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Perspective

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Toward impact-based monitoring of drought and its cascading hazards

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Abstract

Growth in satellite observations and modelling capabilities has transformed drought monitoring, offering near-real-time information. However, current monitoring efforts focus on hazards rather than impacts, and are further disconnected from drought-related compound or cascading hazards such as heatwaves, wildfires, floods and debris flows. In this Perspective, we advocate for impact-based drought monitoring and integration with broader drought-related hazards. Impact-based monitoring will go beyond top-down hazard information, linking drought to physical or societal impacts such as crop yield, food availability, energy generation or unemployment. This approach, specifically forecasts of drought event impacts, would accordingly benefit multiple stakeholders involved in drought planning, and risk and response management, with clear benefits for food and water security. Yet adoption and implementation is hindered by the absence of consistent drought impact data, limited information on local factors affecting water availability (including water demand, transfer and withdrawal), and impact assessment models being disconnected from drought monitoring tools. Implementation of impact-based drought monitoring thus requires the use of newly available remote sensors, the availability of large volumes of standardized data across drought-related fields, and the adoption of artificial intelligence to extract and synthesize physical and societal drought impacts.

Sections

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Introduction

Drought defines an extended moisture deficit. They are often broadly classified into three types[1]: meteorological drought, typically describing a deficit in precipitation; agricultural drought, typically describing a soil moisture deficit; and hydrological drought, typically describing runoff, groundwater level, stream flow and total water storage deficits. Individually and collectively, these droughts have substantial socioeconomic and environmental impact, as evidenced by several severe droughts observed over the past century. For example, the 1928–1930 drought in China led to widespread famine and millions of deaths[2]. Moreover, the Dust Bowl drought of the United States in the 1930s eroded farmland and displaced an estimated 3.5 million people[3]. The Millennium drought in Australia further led to severely reduced winter crop yields and, as a result, economic crisis for farmers[4]. Given these impacts, especially in light of observed and projected increases in drought frequency and intensity[5–8], there is a strong need for drought monitoring[9–13].

Drought monitoring has evolved considerably (Fig. 1). It historically relied on ground-based precipitation observations[10,11], but the lack of consistently available, dense observational networks limited spatial analysis. Indeed, observations have been particularly rare in agricultural areas, where the need for drought monitoring is acute. The emergence and evolution of remote sensing revolutionized drought monitoring, providing global, consistent drought-related variables[11]. Modelling advances are also key in improving drought monitoring. Models offer a means of filling data gaps in cases where relevant drought variables are difficult to measure directly (for example, root-zone soil moisture, which cannot be measured directly via satellite[14]). In addition, models that link hydroclimatic variables to impacts (for instance linking snow drought or soil moisture deficit to expected crop loss or water shortage) advance capabilities for simulating 'what-if' drought scenarios and their societal impacts, improving drought preparedness and planning efforts[15].

Coincident with the emergence of new datasets and technologies has also been an expansion of drought monitoring indicators (Fig. 1), incorporating meteorological, hydrological and biophysical variables depending on the intended purpose and application[1,16]. Yet drought-related variables often interact with each other, resulting in nonlinear relationships between drought drivers and drought types[17]. As a result, defining a drought event in a robust and coherent manner with a single variable is challenging. For example, the 2003 European extreme drought[18,19] propagated from meteorological to hydrological, and then to agricultural drought, each with different time frames (Fig. 2). Effective monitoring must therefore contend with the multivariate nature of drought through multi-index methods[20,21].

Yet traditional, top-down, hazard-focus drought indicators leave key gaps in effective drought monitoring by failing to include the many complicating factors that can add to the functional severity and impacts of a drought. Contrastingly, a bottom-up, impact-based approach would fill many of these gaps, providing relevant information for drought-related planning in real time. For example, drought monitoring methods that include information on the compound and cascading hazards that accompany drought (such as heatwaves, wildfires, floods and debris flows[22]) would offer a clearer picture of the risks associated with drought than monitoring based on traditional hazard-focused indicators alone, benefiting stakeholders involved in drought planning and response decisions.

In this Perspective, we frame an impact-based approach to drought monitoring as a key research direction that can advance operational drought monitoring more effectively than traditional approaches. We first discuss existing drought indicators and their limitations. We follow with discussion of drought-related cascading hazards, before considering the need to move toward impact-based monitoring of drought. We end with recommendations to move the field forward over the coming years.

Existing drought indicators

Before discussing the need for changes in drought monitoring, it is important to take stock of current approaches to highlight their effectiveness and inadequacies. Owing to the complexity and variation of events, more than 70 indicators have been developed for monitoring and characterizing different types of drought[11,20,23–28] (Fig. 1; Supplementary Table 1). These drought indices can be broadly categorized as those derived from a single variable to create a single drought index (Fig. 1); from multiple variables to create multivariate drought indices; and from multiple indicators and/or variables to create a composite drought index (Fig. 1), each of which is now discussed[26].

Single drought indices

A single drought index is defined as an indicator that relies on a single climatic or hydrological variable (for example, precipitation deficit or surplus as a measure of meteorological drought). These single drought indices are widely used in research and operational applications owing to their simplicity. However, these indicators primarily focus on hazards, offering 'upstream' or 'top-down' information only, and do not provide insights into the impacts of drought.

Precipitation indicators. Precipitation is typically used as an indicator of meteorological drought, with common indicators including the Standardized Precipitation Index (SPI[29,30]) and the Palmer Drought Severity Index (PDSI[31]) and its variants[9]. Standardized Relative Humidity Index (SRHI[32]), Percent of Normal Precipitation (PNP[33]) and other percentile-based methods are also used, but less commonly. Drought monitoring with these indicators across spatiotemporal scales has been possible, given a range of ground-based and satellite-derived precipitation datasets[34]. However, indicators based solely on precipitation have limitations in capturing drought persistence owing to rainfall high variability[21]. Additionally, in snow-dominated regions, precipitation indices might fail to capture intricate snow dynamics such as rapid snowmelt and low flow conditions during the dry season[35].

Soil moisture indicators. Soil moisture is typically used as an indicator of agricultural drought[36], with a common indicator being the Standardized Soil Moisture Index (SSI[21]). Other soil moisture indicators include the Soil Moisture Percentile (SMP), Soil Moisture Deficit Index (SMDI), and Normalized Soil Moisture (NSM)[37]. Continental- to global-scale soil moisture monitoring for drought analysis has often relied on model simulations[38–42], but satellite-borne instruments (such as ASCAT[43], SMOS[44] and SMAP[45]) are increasingly providing opportunities for soil moisture assessment[46–49]. These data are limited in that satellite products such as SMAP are too short to provide long-term anomalies for drought analysis; composite multisensor soil moisture datasets[46] do not offer root-zone moisture information; and satellite products only provide moisture information for the top few centimetres of soil[50,51].

Evapotranspiration indicators. Evapotranspiration is typically used as an indicator of meteorological and hydrological drought (as a partial measure of water balance anomalies), and agricultural

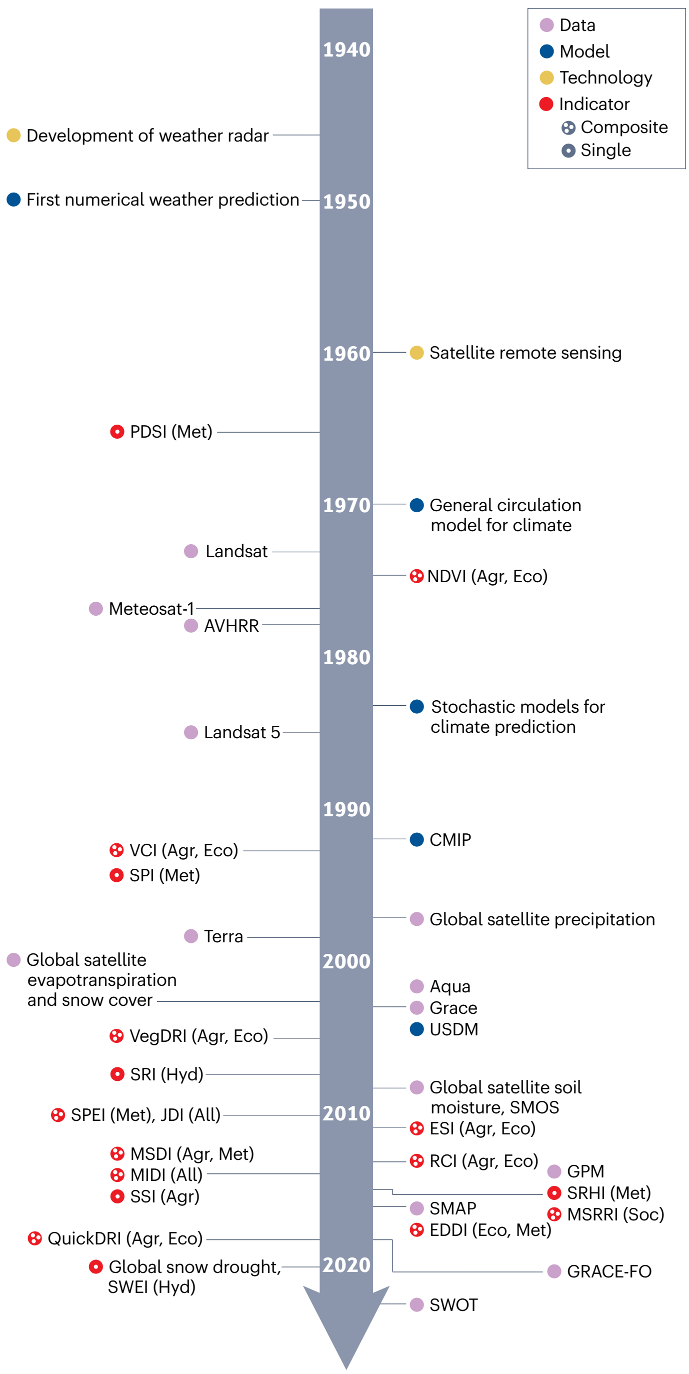

Fig. 1 | Drought monitoring timeline. A non-comprehensive timeline of major drought datasets (purple), indicators (red), model developments (blue), and technological developments (yellow). The drought type measured by the index is represented by agr (agricultural drought), eco (ecological drought), hyd (hydrological drought), met (meteorological drought) and soc (Socioeconomic drought). AVHRR, Advanced Very High Resolution Radiometer; GPM, Global Precipitation Measurement; SMAP, Soil Moisture Active Passive[45]; GRACE-FO, Gravity Recovery and Climate Experiment Follow-on; SWOT, Surface Water and Ocean Topography; CMIP, Coupled Model Intercomparison Project[219]; USDM, The United States Drought Monitor[55]; SMOS, Soil Moisture and Ocean Salinity[44] mission. PDSI, Palmer Drought Severity Index[31]; NDVI, Normalized Difference Vegetation Index[112]; VCI, Vegetation Condition Index[113]; SPI, Standardized Precipitation Index[29]; VegDRI, Vegetation Drought Response Index[93]; SRI, Standardized Runoff Index[220]; SPEI, Standardized Precipitation Evapotranspiration Index[52]; JDI, Joint Drought Index[88]; ESI, Evaporative Stress Index[101]; RCI, Rapid Change Index[96]; MSDI, Multivariate Standardized Drought Index[21]; MIDI, Microwave Integrated Drought Index[95]; SSI, Standardized Soil Moisture Index[21]; SRHI, Standardized Relative Humidity Index[32]; MSRRI, Multivariate Standardized Reliability and Resilience Index[201]; EDDI, Evaporative Demand Drought Index[102]; QuickDRI, Quick Drought Response Index[114]; SWEI, Snow Water Equivalent Index[35]. The unprecedented growth in satellite observations, modelling capabilities and development of drought indicators have allowed near-real-time drought information.

drought (as a partial measure of the moisture available for crops)[34]. Common evapotranspiration-based indicators include Standardized Precipitation-Evapotranspiration Index (SPEI)[52,53] and Climatic Water Balance (CWB)[54]. Evapotranspiration is particularly important for flash droughts, characterized by their rapid intensification and/or onset (on timescales of 2–4 weeks), hypothesized to be driven partly by high atmospheric evaporative demand[55–58].

Although it was traditionally measured using ground-based techniques, evapotranspiration is increasingly measured with remote sensing[59], including products based on Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and the Geostationary Operational Environmental Satellite (GOES)[60–62]. Land-surface models can further make use of the infrared bands of these remote sensing products to derive evapotranspiration from the residual of the surface energy balance[60,63,64]. Empirical models are also widely used, but often require local calibration for improved accuracy. Each of these estimation methods is subject to high uncertainties depending on weather

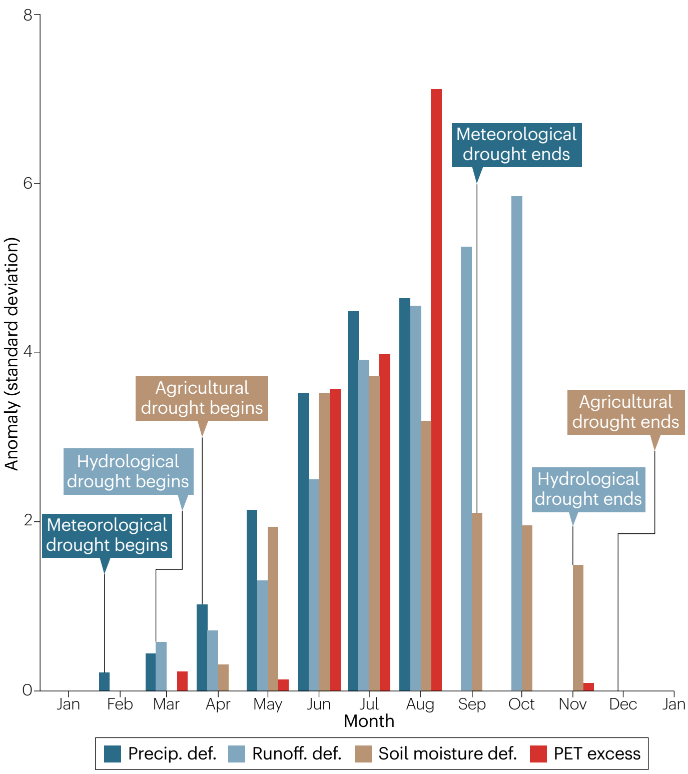

Fig. 2 | The European drought of 2003. Onset, propagation and termination of the 2003 European drought event, decomposed into the standardized deficits associated with the three drought types[19]: meteorological drought, representing precipitation deficit (dark blue); hydrological drought, representing runoff deficit (light blue); and agricultural drought, representing soil moisture deficit (brown). Potential evapotranspiration (PET) excess (red) is depicted for comparison with the precipitation deficit. Drought can be defined from different perspectives including meteorological drought, describing a deficit in precipitation; agricultural drought, typically describing a soil moisture deficit; and hydrological drought, describing runoff, groundwater level, stream flow or total water storage deficits.

and local land-surface and vegetation conditions[63,65,66], but they are collectively enabling large-scale drought assessment[67,68].

Snow indicators. Most drought indicators do not separate snow and rainfall. Accordingly, drought assessments might be biased, especially given the importance of the snowpack as a storage reservoir, and its influence on the timing and occurrence of deficits in other hydrological variables[69]. As such, there is a need to quantifying snow-related processes (for example, snow accumulation and snowmelt rate) for drought monitoring and assessment purposes[70–72], as achieved by the Standardized Snow Water Equivalent Index[35] (Fig. 3). Such approaches aid identification of a period of abnormally low snow for a given region and time of year, referred to as a snow drought[35,73], which can be driven by low accumulation or by elevated loss (for example, owing to rising temperatures, or accelerated snowmelt driven by rain-on-snow)[57].

As the temporal record of snow observations extends, snow indicators for drought should use snow water equivalent (SWE). However, SWE is difficult to estimate robustly across complex and rugged mountainous terrain[74–78]. In fact, larger-scale satellite remote-sensing-based products (such as GlobSnow) only yield estimates of SWE across the non-mountainous Northern Hemisphere[79]. Nevertheless, there have been advances in deriving regional and more local- or basin-scale SWE estimates with remote sensing information and sensors, and/or data fusion and assimilation techniques[74,78,80]. The Airborne Snow Observatory (ASO), for example, demonstrated that high-resolution LiDAR-based observations of snow depth, when combined with snow density measurements and models, could be used to infer SWE[74]. Although important for attaining improved estimates of snowmelt runoff at management scales for water resources, the temporal record from the ASO is generally insufficient for use in drought analysis and limited to select basins[81]. Additionally, high-spatial-resolution global SWE information is still needed, resulting in a primarily local to regional focus so far[82–86].

Multivariate and composite drought indices

Owing to the limitations of single-variable drought indicators, several multivariate and composite drought frameworks have been developed to provide robust and comprehensive monitoring[21,87–90] (Fig. 1, composite). Multivariate drought indicators typically account for the relationship between variables used for drought monitoring, such as the relationship between precipitation and soil moisture. In contrast, composite drought indicators integrate multiple variables with or without explicitly accounting for the relationship between drought-related variables. Hereafter, the term composite indicators is used to reflect both types. They have evolved to include many of the aforementioned variables, constructing a quantitative picture of the total environmental moisture status[10,91] by considering different sources of water supply and water demand. Key indicators include the Multivariate Standardized Drought Index (MSDI, which uses precipitation and soil moisture indices[21,92]), the Vegetation Drought Response Index (VegDRI, which incorporates precipitation, temperature and soil moisture, plus various biophysical and vegetation indicators[93,94]), and the Microwave Integrated Drought Index (MIDI, which uses precipitation, soil moisture and temperature[95]).

Composite indices have several uses beyond that offered by single-metric indicators. For example, they are particularly important for flash drought which are characterized by their rapid intensification and/or onset (on timescales of 2–4 weeks)[56–58]. Conceptually, although a flash drought onset usually involves precipitation deficit, its development typically relies on how rapidly high evapotranspiration rates deplete soil moisture[96–99], shifting from an energy-limited to a moisture-limited regime. Thus, robust flash drought indicators must link changes in precipitation, temperature, vapour pressure deficit and soil temperature, efficiently coupling the rapid soil moisture depletion rates in deeper layers with the changes in atmospheric evaporative demand[100]. Composite indices useful for quantifying flash droughts include the Evaporative Stress Index (ESI[101]), Rapid Change Index (RCI[96]), Evaporative Demand Drought Index (EDDI[102]) and Standardized Precipitation-Evapotranspiration Index (SPEI)[56].

Composite indicators also have marked use in quantifying ecological drought — water deficits that stress ecosystems or coupled natural–human systems[103], driven by the total moisture available for vegetation which is stressed by a combination of low soil moisture and precipitation with high evapotranspiration. A wide range of indices quantify ecological drought based on vegetation condition[104–111], including the Normalized Difference Vegetation Index (NDVI[112]), the Vegetation Condition Index (VCI[113]) and the Quick Drought Response Index (QuickDRI[114]).

Operational drought monitoring systems are also moving toward integration of a wide range of indicators. The United States Drought Monitor (USDM)[55], for example, includes various single and composite indicators, producing weekly drought maps[115] based on in situ data, remote sensing and modelled products, all validated using reports from over 450 local drought experts[116,117]. Similar integrative weekly or monthly drought maps have been produced regionally or globally, but mainly without any human inputs[118–120]. A suite of other integrative systems includes the European Drought Observatory[121]; the United Nations Food and Agriculture Organization (FAO) agricultural drought monitoring system based on the Agriculture Stress Index System (ASIS[122]); and the North American Drought Monitoring System[123].

Limitations

Drought monitoring models and tools remain disconnected from impact assessment models[15,124,125], which is a major limitation as developing adaptation and response plans requires information on the potential impacts of droughts. Furthermore, although considerable progress has been made in multi-index drought monitoring, different hazards (such as drought, heatwave and wildfire) are still monitored individually and separately even when they are closely related. The need for integrating drought and flood monitoring systems has been highlighted[126], but this argument can be extended to all drought-related hazards.

Each of these previously discussed drought indicators has its limitations[127–129] (Supplementary Table 1), but those associated with snow drought have not received much attention relative to other drought-related variables and hence are discussed here. Standardized snow drought indicators that incorporate not only snow information but also variables closely related to snowmelt (such as temperature) are currently lacking. Furthermore, rather than tracking the snowpack throughout the season, the Standardized Snow Water Equivalent Index[35] and other snow drought analysis methods have focused on the peak SWE or SWE at a particular time of the year (1 April as the end of the snow season). However, maximum SWE might inadequately characterize the temporal evolution of snow drought, and thereby obscure identification and understanding of drought impacts occurring before or after the time of peak SWE[35]. An early peak in SWE, followed by rapid snowmelt and/or large sublimation and depletion of the accumulated snowpack, can lead to snow drought conditions accompanied by warming temperatures and increased potential for a longer wildfire season, even with above-average SWE conditions at the time of peak. In addition, when the peak value serves as a proxy for the whole season, the snow drought classification for a season that maintained low SWE until an abrupt increase in SWE just before its peak value could be misrepresented, despite earlier low SWE conditions[35]. These limitations highlight the need to develop more comprehensive snow drought indicators that capture the temporal evolution (onset, persistence, recovery and termination) of snow drought[35,130–132], crucial to efficiently integrate snow information into drought monitoring systems.

Drought-related cascading hazards

Although individual drought indicators are important, they omit information pertaining to drought and drought-related cascading hazards – events that occur in a specific order, where one event or hazard is typically caused or triggered by one or more preceding events or hazards. Ultimately, the feedback loops created by cascading hazards lead to substantial societal or economic damages beyond the initial drought. For instance, the combination of drought and heatwaves increases the likelihood of wildfires. Extreme rainfall over burned areas, subsequently increases the chance of debris flows in burned areas (Fig. 4). Drought monitoring and research must, therefore, move beyond individual drivers and indicators to include the evaluation of various potential cascading hazards, including heatwaves, wildfires, floods and water quality, as now discussed.

Heatwaves

A pronounced example of a drought-related cascading hazard is the connection between droughts and heatwaves. These events act to intensify each other through land–atmosphere interactions[133,134]. Specifically, a soil moisture deficit causes a reduction in evapotranspiration, increasing sensible heat and decreasing latent heat relative to pre-drought conditions[134–136], intensifying surface warming,

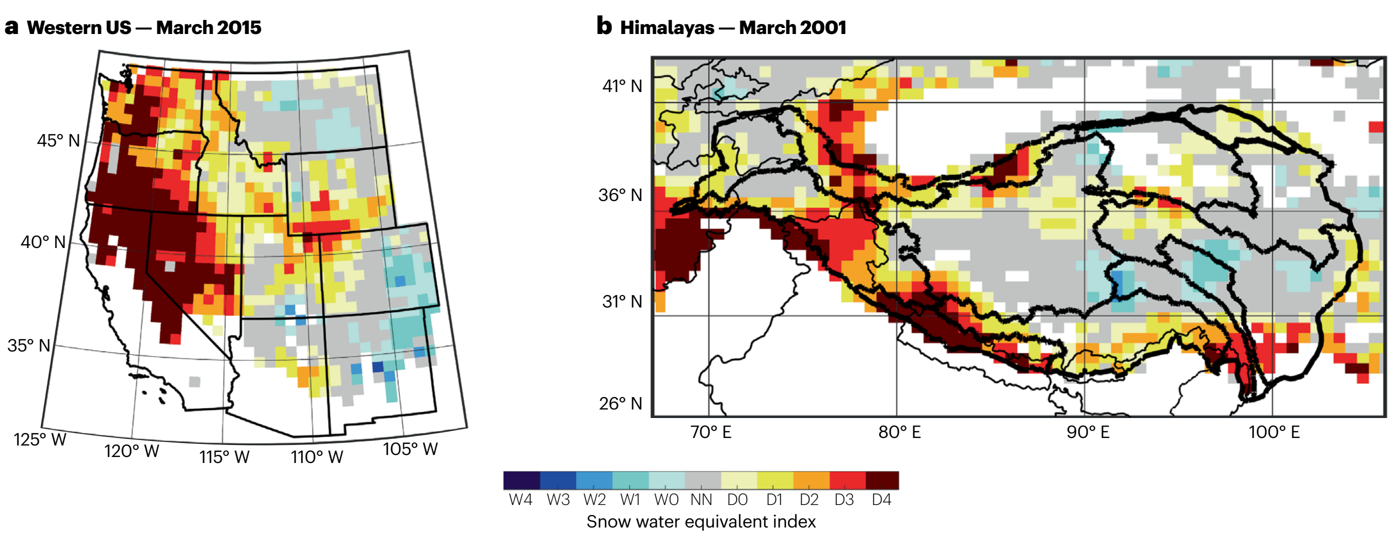

Fig. 3 | Snow drought examples. a, Snow drought in the western United States during March 2015, as determined by the Standardized Snow Water Equivalent Index[35]. **b**, As in **a**, but for the Himalaya region during March 2001. In many regions around the world, snowpack serves as the largest natural water reservoir, making the monitoring of snow drought critical for improving drought monitoring.

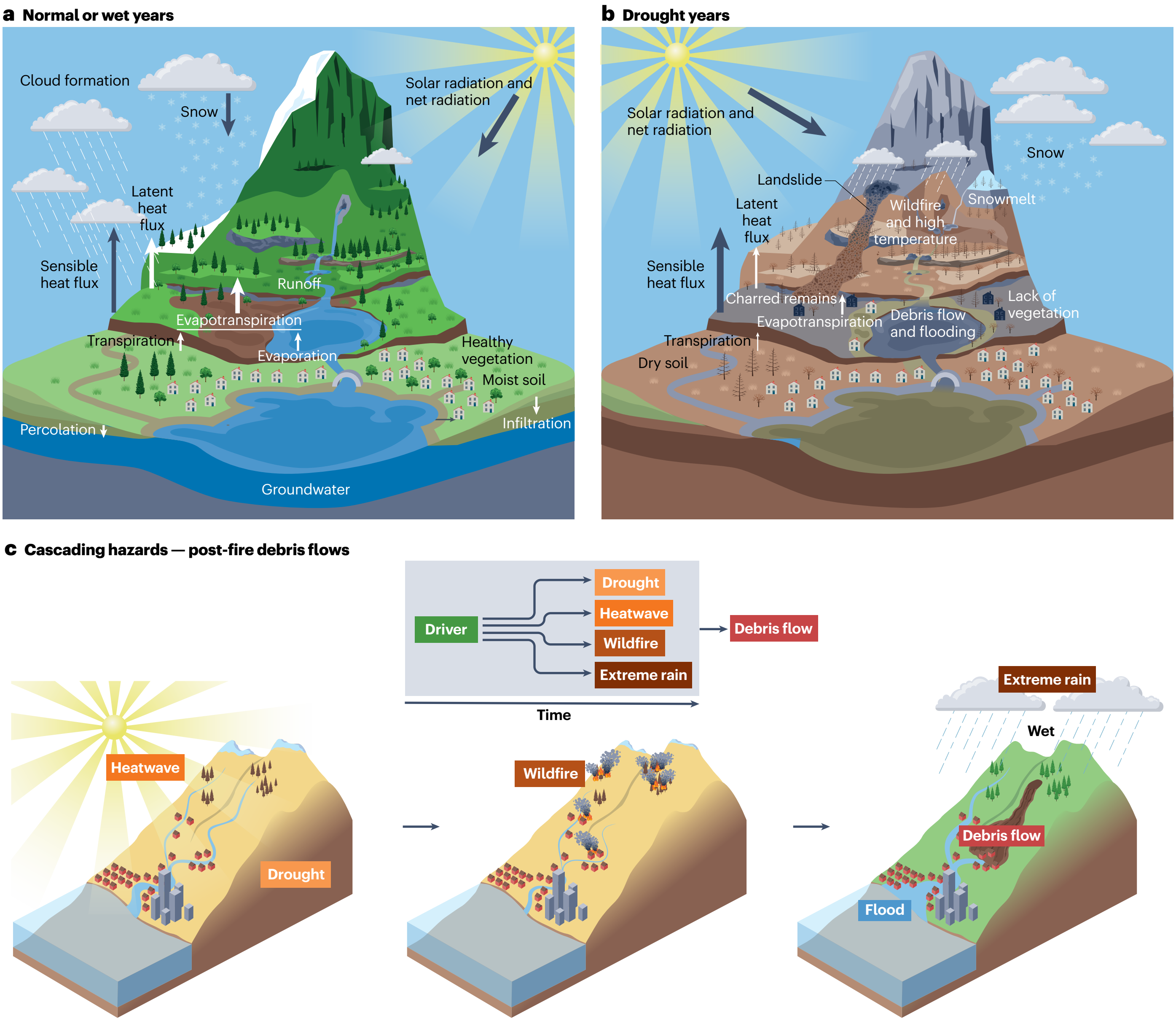

Fig. 4 | Drought-related processes and cascading hazards. a, Select hydrological processes during normal or wet years. **b**, Drought-related processes during extreme drought years, including burned areas due to cascading wildfires. **c**, Post-fire debris flows as an example of a cascading hazard. During drought, soil moisture deficit reduces evapotranspiration, increases sensible heat and decreases latent heat, and enhances surface warming, in turn increasing the likelihood heatwave intensification, contributing to wildfire development which can later cause cascading hazards.

and, in turn, enhancing the likelihood of a heatwave exacerbating the drought and its impacts (Fig. 4). Owing to rising evaporative demand, we can anticipate increased coupling and interactions between heatwaves and (flash) droughts – and thereby increased intensity and frequency of droughts – as the climate warms[6–8], as already reported at regional[137] and global[138] scales.

Such tight coupling of these cascading hazards is evident across many observed droughts. Compound drought and heatwave events often affect socioecological systems[139], which include massive heat-related deaths[140–142], loss of crop yield[143,144], and wildfires[145] that further transform the landscape creating additional public health crises. The 2003 drought and heatwave event[134], for example, resulted in an estimated death toll surpassing 70,000. However, the impacts of drought are increasingly recognized to result in globally networked risks in which drought in one part of the world, especially major food-producing countries, affects regional and local food security elsewhere.

Several indicators incorporate temperature information, such as the PDSI (Fig. 1). However, these indicators do not provide specific information about the co-occurrence of drought and heatwaves, making them less suitable for linking cascading hazards to actual impacts (such as mortality data).

Wildfires

Closely linked to drought and heatwaves are wildfires (Fig. 4). The interactions between these phenomena are intricate and specific to each location, influenced by factors such as climate, vegetation type, topography, soil type and ignitions, amongst others. Drought dries out vegetation, providing fuel for fires, which, in the case of prolonged hot drought, increases susceptibility to natural or anthropogenic ignition[146,147]; drought-related tree mortality exacerbates this situation[148]. The combustion of dried biomass during the hot and dry summers in central Europe led to extreme wildfires across the Czech Republic, Germany and Portugal[149]. Similarly, several years of drought preceded the intense fire seasons witnessed in Australia and the western United States in 2020[150,151]. The changes following a wildfire (for example, reduced soil moisture and lack of canopy) can also further enhance land-surface interactions for drought intensification, and, through impacts on water availability (reduced infiltration and more overland flows), affect drought recovery[152].

Drought monitoring and prediction are invaluable resources for wildfire prediction, monitoring and management[153,154]. Although all drought indices are useful in predicting wildfire activity, soil-moisture-based indices are predictors of live fuel moisture and are excellent early warning metrics, and evaporation-based indices are skilful predictors of dead fuel moisture[155]. However, most current operational and experimental drought and fire monitoring and management systems remain disconnected. If addressed, this could minimize impacts on human lives, livelihood and the environment.

Debris flows

Drought can trigger various processes that weaken soil and slopes[156]. The stability of slopes is primarily dependent on soil shear strength. Drought conditions, characterized by elevated soil temperatures and low soil moisture, can undermine both soil shear strength and tensile strength[157], ultimately leading to increased desiccation cracking. Desiccation cracks commonly develop in fine-grained soils, such as clay, and can extend several metres deep. The formation and propagation of these cracks have substantial implications for the mechanical and hydraulic properties of soils[158]. Desiccation cracks increase soil hydraulic conductivity, establish preferential flow pathways for fluid and contaminant movement, weaken soil shear strength, and accelerate soil weathering, erosion and slope instability. These processes, in turn, increase the susceptibility of burned environments to debris flows when intense rainfall occurs.

Wildfires can further heighten the probability of debris flows and rainfall-induced shallow landslides. These processes include root weakening, reduced evapotranspiration rates, alterations in vegetation coverage and canopy interception, and modifications to soil mechanical and hydraulic properties[159]. A prominent illustration of the impact of wildfires on debris flow events is the catastrophic debris flow that occurred in Montecito, California, in 2018[22]. The region experienced a prolonged drought from 2012 to 2016, followed by a fire in December 2017. Intense rainfall over the previously burned area in January 2018 subsequently triggered the debris flow, the deadliest in California's history.

Floods

Although droughts and floods are two extremes of the same hydrological cycle, droughts themselves contribute to changes in flood hazard[126] (Fig. 4). Cascading impacts of drought on flood risk include increased upstream erosion leading to debris flow and sedimentation in rivers and reservoirs, reducing storage capacity; compaction of soils, leading to less suitable subsurface storage conditions; and populations moving from drought-stricken regions into flood-prone areas, for example along river floodplains[126].

Droughts can further increase the probability of levee and dyke failure caused by soil desiccation cracking and slidings. Soil desiccation cracks that are formed during a drought increase the risk of internal and external soil erosion during and after heavy rain. Further, rapid infiltration through the cracks substantially increases pore water pressure inside the soil domain, decreasing the soil shear strength, potentially leading to loss of stability and failures[156]. Indeed, the 2003 dyke failure at Wilnis, in the Netherlands, led to the inundation of 600 homes and the evacuation of 2000 people[160]. Other examples include the drought in California from 2012 to 2016, which concluded with an onslaught of extreme rain and flooding that caused substantial damage to the Oroville Dam spillway[161]. Similarly, the Millennium drought in Australia concluded in 2011 with widespread flooding[4].

Although many existing indicators include information related to floods (SPI, SRI), none capture drought–flood interactions. In addition to hydrological information, measures such as wetting surfaces, intensity of desiccation cracks, and other soil properties are necessary to improve joint drought–flood monitoring and impact assessment. Monitoring systems should be designed that provide actionable information to decision makers involved across flood and drought management, and should not operate in silos.

Water quality

Drought also has cascading impacts on water quality[162] (Fig. 4). Drought-induced low stream flow increases water detention periods, resulting in algal blooms owing to high nutrient concentrations (less dilution)[163]. Higher temperatures during extreme droughts further affect stream temperatures, respiration and re-aeration rates in rivers and streams[163], affecting fish populations and food supply. In arid and semi-arid regions, the cascading impact of rapid transitions from drought to flood regimes (wet cycles) can increase turbidity and dissolved oxygen, and decrease the magnitude of pH[162]. As an example, the record-breaking hypoxia and massive dead zone in Lake Erie[164] during 2012, which culminated in the closure of the Toledo water supply in 2014 due to high levels of toxins from cyanobacteria in the city's water intake, was attributed to drought. Similarly, extended droughts in conjunction with the bark beetle infestation of the Rocky Mountain forests in the Cache la Poudre River watershed caused the massive High Park wildfire that degraded the source water quality, subsequently limiting its use for drinking water supply[165,166].

Although there are in situ and remotely sensed water quality indicators, drought indicators that establish a connection between water quantity and/or availability and water quality are currently lacking.

Impact-based drought monitoring

Much of the effort to improve drought monitoring systems has focused on either new top-down drought indicators (climatic, hydrological or biophysical) or on the integration of indicators, data and models. However, limitations of traditional drought indicators, particularly with respect to capturing cascading hazards and their systemic risks and impacts, make a compelling argument for developing a consistent global framework for multihazard drought monitoring and impact assessment to inform early action[167]. Specifically, there is a need to link drought information to its potential impacts — that is, linking monitoring tools to impact collection and assessment.

Connecting droughts and impacts

Current indicators (Fig. 1) and existing monitoring systems (such as USDM) primarily focus on identifying droughts and assessing their frequency and severity. However, for decision makers to make informed choices, they require information not only about the location and severity of droughts, but also about the expected impacts associated with them. These impacts encompass a wide range of factors, such as changes in crop yield, food exportation, forest health, water quality, energy generation, greenhouse gas emissions, and unemployment resulting from the effects on the agriculture sector.

To go beyond the realm of drought monitoring and effectively quantify potential drought impacts, additional models are often necessary. Currently, there exist numerous statistical and physically based crop models designed to estimate crop yield under various climate conditions or crop–snowmelt dependence and their associated risks[13,20,168–170]. However, these models are not yet integrated into the existing drought monitoring systems.

Providing real-time drought impact monitoring is expected to bring substantial benefits, particularly with regard to food and water security[171–173]. Such assessments would enable authorities to anticipate potential drought impacts several months in advance, albeit with variations in lead times depending on the affected sector or ecosystem[174,175]. For instance, linking snow drought information to agricultural systems[72] would provide critical information for understanding the consequences of extreme events (such as snow droughts) for human and agricultural systems (for example, irrigated agriculture and food security) (Fig. 5). These benefits would be especially critical in food-producing countries, where drought impacts can propagate globally through trade networks, amplifying drought impacts such as food insecurity[176]. Collectively, these strategies would enable funding and management procedures at an earlier stage than is currently possible, linking to hotspots where adaptation strategies and policy interventions are most vital.

The Drought Impact Reporter[177] and the Condition Monitoring and Observation Reports on Drought are among such attempts, with the latter including citizen science information and a bottom-up approach to drought impact data collection. These systems allow end-user, local decision makers and citizens to report drought-related impacts through an online system. However, operational drought monitoring models and tools largely remain disconnected from impact assessment[15,124,125], preventing broader adoption.

Preventative factors

Several factors prevent the more widespread creation and use of impact-based approaches, primarily a lack of information about socio-economic impacts, water demand, local water storage and groundwater resources. In many cases, drought indices based on climate variables alone do not offer sufficient information about water deficit; they neglect critical human factors at local and regional levels, and hence consideration of water demand and management.

Although demand management is considered a major tool for drought response, current drought monitoring systems do not incorporate demand information into the existing top-down indicators. For example, in the United States, several federal and state agencies collect and disseminate information about river discharge, groundwater tables and reservoir levels at high spatial and temporal resolutions. However, information on the water used by economic sectors is only available from the US Geological Survey Water Use Data at the county level at 5-year intervals. Information about the locations and amounts

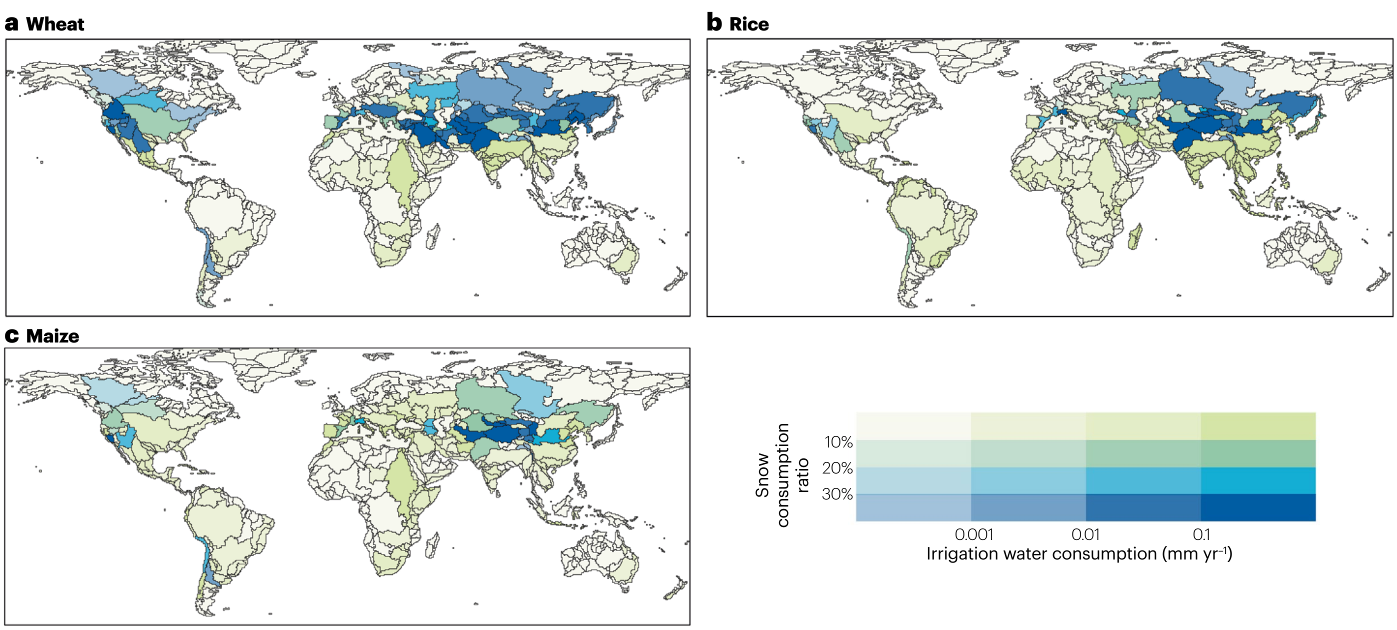

Fig. 5 | Snow drought impacts on the agriculture sector. a, Historical (1985–2015) dependence of wheat growth on snowmelt. Basin-level irrigated agriculture is characterized as snowmelt-dependent along two dimensions: relatively high amounts of irrigation water consumption (*x*-axis in key) and a large share of irrigation surface water demand met by snowmelt runoff (*y*-axis in key). **b**, As in **a**, but for rice. **c**, As in **a**, but for maize. Snow drought can be linked to major crops for impact-based drought monitoring.

of water withdrawals and diversions for various uses is largely lacking across river basins globally, even within developed countries. Moreover, in many locations, knowledge of drought in one region requires data on drought-related variables in another location. For instance, monitoring of urban drought in Los Angeles, California needs to go beyond meteorological drought in that location; it must account for human activities within Los Angeles and its remote supply basins, which includes hydroclimatic factors in the source regions of northern California and the Colorado River Basin.

Lack of information on the quality and accessibility of water and water-use data is an additional limitation to impact-based drought monitoring. Increased resolution data is needed to monitor and quantify water shortages at scales appropriate for local and regional water resources planning and management. The lack of real time and consistent information on local water storage adds to this challenge, particularly the absence of adequate in situ measurements of water surface area and elevation in many parts of the world. Remote sensing of water bodies has become increasingly important in this regard[178,179], particularly using a combination of active and passive sensors[180–188]. Similarly, spatially consistent groundwater information for drought monitoring is not yet available for most regions; in situ groundwater observations are limited and spatially irregular, and satellite-based water storage observations are typically too coarse for local basin-scale drought assessment.

Other challenges in the monitoring of water demand and use include inconsistent methodology and procedures; spatial and temporal discrepancy and inconsistency of data from various socioeconomic sectors[189,190], data privacy and sharing constraints; voluntary laws and statutes for collecting and sharing water-use information; lack of institutional capacity (staffing and financial resources); and robust information technologies for integration of heterogeneous data and information from various sources[191].

The role of governance and local institutions can also not be easily quantified, yet is vital in the context of vulnerability to drought, especially in urban settings[192,193]. Increased efforts are needed to develop frameworks for assessing local vulnerabilities and institutional capacities to actively monitor and respond to droughts. An example of such a framework is a paired event approach; that is, the collection of detailed hazard, exposure, vulnerability, impact and management data from events that have occurred consecutively in the same area. The analysis of changes between events supports the attribution of changes in impacts and enables detailed context-specific and location-specific assessments[194].

Opportunities

These preventative factors act to highlight the needs to make impact-based drought monitoring a reality. However, it is crucial to recognize that achieving effective impact-based monitoring requires drought-related human activities to be taken into account. The concept of anthropogenic drought[195,196] corresponds to a combined top-down/bottom-up perspective for understanding drought, including feedbacks between human activities and climate conditions with a focus on the actual or potential impacts.

Moving toward impact-based drought monitoring requires a bottom-up prospective that starts with actual or potential impacts (crop yield, food prices and availability, accessible water, regional and global food trades, drought-related cascading hazards). Consistent long-term monitoring of drought impacts and their respective causes and costs is essential for identifying global hotspots and developing sustainable, efficient risk management strategies and policies[197–200]. Collecting drought impact data requires protocols to ensure data consistency across space and time. Government agencies should invest in data collection, long-term storage and dissemination.

Research and operational efforts should increasingly prioritize the integration of impact assessment models and drought monitoring tools. For example, crop yield models can be linked with real-time drought severity maps, or energy generation models integrated with hydrological drought conditions. One approach to achieving this integration is by combining traditional drought indicators with indicators that represent local coping and management capacity.

For instance, leveraging data on water consumption and supply can enable the development of an index for measuring vulnerability to socioeconomic drought, such as the Multivariate Standardized Reliability and Resilience Index (MSRRI[201]). This index assesses the ability of surface water supply to meet demand across all sectors, including urban municipalities. Additionally, the use of the Water Resources System Resilience Index offers an alternative approach to investigating socioeconomic drought under growing populations and a changing climate, while also considering the resilience of water resource systems[202]. Various socioeconomic factors have also been integrated to derive a socioeconomic Drought Vulnerability Index, generating composite risk maps that help visualize the information flow within the natural system responsible for the evolution of droughts[203]. Although these existing methods enable the linkage of top-down hazard information with drought impacts and local coping capacity, further efforts should concentrate on the development of regionally relevant and sector-specific impact-based drought models.

Emerging data are also becoming available to make impact-based monitoring more feasible. Specifically, an absence of data on local water storage was identified as a major challenge. The Surface Water Ocean Topography (SWOT) mission[204–206] is a wide-swath instrument that offers area and altimetry information for water bodies at an unprecedented scale and accuracy. In contrast to other remote sensing data, SWOT coincidental readings of area and altimetry enable estimation of the global inland large-body freshwater availability and variability, offering a unique avenue for impact-based drought assessment linking meteorological drought to local coping capacity and local-scale water availability (for example, based on reservoir dynamics). New insights, drought monitoring and impact-based models are expected once the data become available to the science community. Similarly, the exponential growth in data volumes across diverse fields, including non-climate data (such as crop yield, impact data and local infrastructure), contributes to these opportunities in moving from traditional drought monitoring to near-real-time impact assessment[207].

Summary and future perspectives

Current top-down drought monitoring and prediction methods encompass a wide range of approaches, ranging from single-variable indices (precipitation, soil moisture, evapotranspiration) to composite indices (combining multiple single-variable indices) that emphasize climate drivers and indicators of drought (Fig. 1). Although substantial advances have been achieved in multi-index drought monitoring, various hazards (such as drought, heatwaves and wildfires) continue to be monitored in isolation, despite their interconnectedness. The importance of integrating drought and flood monitoring systems has been underscored by experts, but this rationale can be extended to encompass all drought-related hazards.

Top-down drought monitoring models and tools are limited since they remain disconnected from bottom-up, impact-based assessment models[15,124,125]. Decision makers require information beyond the physical drivers of drought in order to forecast the potential impacts of drought events for developing effective adaptation and response plans. Therefore, drought monitoring and prediction methods must advance beyond their current drought-related variable focus and move toward impact-based monitoring systems. To aid the development of impact-based indices, consistent, long-term monitoring of drought impacts (for example health, food security, human migration, economic) and of their respective causes and costs is essential.

Many water-data-related challenges remain that must be addressed to improve drought monitoring metrics for both top-down and bottom-up approaches, and combinations thereof. These challenges include establishing consistent methodology and procedures for data collection and sharing, standardization of data from various socioeconomic sectors spatially and temporally for compatibility, the establishment of laws and statutes for collecting and sharing water-use information, building institutional capacity (staffing and financial resources), and development of robust information technologies for integrating heterogeneous data and information from various sources[189–191]. Increased efforts and collaboration across sectors are needed to develop frameworks for assessing local vulnerabilities and institutional capacities to actively monitor and respond to droughts.

Drought planning tools should allow models and data to work in concert with each other to assess impacts at diverse timescales. Such tools should facilitate exploration of hypothetical scenarios and allow stakeholders to plan data-driven responses based on the expected impacts. Examples include 'what-if' scenario tools for evaluating hypothetical drought scenarios on hydropower energy generation or local food production.

Given the growing data volumes, manual inspection quickly becomes untenable. Drought monitoring and assessment tools should be designed to learn from such big data. Artificial Intelligence (AI) powered by deep neural network architectures offers considerable promise[208–210]. Deep networks leverage representational learning to derive features from complex multi-dimensional data[211,212]. Novel AI methods underpin the ability to assess impacts at diverse timescales, including the impact of cascading and co-occurring stresses.

AI models and rich data availability provide opportunities for science-guided learning[213–215], and could be used to inform the design of loss functions for training deep networks, enforce constraints on expected drought impacts, and set drought thresholds on values/deviations that attributes might possess with respect to each other. Such science-guided deep networks have shown promise by outperforming models that are either exclusively domain-theoretic or machine-learning based[216]. For example, a domain-theoretic snow drought model can be used to inform the spatial extent impacted by variations in snow drought. A deep network could then be used to learn nonlinear relationships across attributes representing the impacted regions for example, estimating the impact of snow drought on agriculture (Fig. 5) in real time based on snow drought monitoring (Fig. 3) and on local crop yield information.

Classes of deep networks enable the generation of embeddings or latent-space representations (that is, a representation of compressed data) that attempt to understand and interpret large datasets[217]. On successful training and validation, predictive models based on these deep networks[218] allow experimentation with extreme hypothetical scenarios that are representative of the nonlinear interactions between different drought drivers. Currently, data systems that reconcile and harmonize data encoding and representational formats across several domains are not available. Increased efforts should focus on developing not only data repositories but also smart systems that make it easier to harness data across sectors, along with powerful learning algorithms for drought monitoring and real-time impact assessment. Moving toward real-time expected drought impacts and systems for hypothetical scenario analysis will substantially advance the current state-of-the-art in drought monitoring and planning capabilities. Given the strong relationship between drought and its cascading hazards, an ideal impact-based drought monitoring system should include impacts caused by other relevant hazards. Therefore, a move toward multihazard monitoring systems is necessary, integrating systems designed for drought and other relevant and potentially cascading hazards.

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