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OVERVIEW

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Advances and gaps in the science and practice of impact-based forecasting of droughts

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Abstract

Advances in impact modeling and numerical weather forecasting have allowed accurate drought monitoring and skilful forecasts that can drive decisions at the regional scale. State-of-the-art drought early-warning systems are currently based on statistical drought indicators, which do not account for dynamic regional vulnerabilities, and hence neglect the socio-economic impact for initiating actions. The transition from conventional physical forecasts of droughts toward impact-based forecasting (IbF) is a recent paradigm shift in early warning services, to ultimately bridge the gap between science and action. The demand to generate predictions of "what the weather will do" underpins the rising interest in drought IbF across all weather-sensitive sectors. Despite the large expected socio-economic benefits, migrating to this new paradigm presents myriad challenges. In this article, we provide a comprehensive overview of drought IbF, outlining the progress made in the field. Additionally, we present a road map highlighting current challenges and limitations in the science and practice of drought IbF and possible ways forward. We identify seven scientific and practical challenges/limitations: the contextual challenge (inadequate accounting for the spatio-sectoral dynamics of vulnerability and exposure), the human-water feedbacks challenge (neglecting how human activities influence the propagation of drought), the typology challenge (oversimplifying drought typology to meteorological), the model challenge

(reliance on mainstream machine learning models), and the data challenge (mainly textual) with the linked sectoral and geographical limitations. Our vision is to facilitate the progress of drought IbF and its use in making informed and timely decisions on mitigation measures, thus minimizing the drought impacts globally.

This article is categorized under:

Science of Water > Water Extremes

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KEYWORDS

drought, drought impact-based forecasting, early action, early warning systems, impacts of drought

1 | INTRODUCTION

Widely known as a complex natural hazard, drought greatly shapes society, which in turn shapes the main characteristics of drought as part of a closely intertwined feedback mechanism (Di Baldassarre et al., 2017; Wang et al., 2022). While humans have long faced droughts throughout our history (Haile et al., 2019; Van Loon, Stahl, et al., 2016b), scientific evidence shows that drought was either a primary cause or a significant contributor to the collapse of several great empires and ancient civilizations (Lucero, 2002). Today, drought threatens the livelihood of 40% of the world's population which directly rely on agriculture as their primary source of income; while others suffer the consequences of food insecurity (Ding et al., 2011) and other indirect social, economic, and environmental impacts.

In recent years, large-scale intense droughts have been observed on all continents, affecting vast areas in Europe, Africa, Asia, Australia, South America, Central America, and North America (Hanel et al., 2018). Among them, European countries have been recently hit by exhausting droughts for several successive years in 2003, 2007, 2010–2013, 2015, 2017–2022 (Caloiero et al., 2021), with a predicted increase in the number and severity of such events (Caloiero et al., 2018; Cook et al., 2020). This is further reinforced by the latest IPCC report, which warns that the frequency and intensity of agricultural and ecological drought will increase rapidly as climate warming intensifies. The report also highlights the need to improve both our understanding of drought propagation and our ability to predict the impacts of droughts (IPCC, 2021). Such information is especially valuable in supporting drought early-warning systems (DEWSs) to make informed and timely decisions on adaptation measures and minimize impacts of droughts.

The United Nations World Meteorological Organization (WMO) has recently launched the Early Warnings for All initiative, envisioning to safeguard every person on Earth with (multi-hazards) early warning systems by 2027 (WMO, 2022). While the current coverage stands at only two-thirds of the world's wealthiest population (WMO, 2022), this vital plan, if successful, will go a long way in saving lives. The main challenge, however, lies not only in providing early warnings, but in accurately predicting the impacts of hazards to allow for taking timely action to minimize them. This task becomes even more complex when dealing with slow-onset and multifaceted hazards, such as droughts.

Substantial progress has been made in hydro-climatic forecasting of droughts, with advancements in detection, causation, prediction, and climate change attribution (AghaKouchak et al., 2022; Fung et al., 2020; Sutanto, Wetterhall, et al., 2020a). However, the gap between predicting drought as a hydro-meteorological event and understanding its real-world impact on the society and the economy hinders effective response measures (WMO, 2015). Existing drought indices primarily focus on hydro-climatic aspects and lack direct links to impacts, impeding integration into drought early warning systems (Kreibich et al., 2020; Sutanto et al., 2019; Wanders et al., 2017). To address this, the emerging field of impact-based forecasting (IbF) of droughts aims to develop methods that target the forecasting of impacts rather than hazards, thus providing more actionable information for better preparedness and response (AghaKouchak et al., 2023).

In this article, we provide an overview of the burgeoning field of drought IbF, review the progress in drought IbF from both scientific and practical perspectives, and present a road map outlining the current challenges and limitations

and related needs to advance this emerging field. We further provide an outlook to facilitate the practical implementation of IbF within DEWS, while ensuring local representation and targeted adaptation actions for drought mitigation.

2 | THE EVOLUTION OF THE EMERGING FIELD OF IbF OF DROUGHTS

Progress in the hydro-climatic forecasting of drought is mainly driven by advances in process-based impact modeling, numerical weather prediction systems, postprocessing methods, and machine learning (ML) algorithms (Dasgupta et al., 2023; White et al., 2022). However, every year drought events cause unnecessary severe damages and fatalities. This failure can be partly explained by the existing gap between predicting drought as a hydro-meteorological event and understanding its potential impact felt on the ground affecting the society and economy (WMO, 2015).

In response to this challenge, IbF has emerged as an approach that specifically focuses on predicting and communicating the potential impacts and consequences of weather events, such as droughts, on various sectors and systems (UN ESCAP & WMO, 2021). It aims to provide actionable information to decision-makers and the public, emphasizing the potential effects on human lives, infrastructure, agriculture, and other vulnerable sectors. The ultimate goal is to drive early action that minimizes damages and loss of life caused by these hazards (UN ESCAP & WMO, 2021). The motivation behind impact forecasting is rooted in the understanding that individuals are more likely to heed warnings when they are provided with specific information regarding the potential impacts and accompanied by behavioral recommendations (Weyrich et al., 2018). Combining this approach with the identification of various risk levels, which considers the probability and magnitude of harm resulting from exposure and vulnerability to hazards as shown in Figure 1 (UN ESCAP & WMO, 2021; WMO, 2015), enables the issue of tailored warnings. These warnings, in turn, prompt appropriate responses from relevant users (UN ESCAP & WMO, 2021). This holistic and targeted approach is crucial in effectively managing drought risks.

The key difference between the traditional drought forecasting and IbF lies in the scope and focus. Traditional (or physical) drought forecasting mainly focuses on predicting the onset, severity, and duration of drought using indicators derived from hydroclimatic variables such as precipitation, soil moisture etc. Calculated based on these indicators, indices of drought as a hazard (e.g., Standardized Precipitation Index, SPI (McKee et al., 1993), and Standardized Precipitation Evapotranspiration Index, SPEI (Vicente-Serrano et al., 2009)) are primarily hydro-climatic in nature and not directly linked to drought impacts. This is because the spatio-temporal dynamics of vulnerability to droughts and impacts, that are multi-sectorial and socio-economic, are unknown or difficult to characterize (Kreibich et al., 2020). Correspondingly, the drought indices used to predict drought conditions do not directly translate hazard into impacts (Sutanto, Van Der Weert, et al., 2020b). This impedes the integration of drought impacts information into DEWSs, which employ these physical indices as explicit drought impact indices are still lacking (Wanders et al., 2017). Thus, there is an urgent need to develop new methods for targeted forecasting of impacts rather than hazards. IbF expands the scope to include detailed contextual knowledge (UN ESCAP & WMO, 2021) with a wide range of factors (e.g., information on exposure

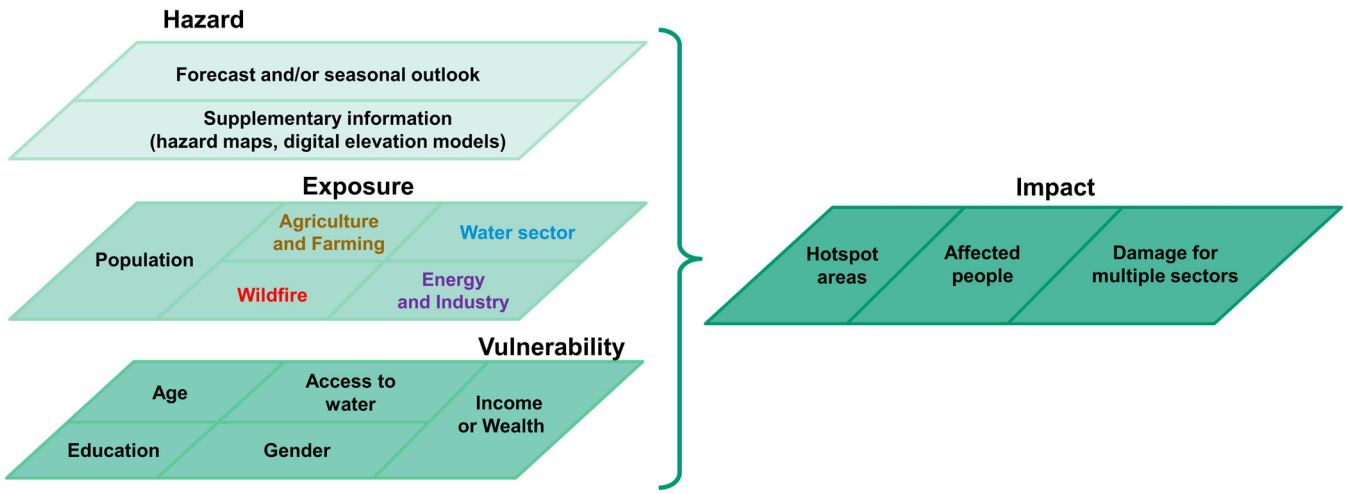

FIGURE 1 Components of an impact-based approach to forecasting (redrawn after UN ESCAP & WMO, 2021).

and/or vulnerability) and their potential impacts (Figure 1), providing a comprehensive and actionable understanding of drought events (Merz et al., 2020).

Owing to its novelty and broad scope, the risk theory-based concept of IbF permits the use of different methods across different disciplines and facilitates close cooperation among the numerous actors involved (Robbins et al., 2022). The most common approach to IbF is to develop drought impact functions using hazard indices of different drought types as predictors and their associated impacts as predictands (Boult et al., 2022; Sutanto et al., 2019). The choice of predictors and predictands depends on data availability and end users' requirements. Several methods have been introduced to derive impact functions, as summarized in Sutanto et al. (2019):

- *top-down approach*: dynamic climate models combined with deterministic impact models to predict crop yields or navigation on rivers (e.g., (Cantelaube & Terres, 2005; Meissner et al., 2017)).
- *bottom-up approach*: statistical models to assess the relationship between crop yield and hydroclimatic variables (e.g., linear regression approach from (Bayissa, 2018)).
- *hybrid*: ML approaches (e.g., logistic regression and Random Forest (RF)) to translate drought hazard into the likelihood of drought impact occurrence (LIO) as implemented by (Sutanto et al., 2019). The hybrid approach based on machine-learning methods has shown high predictive performance and, therefore, proved to be valuable in developing drought impact functions (Sutanto, Van Der Weert, et al., 2020b).

IbF further inputs to other natural hazard mitigation and adaptation measures, including forecast-based action and forecast-based financing, namely actions to be taken based on forecast (humanitarian action forecasts) and funding mechanisms to be activated in anticipation of impacts of droughts (financial impact forecast) (Van Aalst et al., 2015). These concepts were developed by the International Federation of the Red Cross (IFRC) and partners to enable national societies to access funds in anticipation of hazards through a peer-reviewed early action protocol (EAP) (Boult et al., 2022; Heinrich & Bailey, 2020). Several African countries, including Kenya, Niger, Zimbabwe, and Ethiopia (Figure 2), have already established their EAPs and initial IbF systems for droughts. Other countries, such as Uganda, Mozambique, Namibia, Zambia, Mali, Philippines, Pakistan, the Democratic People's Republic of Korea, and those in the Latin America and the Caribbean region, are currently in the process of developing or considering the development of their systems with the intention of implementing IbF (Heinrich & Bailey, 2020). The outputs of IbF have proven valuable in addressing real-world challenges by providing actionable information to decision-makers and users. For instance, the ForPAc IbF project, implemented in Kenya, focuses on monitoring biophysical indicators and vulnerability-related indicators such as food security and livelihood zones (Robbins et al., 2022). This project provides information on drought impacts and supports actions in anticipation of normal, alarm and emergency conditions, rather than in response to them (Robbins et al., 2022).

The progress in development of IbF models can be seen from the two perspectives of science and practice: (i) the development of impact functions in scientifically-oriented literature and (ii) practice-oriented literature targeting early-warning actions and forecast-based finance initiatives. There is a clear consensus between the scientific and practical sides that IbF possesses greater value than physical drought forecasts in making forecasts and early warnings actionable and in supporting the allocation of drought relief funds. Hence, both sides strongly advocate for IbF and provided guidelines (RCCC, 2020; UN ESCAP & WMO, 2021; WMO, 2015, 2021) for its development and implementation. Despite having different immediate goals and targeted beneficiaries (e.g., local farmers, national authorities, and scientific community), the ultimate goal of both bodies of literature is to alleviate drought impacts.

To identify relevant scientific studies that have assessed the hazard-impact link, we conducted a systematic review on Google Scholar using the keywords "drought," "impact," and/or "forecasting." Additionally, practical reports on establishing drought IbF were obtained by searching the websites of various international and humanitarian agencies, such as the Anticipation Hub (https://www.anticipation-hub.org/). As a result of our search, we identified 14 scientific articles and 3 practical reports. For a comprehensive list, refer to Note 1.

Figure 2 illustrates the evolution of both the science and practice of drought IbF based on literature across multiple criteria (geographical distribution, temporal scale, sectors, IbF methods, drought indices). The upper panel of the Figure provides a timeline displaying all the included articles and reports, starting from the first publication by Gudmundsson et al. (2014). Each study is represented by specific symbols on the timeline to indicate the sectors analyzed: wildfire, agriculture and livestock, water-related aspects such as water supply, quality, and freshwater ecosystems, and energy & industry. The name of the first author for each study and the countries focused on in the research are indicated on the left side of the timeline. On the right side of the timeline, information is provided regarding the

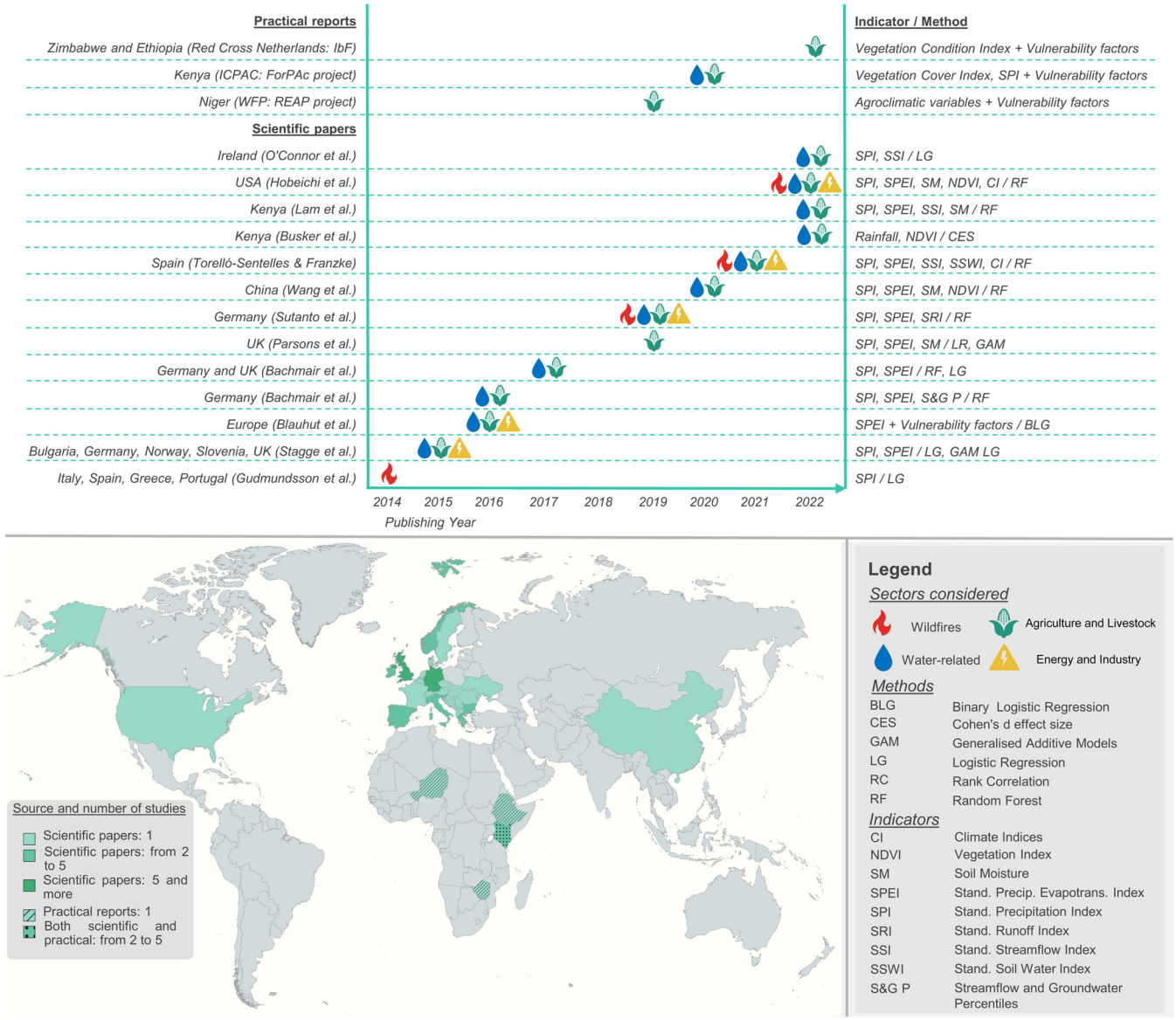

FIGURE 2 The evolution of the drought IbF in scientific and practical literature across multiple criteria (geographical distribution, temporal scale, sectors, IbF methods, and drought indices). For further details, see Note 1.

drought indicators used in the analysis and the methods employed to establish the relationships between drought indicators and impacts. The lower panel displays the geographical distribution of the literature, with the number of published articles and reports per country distinguished between scientific and practical literature.

As can be seen in Figure 2, the literature on drought IbF started quite recently and its development in the two bodies of literature has followed different methodological and conceptual paths. The spatial focus of the scientific literature appears to be mostly limited to Europe, whereas the practical literature focuses on developing areas, especially in Africa. Further key differences are discussed below in detail.

3 | SEVEN CHALLENGES AND LIMITATIONS FACING THE IbF OF DROUGHTS AND THE WAY FORWARD

Despite encouraging results in terms of good forecasting performance achieved by recent IbF models (Sutanto et al., 2019), there are a number of challenges and limitations still being faced in the drought IbF field. Challenges here refer to the broad, overarching research difficulties encountered related to the drought phenomenon and its inherent characteristics;

while limitations arise from shortcomings or lack of currently adopted practices. The main ones are conceptualized in Figure 3, followed by a broader discussion of potential solutions to address each challenge and limitation.

3.1 | Contextual challenge: Account for multi-sectoral, spatially heterogeneous, and dynamic vulnerability and exposure

The process of establishing an indicator-impact relationship faces the challenge of defining and integrating multi-sectoral spatial complexities of vulnerability and exposure to droughts, as such relationships are nonlinear with delays and feedback loops (Boult et al., 2022; Hagenlocher et al., 2019). Additionally, the vulnerability is a time-variant variable due to adaptation and preparedness measures and needs to be incorporated as such, particularly for slow-onset hazards such as drought (Merz et al., 2020). Further, water scarcity is usually not distinguished from drought and is not included as a relevant component or factor in relation to drought vulnerability (De Stefano et al., 2015).

Most scientific studies (Bachmair et al., 2017; Parsons et al., 2019; Stagge et al., 2015) used annual impact occurrence as a proxy for trends in vulnerability and to account for seasonality. This allows seeing the general trend assuming that if a system was affected it was vulnerable (Blauhut et al., 2016). However, it fails to grasp sectoral heterogeneity and episodic changes in resilience, such as those triggered by the drought events themselves.

Recent findings demonstrate that a drought index linked to a given impact can be combined with exposure and vulnerability factors (Blauhut et al., 2016; De Stefano et al., 2015) and other socio-economic and environmental data to

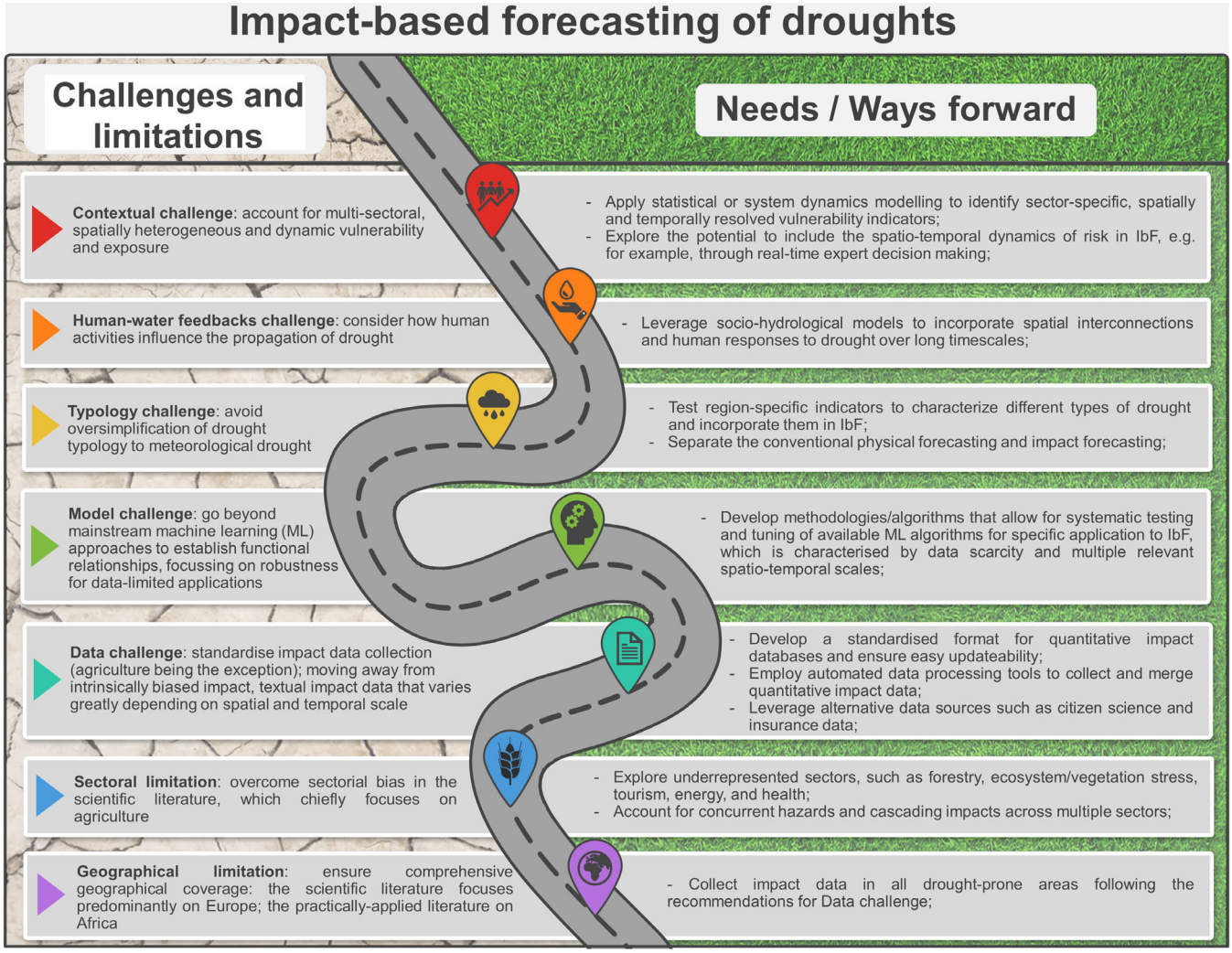

FIGURE 3 List of challenges and limitations in the context of drought IbF and needs/ways forward.

provide enough inputs for reliable and robust drought impact forecasting (Heinrich & Bailey, 2020; Stagge et al., 2015). As such, some practically-implemented IbF projects (ForPAc in Kenya and REAP in Niger) monitor livelihood zones and use specific vulnerability-related indicators of production (market food prices, loss of crops and livestock) as well as access and use (milk consumption, cost of water, malnutrition risk) to understand socio-economic coping strategies (Heinrich & Bailey, 2020). Additional area-dependent factors, as pointed out by IbF practitioners (Robbins et al., 2022), can include socio-economic indicators as poverty, literacy levels, population density, household income and other coping strategies (children school attendance, forced marriage and rural migration), all of which preferably need to be integrated in a quantitative format as qualitative data in this case lacks sufficient granularity. Overlaying these indicators as input data layers can allow identifying the distribution of entities of interest (exposure) and the evolving state of those entities (vulnerability) (UN ESCAP & WMO, 2021).

Furthermore, a range of methods (from statistical to system dynamics modeling and hybrid approaches) can be applied to select specific vulnerability (González Tánago et al., 2016; Hagenlocher et al., 2019; Martin et al., 2016) and exposure factors for each study (e.g., depending on climatic hotspot, drought type explored, etc). For example, to characterize the vulnerability of pastoral households to different driving forces of variability intrinsic in semi-arid regions (namely severe droughts, natural rainfall variability, and oscillations induced by resource–consumer interactions), Martin et al. (2016) took an exploratory modeling approach to study the system dynamics. They employed a spatially-explicit social-ecological model for systematic vulnerability assessments of pastoral households by scenario comparison. The selected vulnerability and exposure factors can further be weighted by the expert knowledge in the field (Stephan et al., 2023; Zebisch et al., 2021). To account for dynamics and move toward a "non-static" IbF, Boult et al. (2022) suggest incorporating real-time expert decision making into operational systems and assessing the emerging drivers of vulnerability at different stages of system exploitation. This contrasts the widely used predefined forecast threshold triggers for preagreed actions. Being more reliable and transparent, this predefined option helps to avoid the real-time subjectivity and extra costs; however, even predefined systems can allow for flexible elements to be included to account for vulnerability dynamics (Boult et al., 2022). This is further reinforced by the latest GAR2021 report (UNDRR, 2021), which emphasizes that iterative learning is a must when modeling an action in response to a threat as complex as drought.

3.2 | Human-water feedbacks challenge: Consider how human activities influence the propagation of drought

In today's human-dominated world, which some scholars refer to as the Anthropocene (Lewis & Maslin, 2015), societies have increasingly influenced the frequency, severity and spatio-temporal distribution of drought (AghaKouchak et al., 2021; Di Baldassarre et al., 2017; Van Loon, Gleeson, et al., 2016a). This is illustrated in Figure 4, showing how the propagation of drought from the atmosphere (climate variability) to its potential impacts (energy or food crisis) is substantially altered by: (i) changing land-use (e.g., deforestation or urbanization), (ii) diverting water flows for irrigation or other purposes, and (iii) building and operating water infrastructure (e.g., dams and reservoirs).

While altering the propagation of droughts, societies respond to drought impacts. Humans respond (and potentially adapt) through a combination of informal processes and deliberate strategies, including changing agricultural practice, revising social contracts, as well as temporary or permanent migration (Ward et al., 2020). Water infrastructure, such as reservoirs, can also be planned, built or revised after the drought occurrence, and this will in turn (again) change the frequency, magnitude and spatial distribution of agricultural and hydrological droughts (Figure 4).

An increasing number of (socio-)hydrological models have been developed over the past decade to account for the role of humans as agents of change in the propagation of extremes, however these models are still to be refined and tested for being applied in the context of drought IbF (Vanelli et al., 2022).

3.3 | Typology challenge: Avoid oversimplification of drought typology to meteorological drought

Droughts are commonly categorized into meteorological (precipitation deficit), agricultural (soil moisture deficit) and hydrological (streamflow and groundwater deficit). The connection between these drought types, known as "drought propagation," denotes a chain of processes that describes the transformation of the drought signal through the terrestrial hydrological cycle (Figure 4). This involves the interaction between precipitation, soil moisture, runoff, recharge,

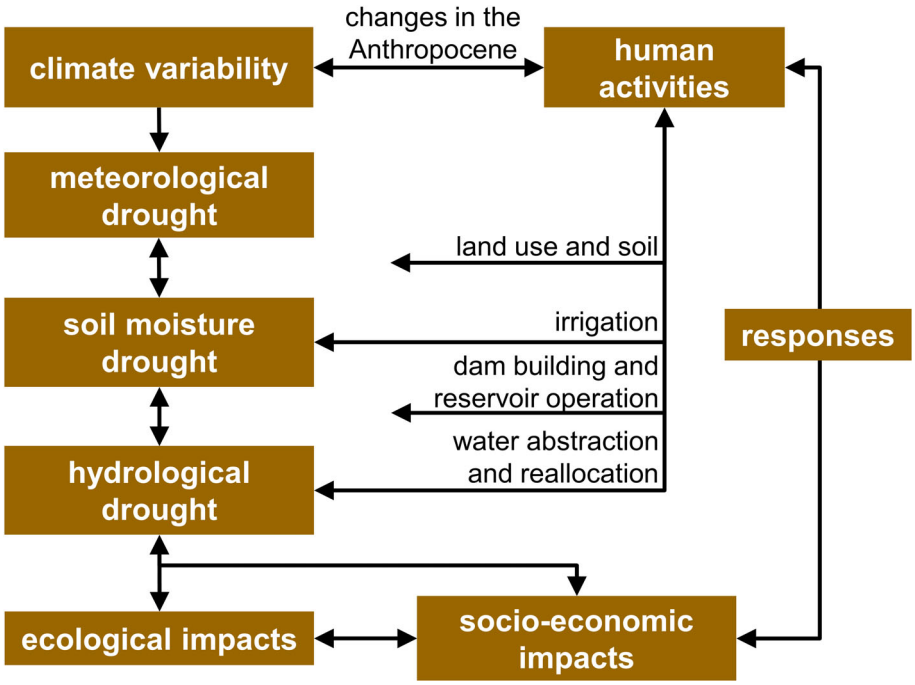

FIGURE 4 Examples of human alterations of (and responses to) drought (redrawn after Van Loon, Gleeson, et al., 2016a).

groundwater, discharge and feedback with the human system. Traditionally, the concept of drought propagation in the literature has been depicted as a unidirectional flow, progressing from meteorological through agricultural to hydrological drought (Figure 4). However, in reality, when accounting for complexity of the water cycle and interlinked human activities (Human-water feedbacks challenge), the propagation does not always complete the entire cycle (Tijdeman et al., 2021), or could even progress in the opposite direction (Figure 4). In view of the growing complexity of drought processes, and increasing interactions with the human systems, several scholars have recently introduced the term anthropogenic drought (AghaKouchak et al., 2021).

Detected by a range of various drought indices, different drought types can lead to different impacts with various response times across multiple affected sectors (Lam et al., 2022; Wanders et al., 2017). Meteorological drought typically manifests earlier, while agricultural drought requires time to propagate and visibly affect crops or ecosystems (Stagge et al., 2015). Despite considerable variety in drought indicators, there is a tendency to simplify the complex phenomenon of drought down to meteorological drought only that can be easily tracked with, for example, precipitation-based SPI (Bachmair et al., 2016; Kchouk et al., 2021). A single index is certainly easier to compute across a large area, communicate, and use to motivate aid. However, it has been well studied that drought monitoring based on a single drought index seldom captures the full complexity of the multifaceted drought phenomenon (Bachmair et al., 2016; Wanders et al., 2017). There is, hence, a clear need to identify a suitable region- and sector-specific indicator to characterize each drought type separately (Sutanto et al., 2019). Another suggestion is to break down the current IbF approach into 2 stages and consider a clear separation between the conventional physical and impact-based forecasting. This way, the physically measurable variables (e.g., precipitation, soil moisture, and streamflow) can be forecasted first and incorporated into impact models, rather than forecasting drought indicators which are unobservable quantities (e.g., SPI or SPEI), thus adding uncertainty to the physical forecasts due to, for instance, to distribution fittings necessary for calculating indicators.

3.4 | Model challenge: Go beyond mainstream ML approaches to establish functional indicator-impact relationships, focusing on robustness for data-limited applications

ML approaches are widely used to establish the drought statistical indicator-impact relationship since they bypass the need to explicitly define process-based (causal) relationships between hazards, exposure, vulnerability, and impacts (Bachmair et al., 2015; Carrão et al., 2016; Naumann et al., 2014; Sutanto, Van Der Weert, et al., 2020b). However, such

methods are data-hungry as they rely heavily on the accuracy and availability of long time series of impact data of extreme events. Extreme events are by definition "rare at a particular place and time of year" (IPCC, 2021), which poses significant challenges in acquiring the necessary data. This also means that ML methods are limited in their ability to simulate events that have not been observed in the training data, despite having access to a lengthy historical training dataset. ML methods are also prone to exhibit "overfitting," which impedes the extrapolation beyond the training data in both space and time. This data sensitivity makes their application to IbF challenging and calls for process-based models which in turn require process understanding.

A review of the scientific (vs. practical) literature of drought IbF highlights the prevalence of RF functions among the ML family of methods. This can be explained by their relative simplicity, low computational demands and effectiveness while working in a data-limited context. However, no systematic inter-comparison has been performed (to the best of authors' knowledge) on the performance or fidelity of ML models for drought IbF. Future research should therefore focus on systematic benchmarking of ML models for IbF. Within ML, deep learning approaches are considered to be more powerful than RF to capture the spatio-temporal characteristics of droughts, but are even more reliant on data availability (Hobeichi et al., 2022). Apart from ML, a recently proposed methods include applying storyline-based concepts to disentangle a physical process leading to the event of interest (van der Wiel et al., 2021) and develop impact-based drought prediction models based on logical rationale of this approach (AghaKouchak et al., 2022). Regardless of the chosen method, introducing an impact model for developing areas implies high costs, which should be accounted for to make IbF practically feasible for implementation (WMO, 2021).

3.5 | Data challenge: Standardize impact data collection (agriculture being the exception); moving away from intrinsically biased impact, textual impact data that varies greatly depending on spatial and temporal scale

It is the complex, multifaceted (Van Loon, Stahl, et al., 2016b) and elusive (Kchouk et al., 2021) nature of drought that challenges detecting, quantifying and collecting the information on impacts of droughts. There has been an ongoing debate about the operational needs for drought monitoring (Lam et al., 2022), which constantly results in an urgent call to gather the information of impacts of droughts in a systematic and uniform way. This "missing piece" of information on impacts in drought monitoring affects greatly the capacity to decrease vulnerabilities, anticipate and respond in a timely fashion to droughts and their impacts (Lackstrom & Crimmins, 2013).

The process of establishing an indicator-impact relationship is sensitive to data availability (Bachmair et al., 2017; Sutanto et al., 2019). The available real-time and retrospective impact data typically do not rest on standardized data collection methods (except for the US DIR and agricultural statistics) and vary greatly depending on the spatio-temporal resolution and scale (Bachmair et al., 2016; Merz et al., 2020). Despite their relative accessibility, agricultural statistics pose challenges in terms of aggregation format (e.g., annually or by administrative units), but also in attributing observed changes specifically to droughts rather than other associated hazards like heatwaves, hail, pests, fires, or windstorms.

Alternative methods for extracting impact data include widely used text mining with manual (Stahl et al., 2016) or automatic (de Brito et al., 2020) classification and novel automatized detection methods that surpass the need to develop manual or automatic classification (Sodoge et al., 2023). These methods can be applied to diverse sources, including newspaper articles, impact reports and academic texts. Despite the ability to capture the range of drought impacts, textual impact monitoring also presents a number of challenges (Bachmair et al., 2016; Lam et al., 2022; de Brito et al., 2020; Stahl et al., 2016):

1. Media reporting bias on what types of impacts are reported, where they are reported and how regular the reporting is depending on other unrelated local, national, or global events;
2. Human factors affecting perception of impacts over time;
3. Inconsistency in search keywords (except for the automatized detection methods), the selection of relevant texts, and the choice of information channels for retrieving articles (especially for different languages);
4. Difficulty in extracting specific geographical information from textual data that directly links to drought-related impacts; and
5. Challenging to merge qualitative and quantitative data and/or use as quantitative data only and incorporate into DEWSs;

These challenges hinder a systematic monitoring and evaluation of drought impacts and their links to drought indicators. It is especially crucial to be able to create standardized and long-term impact data records (e.g., US DIR records start in 2005). Promoting low-cost citizen science initiatives while developing methods to coordinate and connect data collection efforts may be a step toward utilizing local knowledge in high-tech drought crowdsourced monitoring (e.g., using cell phones to report drought impacts in Ethiopia and Somalia). The key challenge here lies in engaging citizens over an extended period to ensure continuous collection of impact data, while also ensuring the accuracy of the gathered information. Another readily available proxy of impact severity is the amount of humanitarian aid expended; however, its uneven distribution and underlying complex political process make it an inaccurate reflection of the severity of the impact (Boult et al., 2022).

Further research efforts should consider developing an improved impact database in terms of higher spatial and temporal resolution, differentiating between sectors and regions to alleviate reporting bias and enable systematic and standardized collection of quantitative impact information (Kreibich et al., 2020; Lam et al., 2022). One way to achieve this is to employ enhanced data processing tools to collect and merge such quantitative data from validated governmental impact reports in combination with alternatives like insurance data or citizen science that has capacity to be maintained over the long term. Many parties would benefit from negotiating with the insurance industry free use of aggregated loss data for noncommercial purposes, similar to the current conditions for accessing weather forecasts (very expensive for commercial use, free for research use albeit released with some temporal delay). Exploring this together with efforts toward achieving common cross-border agreements and data policies on how impact data is collected and stored (Robbins et al., 2022) should lead to a better understanding of the link between drought drivers and their impacts and, ultimately, to a better management of drought risks (Van Loon, Stahl, et al., 2016b).

The following two limitations are emerging from the data challenge discussed above, but address different aspects of current data collection practices. These limitations stem from the sector-specific and geographical focus of data collection practices, and we discuss them separately.

3.6 | Sectoral limitation: Overcome sectorial constraint in the scientific literature, which chiefly focuses on agriculture

The prevailing data collection practices contributed to a significant limitation in drought research in general, and specifically within IbF, as it tends to be highly agriculture-centric. Indeed, agriculture bears a significant burden of the impact, particularly in economically developing countries where it is the most vulnerable sector, experiencing up to 80% of all direct impacts (FAO, 2017; King-Okumu, 2021). Yet, this focus is further associated with the utilization of data from various sectors, depending on the intended course of action. Ad-hoc data collection among other data collection methods is essential for food security monitoring, and the quantification and tradability of crops makes agricultural statistical data the most accessible resource in this regard.

Consequently, several scientific studies assessed the link between drought statistical indices and agricultural impact indicators (Bachmair et al., 2016; Bayissa, 2018; Parsons et al., 2019; Ribeiro et al., 2019; Vicente-Serrano et al., 2012), due to the availability of consistent, long-term statistical data on crop yields. Similarly, the practically-applied literature of IbF has mostly focused on the drought impact on agriculture and food (in)security, particularly in the humanitarian sector by UN agencies such as FAO and WFP (Heinrich & Bailey, 2020). The scientific literature has additionally focused on forecasting impacts on the water sector, indicated by the high numbers of water-related reports in the European Drought Impact Report Inventory (EDII) database (Stahl et al., 2016).

Despite the extensive literature on droughts and their impacts on other sectors, such as forestry (Brun et al., 2020; Luce et al., 2016; Mcdowell et al., 2020; Schuldt et al., 2020), ecosystem and vegetation stress (Bastos et al., 2020; Khazaei et al., 2019; Wu et al., 2022; Zhang et al., 2021), tourism (Dube et al., 2022; Koutroulis et al., 2018; Smith & Fitchett, 2020), energy (Byers et al., 2020; Herrera-Estrada et al., 2018), and health (Charnley et al., 2021; Mora et al., 2022; Salvador et al., 2020), more attention should be devoted to exploring the potential of drought IbF for these sectors. Following recent advances in terrestrial monitoring and modeling, the number of studies on droughts and their broad ecosystem impacts has grown exponentially (Bastos et al., 2020, 2021; Wu et al., 2022; Zhang et al., 2021); however, the sensitivity of terrestrial ecosystems and vegetation response to extreme dry conditions requires further research (AghaKouchak et al., 2015; Xu, 2021). In addition, hot and dry conditions that lead to human discomfort and a high risk of wildfires can result in decreased visitations and shortened or shifted seasons for all recreational activities. This, in turn, reduces revenues in the tourism sector and affects the livelihood of dependent communities that have limited resources to

cope with the financial burden of drought. Some studies (Koutroulis et al., 2018) have revealed that climatic changes are projected to affect the existing European tourist regime. Finally, a greater understanding of the relationships between drought events and their direct and indirect repercussions on human health (Haile et al., 2019) and livelihoods can support public health authorities and emergency managers to prepare for drought-associated health impacts and save lives.

Droughts further tend to have a cascading effect and indirect consequences within and across sectors (de Brito et al., 2020; Vogt et al., 2018). This cross-sectoral interaction occurs when outputs from one sector serve as inputs for another sector (Ding et al., 2011). In case of agriculture, the impacts are not solely borne by farmers; rather, a portion of the losses is passed on to consumers through increased prices of agricultural commodities (Ding et al., 2011). This, in turn, has implications on other interrelated sectors as cascading impacts are often nonlinear (AghaKouchak et al., 2020) and require specific methods to unravel impact interdependencies (de Brito, 2021). To be more effective, drought IbF should account for multiple hazards that can co-occur with droughts and lead to cascading impacts across several of the aforementioned sectors (AghaKouchak et al., 2023; WMO, 2021).

3.7 | Geographical limitation: Ensure comprehensive geographical coverage: The scientific literature focuses predominantly on Europe; the practically-applied literature on Africa

Another limitation arising from the data challenge is the heterogeneous availability of data across the globe. This heterogeneity extends beyond drought research and can be attributed to varying capacities in monitoring systems and infrastructure. Regions with more advanced monitoring systems and infrastructure in place tend to have more comprehensive and easily accessible data. In contrast, economically developing countries often encounter limitations in data collection due to factors such as financial constraints, technological gaps, limited institutional support and data sharing practices (Bachmair et al., 2016; Lam et al., 2022).

Spatially, scientific IbF studies have mostly focused on Europe (Bachmair et al., 2015, 2017; Parsons et al., 2019; Stagge et al., 2015; Stephan et al., 2021; Torelló-Sentelles & Franzke, 2021), and only have recently expanded to China (Wang et al., 2020), the United States (Hobeichi et al., 2022), and Africa (Busker et al., 2022; Lam et al., 2022). Some studies (Bachmair et al., 2016; Lam et al., 2022) pointed to a lack of drought impact information in areas outside of Europe and the United States, such as the Horn of Africa, where there is an urgent need for effective drought monitoring. This can explain the European focus in the scientific literature and urges the need to collect the impact data in other drought-prone regions following the recommendations provided in Data challenge above. In contrast to the scientific literature, the practical literature has applied IbF methods in economically developing areas only, particularly in Africa. This is partly driven politically and socio-economically (e.g., higher reliance on water irrigation in Africa among other factors leads to severe famines and loss of lives (Merz et al., 2020)), and partly due to the fact that different regions are governed by different drivers of predictability, which gives a higher drought forecast skill in the lower latitudes and makes it more feasible to implement IbF initiatives there. By focusing on economically developing areas, practical literature has ensured a relatively comprehensive geographical focus there with a good institutional support (e.g., drought EAPs).

4 | IMPLICATIONS AND ACTIONS TO IMPROVE IbF DEWS

The severity and frequency of droughts are modulated by changes in climate, with the available projections indicating an increase in both statistical properties in the mid-century (IPCC, 2021; Krysanova et al., 2017; Pechlivanidis et al., 2017). As exposure and vulnerabilities are anticipated to rise, socio-economic impacts are consequently expected to increase in space and time, including intensified detrimental consequences from compound and cascading effects affecting various sectors simultaneously (Brás et al., 2021; de Brito, 2021; Schumacher et al., 2022). This highlights the urgency for targeted adaptation actions that can lead to drought mitigation, including for instance the implementation of accurate impact-based DEWS (Göber et al., 2023). Improvements in the accuracy in drought IbF can specifically be achieved through the recent evolution of the ML field and increased availability of impact datasets to train the data-driven models (Torelló-Sentelles & Franzke, 2021). We previously highlighted that the existing literature on drought IbF is "biased" toward mainstreamed ML-based approaches. We further argue that the opportunities that can be found in the emerging ML field are twofold. One, to enhance the forecast skills of traditional ML approaches by developing or using novel ML algorithms. The higher forecast skills would serve as upper benchmarks for the performance of

process-based (causal) models of drought impacts—also known as model benchmarking predictions and which often focus solely on optimizing predictive accuracy on specific sets of test data without providing explicit explanations for their predicted impacts (Roscher et al., 2020). Novel ML methodologies can bridge the gap between the accuracy of the predicted socio-economic and environmental consequences and the capacity to provide transparency and interpretability (Belle & Papantonis, 2021). Two, statistical including ML methods can be used toward process understanding: to identify both scale dependent and scale independent casual relationships (or dominant processes) from drought hazard to drought impacts. This would be a crucial steppingstone for developing process-based models of drought impacts that are required for natural resources planning and decision making in the face of future droughts.

Furthermore, forecasting the impact of drought events can identify which areas are most vulnerable and prioritize the aid from an emergency responder. However, the limited knowledge on interpreting uncertain/probabilistic drought forecasts, the lack of their rigorous impact assessments, and the lack of clear and effective communication practices are factors that limit the adoption of an essential IbF-based risk management. Therefore, the transferability of IbF knowledge and techniques for improving decisions across local studies is crucial to drive mitigation actions. Knowledge needs to be regionalized and transferred across geographical locations, allowing the evolution of scientific and technical developments particularly in vulnerable areas with limited local resources. The enhancement of IbF DEWS includes advancements in information collection from different data types (i.e., Earth Observations) and incorporation of feedback from stakeholders. Innovative proactive actions should focus on enhancing the understanding of the complex interactions between meteorological, hydrological, and socio-economic factors across the globe, and further translate science to practice by integrating impact models into DEWS (Cammalleri et al., 2022).

To stimulate the implementation of IbF DEWS, we urge the need to co-develop prototypes for local IbF driven by a strong user engagement. Existing DEWS-based impact assessments are limited by coarse process representation and spatial differentiation, despite their advantage of geographically covering national or continental areas (i.e., Copernicus EDO evolution plan). This limits the accuracy of the impact evaluation, which is a requirement for local applications and actions. We need to overcome the spatial scale limitation and calculate impacts at the administration unit levels, incorporating factors such as impacted area, exposed population, land cover type, and so on, to build risk matrices relevant for decision-making. Engagement with different local users is a key need for co-developing services for local IbF and assessments for droughts. This effort can create a continuous communication link with local users and practitioners, foster trust and lead to enhanced decision-making by considering the likely consequences and trade-offs associated with different actions (mitigation strategies, resource management and emergency response planning).

5 | CONCLUSION

While considerable progress has been made to date within the science and practice of drought IbF, we identified their challenges and limitations in this work. Namely, the contextual challenge (inadequate accounting for the spatio-sectoral dynamics of vulnerability and exposure), human-water feedbacks challenge (neglecting how human activities influence the propagation of drought), typology challenge (oversimplifying drought typology to meteorological drought), model challenge (mostly reliant on mainstream ML models), data challenge (mainly textual and lacking collection protocols for all sectors) with the linked sectoral limitation (mainly agriculture in the scientific literature), and geographical limitations (mainly Europe for the scientific literature, and economically developing regions in the practical literature).

The scientific and practical perspectives have often developed in parallel, yet there is a clear advantage to bridging the gap. An example could be applying scientifically robust impact functions to highly vulnerable areas and/or at climatic hotspots, while leveraging the findings from the past practical implementation of IbF in these regions. This is a highly sophisticated but feasible step that requires significant multidisciplinary research to consider all the aspects discussed above as well as strong intersectoral collaboration. Successful IbF indeed requires continuous cooperation between researchers, forecast providers, such as national hydro-meteorological services, and disaster management authorities. Collaboration with local communities (often referred to as indigenous knowledge) could bring further benefits, such as knowledge on missing exposure and vulnerability aspects and understanding local coping strategies and types of early actions to be taken. An additional challenge with IbF warnings is that they are probabilistic in nature, but need to be communicated in a specific and precise fashion since they require taking concrete actions and should be designed for agencies and the general public in an easily accessible and comprehensible way. This is a problem common to several weather-related forecasting products, such that communication advances achieved in IbF could be applied more broadly. Similarly, different forecast uncertainties at different lead times require different communication practices

and actions to be taken. Further, to support the conceptual and financial interest in cost-efficient IbF and increase public trust in its forecasts and warnings, a cost–benefit analysis (or other evaluation methods) should be applied to evaluate the added value brought by facilitating early action based on IbF. Ultimately, such evaluation should be conducted as an ongoing, iterative process that allows modification and factoring in additional aspects into IbF systems.

Ensuring the coverage of the aforementioned aspects while developing and operationalizing drought IbF systems will allow to overcome current challenges. As the new impact-based paradigm emerges and evolves, it is equally important to progress scientifically in terms of methodology in impact forecasting while securing its practical feasibility for better informed and timely drought risk management. This article emphasizes the urgent need to further develop and integrate IbF practices into DEWSs, highlighting the critical importance of global scientific efforts to better assess local impacts amidst the ongoing challenge posed by the rising threat of droughts.

AUTHOR CONTRIBUTIONS

Anastasiya Shyrokaya: Conceptualization (lead); data curation (lead); formal analysis (lead); investigation (lead); methodology (lead); visualization (lead); writing – original draft (lead). **Florian Pappenberger:** Conceptualization (supporting); investigation (supporting); methodology (supporting); supervision (supporting); writing – review and editing (lead). **Ilias Pechlivanidis:** Conceptualization (supporting); methodology (supporting); supervision (supporting); writing – original draft (supporting); writing – review and editing (supporting). **Gabriele Messori:** Conceptualization (supporting); funding acquisition (lead); methodology (supporting); supervision (supporting); writing – review and editing (supporting). **Sina Khatami:** Conceptualization (supporting); methodology (supporting); visualization (supporting); writing – review and editing (supporting). **Maurizio Mazzoleni:** Conceptualization (supporting); methodology (supporting); writing – review and editing (supporting). **Giuliano Di Baldassarre:** Conceptualization (supporting); funding acquisition (supporting); methodology (supporting); supervision (supporting); visualization (supporting); writing – review and editing (supporting).

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the Notes section of this article.

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RELATED WIREs ARTICLES

Drought indicators revisited: The need for a wider consideration of environment and society

Drought: Progress in broadening its understanding

FURTHER READING

Notes

Note 1: A list of scientific and practical IbF literature from Figure 2.

Practical reports

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Niger (WFP: REAP Project) *REAP: Forecast-based financing (FbF) system for drought*. https://www.anticipation-hub.org/Documents/Case_Studies/REAP_Case_Study-Niger-FINAL.pdf

Zimbabwe and Ethiopia (Red Cross Netherlands) *IBF: Drought impact-based trigger warning model*. https://www.510.global/ibf-drought-trigger-warning-model/

Scientific papers

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