

Response to Reviewers

Dear Editor and Reviewers,

We sincerely thank the Editor and all reviewers for their thorough and constructive comments on our manuscript. We have carefully considered all the suggestions and have substantially revised the manuscript accordingly.

In the revised manuscript, changes responding to Reviewer 1 are highlighted in red, to Reviewer 2 in blue, and to Reviewer 3 in green, to facilitate cross-referencing with our point-by-point responses below.

Below we provide our detailed responses to each reviewer's comments. All section and paragraph references cited in our responses refer to the marked-up revised manuscript. We believe that the revisions have adequately addressed all the concerns raised, and we hope that the revised version is now suitable for publication.

Sincerely,

Haixing Li (on behalf of all authors)

Reviewer 1

Reviewer's comment 1 (Title precision):

“The title uses the broad term ‘Snow-Temperature Interactions,’ which does not accurately reflect the actual variables analyzed in the paper. The study focuses specifically on snow depth and land surface temperature, not on snow or temperature in a general sense. I recommend revising the title to a more precise expression, such as ‘Mechanisms and Patterns of Snow Depth and Land Surface Temperature Interactions in Arid Mountains: Coupling Coordination and Lagged Responses Across Xinjiang, China.’ Similar precision should be applied consistently throughout the abstract and the main text to avoid misleading readers about the core study object.”

Our Response to comment 1:

We fully agree. The current title is indeed too general. We will revise the title to be more precise. Following your suggestion, we propose a new title:
“Mechanisms and Patterns of Snow Depth and Land Surface Temperature Interactions in Arid Mountains: Coupling Coordination and Lagged Responses Across Xinjiang, China”

We will also check the abstract and the main text to ensure that the terms “snow depth” and “land surface temperature” (rather than generic “snow” or “temperature”) are used consistently. Thank you for pointing this out.

Reviewer's comment 2 (Scientific significance and practical value):

“The scientific significance and practical value of the study are not sufficiently highlighted. Readers need to understand, from the outset, what concrete scientific advances or practical improvements can be achieved by quantifying the coupling coordination and time-lagged responses between snow depth and land surface temperature. For example, does this approach help quantitatively identify changes in snowpack thermal inertia, improve the timing of snowmelt predictions, provide empirical constraints for snow parameterization schemes in land surface models, or establish critical thresholds for water resource management in arid regions? I suggest that the authors add a concise, forceful paragraph at the end of the Introduction and

another at the beginning of the Conclusions to clearly articulate the unique contributions and specific application scenarios of this work, rather than dispersing these points vaguely across multiple sections.”

Our Response to comment 2:

We have followed your suggestion and made substantial revisions to both the Introduction and the Conclusions, going beyond simply adding two paragraphs.

Overall revision of the Introduction: We have substantially restructured the Introduction to better motivate the need for an integrated framework coupling coordination analysis with time-lag diagnostics. The opening paragraph now emphasizes the co-evolution of SD and LST rather than isolated variables. The third paragraph highlights the snowpack memory effect and the inadequacy of treating SD and LST separately, establishing why a coupled-system view is necessary. The fourth paragraph articulates two fundamental limitations of conventional correlation (conflating interaction strength with system health and ignoring time lags) and poses three progressive scientific questions: system stability under warming, hierarchical controls on coupling strength, and characteristic response time scales across seasons, elevations, and mountain ranges. We then explicitly state that answering these questions requires the combination of the Coupling Coordination Degree Model (CCDM) and time-lagged cross-correlation analysis. A concise paragraph specifies that using long-term high-resolution remote sensing data we quantify coupling degree, coordination level, and response lag patterns, followed by three primary contributions. Finally, a new concluding paragraph explains the diagnostic power of combining coupling coordination with time-lag analysis and details four practical outputs: maps for melt predictability, region-specific parameters for model calibration, elevation-based reference for water planning, and the CD-CCD decoupling as an indicator of vulnerable areas. These revisions ensure readers understand the limitations of conventional methods, the key scientific questions, and how our framework uniquely addresses them.

The fully revised Introduction is provided below. The new concluding paragraph requested by the reviewer appears as the final paragraph of this revised Introduction

Revised Introduction (full text):

Understanding the interaction between snow depth (SD) and land surface temperature (LST) is critical for predicting hydrological responses and climate feedbacks in snow-dominated regions. As a key interface in land-atmosphere interactions, the seasonal snowpack governs surface energy budgets through its high albedo and low thermal conductivity, while simultaneously modulating water availability via its accumulation and melt (Barnett et al., 2005; Essery, 2013). Within this context, snow depth serves as an integrative state variable that captures the net effect of meteorological forcing and snowpack evolution, and LST provides the primary thermal forcing that drives snowmelt (Lehning et al., 2002a; Marks and Dozier, 1992). Consequently, the co-evolution of SD and LST—rather than either variable in isolation—determines the timing and magnitude of snowmelt runoff, the stability of snow-albedo feedbacks, and the vulnerability of water resources to climate change.

The Xinjiang Uygur Autonomous Region is a hydrologically critical zone in arid Central Asia, encompassing a unique mountain–basin system comprising the Altai, Tianshan, and Kunlun ranges, along with the intervening Junggar and Tarim Basins (Chen et al., 2015). This configuration creates a natural laboratory with pronounced climate, topographic, and snow accumulation gradients (Zhang et al., 2019). The region's water security is fundamentally dependent on snowmelt from these high mountains. However, the mechanistic responses of snowpack dynamics to thermal forcing—particularly across different mountain ranges and elevation zones—remain poorly quantified at process-relevant scales. The complex interplay between continental climate and extreme topography generates heterogeneous SD-LST interactions that challenge existing models (Li et al., 2020; Wang et al., 2022).

The SD-LST relationship is inherently complex—exhibiting non-linearities, hysteresis, and strong spatiotemporal heterogeneity (Beniston et al., 2018). Interactions

between SD and LST include both immediate thermodynamic adjustments and delayed hydrological feedbacks that vary systematically with elevation, season, and regional climate. For instance, in the Tianshan Mountains, warming has reduced snow duration, delayed accumulation, and accelerated melt (Aizen et al., 2007). The snowpack also possesses a memory effect: the influence of temperature on snow depth persists over time, meaning that the true strength of SD-LST interaction depends on when the thermal forcing occurred; snow can introduce significant lags in thermal responses (Zhang et al., 2021; Li et al., 2016). These elevation-dependent and seasonally variable patterns are widely observed in other mountain ranges as well (Immerzeel et al., 2010; Pepin et al., 2015; Zhang et al., 2013).

The prevailing analytical paradigm that relies on statistical correlations, while robustly establishing empirical relationships, harbors two fundamental limitations (Clark et al., 2011) when applied to snow-climate systems. First, it treats SD and LST as separate variables rather than as an interacting system. Consequently, it cannot distinguish whether the snow-thermal system evolves stably and synergistically or fluctuates erratically under stress. For instance, a strong negative correlation between SD and LST could arise from two fundamentally different situations: a deep, cold snowpack that buffers temperature fluctuations and melts gradually (a well-coordinated, resilient system), versus a thin, vulnerable snowpack that collapses rapidly under warming, with temperature driving snow loss but no buffering capacity remaining (a maladaptive system). Conventional correlation treats these two scenarios identically, thereby masking the critical distinction between coupling intensity and coordination quality. Second, this approach largely overlooks the temporal dimension of snow-temperature interactions. The response of snow to thermal forcing is not instantaneous; heat propagates through the snowpack at a rate determined by its depth, density, and liquid water content. Conventional correlation-based methods ignore such time lags, and therefore cannot measure how long it takes for temperature changes to affect snow. This propagation delay—ranging from near-zero in shallow ephemeral snow to several weeks in deep, cold snowpacks—is a direct manifestation of snow thermal inertia. Neglecting these time-lags ignores the memory effect inherent to

seasonal snowpacks, which is essential for understanding melt timing, energy storage, and the elevational dependence of snow-climate feedbacks.

Consequently, several fundamental scientific questions remain unanswered. First, under warming pressure, is the SD-LST system maintaining stable and sustainable co-evolution, or has it already shifted toward a maladaptive, unsustainable relationship? Second, what hierarchical control structure, operating from macro-scale climate regimes down to micro-scale local factors, determines the spatial pattern of snow-temperature coupling strength across mountain ranges? Third, what are the characteristic time scales of SD response to thermal forcing, and how do these response lags—ranging from near-instantaneous in shallow ephemeral snow to several weeks in deep, cold snowpacks—vary across seasons, elevations, and mountain ranges? Answering these questions requires an integrated analytical framework that jointly diagnoses coupling strength, coordination quality, and response lags—exactly the combination of the Coupling Coordination Degree Model and time-lagged cross-correlation analysis that this study proposes. The absence of such a framework has long hindered the physical representation of snow processes in land surface and hydrological models (Nijssen et al., 2001).

Using long-term, high-resolution remote sensing data, we apply this framework to systematically investigate SD-LST interactions across Xinjiang and quantify: (1) the degree of coupling; (2) the coordination level across climatic seasons and topographic settings; and (3) the spatiotemporal patterns of response time lags. This investigation makes three primary contributions to cryospheric science: First, it establishes a quantitative, process-informed understanding of how snowpack responds to thermal forcing across one of Central Asia's most hydrologically critical regions. Second, it introduces and validates an analytical framework—combining coupling, coordination, and lag analysis—that can be applied to other snow-dominated regions globally. Third, it reveals that these interactions are governed by a hierarchical control system—from macro-scale climate regimes down to micro-scale local factors—providing a transferable framework for diagnosing snow-climate vulnerability in other arid mountains.

Critically, the joint use of coupling coordination and time-lag analysis offers diagnostic power that neither metric alone can achieve. Time lags quantify snowpack thermal inertia, while the CCD reveals whether that inertia reflects a healthy, well-buffered system or a dysfunctional one under stress. Their combination identifies regions where strong temperature forcing is no longer matched by sustainable snowpack evolution—an early warning of emerging vulnerability. Applied across Xinjiang’s Mountain-basin systems, this framework delivers practical outputs. Maps of lag times and CCD help pinpoint where snowmelt is regular and predictable versus abrupt and erratic, directly informing forecast lead time adjustments. Region-specific parameters—elevation-dependent CCD thresholds and directional lag changes—provide empirical targets for calibrating snow thermal schemes (e.g., thermal conductivity, albedo decay) in land surface models such as Noah-MP and VIC. The elevation zone where coupling shifts from low to high coordination offers a science-based reference for water resource planning in arid basins. Finally, the decoupling between high CD and low CCD serves as a ready-to-use indicator for targeted monitoring of climatically vulnerable areas. By translating complex snow-climate interactions into measurable, region-specific metrics, this work bridges cryospheric research and operational climate adaptation.

Revision of the Conclusions: We have replaced the original opening paragraph with a concise, forceful paragraph. This paragraph now clearly articulates three unique contributions: distinguishing coupling strength from system state, establishing response lag time as a metric of thermal inertia, and providing a transferable analytical framework for data-scarce, topographically complex regions. The rest of the Conclusions has been condensed to focus on core findings, removing repetitive descriptions and specific numerical values (e.g., exact lag days, years) as also suggested in Comment 3.

New paragraph added at the beginning of the Conclusions (exact wording):

This study delivers three tangible advances for snow-climate science and water management in arid mountains. First, it distinguishes coupling strength from system state, revealing that a strong correlation between SD and LST can mask underlying system dysfunction—a critical insight for identifying vulnerable regions. Second, it establishes response lag time as a physically meaningful metric of snow thermal inertia, enabling regional - scale diagnosis of buffering capacity. Third, it provides a transferable analytical framework that moves beyond conventional correlation to diagnose system stress in data-scarce, topographically complex regions.

We believe that these comprehensive revisions – including the overall reorganization of the Introduction – have made the scientific significance and practical value of our work much more visible and compelling.

Reviewer's comment 3 (Heading hierarchy and Conclusions length)

“The deepest heading level used in the manuscript is level three, for a journal article this makes the structure appear somewhat fragmented and increases the cognitive load for readers. I recommend simplifying the heading hierarchy to no more than two levels, i.e., only main sections and subsections, without deeper numbering such as 4.2.1 or 4.3.2. Different subtopics within a subsection can be separated by lead-in sentences or bolded phrases without creating additional numbered headings. Furthermore, the Conclusions section is overly long, containing many specific numerical values and repetitive descriptions, which dilutes the key messages. I advise condensing the Conclusions to core findings, each focusing on one essential insight, and moving the remaining detailed information to the Discussion or to supplementary materials.”

Our Response to comment 3:

Headings: We will simplify the heading hierarchy in the final revised manuscript. All third-level headings (e.g., 4.2.1, 4.3.2) will be removed and replaced by bold or italic lead-in phrases within the corresponding subsections. This will improve readability without breaking the logical flow.

Conclusions: As noted above, we have already condensed the Conclusions

section from six paragraphs to three, removing specific numerical values and detailed seasonal trend descriptions. The revised Conclusions now focuses only on the essential insights: (1) three tangible advances, (2) the hierarchical control system and the CD-CCD mismatch as an early warning, and (3) the transferability of the framework and future directions. The remaining detailed information (e.g., exact lag times in days, long-term trend slopes) remains in the Results and Discussion sections, as appropriate.

The revised Conclusions (exact wording):

This study delivers three tangible advances for snow-climate science and water management in arid mountains. First, it distinguishes coupling strength from system state, revealing that a strong correlation between SD and LST can mask underlying system dysfunction—a critical insight for identifying vulnerable regions. Second, it establishes response lag time as a physically meaningful metric of snow thermal inertia, enabling regional - scale diagnosis of buffering capacity. Third, it provides a transferable analytical framework that moves beyond conventional correlation to diagnose system stress in data -scarce, topographically complex regions.

We demonstrate that SD-LST interactions are governed by a three - tiered hierarchical control system involving macro -scale climate gradients, meso -scale topography, and micro - scale local factors. Critically, coupling degree and coordination degree are distinct metrics; their spatial mismatch serves as an early warning of system stress, identifying where rapid warming outpaces snowpack adaptive capacity. Response lag time exhibits region -specific signatures, from long, stable lags in deep, cold snowpacks to elevation -threshold -dependent behavior in marginal snow environments. Long - term trends reveal seasonally differentiated and regionally heterogeneous responses, precluding one -size -fits -all modeling approaches.

The proposed framework is applicable to other snow -dominated mountain regions facing similar data and topographic challenges. For Xinjiang and analogous arid areas, the identified vulnerability and resilience hotspots provide a scientific basis for prioritizing monitoring and climate adaptation. Future research should integrate

process-based snowpack modeling to attribute lag patterns to specific energy balance components, and extend this framework to other Central Asian ranges to advance continental-scale understanding of cryosphere-climate-hydrology interactions under accelerating warming.

Reviewer's comment 4 (Font size)

“The font size used in the main text is somewhat small, which makes reading somewhat tiring. While the line spacing is not excessively dense, the small font size still impairs readability and the overall reading experience. I suggest that the authors increase the font size appropriately, for example to 11 or 12 points, while maintaining clear line spacing, so as to improve the accessibility and communication efficiency of the paper.”

Our Response to comment 4:

We thank the reviewer for the valuable suggestion. Regarding the font size, the journal's template specifies a main text font of 10 pt, which we have strictly adhered to in the revised manuscript. To enhance readability within this constraint, we have carefully reformatted the entire paper according to the template, including maintaining a clear 1.5-line spacing and optimizing paragraph and margin settings. We believe these adjustments, together with the legible line spacing, have improved reading comfort. If the journal's policy permits, we are open to considering a larger font, but we will primarily follow the template requirements. We appreciate the reviewer's understanding and constructive feedback.

Additional minor corrections

We have also carefully proofread the manuscript and corrected several typographical errors and inconsistencies (e.g., standardising the use of “snow depth (SD)” and “land surface temperature (LST)” throughout). A detailed list of technical corrections is available upon request.

Reviewer 2

Reviewer's comment 1:

"Abstract. Some statements in the abstract are slightly strong. The manuscript mentions a 'hierarchical control system', a 'process-aware framework', and metrics that may improve the representation of mountain snow–climate feedbacks in hydrological and climate models. However, the current study mainly provides an empirical diagnostic analysis. The authors should tone down these claims or provide clearer support for them."

Our Response to comment 1:

We thank the reviewer for this constructive comment. We fully agree that our study is primarily an empirical diagnostic analysis, and that several statements in the original abstract were overstated. Rather than making piecemeal revisions, we took this as an opportunity to substantially rework the abstract—reframing the opening, narrative structure, and methodological positioning to more accurately reflect the scope and nature of our study.

The key conceptual shifts are: (1) the opening now explicitly identifies the three quantifiable dimensions we address—interaction strength, system harmony, and response timing—which directly correspond to our three analytical components (CD, CCD, and lag analysis); (2) we consistently frame our approach as a "diagnostic framework" and explicitly contrast it with "mechanistic" modeling, directly addressing the reviewer's core concern; (3) the "hierarchical control system" language has been replaced with empirically descriptive phrasing; and (4) the model-relevance claim has been reframed from direct improvement ("to improve") to diagnostic reference ("targets for evaluating"), with the "diagnostic rather than mechanistic" limitation clearly stated. The full revised abstract is provided below for the reviewer's convenience:

***Abstract.** Snow depth (SD) and land surface temperature (LST) interact through energy*

and mass exchanges that govern meltwater supply in arid mountain regions, yet the strength, quality, and timing of this interaction remain poorly quantified across topographically complex terrain. Here we develop a diagnostic framework that integrates coupling coordination analysis with time-lagged cross-correlation to simultaneously assess, between SD and LST, the intensity of their systemic association (coupling degree, CD), the harmony of their co-evolution (coupling coordination degree, CCD), and the spatiotemporal scales of their lagged response. Applied across the mountain-basin systems of Xinjiang, China, using long-term remote sensing and reanalysis data, the framework reveals three principal findings. First, SD-LST interactions are organized along a hierarchical environmental gradient: broad climatic setting shapes the north–south potential for coupling, while elevation modulates this pattern in southern ranges and local factors shape east–west variations in lagged responses. Second, a systematic decoupling emerges between interaction strength and system coordination—most notably in the southern Tianshan, where high CD coincides with low and declining CCD, suggesting that strong thermal forcing is no longer matched by sustainable snowpack evolution. Third, response lags exhibit distinct regional signatures: long and stable lags (14–22 days) in the snow-rich Altai reflect high thermal inertia; the Tianshan shows a north–south asymmetry with significant spring lag lengthening on the south slope; and the Kunlun displays elevation-threshold behavior, where coordination improves only above ~3500 m. These lag patterns serve as empirical indicators of snowpack buffering capacity and its regional variation. As a diagnostic tool, the framework provides quantifiable, spatially explicit metrics for evaluating snow thermal schemes in land surface models and identifying climate-vulnerable zones in water-limited mountain regions.

Reviewer's comment 2:

Section 1. 1) L46-48: “The dominant thermal driver is not static but can shift across ablation phases, as seen in the central Tianshan where surface temperature initiates melt while air temperature governs peak ablation (Li et al., 2022).” was mentioned. So why you only choose land surface temperature (LST) as the driving variable in your manuscript. 2) The authors should explain why CCDD is suitable for studying snow-

temperature relationships. They should also clarify how this method improves upon simple correlation analysis. "

Our Response to comment 2:

We thank the reviewer for these two thoughtful questions. We would also like to note that, in response to comments from another reviewer, we have substantially revised and restructured the entire Introduction. This revision includes the removal of the sentence concerning air temperature that the reviewer referenced, and a comprehensive re-organization of the methodological motivation, which we believe has also helped clarify both of the issues raised here.

Regarding the choice of LST over air temperature: We thank the reviewer for pointing out our previous citation of Li et al. (2022), which indeed showed that surface temperature initiates melt while air temperature governs peak ablation. We fully agree that air temperature, radiation, and wind also influence snowpack evolution—particularly during peak ablation. Nevertheless, we selected LST as the thermal forcing variable in this study based on three considerations. First, LST represents the direct thermal boundary condition at the snow–atmosphere interface, governing surface energy exchange and melt initiation, whereas air temperature is measured above the surface and can be decoupled from snow surface conditions under stable stratification or in complex terrain. Second, the TRIMS LST dataset provides long-term, gap-free, high-resolution records specifically reconstructed for all-weather conditions; moreover, it can be resampled to match the 500 m resolution of our downscaled snow depth dataset, ensuring consistent spatial analysis across the two variables. Third, our framework is diagnostic rather than energy-balance-based; we aim to quantify the empirical coupling between SD and the most proximate thermal variable at the surface, rather than to fully attribute snowmelt to all meteorological drivers. We acknowledge that incorporating air temperature and other variables in future work would extend the framework toward a more complete mechanistic understanding.

Correspondingly, we have supplemented the Introduction in two places to clarify our choice of LST. First, at the end of the first paragraph, we have added a sentence highlighting the academic significance of LST as the direct thermal boundary condition—establishing why the SD-LST relationship merits focused investigation. Second, at the end of the third paragraph, we have added a brief explanation of the specific reasons for selecting LST over other thermal variables (data availability, resolution matching, and the diagnostic nature of our framework).

For the reviewer's convenience, the relevant additions are extracted below:

End of first paragraph of section 1:

"As the direct thermal boundary condition at the snow–atmosphere interface, LST governs the surface energy exchange that drives melt, making the SD-LST relationship a critical focus for understanding snowpack responses to climate forcing."

End of third paragraph of section 1:

"Given this complexity, we focus on LST as the primary thermal forcing variable in our diagnostic framework. LST represents the direct boundary condition at the snow surface and is available from the TRIMS dataset as a long-term, gap-free, high-resolution product that can be resampled to match our 500 m snow depth data."

Regarding the suitability of CCDM and its improvement over correlation

analysis: We thank the reviewer for this question. In the revised Introduction, we have explicitly addressed why CCDM is appropriate for studying SD-LST relationships and how it advances beyond conventional correlation analysis.

Specifically, we now clarify two fundamental limitations of the prevailing correlation-based paradigm: (1) it treats SD and LST as separate variables rather than as an interacting system, and (2) it overlooks the temporal dimension of snow-temperature interactions. To illustrate the first limitation, we provide a concrete example: a strong negative correlation between SD and LST could arise from two fundamentally different situations—a deep, cold snowpack that buffers temperature fluctuations and melts gradually (a well-coordinated,

resilient system), versus a thin, vulnerable snowpack that collapses rapidly under warming (a maladaptive system). Conventional correlation treats these two scenarios identically, thereby masking the critical distinction between coupling intensity and coordination quality.

CDDM resolves this ambiguity by quantifying two separate metrics—coupling degree (CD), which measures interaction intensity, and coupling coordination degree (CCD), which assesses whether the co-evolution of the two variables is stable, balanced, and sustainable. This distinction provides a diagnostic lens for system health that correlation alone cannot offer. Furthermore, by integrating CDDM with time-lagged cross-correlation, our framework adds response timescale as a third diagnostic dimension, addressing the second limitation noted above.

These points are now presented in the revised Introduction (Section 1, paragraphs 4–6) and are highlighted in the revised manuscript for easy reference.

Corresponding revision in the Introduction (fourth and fifth paragraphs) :

“A range of analytical methods have been developed to examine snow–climate relationships, broadly falling into two categories: those that characterize correlation or coherence structures—including correlation analysis, wavelet coherence, and spectral methods (Grinsted et al., 2004)—and those that infer causal or predictive links, such as Granger causality and convergent cross-mapping (Granger, 1969; Sugihara et al., 2012; Kim et al., 2025). These methods have advanced our understanding—for example, by revealing time-lagged responses or directional dependencies—but they differ from a diagnostic framework that jointly assesses interaction intensity, coordination quality, and response timing.

Specifically, the prevailing analytical paradigm relying on statistical correlations harbors two fundamental limitations (Clark et al., 2011; see also Mudelsee, 2019) when applied to snow climate systems. First, it treats SD and LST as separate variables rather than as an interacting system, and thus does not distinguish whether the system evolves

synergistically or fluctuates erratically under stress. A strong negative correlation could arise from either a deep snowpack that buffers temperature fluctuations and melts gradually, or a thin snowpack that collapses rapidly under warming—yet correlation treats these scenarios identically, masking the distinction between coupling intensity and coordination quality. Second, this approach overlooks the temporal dimension of snow temperature interactions. Heat propagates through the snowpack at a rate determined by its depth, density, and liquid water content; correlation-based methods do not systematically quantify how response times vary across regions, seasons, and elevations—information essential for understanding snowpack thermal inertia and memory effects. While Granger causality and convergent cross-mapping can infer directional influences, they are not designed to evaluate whether a strongly interacting system is evolving in a coordinated, healthy manner or is under stress. This propagation delay—from near zero in shallow ephemeral snow to weeks in deep, cold snowpacks—highlights the need for a framework that jointly diagnoses coupling strength, coordination quality, and response timescales.

To address these questions, this study proposes an integrated analytical framework combining the Coupling Coordination Degree Model and time-lagged cross-correlation analysis, aiming to answer three key questions: (1) Is the SD-LST system maintaining stable, sustainable co-evolution under warming, or has it shifted toward a maladaptive, unsustainable state? (2) What hierarchical control structure—from macro-scale climate to micro-scale local factors—determines the spatial pattern of snow-temperature coupling strength across mountain ranges? (3) What are the characteristic response timescales of SD to thermal forcing, and how do they vary across seasons, elevations, and mountain ranges?”

Reviewer's comment 3

Section 3. The physical meaning of CD and CCD should be explained more carefully. The authors should clearly state whether SD and LST were normalized before the calculation.

Our Response to comment 3:

We thank the reviewer for this suggestion. We agree that CD and CCD should be explained more thoroughly—both in terms of their general meaning within the CCDM framework and their specific interpretation in the context of SD-LST systems. We have also added a clear statement regarding the normalization procedure.

Specifically, we have revised Section 3.1 in three ways. First, we added a normalization statement prior to the CD formula. Second, we restructured the explanation of CD to follow a two-tier structure: general meaning within the CCDM framework, followed by specific interpretation in our SD-LST system. Third, we applied the same two-tier structure to the explanation of CCD.

For the reviewer's convenience, the full revised Section 3.1 is extracted below:

"The concept of coupling, derived from physics, describes the phenomenon of mutual influence and interaction between two or more systems (Song et al., 2020). Building upon this, the notion of coupling coordination expands the framework to represent how systems can co-evolve toward a more ordered, synergistic state (Song et al., 2020). This approach has been effectively adapted to investigate interdependent systems across various fields, including ecology, geography, and economics (Lai et al., 2020; Zhao et al., 2025).

The Coupling Coordination Degree Model (CCDM) is an analytical framework that quantifies such relationships through two key metrics: the Coupling Degree (CD) and the Coupling Coordination Degree (CCD) (Huang et al., 2020; Liu et al., 2005). The CD measures the strength of association and mutual influence between systems, while the CCD further assesses the degree to which their development is harmonized. In this study, we apply the CCDM to analyze the interaction between SD and LST. Prior to calculation, both SD and LST time series at each grid cell were normalized to the [0, 1] range using min-max normalization to eliminate the effects of differing units and magnitudes. The normalization was performed separately for each grid cell across the 20-year study period to preserve spatial heterogeneity in the relative variability of each variable. The CD is calculated as follows:

$$C = \left[\frac{S \times E}{[(S+E)/2]^2} \right]^{\frac{1}{2}} \quad (1)$$

where S and E represent the SD and LST, respectively, and C denotes the coupling degree. In the CCDM framework, CD quantifies the intensity of mutual influence between two subsystems, irrespective of the direction or quality of that exchange; it ranges from 0 to 1, with higher values indicating stronger interdependence. In the context of our SD-LST system, a high CD (>0.8) indicates that temperature changes are closely mirrored by snow depth variations, reflecting efficient energy transfer at the snow surface. A low CD (<0.3) indicates weak or decoupled interaction, where thermal forcing does not translate into detectable snowpack response—either due to snow absence or to other factors overriding the temperature control. However, CD alone does not distinguish whether this interdependence is sustainable or stressful; it only reflects interaction strength.

To assess coordinated development, CCD is introduced, which evaluates both interaction magnitude and mutual promotion/restraint (Huang et al., 2020). In the CCDM framework, CCD assesses the degree of harmonious co-evolution between two subsystems—quantifying not just whether they interact, but whether that interaction is balanced, stable, and mutually adaptive. In our SD-LST system, a high CCD indicates that the snowpack and thermal regime are evolving in a coordinated manner: for example, a deep snowpack that buffers temperature fluctuations and melts gradually under warming, maintaining a stable energy balance. A low CCD indicates maladjustment or system stress—for instance, a thin snowpack that collapses rapidly under thermal forcing, with no buffering capacity remaining to moderate the response. Thus, CCD provides a diagnostic measure of snow-thermal system health that complements the intensity-based information provided by CD . The calculation method is as follows:

$$T = \alpha \cdot S + \beta \cdot E \quad (2)$$

$$D = (C \times T)^{\frac{1}{2}} \quad (3)$$

where D denotes the CCD , ranging from 0 to 1. T represents the comprehensive evaluation index reflecting subsystem contributions. α and β (both set at 0.5 here)

signify subsystem interaction weights. CD and CCD are classified via Meng et al.'s (2024) and Zhang et al.'s (2023) standards (Table 1).

For grid cells where mean snow depth was consistently below 1 cm throughout the study period, these pixels were excluded from the CD, CCD, and lag correlation analyses to avoid spurious results arising from near-zero values. These areas are indicated as snow-free in the relevant figures. For pixels with intermittent snow cover (i.e., snow present in some seasons but not others), the analyses were conducted on a seasonal basis using only the days when snow was present, ensuring that the calculated metrics reflect actual snow-temperature interactions rather than artifacts of snow absence"

We believe these revisions adequately address the reviewer's concern by providing both the general meaning of CD and CCD within the CCDDM framework and their specific diagnostic interpretation in the context of our SD-LST system, while also clarifying the normalization procedure. All changes are highlighted in the revised manuscript.

Reviewer's comment 4:

Section 4.2. The manuscript shows that some regions have high coupling degree, while their coordination degree remains moderate or even low. This difference is important, but it is not fully discussed. The authors should explain more clearly what a high CD but relatively low CCD means for the SD–LST relationship.

Our Response to comment 4:

We thank the reviewer for this comment. We agree that the CD-CCD decoupling—where high coupling degree coexists with low or declining coordination degree—is a key finding that warrants more explicit interpretation.

To address this, we have made complementary revisions in Section 4.2. In Section 4.2 (Results): We have added a descriptive analysis examining the CD-CCD mismatch ($\Delta = \text{CD} - \text{CCD}$) across sub-regions and elevation zones. This analysis reveals systematic regional contrasts: the Altay Mountains show stable and moderate mismatch across all elevations (0.21–0.31); the Tianshan system exhibits the most pronounced mismatch, particularly on the southern slope

above 2700 m where mismatch reaches up to 0.34; and the Kunlun Mountains show only modest divergence (Δ up to 0.168). This descriptive analysis now provides a clear observational basis for the interpretive discussion. In addition, we have substantially revised the corresponding discussion in Section 5.2 to provide a more explicit interpretation of what the CD-CCD mismatch means for the SD-LST system across different regions; these interpretive revisions are detailed in our response to Comment (7) below.

For the reviewer's convenience, the key additions in section 4.2 are extracted below:

"To further characterize the spatial pattern of CD-CCD mismatch, we examined the difference between the two metrics ($\Delta = CD - CCD$) across sub-regions and elevation zones (Figure. 8). The results reveal that Δ exhibits distinct elevational patterns that vary systematically across regions. In the Altay Mountains (N1), Δ remains stable across all elevations (0.21–0.31), indicating that coupling strength and coordination quality evolve in broad alignment regardless of altitude—suggesting a well-buffered system where snowpack properties and thermal forcing remain relatively synchronized throughout the vertical extent. In the Tianshan system, however, Δ exhibits strong elevational dependence: on the northern slope (N3), Δ is moderate at low elevations (0.20–0.28) but increases steadily above 2700 m, reaching 0.34 at >3800 m; on the southern slope (S1), a more complex pattern emerges, with Δ negative at low elevations (<1600 m, ranging from -0.044 to -0.035), crossing zero between 1600–2700 m, and rising sharply to 0.34 above 2700 m—a threshold-type transition from coordination-dominated at low elevations to coupling-dominated but poorly coordinated at high elevations that is unique to the southern Tianshan. In contrast, the Kunlun Mountains (S3) show a much more modest elevational response, with Δ turning from negative to positive only above 3000 m and reaching a maximum of 0.168, far lower than the Tianshan peaks—likely reflecting the limited snow cover and weaker thermal forcing in this hyper-arid environment. The two basins (N2, S2) exhibit near-zero Δ values throughout their snow-bearing elevations, confirming that the CD-CCD mismatch is primarily a mountain phenomenon. These patterns confirm that the CD-

CCD mismatch is not a uniform phenomenon but is concentrated in specific topographic settings—particularly the Tianshan above 2700 m—and that the elevational expression of this mismatch differs fundamentally between regions: the southern Tianshan(S1) shows a threshold-type transition, the northern Tianshan(N3) shows a monotonic increase with altitude, and the Altay and Kunlun show either stable or muted responses.”

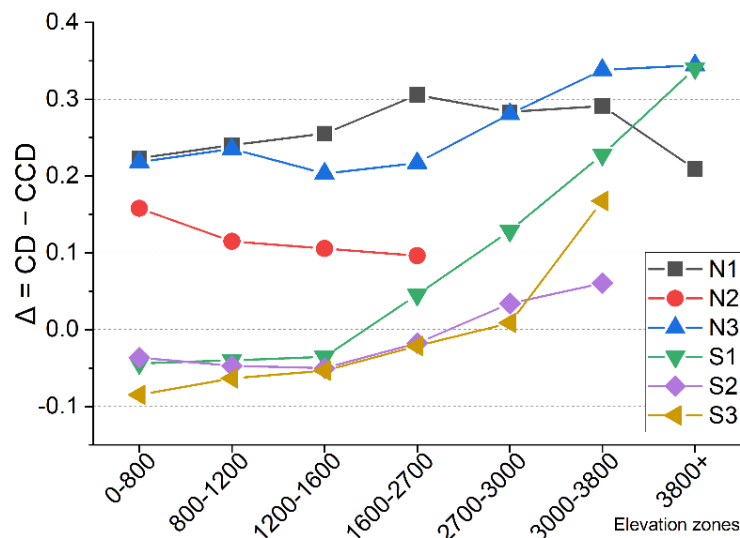


Figure 8. Elevation-dependent differences between coupling degree (CD) and coupling coordination degree (CCD) across the six sub-regions ($\Delta = CD - CCD$).

We believe these revisions, together with the interpretive extensions in Section 5.2 (detailed in our response to Comment 7 below), adequately address the reviewer's concern by providing both a quantitative observational basis for the CD-CCD mismatch and a clear explanation of its physical meaning across different regions.

Reviewer's comment 5:

Section 4.3. The manuscript links lag time directly to snow thermal inertia or memory effects. These explanations are reasonable, but they are not directly measured in this study. The authors should state that the lag patterns may indicate these processes.

Our Response to comment 5:

We thank the reviewer for this careful comment. We agree that lag time is a statistical metric derived from correlation analysis, whereas thermal inertia

and memory effects are physical processes that we did not directly measure. To address this, we have revised Section 4.3 to focus on the descriptive presentation of lag patterns—their magnitude, spatial distribution, seasonal variation, and elevation dependence—without embedding physical interpretations. The corresponding discussion of what these lag patterns may physically imply has been moved to Section 5.2, where we now discuss potential links to snowpack thermal properties using cautious, inferential language such as “may indicate” and “is consistent with.” We also explicitly acknowledge that direct attribution would require additional in situ or modeling work. In addition, in response to another reviewer's suggestion, we have streamlined the subheading structure of Section 4.3 by converting numbered subsubsections to bold text.

For the reviewer's convenience, the full revised Section 4.3 is extracted below. The corresponding discussion text we have added to Section 5.2 is presented in full in our response to Comment (7) below, where we also address related interpretive issues.

4.3 Spatiotemporal Patterns in the Lagged Response of LST to Snow Depth Changes

Overall Characteristics of the SD–LST Lag: *The time-lagged correlation between SD and LST was quantified by identifying the specific lag (in days) at which their correlation reached a maximum or minimum. This lag period can be interpreted as an empirical indicator of the response time of SD to LST variation. We interpret these lag patterns as empirical indicators that may reflect differences in snowpack thermal properties, although direct attribution to specific physical processes would require complementary in situ measurements or process-based modeling. A spatial assessment was conducted to examine the distribution of these lag days across seasons, with results categorized and mapped in Fig. 9.*

Autumn (Fig. 9a): Snow cover was present except in the arid S2 region and eastern N2, where temperatures remain above freezing or wind-driven ablation prevails. The SD–LST lag time was typically 7 to 14 days across most of Xinjiang. Exceptions

included: (1) central N2 and western S1, where lags shortened to 0 to 7 days, which may be associated with elevated terrain and shallow snow reducing thermal inertia; (2) southeastern S3, where similarly short lags resulted from enhanced solar radiation and patchy snow cover with lower albedo; and (3) localized areas in northern S3 near the Tarim Basin, which exhibited near-instantaneous (0-day) response under extremely arid, wind-compacted snow conditions.

Winter (Fig. 9b): Lag times increased significantly relative to autumn (mean = 12.6 ± 4.3 days), with greater spatial variability (coefficient of variation = 34.2%). In N1, N2, N3, and S1, a bimodal distribution emerged: 7 to 14 day lags dominated mid-elevations, while 14 to 22 day lags occurred at higher latitudes, consistent with a latitudinal gradient in snowpack thermal inertia. Within S2, lag times varied widely (0 to 22 days), influenced by topographic barriers and cold-air advection. S3 showed predominantly 7 to 14 day lags but exhibited a clear east–west contrast: eastern sectors consistently displayed shorter lags (0 to 7 days), which may be associated with higher afternoon solar radiation and differing synoptic cold-front frequencies.

Spring (Fig. 9c): A pronounced north–south gradient in lag days was observed, except in the largely snow-free S2 region. Lag duration generally increased from north to south. Notable patterns included: near-instantaneous response (0-day lag) across N2; shortening lags from 7–14 days in the north to 0 days in the south within N1 and S1; and an eastward extension of lags from 0 to 7 days to 7 to 14 days in N3. In S3, lags shortened from 7 to 14 days in the south to 0 to 7 days in the north, suggesting possible influences from precipitation or snow density gradients.

Summer (Fig. 9d): Snow persisted only in high-elevation zones of N1, N3, S1, and S3. Lag times within these areas ranged mainly between 0 to 14 days, with minimal latitudinal variation but a distinct longitudinal pattern: eastern sectors exhibited shorter lags (0 to 7 days), while western sectors showed longer delays (7 to 14 days), which may be associated with differences in topography, radiation regimes, or precipitation phase.

Altitudinal and Seasonal Variability of SD–LST Lag Times : For this analysis, seasons

are defined as: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). Figure 10 presents the seasonal statistics of lag duration between SD and LST across elevation zones in each sub-basin. The analysis reveals that both the mean lag and its altitudinal dependence undergo pronounced seasonal reversals and regional contrasts.

Autumn (Fig. 10a) was characterized by spatially homogeneous lag times (mean: 9 ± 1 days) and weak, regionally divergent altitudinal controls. While northern Xinjiang exhibited a unimodal relationship with elevation (peak at approximately 2500 to 3000 m), the southern basins (S1, S2) showed no systematic elevational trend. In contrast, the Kunlun Mountains (S3) displayed a strong, linear altitudinal increase (0.8 to 1.2 days per 1000 m, $R^2 = 0.78$).

Winter (Fig. 10b) introduced a clear latitudinal gradient in mean lag (north: 11 ± 2 days; south: 9 ± 2.5 days) and a strengthening of average altitudinal variability (+20% compared to autumn). A fundamental north-south dichotomy emerged: northern basins showed a parabolic altitudinal pattern, whereas southern regions lacked a consistent elevational signal, despite a persistent positive correlation in S3.

Spring (Fig. 10c) exhibited the most extreme spatial heterogeneity. Mean lag spanned an order of magnitude from south to north (1 ± 0.5 to 9 ± 2 days), and altitudinal sensitivity reached its annual maximum (average within-basin variability: 11 ± 3 days). A near-universal positive lag-elevation relationship was observed across all sub-basins (1.5 to 2.5 days per 500 m), steepest in the Tianshan Mountains. The bimodal elevational response in the Altay Mountains (N1) contrasted with the simpler linear patterns elsewhere.

Summer (Fig. 10d), with snow limited to alpine zones, revealed a striking east-west disparity in lag times (east: 0 to 7 days; west: 7 to 14 days) in the absence of a clear latitudinal gradient.

Long-Term Trends in Seasonal Lag Times Across Mountain Regions: All trend slopes and *p*-values reported in this section are derived from Sen's slope estimation combined with the Mann–Kendall significance test (see Section 3.3 for method details). Long-term (2001–2020) trends in seasonal SD–LST lags reveal asynchronous regional

trajectories across Xinjiang's mountain regions (Fig. 11). While some regions exhibit significant shifts in specific seasons, others remain stable, indicating distinct climatic and snowpack regimes across mountain ranges.

Autumn Trends (Fig. 11a): Autumn lag times demonstrated the most pronounced long-term declines in the Tianshan regions. In the North Tianshan (N3), lags decreased from approximately 15 to 6 days (slope = -0.45 days/year, $p < 0.001$). A similar but less steep decline occurred in the South Tianshan (S1; from 11 to 8 days). The Altay Mountains (N1) showed high interannual variability (5 to 15 days) without a significant trend, while the Kunlun Mountains (S3) remained stable (8 to 10 days).

Winter Trends (Fig. 11b): Winter lag times also exhibited region-specific patterns. The North Tianshan (N3) showed a significant decline from 15 to 11 days (slope = -0.20 days/year, $p < 0.01$). The South Tianshan (S1) maintained consistently higher lags than autumn (10 to 13 days after 2006) but without a clear trend. The Altay Mountains (N1) exhibited elevated lags during 2010–2015 (8 to 15 days), while the Kunlun Mountains (S3) remained stable (8 to 10 days).

Spring Trends (Fig. 11c): Lag times exhibited clear regional divergence. The Altay Mountains (N1) maintained stable, near-immediate responses (0 to 2 days), with no significant trend detected (slope ~ 0 days/year, $p = 0.922$). In contrast, both the North and South Tianshan (N3, S1) experienced significant lengthening of lags (N3: from approximately 2 to 5 days, slope = $+0.15$ days/year, $p < 0.001$; S1: from less than 4 to 8 days, slope = $+0.20$ days/year, $p < 0.001$). The Kunlun Mountains (S3) displayed the highest absolute values (8 to 13 days) but showed a significant declining trend (-0.18 days/year, $p = 0.015$).

Summer Trends (Fig. 11d): Summer lag times showed moderate interannual variability without strong directional trends. The Altay (N1) and North Tianshan (N3) regions exhibited relative stability (N1: 4 to 8 days; N3: 7 to 11 days). The South Tianshan (S1) displayed greater fluctuation (6 to 10 days) and a slight overall decline (-0.03 days/year, $p = 0.12$). In the Kunlun Mountains (S3), summer lags were the most stable (7 to 9 days). The increased variability in N1 after 2010 suggests a possible shift in late-season snowpack stability or ablation energy sources.

Reviewer's comment 6:

Section 5.1. The authors should specify which findings support climate control in the Altay Mountains, elevation control in the Kunlun Mountains, and slope-related contrast in the Tianshan Mountains. This would make the framework easier to follow.

Our Response to comment 6:

We thank the reviewer for this suggestion. We agree that the hierarchical control framework in Section 5.1 requires clearer specification of the evidence supporting each level of control. To address this, we have revised Section 5.1 in two ways.

First, we have explicitly cited the specific findings that underpin each interpretation: for the Altay Mountains, the consistently high CD across all elevations ($CD > 0.8$) and stable mismatch (Δ from 0.21 to 0.31) as evidence of climate control; for the Kunlun Mountains, the elevation-dependent CD and CCD patterns, with a threshold at ~ 3500 m, as evidence of elevation control; and for the Tianshan, the quantitative CD-CCD differences between the northern and southern slopes (N3: 0.5–0.6 vs S1: 0.2–0.4; Δ up to 0.34 above 2700 m in S1) as evidence of slope-aspect control.

Second, we have added brief reasoning for each interpretation to clarify why these particular findings point to that specific control mechanism. For the Altay, we now explain that the absence of elevational gradients in CD/CCD suggests basin-scale climatic forcing rather than topographic control. For the Kunlun, we explain that elevation must be the primary control because the macro-climate is uniformly hyper-arid across the region, yet CD and CCD improve systematically with altitude. For the Tianshan, we explain that slope aspect is the key factor because the two slopes share similar elevations and climate but exhibit systematically different coupling and coordination patterns.

We believe these revisions make both the evidence and the reasoning more explicit and transparent, directly addressing the reviewer's concern. For the reviewer's convenience, the full revised Section 5.1 is extracted below:

“5.1. Hierarchical Controls on Snow–Temperature Interactions

Our analysis reveals that the spatial patterns of snow–temperature interactions across Xinjiang are governed by a coherent hierarchical control framework (Fig. 12), which is distinctly expressed through the unique climatic and cryospheric characteristics of its three major mountain systems: the Altay (N1), Tianshan (N3, S1), and Kunlun (S3). This integration of scale-dependent controls and regional specificity provides a integrated understanding of the observed heterogeneity.

At the macro-scale, the fundamental contrast between the cold-humid north and the hyper-arid south establishes the baseline potential for strong snow–temperature coupling (Sato, 2005). This is most clearly manifested in the Altay Mountains (N1), where abundant snowfall and a long snow season create a deep, persistent snowpack. This system operates under climate-dominated control, resulting in the highest and most stable coupling degrees observed (CD consistently exceeding 0.8 across all elevations, as shown in Fig. 5; $\Delta = 0.21\text{--}0.31$, indicating well-matched CD and CCD), alongside the longest winter response lags (14–22 days, Section 4.3)—a signature of high thermal inertia. The absence of significant elevational gradients in CD and CCD across N1, combined with consistent lag structures across elevations, suggests that the climatic regime—rather than local topographic or elevational factors—is the primary control. In other words, the snowpack response is uniform across the mountain’s vertical extent, a pattern expected under a dominant climatic forcing that operates at the basin scale. This pattern aligns with stable seasonal snow–climate feedbacks typical of high-latitude regions.

The meso-scale control of elevation and topography modifies or even overrides the macro-scale template, particularly in the drier southern regions (Pepin et al., 2015). In the Kunlun Mountains (S3), elevation becomes the dominant, overriding control. The robust correlation between altitude and both coupling and coordination degrees (CD rising from <0.3 at low elevations to >0.7 above 3000 m; CCD improving markedly above 3500 m, as shown in Fig. 7) illustrates a strict elevation-gating mechanism: only above a critical altitude (~ 3500 m) does a sufficiently persistent snowpack exist to establish a coordinated interaction with temperature. The lag-elevation relationship further supports this control (autumn lag increasing by 0.8–1.2 days per 1000 m,

Section 4.3), confirming that snowpack thermal properties are systematically modulated by altitude. The strong correlation between elevation and both CD and CCD indicates that elevation exerts a primary control that cannot be explained by the macro-scale climate alone, which is uniformly hyper-arid across the region; rather, it reflects the elevational control on snow accumulation and persistence, where higher elevations capture more precipitation and sustain lower temperatures.

In the Tianshan Mountains, topography manifests as a sharp intra-mountain contrast. The pronounced north–south asymmetry in coupling and coordination is a direct result of the rain-shadow effect and differential solar radiation, making the south slope (S1) a more sensitive and vulnerable subsystem. The rain-shadow effect reduces precipitation on the southern slope, leading to thinner snowpack with lower cold content and reduced thermal buffering capacity. This directly limits the snowpack's ability to absorb and modulate thermal forcing, manifesting as lower CCD values (0.2–0.4) and greater CD-CCD divergence (Δ up to 0.34) compared to the northern slope. Here, topography amplifies the macro-climatic gradient, creating strong internal heterogeneity. This is supported by the contrasting CD and CCD patterns between N3 and S1: the northern slope maintains higher CCD values (0.5–0.6) and more stable Δ (0.20–0.28 at low elevations), whereas the southern slope exhibits lower CCD (0.2–0.4) and the largest CD-CCD divergence above 2700 m (Δ up to 0.34, Section 4.2). The greater solar radiation on the south-facing slope accelerates melt and shortens snow duration, increasing sensitivity to temperature fluctuations—as reflected in the significant spring lag lengthening observed on the southern slope (Section 4.3). Lag patterns further reinforce this asymmetry: the southern slope shows significant spring lag lengthening, suggesting heightened sensitivity to seasonal transitions, whereas the northern slope maintains more stable seasonal lag structures. The combination of reduced moisture supply and enhanced radiative forcing makes the southern slope particularly vulnerable to warming. Even moderate temperature increases can trigger rapid snow loss, whereas the northern slope—sustained by greater snowfall and lower radiation—maintains more stable snowpack conditions and higher CCD. This vulnerability is further evidenced by the intensification of the CD-CCD mismatch with

elevation on the south slope (Δ increasing from 0.13 at 2700–3000 m to 0.34 at >3800 m), confirming that topographic modulation of snowpack properties is the dominant mechanism underlying the north–south asymmetry.”

Reviewer’s comment 7:

Section 5.2. Could the authors further explain the physical meaning of high CD but relatively low CCD in different regions? For example, does this mismatch indicate different snow–temperature interaction states in the southern Tianshan and northern Tianshan?

Our Response to comment 7:

We thank the reviewer for this question. We have expanded the interpretive discussion in Section 5.2 to clarify the physical meaning of high CD but low CCD across different regions, with particular attention to the contrast between the southern and northern Tianshan.

In general terms, high CD with low CCD indicates that LST remains the dominant driver of snowpack change (hence high interaction intensity), but the snowpack has lost sufficient buffering capacity to respond in a coordinated, sustainable manner (hence poor coordination). Physically, this manifests as a system where snowpack properties—depth, cold content, and albedo—no longer effectively modulate the thermal response, resulting in a forced rather than adaptive evolution.

Importantly, this general interpretation manifests differently across regions, and we now explicitly distinguish four system states: (1) the southern Tianshan above 2700 m shows the most pronounced mismatch (Δ up to 0.34), representing acute system stress where the snowpack is approaching a critical transition; (2) the northern Tianshan at high elevations shows high CD but declining CCD, representing incipient system stress signaling a trajectory toward the southern Tianshan state; (3) the Altay Mountains show stable and moderate mismatch across all elevations, representing a well-coordinated state where the deep, cold snowpack buffers thermal forcing; and (4) the Kunlun

Mountains show modest mismatch and limited snow cover, representing a weakly coupled but balanced state. This regional differentiation confirms that the same high-CD-low-CCD signature indicates different snow–temperature interaction states depending on the regional snowpack and climatic context.

The full revised Section 5.2 is extracted below:

5.2. Decoupling Between Interaction Strength and System Harmony in Xinjiang

A high Coupling Degree (CD) reflects strong statistical interdependence between snow depth (SD) and land surface temperature (LST), indicating efficient energy exchange at the snow–atmosphere interface. This is characteristic of thermally responsive snowpacks, as evidenced by the consistently high CD values in the snow-rich Altay Mountains and the high-elevation Kunlun Mountains.

However, a high CD does not guarantee a high Coupling Coordination Degree (CCD). The CD-CCD decoupling observed in the southern and parts of the northern Tianshan reveals a critical state: strong thermal forcing persists as the dominant driver (hence high CD), but the snowpack has lost sufficient buffering capacity to respond sustainably (hence low CCD). The relationship has shifted from coordinated co-evolution—where snowpack properties such as depth, cold content, and albedo modulate the thermal response—to a forced, maladaptive response, where warming drives snow loss with little modulating feedback. Physically, this decoupling manifests as a progressive loss of buffering capacity: the ability to absorb thermal perturbations diminishes as snow depth decreases and snowpack structure deteriorates. Thus, the CD-CCD discrepancy serves not merely as a descriptive metric but as an early warning indicator of system stress, identifying regions where snowpack buffering capacity is eroding under accelerating warming.

This decoupling manifests differently across regions, forming a spectrum of system states as revealed by the Δ analysis in Section 4.2. At one end, the Altay Mountains represent a well-coordinated state, where the deep, cold snowpack effectively buffers thermal forcing and maintains synchronized SD-LST evolution. At the opposite end, the southern Tianshan above 2700 m exhibits acute system stress, where a marginal snowpack responds quickly to temperature (high CD) but collapses rather than melts

gradually (low CCD)—approaching a critical transition. Between these extremes, the northern Tianshan at high elevations shows incipient system stress: high CD but declining CCD indicates that the snowpack retains thermal inertia but is beginning to lose coordination capacity. In contrast, the Kunlun Mountains occupy a distinct position—limited snow cover and weaker thermal forcing yield weak but balanced interactions, representing a low-energy system where CD-CCD separation is less pronounced. This regional differentiation demonstrates that the same high-CD-low-CCD signature can have different physical meanings depending on the regional snowpack and climatic context.

The lag patterns presented in Section 4.3 add a temporal dimension to this diagnostic framework. In the Altay Mountains, long and stable winter lags are consistent with a deep, cold snowpack possessing high thermal inertia. In contrast, shorter lags in the Tianshan low-elevation zones suggest reduced thermal buffering capacity. The long-term trends also exhibit seasonal asymmetry: declining autumn lags—particularly in the Tianshan—may indicate accelerated snowpack establishment under cooling, while declining winter lags in the North Tianshan may reflect snowpack thermal degradation under warming winters. This asymmetric interpretation is supported by concurrent regional trends: autumn cooling rates have accelerated over the study period, while winter warming trends have been documented in the same region (Chen et al., 2015). These interpretations are inferential—lag time is a statistical metric, whereas thermal inertia and cold content are physical properties we did not directly measure. Direct attribution would require complementary in situ measurements or process-based modeling.

Several mechanisms may explain the observed patterns. First, loss of buffering capacity is most relevant to the Tianshan, where thinning snowpacks lose thermal inertia and latent heat capacity, triggering rapid ablation rather than gradual melt—shifting snow from a climate moderator to a change amplifier (Shengdi et al., 2023). Second, asynchronous response rates help explain why the Altay maintains stable Δ whereas the Tianshan does not: in the Altay, abundant snowfall sustains a deep snowpack that buffers temperature variability, allowing SD and LST to evolve in

synchrony; in the Tianshan, the rate of LST increase outpaces stabilizing feedbacks, with snow-albedo feedback likely exacerbating this asynchrony (Flanner et al., 2011). Third, seasonal shifts in interaction mechanisms help interpret the modest CD-CCD divergence in the Kunlun, where limited snowpack and weaker thermal forcing yield less pronounced separation. Pronounced spring lag lengthening indicates a change in energy processing: early ablation is driven by surface heating (short lags), while peak ablation involves energy storage within the snowpack (Wei et al., 2014), degrading the synchrony essential for high CCD.

The CD-CCD discrepancy is not an analytical artifact but a meaningful indicator. It moves the assessment beyond whether temperature drives snow changes, to evaluate how healthily the snow-climate system is co-evolving. Regions with this decoupling—particularly the southern Tianshan above 2700 m and high-elevation northern Tianshan—are most vulnerable to rapid, potentially irreversible change under continued warming.

We believe these revisions adequately address the reviewer's concern by providing both a general physical interpretation of the CD-CCD mismatch and a regionally differentiated analysis that distinguishes the physical states of the southern and northern Tianshan, as well as those of the Altay and Kunlun Mountains.

Reviewer's comment 8:

Section 6. The CD-CCD-lag framework is a useful analytical approach. The authors should state that the framework may support future model development, rather than saying that it directly improves model representation.

Our Response to comment 8:

We thank the reviewer for this suggestion. We fully agree that our framework is primarily diagnostic rather than model-improvement oriented, and that the language in Section 6 should reflect this distinction.

Specifically, in the original manuscript we stated that the framework "directly improves model representation"—a claim that overstates its scope. This has

been revised to "may support future model development by providing spatially explicit, empirically based reference targets for evaluating snow thermal schemes"—emphasizing the framework's role as a diagnostic reference rather than a demonstrated model improvement.

For the reviewer's convenience, the full revised Section 6 is extracted below:

"This study offers three diagnostic insights for snow-climate science and water management in arid mountains. First, it distinguishes coupling strength from system state, revealing that a strong correlation between SD and LST can mask underlying system dysfunction—a critical insight for identifying vulnerable regions. Second, it identifies response lag time as a physically meaningful metric of snow thermal inertia, enabling regional-scale diagnosis of buffering capacity. Third, it offers an analytical framework that moves beyond conventional correlation to diagnose system stress in data-scarce, topographically complex regions.

We demonstrate that SD-LST interactions are governed by a three-tiered hierarchical control system involving macro-scale climate gradients, meso-scale topography, and micro-scale local factors. Critically, coupling degree and coordination degree are distinct metrics; their spatial mismatch serves as an early warning of system stress, identifying where rapid warming outpaces snowpack adaptive capacity. Response lag time exhibits region-specific signatures, from long, stable lags in deep, cold snowpacks to elevation-threshold-dependent behavior in marginal snow environments. Long-term trends reveal seasonally differentiated and regionally heterogeneous responses, precluding one-size-fits-all modeling approaches.

The proposed framework is applicable to other snow-dominated mountain regions facing similar data and topographic challenges. For Xinjiang and analogous arid areas, the identified vulnerability and resilience hotspots provide a scientific basis for prioritizing monitoring and climate adaptation. Future research should integrate process-based snowpack modeling to attribute lag patterns to specific energy balance components, and extend this framework to other Central Asian ranges to advance continental-scale understanding of cryosphere-climate-hydrology interactions under accelerating warming. The CD-CCD-lag metrics proposed here may support future

model development by providing spatially explicit, empirically based reference targets for evaluating snow thermal schemes—such as thermal conductivity and albedo decay parameterizations—in land surface and hydrological models.”

Comments of minor issues:

- (1). The treatment of snow-free pixels should be explained.*
- (2). Some figure labels are small. Increasing the font size would improve readability.*
- (3). Some strong words should be used more cautiously.*
- (4). Some expressions could be polished for clarity. Could the authors check non-standard phrases such as ‘Data introduction’ and ‘Break-in stag’? In addition, the explanatory sentences after equations could be revised in a more standard style.*

Our Response to Minor Issues:

(1) Treatment of snow-free pixels. We have added a statement in Section 3.1 clarifying that grid cells with mean snow depth below 1 cm (primarily in the Tarim Basin and low-elevation desert areas) were excluded from the analysis to avoid spurious results. For pixels with seasonal snow cover, analyses were conducted on a seasonal basis using only days when snow was present.

“For grid cells where mean snow depth was consistently below 1 cm throughout the study period, these pixels were excluded from the CD, CCD, and lag correlation analyses to avoid spurious results arising from near-zero values. These areas are indicated as snow-free in the relevant figures. For pixels with intermittent snow cover (i.e., snow present in some seasons but not others), the analyses were conducted on a seasonal basis using only the days when snow was present, ensuring that the calculated metrics reflect actual snow-temperature interactions rather than artifacts of snow absence.”

(2) Figure font sizes. We have increased the font size of all figure labels and legends to improve readability.

(3) Strong wording. We have systematically checked the manuscript and

replaced overstatements with more cautious language throughout (e.g., “demonstrates” → “suggests,” “confirms” → “is consistent with”).

(4) Non-standard expressions and equation explanations. We have corrected “*Data introduction*” to “*Data sources*,” and “*Break-in stag*” to “*Break-in stage*” in Table 1. We have also revised the explanatory sentences following equations to adopt more standard academic phrasing.

Reviewer 3

Reviewer's comment 1:

Introduction (L51-59): The expression "cannot distinguish" feels somewhat too strong. For instance, established methods such as wavelet coherence do allow for the examination of time lags and phase differences between variables. Furthermore, in a paragraph that argues the limitations of previous studies, citing only Clark et al. (2011) appears insufficient. The motivation for the proposed framework would be strengthened by a broader review of previous studies.

Our Response to comment 1:

We thank the reviewer for this constructive criticism. We agree that the original Introduction presented an overly narrow view of existing methods and overstated the limitations of correlation-based approaches, particularly by failing to acknowledge that methods such as wavelet coherence can effectively examine time-lagged relationships and phase differences between variables.

To address this, we have substantially revised the fourth paragraph of the Introduction. We have expanded the literature review by incorporating additional references, including Grinsted et al. (2004) on wavelet coherence, Granger (1969) and Sugihara et al. (2012) on causal inference methods, Mudelsee (2019) on time series analysis challenges, and Kim et al. (2025) on convergent cross-mapping applications in snow research. We now broadly categorize existing analytical methods into two groups: those that characterize correlation or coherence structures—including wavelet coherence and spectral methods—and those that infer causal or predictive links, such as Granger causality and convergent cross-mapping. We acknowledge that these methods have advanced our understanding of snow–climate interactions, but we also clarify that they differ in methodological objectives from a diagnostic framework that jointly assesses interaction intensity, coordination quality, and response timing. We have also tempered the language throughout the paragraph to avoid

overstatement, using more cautious phrasing where the original wording was overly absolute.”

For the reviewer’s convenience, the revised paragraphs are extracted below:

A range of analytical methods have been developed to examine relationships between snow and climatic variables, broadly falling into two categories: those that characterize correlation or coherence structures, including correlation analysis, wavelet coherence, and spectral methods, which quantify the strength, frequency, or phase relationships between variables (Grinsted et al., 2004); and those that infer causal or predictive links, such as Granger causality and convergent cross-mapping, which assess whether one variable can predict or drive another (Granger, 1969; Sugihara et al., 2012; Kim et al., 2025). These methods have advanced our understanding of snow–climate interactions—for example, by revealing time-lagged responses or directional dependencies—but they differ in methodological objectives from a diagnostic framework that jointly assesses interaction intensity, coordination quality, and response timing.

Specifically, the prevailing analytical paradigm that relies on statistical correlations, while robustly establishing empirical relationships, harbors two fundamental limitations (Clark et al., 2011; see also Mudelsee, 2019, for a review of related challenges in time series analysis) when applied to snow-climate systems. First, it treats SD and LST as separate variables rather than as an interacting system. Consequently, it does not explicitly distinguish whether the snow-thermal system evolves stably and synergistically or fluctuates erratically under stress. For instance, a strong negative correlation between SD and LST could arise from two fundamentally different situations: a deep, cold snowpack that buffers temperature fluctuations and melts gradually (a well-coordinated, resilient system), versus a thin, vulnerable snowpack that collapses rapidly under warming, with temperature driving snow loss but no buffering capacity remaining (a maladaptive system). Conventional correlation treats these two scenarios identically, thereby masking the critical distinction between coupling intensity and coordination quality. Second, this approach largely overlooks

the temporal dimension of snow-temperature interactions. The response of snow to thermal forcing is not instantaneous; heat propagates through the snowpack at a rate determined by its depth, density, and liquid water content. Conventional correlation-based methods, while able to detect lagged correlations, do not systematically quantify how response times vary across regions, seasons, and elevations—information essential for understanding snowpack thermal inertia and memory effects. While methods such as Granger causality and convergent cross-mapping can infer directional influences, they are not designed to evaluate whether a strongly interacting system is evolving in a coordinated, healthy manner or is under stress—a distinction that is central to assessing snowpack vulnerability. This propagation delay—ranging from near-zero in shallow ephemeral snow to several weeks in deep, cold snowpacks—highlights the need for a framework that jointly diagnoses coupling strength, coordination quality, and response timescales.

Reviewer's comment 2:

Method section: Overall, the Methods section would benefit from additional methodological details. In particular, I suggest providing the following information.

We thank the reviewer for these detailed methodological suggestions. We address each sub-comment below.

Comment 2-1:

General for Section 3: When CD and CCD are applied to SD and LST, what physical meaning do these metrics carry in this context? Please clarify the physical interpretation more explicitly.

Our Response to comment 2-1:

We have substantially revised Section 3.1 to clarify the physical interpretation of CD and CCD in the context of SD-LST systems. We now first explain their general meaning within the CCDD framework, then extend this to their specific diagnostic interpretation in our snow-temperature system, with explicit reference to what high/low values indicate for snowpack behavior.

Comment 2-2:

L116: The basis for the claim that "the larger the value, the better the system development" is unclear. Please provide justification for why a higher coupling degree C is considered to indicate a more favorable system state.

Our Response to comment 2-2:

We have removed this statement and replaced it with a more precise explanation: CD ranges from 0 to 1, with higher values indicating stronger interdependence, but it does not indicate whether the system state is favorable or not. This distinction is now explicitly stated in Section 3.1.

For the reviewer's convenience, the full revised Section 3.1 is extracted below:

"The concept of coupling, derived from physics, describes the phenomenon of mutual influence and interaction between two or more systems (Song et al., 2020). Building upon this, the notion of coupling coordination expands the framework to represent how systems can co-evolve toward a more ordered, synergistic state (Song et al., 2020). This approach has been effectively adapted to investigate interdependent systems across various fields, including ecology, geography, and economics (Lai et al., 2020; Zhao et al., 2025).

The Coupling Coordination Degree Model (CCDM) is an analytical framework that quantifies such relationships through two key metrics: the Coupling Degree (CD) and the Coupling Coordination Degree (CCD) (Huang et al., 2020; Liu et al., 2005). The CD measures the strength of association and mutual influence between systems, while the CCD further assesses the degree to which their development is harmonized. In this study, we apply the CCDM to analyze the interaction between SD and LST. Prior to calculation, both SD and LST time series at each grid cell were normalized to the [0, 1] range using min-max normalization to eliminate the effects of differing units and magnitudes. The normalization was performed separately for each grid cell across the 20-year study period to preserve spatial heterogeneity in the relative variability of each variable. The CD is calculated as follows:

$$C = \left[\frac{S \times E}{[(S+E)/2]^2} \right]^{\frac{1}{2}} \quad (1)$$

where S and E represent the SD and LST, respectively, and C denotes the coupling degree. In the CCDM framework, CD quantifies the intensity of mutual influence between two subsystems, irrespective of the direction or quality of that exchange; it ranges from 0 to 1, with higher values indicating stronger interdependence. In the context of our SD-LST system, a high CD (>0.8) indicates that temperature changes are closely mirrored by snow depth variations, reflecting efficient energy transfer at the snow surface. A low CD (<0.3) indicates weak or decoupled interaction, where thermal forcing does not translate into detectable snowpack response—either due to snow absence or to other factors overriding the temperature control. However, CD alone does not distinguish whether this interdependence is sustainable or stressful; it only reflects interaction strength.

To assess coordinated development, CCD is introduced, which evaluates both interaction magnitude and mutual promotion/restraint (Huang et al., 2020). In the CCDM framework, CCD assesses the degree of harmonious co-evolution between two subsystems—quantifying not just whether they interact, but whether that interaction is balanced, stable, and mutually adaptive. In our SD-LST system, a high CCD indicates that the snowpack and thermal regime are evolving in a coordinated manner: for example, a deep snowpack that buffers temperature fluctuations and melts gradually under warming, maintaining a stable energy balance. A low CCD indicates maladjustment or system stress—for instance, a thin snowpack that collapses rapidly under thermal forcing, with no buffering capacity remaining to moderate the response. Thus, CCD provides a diagnostic measure of snow-thermal system health that complements the intensity-based information provided by CD. The calculation method is as follows:

$$T = \alpha \cdot S + \beta \cdot E \quad (2)$$

$$D = (C \times T)^{\frac{1}{2}} \quad (3)$$

where D denotes the CCD, ranging from 0 to 1. T represents the comprehensive evaluation index reflecting subsystem contributions. α and β (both set at 0.5 here)

signify subsystem interaction weights. CD and CCD are classified via Meng et al.'s (2024) and Zhang et al.'s (2023) standards (Table 1).

For grid cells where mean snow depth was consistently below 1 cm throughout the study period, these pixels were excluded from the CD, CCD, and lag correlation analyses to avoid spurious results arising from near-zero values. These areas are indicated as snow-free in the relevant figures. For pixels with intermittent snow cover (i.e., snow present in some seasons but not others), the analyses were conducted on a seasonal basis using only the days when snow was present, ensuring that the calculated metrics reflect actual snow-temperature interactions rather than artifacts of snow absence."

Comment 2-3:

L156/160: Both SD and LST exhibit large interannual variability, which makes visual trend detection unreliable. Please verify whether the reported increase/decrease trends are statistically robust using an appropriate significance test, such as the Mann-Kendall test.

Our Response to comment 2-3:

We thank the reviewer for this important methodological suggestion. We agree that the large interannual variability in both SD and LST makes visual trend detection unreliable. To address this, we have applied the Mann–Kendall test combined with Sen's slope estimation (Section 3.3) to statistically verify the trends reported in Section 4.1. The results show that none of the six sub-regions exhibit statistically significant trends in either SD or LST at the 95% confidence level ($p > 0.05$ for all). Although several sub-regions show directional tendencies (SD declining in N1–N3 and S1–S2 but slightly increasing in S3; LST increasing in R2–R5 but declining in R1 and R6), none of these tendencies are statistically robust. We have revised Section 4.1 to include these statistical results, ensuring that only verified trends are discussed. The corresponding method has been added to Section 3.3.

For the reviewer's convenience, the full revised Section 4.1 is extracted

below:

4.1 Spatial-Temporal Patterns of SD and LST across Xinjiang

Figure 2 shows the interannual variations of annual average SD and LST across six sub-regions of Xinjiang over the 20-year study period. The 20-year mean SD (Fig. 2a) exhibits marked spatial heterogeneity, with deeper snowpacks predominantly located in the northern regions. The mean SD values for the six sub-regions were: N1 = 5.32 cm, N2 = 2.89 cm, N3 = 4.25 cm, S1 = 2.00 cm, S2 = 0.06 cm, and S3 = 1.58 cm. The highest mean SD occurred in N1 (5.32 cm), followed by N3 (4.25 cm) and N2 (2.89 cm), while the lowest was in S2 (0.06 cm). Overall, snow accumulation is most pronounced in the northern zones (N1, N3, N2) and the southern alpine zone (S3), showing a clear north-to-south gradient. Maximum accumulation occurs on the northern slopes of the Tianshan Mountains (N3), while the Tarim Basin (S2) remains largely snow-free throughout most of the year.

To statistically verify these visual trends, we applied the Mann–Kendall test combined with Sen's slope estimation (Section 3.3). The results show that none of the six sub-regions exhibit statistically significant trends in SD at the 95% confidence level ($p > 0.05$ for all). Although several regions show directional tendencies—SD declining in N1–N3 and S1–S2 but slightly increasing in S3—none of these tendencies are statistically robust. The Sen's slopes for SD were $-0.039 \text{ cm yr}^{-1}$ (N1), $-0.015 \text{ cm yr}^{-1}$ (N2), $-0.026 \text{ cm yr}^{-1}$ (N3), $-0.031 \text{ cm yr}^{-1}$ (S1), $-0.001 \text{ cm yr}^{-1}$ (S2), and $+0.016 \text{ cm yr}^{-1}$ (S3), with the largest declining tendency occurring in N1 and the only increasing tendency in S3.

Temporal trends of LST show differentiated variations across the six sub-regions (Fig. 2b). The highest mean annual LST values ($>30^{\circ}\text{C}$) occur in the arid Tarim Basin (S2), followed by the Junggar Basin (N2, $>25^{\circ}\text{C}$). The remaining mountain-dominated regions (S1, S3, N1, N3) maintain moderate LST regimes ranging between 10 and 18°C . Temporal analysis shows varied tendencies across regions, with warming tendencies in N2, N3, S1, and S2, and cooling tendencies in N1 and S3, though none are statistically significant. However, Mann–Kendall test results indicate that none of these LST trends

are statistically significant at the 95% confidence level ($p > 0.05$ for all), with N2, N3, S1 and S2 showing weak increasing tendencies and N1 and S3 showing weak declining tendencies. The Sen's slopes for LST ranged from $-0.018\text{ }^{\circ}\text{C yr}^{-1}$ (S3) to $0.011\text{ }^{\circ}\text{C yr}^{-1}$ (N3), indicating generally weak thermal trends across the region. The absence of significant trends in both SD and LST underscores the importance of using statistical significance tests rather than visual inspection alone to identify robust changes in these highly variable climate variables.

Scatter plot analyses were conducted to quantify the SD-LST interactions across the six sub-regions (Fig. 3). Each panel displays the scatter distribution, linear regression fit, 95% confidence interval (shaded band), coefficient of determination (R^2), and Spearman's rank correlation coefficient (ρ). In five of the six sub-regions (N1, N2, N3, S1, and S3), both Spearman's ρ and R^2 indicate statistically significant negative correlations ($p < 0.01$ for ρ ; R^2 ranging from 0.49 to 0.76, all $p < 0.001$). The majority of data points fall within the confidence intervals, supporting the robustness of the inverse relationship. In contrast, no significant correlation is observed in S2 (Tarim Basin): $\rho = -0.0011$ ($p \approx 1.0$) and $R^2 \approx 0$ ($p \approx 0.98$), indicating no linear or monotonic relationship between SD and LST due to limited seasonal snow cover and persistently high LST.

These results demonstrate that in snow-abundant regions of Xinjiang, SD is consistently negatively correlated with LST, though the strength of this relationship varies spatially. However, correlation alone does not elucidate the directionality, lagged responses, or synergistic interactions between the two variables. This highlights the necessity of employing more nuanced analytical frameworks—such as coupling coordination and time-lag models—to better characterize the underlying SD-LST interaction mechanisms across different geographical and climatic contexts.

Comment 2-4 and 2-5:

(2-4) L188-192 & Figure 4b: The text discusses the annual trend in CD, but no description of the trend analysis method is provided. Please add this information to the Methods section. In addition, please include a discussion of statistical significance. As

it is likely that some pixels will show statistically significant trends while others will not, Figure 4b should be revised to make this distinction clearly visible (e.g., by coloring only statistically significant pixels, or by overlaying stippling on non-significant areas). (2-5) L219-226 & Figure 6b: As with Comment 2-4 above, please provide a description of the trend analysis method used, and address the issue of statistical significance.

Our Response to comment 2-4 and 2-5:

We have added a new subsection (Section 3.3) describing the trend analysis methodology. Specifically, we applied Sen's slope estimation combined with the Mann–Kendall significance test ($\alpha = 0.05$). All trend analyses were performed on a per-pixel basis and summarized by sub-region. The text in Sections 4 has been updated to reflect this methodological clarification. The significance levels are now reported alongside the trend magnitudes in the revised text, ensuring that only statistically robust trends are discussed.

For the reviewer's convenience, the new Section 3.3 is extracted below:

“3.3 Trend Analysis

To quantify long-term changes in snow depth (SD), land surface temperature (LST), CD, CCD, and lag times, we applied Sen's slope estimation combined with the Mann–Kendall significance test. Sen's slope estimator calculates the median of all pairwise slopes between data points, providing a robust trend magnitude that is insensitive to outliers and does not assume normality of the data distribution (Sen, 1968). For a time series with n data points, the slope between any two points i and j ($i < j$) is computed as:

$$\beta_{ij} = (x_j - x_i) / (j - i) \quad (8)$$

The overall trend slope β is the median of all pairwise slopes:

$$\beta = \text{median}(\beta_{ij}) \text{ for all } i < j \quad (9)$$

Statistical significance of the observed trends was assessed using the Mann–Kendall test, a non-parametric test for monotonic trends that does not require normally distributed data (Mann, 1945; Kendall, 1975). The test statistic S is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (10)$$

where $\text{sign}(x_j - x_i) = 1$ if $x_j > x_i$, 0 if $x_j = x_i$, and -1 if $x_j < x_i$. And the standardized

test statistic Z is computed to assess significance. A significance level of $\alpha = 0.05$ was used; trends with $p < 0.05$ were considered statistically significant. All trend analyses were performed on a per-pixel basis and then summarized by sub-region (N1–N3, S1–S3) for reporting.”

Figures 4b and 6b: We thank the reviewer for these comments. We realize that the original manuscript did not clearly specify what is shown in Figures 4b and 6b. These figures display the magnitude of Sen's slope (annual trend rate) for pixels with statistically significant trends ($p < 0.05$, Mann–Kendall test), while non-significant areas are shown in gray to avoid visual misinterpretation. The slope magnitudes are computed from the per-pixel trend analysis using Sen's slope estimation, which we have now added as a new subsection (Section 3.3) in the Methods. We have also revised the figure captions and the corresponding text in Sections 4.2 and 4.3.3 to clarify that the maps show only significant trends, with gray areas denoting non-significant trends. This revision ensures that readers can clearly distinguish regions with statistically robust trends from those without, while the color scale still conveys the magnitude of the observed changes where trends are significant.

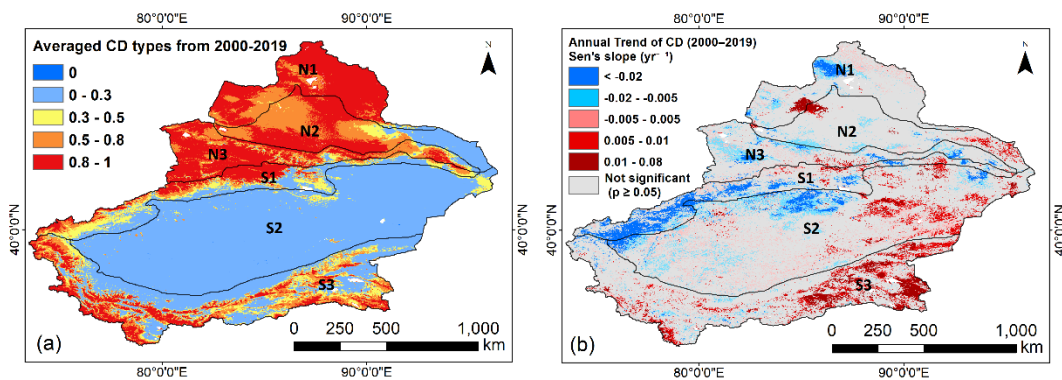


Figure 4. (a) Spatial distribution of average annual SD-LST coupling degree (CD) types across Xinjiang (see Table 1 for type definitions). (b) Twenty-year annual trend in CD (Sen's slope, yr^{-1}), with only statistically significant pixels colored ($p < 0.05$). Gray areas denote non-significant trends.

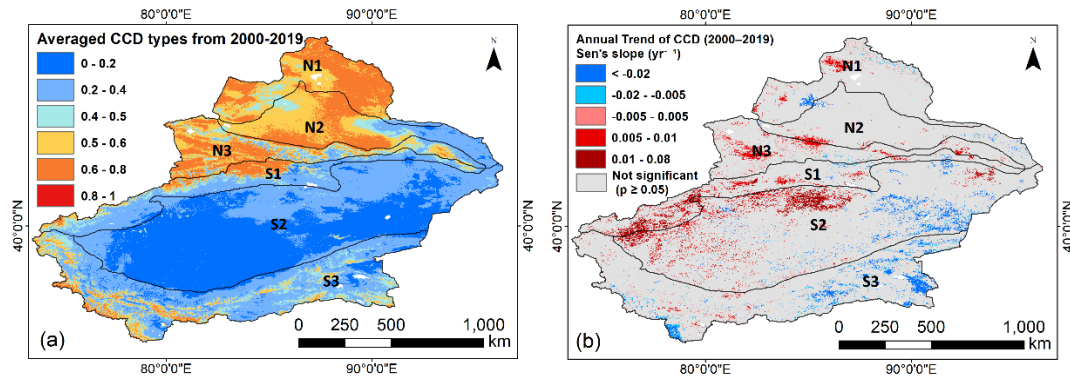


Figure 6. (a) Spatial distribution of average annual SD-LST coupling coordination degree (CCD) types across Xinjiang (see Table 1 for type definitions). (b) Twenty-year annual trend in CCD (Sen's slope, yr^{-1}), with only statistically significant pixels colored ($p < 0.05$). Gray areas denote non-significant trends.

Comment 2-6:

L241: The text states "statistically significant," but the statistical method used is not described. Please specify which test was used to confirm significance, and add this information to Section 3.

Our Response to comment 2-6:

We thank the reviewer for this comment. We have now explicitly described the statistical method used to assess significance in Section 3.3. Specifically, we applied the Mann–Kendall test at the 95% confidence level ($p < 0.05$) to all trend analyses. All references to “statistically significant” trends in Sections 4.2, 4.3.3, and elsewhere now refer to this test. For the reviewer's convenience, the methodological details are provided in Section 3.3 as extracted above.

Reviewer's comment 3:

Section 4.3.3: Trend slopes and p-values are reported in this section, but the methods used to calculate the slopes and to conduct the significance tests are not described. Please add these methodological details to Section 3. Furthermore, the concluding sentences of several paragraphs in this section contain interpretations that extend beyond what the data directly demonstrate. Please ensure that the Results section is confined to findings that are directly supported by the data, and that any broader interpretation is reserved for the Discussion.

Our Response to comment 3:

We thank the reviewer for this comment. We address each sub-comment below.

Trend analysis methods: We have added a new subsection (Section 3.3) describing the trend analysis methodology, including Sen's slope estimation and the Mann–Kendall significance test. This addresses the reviewer's concern that the methods for calculating slopes and p-values in Section 4.3.3 were not previously described. The methodological details are now fully documented before the results are presented. In addition, we have added a statement at the beginning of Section 4.3.3 to explicitly indicate that all reported slopes and p-values are derived from Sen's slope estimation combined with the Mann–Kendall significance test (see Section 3.3 for method details), ensuring that readers can readily connect the results to their methodological basis.

Results vs. Discussion: We agree with the reviewer that the Results section should be confined to findings directly supported by the data, and that broader interpretation should be reserved for the Discussion. We have revised Section 4.3.3 accordingly: all interpretive concluding sentences in the trend paragraphs (e.g., attributions of autumn and winter lag declines to cooling or warming) have been removed from the Results. These interpretations have been moved to Section 5.2, where we now discuss the potential physical mechanisms underlying the observed lag patterns using cautious, inferential language. This separation ensures that Section 4.3.3 presents only observed trends and their statistical significance, while Section 5.2 provides the physical interpretation.

We also note that, in response to another reviewer's suggestion regarding overly granular subheadings, the subsubsection 4.3.3 structure in Section 4.3 has been streamlined, with the heading “**Long-Term Trends in Seasonal Lag Times Across Mountain Regions**” now formatted as bold text.

For the reviewer's convenience, the relevant additions and revisions are highlighted in the revised manuscript.

Reviewer's comment 4:

Section 4.3.3 のAutumn と Winter: Both paragraphs report a decrease in lag time over the study period, yet the interpretations offered are asymmetric: the autumn

decrease is attributed to "cooling temperatures," while the winter decrease is attributed to "warming winters." Please provide clear justification for this asymmetric interpretation. Note, however, that this type of interpretive discussion is more appropriately placed in the Discussion section rather than the Results.

Our Response to comment 4:

We thank the reviewer for this important observation. We agree that the asymmetric interpretation of autumn versus winter lag declines requires clear justification, and that such interpretive discussion belongs in the Discussion section rather than Results.

We fully acknowledge that autumn and winter represent two distinct phases of snowpack evolution, and the same observed trend—decreasing lag time—can arise from different mechanisms depending on the seasonal context. In autumn, the snowpack is in its establishment phase: when cooling accelerates, snow cover forms earlier and more rapidly, shortening the time required for SD to couple with LST. In winter, by contrast, the snowpack is in its maintenance phase: when winter temperatures warm, snowpack thickness decreases and densification accelerates, reducing cold content and thermal inertia. Lower thermal inertia allows thermal forcing to propagate more quickly through the snow column, again shortening the response time. Thus, the asymmetric interpretation is not contradictory but reflects the different dominant processes operating in each season—one driven by the rate of snow cover establishment, the other by snowpack thermal degradation. This physical distinction is now explicitly stated in Section 5.2, supported by concurrent regional trends: autumn cooling rates have accelerated over the study period, while winter warming trends have been documented in the same region (Chen et al., 2015).

To address the reviewer's concern regarding placement, we have removed all causal attributions from Section 4.3.3 (e.g., “cooling temperatures” for autumn and “warming winters” for winter). These interpretive discussions have been moved to Section 5.2, where the physical mechanisms underlying the asymmetric lag responses are now discussed using cautious, inferential

language. This revision ensures that Section 4.3.3 presents only the observed trends, while Section 5.2 provides the physical interpretation with appropriate justification and supporting evidence.

Reviewer's comment 5:

Section 5.1: While this section addresses important mechanisms governing snow–temperature interactions, the discussion of the Tianshan Mountains feels relatively underdeveloped compared to the treatment of the other mountain systems. Adding an explanation of how "the rain-shadow effect and differential solar radiation" specifically influence CD and CCD, and why these factors render SI a more sensitive and vulnerable subsystem, would make this section considerably more convincing.

Our Response to comment 5:

We thank the reviewer for this suggestion. We agree that the Tianshan discussion in Section 5.1 is relatively underdeveloped compared to the treatment of the Altay and Kunlun systems, and that the mechanisms linking rain-shadow effects and solar radiation to CD and CCD need to be made more explicit.

To address this, we have expanded the Tianshan discussion by adding three mechanistic explanations. First, we now explain that the rain-shadow effect reduces precipitation on the southern slope, leading to thinner snowpack with lower cold content and reduced thermal buffering capacity, which directly manifests as lower CCD and greater CD-CCD divergence. Second, we now explain that greater solar radiation on the south-facing slope accelerates melt and shortens snow duration, increasing sensitivity to temperature fluctuations—as reflected in the significant spring lag lengthening observed on the southern slope. Third, we now explicitly state that the combination of reduced moisture and enhanced radiation makes the southern slope particularly vulnerable to warming, and that the intensification of the CD-CCD mismatch with elevation on the south slope (Δ increasing from 0.13 at 2700–3000 m to 0.34 at >3800 m) provides quantitative evidence of this vulnerability.

These additions make the Tianshan discussion more balanced with the

treatment of the other mountain systems, and more convincingly demonstrate why slope aspect is the key factor governing the observed north–south asymmetry.

For the reviewer’s convenience, the revised Tianshan paragraph in Section 5.1 is extracted below:

“In the Tianshan Mountains (N3 and S1), topography manifests as a sharp intra-mountain contrast. The pronounced north–south asymmetry in coupling and coordination is a direct result of the rain-shadow effect and differential solar radiation, making the south slope (S1) a more sensitive and vulnerable subsystem. The rain-shadow effect reduces precipitation on the southern slope, leading to thinner snowpack with lower cold content and reduced thermal buffering capacity. This directly limits the snowpack’s ability to absorb and modulate thermal forcing, manifesting as lower CCD values (0.2–0.4) and greater CD-CCD divergence (Δ up to 0.34) compared to the northern slope. Here, topography amplifies the macro-climatic gradient, creating strong internal heterogeneity. This is supported by the contrasting CD and CCD patterns between N3 and S1: the northern slope maintains higher CCD values (0.5–0.6) and more stable Δ (0.20–0.28 at low elevations), whereas the southern slope exhibits lower CCD (0.2–0.4) and the largest CD-CCD divergence above 2700 m (Δ up to 0.34, Section 4.2). The greater solar radiation on the south-facing slope accelerates melt and shortens snow duration, increasing sensitivity to temperature fluctuations—as reflected in the significant spring lag lengthening observed on the southern slope (Section 4.3). Lag patterns further reinforce this asymmetry: the southern slope shows significant spring lag lengthening, suggesting heightened sensitivity to seasonal transitions, whereas the northern slope maintains more stable seasonal lag structures. The combination of reduced moisture supply and enhanced radiative forcing makes the southern slope particularly vulnerable to warming. Even moderate temperature increases can trigger rapid snow loss, whereas the northern slope—sustained by greater snowfall and lower radiation—maintains more stable snowpack conditions and higher CCD. This vulnerability is further evidenced by the intensification of the CD-CCD mismatch with elevation on the south slope (Δ increasing from 0.13 at 2700–3000

m to 0.34 at >3800 m), confirming that topographic modulation of snowpack properties is the dominant mechanism underlying the north–south asymmetry.”

Comments of additional minor issues:

*(1) **General** – The manuscript employs a six-region classification (N1–N3, S1–S3), but in some parts of the text, only regional names are provided without the corresponding region codes. Consistently including the region codes (N1–N3, S1–S3) throughout the text would improve readability.*

*(2) **Section 2.2.1** – While I understand that the full methodological details are available in the referenced data repository, it would be helpful to include at minimum the source satellite data, the original spatial resolution, and any auxiliary datasets used. These basic pieces of information should be provided directly in the manuscript.*

*(3) **L153** – According to Figure 2a, S1 and S3 appear to follow similar trajectories throughout the study period. Please report the mean SD values for both S1 and S3 explicitly, and explain why S3 alone is highlighted in this context.*

*(4) **Figure 5 and Figure 7** – Please add an explanation of the gray color to both the legend and the figure caption.*

*(5) **L237** – The term "resilience" generally implies recovery from some form of loss or disturbance. Please consider rephrasing with a more appropriate term.*

*(6) **Section 4.3.2** – Please define which months are assigned to each season (spring, summer, autumn, and winter).*

*(7) **L304** – Please add a p-value for the trend reported for the Kunlun Mountains (S3).*

Our Response to Minor Issues:

Response to Minor Comment (1):

We have checked the entire manuscript and ensured that region codes (N1–N3, S1–S3) are consistently included alongside regional names throughout the text, particularly where sub-regional comparisons are discussed. This improves readability and allows readers to quickly reference the regional classification defined in Section 2.1.

Response to Minor Comment (2):

We have expanded the data description in Section 2.2.1 to include the

source satellite data, original spatial resolution, and auxiliary datasets used. For the SD dataset, we now specify that it was produced using a random forest downscaling approach at 500 m resolution for 2000–2020, integrating: (1) the long-term snow depth dataset from the National Tibetan Plateau Data Center; (2) MODIS daily snow cover (MOD10A1), AMSR2 snow water equivalent, and IMS snow/ice data; (3) SRTM DEM-derived topographic variables (elevation, slope, aspect, roughness); and (4) MOD13A1 NDVI, along with auxiliary LST and meteorological data. For the LST dataset, we now explicitly note that the TRIMS product integrates Terra/Aqua MODIS LST (MOD11A1/MYD11A1, 1 km) with GLDAS reanalysis data, with NDVI as auxiliary variables for the reconstruction. For the reviewer's convenience, the revised Section 2.2.1 is extracted below:

“The daily snow depth dataset used in this study is a downscaled product at 500 m spatial resolution over Xinjiang for the period 2000–2020. The dataset was produced using a random forest machine learning approach, integrating multiple source datasets. The primary training target was the 25 km long-term snow depth dataset from the National Tibetan Plateau Data Center (China). Remote sensing inputs included 500 m MODIS daily snow cover data (MOD10A1), 10 km AMSR2 satellite snow water equivalent data, and 4 km IMS snow/ice data. Topographic variables (elevation, slope, aspect, and surface roughness) were derived from SRTM DEM (90 m) via the Geospatial Data Cloud platform. Additional predictor variables included MOD13A1 NDVI data from the NASA LP DAAC (available via Earthdata), land surface temperature, and meteorological data. Spatial location and snow cover days were also incorporated as auxiliary predictors. The final product provides daily snow depth at 500 m resolution for the period 2000–2020, with cloud removal applied to minimize data gaps. This 500 m daily product was developed by the authors; detailed methodological descriptions and validation procedures are available in the referenced data repository at the National Cryosphere Desert Data Center of China. The dataset is publicly accessible under the same citation as the original data product.”

Response to Minor Comment (3):

We thank the reviewer for this observation. We have added the 20-year mean SD values for all six sub-regions in Section 4.1, including S1 (1.998 cm) and S3 (1.580 cm). We acknowledge that S1 and S3 exhibit similar interannual variability (Fig. 2a), particularly during certain periods. However, their long-term trends differ in direction: S1 shows a declining tendency (-0.031 cm/yr, $p = 0.064$), while S3 shows an increasing tendency ($+0.016$ cm/yr, $p = 0.127$). S3 is highlighted in the text because it is the only mountainous sub-region with an increasing tendency, which is particularly relevant to our subsequent discussion of elevation-dependent coupling behavior (Sections 4.2 and 5.1). In contrast, S1 is discussed primarily in the context of the Tianshan north–south asymmetry (Section 5.1), where its role is defined by slope-aspect contrasts rather than elevation-driven dynamics.

Response to Minor Comment (4):

We have added an explanation of the gray color to both the legends and the captions of Figures 5 and 7. The caption for Figure 5 now reads: “Gray areas indicate elevations where snow cover is absent.” Similarly, the caption for Figure 7 now includes: “Gray areas indicate elevations where snow cover is absent.” The same explanation has been added to the figure legends to ensure readers can easily interpret the gray regions.

Response to Minor Comment (5):

We thank the reviewer for this careful observation. We agree that “resilience” may imply recovery from disturbance, which is not the focus of our analysis. We have replaced it with “buffering capacity” at L237 and in other relevant locations throughout the manuscript to more accurately reflect the snowpack’s ability to absorb and modulate thermal forcing without implying recovery from loss.

Response to Minor Comment (6):

We have added a clear definition of seasonal assignment at the beginning of Section 4.3.2: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February).

Response to Minor Comment (7):

We thank the reviewer for this careful observation. Accordingly, we have added the p-value for the Kunlun Mountains (S3) trend in Section 4.3.3, which now reads: "...showed a significant declining trend (-0.18 days/year, $p = 0.015$, Mann–Kendall test)."

We are grateful again to the Editor and all reviewers for their time and constructive feedback. We believe that addressing these comments has substantially improved the clarity, rigor, and overall quality of our manuscript. We hope that the revised version now meets the standards for publication in *The Cryosphere*.

We look forward to your final decision.

Sincerely,

Haixing Li (on behalf of all authors)