

Systematic Review

Compound Spring Flood Hazards in Kazakhstan and Comparable Cold-Continental Regions: Mechanisms, Indicators, and Recovery Assessment

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Abstract

Compound spring floods in cold-continental and semi-arid interiors arise from interacting snowmelt, rain-on-snow events, intense precipitation, and frozen or saturated soils, yet these mechanisms remain poorly synthesized for Central Asia. This review develops a process-oriented framework linking preconditioning, triggers, propagation/amplification, impacts, and recovery outcomes. The synthesis shows that the most destructive spring floods occur when substantial antecedent snow storage and restricted infiltration coincide with rapid warming and rainfall, producing efficient runoff generation and widespread impacts. Evidence from Kazakhstan and comparable continental regions indicates that mechanistic understanding is relatively robust, but standardized event-level reporting of snow-water equivalent, soil wetness, precipitation phase, routing constraints, and recovery indicators remains uneven. To support post-disaster comparison, we introduce and demonstrate a Recovery Effectiveness Index (REI) combining housing resettlement, compensation, infrastructure restoration, and equity of assistance. A proof-of-concept application to the 2024 Kazakhstan floods produced a 21 June 2024 snapshot REI of 0.607–0.757 and an end-year REI of 0.850–1.000, depending on the treatment of the equity component. The framework supports compound-driver monitoring, early warning, recovery benchmarking, and more harmonized flood-risk assessment in data-sparse continental regions.

Keywords: compound flood hazards; rain-on-snow events; Recovery Effectiveness Index (REI); cold-continental hydrology; process-based flood risk framework; Central Asia flood risk



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1. Introduction

Natural hazards including floods, droughts, and heatwaves, are often interconnected rather than isolated phenomena and pose significant challenges to disaster risk management, particularly in areas that are highly vulnerable to climate change impacts [1]. When extreme events occur concurrently or consecutively, they can lead to devastating consequences for both human and natural systems, amplifying their individual impacts [2]. Recently, extreme precipitation and floods have been observed co-occurring in areas like arid and semi-arid regions, where such events were less common historically, indicating a

shift in hazard patterns attributable to climatic shifts [1,3]. In the spring of 2024, the Republic of Kazakhstan and its adjacent regions experienced unprecedented flooding, driven by a complex interplay of hydrometeorological factors [4]. This catastrophic event occurred due to the rapid melting of accumulated snow, combined with substantial rainfall and saturated ground conditions [5,6]. Authorities in Kazakhstan evacuated over 90,000 people as floodwaters inundated numerous settlements and damaged infrastructure, resulting in damages amounting to roughly 300 billion tenge (~USD 600,000,000) [7]. These floods represent a critical instance of extreme events where multiple hazards synergistically exacerbated the disaster, highlighting the urgent need for enhanced understanding and management of cascading risks in continental climates [5,8]. This phenomenon underscores the necessity of analyzing compound hazard patterns, wherein initial events trigger a sequence of subsequent hazards, leading to a complex web of environmental and socioeconomic impacts [3,9].

In recent years, climate researchers and organizations have emphasized that extreme impacts often arise not from single events but from compound events that is, the interaction of multiple climatic stressors or drivers that exacerbate societal or environmental risks [10]. These compound events, which can involve simultaneous or sequential occurrences of hazards, often result in more severe ecological and socioeconomic damage than individual hazards occurring in isolation [11]. The latest IPCC report emphasizes that the likelihood of such compound events, including heatwaves, droughts, and compound flooding from extreme rainfall and storm surges, has increased and is projected to rise further with ongoing climate change [2]. The 2024 floods in Kazakhstan serve as a stark illustration of these compound extreme events, where antecedent conditions like saturated soils and heavy snowpack, coupled with rapid warming and precipitation, collectively amplified the flood's magnitude and impact [12]. Understanding these intricate interactions and their cascading effects is crucial for developing robust adaptation and mitigation strategies, particularly in vulnerable continental regions susceptible to such multi-hazard phenomena [12,13].

Floods are complex and multifaceted phenomena, often resulting from various interconnected factors, including intense rainfall, snowmelt, dam breaches, and storm surges [14]. Snowmelt-driven floods are prevalent in extreme continental climates, particularly in high-altitude and high-latitude regions. Snowmelt is impacted by the amount of precipitation received during winter, its accumulation and subsequent thawing rates, which are significantly influenced by temperature fluctuations and incoming solar radiation [15]. Due to climate change, the timing and occurrence of these processes are becoming increasingly unpredictable. Studies have highlighted the change in timing and magnitude of spring snowmelt events over different regions [6,16,17]. This variability further impacts the seasonality, magnitude, and spatial distribution of stream flow, complicating flood forecasting and water resource management [6].

Excessive rainfall has the tendency to trigger flash floods, especially in urbanized areas with extensive impervious surfaces that accelerate runoff [12]. With global warming, the frequency and intensity of extreme precipitation events are projected to increase, intensifying the risk of such flash floods [18]. Precipitation induced by warming temperatures can also lead to a reduction in snow fraction and a shift from snow to rain, amplifying the overall runoff volume and altering hydrological regimes [19]. These shifts are particularly critical in regions reliant on snowmelt for water resources, where changes can destabilize water availability and increase flood risk [20]. Both factors, including excessive rainfall and snowmelt, can interact in complex ways, such as during rain-on-snow events, further exacerbating flood potential by rapidly releasing stored water from the snowpack and increasing runoff [12,21,22].

Compound heatwaves with drought, or coincident river and coastal floods, have received considerable attention, but compound rain-on-snow floods in semi-arid regions have not been systematically reviewed. Only a few studies have examined scenarios like heavy rain atop existing snowpack leading to rapid melt/flood, which are often treated as special cases (e.g., North American rain-on-snow events) rather than as part of a unified framework [22–24]. A recent synthesis found that more than 70% of compound-event studies focus on multivariate or simultaneous events [25], whereas temporally compounding sequences, such as a preconditioning event followed by a trigger, and spatially compounding occurrences receive far less attention. The same study also noted that compound floods are among the more commonly studied event types, but highlighted stark geographic and thematic biases: most research comes from Europe, North America, and parts of Asia, leaving many water-critical regions understudied.

Despite the increasing frequency of compound extreme events globally, the effectiveness of current resilience strategies in mitigating their impacts remains largely limited to individual hazards [15]. Traditional frameworks often fail to capture the synergistic interactions and cascading effects of snowmelt, rain-on-snow events, and extreme precipitation, which together can lead to significantly enhanced flood magnitudes [26,27]. There is limited research explicitly quantifying the combined impact of these mechanisms on continental flood regimes, particularly concerning the interaction between antecedent snowpack conditions and subsequent rainfall extremes [26,28]. Moreover, there is no consensus on standardized post-recovery assessment methods and long-term adaptation strategies for these compound events in continental climates. This gap in understanding critically impedes the development of robust predictive models and effective risk management protocols essential for protecting vulnerable populations and infrastructure. Therefore, a systematic review of compound flood dynamics, drivers, and recovery mechanisms in these rapidly changing environments is urgently required to inform early warning systems, recovery planning, and regional cooperation.

Given the context and the research gaps, this review aims to synthesize existing knowledge on cascading flood risks in continental climates, focusing on the interplay between extreme precipitation, snowmelt dynamics, and their compounding effects in regions such as Kazakhstan and comparable cold-continental interiors. To our knowledge, no prior review has synthesized compound spring flooding mechanisms and recovery evaluation for Central Asia and comparable cold-continental interiors using a harmonized indicator and a recovery benchmarking framework. The novelty of this review lies in combining four elements that are usually treated separately: a process-oriented taxonomy of compound spring-flood mechanisms, a harmonized indicator framework for driver–impact–recovery comparison, a Kazakhstan-centered synthesis for a data-sparse cold-continental region, and a proof-of-concept Recovery Effectiveness Index (REI) application for the 2024 Kazakhstan floods. The contribution is therefore not the taxonomy, indicator framework, or REI in isolation, but their integration into a mechanism-to-recovery framework for compound spring-flood assessment.

Given the uneven availability of event-level hydrometeorological and recovery indicators across Central Asia and adjacent cold-continental regions, this review does not attempt a fully quantitative cross-event attribution or ranking of flood drivers. Instead, it is framed as a mechanism-based systematic review supported by a curated event inventory. The event records are used to identify recurring compound-flood pathways, document reporting gaps, and demonstrate the operational use of selected indicators through a proof-of-concept REI application to the 2024 Kazakhstan floods.

Specifically, we investigate the typical hazard patterns, the contributing hydro-meteorological factors, and the efficacy of current recovery interventions against these

complex events. First, we explicitly frame the definition of compound flooding disasters within the context of continental climates, acknowledging that compound flood events often result from the co-occurrence of multiple flood drivers, leading to more extreme impacts than individual events. Second, we introduce standardized comparable impact metrics for assessing the severity and spatial extent of such events across diverse geographical settings. Third, we propose and illustrate a Recovery Effectiveness Index (REI) that integrates resettlement progress, compensation timeliness, infrastructure restoration, and equity of relief coverage to evaluate post-disaster recovery where comparable data are available.

2. Methodology

This review synthesizes evidence on compound spring floods in cold-continental and semi-arid basins, with a particular focus on Central Asia and adjacent mid- to high-latitude interiors. Our central aim is to integrate hydrometeorological drivers, including snowmelt and rain-on-snow (ROS), extreme precipitation, and antecedent soil moisture or frozen ground, into a coherent account of flood generation, impacts, and recovery, while providing standardized indicators that can support future cross-event comparison where sufficiently complete and comparable data are available. This review was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist, where applicable to a mechanism-focused literature review. The completed PRISMA 2020 checklist is provided as Supplementary Table S1, and the PRISMA flow diagram is included in the main text as Figure 1. The PRISMA workflow covered identification, title–abstract screening, report retrieval, eligibility assessment, and final inclusion. This was complemented by a curated gray-literature protocol for event-scale indicators where peer-reviewed reporting lags behind real-time conditions. The peer-reviewed literature corpus and gray-literature event documentation were treated as separate evidence streams: the former supported mechanism synthesis and framework development, while the latter supported event-level impact and recovery indicators.

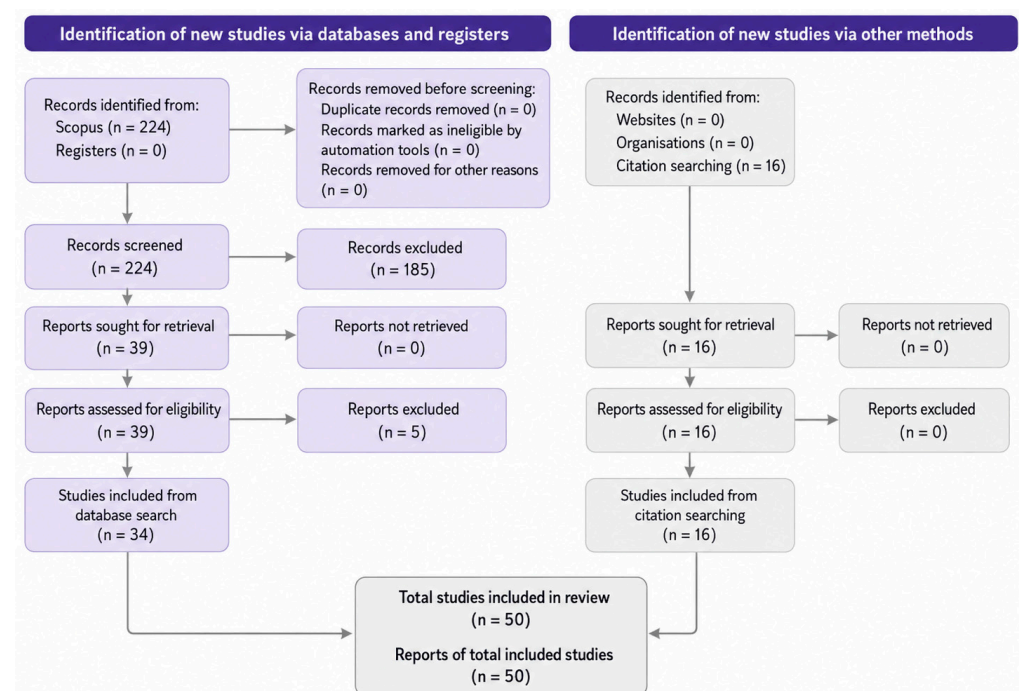


Figure 1. PRISMA-style flowchart of study identification, screening, eligibility assessment, and inclusion. The broader identification-stage Scopus search identified 224 records. After title–abstract

screening, 39 reports were assessed for eligibility, of which 5 were excluded after full-text review. Citation searching identified 16 additional studies, resulting in a final peer-reviewed corpus of 50 studies. Gray-literature sources used for event-level impact and recovery documentation were screened separately and were not counted within the peer-reviewed study corpus.

2.1. Literature Search and Selection

The peer-reviewed literature search was conducted in the Scopus database. Scopus was selected as the primary peer-reviewed database because of its broad multidisciplinary coverage across hydrology, climate-risk, environmental science, Earth observation, and disaster-risk literature. The objective of the review was not to conduct an exhaustive bibliometric mapping of all regional publications, but to synthesize peer-reviewed evidence on compound spring-flood mechanisms and to develop a transferable taxonomy and recovery-assessment framework. To reduce regional evidence bias, the Scopus-based search was complemented by backward and forward reference screening and by a structured gray-literature protocol covering official reports, hydrometeorological agencies, disaster-management documents, and reputable event documentation.

The search was limited to publications from 2000 to 2025 to capture contemporary methods and climate context while retaining sufficient historical material for trend interpretation. The peer-reviewed literature search was conducted in the Scopus database using the TITLE-ABS-KEY fields. The search was performed as a broad identification-stage retrieval in January 2026 using four thematic Boolean blocks: (i) snowmelt/rain-on-snow terms: snowmelt OR “snow melt” OR snowpack OR “snow cover” OR “rain-on-snow” OR “rain on snow” OR ROS; (ii) precipitation and warming terms: “extreme rainfall” OR precipitation OR rainfall OR “rapid warming” OR thaw; (iii) antecedent-state terms: “soil moisture” OR “antecedent wetness” OR preconditioning OR “frozen soil” OR “frozen ground” OR “freeze-thaw”; and (iv) flood-outcome terms: flood* OR inundation OR “spring flood*” OR “river flood*”. Terms were combined using OR within each thematic block, and combinations across blocks were used to identify records relevant to compound spring-flood processes. Using combinations of these search terms during the original broad Scopus identification-stage search, 224 records were retrieved at the time of search. These records were then screened using the inclusion criteria described in Section 2.2, which required relevance to cold-continental or semi-arid spring flooding and documentation of at least two flood-relevant drivers or a clear interaction between a dominant driver and an amplification mechanism. This broad retrieval strategy was used intentionally to maximize sensitivity at the identification stage, while specificity was enforced during title–abstract screening and full-text eligibility assessment.

2.2. Screening and Selection

We then undertook an initial title–abstract appraisal to eliminate clearly out-of-scope items and to restrict the geographic scope to Kazakhstan, neighboring Central Asian basins and southwestern Russia, and closely comparable cold-continental settings in the mid- to high-latitudes. We retained studies that analyzed inland floods in cold-continental or semi-arid contexts and documented at least two of the following: snowmelt or ROS, extreme precipitation, antecedent soil moisture or frozen soils, reservoir operations or failures, and explicit flood outcomes. We excluded purely coastal or estuarine surge studies, tropical monsoon floods without a cryospheric or frozen-ground component, urban drainage or hydraulic-engineering papers that lacked climatic or hydrologic driver analysis, conceptual commentaries without case evidence, and duplicates. Duplicates were negligible due to the single-database primary retrieval; exclusion reasons for full-texts not proceeding to

synthesis were recorded as non-compound mechanism, non-regional focus, absence of flood outcomes, or insufficient methodological detail.

The screening followed the sequence shown in Figure 1. The broader Scopus identification-stage search yielded 224 records. No duplicate records, automation-based exclusions, or other pre-screening removals were recorded; therefore, all 224 records were screened by title and abstract. Of these, 185 records were excluded as clearly outside the review scope, leaving 39 reports for retrieval and full-text eligibility assessment. All 39 reports were retrieved. Five reports were excluded after full-text review because they did not meet one or more of the predefined inclusion criteria. The exclusion reasons were grouped into four categories: non-compound or non-cascading mechanism, non-regional or non-transferable setting, absence of explicit flood outcomes, and insufficient methodological detail. Because some excluded reports met more than one exclusion condition, these categories were treated as screening-reason groups rather than mutually exclusive record counts. This resulted in 34 studies included from the database search. Citation searching of included articles identified 16 additional studies, all of which were retrieved, assessed, and included. The final peer-reviewed corpus therefore comprised 50 studies.

Screening and eligibility decisions were made against predefined inclusion and exclusion criteria. Borderline cases were discussed among the author team before final inclusion. Because the review aimed to synthesize mechanisms and indicators rather than perform a statistical meta-analysis, studies were not assigned a single numerical quality score. Instead, full-text relevance was assessed qualitatively using four appraisal considerations: clarity of flood-driver attribution, relevance to cold-continental or semi-arid spring-flood settings, transparency of data and methods, and availability of mechanism, impact, or recovery-relevant information.

The compound-event basis of the final corpus was ensured through the inclusion criteria rather than through post hoc classification. Studies were retained for detailed synthesis only when they documented at least two flood-relevant drivers or a clear interaction between a primary driver and an amplification mechanism. These drivers included snowmelt or snowpack conditions, rainfall or rain-on-snow, rapid warming, antecedent wetness or frozen ground, and propagation controls such as ice processes, routing constraints, reservoir operations, or infrastructure effects. Therefore, the final corpus was not intended to represent isolated single-driver floods, but studies where flood generation or impacts were shaped by interacting or cascading processes.

2.3. Identification of Gray Literature and Event Documentation Protocol

To complement the peer-reviewed literature, a systematic collection of gray-literature was undertaken to gather detailed, event-specific information that is often not available in academic databases, such as local government reports, disaster assessments, and news archives. This included reports from national hydrometeorological services, governmental agencies responsible for emergencies, and reputable international organizations, ensuring a comprehensive understanding of specific flood events. These gray literature sources were crucial for documenting event frequency, affected areas, and specific management responses, which are often overlooked in academic discourse but vital for a holistic assessment of flood risk and recovery. Reputable international media were consulted only when they quoted named officials or reproduced official statistics; such items were used for triangulation rather than as sole sources. Each gray-literature datum was assigned a provenance record with URL or document identifier and access date, and key figures were cross-checked against at least one corroborating source whenever available. Earth observation (EO) products, including satellite-derived flood-extent or snow-cover information where available, were used to confirm flood timing and spatial extent rather than to infer

mechanisms, unless a technical note explicitly supported such attribution. This rigorous approach allowed for the inclusion of real-world event characteristics, encompassing not only the physical drivers like rain-on-snow events but also the cascading impacts and recovery challenges in specific regional contexts.

Gray-literature sources were not treated as a separate quantitative corpus but as an event-documentation stream for impact and recovery indicators. All gray-literature documents used in the synthesis are included in the reference list together with their source details. Source reliability was assessed hierarchically: official government and emergency-management reports were prioritized first, followed by national hydrometeorological agencies and international organizations, then disaster databases and reputable media reports that reproduced official statistics or quoted named officials. Where Russian- or Kazakh-language sources were consulted, figures were extracted only when the relevant event information could be clearly verified. Key impact and recovery figures were triangulated against at least one additional official or reputable source where available; where triangulation was not possible, the value was treated as provisional or used only qualitatively.

2.4. Data Extraction and Harmonization

A standardized data extraction protocol was developed and applied to systematically retrieve pertinent information from the selected peer-reviewed articles and gray literature, focusing on hazard characteristics, vulnerability factors, and reported recovery outcomes (Table 1). This protocol facilitated the systematic categorization of data into thematic areas, including hydrological drivers, flood types, socioeconomic impacts, and institutional responses, thereby ensuring consistency across diverse document types. For each included paper, and for each event or administrative unit covered within it, we recorded the event identifier, country, first- and second-level administrative units (e.g., oblast and rayon), river basin (e.g., Ural/Zhaiyk, Ishim/Yesil, Tobol), and start–end dates using ISO formats. We coded drivers as multi-select fields spanning snowmelt and ROS, extreme precipitation, antecedent soil moisture or frozen soils, and operational or structural factors such as reservoir drawdown, spill, overtopping, or breach. Impact variables included numbers of evacuees and sheltered persons, houses flooded and destroyed, fatalities and injuries, and counts of critical infrastructure outages (washed-out bridges and roads, power and water disruptions). When reported, monetary losses were captured in local currency with the year of valuation. Recovery variables included the design and value of cash-assistance schemes (e.g., one-time payments per household), coverage rates among eligible claimants, average delay to first payment, and the proportion of critical infrastructure restored by designated timepoints (e.g., day 30, 60, or 90). For each observation, we stored primary and corroborating sources, flagged whether the value was a point estimate or a range, and annotated known sources of uncertainty or revision (e.g., consolidation of evacuee counts after multi-wave flooding). Population and household denominators were obtained from official statistics; where household counts were absent, we estimated them as population divided by the reported or standard persons-per-household for the jurisdiction and recorded the assumption explicitly.

All monetary figures were converted to USD-2024 using the event-date exchange rate, followed by CPI adjustment to 2024 values. We then computed normalized indicators to facilitate comparability across regions of different size: evacuees per 1000 residents, homes flooded per 1000 households, fatalities per 100,000 residents, and loss per capita in USD-2024. These normalized metrics anchor the comparative synthesis and reduce scale bias that would otherwise favor larger jurisdictions in absolute counts.

Table 1. Harmonized event-level dataset schema.

Field	Description
Event ID	Unique identifier (e.g., “KAZ_2024_SpringFlood”)
Dates (start–end)	Period of flood event
Location(s)	Country, region(s), river basins affected
Drivers	Flood drivers (snowmelt, rainfall, dam failure, etc.)
Precursor conditions	Winter snowpack, soil moisture, reservoir levels
Peak river levels	Highest gauge heights reached (with dates)
Evacuated population	Number of people evacuated (total & by region)
Houses inundated	Residential houses flooded
Crops/land flooded	Area of agricultural land/fields affected
Infrastructure damage	Roads, bridges, power lines (length/units damaged)
Casualties	Deaths and injuries (directly attributed)
Relief measures	Emergency shelters, agencies involved
Compensation schemes	Type and scale of cash payments, loans, insurance
Rebuilding	New housing built, repairs conducted (units)
Recovery timeline	Key milestones (e.g., aid disbursement dates)
Source references	Primary data sources (reports, news, studies)

2.5. Construction of the Recovery Effectiveness Index

To evaluate post-disaster recovery in a way that is both interpretable and comparable across events, we constructed a composite Recovery Effectiveness Index (REI) defined as

$$\text{“REI”} = w_1 R_1 + w_2 R_2 + w_3 R_3 + w_4 R_4 \quad (1)$$

where the weights w_1 – w_4 sum to unity. R_1 measures the proportion of displaced households resettled within the observation window; R_2 represents the compensation timeliness score, normalized to the unit interval so that higher values indicate faster assistance delivery. Where exact payment-delay data are available, R_2 can be calculated as $R_2 = 1 - \min(D/\Theta, 1)$, where D is the delay between flood impact and first compensation payment, and Θ is the reference delay threshold.; R_3 is the share of critical infrastructure restored by a specified day t ; and R_4 captures distributional equity, proxied by the proportion of low-income or otherwise vulnerable households reached by assistance. For illustration, we propose default weights $w_1 = 0.35$, $w_2 = 0.25$, $w_3 = 0.25$, and $w_4 = 0.15$. This allocation reflects the emphasis often placed on housing recovery and livelihood restoration as a top priority [29], followed by the speed of economic assistance and infrastructure restoration. Equity of relief (R_4) is assigned a lower default weight not because it is less important, but because many existing policy frameworks continue to emphasize quantitative recovery outputs, such as total aid delivered or infrastructure restored, over distributional fairness. We note that compensation fairness and equity remain critical recovery dimensions [30]. The default weights are intended as an illustrative policy-oriented weighting scheme rather than a universal or empirically optimized set of coefficients. They can be adjusted to reflect local policy values, stakeholder priorities, or event-specific recovery objectives; indeed, past studies caution that composite-index outcomes can shift when weights or normalization choices are changed [31]. For this reason, we report REI components and assumptions transparently so that users can reproduce the index, modify the weights, or conduct formal sensitivity analysis when complete event-level recovery datasets are available.

2.6. Bias, Uncertainty, and Limitations

Event reporting during the first seventy-two hours is prone to under- or over-counting evacuees and damages, and figures are often revised during consolidation [32]. To manage data drift, we recorded version dates and privileged later consolidated official totals; where discrepancies persisted across credible sources, we retained ranges and documented the spread. Administrative boundaries rarely align perfectly with hydrologic units; when events spanned multiple oblasts or rayons, we harmonized to the smallest common geography or used population-weighted aggregation. Multi-wave evacuations risk double-counting; our rule was to adopt the latest consolidated total for the event period unless the underlying ministry explicitly reported cumulative and unique counts separately. Mechanism attribution can be ambiguous when operational releases and meteorology coincide; we coded an event as “compound” only when at least two drivers were documented in the text or technical appendices; otherwise, we flagged the attribution as uncertain. The REI also involves uncertainty related to weighting and normalization choices. The default weights were used as an illustrative policy-oriented scheme rather than as empirically optimized coefficients. Because the proof-of-concept application required proxy treatment for compensation timing and infrastructure restoration, and because the equity component could not be fully normalized from public aggregate data, we did not present extensive alternative-weight scenarios. Under these data constraints, multiple weighting scenarios could imply a level of numerical precision not supported by the available evidence. Instead, we report component-level scores, proxy choices, and uncertainty ranges transparently so that future applications with complete recovery datasets can conduct formal weight-sensitivity analysis. Finally, we acknowledge publication bias toward Europe and North America and the relative scarcity of peer-reviewed Central Asian materials; our gray-literature protocol mitigates this gap for impact indicators but does not fully substitute for detailed scientific analyses, a limitation we note in interpreting results.

3. Hazard Mechanisms and Compound Driver Taxonomy

Compound spring floods in cold-continental and semi-arid basins arise from interacting processes across the cryosphere, land surface, atmosphere, and built systems [6,33,34]. We can characterize these interactions into several distinct categories, including hydrological, meteorological, and anthropogenic factors, which often co-occur to amplify flood risk [22,35,36]. Specifically, antecedent snowpack and frozen soil conditions frequently precede extreme precipitation events or rapid snowmelt, leading to significantly enhanced runoff generation and increased flood magnitudes [37,38]. The interplay of these factors often results in complex hydrological responses that challenge conventional flood prediction and management strategies (Figure 2) [39].

Preconditioning of the landscape by prior conditions, such as antecedent snowpack and basin wetness, strongly controls spring flood potential [12,40]. For instance, events driven primarily by snowmelt may be further exacerbated by saturated soils or concurrent extreme precipitation, such as rain-on-snow incidents, highlighting the intricate nature of compound flood events in these regions [41]. Long-record reconstructions that couple precipitation (P), soil moisture (SM), and snow water equivalent (SWE) demonstrate why: when P, SM, and SWE co-evolve under shared forcing, even modest storms can produce outsized runoff if soils are already wet and snow is primed to melt. A national 0.1° daily reconstruction for 1981–2017 shows how machine-learning-assisted hydrologic modelling can generate consistent P–SM–SWE fields suitable for diagnosing driver co-variability and basin sensitivity, precisely because the drivers are produced independently of stream-flow and jointly calibrated against satellite benchmarks (SMAP-L4, MODIS snow cover) (methods and dataset scope; suitability for driver–flow studies) [42].

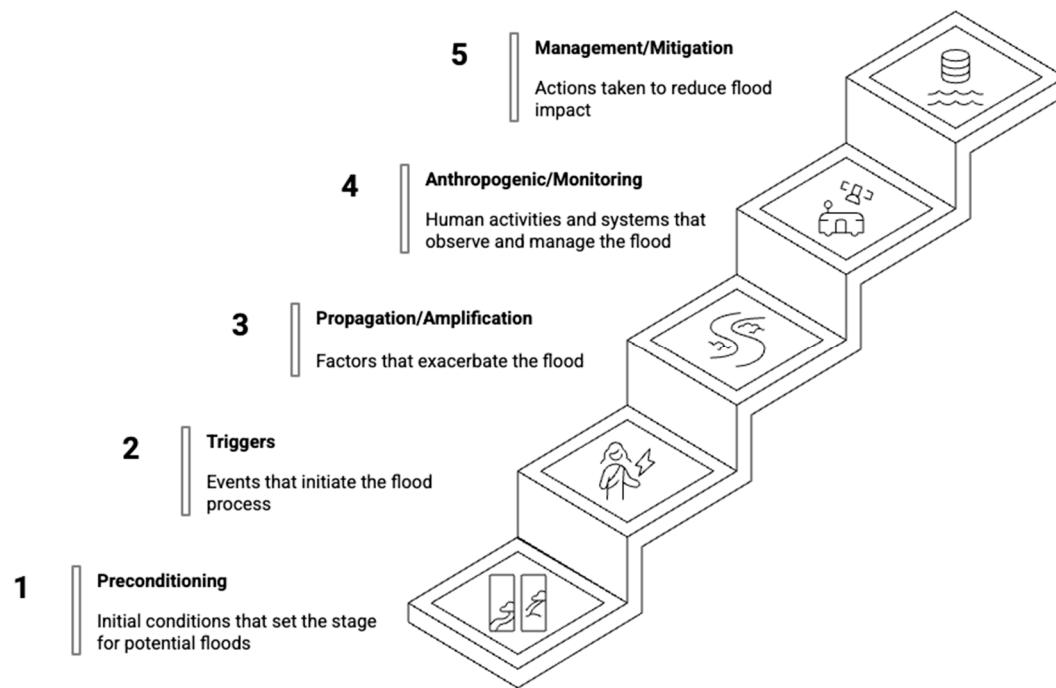


Figure 2. Mechanistic pathways of compound floods.

In Kazakhstan and wider Central Asia, winter accumulation of snow water equivalent (SWE), high late-autumn soil moisture, and prolonged frost commonly co-occur, suppressing infiltration and setting up efficient runoff generation at thaw [43,44]. Country-scale hydro-climatic regionalization shows a persistent north–south contrast that helps explain where such preconditioning matters most: northern basins exhibit nival (snow-dominated) flow regimes, whereas southern lowlands are fed by mountain headwaters with nival-glacial regimes, all within a broadly cold, dry macro-climate with strong seasonality [45]. The result is a system predisposed to sharp spring responses when deep SWE and wet/frozen soils are in place before warming arrives. During the 2024 season, event syntheses emphasize precisely this antecedent setup—wet soils going into winter and a late-season Arctic intrusion that maintained frozen conditions—thereby lowering soil absorptivity as the melt period began and tilting the hydrologic balance toward rapid surface and near-surface flow once temperatures rose [46].

Triggering factors that dominate compound spring flooding in these climates include extreme precipitation from synoptic systems that import heat and moisture, and rapid melt pulses that convert stored snow into liquid water over hours to days [37,47]. Where these coincide as rain-on-snow (ROS), the hazard is nonlinearly amplified by both mass addition (rain) and energy input (warming, turbulent fluxes) to a ripe snowpack [48]. Cold-climate stormwater research highlights the physics underlying these rapid releases: while net radiation and air temperature govern bulk snowmelt, the latent-heat contribution from condensation can be surprisingly efficient, meaning brief warm, moist intrusions can unlock large melt volumes even when rainfall totals are modest (energy-balance emphasis; condensation vs. rain heat) [22,49,50]. In parallel, winter and early-spring precipitation stored as snow or immobilized by frozen ground can be abruptly mobilized when thaw and rainfall co-occur; even small rain/melt events on impermeable or frost-hardened surfaces yield disproportionately large runoff pulses that overwhelm drainage (winter hydrology and runoff sensitivity) [51,52]. During March and April 2024, several regions across Central Asia experienced record or near-record rainfall occurring atop deep snowpack, with Kazakhstan most prominently affected [4]. This period was characterized by a sequence of two waves of flooding that moved westward and northward through

the affected areas. These events unfolded within a highly continental climate, which is distinguished by abrupt temperature changes during late winter and early spring. Such sharp transitions played a crucial role in intensifying the snowmelt and subsequent flood processes in the region [6]. The joint mass addition from rainfall and energy input to a ripe snowpack amplified hydrograph peaks well beyond what either driver would have produced in isolation—a pattern consistent with global trends of increasing ROS-linked flood risk under warming [53].

Another important factor is the propagation or routing or amplification, which determines whether generated runoff becomes widespread flooding or remains a manageable discharge [33,54]. Natural features such as basin shape, slope, channel capacity, floodplain connectivity, frozen-ground impermeability, frazil/ice limiting channel flow, and soil infiltration constraints greatly influence routing efficiency and flood potential [47,55]. Seasonal constraints for instance, frozen soils or residual ice in channels and floodplains can further reduce infiltration and channel capacity, causing overland flow and floodplain inundation. In basins where storage and conveyance capacity are limited, even runoff volumes that would normally be manageable can result in bankfull exceedance and flooding [56]. In urbanized corridors, frost-affected permeable areas offer little storage; empirical monitoring of cold-season roof hydrology in Oslo shows that even thin extensive green roofs can still attenuate and retain a portion of snowmelt and mixed rain–melt inputs compared to bitumen roofs, reducing peak intensities during the snow-covered period despite saturated substrates (11-year multi-site evidence) [57]. This indicates that urban drainage responses under cold conditions are highly sensitive to surface type and micro-storage, and that mitigation potential persists in winter. Regional risk assessments consistently identify northern regions of Akmol, Pavlodar, Karaganda, East Kazakhstan as repeatedly prone to damaging spring floods, with losses linked to both seasonal melt pulses and, in some corridors, the behavior of dams and reservoirs [58]. These patterns align with the nival regime's concentration of annual discharge into a short freshet window in which routing and local storage (natural and engineered) govern whether high flows translate into widespread inundation.

Human built infrastructure and management practices play a dual role of either mitigating or exacerbating the flood risk under compound drivers. Reservoirs, dams, levees and drainage schemes built for traditional seasonal flood regimes may be ill-equipped to handle simultaneous or sequential inputs from melting snow and heavy rainfall [59,60]. If reservoir release rules or storage capacities do not account for compound spring floods, rapid inflows may lead to overtopping, spillway activation, or forced discharge, amplifying downstream flood peaks. In contrast, green-infrastructure (e.g., permeable surfaces, retention basins, green roofs), proper land-use planning, and preserving natural flood-storage zones (wetlands, floodplains) can provide distributed storage and delay surface runoff, offering resilience even under mixed snowmelt–rainfall events [61]. While urban and cold-season evidence remains limited, emerging studies suggest that such measures can meaningfully reduce mixed rain–melt runoff peaks, especially when combined with natural storage and adaptive management.

Finally, Earth-Observation (EO) and remote-sensing systems offer critical monitoring leverage, especially in data-sparse regions. High-resolution satellite products, snow-cover maps, snow-water equivalent (SWE) reconstructions, soil moisture proxies, total-water-storage (TWS) anomalies, inundation masks, and flood-extent imagery enable near-real-time tracking of preconditioning states (snowpack, basin wetness), detecting triggering events (rainfall, snowmelt), map flood propagation and the extent of the post-event effects [18,62–64]. These tools are especially valuable for continental interiors (e.g., Central Asia) where long-term ground hydrometeorological networks are often sparse or absent.

In this framework, preparedness and early-warning systems form the bridge between monitoring and management/mitigation, translating information on preconditioning, triggers, and propagation constraints into anticipatory action.

Based on these mechanism layers, we propose a conceptual taxonomy of compound spring floods in cold-continental and semi-arid basins, with three archetypal classes. First, ROS-dominant events arise when rainfall over existing snowpack provides both mass and energy input, rapidly converting snowpack to runoff. Second, preconditioned-rainfall events occur where antecedent wetness or frozen/saturated soils, and sometimes residual basin water storage, amplify surface runoff from rainfall even without direct rain-on-snow. Third, melt-dominant events involve rapid snowmelt driven by warming, thermal forcing, or radiative forcing, with minimal rainfall, producing high runoff from snowpack ablation.

These taxonomy classes should not be interpreted as mutually exclusive categories. Many real-world spring floods occupy boundary positions because antecedent snowpack, frozen or saturated soils, rapid warming, rainfall, rain-on-snow, and routing constraints may occur together. We therefore recommend assigning each event a primary class based on the dominant trigger and secondary modifiers based on antecedent state and propagation controls. For example, an event may be classified as preconditioned-rainfall with melt and frozen-ground modifiers, or as rain-on-snow dominant with reservoir-routing amplification. The 2024 Kazakhstan floods are best interpreted as a mixed preconditioned-rainfall-plus-melt sequence rather than as a purely rain-on-snow or purely melt-dominant event. Where one driver clearly dominates and a secondary factor is weak or only contextually mentioned, the event should be treated as a single-dominant event with secondary modifiers rather than as a fully compound case.

To make the taxonomy more operational, event classes should be assigned using basin-specific relative thresholds rather than universal fixed values, because snowpack, rainfall climatology, soil moisture, and freeze–thaw regimes vary strongly across Central Asia and comparable cold-continental regions. Where gridded, station, or reanalysis data are available, SWE or snowpack preconditioning may be identified using positive SWE anomalies or values above a local high-percentile threshold, such as the 75th percentile. Antecedent wetness may be identified using soil-moisture or total-water-storage anomalies at short lead times, such as T–7 or T–1 days, again relative to local climatology. Frozen-ground influence may be recorded where soil temperature, frost-index, freeze–thaw products, or official documentation indicate frozen or infiltration-limited ground before the event. ROS-dominant events may be assigned where liquid precipitation occurs over confirmed snow cover or positive SWE, particularly when rainfall over 24–72 h is substantial or when a meaningful fraction of event precipitation falls as rain over snow. Preconditioned-rainfall events may be assigned where heavy rainfall exceeds a local high-percentile or official warning threshold and antecedent wetness or frozen-ground constraints are documented, while direct rain-on-snow is absent or secondary. Melt-dominant events may be assigned where rapid warming, typically involving a transition above 0 °C over 1–3 days or a strong positive temperature anomaly, coincides with snowpack or snow-cover loss and rainfall remains below the main event-trigger threshold. In cases where quantitative thresholds are unavailable, the same decision rules should be applied qualitatively using official reports, technical notes, or documented descriptions of deep snowpack, frozen ground, rapid warming, rainfall over snow, or snow-cover loss.

Applying this taxonomy consistently requires tracking a minimal set of coupled indicators: snow-water equivalent (SWE) and snow-cover evolution; soil moisture/basin wetness or total-water storage (TWS) anomalies; precipitation inputs (intensity, phase, duration); meteorological inputs (temperature, humidity, radiation, wind); and routing capacity metadata (channel geometry, soil/frozen-ground status, storage infrastructure). Where possible,

these should be complemented by EO-based spatial diagnostics (snow-cover destruction, flood-inundation masks) and basin-scale storage and conveyance metadata.

While this framework draws on robust literature from snow-dominated and mid-latitude mountain basins, its direct application to semi-arid cold interiors (e.g., many basins in Central Asia) remains conditioned by data availability and heterogeneity. Comprehensive long-term empirical studies capturing the full chain from preconditioning through runoff generation, routing, to inundation and impacts are limited in these regions. Therefore, until more region-specific data become available, the taxonomy should be treated as a working hypothesis, a heuristic guiding data collection, monitoring, and future research rather than a definitive classification.

The Kazakhstan spring floods of 2024 exemplify a preconditioned-rainfall-plus-melt sequence: antecedent near-saturation and active snowmelt combined with extreme precipitation to produce sustained peaks. In our taxonomy, this is a case of sequential compounding with mixed triggers, with SM and SWE anomalies detectable days to weeks in advance. In parallel, urban winter observations in the region show that where frost limits infiltration, even moderate ROS episodes can yield large peak discharges unless micro-storage and detention are available; targeted green-infrastructure and conveyance upgrades can therefore reduce neighborhood-scale flood propensity during the snow-covered season. Collectively, these lines of evidence motivate a taxonomy that is explicitly operational: classify by dominant trigger (rain, melt, ROS), annotate by antecedent state (wetness, frost, storage anomalies), and index anthropogenic context (routing capacity, green/gray infrastructure). Framed this way, mechanisms connect directly to monitoring targets, warning thresholds, and mitigation levers across Kazakhstan's cold-continental to semi-arid spectrum.

4. Standardized Indicators, Normalization, and Composite Indices

To support structured comparison of compound spring floods across Kazakhstan and the wider Central Asian region, we operationalize the preceding taxonomy namely, preconditioning, triggers, and propagation/amplifiers into a set of standardized indicators (Table A1) and normalization rules. The objective is to place heterogeneous case reports on a common footing so that differences in population, housing stock, administrative boundaries, and price levels do not obscure process signals or bias cross-event inference. Indicators are grouped along two axes: (i) driver diagnostics which capture pre-event and event-time hydrometeorological and land-surface states (antecedent snowpack, soil/frost, storm characteristics), and (ii) impact-and-recovery metrics that reflect human and infrastructure outcomes and the pace and equity of response.

For preconditioning and forcing conditions, we summarize cryosphere–land–atmosphere states using anomalies or percentiles relative to multi-year baselines. Snowpack is represented by the snow-water equivalent (SWE) anomaly and the timing of snow-cover destruction; basin wetness is represented by surface and root-zone soil moisture percentiles and, where available, total water storage (TWS) anomalies to capture integrated storage changes. Frozen-ground constraints are summarized via frost indices or freeze–thaw status derived from reanalysis or remote sensing. For the triggering phase, indicators include precipitation intensity and duration (e.g., 24- to 72 h maxima, or exceedance relative to local intensity-duration-frequency curves), rain/snow partition during precipitation (e.g., fraction of liquid precipitation; 0 °C isotherm elevation), a binary or fractional rain-on-snow (ROS) flag (liquid precipitation over confirmed snow cover), and thermodynamic energy-context descriptors (air temperature, humidity, net radiation, wind) to assess conditions favorable for melt or rapid snow/ice ablation. For propagation and amplification, we include routing-capacity and threshold indicators: bankfull exceedance (gauged stage relative to bankfull), constraining factors (e.g., frozen ground, ice/jam/frazil presence,

reduced channel capacity), and engineered or anthropogenic constraints and affordances (e.g., reservoir storage and operations, levee/dam status, urban drainage capacity under frozen ground).

Impacts are normalized to per capita or per-household scales to reduce bias from varying population sizes and asset bases. Specifically, we record: evacuees per 1000 residents; homes flooded or destroyed per 1000 households; fatalities per 100,000 residents; and economic losses converted to a common baseline (e.g., USD-2024) and expressed as loss per capita. Where household count data are missing, we estimate households by dividing population by average persons-per-household (from latest census) noting this assumption explicitly. For multi-wave events or repeated evacuations, we adopt the final consolidated totals where available; otherwise we report ranges, time-stamped, to preserve revision history and uncertainty.

To facilitate cross-event comparison, we curate a compact panel of comparability indicators: on the driver side—standardized SWE anomaly, soil-moisture percentile at T–7 and T–1 days, freeze–thaw status at T–1, precipitation return-level or exceedance relative to local IDF, and ROS flag (with fraction of event precipitation falling on snow cover). On the impact side—evacuees per 1000, homes flooded per 1000 households, fatalities per 100,000, and loss per capita. We also record recovery or mitigation variables where data are available, e.g., percentage of critical infrastructure (roads, bridges, power, water) restored by specific timepoints (day 30, 60, 90), design and value of compensation schemes, coverage among eligible households, and delay from event to first payment.

We then aggregate recovery performance into a Recovery Effectiveness Index (REI) (Table 2) designed to be interpretable and auditable. The index combines four dimensions: resettlement progress for displaced households, timeliness of compensation delivery, restoration of critical infrastructure, and distributional equity of assistance across vulnerable groups. Each dimension is normalized to the unit interval so that higher scores represent better performance. A default set of weights places greatest emphasis on permanent housing solutions and timely financial support while retaining substantial weight for infrastructure functionality and equity. Although a single composite aids comparison, we report all components alongside the REI and perform sensitivity checks to alternative weightings and normalization choices; the aim is to support evidence-based discussion rather than to reduce complex recovery trajectories to a single number.

Table 2. Recovery effectiveness index.

Component	Symbol	Normalization (0–1)	Default Weight	Rationale
Displaced households resettled	R_1	Resettled/total displaced	0.35	Housing is primary welfare outcome
Compensation timelines	R_2	$1 - \min(\text{Delay}/\Theta, 1)$ Θ is threshold delay, i.e., a reference time window (in days) against which the actual delay payment is compared	0.25	Liquidity relief; capped penalty
Infrastructure restored by day t	R_3	% restored (choose $t = 60$ d)/100	0.25	Mobility/services recovery
Equity of coverage (aid distribution)	R_4	Vulnerable Households (HH) aided/eligible	0.15	Distributional fairness
Composite	REI	$w_1 R_1 + w_2 R_2 + w_3 R_3 + w_4 R_4$		Report components + sensitivity

Standardization also requires harmonizing across geographical and administrative units. Therefore, two additional rules improve comparability across the heterogeneous

Central Asian evidence base. First, we harmonize geography by mapping all events to the smallest common administrative unit used in reporting and, when necessary, aggregating to that level using population weights. Second, we separate attribution from description by coding the mechanism class only when at least two drivers are documented snowmelt or ROS, extreme precipitation, and antecedent wetness or frozen soil so that nominally single-driver floods are not misclassified as compound. Together, these conventions allow the synthesis to isolate patterns that are genuinely indicative of compounding years with high antecedent SWE and suppressed infiltration, storms that fall as rain on snow, and basins where routing capacity is seasonally constrained and to quantify how those patterns translate into human and infrastructure outcomes on a common scale.

Finally, the indicator definitions and transformations are presented in a transparent form so that future event datasets can reproduce and update the calculations as new official figures or peer-reviewed analyses become available. Where public data are incomplete, the framework records provenance, proxy choices, and uncertainty rather than forcing numerical comparability. This ensures that the synthesis remains auditable while avoiding unsupported quantitative scaling across events with uneven reporting.

5. Evidence Synthesis and Regional Patterns (2000–2025)

This section synthesizes the included studies and a curated inventory of flood events to identify consistent patterns in drivers, impacts, and recovery across Kazakhstan and the wider Central Asian cold-continental region. We organize the synthesis around the process taxonomy established earlier—preconditioning, triggers, and propagation/amplifiers—and interpret evidence using a standardized indicator lens to improve comparability across basins, administrative units, and years. To ensure transparency in data availability, Table 3 presents a heatmap-style evidence matrix summarizing indicator completeness across curated events. Because several driver and recovery indicators are inconsistently reported across events, this synthesis emphasizes robust mechanistic regularities supported by multiple studies and uses event records for structured evidence profiling rather than formal statistical scaling or ranking. The 2024 Kazakhstan floods are used as a proof-of-concept case to demonstrate how selected recovery indicators can be operationalized where sufficient public data are available.

At the multi-year scale, the reviewed studies consistently identify antecedent basin state as a major determinant of spring flood potential in cold-continental and semi-arid basins. Evidence most often points to above-normal snow storage, elevated antecedent wetness, and frozen-ground conditions as key preconditioning factors associated with larger spring responses. However, the curated event inventory shows that these variables are not consistently reported in standardized form. Snow-water-equivalent anomalies, soil-moisture percentiles, and freeze–thaw indicators are frequently absent or described only qualitatively in event reports (Table 3). Therefore, preconditioning emerges as a robust mechanism across the literature, but remains difficult to compare quantitatively across individual events.

Trigger evidence similarly supports the compound-event framing, but with uneven event-level documentation. Across the reviewed corpus, high-impact spring floods are most commonly associated with rainfall, rapid warming, snowmelt, or rain-on-snow sequences occurring after a primed antecedent state. However, in the curated event ledger, trigger variables such as precipitation phase, liquid precipitation over snow cover, rapid warming intensity, and event-scale rainfall thresholds are sparsely recorded (Table 3). This limits formal testing of trigger–impact relationships across the inventory and supports the need for standardized reporting of precipitation phase, snow-cover status, and temperature anomalies during future events.

Table 3. Evidence availability heatmap for curated flood events in Kazakhstan and Central Asia, 2000–2025. Cells summarize the availability of standardized indicators for preconditioning, triggers, propagation/amplification, impacts, and recovery. ■ = quantitative data available; □ = partial or qualitative evidence available; ▨ = not reported or insufficient evidence. Preconditioning includes snow-water equivalent (SWE), snow cover, antecedent soil wetness, and frozen-ground indicators. Triggers include rainfall, rain-on-snow (ROS), rapid warming, and precipitation phase. Propagation/amplification includes ice processes, routing constraints, reservoir operations, drainage limitations, and infrastructure controls. Impacts include evacuees, affected population, flooded or destroyed houses, fatalities, and economic losses. Recovery includes compensation, housing resettlement, infrastructure restoration, social assistance, and equity-related indicators.

Event ID	Date Window	Region/Location (as Recorded)	Preconditioning (SWE/Frost/ Wetness)	Trigger (ROS/Rainfall/ Rapid Warming)	Propagation (Ice/Routing/ Reservoirs)	Impacts (Evacuees/Homes/ Fatalities)	Recovery (Compensation/ Resettlement/Infra)
KAZ_2024_03_28_001	28 March–10 April 2024	Aktobe; Kostanay; Karaganda; Akmola; Atyrau; Pavlodar; East & North Kazakhstan	□	□	□	■	□
KAZ_2024_02_08	8–10 February 2024	-	▨	▨	▨	▨	▨
KAZ_2023_03_23	23–25 March 2023	-	▨	▨	▨	▨	▨
KAZ_2023_02_02	2–4 February 2023	-	▨	▨	▨	▨	▨
KAZ_2022_05_15	15–17 May 2022	-	▨	▨	▨	▨	▨
KAZ_2015_04	8–9 April 2015	Temirtaou; Karkaraly; Shet; Abay; Akmolinskaya	▨	▨	▨	■	▨
KAZ_2014_03_31	31 March–2 April 2014	Kokpekty village	▨	▨	▨	■	▨
KAZ_2010_03_11	11 March 2010	Karasay; Karatal; Zhambyl; Ili; Panfilov; Koksus; Alakol	▨	▨	▨	■	▨

Propagation and amplification evidence is also stronger at the conceptual and case-study level than in the harmonized event inventory. The reviewed literature identifies routing capacity, seasonal ice processes, frozen-ground constraints, reservoir operations, floodplain storage, and urban drainage limitations as important controls on whether generated runoff becomes damaging flooding. In the curated event matrix, however, propagation indicators are rarely reported in a comparable quantitative format (Table 3). As a result, the synthesis supports propagation and engineered controls as important modifiers of flood severity, but does not yet permit systematic cross-event ranking of their relative contribution.

Where documented, impacts indicate substantial societal disruption, but systematic normalization and cross-event scaling are constrained by uneven reporting of standardized outcomes and denominators (Table 3). Many curated events do not consistently report evacuee totals, housing loss, affected population, or comparable administrative-unit denominators, limiting quantitative comparisons of outcomes across basins and years. Nevertheless, the subset of events with documented outcomes is broadly consistent with compound-driver interpretations: large evacuations and widespread housing losses are most plausibly associated with strongly primed years (deep snowpack, wet or frozen ground) coupled with rapid warming and/or rainfall during the melt window, while fatalities tend to be higher in settings characterized by rapid hydrograph rise, constrained egress, or night-time peaks. Loss severity also reflects exposure concentration, including floodplain settlement pockets, legacy embankments that amplify local flow, and critical infrastructure located near confluences.

Recovery indicators remain the least consistently reported component across the curated inventory, limiting full cross-event benchmarking at present (Table 3). Where recovery information is available, post-event timelines for compensation disbursement, temporary or replacement housing, and restoration of connective infrastructure appear to be critical determinants of recovery momentum. To avoid leaving the Recovery Effectiveness Index (REI) as a purely conceptual contribution, we applied it to the 2024 Kazakhstan floods as a proof-of-concept case (Table 4) using official recovery reporting snapshots. The national administrative reference date was set as 7 April 2024, when a local state of emergency was reported in ten affected regions: Abai, Akmola, Aktobe, Atyrau, West Kazakhstan, Karaganda, Kostanay, Pavlodar, Ulytau, and North Kazakhstan [65–70]. Because flood timing differed by region, the reporting dates were treated as official administrative snapshots rather than hydrologically identical post-flood days across all affected areas.

For the REI calculation, four components were operationalized: housing resettlement, compensation timeliness or coverage, infrastructure restoration, and equity of assistance. For housing resettlement (R1), the denominator was defined as houses declared uninhabitable, because this component measures replacement housing rather than repair-based recovery. By 21 June 2024, 3155 families had received new housing, and by the end of 2024 full replacement-housing coverage was reported for the 8447 houses declared uninhabitable [66]. Thus, R1 was scored as 0.374 for the near-60/day-75 snapshot and 1.000 for the end-year estimate. For compensation (R2), exact household-level payment dates were not publicly available; therefore, this component was treated as a compensation-coverage proxy. By 21 June 2024, 33,141 families had received the one-time payment, compared with a final reported total of 36,455 families by 25 December 2024, giving an interim score of 0.909 and an end-year score of 1.000. For infrastructure restoration (R3), no complete multi-sector restoration percentage was available exactly at day 60. The nearest quantified snapshot, 21 June 2024, reported that traffic had been interrupted on 290 road sections and restored on all except one section in Atyrau Region. Road-connectivity restoration was

therefore used as a transparent infrastructure proxy, giving an interim score of 0.997 and an end-year road-connectivity score of 1.000.

Table 4. Proof-of-concept Recovery Effectiveness Index calculation for the 2024 Kazakhstan floods.

Component	Weight	Operationalization	21 June 2024 Snapshot Score	End-Year Score	Treatment
R ₁ Housing resettlement	0.35	Replacement housing provided/houses declared uninhabitable	0.374	1.000	Directly computed
R2 Compensation coverage proxy	0.25	Families receiving one-time payment/final reported families receiving payment	0.909	1.000	Proxy for timeliness
R3 Infrastructure restoration proxy	0.25	Road sections restored/road sections with interrupted traffic	0.997	1.000	Road-connectivity proxy
R4 Equity of coverage	0.15	Vulnerable households aided/eligible vulnerable households	Not fully computable	Not fully computable	Sensitivity range
Composite REI	1.00	Weighted Sum	0.607–0.757	0.850–1.00	Range reflects missing R4 denominator

Note: R2 is treated as a compensation coverage proxy because household-level payment delay data were not publicly available. R3 is treated as a road-connectivity proxy because a complete multi-sector infrastructure restoration percentage was unavailable. R4 is reported as a sensitivity range because the eligible vulnerable-household denominator was not publicly reported.

The equity component (R4) could not be fully normalized from public aggregate data because the denominator of eligible vulnerable households was not reported. Public sources describe targeted social assistance and disability-related support measures, but do not provide eligible-versus-assisted coverage for vulnerable households. Therefore, R4 was treated as a sensitivity range from 0 to 1 rather than a fixed score. Using the default REI weights of 0.35 for housing resettlement, 0.25 for compensation, 0.25 for infrastructure restoration, and 0.15 for equity, the near-60/day-75 (21 June 2024) REI was calculated as:

$$\text{REI} = 0.35(0.374) + 0.25(0.909) + 0.25(0.997) + 0.15R4$$

$$\text{REI} = 0.607 + 0.15R4$$

Since R4 is unknown, the near-60/day-75 REI is reported as 0.607–0.757. By the end of 2024, housing resettlement, compensation coverage, and road-connectivity restoration were all reported as complete, giving:

$$\text{REI} = 0.35(1.000) + 0.25(1.000) + 0.25(1.000) + 0.15R4$$

$$\text{REI} = 0.850 + 0.15R4$$

Accordingly, the end-year REI is reported as 0.850–1.000, depending on the treatment of the equity component. This application demonstrates that the REI can distinguish interim recovery progress from near-complete end-year recovery while explicitly identifying where public recovery reporting remains insufficient. The 2024 case therefore supports the REI as an operational benchmarking tool, provided that component scores, proxy choices, and missing-data assumptions are reported transparently.

Regionally, the synthesis points to recurrent spatial contrasts in compounding pathways across Kazakhstan and Central Asia. Northern nival-dominated oblasts show pronounced sensitivity to snow accumulation and spring transition dynamics, while western

arid and semi-desert basins can experience sharp localized impacts when deep snow coincides with warm, moist intrusions and constrained routing capacity. Southern mixed regimes show compound behavior mainly when late-winter storms affect ripe snow near the rain–snow transition zone, rapidly transferring runoff downslope into populated plains. Overall, these patterns indicate that high-impact spring floods in continental interiors are shaped by the alignment of antecedent priming, event-scale triggers, seasonal routing constraints, and engineered context. They also show that mechanistic understanding is stronger than standardized event-level driver and recovery reporting, which remains the main constraint on deeper cross-event quantitative attribution and benchmarking.

6. Advantages, Limitations, and Future Refinements

The proposed Recovery Effectiveness Index (REI) framework offers several advantages. It aggregates diverse recovery metrics into a single interpretable score, enabling comparison across events, regions, or recovery stages while preserving transparency and modifiability. Analysts can adjust weights, add components, or report component-wise scores alongside the composite index to reflect local policy priorities. By explicitly including an equity dimension (R4), the REI also accounts for the distributional fairness of recovery assistance, a factor that shapes long-term well-being and is often overlooked in quantitative recovery assessments [30]. Importantly, the REI is easy to interpret: values closer to 1 indicate faster and broader recovery, whereas values closer to 0 indicate slower or more limited recovery.

The proof-of-concept application to the 2024 Kazakhstan floods demonstrates the operational value of the index. Using official recovery reporting snapshots, the REI was able to distinguish between interim recovery progress and near-complete end-year recovery. The 21 June 2024 administrative snapshot produced an REI range of 0.607–0.757, while the end-year estimate increased to 0.850–1.000, depending on treatment of the equity component. This shows that the REI can serve not only as a post-disaster benchmarking tool, but also as a dynamic monitoring framework for tracking recovery progress over time. At the same time, the application also illustrates the importance of transparent proxy choices and missing-data treatment. In the Kazakhstan case, housing resettlement, compensation coverage, and road-connectivity restoration could be quantified, whereas equity of coverage could not be fully normalized because the denominator of eligible vulnerable households was not publicly reported.

Indicator-based frameworks and composite indices are increasingly employed in flood-risk, vulnerability, and resilience research because they can distill multidimensional hazard, exposure, impact, and recovery processes into decision-relevant metrics [71]. These approaches facilitate comparison across regions, events, and time, especially where decision-makers require concise but auditable evidence. However, recent reviews also highlight that empirical validation of many flood-resilience and flood-risk indicators remains limited, particularly in data-sparse or remote regions. Indicator performance depends strongly on the quality, resolution, and consistency of the underlying data, while composite-index outcomes can be sensitive to the choice of weighting, normalization, and aggregation methods [72]. Remote sensing, including satellite imagery, multispectral data, and synthetic aperture radar (SAR), offers important enabling potential in such contexts by supporting synoptic mapping of flood extent, inundation dynamics, land-cover change, and damage to environmental or structural features where ground observations are sparse [73,74].

As with all composite indicators, the accuracy of the REI depends on the quality of its sub-indicators and the choice of normalization. For example, the original compensation-timeliness component requires information on the delay between flood impact and first payment. In practice, household-level payment dates may not be publicly available, requiring the use of compensation coverage as a proxy. Similarly, infrastructure restoration may

be reported for only one sector, such as road connectivity, rather than as a complete multi-sector restoration percentage. Equity of coverage is particularly difficult to operationalize unless both the number of vulnerable households assisted and the total eligible vulnerable-household denominator are reported. These limitations do not invalidate the REI, but they require careful documentation of proxy choices, assumptions, and uncertainty ranges.

The weighting of REI components also introduces subjectivity. Although the default weights emphasize housing resettlement, compensation, infrastructure restoration, and equity, different policy contexts may legitimately prioritize these dimensions differently [31]. In the present proof-of-concept application, formal alternative-weight scenarios were not emphasized because several components were incomplete or proxy-based. Compensation was represented by coverage rather than household-level delay to first payment, infrastructure restoration was represented by road-connectivity restoration rather than a complete multi-sector restoration score, and equity could not be normalized because the eligible vulnerable-household denominator was unavailable. Under these data constraints, extensive alternative-weight scenarios could imply a level of numerical precision not supported by the available public data. Therefore, the REI should be reported together with component-level scores, proxy choices, missing-data assumptions, and uncertainty ranges. Future applications based on complete event-level recovery datasets should conduct formal sensitivity analysis using alternative weighting scenarios.

Component-level reporting is equally important because a high composite score may mask uneven performance across recovery dimensions. For example, rapid restoration of housing and roads may coexist with incomplete equity reporting or uneven assistance to vulnerable groups. The REI should therefore be interpreted as a transparent recovery profile and benchmarking tool rather than as a definitive ranking metric.

Finally, the current REI remains focused on four core recovery dimensions: resettlement, compensation, infrastructure restoration, and equity of assistance. Future refinements could expand the framework to include livelihood recovery, business continuity, psychosocial well-being, environmental restoration, agricultural recovery, insurance access, and long-term adaptation outcomes. Future applications should also prioritize standardized post-disaster reporting templates that record payment dates, eligible and assisted households, infrastructure restoration by sector, and vulnerable-group coverage. Such improvements would allow the REI to evolve from a proof-of-concept recovery index into a more robust and comparable tool for recovery monitoring in Central Asia and other cold-continental and semi-arid flood-prone regions.

7. Conclusions

This review has examined the current state of knowledge on compound spring floods in cold-continental and semi-arid basins, with a particular focus on Central Asia and adjacent interior regions. Through a systematic inventory of peer-reviewed literature and a curated selection of gray-literature event reports, we have mapped the mechanisms by which antecedent states, event triggers, and propagation/amplification pathways interact to generate high-impact floods. We introduced a harmonized indicator framework to support comparative analysis across events, geographies and time, and proposed a Recovery Effectiveness Index (REI) to benchmark post-disaster responses in a structured and reproducible way.

The synthesis indicates that high-impact spring floods in Kazakhstan and comparable cold-continental regions are often poorly explained by single-driver framings, particularly where antecedent and trigger interactions dominate. Evidence from the reviewed literature repeatedly points to above-normal snow-water equivalent, elevated antecedent wetness and/or frozen ground, and warm frontal precipitation, including rain-on-snow conditions,

as recurrent pathways for severe spring flooding. However, because standardized event-level indicators for SWE, soil moisture, freeze–thaw state, precipitation phase, routing constraints, and recovery outcomes remain incomplete across the curated inventory, these findings should be interpreted as a mechanism-based synthesis supported by partial event evidence rather than as a fully quantified cross-event attribution. The routing capacity of the landscape, modulated by seasonal ice, limited infiltration, valley morphology, and engineered storage or transfer systems, acts as an important filter determining whether high runoff translates into widespread inundation. Recovery outcomes can diverge markedly even under similar hazard forcing, and the REI provides a structured lens for evaluating compensation timeliness, restoration pace, and institutional readiness where comparable data are available.

Importantly, the regional synthesis revealed two major knowledge gaps that limit the strength of cross-event inference. First, cold-continental and semi-arid regions, including Central Asia, Siberia, and Mongolia, remain under-represented in compound-flood research, limiting transferability from better-studied hydroclimates. Second, the scarcity of standardized and comparable event-level datasets constrains deeper understanding of how specific driver combinations, such as deep SWE, frozen ground, and ROS, translate into impacts across differing contexts. The harmonized indicators and REI framework introduced here provide a starting structure for future shared datasets, but the present results should be viewed as a structured synthesis and proof-of-concept application rather than as a complete regional quantification.

Looking forward, a rapidly evolving climate context adds urgency to improved understanding and monitoring of these mechanisms. Shifts in snow–rain partitioning, changes in antecedent wetness, and altered freeze–thaw regimes may increase the likelihood of compound spring flooding and change its spatial and temporal clustering in continental interiors. Risk management systems should therefore transition from single-hazard paradigms toward monitoring and modelling approaches that explicitly incorporate compound drivers, seasonally evolving preconditioning states, and routing thresholds. The indicator framework and taxonomy developed here can support this transition by guiding early-warning thresholds, preparedness planning and retrospective evaluation of response and recovery interventions.

In conclusion, effective risk reduction in cold-continental and semi-arid regions depends not only on improved forecasting of individual drivers, but on integrated systems awareness linking snow–soil–rain interactions, catchment response potential and downstream consequences. By integrating process-based understanding, harmonized indicators, and recovery-oriented evaluation, this review provides a preliminary scaffold for research and practice to anticipate, compare, and mitigate compound flood risk in understudied yet highly vulnerable interior settings. Future work anchored in transparent datasets, cross-basin comparative studies, and decision-oriented metrics will be essential to realize this goal.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/w18141717/s1>, Table S1: PRISMA checklist. The template has been taken from “TheBMJ” [75].

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Appendix A

Table A1. Indicator dictionary and normalization.

Domain	Indicator (Symbol)	Definition/ Calculation (Short)	Units/Scale	Spatio-Temporal Resolution	Typical Data Availability	Comment/Use/ Rationale
Preconditioning (Core)	Snow-cover/SWE presence	Presence/depth of snow (or snow-water equivalent) at event pre-season or prior winter	mm w.e. or snow depth	Basin/seasonal/daily	Medium–High	Many cold-continental basins have at least snow-cover maps or precipitation-snow reconstructions. Good first-order precondition.
Preconditioning (Optional)	SWE anomaly (SWE Δ)	Event-month SWE minus climatological baseline (e.g., 2001–2020)	mm w.e.	Basin/monthly to daily	Low–Medium	Requires long-term SWE climatology or reconstructions; more rarely available in Central Asia.
Preconditioning (Optional)	Soil moisture/wetness proxy (SM%, root-zone or surface)	Percentile or deviation of soil moisture or wetness prior to event (e.g., T-7/T-1)	% or relative index	Basin/weekly–daily	Low	Rarely reported in gray literature; may be inferred from reanalysis or remote-sensing, but with large uncertainty.
Preconditioning (Optional)	Frozen-ground/freeze–thaw index (FrostIdx)	Number of frost days/freeze–thaw state in prior period	days or binary/index	Basin/monthly–daily	Low	Freeze–thaw data not routinely available for many basins; remote-sensing or reanalysis proxies may offer but need validation.
Trigger (Core)	Precipitation (total/intensity)	24–72 h (or event-window) rainfall/precipitation amount	mm; mm/day	Basin/event window	High	Precip gauge or reanalysis data usually available; essential to detect triggering rainfall episodes.
Trigger (Core)	Precipitation phase/Rain-on-snow (ROS) flag	Fraction of precipitation as liquid; binary flag if rain falls on snow-covered ground	-/0–1	Basin/event window	Medium	Snow-cover + precip-type data needed; often inferred but sometimes uncertain.
Trigger (Optional)	Melt/energy context (temperature, radiation, RH, melt proxies)	Metrics indicating thermal or radiative forcing for snowmelt (e.g., air temp > 0 °C, net radiation)	°C, W m ⁻² , etc.	Basin/daily–hourly	Low–Medium	Requires meteorological/reanalysis data; may be available but often not reported in event reports.

Table A1. Cont.

Domain	Indicator (Symbol)	Definition/ Calculation (Short)	Units/Scale	Spatio-Temporal Resolution	Typical Data Availability	Comment/Use/ Rationale
Propagation/ Routing (Core)	Flood occurrence/inundation (yes/no/area)	Documented flood/inundation occurrence, ideally with area extent	binary, km ² , or relative	Basin/event (date)	Medium	Flood reports or remote-sensing inundation maps sometimes available; better where EO/satellite monitoring used.
Propagation/ Routing (Optional)	Channel/ infrastructure constraint indicators (e.g., ice jams, frozen soil, reservoir operation)	Qualitative or binary flags for conditions limiting infiltration or routing, or affecting flow (e.g., frozen soil, ice, dam releases)	-/0–1 or descriptive	Basin/event	Low	Often missing or not reported; relies on detailed event or hydrology reports, rarely available in gray literature.
Impact (Core)	Evacuees per 1000 residents	Number evacuated normalized by population size	‰ (per 1000)	Admin unit/event	Medium	Evacuation numbers often reported in media or government bulletins; population data available for normalization.
Impact (Core)	Houses flooded or destroyed per 1000 households	Number of homes flooded or destroyed normalized by household count	‰ (per 1000 hh)	Admin unit/event	Medium–Low	Home-damage data sometimes reported; household counts may require estimation (population/average hh size).
Impact (Core)	Fatalities per 100,000 residents	Number of flood-attributed deaths normalized to population	per 100,000	Admin unit/event	Medium	Mortality often reported, though attribution to flood may be uncertain; population data available.
Impact (Optional)	Economic loss per capita (USD-2024)	Monetary value of losses (converted to common currency and baseline) divided by population	USD/capita	Admin unit/event	Low	Loss estimates often missing, inconsistent (local currencies, different valuation years), or under-reported; would require assumptions/conversions.
Recovery/ Response (Optional)	Relief/ compensation indicators, infrastructure restoration, recovery timeline (e.g., % infrastructure restored by day X; delay in compensation)	Measures of damage recovery and response efficiency	% restored, days, % coverage	Admin unit/post-event	Very Low	Rarely consistently reported across events; data may be scattered in media/government bulletins or missing entirely.

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