were defined from snow and terrain attributes before outcome comparison, so vegetation damage was not used to assign groups. The analysis therefore avoids selecting low-damage patches first and then interpreting their environmental attributes as protective factors. The potential benefit of late-lying snow depends on when meltwater becomes available, while delayed growth initiation also changes the relative timing of vegetation demand and compound dry-hot exposure. Links between snowmelt timing, green-up, and peak timing indicate that snow disappearance first shifts the seasonal arrangement of growth; experimental evidence that peak biomass can remain stable after a shift in snowmelt date further shows that phenological displacement does not necessarily translate into a productivity gain [9,60]. The interpretation of late-snow patches should therefore consider both delayed water supply and the way this timing aligns vegetation growth with event exposure. The local matching estimates describe the vegetation response associated with these prespecified environmental conditions rather than a buffering capacity inferred directly from snow persistence [61].

Mountain-system composition changed the relative ordering of late-snow and terrain candidates. Excluding the Tianshan generally reduced the differences for compound and terrain candidates. Excluding the Qilian lowered the late-snow candidate in the ordering, while the compound candidate's seasonal cumulative deficit increased and exceeded that of the late-snow candidate. The Tianshan sample mainly affected the magnitude of differences for compound and terrain candidates, whereas the Qilian sample affected the comparison between late-snow and compound candidates. These results identify the candidate comparisons most sensitive to the regional sample composition. Terrain-generated local environments are conditioned by the regional hydroclimatic background, so their effects reflect the combined conditions of water supply, energy availability, and growth timing. This provides an ecological basis for interpreting the mountain-system exclusion results: the relative importance of the same snow or terrain attribute can change when it is placed in a different regional hydroclimatic context [62]. Regional associations and local matched contrasts offer complementary interpretations at their respective spatial scales. Maximum damage and accumulated deficit describe peak and cumulative responses,

while annual- and pre-event-baseline local comparisons retain their distinct temporal references.

4.4. Practical Implications of Future Scenarios and Study Limitations

The concentration of future-scenario risk in particular regions and climate combinations provides guidance for future monitoring and risk preparation in the mountains of northwestern China. In some combinations, the Altai showed both high maximum damage and a large seasonal cumulative deficit, indicating that monitoring in this mountain system should capture both intense event impacts and the cumulative burden over the growing season. Historical combinations with a relatively small peak but a large cumulative deficit likewise show why a small short-term decline does not imply a small seasonal loss; observations should extend from the compound dry-hot event through the end of the growing season. The separation among climate models in Tianshan damage estimates persisted after replacing the vegetation-response model. Preparedness efforts can therefore account for the climate combinations associated with higher and lower damage estimates rather than relying on a single average scenario. As warming may increase compound dry-hot exposure [59,63], continuous monitoring should link post-snowmelt moisture dynamics with event-period vegetation decline and seasonal cumulative deficit, covering both antecedent moisture status and the accumulation of impacts after event onset.

Long-term assessment of snow and vegetation responses in the mountains of northwestern China is constrained by the continuity of observations and by the representation of processes across spatial scales. Cloud cover and gaps between usable satellite observations leave residual uncertainty in the timing of snow disappearance. Multi-source imagery can reduce this uncertainty [64], but it cannot fully reconstruct melt processes during unobserved intervals. Fine-scale snow patches and climate-grid root-zone moisture also have different spatial supports; a common grid does not recover slope-scale moisture variation within a grid cell, so the local delivery and use of meltwater remain only partly represented. The physiological explanations for the divergence between peak damage and cumulative deficit remain tentative and require independent field validation. Future projections are further conditioned by the transferability of historical climate-vegetation relationships across periods; changes in ecological response relationships as environmental conditions evolve introduce uncertainty into long-term prediction [65].

5. Conclusions

Regional estimates for the mountains of northwestern China during 2006–2025 showed that earlier snowmelt was associated with lower maximum vegetation damage but a larger seasonal cumulative deficit. A smaller event-period damage peak therefore did not imply a smaller cumulative vegetation deficit from event onset to the end of the growing season. In addition to the anomaly of snowmelt timing relative to the usual date, the interval between snowmelt and event onset was associated with vegetation damage. When this interval increased from the 25th to the 75th percentile, the estimated seasonal cumulative deficit decreased by 9.30 and 9.51 z-observations in the linear and quadratic models, respectively, whereas maximum damage increased by 0.64 and 0.98 z. Moisture evidence provides the environmental context for this timing relationship. The mean standardized root-zone moisture residual in the post-snowmelt process sample declined from 0.12 at the beginning to −0.43 at the end, while event-preceding root-zone moisture was generally below the seasonal norm. These results show that the relative moisture advantage shortly after snow disappearance did not persist through the observation window. The association between antecedent moisture and vegetation damage varied with mountain system, ecosystem, and response metric, connecting snowmelt timing with specific hydroclimatic and ecological contexts.

At the local scale, late-snow candidate pixels showed higher vegetation damage under the annual baseline: their matched EVI2 maximum damage and seasonal cumulative deficit were 0.0124 and 0.0547 higher than those of controls, respectively. In a sensitivity analysis with relaxed land-cover stability screening and pre-event vegetation level as the reference, candidate pixels had an EVI2 cumulative deficit 0.0489 lower than controls. Sequential exclusion of mountain systems changed the magnitude of the difference, but candidate pixels continued to show lower cumulative deficit. Future scenarios further identified the regions and climate combinations where risk was concentrated. Under some combinations, the Altai showed both high maximum damage and a large seasonal cumulative deficit; the maximum seasonal cumulative deficit in the main analysis reached 6.08 standardized observations under MPI-ESM1-2-HR, SSP5-8.5, and 2061–2080. Tianshan damage estimates remained stratified among climate models after the response model was replaced, informing monitoring design and preparedness across multiple scenarios. Overall, this study shows that snowmelt preconditioning in the mountains of northwestern China is expressed through a divergence between event peaks and seasonal cumulative responses and is jointly conditioned by regional moisture background and local snow–terrain settings.

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Data Availability Statement: The source datasets used in this study are publicly available from the repositories cited in Section 2.2. The derived data are available from the corresponding author upon reasonable request.

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Abbreviations

CDHE, compound dry–hot event; CMIP6, Coupled Model Intercomparison Project Phase 6; CR2, bias-reduced cluster-robust variance estimator; EOS, end of the growing season; ESGF, Earth System Grid Federation; EVI, Enhanced Vegetation Index; EVI2, two-band Enhanced Vegetation Index; LAI, leaf area index; MEG, snowmelt-to-event gap; NIRv, near-infrared reflectance of vegetation; PML, Penman–Monteith–Leuning; SMA, standardized snowmelt-date anomaly; SMOD, snow disappearance date; SOS, start of the growing season.

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