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To cite this article: Shreya Some *et al* 2026 *Environ. Res.: Climate* **5** 035052

ENVIRONMENTAL RESEARCH
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OPEN ACCESS

RECEIVED
1 May 2026

REVISED
10 July 2026

ACCEPTED FOR PUBLICATION
5 August 2026

PUBLISHED
25 August 2026

PAPER

Integrating socio-economic dimensions into climate change hotspot identification

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Keywords: climate change hotspot, flash floods, mountain, socio-economic impact, snow avalanches, stakeholder engagement, storylines

Supplementary material for this article is available online

Abstract

As climate impacts accelerate, 'climate change hotspots' (CCHs) are increasingly used to prioritise limited adaptation resources. However, hotspot conceptualisation remains fragmented. To address this gap, this study first conducts an evidence synthesis of 353 studies to investigate how CCHs are conceptually defined and analytically identified across four major climate hazards (heat, drought, flood and snow). This synthesis shows that most existing hotspot methodologies are dominated by potential hazard intensity, while socio-economic dimensions, stakeholder knowledge and impact-based validation are rarely integrated. To address this knowledge gap, we develop a bottom-up integrated framework for CCHs identification. Transitioning away from a top–down hazard-centric approach, our bottom-up approach integrates biophysical and socio-economic data with event-based storylines and stakeholder consultation. The transferability of our framework is demonstrated through two European case studies, snow avalanches in Alps and Carpathians, and flash flood in Trentino-Alto Adige, Italy. The case studies identify hotspots by intersecting climate hazard data with local geographic characteristics and socio-economic information. In both applications, historical event-based storylines ground quantitative risk classifications in real-world disaster dynamics, while stakeholder consultations refine the localised exposure. The results reveal that Alpine and Carpathian snow hotspots are projected to persist and intensify by 2100. The flash flood hotspots remain concentrated in alluvial valley bottoms, where the hazard converges with dense socio-economic and infrastructural exposure. Our integrated framework provides an adaptable and transferable approach for identifying CCHs. It can serve as good practice and can support the prioritisation of adaptation effort and planning across administrative regions and sectors.

1. Introduction

Accelerating climate change necessitates prioritisation of adaptation resources (Forster *et al* 2025, Votsi *et al* 2025). The challenge is no longer solely about understanding the physical climate changes, but also about managing the finite resources available to address their impacts. While the need for adaptation is universal, the capacity to adapt is not, and policymakers face the challenge of limited adaptation resources (Amorim-Maia and Olazabal 2025, Zahnow *et al* 2025). Furthermore, attempting to implement uniform adaptation strategies across vast scales is not only economically infeasible but also socially inequitable (Manuamorn *et al* 2020, Venner *et al* 2024).

One way in which resource prioritisation may be achieved is through the identification of hotspot areas (Myers 1988, Myers *et al* 2000). Biodiversity conservation addressed the challenge of resource prioritisation as early as 1988 (Myers 1988). The Working Group II contribution to the Fifth Assessment Report of the IPCC (IPCC 2014) defines a hotspot as 'a geographical area characterised by high vulnerability and exposure to climate change'. In the climate arena there has been much interest in the use of hotspots to inform policy debates around the allocation and prioritisation of funding/financing for adaptation and risk reduction (Barr *et al* 2010, Rannow *et al* 2010, de Sherbinin 2014, Muccione *et al* 2016, Kasecker *et al* 2018, Robinson *et al* 2023, Verschuur *et al* 2025) to identify areas where the hazards or risks are more severe or pressing than in other areas.

Within these discussions, it is possible to identify two main strands of hotspot mapping: one which investigates changes in climate hazards typically involving one or a small number of biophysical variables, which we refer to as hazard hotspots; and another which combines changes in climate hazards with socio-economic data to identify climate vulnerability and risk hotspots. Here, vulnerability hotspots focus on socio-economic aspects related to sensitivity and adaptive capacity while risk hotspots combine all three risk elements of hazard, exposure, and vulnerability. In this paper, we differentiate between hotspots of potential harm (hazard hotspots), where hazard or climate change signals are strong, and hotspots of potential consequences (vulnerability and risk hotspots), where the combination of biophysical and socio-economic information leads to strong signals in, among others, exposure, vulnerability, and/or risk.

Using climate change hotspots (CCHs) to inform decisions relating to the allocation and prioritisation of resources for adaptation planning, is not without its challenges, however. Studies need to consider that not only the climate but also the socio-economic factors and vulnerabilities will change over time. Furthermore, a key consideration is whether to focus specifically on vulnerability hotspots or to undertake a broader assessment of risk hotspots (e.g. Muccione *et al* 2016). Approaches to hotspot identification are also sensitive to the data sources and the chosen indicators (e.g. Feldmeyer *et al* 2021), which can lead to inconsistencies in the areas that are identified as being a hotspot area. Birkmann (2007) highlights that there may be a gap between the mapped hotspots and how actors take up this information. The spatial scale at which such questions are asked will also influence the establishment of priority areas, for example, whether the question is being asked at the city scale or global scale (Birkmann 2007).

Notwithstanding these challenges, the use of CCHs remains a valuable tool to support policy- and decision-makers in identifying which regions to prioritise (Giorgi 2006, Cradock-Henry *et al* 2023, Rastegar *et al* 2024). The results of any hotspot identification process need, however, to provide robust evidence if they are to inform decision making and the development of climate policies. Over recent years there has been a marked interest in CCHs, both in popular discourse, as evidenced by the Google Trends data[15] where searches for CCHs have more than doubled after 2020, and in the academic literature where we even find an exponential growth after 2020 (also see section 3.1, figure 2). While the concept of a 'hotspot' is being increasingly used in the scientific community, its definition, application, and context remain fragmented and inconsistent. This highlights an urgent need for a systematic synthesis of the current evidence base.

Against this backdrop, this study has two primary objectives: (1) to investigate how CCHs are conceptually defined and analytically identified across four major climate hazards (heat, drought, flood and snow) and (2) to develop and demonstrate an integrated framework for hotspot identification through exemplar case studies from Europe. By using climate hazard indicators and socio-economic dimensions

[15] We searched for climate hotspot and climate change hotspot on 10 March 2026, an equivalent search can be performed at https://trends.google.com/explore?q=climate%2520change%2520hotspot%2Cclimate%2520hotspot&date=2004-01-01%202024-12-31&geo=Worldwide; here we limited the timeframe until the end of 2024 as our searches in 2025 may have influenced the search trend data subsequently.

with event-based storylines and stakeholder engagements, we illustrate how an integrated framework ensures that hotspot identification is both scientifically grounded and policy-relevant.

This paper is structured as follows: section 2 introduces the method of our evidence synthesis and then section 3 presents the synthesis results and elaborates on the knowledge gaps. In section 4, we introduce case studies as examples of how we integrated the biophysical hazard data with socio-economic data, storylines and stakeholder knowledge to identify hotspots. Section 5 discusses the findings with some concluding recommendations.

2. Mapping the state-of-the-art: evidence synthesis

We used preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines (Page *et al* 2021) for a comprehensive exploration of the existing evidence base across the four selected hazards: heat, drought, flood, and snow. Here, the aim is to explore the methodological paradigms applied for CCHs identification, understand the extent to which sectoral impacts are incorporated, and identify specific gaps that hinder an integrated assessment of socio-economic risk.

Search strategy: A structured keyword search was performed to identify peer-reviewed articles that explicitly address 'hotspots' in the context of climate hazards. We used two primary bibliographic databases, Web of Science (Clarivate) and Scopus. We combined terms related to the following three sets: (1) CCHs; (2) hazard-specific terms such as heatwave, drought, flood, snow; and (3) sectors. Different variations of these terms were used. The details of the terms and search strings in the supplementary material (SM) 1. The final query for each hazard was constructed as: (Set 1 AND Set 2 AND Set 3). This design allowed us to filter for studies that not only identify high-risk areas but also explicitly link them to sectoral vulnerabilities. The keyword searches were performed in May 2025. As a result, the temporal coverage of the literature for the year 2025 is partial.

Screening and coding: The screening process was conducted in two stages. First, titles and abstracts were screened for relevance against the eligibility criteria (see SM2). Second, the full texts of potentially relevant articles were retrieved and assessed for final eligibility. Any uncertainties regarding the inclusion of specific papers (e.g. 'maybe' cases concerning compound hazards or unclear definitions) were resolved through discussion within the hazard-specific research teams. To ensure inter-coder reliability and validate the information extraction framework, a pilot coding phase was conducted in June/July 2025. This phase consisted of two iterative rounds where each hazard specific research team coded a random subset of papers (20–30 papers in total). These rounds also helped to validate and refine the classification categories for methods/approaches used for CCHs identification in the identified papers (see SM3). These approaches are primarily identified based on existing literature (e.g. Giorgi 2006, UNDP 2010, de Sherbinin 2014, Piontek *et al* 2014, de Sherbinin *et al* 2019, Votsi *et al* 2025). Throughout the pilot coding period, regular consensus meetings were convened to understand and resolve interpretative discrepancies and harmonise the application of eligibility criteria. Following this validation, the final coding phase was conducted from August to November 2025. During this stage, in addition to the primary database search, targeted supplementary searches were conducted (e.g. using google scholar, expert knowledge) to identify methodological papers that might have been missed in the initial query.

The selection and screening process, including the number of records identified, screened, and included for each hazard, is summarised in the PRISMA flow diagram (figure 1). From the final set of included articles, information was extracted using a standardised coding framework in MS excel (SM5) to ensure consistency and comparability across hazards. Information on hotspot definition, hotspot identification approaches, input data used, sectors covered and geographical scale were recorded from each included article (see SM4 for details).

Methodological limitation: While this evidence synthesis method provides a comprehensive synthesis of studies on CCHs, two methodological limitations should be noted. First, this review was restricted to peer-reviewed literature published in English. Therefore, this may introduce a geographical bias, potentially underrepresenting research from non-English speaking regions. Second, we acknowledge the potential for inter-coder variability, particularly given that individual studies may be interpreted differently based on a coder's specific field of expertise. Due to constraints in time and resources, and the dual objective of providing both a comprehensive evidence synthesis and case study applications, we could not employ the 'gold standard' of multiple independent coders (at least 2). However, we reduced this inter-coder variability risk by using a detailed coding manual (SM2 and 3), conducting pilot testing, and holding regular consensus meetings.

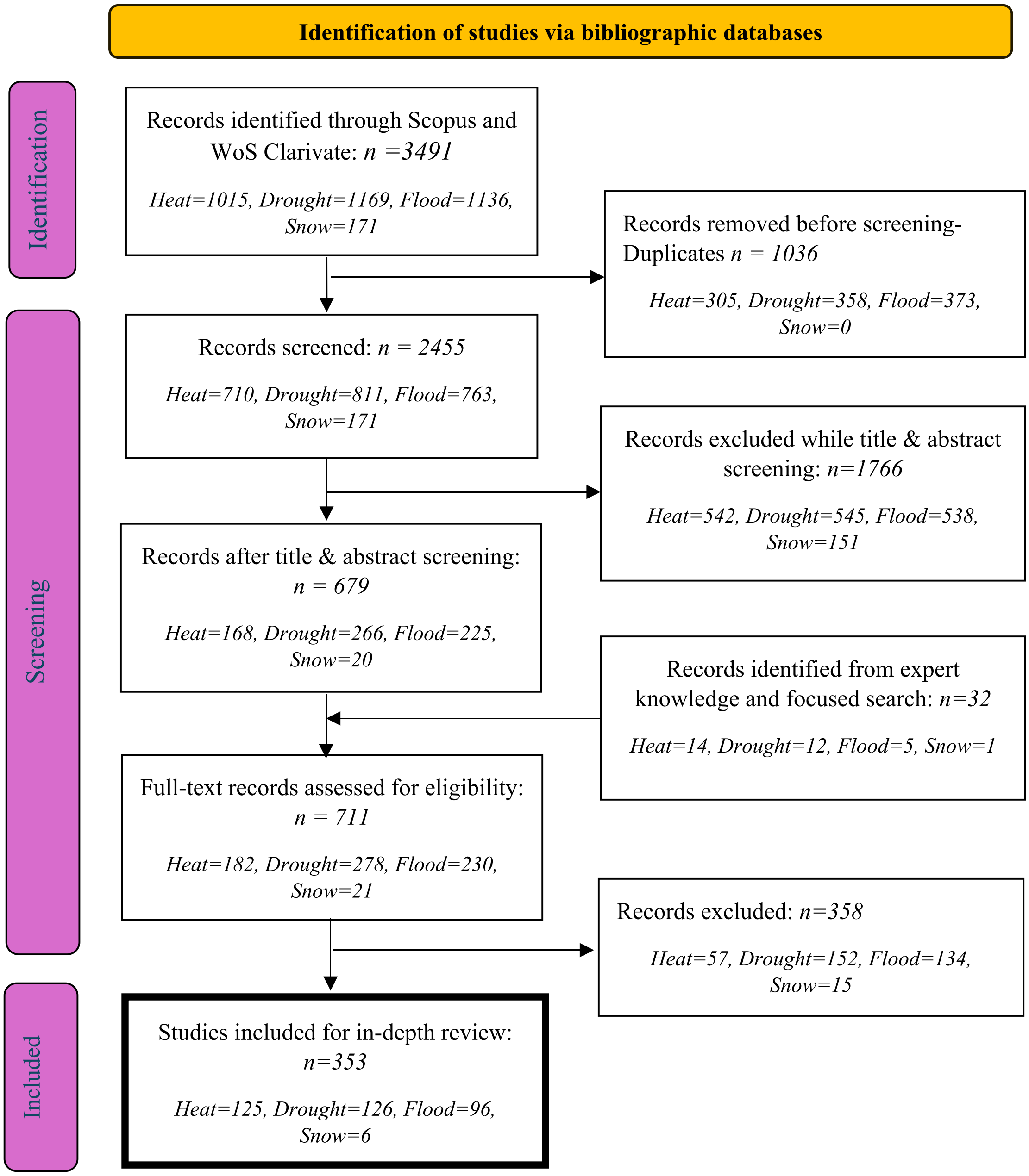

Figure 1. PRISMA flow diagram.

3. Evidence synthesis results

Our search queries across Web of Science and Scopus yielded a total of 3491 records. After removing duplicates and performing the initial title and abstract screening against the eligibility criteria, a subset of articles was assessed for full-text eligibility. This stepwise screening process resulted in the final inclusion of 353 peer-reviewed studies. The distribution of the included studies reveals a significant heterogeneity across different hazards (figure 2).

3.1. Descriptive statistics of evidence synthesis

Research on CCHs is rapidly expanding (figure 2) and has experienced exponential growth, particularly since 2020. For instance, over 80% of the included *Heat, Drought and Snow* studies and over 70% of *Flood* studies were published in the last five years (2021–2025). This increase likely reflects the growing use of the term and the urgency of extreme events in global policy agendas alongside increased availability of high-resolution climate data. However, the characteristic of the research varies widely across hazard.

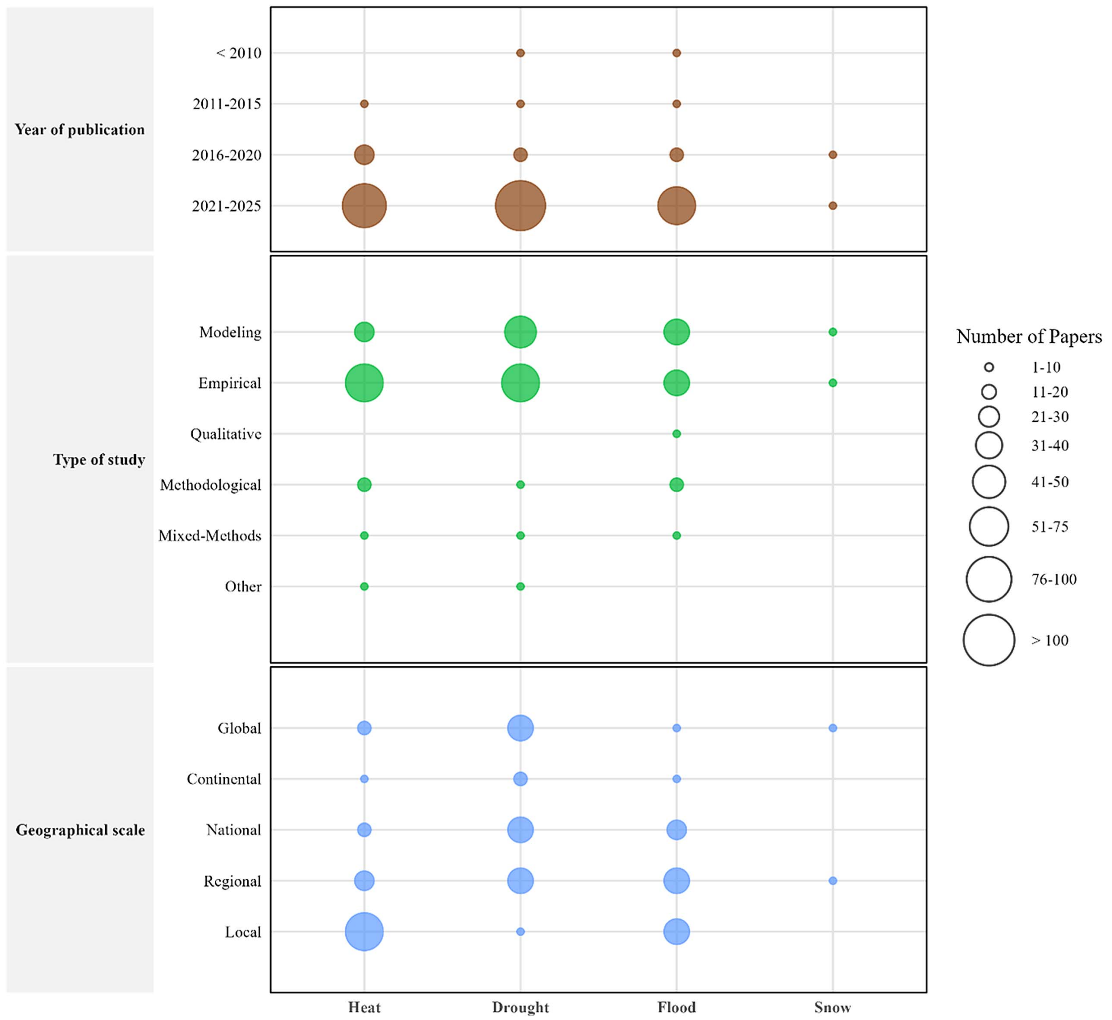

Figure 2. Bibliometric distribution of literature on climate change hotspots for heat, drought, flood and snow: Year of publication, Type of study, Geographical scale. Note that the keyword searches were performed in May 2025, implying literature coverage for 2025 is partial.

Heat related studies are predominantly empirical (physical) (60%, $n = 75$) in nature and local in scale (54%, $n = 67$). This may be driven by the need to capture microclimatic variabilities, such as the Urban Heat Island effect, which requires fine-scale observational data (e.g. Lauwaet *et al* 2024). *Drought* related research focuses on larger spatial scales, dominated by global (31%, $n = 39$) and regional scale (31%, $n = 39$) level analyses. This aligns with the climatic drivers of drought, such as large-scale atmospheric circulation and sea surface temperature patterns (e.g. Ionita and Nagavciuc 2020). *Flood*-related studies are largely at sub-national (67%, comprising $n = 31$ for regional level and 34 for local level) and national (23%, $n = 22$) scales, aligning with the fact that flood responses are primarily at the national/sub-national levels. Here, modelling (38%, $n = 36$) and empirical-physical (35%, $n = 34$) studies dominate. The prominence of modelling studies in flood hazard hotspot research reflects the necessity of hydrological simulations to predict catchment responses and inundation risks (Bates 2022). For *Snow*, studies focus on regional to sub-continental scales, reflecting spatial variability and topographic control of snow processes (Bonsoms *et al* 2023, Conyers and Roy 2023, Ma *et al* 2024).

3.2. Definition of CCHs

The definitions across all hazards clearly fall into the two broad categories. A large proportion of the literature focuses on the biophysical variable of interest or generally climate change, i.e. refers to *hazard hotspots*. Some literature also includes socio-economic factors and identified *risk hotspot*, where hazard, exposure, and vulnerability intersect.

Heat hotspots can be classified into three conceptual themes under the two broad categories. The first and most common is the thermal extreme hotspots, which define hotspots as purely biophysical phenomena (Strebel *et al* 2024, Liu *et al* 2025). In this view, a hotspot is a localised area, typically urban, where absolute temperatures or heat-stress metrics exceed a specific threshold, representing a thermal anomaly relative to the surrounding environment. The climate change driven hotspot definition defines emerging hotspots as regions where heat extreme occurrence responds strongest to the climate change (Lewis *et al* 2019, Mustofa *et al* 2021, Kornhuber *et al* 2024). This concept focuses on the rate of change, identifying areas where the frequency or intensity of extremes is accelerating faster than the global average (i.e. changes in the upper tail of the temperature distribution, not just to present-day extremes). Lastly, the integrated and multi-hazard approach defines the hotspot as a nexus of risks. This approach locates hotspots not merely where it is hot, but where heat amplifies other hazards (e.g. drought, air pollution, wildfires) (Abella and Ahn 2024, Esperon-Rodriguez *et al* 2024, Olgun *et al* 2024) or intersects with socio-economic vulnerability/risk, accounting for social inequity in the exposure (Warren *et al* 2022, Adélaïde *et al* 2024, Verde 2024).

Drought studies define hotspot mostly based on statistical measures of hazard intensity but occasionally also consider risk. Hazard intensity focussed on meteorological and hydrological approaches characterise hotspots through statistical extremity and recurrence, identifying regions with high probability thresholds, short return periods, or statistically significant negative trends in precipitation and soil moisture (Lee *et al* 2018, Trancoso *et al* 2024, Khosravi and Ouarda 2025). Spatial applications search for hotspots as isolated extremes or as significant clusters (Kipkulei *et al* 2025). Finally, a rare subset of the literature (approx. 5%) adopts an integrated risk framework, defining hotspots not merely by physical dryness but, e.g. by the convergence of high exposure and low adaptive capacity (Fraser *et al* 2013). These studies highlight regions where climatic stress co-occurs with socio-economic fragility (e.g. gender inequality or limited water infrastructure). Lastly, studies consider compound hazards where combined, e.g. heat and drought hazards amplify the severity of impacts beyond what individual hazards would cause (Gao *et al* 2024).

Flood hotspots are defined as areas of high 'flood susceptibility' or 'flood vulnerability' and conceptualised through three conceptual themes. The hazard threshold lens characterises hotspots by hydrological magnitude or probability. In this view, a hotspot is a specific geographic area, such as a grid cell or coastal segment, where physical metrics like water levels (e.g. bathtub model), rainfall intensity, or flow magnitude exceed a critical statistical threshold (typically the 80th or 90th percentile) (Iglesias *et al* 2021, Fandé *et al* 2022). In these studies, hotspots essentially denote the upper tail of hazard or risk distributions, with social vulnerability at most indirectly embedded in the indicator. While the integrated risk and infrastructure failure lens defines hotspots by the likelihood of system failure or asset damage due to flood (Chakraborty *et al* 2023, Nawrotzki *et al* 2023, Ricciardi *et al* 2024, Sharkus *et al* 2025).

The limited literature on *snow* related hotspots shows that hotspot identification is still dominated by biophysical hazard assessments. Although a few studies extend this perspective to sector-specific infrastructure risk (e.g. railway transport), broader integration of socio-economic exposure, social vulnerability, adaptive capacity and cross-sectoral interactions into CCH definitions remains largely absent. These studies primarily identify hazard hotspots through spatial coherence extremes (Huning and AghaKouchak 2020, Bahramimehr and Kabir 2024), focusing on significant clustering of values rather than isolated extremes, or through statistical anomalies defined by extreme behaviour and percentile exceedances (Notarnicola 2020, Bonsoms *et al* 2023, Conyers and Roy 2023, Ma *et al* 2024).

Overall, the conceptual maturity of hotspot definitions varies widely across hazards. *Heat*, and *flood* research show signs of moving beyond purely physical definitions to incorporate integrated risk frameworks, where hotspots are increasingly defined by human impacts, infrastructure failure, and socio-economic inequity in recent years. While this is partially also visible in the drought literature, but it is less common. *Snow* hotspots are understudied.

3.3. Methodological approaches for hotspot identification

In terms of analytical methods used to identify hazard hotspots, spatial analysis is widely used followed by descriptive/visual analysis. However, a deeper dive into each hazard reveals that the analytical methods range from purely physical detection of signals to multi-criteria risk assessments. In the description below, percentages (%) indicate the proportion of papers within a specific hazard category using the specific approach/criteria, and n represents the absolute number of studies.

For *Heat* hotspots, the analytical approach is dominated by GIS-based spatial analysis (figure 3, top panel). In general, this approach employs spatial statistics like the Getis-Ord Gi* statistic and Local Moran's I (Getis and Ord 1992, Anselin 1995), to distinguish statistically significant clusters of high temperatures from random noise. While econometric and statistical modelling (e.g. machine learning algorithms like random forest) are also used (Vogel *et al* 2019), they are frequently embedded within a broader GIS framework to map temporal trends or exposure gradients. This spatial focus shapes the

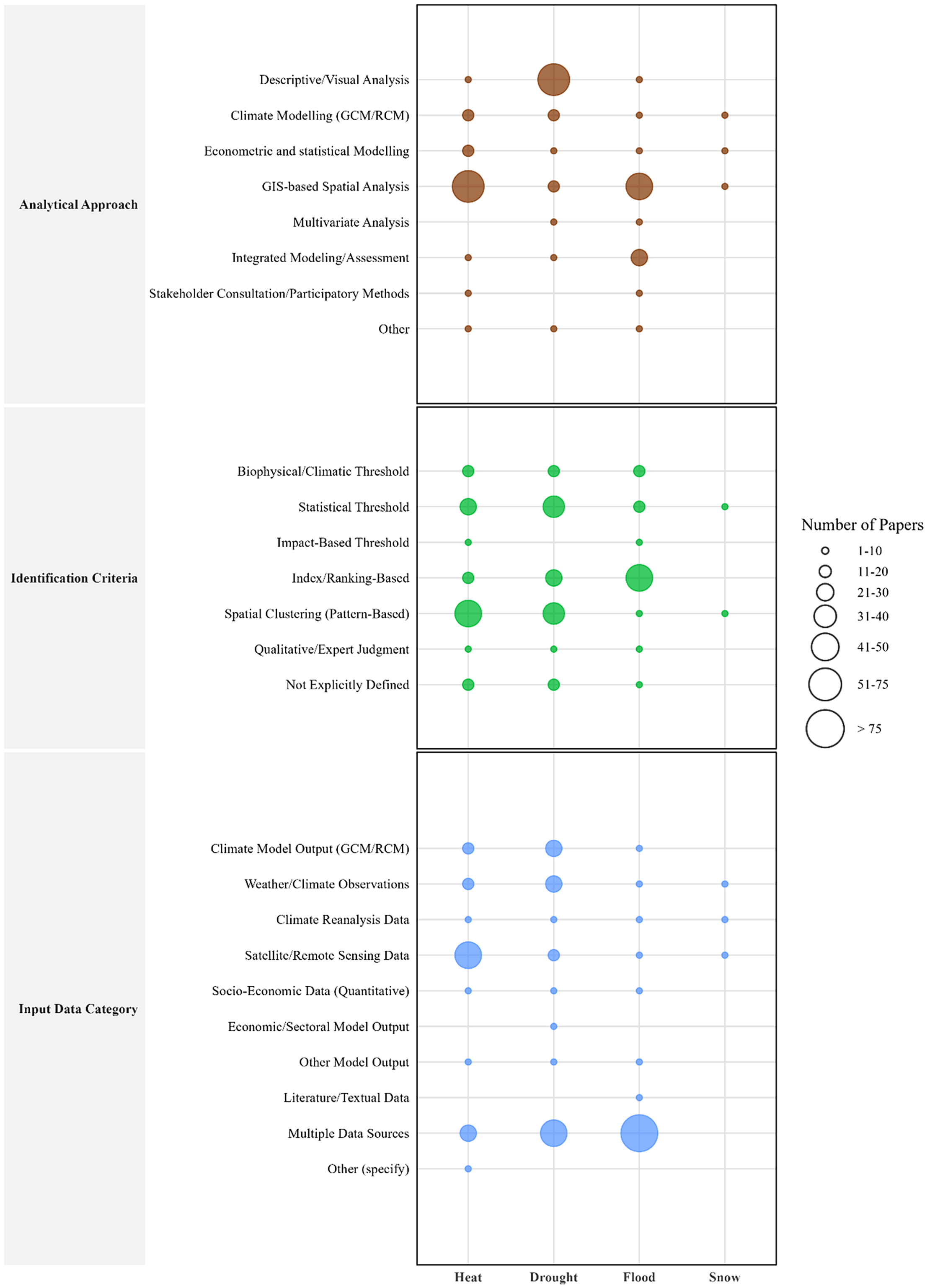

Figure 3. Methodology used in climate change hotspots literature for heat, drought, flood, and snow: analytical approach, identification criteria, and input data category.

hotspot identification criteria. As illustrated in the middle panel of figure 3, spatial clustering (34%, $n = 43$) (e.g. Zendeli *et al* 2025) and statistical thresholds (24%, $n = 30$) (e.g. Warren *et al* 2022) are the primary bases for identification. In these studies, a 'hotspot' is defined by relative extremity, such as pixels exceeding the 90th or 95th percentile, values >2 standard deviations from the local mean, or statistically significant 'high-high' clusters (Warren *et al* 2022, Gupta *et al* 2024, Zendeli *et al* 2025). Additionally, index/ranking-based criteria (13%, $n = 16$) are also prominent, with studies layering exposure data over physical hazard maps (Lung *et al* 2013). The impact-based threshold criteria define hotspots by specific societal outcomes (e.g. excess mortality or economic loss) (Verde 2024) but are rare in the literature (2%, $n = 3$). In short, most heat hotspot definitions present the potential for harm (hazard intensity) rather than the potential consequence of the hazard.

The dominance of spatial methods connects to the input data used (figure 3, bottom panel). Satellite and remote sensing data (e.g. Landsat, MODIS, ASTER) are the dominant input data sources (38%, $n = 48$) (Bartesaghi-Koc *et al* 2019, Hu *et al* 2024, Krenz and Amann 2025). This may be because remote sensing Land Surface Temperature (LST) data is the best available data set that allows assessing temperature and thus heat spatially, continuously and at small scales required in urban settings. While weather/climate observations and climate model outputs (GCM/regional climate models (RCMs)) are used in 14% ($n = 17$ each) (Silva *et al* 2024, Carr *et al* 2024b). Studies focusing on integrated risk, though rare, rely in addition on quantitative socio-economic data. This typically includes national census records (for population density, age structure, and income), health statistics (e.g. mortality records, ambulance dispatches), and composite deprivation indices (e.g. the European deprivation index) (Adélaïde *et al* 2024, Krenz and Amann 2025).

For *Drought* hotspots, analytical approaches tend towards descriptive/visual analysis (52%, $n = 66$). Literature has focused on the identification of temporal trends (Saleem *et al* 2021, Paredes-Trejo *et al* 2022, Verhoeven *et al* 2022, Řehoř *et al* 2023). Common analytical workflows involve calculating standardised indices (e.g. SPI, SPEI) and applying statistical tests, such as the Mann–Kendall test and Sen's slope estimator, to identify regions where dryness characteristics are significantly increasing over time (Kamruzzaman *et al* 2022, CM *et al* 2023, Kirkpatrick Baird *et al* 2023). Integrated modelling/assessment is also a key analytical approach, where physical climate outputs are coupled with hydrological or crop models to simulate future water deficits (Warren *et al* 2022). This temporal focus shapes the hotspot identification criteria. Spatial clustering (25%, $n = 32$), statistical thresholds (25%, $n = 32$) and index/ranking-based (21%, $n = 26$) criteria dominate the literature (Torres *et al* 2012, Prudhomme *et al* 2014, Spinoni *et al* 2014, Ji and Yuan 2024). The input data used in the literature rely on multiple data sources (34%, $n = 43$), synthesising Weather/Climate Observations (e.g. station data) (22%, $n = 28$) with Climate Model Outputs (CMIP5/6) (18%, $n = 23$) to capture the multi-scalar nature of drought (Ravinandrasana and Franzke 2025). Additionally, the integration of socio-economic data, though rare, is highly sector-specific. Drought studies incorporate detailed agricultural and economic indicators. This includes crop production statistics (yields and sown area), water withdrawal rates (agricultural vs municipal), and specific economic proxies such as insurance loss data (Vogel *et al* 2019, Bundy *et al* 2022).

For *Flood* hotspot studies, the analytical approach is dominated by GIS based spatial analysis (49%, $n = 47$) followed by integrated modelling/assessment (30%, $n = 29$). These approaches combine hydrological and hydraulic modelling with geospatial tools to simulate inundation extents (Andimuthu *et al* 2019, Mediero *et al* 2022, Zhu *et al* 2023). They often employ multi-criteria decision analysis and machine learning algorithms (e.g. random forest) to weigh diverse risk factors (Korah and Cobbinah 2017, Wongthongtham *et al* 2023, Liu *et al* 2024, Tian *et al* 2024). Index/ranking-based criteria is the most dominant form of hotspot identification criteria (45%, $n = 43$), reflecting the widespread construction of composite flood vulnerability indices. In these studies, a hotspot is identified by a composite risk score (Das *et al* 2020, Jian *et al* 2021, Azizi *et al* 2022, Enomah *et al* 2024). Statistical (19%, $n = 18$) and biophysical thresholds (13%, $n = 12$) are also used to delineate hotspots through specific recurrence intervals or physical limits, such as the 100 year flood, peaks over threshold models, or coastal 'bathtub' inundation levels (Nguyen and Woodroffe 2016, Andimuthu *et al* 2019, Camus *et al* 2022, Fandé *et al* 2022). Complementing these, spatial clustering algorithms (10%, $n = 10$, e.g. Getis-Ord Gi*, Kernel Density, Local Moran's I) are often employed to validate geographic coherence, ensuring hotspots represent statistically significant, neighbouring risk zones rather than isolated outliers (Leis and Kienberger 2020, Hinojos *et al* 2023, Langlois *et al* 2023, Zhang *et al* 2024, 2025). Impact-based thresholds are also used (8%, $n = 8$) where hotspots are identified based on tangible system failures such as road network disruption, or number of inundated houses (van Ginkel *et al* 2021, Steinhausen *et al* 2022, Carr *et al* 2024a). These studies often employ composite indices to locate areas where high population density and inadequate infrastructure coincide to produce heightened risk. Studies also move beyond single hazard events to identify areas of compound hydro-hazards (e.g. concurrent flood and drought increase) (Rashid and Wahl 2022, Verhoeven *et al* 2022, Ibrahim *et al* 2024). Here, a hotspot arises from nonlinear interactions between the built environment, topography, and multi-hazard synergies (e.g. coastal syndromes) (Newton *et al* 2012, Satta *et al* 2016).

The input data used relies on multiple sources (80%, $n = 62$), synthesising climate/hydrological model outputs with high-resolution satellite/remote sensing data (e.g. Sentinel-1 SAR) and socioeconomic data (e.g. population density, land use, GDP, infrastructure, road density, sectoral employment, locations of critical facility like hospitals, dams) (van Ginkel *et al* 2021, Collins *et al* 2022, Kumar *et al* 2024). Note that, in many studies, demographic variables are used as proxies for exposure, quantifying the density of people or assets located within inundation zones to modulate risk intensity. Only very few studies (Nussbaumer *et al* 2014, Marks *et al* 2022, Sharkus *et al* 2025) construct dedicated indices of social vulnerability, environmental justice or livelihoods by incorporating multiple dimensions e.g. income, poverty, education, age structure, housing conditions or access to services, and explicitly link them to hotspot identification.

For *Snow* hotspots, the analytical approach is dominated by econometric/statistical modelling (50%, $n = 3$) and GIS-based spatial analysis (33%, $n = 2$). These studies in the first group focus on detecting historical patterns of snow cover or depth variations using statistical trend tests, specifically the Mann–Kendall test and Sen's slope estimator, to identify regions of significant decline (Notarnicola 2020). GIS-based spatial analysis uses interpolation of meteorological observations (e.g. Cokriging, ordinary and universal Kriging) and spatial clustering routines that identify statistically significant concentrations of high (or low) values (Bahramimehr and Kabir 2024). Such methods are particularly relevant for studies relying on weather station networks or gridded climate fields (Bonsoms *et al* 2023). A notable methodological innovation in this field is the application of emerging hotspot analysis (Conyers and Roy 2023), which uses space-time cubes to classify hotspots not just by location, but by their temporal evolution (e.g. persistent vs. sporadic patterns). This physical focus shapes the hotspot identification criteria. Statistical thresholds (67%, $n = 4$) is the primary basis for identification. Here, hotspots are defined by statistical extremity or trend significance, such as grid cells exceeding specific percentile thresholds or regions exhibiting significant negative trends in snow water equivalent (SWE) with the use of metrics like the standardised SWE index to map 'snow drought' hotspots (Huning and AghaKouchak 2020). In a few cases, hotspots are defined in terms of risk concentrations, as seen in the transport-sector study (Bahramimehr and Kabir 2024) where hotspot regions represent areas of increased vulnerability for railway infrastructure under snow, rainfall, and temperature extremes. This study integrates multiple meteorological hazards with railway infrastructure exposure to identify sector-specific risk hotspots but does not explicitly consider wider socio-economic vulnerability, adaptive capacity or cross-sectoral impacts, distinguishing it from integrated CCH frameworks.

The input data used for *Snow* hotspot analysis relies on satellite/remote sensing data (particularly MODIS snow cover products) (50%, $n = 3$) to achieve consistent large-area monitoring (Notarnicola 2020, Ma *et al* 2024). This is complemented by climate reanalysis data (e.g. MERRA-2, ERA5) and *in-situ* weather observations to fill spatial gaps (Huning and AghaKouchak 2020). The integration of socio-economic data is almost entirely absent, reinforcing the physically oriented (hazard based) nature of current snow hotspot research.

3.4. Sectoral focus

As illustrated in figure 4, hazard specific research does not consider sectors evenly. *Heat* hotspot studies focus typically on the two sectors, health (19%, $n = 22$) and urban/cities (18%, $n = 21$), as they study the impacts on physical urban form and human physiological exposure (public health outcomes like mortality risk, ambulance dispatches, and thermal discomfort) (Schneider *et al* 2023, Carr *et al* 2024b). Impacts on sectors like agriculture (2%, $n = 3$) remain largely peripheral, despite the significant risks heat poses to outdoor labour and crop physiology (Vogel *et al* 2019). Numerous papers (38%, $n = 47$) do not have a sectoral focus and remain purely biophysical hazard focused. These cases reference societal impacts–if at all–only as potential implications rather than quantified outcomes, underscoring a persistent gap in heat hazard research.

Whereas *drought* hotspot research considers sectoral impacts, it focuses on agriculture (13%, $n = 17$) or the water sector (6%, $n = 8$). The literature often assesses drought hotspots through a food security lens considering yield gaps (Bundy *et al* 2022, Warren *et al* 2022). Additionally, the water sector is often analysed in conjunction with agriculture to map the competition between irrigation withdrawals and municipal-industrial demand (Zamani Sabzi *et al* 2019). Around 63% of papers do not have any sector focus and do not reference sectoral impacts but present a purely meteorological or hydrological perspective.

The majority of *Flood* hotspot studies (51%, $n = 49$) focusses on multiple sectors but often prioritises the built environment over the social environment. Such studies define hotspots by the exposure of tangible assets such as road networks, sewer systems, critical facilities (hospitals, dams), and residential building stock. Co-occurrence of urban and cities, and buildings and infrastructure is common in studies focussed on multiple sectors (Collins *et al* 2022, Li *et al* 2024, Carr *et al* 2024a) These are also frequently coupled with agriculture and food security (Nussbaumer *et al* 2014, Nguyen and Woodroffe 2016, Satta *et al* 2016), water (Langlois *et al* 2023, Zhu *et al* 2023) and, to a lesser extent, tourism and recreation (Newton *et al* 2012, Aloscious *et al* 2025). The small number of studies found for

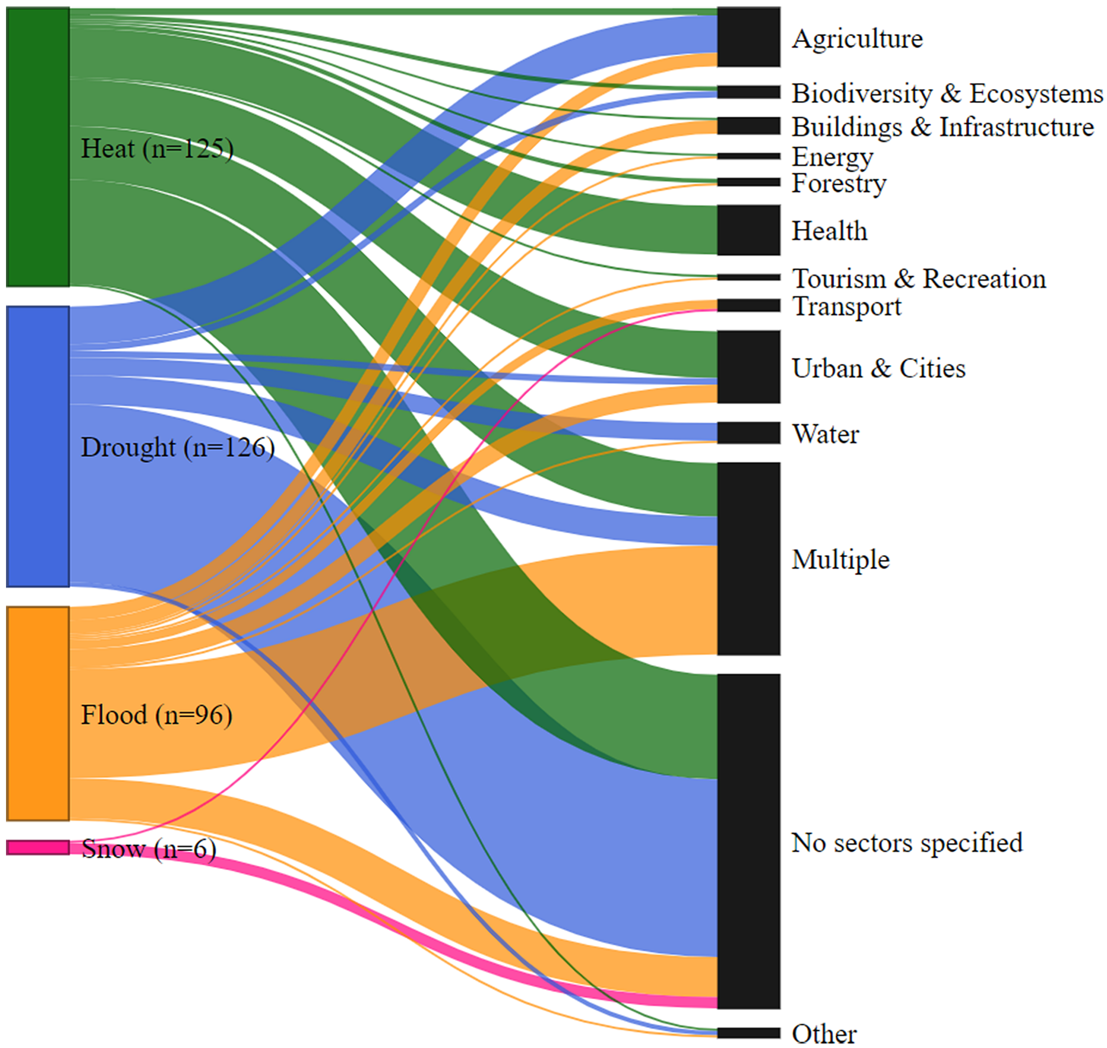

Figure 4. Sectoral distribution of literature on climate change hotspots for heat, drought, flood and snow.

snow hotspots prohibits conclusions on how they cover sectors. We note that Bahramimehr and Kabir (2024) from our *snow* hotspot assessment address the transport sector by mapping weather-related risk hotspots along the Canadian freight railway network.

3.5. Gaps identified

Our synthesised evidence helped in identifying three broad knowledge gaps in the CCHs identification literature. First, CCHs identification methods focus on biophysical variables, such as temperature thresholds or precipitation anomalies, while neglecting the socio-economic dimensions. Identifying physical changes is a necessary first step, but the socio-economic dimensions determine exposure, vulnerability and risks to economies and societies (Giorgi 2006, de Sherbinin 2014, Byers *et al* 2018, IPCC 2023a). Despite the increasing availability of damage data, most studies continue to define hotspots based on the potential for harm, relying on hazard intensity rather than exposure, vulnerability, and realised impacts. Impact-based thresholds, where hotspots are defined by damage caused (e.g. mortality counts, economic loss, or infrastructure failure), remain rare as do definitions that consider vulnerability or risk. This continues into the methodological dimension, where the synthesis reveals a disconnect between capability and application. While researchers possess sophisticated tools such as GIS, integrated assessment models, and complex statistical approaches (e.g. artificial intelligence) capable of combining complex socio-economic and hazard information, the actual basis for identification often reverts to simple spatial clustering or the description of maps. Therefore, available information on the underlying social vulnerability that turns a hazard into an impact or even a disaster remains missing. Such biophysical hotspot studies remain of value for understanding the dynamics of climate change and identifying regions of major impacts. However, going beyond the potential for harm can enable cost-effective responses to climatic changes (e.g. Piontek *et al* 2014).

Second, a validation gap is evident in the studied CCHs literature across the different hazards. Data sources and model systems for studying biophysical hotspots present their results in high precision and relatively high spatial and temporal resolution. On the other hand, there are few applications that validate the biophysical hotspots with respect to their real-world impacts and importance by, e.g. mixed-methods approaches. We especially note that only a small subset of studies integrates participatory methods or stakeholder consultations to validate model outputs against local lived experience (Gil-Guirado *et al* 2022, Dube *et al* 2023).

Third, considering the variety of economic sectors, the literature on CCHs appears unbalanced. For example, while flood research assesses impacts on transport, energy, and physical assets, heat research remains disconnected from infrastructure sectors. This is a critical oversight given the physical reality that extreme temperatures (cold and warm) impact transport networks (Gössling *et al* 2023) and strain energy grids (Hawker *et al* 2024) just as severely as inundation events. Similarly, drought is studied with respect to agriculture in rural regions, but the impacts on urban green infrastructure are rarely considered; and, heat wave hotspots descriptions may focus on health in the urban domain, but rural outdoor labour impacts are not often studied.

Cross-sectoral analyses remain scarce in the CCH literature too. Noteworthy, Piontek *et al* (2014) describe multi-sectoral impact hotspots considering health, agriculture, water, and ecosystems, with the ecosystem dimension further examined by Cheval *et al* (2020). Byers *et al* (2018) choose a multi-indicator multi-sector approach. They consider the broad sectors of water, energy, and land and highlight the benefits of sustainable developments in reducing risk for the most vulnerable. The European Environment Agency (2017) distinguishes in their chapter on multi-sectoral vulnerability explicitly between multi-sectoral and cross-sectoral. Where the former considers separate assessments for multiple sectors, the latter also integrates the interactions and dependencies between the sectors. Neither Byers *et al* (2018) nor Piontek *et al* (2014) consider cross-sectoral aspects explicitly. The European Environment Agency (2017) presents how one can study multi-sectoral ecosystem service impacts with a cross-sectoral focus. Kebede *et al* (2015) choose indicators that reflect cross-sectoral interdependencies for the sectors of agriculture, water, forestry, flooding, water, biodiversity, and urban areas.

The identified gaps highlight the need for applied examples that move beyond biophysical hazard hotspot detection toward integrated, impact-based risk assessments. The limited incorporation of socio-economic exposure, institutional context, and sectoral interdependencies underscores the value of testing hotspot frameworks in real-world settings. The following section presents two case study results, using an integrated framework for CCHs identification that incorporates climate hazard indicators, socio-economic dimensions, event-based storylines, and stakeholder engagements.

4. Case study applications

Europe represents a suitable area for addressing the methodological challenges explained in section 3.5. The continent is warming at a rate significantly faster than the global average (Copernicus Climate Change Service 2025), exacerbating a complex array of hazards, from intensifying heatwaves and droughts in the mediterranean to changing snow patterns and floods in the Alps, Northern and Central Europe. The challenge in Europe is not merely the pace of physical change, but the high density of interconnected socio-economic systems and diverse governance landscapes. Additionally, the European Union (EU)'s ambitious adaptation strategies and initiatives (European Environment Agency 2024, OECD 2024) require knowledge that transcends simple meteorological anomalies to identify where adverse climate signals intersect with infrastructure, vulnerable populations, and transnational economic corridors.

The two case studies presented are designed to address the gaps identified in the evidence synthesis. Both the case studies focus on the mountain regions in Europe because, mountain regions are characterised by strong climatic gradients, steep topography, and a concentration of population and assets in valley bottoms, which together amplify sensitivity to hydro-meteorological extremes and related hazards (IPCC 2022a). Despite this risk profile, climate stress in mountain areas is still predominantly characterised using biophysical indicators, such as elevation-dependent warming and changes in precipitation regimes and extremes (Beniston and Stoffel 2014, Mountain Research Initiative EDW Working Group 2015).

Moving beyond conventional hazard-centric models, we present a forward-looking, bottom-up integrated framework (figure 5) that uses multiple knowledge sources and evidence bases for CCHs identification. Our framework follows a flexible, iterative workflow and is driven by quantitative and qualitative streams of evidence. Quantitative stream includes biophysical data, which capture physical climate signals, hazard indices, and topographic pre-conditions. These are integrated with socio-economic data

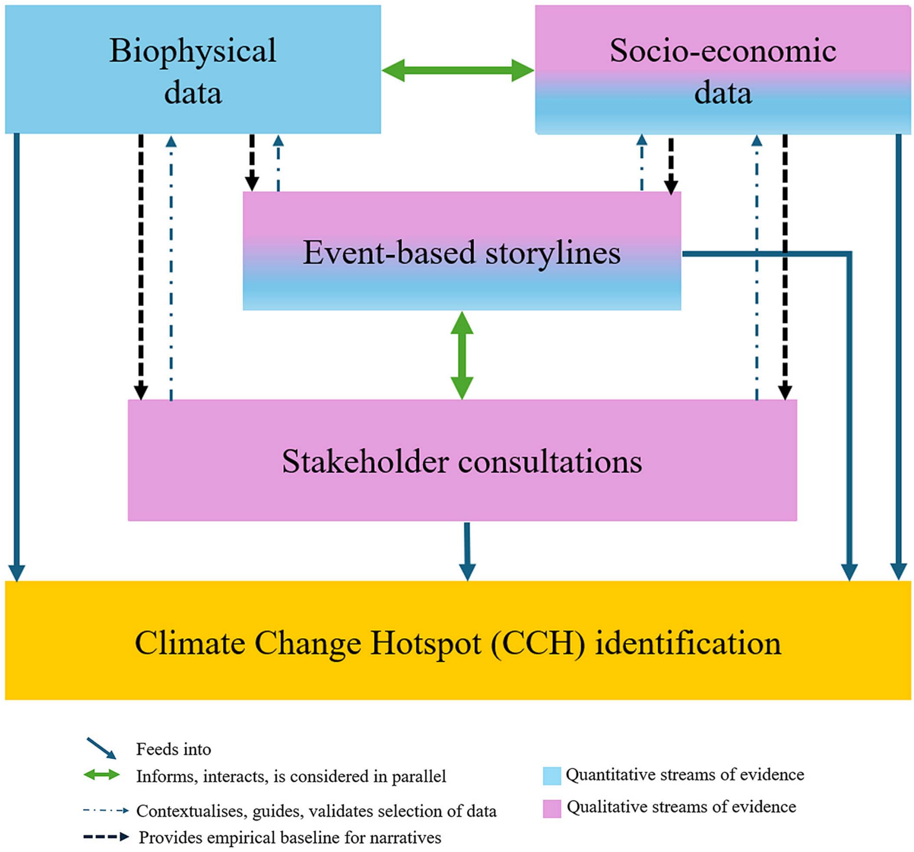

Figure 5. Integrated framework for CCHs identification. Solid and dashed arrows denote the continuous cross-stream interactions between quantitative data and qualitative insights.

that include societal variables, infrastructural assets, and demographic contexts. To ensure the outputs are systematically anchored in real-world evidence, the framework incorporates event-based storylines constructed from historical events. These storylines can draw upon both quantitative empirical records (such as historical hazard inventories) and qualitative impact narratives (Sillmann *et al* 2021, Baulenas *et al* 2023). Simultaneously, structured stakeholder consultations provide crucial qualitative insights, contextualising these quantitative metrics and impact narratives within on-the-ground risk perceptions.

Application of this integrated framework requires that components continuously interact and inform one another. Cross-stream interactions ensure that biophysical and socio-economic data provide an empirical baseline for the narratives, while the stakeholder insights and the event-based storylines (historical events) guide and contextualise the selection of relevant quantitative metrics. Finally, all four components feed directly into the CCH identification. This forward-looking, bottom-up integrated framework is adaptable, allowing individual case studies to modify the specific entry points, evidence classifications, and procedural sequencing based on their unique hazard focus and data availability (figures 6 and 9). To demonstrate the practical application of the framework, the following sections present two case studies.

4.1. Snow avalanches in the Alps and Carpathian Mountains

The Alps and the Carpathian Mountains represent two contrasting but highly relevant mountain systems for assessing climate-change-driven avalanche risk in Europe. Both regions are characterised by strong climatic gradients, steep topography, and sensitivity to changes in snow and temperature regimes, which influence avalanche occurrence, typology, and seasonality (Beniston and Stoffel 2014, IPCC *et al* 2019, IPCC 2022b). At the same time, they differ markedly in exposure patterns, institutional capacity, and risk governance, with the Alps characterised by long-established avalanche risk management systems and the Carpathians by more emerging frameworks. This contrast provides a robust basis for testing our integrated framework to CCHs identification.

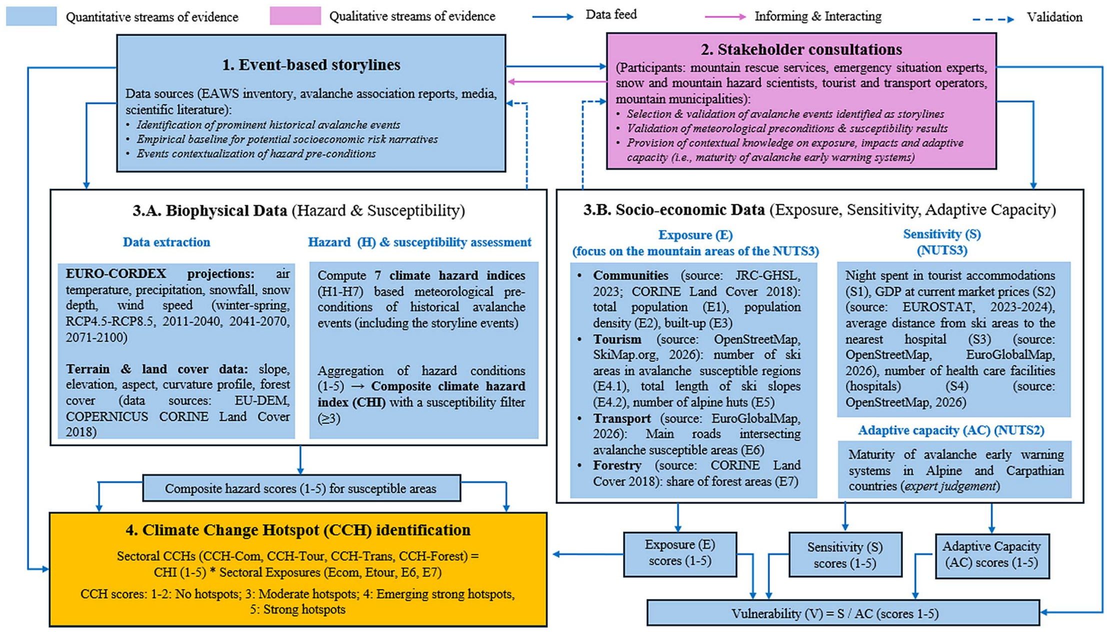

Figure 6. Methodological framework for snow climate change hotspot identification in Alps and Carpathian Mountains.

4.1.1. Methodological framework and data used

In this case study, a harmonised methodological workflow was applied at NUTS3 level to assess potential climate-change-driven socio-economic risk from snow avalanches by integrating hazard, exposure, and vulnerability dimensions. The workflow comprises three main steps (see figure 6) following figure 5. Note that, NUTS3 (Nomenclature of Territorial Units for Statistics, Level 3, Eurostat 2024) represents the smallest harmonised statistical and administrative unit for which consistent socio-economic, demographic, and territorial data are available across Europe.

Step 1. *Avalanche susceptibility assessment and event contextualisation* (figure 6, *panels 1 and 2*). Avalanche susceptibility was estimated using a multi-criteria approach based on terrain and land cover factors, including slope, elevation, aspect, plan curvature, and forest cover, which are widely recognised as key controls on avalanche release (Schweizer *et al* 2003, Bühler *et al* 2018). These factors were combined using the analytical hierarchy process (Saaty 1987, Varol 2022) to derive spatial susceptibility patterns. The resulting susceptibility was classified on a 1–5 scale (1—very low to 5—very high) using a quantile-based approach. Validation was performed against recorded fatal avalanche events compiled from multiple sources including European, national and regional avalanche databases (e.g. European Avalanche Warning Service—EAWS, the WSL Institute for Snow and Avalanche Research, International Commission for Alpine Rescue, the Avalanche Warning Service for Tyrol), mountain rescue records (e.g. Salvamont Romania) and mountaineer reports (e.g. Avalanseincarpati.ro), media sources, and scientific literature. For each event, terrain and vegetation preconditions, as well as meteorological preconditions derived from 3 d windows prior to the event, were extracted to support event contextualisation and ensure consistency with the hazard processes analysed in Step 2.

To complement the quantitative hotspot assessment, a storyline approach (figure 6, panel 1) was adopted (Shepherd *et al* 2018, Shepherd 2019). Representative historical avalanche events were selected through stakeholder consultations and expert knowledge (figure 7) to reconstruct physically plausible sequences of avalanche occurrence, from meteorological and snowpack preconditions to impacts and emergency response. Rather than estimating the probability of future events, the storylines were used to understand the causal relationships between climatic drivers, terrain conditions, exposure, vulnerability and observed impacts, thereby supporting the identification of relevant hazard indicators and the interpretation of CCHs. The seven event-based avalanche storylines provided contextual evidence for the subsequent analysis (Sillmann *et al* 2021, Baulenas *et al* 2023). Stakeholder consultations (figure 6, panel 2) further informed the interpretation of exposure, vulnerability, and governance contexts.

Step 2. *Climate hazard analysis* (figure 6, *panel 3A*). To assess avalanche-related climate hazard conditions, we used climate simulation data from a high-resolution (0.11° grid, approximately 10 km) ensemble of multi-RCMs, available from the European branch of the Coordinated Downscaling Experiment (EURO-CORDEX, Kotlarski *et al* 2014) for the 21st century. The focus is on three future time slices

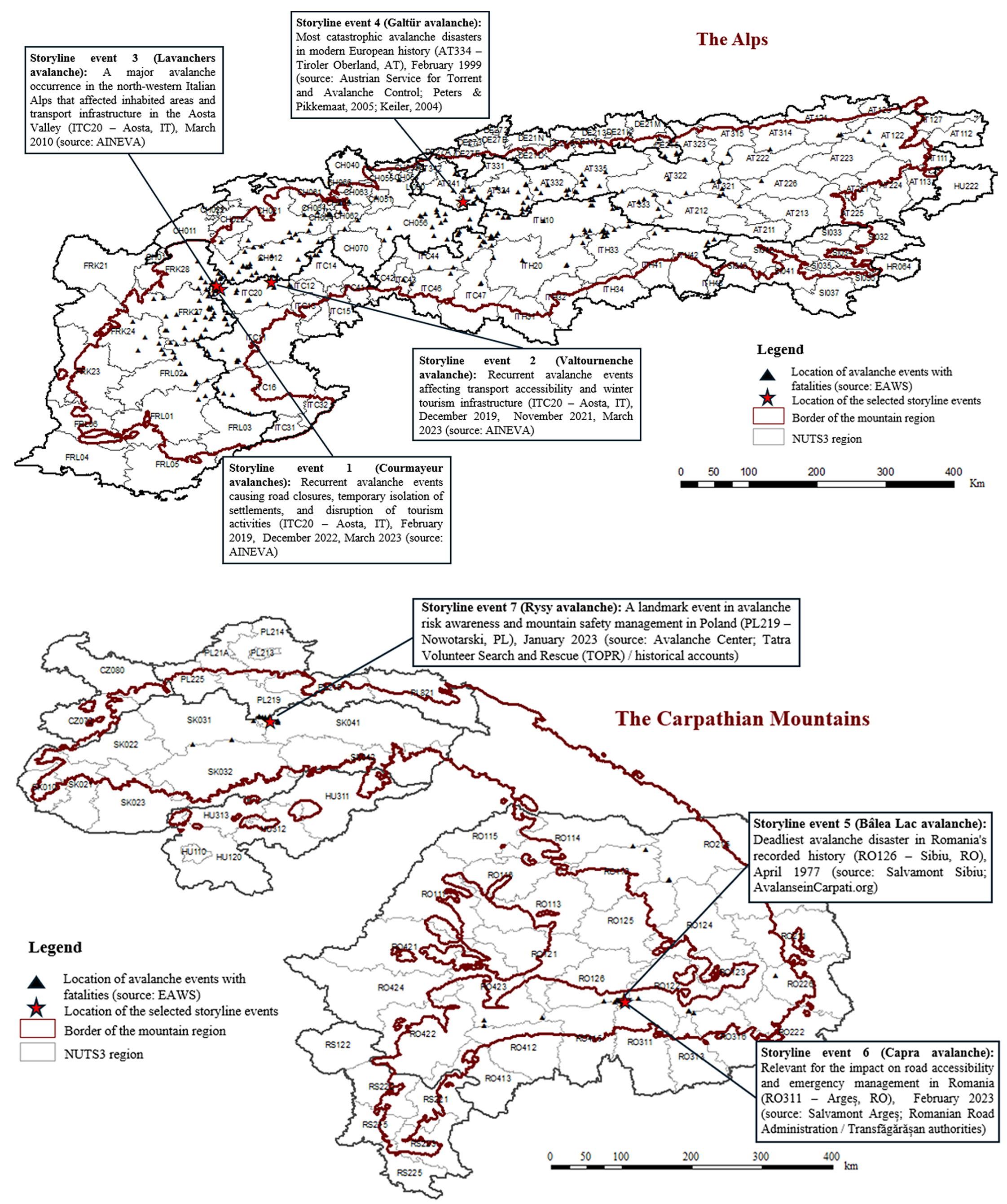

Figure 7. Selected storyline avalanche-events.

(near future 2011–2040; mid-century 2041–2070; far-future 2071–2100), relative to the baseline reference period 1971–2000. We use the simulations for the concentration pathways RCP4.5 and RCP8.5 from 9 GCM-RCM pairs (see supplementary table SM6.2). Data was obtained from local paths at the German Climate Computing Centre (DKRZ) but was at that point in time also available from ESGF[16].

Seven avalanche-related climatic hazard indices were derived from meteorological preconditions of historical avalanche events and the storyline events based on the European Avalanche Warning Services inventory (EAWS, www.avalanches.org), avalanche reports and stakeholder consultations. The selected hazard indices reflect proxy climate conditions relevant to dry, wet/melting, and slab-like avalanche occurrence. The indices were calculated for each analysis period and subsequently standardised using a quantile-based scoring approach. Climatic hazard index values were transformed into five ordinal classes, with scores ranging from 1 (very low) to 5 (very high), ensuring comparability among variables characterised by different units and value ranges. The classified indicators are aggregated into a composite

[16] https://esgf-metagrid.cloud.dkrz.de/search

climate hazard index (CHI) at 10 km grid resolution as the arithmetic mean of the seven hazard index scores (see equation (1)).

$$\mathrm{CHI} = \frac{(H_1 + H_2 + H_3 + H_4 + H_5 + H_6 + H_7)}{7}, \tag{1}$$

where $H_1 - H_7$ represent the classified hazard indices.

The resulting CHI values range from 1 to 5, where 1 indicates very low climatic hazard and 5 indicates very high climatic hazard. Further details of the seven avalanche climatic hazard indices, the EURO-CORDEX GCM-RCM ensemble used, and the quantile-based standardisation thresholds are provided in supplementary material SM6 and 7. Equal weighting was applied to all indicators to avoid introducing subjective expert judgement into the aggregation process and because no robust empirical evidence exists to support differential weighting of avalanche-conditioning climatic factors across the diverse mountain environments considered in this study. To ensure physical consistency, the terrain-vegetation cover-based avalanche susceptibility, derived in Step 1, was integrated as a spatial filtering condition. CHI values were calculated only for mountain areas characterised by moderate, high, or very high avalanche susceptibility (scores $\geqslant$3), while areas classified as very low or low susceptibility were excluded from further hazard and hotspot analyses. This approach reflects current understanding that avalanche activity is strongly influenced by meteorological drivers such as snowfall, temperature fluctuations, and rain-on-snow events (Marty *et al* 2017, Mayer *et al* 2024).

Step 3. *Assessment of the potential socio-economic risk* (figure 6, *panel 3B*). The ESPON-CLIMATE framework was applied to estimate potential socio-economic risk at the NUTS3 level in a harmonised, policy-aligned, and IPCC-consistent manner (ESPON 2022). The assessment follows the IPCC AR5 and AR6 risk concept, where risk is defined as the interaction between hazard (H), exposure (E), and vulnerability (V), with vulnerability conceptualised as a function of sensitivity (S) and adaptive capacity (AC) (IPCC 2022b). The analysis was conducted for NUTS3 regions with at least 30% mountainous area, ensuring relevance for mountain-specific processes and impacts.

The assessment considered three key socio-economic sectors such as tourism, transport, and forestry, as well as local communities, capturing a broad range of potential impacts across economic, environmental, and social dimensions. Exposure was represented by key sector-specific elements at risk including population concentration in mountain areas, built-up area, ski slope number and length, number of alpine huts, main road density, forest share, which are important assets for mountain economies (e.g. Steiger *et al* 2019). Socio-economic vulnerability was characterised through indicators of sensitivity and adaptive capacity, reflecting both socio-economic conditions and institutional capabilities to anticipate, respond to, and recover from avalanche-related impacts. Following the ESPON-Climate methodology, exposure and vulnerability indicators were first standardised to a common ordinal scale (1–5) and aggregated (as arithmetic mean of the equally weighted standardised indicators), into composite indices at the NUTS3 level without weighting their importance. This procedure aimed to ensure methodological consistency and enabling cross-regional comparison between the Alps and Carpathian Mountains. The potential socio-economic risk was qualitatively assessed (no monetisation) by combining the standardised hazard, exposure and vulnerability information within the ESPON-climate framework, providing the basis for comparing the potential risk levels across the two mountain regions.

Sector-specific CCHs were then identified by combining the classified CHI, which combines climate hazard conditions with avalanche susceptibility, and the corresponding classified composite sector-specific exposure indicators at the NUTS3 level using a multiplicative interaction rule (CHI $\times$ Exposure). This multiplicative rule was used specifically for hotspot identification, whereas vulnerability informed the broader socio-economic risk assessment and interpretation of the resulting hotspot patterns. To ensure physical consistency, CHI was calculated only within areas characterised by moderate to very high avalanche susceptibility (susceptibility classes 3–5), thereby restricting the analysis to terrain where avalanche release is physically plausible. The hotspot score for each sector was calculated as the product of the CHI class and the sectoral exposure class, resulting in values ranging from 1 to 25. These scores were subsequently classified (quantile-based) into five hotspot categories as follows: Classes 1–2 (1–8, No hotspot), Class 3 (9–12, Moderate hotspot), Class 4 (13–16, Emerging hotspot), and Class 5 (17–25, Hotspot). The procedure was applied for the baseline period (1971–2000) and for all future climate projections (near-, mid- and far-future) under the RCP4.5 and RCP8.5 scenarios, enabling the assessment of changes in the spatial distribution and intensity of sector-specific CCHs. The resulting hotspots therefore represent areas where elevated climatic hazard conditions coincide with high concentrations of exposed socio-economic assets and activities, indicating increased potential socio-economic risk. Vulnerability, expressed through sensitivity and adaptive capacity, informed sectoral exposure-risk

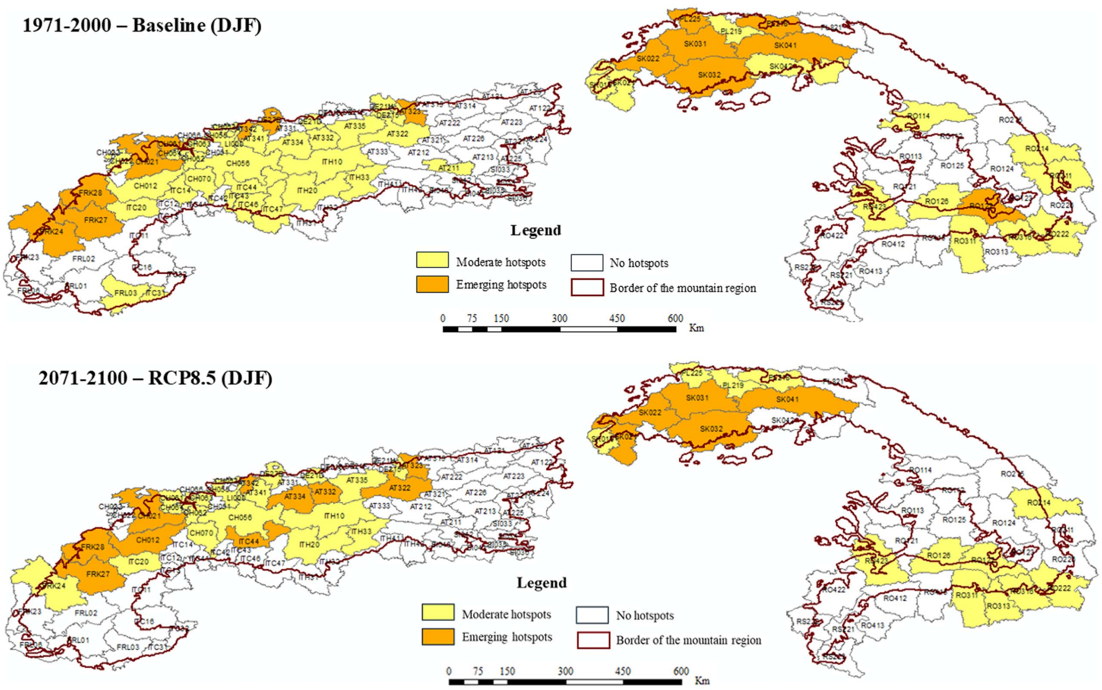

Figure 8. Spatial distribution of CCHs for the communities sector at the NUTS3 level, for the winter season (DJF, December, January, February) during the baseline period (1971–2000) and the far-future period (2071–2100) under the RCP8.5 scenario across the European Alps and Carpathian Mountains.

assessment within the ESPON framework and supported the interpretation of the identified hotspot classes.

4.1.2. Results

Snow hotspots are identified at the NUTS3 level based on the proposed framework (figure 6) where projected avalanche-prone climatic conditions coincide with concentrations of socio-economic exposures. This provides a basis for comparing present and future sector-specific potential climate risks across the two mountain regions. This workflow ensures that hotspots reflect the interaction between hazard and exposure, moving beyond purely biophysical hotspot identification (de Sherbinin 2014, IPCC 2022b). Figure 8 illustrates the hotspot assessment for the communities sector.

In the far-future projections, the spatial configuration of CCHs remains broadly consistent across both mountain systems, indicating a strong persistence of hazard-prone regions. However, an intensification of CHI values is observed within existing hotspots, particularly in parts of the western and central Alps and in the Romanian Carpathians. This pattern is consistent with recent studies showing that climate change is expected to modify avalanche regimes primarily through changes in snowpack properties, increased frequency of wet-snow and rain-on-snow events, and elevation-dependent warming, rather than through uniform spatial expansion of hazard zones (Beniston *et al* 2018, Mayer *et al* 2024). Similar patterns are observed for both winter and spring seasons, indicating sustained relevance of avalanche hazard across the tourism season.

The identified CCHs coincide with well-known avalanche-prone regions and areas with recurrent impacts, supporting their validity under present climate conditions. In the Alps, long-term fatality statistics confirm persistent and widespread avalanche risk across multiple countries (Techel *et al* 2016). In the Carpathians, studies identify the Făgăraș Massif and surrounding areas as recurrent avalanche hotspots affecting transport and tourism (Voiculescu 2009, Voiculescu *et al* 2023). This spatial agreement between our framework-derived hotspots and documented avalanche activity demonstrates the robustness of our CCHs identification approach.

Event-based storylines (figure 7) supported the susceptibility evaluation by confirming that the mapped susceptible areas correspond to locations where documented avalanche events occurred and where similar terrain and climatic preconditions exist. Thus, they link the identified hotspots to real-world disaster dynamics and cross-sectoral impacts. Rather than serving as an independent basis for hotspot delineation, the storylines provide contextual validation, illustrating how combinations of terrain predisposition and short-term meteorological conditions result in high-impact avalanche events.

A clear regional differentiation emerges between the Alps and the Carpathians (figure 8). In the Alps, CCHs are spatially extensive and closely associated with high exposure, reflecting dense tourism infrastructure and transport networks. Despite well-developed monitoring and protection systems, risk remains structurally high due to the strong co-location of hazard and exposure, combined with projected shifts towards wet-snow and rain-on-snow avalanche processes (Castebrunet *et al* 2014, Maina and Kumar 2025). In contrast, Carpathian hotspots are more localised, with generally lower exposure but higher relative socio-economic vulnerability due to more limited protective infrastructure and emerging risk management systems. Under future climate variability, hazard signals in these regions become more pronounced but remain spatially heterogeneous.

These results demonstrate that avalanche-related CCHs in Europe are characterised by the persistence of hazard-prone regions under climate change, with increasing intensity rather than widespread spatial expansion. By integrating historical storylines, hazard dynamics, susceptibility conditions, and socio-economic exposure with hotspot mapping, the proposed framework provides a basis for interpreting the potential regional socio-economic risks while offering a transferable and adaptable framework for identifying areas where climate-driven hazard signals intersect with vulnerable systems, thereby supporting targeted adaptation planning in mountain regions.

4.2. Flash flood in the Trentino-Alto Adige region, Italy

Flash floods and debris flows are among the most destructive and rapidly evolving natural hazards in Alpine environments (Destro *et al* 2018). In mountain catchments, the combination of steep gradients, thin soils, and confined valley morphology means that intense precipitation events translate almost instantaneously into high-energy flows capable of mobilising large volumes of sediment and causing severe damage to settlements and infrastructure concentrated in valley bottoms. In the European Alps, this hazard profile is being reshaped by climate change (Beniston and Stoffel 2016, Zander *et al* 2023). Sub-daily precipitation extremes are intensifying, driven by enhanced atmospheric moisture content and convective dynamics at higher elevations, increasing both the frequency and severity of flash flood and debris-flow events (Dallan *et al* 2024, Pesce *et al* 2025). The trentino-alto adige region of northeastern Italy sits at the heart of this evolving risk landscape. The region combines steep orography, highly heterogeneous catchment characteristics, and a dense concentration of settlements, transport infrastructure, and economic activities in valley floors and on alluvial fans. These geomorphological and socio-economic configurations substantially amplify the potential consequences of extreme precipitation events.

4.2.1. Methodological framework and data used

In this case study, we applied an integrated bottom-up workflow to hotspot identification, following figure 5. This workflow (figure 9) combines quantitative hydro-climatic evidence with qualitative insights derived from a participatory process involving local institutions and stakeholders. Therefore, it moves beyond hotspot definitions based solely on historical flood occurrence or hazard-based mapping, allowing the hotspot to be identified at the regional scale from the established body of hydrogeological knowledge for the area and characterise it through the co-occurrence of three mutually reinforcing conditions: a pronounced, climate-driven intensification of the precipitation hazard; a geomorphological setting that favours flash floods and debris flows; and a marked concentration of population, settlements, infrastructure, and economic activity in the exposed valley floors. This co-occurrence is interpreted within the institutional and governance context that shapes how the resulting risk is managed. Evidence on these conditions was assembled through two complementary strands of evidence.

From a physical hazard perspective (figure 9, Pane 1), the hotspot identification is based on regional-scale evidence indicating a marked intensification of sub-daily precipitation extremes in Alpine environments (Dallan *et al* 2024). We drew on high-resolution climate and hydrological modelling; the principal elements of this modelling chain are summarised here, while full technical specifications are reported in SM8 (table SM8.1). Future changes in short-duration precipitation extremes were derived from a seven-member ensemble of convection-permitting RCM from the CORDEX flagship pilot project on convective phenomena over Europe and the mediterranean (Coppola *et al* 2020, Fosser *et al* 2024). The simulations for the RCP8.5 scenario were remapped onto a common grid of approximately 3 km for three ten-year time slices: 1996–2005, 2041–2050, and 2090–2099. Because the limited length of convection-permitting simulations constrains conventional extreme-value analysis, extreme precipitation return levels were estimated using the simplified metastatistical extreme value approach (Marani and Ignaccolo 2015, Marra *et al* 2019), a non-asymptotic method that exploits the full distribution of ordinary events to reduce sampling uncertainty. Return levels were computed for a 50 year return period across five durations, i.e. 1, 3, 6, 12, and 24 h, and used to construct depth–duration–frequency relationships for a set of twenty representative mountain catchments in the region, with drainage areas of the order of 4–10 km^2. These

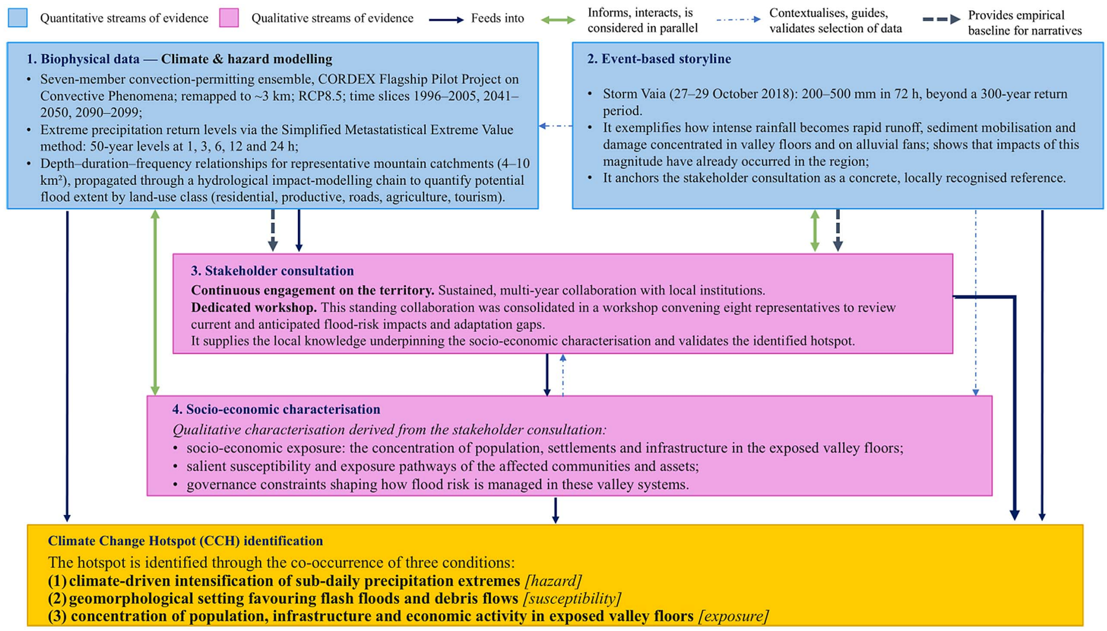

Figure 9. Methodological framework for flood climate change hotspot identification in trentino-alto adige region, Italy.

relationships were then propagated through a hydrological impact-modelling chain, the SAFER PLACE modelling tool[17], to quantify the potential flood extent across the principal exposed land-use categories, including residential and productive areas, roads, agricultural land, and tourism infrastructure.

To exemplify the flood-generating mechanisms behind such events, we draw on an event-based storyline built around Storm Vaia (figure 9, Panel 2), a real event that affected the Eastern Italian Alps, including Trentino-Alto Adige, between 27 and 29 October 2018. Following a prolonged dry spell, the storm produced cumulative rainfall of approximately 200–500 mm over 72 h, exceeding local historical records and reaching a severity beyond a 300 year return period. This triggered widespread flooding, debris flows, and slope failures with loss of life and substantial socio-economic disruption. It shows how intense, persistent rainfall is converted into rapid runoff, sediment mobilisation, and the concentration of damage in valley floors and on alluvial fans, and it demonstrates that impacts of this magnitude have already occurred in the region. The storm Vaia was therefore used to anchor the subsequent stakeholder consultation phase. As a concrete and locally recognised event, it gave participants a common starting point for discussing local exposure and how flood risk is governed in these valleys.

The second evidence stream draws on qualitative knowledge co-produced with local institutions and stakeholders (figure 9, panel 3 and 4) to characterise the socio-economic exposure, vulnerabilities and governance dimensions of flood risk in the region. It rests on a long-standing, empirically grounded knowledge base on hydrogeological risk in Trentino-Alto Adige (Chiogna *et al* 2016, Mondino *et al* 2020), built over several decades through sustained collaboration, continuous dialogue, joint problem framing, and collaborative planning with regional and local bodies responsible for civil protection, land-use planning, hydrographic and river-basin services, environmental protection agencies, and water-management authorities.

This hotspot characterisation was further refined through a dedicated stakeholder workshop held on March 2024, which convened eight representatives from regional organisations. The full list of the workshop participants is reported in table SM8.2. The workshop focused on current and anticipated climate-change and flood-risk impacts across the participants' respective sectors, as well as on the identification of critical gaps for adaptation planning. These inputs were integral to characterising and validating the hotspot. The methodological framework is illustrated in figure 9.

4.2.2. Results

The integrated framework outlined in 4.2.1 identified flood-risk CCHs concentrated in the Alpine valley systems of trentino-alto adige, northeastern Italy. The hotspot is delineated by the spatial coincidence of three conditions: the increasing frequency and severity of short-duration precipitation extremes, the

[17] https://saferplaces.co

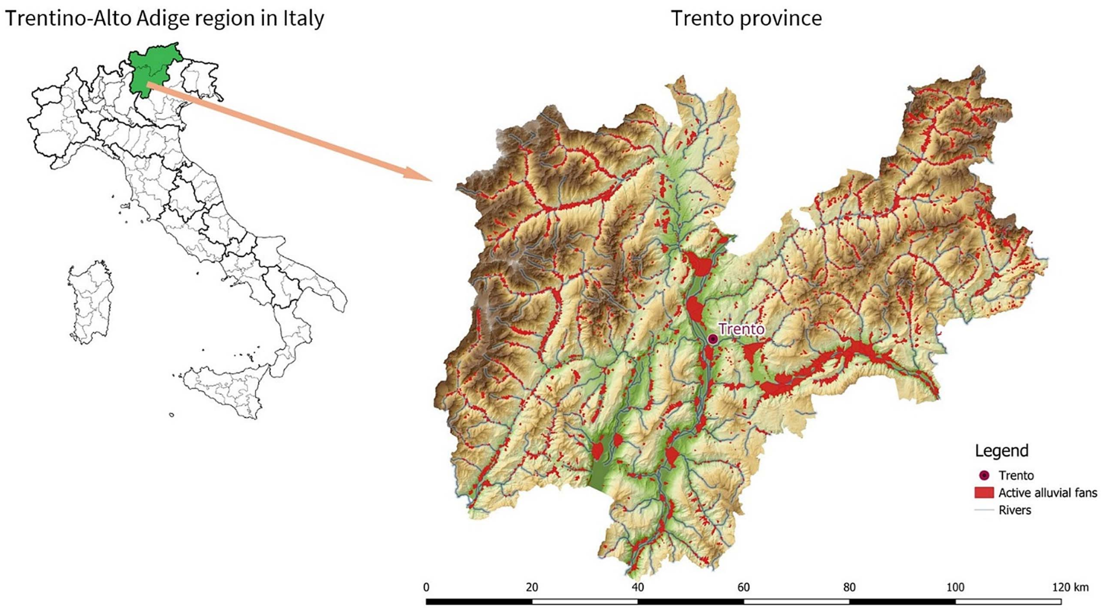

Figure 10. Spatial distribution of alluvial fans in the province of Trento.

geomorphological predisposition of valley floors and alluvial systems to rapid, sediment-laden flows, and the concentration of settlements, infrastructure and economic activity in the same valley bottoms. This hydro-climatic signal has strengthened over recent decades and is projected to intensify further under future climate scenarios (IPCC 2023b, Dallan *et al* 2024, Peleg *et al* 2025). The modelling chain quantifies and projects the hazard. Storm Vaia is used as an event-based storyline to illustrate the type of conditions already plausible in the region and likely to become more consequential under climate change. Beyond its physical delineation, the CCHs definition was further refined and interpreted through stakeholder co-production. Inputs from local and regional public authorities responsible for civil protection and land-use planning, river basin and hydrogeological agencies, and sectoral actors involved in infrastructure and risk management contributed to contextualising the hazard signal.

In a recent workshop, stakeholders consistently reported that recent extreme-precipitation events had already produced tangible damage within the valley systems, from the disruption of water-supply and treatment services and attendant concerns over water quality, to damage to tourism and recreational infrastructure and the interruption of transport and utility networks. This corroborates the modelled hazard and confirms that impacts concentrate where people and assets cluster on the valley floors. They further pointed to an ongoing intensification of hydro-geological risk, manifest in more frequent events and a growing stock of exposed assets, consistent with the strengthening hazard trend obtained from the physical analysis. A recurrent concern was the limited institutional capacity to keep pace with this evolving risk, and in particular the absence of a dedicated regulatory and planning framework connecting climate-change assessment to the design of hydraulic works and to spatial planning, which currently constrains anticipatory adaptation. Considered together, these convergent observations substantiate the delineated hotspot, in which an intensifying precipitation hazard, exposure concentrated in the valley bottoms, and constrained adaptive capacity coincide, and they reflect a shared willingness among the participating bodies to contribute event records, inventories of protective works, and monitoring data to its continued assessment. These perspectives provided locally grounded information on exposure pathways, salient vulnerabilities, and governance constraints affecting flood risk in northeastern Italian Alpine valley systems. As a result, the delineated CCHs reflects not only heightened hazard propensity but also the convergence of biophysical processes with socio-economic exposure and institutional challenges. A defining structural feature of the identified CCHs is the widespread presence of alluvial fans, which play a central role in shaping local flood dynamics. These landforms act as preferential pathways for debris-laden flows and increase the concentration of flood impacts in valley areas where settlements, infrastructure, and economic activities are located. The spatial distribution of alluvial fans across the province of Trento, shown in figure 10, provides an indicative representation of the geomorphological configurations underpinning flood risk within the CCHs.

5. Discussions and conclusions

Our evidence synthesis of 353 studies substantiates the biophysical bias in the identification of CCHs. Despite the growing urgency of adaptation, most existing methodologies still define hotspots based on the potential for harm (hazard intensity) rather than realised consequences (risk hotspots). This evidence synthesis reveals a stark imbalance in research volume across different climate hazards. There are robust, rapidly expanding literature bases for the main hazards, *Heat* ($n = 125$), *Drought* ($n = 126$), and *Flood* ($n = 96$). Cold climate hazards like *Snow* ($n = 6$) remain niche research categories. Furthermore, the conceptualisation of hotspot is far from uniform across hazard types. Research into heat, drought, and flood has, to varying extents, begun to evolve toward integrated risk frameworks that incorporate human impacts and socio-economic inequity. In contrast, cold climate hazards remain significantly understudied. While the available literature suggests this hazard is typically viewed through a purely meteorological lens, the limited literature size ($n = 6$) means these observations should be treated as preliminary indications rather than definitive trends; therefore, they are not presented with the same level of confidence as the conclusions drawn for the other established hazard literatures. Nonetheless, this highlights a critical gap where potentially vulnerable populations and infrastructure in mountainous or cold regions are currently overlooked in adaptation planning.

Our findings also reveal that CCHs research does have a sectoral focus. For example, *Heat* hotspot research concentrates on public health outcomes and urban morphology. Similarly, *Drought* hotspots are viewed predominantly through a food-security lens, focusing on crop yields and insurance losses, but rarely account for broader social vulnerability. Furthermore, the use of socio-economic data remains limited to single sectors. For example, *Drought* research may incorporate agricultural data like crop yields and insurance losses but usually does not link these to broader social vulnerability for hotspot identification. Similarly, for *Flood* hotspot research, only a few studies move beyond physical exposure to construct dedicated indices of social vulnerability or environmental justice. Indicators such as income levels, education, age structure, and housing quality are rarely explicitly linked to the primary hotspot identification criteria. Additionally, there is a critical need to invest in the development of new and better socio-economic datasets, which would facilitate the investigation of risk hotspots.

While most of the studies exhibits this biophysical bias, our review (section 3) highlights emerging, innovative approaches that address this gap. For instance, in the *Flood* hotspot research, Gil-Guirado *et al* (2022) reconstructed long-term, socially grounded databases using newspaper archives and press reports, providing a rare historical perspective on the societal dimensions necessary for holistic hotspot identification. Similarly, Dube *et al* (2023) used data triangulation to map and evaluate flooding hotspots in 19 South African national parks and assesses their impact on tourism. They use employee surveys on flood perceptions, annual reports on economic losses, and detailed records of infrastructure repair costs to assess impacts on specific sectors like tourism and business.

Our case studies operationalise a adaptable, forward-looking, bottom-up framework for CCHs identification (figures 5, 6 and 9). In doing so, the framework addresses two of the three key knowledge gaps identified in section 3.5. First, it moves beyond predominantly biophysical hotspot identification by integrating climate hazards with socio-economic exposure, sensitivity and adaptive capacity indicators. Second, it strengthens the interpretation and validation of hotspot assessments through stakeholder consultations and the use of historical event-based storylines, thereby linking model outputs with documented impacts and local knowledge. Our integrated framework shifts from conventional, top–down mapping to a bottom-up mapping. A central, distinctive contribution of this methodology is the integration of stakeholder consultation. Rather than treating local stakeholder engagement as a supplementary, ex-post validation exercise, our framework operationalises it as a constitutive component of the CCHs identification process itself, a necessary trajectory also supported by recent initiatives (e.g. Votsi *et al* 2025). By explicitly embedding local stakeholder consultations into our core analysis, our framework captures dimensions of climate risk that remain entirely invisible in large-scale biophysical assessments.

Furthermore, our case studies enrich CCHs identification by linking quantitative risk classifications with event-based storylines. By synthesising historical disaster data with future climate change signals and socio-economic vulnerabilities, we develop temporally informed narratives of risk evolution. For instance, the snow avalanche case study leverages documented historical events across the Alps and Carpathian Mountains (e.g. in the Făgăraș Massif) to contextualise how shifting meteorological triggers, specifically the projected increase in wet-snow and rain-on-snow events, threaten exposed winter tourism and transport infrastructure. Similarly, in the trentino-alto adige flood case, the Storm Vaia (2018) storyline is used to illustrate how compounding physical mechanisms, such as unprecedented precipitation interacting with fragile alluvial fans, creates severe socio-economic disruption within highly exposed valley bottoms. These specific storylines demonstrate how localised past events can ground future hazard evaluations. Overall, the results reveal that Alpine and Carpathian snow hotspots persist and intensify by 2100 rather than spatially expand, while the flood hotspots are concentrated in highly exposed alluvial valley bottoms. Additionally, they also provide a robust methodological foundation for upscaling and transferring our integrated CCHs identification framework to other European regions confronting similar hazard challenges.

The third knowledge gap identified in the review, namely the explicit assessment of cross-sectoral interactions and cascading climate risks, is only partially addressed. Although the proposed framework applies a common methodological structure across multiple sectors, the two applications incorporate sectoral dimensions in different ways. In the avalanche case, sector-specific hotspots are identified separately for tourism, transport, forestry, and local communities. In the flood case, by contrast, the analysis delineates the hotspot where multiple exposed sectors, including residential areas, productive activities, transport infrastructure, agricultural land, and tourism assets, coincide in exposed valley bottoms. In both applications, however, the assessment remains multi-sectoral rather than cross-sectoral, since interactions, dependencies, and cascading effects among sectors are not explicitly modelled. Future applications should therefore extend the framework to analyse interactions among sectors, cascading impacts and compound climate risks to support integrated adaptation planning.

Our framework is valuable for adaptation planning that need to prioritise limited resources. Policymakers not only have to coordinate across sectors and scales, but they have to justify sensitive choices, especially when to decide which regions and communities are chosen as priorities. For this, our integrated hotspot assessments serve as potential good practices that combine biophysical indicators, socio-economic indicators alongside event-based storylines and stakeholder consultations. Such an integrated framework can also help in including local governance realities, capacities, and lived experiences instead of solely top-down model outputs. This way, adaptation policies can follow more integrated options for broader systemic risks, not single hazards or single sectors. Therefore, the insights can become useful for informed cooperation and joint planning across ministries, administrative entities, neighbouring countries and private actors.

The contributions of this study are four-fold: (1) the evidence synthesis provides an overview of the dispersed CCHs definitions, and the analytical approaches used in the literature, highlighting the biophysical bias (2) the study identifies critical sectoral policy decision gaps that currently hinder societal risk assessment, (3) we propose an integrated bottom-up framework to identify hotspots by using biophysical data, socio-economic data, event-based storylines, and stakeholder information, (4) applying the framework to two case studies in European mountains, we demonstrate that hotspot identification is both temporally dynamic and grounded in local governance realities and lived experiences, and therefore forward looking.

Lastly, we identify the following main avenues for future research: (1) synthesising regional and local knowledge and data to allow a more globally representative understanding of climate risk dynamics, (2) prioritise integrated hotspot definitions based on all dimensions of climate risk, actual on-site realities and localised vulnerabilities, (3) extending hotspot identification frameworks to explicitly represent cross-sectoral interactions, cascading climate impacts and spillover effects between regions, thereby addressing one of the principal knowledge gaps identified in this review, (4) conducting stakeholder based studies to understand how being in a hotspot influences political and institutional resource allocation decisions.

Acknowledgments

The authors gratefully acknowledge the support of the Horizon Europe CROSSEU project (‘Cross-sectoral Framework for Socio-Economic Resilience to Climate Change and Extreme Events in Europe’; Horizon Europe, Grant Number ID: 101081377)). We extend our appreciation to the broader CROSSEU consortium for fostering the collaborative environment and providing the stakeholder engagement platforms that made this research possible. For more details on the project, see: https://doi.org/10.3030/101081377. We also sincerely thank the anonymous reviewers for their constructive and insightful feedback, which significantly improved the quality of this manuscript. Finally, the authors would like to thank the student research assistant, Marie Leitner, University of Graz, Department of Environmental Systems Sciences for her support with checking the references.

Data availability statement

Data will be made available upon request.

Restrictions apply. Data cannot be shared publicly via a URL/DOI. Fer data are restricted by GDPR. SM_Hotspot Identification available at: https://doi.org/10.1088/2752-5295/ae958d/data1.

Conflict of interest

The authors declare that they have no conflicts of interest to disclose.

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