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Climate risk management must move from hazards to impacts

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The next frontier in climate risk management is not just better hazard detection, but better impact prediction. A five-layer framework could help transform physical observations into forecasts of real-world consequences and more effective responses.

Hydrologic extremes are experienced as impacts and not merely as indices, anomalies, or thresholds reported by monitoring systems. Flood manifests as displacement, supply chain disruption, contamination, and prolonged recovery, while droughts are felt through curtailed water allocations, mounting crop losses, ripple effects on unemployment, and progressive ecosystem degradation. Drought also strains energy systems through hydropower shortfalls and amplifies cascading hazards such as wildfires, dust storms, and deteriorating water quality. Yet, operational monitoring systems remain hazard-centric. They quantify anomalies in physical variables but rarely translate them into consequences that matter for decision making. Although increasingly accurate hazard data are available, we lack operational, near-real-time climate impact prediction capabilities.

Drought monitoring, for example, has benefited from major advances in remote sensing, land-surface modelling, and composite indicators, yet remains largely disconnected from real-time assessments of consequences such as crop yield, water access, soil degradation, energy generation, and livelihoods. The same drought severity can produce vastly different outcomes depending on exposure, infrastructure, governance, and adaptive capacity. Impact-based monitoring explicitly bridges this gap by linking evolving hazards to sector-specific consequences in near real time[1]. Building on recent advances in hazard detection or prediction, we argue that the next frontier is operational, multi-hazard impact intelligence built on standardized impact data infrastructure. The rise of increasingly severe, compound, and cascading events means that the impact of one hazard is increasingly determined by the state of other hazards, changes in conditions of exposure and vulnerability, and through policy responses, whether created by the hazards themselves or by historical and societal factors independent of the hazards[2].

Why hazard monitoring is not enough

Hazards become disasters through exposure, vulnerability, and human responses. Monitoring systems show when precipitation, soil moisture, or streamflow depart from normal conditions, but they often do not yet provide what decision makers need most. Examples include estimates of where crop losses may occur and how large those losses could be, which reservoirs may reach restriction levels and when, which communities may face well failures or unsafe drinking water, and which areas may experience elevated wildfire risk followed by debris flows. Answering these questions requires linking physical hazard signals to sector-specific impacts, their coupling and accounting for management and governance. Progress in near-term climate impact prediction from other fields has demonstrated the value of statistical–dynamical approaches that link predictions of slow physical variables to sectoral impact models, often through regression techniques. These approaches have shown decade-ahead skill in predicting ecological and economic outcomes, such as fish stock biomass[3]. Applying such tools to drought presents a critical gap. Many drought indicators exist, including precipitation, streamflow, soil moisture, evapotranspiration, and multivariate indices, but they often describe severity without clearly translating it into quantifiable impacts such as crop losses, food prices, hydropower reductions, or broader social and ecosystem impacts. Studies show these hazard-impact relationships are real but highly nonlinear and context-dependent, and impacts are often represented better when impact data are incorporated directly rather than inferred indirectly[4–6]. Without explicitly modelling these relationships, hazard monitoring systems cannot support actionable decision making. Similar gaps exist for floods, heat, wildfire smoke, land subsidence, coastal storms, landslides, and ecosystem degradation. Although hazard monitoring has improved substantially and many studies have linked hazards to impacts[1,5–9], a key challenge remains turning that knowledge into operational systems that support policy and real-time decision making.

The challenge of multi-hazard impact intelligence

Extreme events do not occur in isolation; they interact through compound and cascading processes across space and time[10]. Yet most monitoring and prediction systems treat hazards independently, often missing the risks arising from their interactions, even though these linkages are now well established. For example, soil moisture deficits can intensify heatwaves, hot drought can increase wildfire susceptibility, and wildfire can, in turn, alter infiltration and slope stability, increasing debris flow and flood risk when heavy rainfall returns[11]. These interactions are mediated through shared state variables and feedback mechanisms, creating nonlinear pathways from hazard to impact.

This argues not for a single all-in-one model, but for a consistent, integrated framework with interoperable data and coordinated hazard-to-impact translation. Siloed systems overlook how one hazard can alter the likelihood or severity of another. An integrated impact-based approach instead treats impact intelligence as the common reference point, linking different hazards through shared consequences such as mortality, displacement, economic losses, ecosystem stress, water insecurity, infrastructure disruption, and recovery time. This direction aligns with the growing emphasis on impact-based forecasting in emergency management and with broader recognition that unprecedented extremes require more consistent data and methods across events[8].

The architecture of an impact-based, multi-hazard system

As shown in Fig. 1, we conceptualize an operational impact-based system as a layered architecture that transforms hazard states into probabilistic impact outcomes, comprising five connected layers. Layer 1 represents the evolving multi-hazard state, described by observations and models of key physical variables such as precipitation, soil moisture, streamflow, heat, wind, fire weather, inundation, slope stability, or ocean conditions. Layer 2 captures exposure and assets, including people, infrastructure, crops, water systems, and ecological resources, as well as their interdependencies. Layer 3 represents vulnerability dimensions where existing inequalities, lack of adaptive capacity, poor governance, storage limits, lack of access to resources, and limited response capacity shape consequences, even when hazard conditions are similar. Layer 4 contains the impacts themselves, that is, the expected consequences of hazard conditions, such as service disruption, health outcomes, water insecurity, or ecosystem stress. These layers are not independent; they are dynamically coupled through translation functions that propagate uncertainty and system state across layers.

In this framework, Layer 1 is highly dynamic, whereas Layers 2 and 3 usually change more slowly, and Layer 4 must be updated as new impact data become available. The central scientific and technical challenge is constructing robust, generalizable translation functions between layers, with clear decision-relevant uncertainty quantification and propagation. These functions may be mechanistic, statistical, or artificial intelligence (AI)-based, depending on the level of process understanding and data availability. Ultimately, the system should be judged by how well it predicts impacts, not simply hazard indices.

This architecture captures the core pathway from hazard to potential impact. But a critical extension of this framework is the explicit inclusion of response dynamics (Layer 5) as a fifth component[12]. This separates adaptive capacity (a dimension of vulnerability) from actual responses and their consequences[12]. Human responses range from risk-reducing interventions, such as forecast-based pre-positioning of resources, to risk-amplifying ones. For example, sustained groundwater drawdown in response to surface drought can be a form of maladaptation when it depletes a slow-recharging buffer and shifts risk forward in time[12]. Drought risk can also be compounded by ecological responses beyond the direct impacts of the physical hazard. Such ecological responses are equally important but generally overlooked. For example, climate-driven 'early spring' events can generate crop frost damage when early budburst precedes the last frost. Also, drought-induced vegetation stress alters fuel load and fire behaviour, eroding the natural buffering that translation functions implicitly assume. As human and ecosystem responses modify the hazard-to-impact relationship itself, response metadata is essential for robust impact prediction, particularly for irrigation, groundwater, and curtailment policies[12].

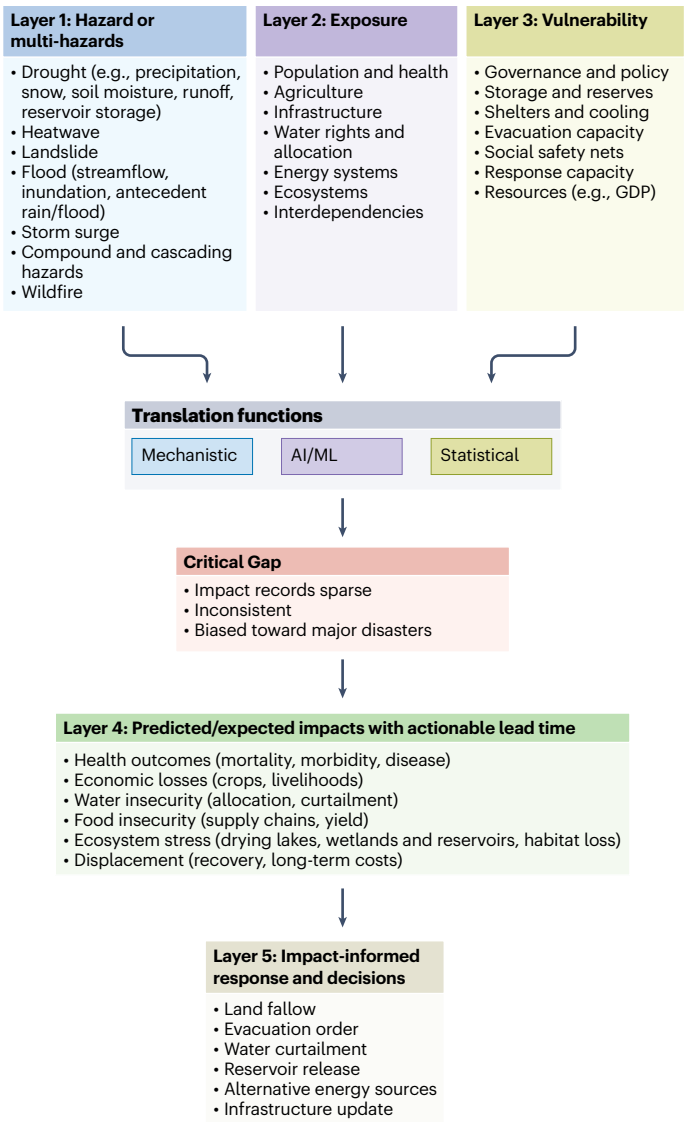

Fig. 1 | Schematic of the architecture of an impact-based, multi-hazard system.

Impact prediction is most valuable when it creates actionable lead time. Drought often provides that lead time because it develops over weeks to seasons, and because state variables such as snowpack, soil moisture, and reservoir storage carry memory of antecedent conditions. Snow drought[13] is an illustrative example. In fact, in snow-dominated basins, deficits in snow water equivalent during the accumulation season can lead to irrigation shortages and crop-yield losses months later during the growing season[9]. This 'lag' creates a practical forecasting window. That said, if snow drought conditions can be monitored reliably, they can inform predictive information for agricultural impacts, guide water-allocation decisions, and support early interventions such as adjusting planting choices, securing alternative supplies, or preparing curtailment plans[1] (see Fig. 2 for an example application).

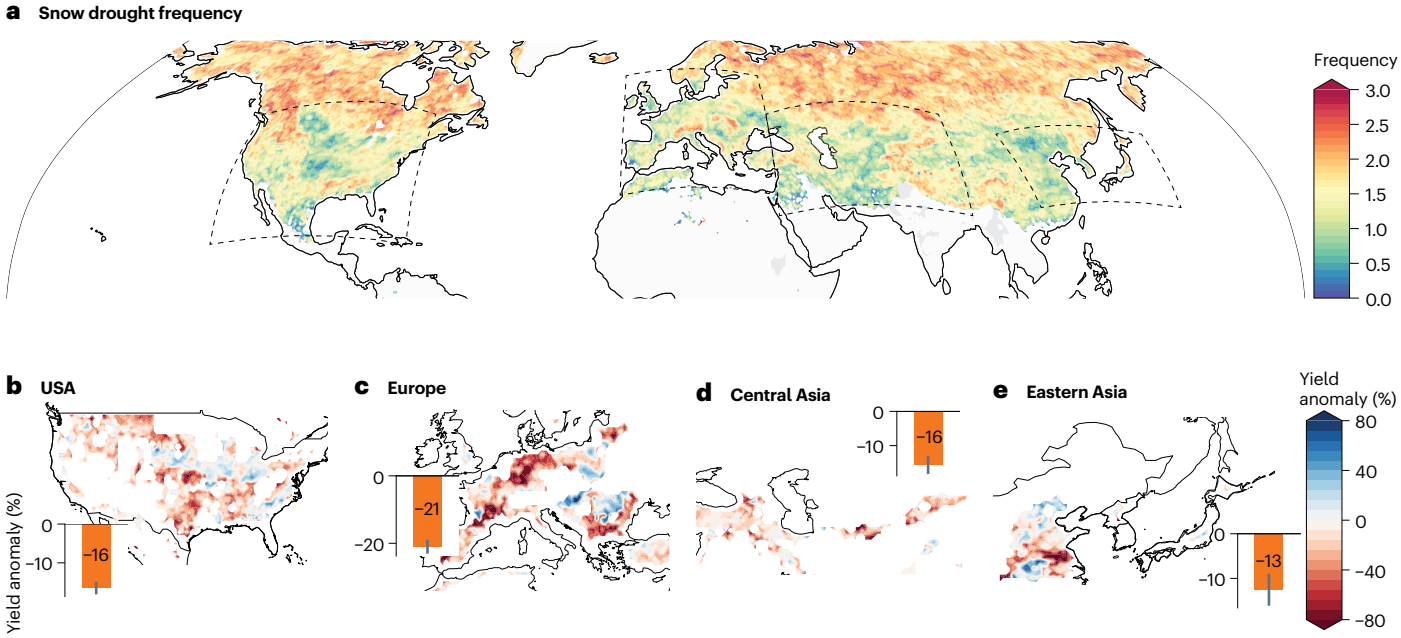

Fig. 2 | Snow drought as an early indicator of crop yield impacts. a, Global snow drought frequency across snow-dominated regions. **b**–**e**, Regional crop yield responses in the United States, Europe, Central Asia, and Eastern Asia, respectively. Patterns illustrate how deficits in snow water equivalent during the accumulation season propagate into agricultural impacts during subsequent growing seasons, demonstrating the predictive value of snowpack conditions for impact-based drought forecasting[15]. In the bar plots, each bar shows the mean value, with grey error bars spanning the 25th to 75th percentiles. Made with Natural Earth. Publ. note: Springer Nature is neutral about jurisdictional claims in maps.

Figure 3 shows hydropower generation at Lake Oroville, California, as an example of drought impact. The results indicate a strong relationship between wet-season precipitation anomalies and summer hydropower output, with generation increasing by about 1.9 GWh for each additional millimetre of precipitation anomaly. A moderate drought year, defined here by a wet-season deficit of −117 mm, is associated with an estimated summer generation loss of about 221 GWh, or roughly 20% below average. In contrast, wetter conditions near the 80th percentile of precipitation are associated with an estimated surplus of 166 GWh relative to average summer generation.

This rationale extends well beyond drought. Many hazards are shaped by slowly evolving precursor conditions. For example, soil moisture deficits can increase the likelihood or severity of heat extremes and wildfire risk; antecedent wetness can raise landslide susceptibility; and ocean heat content can influence the impacts of coastal storms. For impact-based systems, the key challenge here is to identify these precursors and link them to probabilistic, sector-specific outcomes. This is also the basis of forecast-based action, in which early warnings trigger pre-agreed financing and interventions before impacts reach their peaks.

The bottleneck: impact data, especially for non-extreme events

A major obstacle to operational impact-based systems is the absence of standardized, systematic, and scalable impact data[1]. Existing datasets are heavily biased toward extreme events, creating a survivorship bias that limits model generalization. Many smaller but recurring events go undocumented, even though they can produce substantial cumulative damage, such as groundwater depletion, repeated crop losses, and infrastructure deterioration. As a result, models are often trained on a biased sample of major disasters and may not generalize well.

Drought impact databases show both progress and limitations. Although reporting platforms and international datasets have improved documentation of impacts[5,6], records remain uneven in quality, coverage, timing, and context, and they rarely include standardized information on severity, exposure, vulnerability, or economic losses. This lack of standardization weakens hazard-to-impact translation and encourages continued reliance on hazard severity as a proxy for consequence. Advancing impact-based systems will require not just more data, but also standardized impact data collection protocols across space and time, with metadata on exposure, vulnerability, management, and coping capacity.

Data synthesis and the role of artificial intelligence

As data volumes grow, the main challenge is to harmonize and integrate information across diverse datasets, timescales, and institutions. Impact-based multi-hazard monitoring cannot rely on manual integration, and AI can support scalable data integration, feature extraction, and probabilistic impact prediction, particularly when physical understanding is limited. However, biased records can lead directly to biased forecasts, so operational systems should provide well-calibrated, decision-relevant uncertainty for outcomes such as curtailment risks, yield losses, or post-fire debris flows. Progress also requires closing the validation gap, since many impacts are qualitative, inconsistently recorded, or difficult to represent in standardized units. Additionally, the use of socioeconomic and health data adds further constraints because access to detailed records is often limited by privacy, ethical, and legal considerations. For these reasons, hybrid

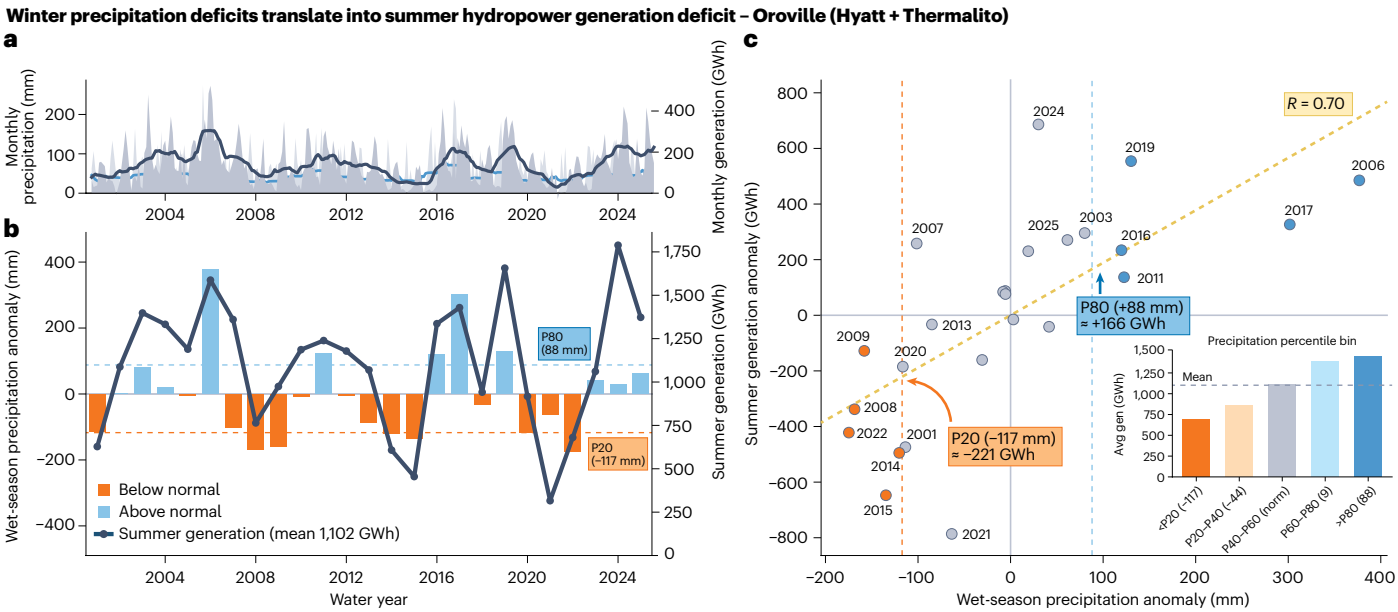

Fig. 3 | Winter precipitation deficit translates into summer hydropower generation deficit. a, Historical precipitation and hydropower generation. **b**, Wet-season precipitation anomalies by water year, highlighting below normal and above normal conditions. **c**, Relation between summer generation anomalies and wet-season precipitation anomalies, showing the sensitivity of hydropower output to seasonal hydroclimate variability. Monthly net hydropower generation for the Lake Oroville complex was obtained from the US Energy Information Administration (EIA) Electricity Data Browser (https://eia.gov/electricity/data/browser), covering the Edward C. Hyatt Powerplant (EIA plant 437) and the Thermalito Pumping-Generating Plant (EIA plant 438). Basin-averaged monthly precipitation for the Feather River watershed above Oroville Dam was derived from the PERSIANN UNET-CDR satellite precipitation dataset, provided by the Center for Hydrometeorology and Remote Sensing (CHRS) at the University of California, Irvine (https://chrsdata.eng.uci.edu). PERSIANN UNET-CDR provides daily precipitation estimates at 0.04° × 0.04° spatial resolution. The time span for both datasets was from January 2001 to November 2025.

approaches that combine physical knowledge with machine learning are likely to be the most robust path forward.

Pathways forward

1. **Build national and international infrastructure for impact data**. Require sustained investment in systematic, standardized collection and sharing of impact data across hazards, sectors, and event severities. Common metadata should be required, including location, timing, exposure context, vulnerability indicators, and management actions. Data collection should include impacts from non-extreme events as well as major disasters, because these records reduce bias and improve the generalizability of impact models.
2. **Treat impact data as critical public infrastructure**. Establish clear mandates and incentives for agencies, utilities, and other data holders to share relevant impact and response data, including water withdrawals, diversions, demand, and restriction actions. These arrangements should be paired with privacy-preserving protocols to ensure that real-time intelligence supports decision making without compromising ethical or legal standards.
3. **Require interoperability across hazard systems**. Fund multi-hazard architectures that use consistent definitions, uncertainty reporting, and shared exposure and impact layers. Priority should be given to integration across drought, heat, wildfire, flood, debris flow, and water quality, where physical linkages are strong. Additionally, cross-agency coordination should be incentivized to support coherent response options, reduce jurisdictional barriers, and avoid fragmented, parallel systems.
4. **Move from hazard forecasts to impact forecasts in operations**. Expand operational mandates to include probabilistic impact prediction products, not only hazard severity maps. Encourage agencies to evaluate forecasts with decision-relevant metrics and to co-design thresholds and triggers with end users, including emergency managers, water agencies, and agricultural stakeholders.
5. **Invest in end-to-end pilots that demonstrate value**. Support regional pilots that implement multi-hazard impact monitoring from data collection to decision support, with explicit evaluation of outcomes. Prioritize regions where snowpack, drought, heat, wildfire, and flood are tightly coupled, and where water allocation and curtailment decisions are frequent and politically sensitive. Explicitly include marginalized communities to ensure data collection bridges the digital divide and avoids algorithmic bias.
6. **Deepen understanding of indirect and cascading impacts**. Invest in systematic monitoring of secondary impacts and responses to them, which are often underreported but societally important. Such examples include indoor air contamination and health effects after flooding, and drought-driven degradation of surface water quality.

Without impact intelligence, increasingly precise hazard monitoring risks becoming a more detailed description of failure rather than a tool for prevention. Although building and maintaining such systems

will require sustained investment, the technical debt of fragmented systems and the social cost of reactive disaster management are far greater. The benefits could include better timing and targeting of allocation adjustments, more defensible curtailment decisions, improved planning for groundwater reliance, and clearer communication of trade-offs to the public. More broadly, integrated impact-based systems can help societies anticipate cascading pathways, allocate scarce resources earlier, and reduce the compounding nature of disasters in a changing world[14]. Hence, a key priority should be the development of standardized protocols for recording not only impacts, but also response actions, as these directly influence future hazard-to-impact relationships and system resilience. Looking ahead to the 2026 United Nations Water Conference, Member States should prioritize developing international frameworks and protocols for sharing hazard-impact data, analogous to the standardized data-sharing approaches long advanced through World Meteorological Organization reporting and information systems.

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Competing interests

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