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SPECIAL ISSUE

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Connecting hydrological modelling and forecasting from global to local scales: Perspectives from an international joint virtual workshop

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Abbreviations: C3S, Copernicus climate change service; CDS, climate data store; CEMS, Copernicus emergency management service; CML, commercial microwave links; ConvLSTM, convolutional long short-term memory; DA, data assimilation; DestinE, destination earth; DL, deep learning; EC-HEPEX, early career Hepex; ECMWF, European Centre for medium-range weather forecasts; EFAS, European flood awareness system; EO, Earth observation; ESMs, earth system models; ET, evapotranspiration; FAIR, findable, accessible, interoperable, reusable; GAN, generalised adversarial networks; GCM, global climate model; GFP, global flood partnership; GloFAS, global flood awareness system; GLOFFIS, global flood forecasting information system; HEFS, hydrologic ensemble forecasting system; HEPEX, hydrologic ensemble prediction experiment; HEPS, hydrological ensemble prediction system; I-CISK, innovating climate services through integrating scientific and local Knowledge; LSTM, long short-term memory; ML, machine learning; NWP, numerical weather prediction; PINN, physics-informed neural networks; SSM, surface soil moisture; S2S, sub-seasonal to seasonal; TAMIR, advanced tools for pro-active management of impacts and risks induced by convective weather, heavy rain and flash floods in Europe; TC, tropical cyclone.

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Abstract

The unprecedented progress in ensemble hydro-meteorological modelling and forecasting on a range of temporal and spatial scales, raises a variety of new challenges which formed the theme of the Joint Virtual Workshop, 'Connecting global to local hydrological modelling and forecasting: challenges and scientific advances'. Held from 29 June to 1 July 2021, this workshop was co-organised by the European Centre for Medium-Range Weather Forecasts (ECMWF), the Copernicus Emergency Management (CEMS) and Climate Change (C3S) Services, the Hydrological Ensemble Prediction EXperiment (HEPEX), and the Global Flood Partnership (GFP). This article aims to summarise the state-of-the-art presented at the workshop and provide an early career perspective. Recent advances in hydrological modelling and forecasting, reflections on the use of forecasts for decision-making across scales, and means to minimise new barriers to communication in the virtual format are also discussed. Thematic foci of the workshop included hydrological model development and skill assessment, uncertainty communication, forecasts for early action, co-production of services and incorporation of local knowledge, Earth observation, and data assimilation. Connecting hydrological services to societal needs and local decision-making through effective communication, capacity-building and co-production was identified as critical. Multidisciplinary collaborations emerged as crucial to effectively bring newly developed tools to practice.

KEYWORDS

communication, co-production, earth observation, earth system, forecasting, hydrological modelling, hydrological services, uncertainty

1 | INTRODUCTION

Recent decades have seen unprecedented advances in Earth observation (EO), which has helped transition global-scale hydrology from a data-poor to a data-rich science (Bates, 2012; Di Baldassarre & Uhlenbrook, 2012) and contributed to an enhanced understanding of the water cycle. The increased availability of satellites (e.g., EUMETSAT, SMOS, Sentinel-1, GPM, GRACE), ground-based remote sensing, weather reanalysis, or crowdsourced datasets, with focus on providing global information on the hydrological cycle variables, has given hydrology a more global perspective (Kratzert et al., 2019). However, large-sample hydrology brings additional challenges such as processing, handling and storing large data volumes, integrating multiple data sources, quantifying uncertainties, and linking global observations to relevant local impacts (Nearing et al., 2021). These challenges are particularly important to hydrological modelling and forecasting, and the joint virtual workshop discussed in this article was organised as an effort to jointly reflect on these challenges as a community.

The workshop themed 'Connecting global to local hydrological modelling and forecasting: challenges and scientific advances' (referred to hereafter as 'workshop') was co-organised by the European Centre for Medium-Range Weather Forecasts (ECMWF), the Copernicus Emergency Management (CEMS) and Climate Change (C3S) Services, the Hydrological Ensemble Prediction EXperiment (HEPEX) and the Global Flood Partnership (GFP) from 29 June to 1 July 2021 with over 1000attendees. Calling on the wider hydrological research sphere, it aimed to bring together a diverse

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global community (Figure 1) of scientists, forecasters, disaster managers and stakeholders to discuss recent advances and ongoing water-related challenges. Covering broad aspects across the field from hydrological modelling and uncertainty communication to forecast-based early action, the workshop revealed the attempts of the community to break the boundaries of the state-of-the-art, and to make modelling and forecasting more accessible and useful locally.

As the workshop was scheduled during the COVID-19 pandemic, the organisers were aware of increasing apathy towards online virtual events and the concept of 'Zoom-fatigue' (Shoshan & Wehrt, 2021). To combat the ongoing strains of virtual working, the organisers endeavoured to create a workshop that would be engaging and exciting for attendees, while also providing unique opportunities for networking and knowledge exchange (Keeley et al., 2021). These efforts resulted in a hybrid solution; a mix of live-streamed presentations hosted via Zoom, and interactive events hosted through the Gather.Town platform (Gather, 2021). Gather.Town is a customisable virtual space where participants can move an avatar around the virtual venue and interact with other participants nearby through video call. For this workshop, the Gather.Town space was designed to be a replica of the ECMWF headquarters in Reading, UK (Figure 2). The solution proved to be a huge success, receiving praise from attendees who admired the 'real' human connection they were able to achieve on the virtual platform. The workshop also facilitated many interactive sessions, such as poster presentations, a Sci-Art (science and art) activity, and various information booths on the Climate Data Store (CDS), C3S and CEMS. Informal networking and social events were hosted at the virtual ECMWF in Gather.Town. This resulted in spontaneous and planned splinter meetings. For example, the Early Career HEPEX (EC-HEPEX) meet-up proved to be a popular opportunity to discuss early career perspectives on the state-of-the-art in hydrological forecasting.

Another example of how a virtual environment does not have to be limiting is how the artwork 'Hydrological Constellations' was created (Arnal, 2021). Art can be used not only to communicate science but also to inspire scientists (Halpine, 2008). Prior to the workshop, a short online questionnaire was sent to participants with questions related to their practice and perspectives on hydrological modelling and forecasting. The responses were used to create digital art pieces, transforming clusters of answers into night sky constellations (Figure 3). The artwork was displayed virtually, and participants could form ad hoc groups, leading to spontaneous discussions. These discussions were then added to the digital artwork in the form of storylines behind each constellation/art piece. A full discussion of the art pieces is presented in Arnal (2021).

This article summarises and reviews the achievements of the workshop. It places its focus on five themes at the forefront of global hydrological forecasting (Figure 4), which encompass the wide variety of topics discussed during the workshop. The 90 posters presented at the workshop (Table A1) were grouped in virtual rooms according to these themes, with authors giving a short pitch (2-min duration) during the online Zoom sessions ahead of the interactive poster sessions in Gather.Town. The poster sessions emulated a conference environment and participants were able to move between posters, joining active conversations and discussions around the posters, closely emulating an in-person event.

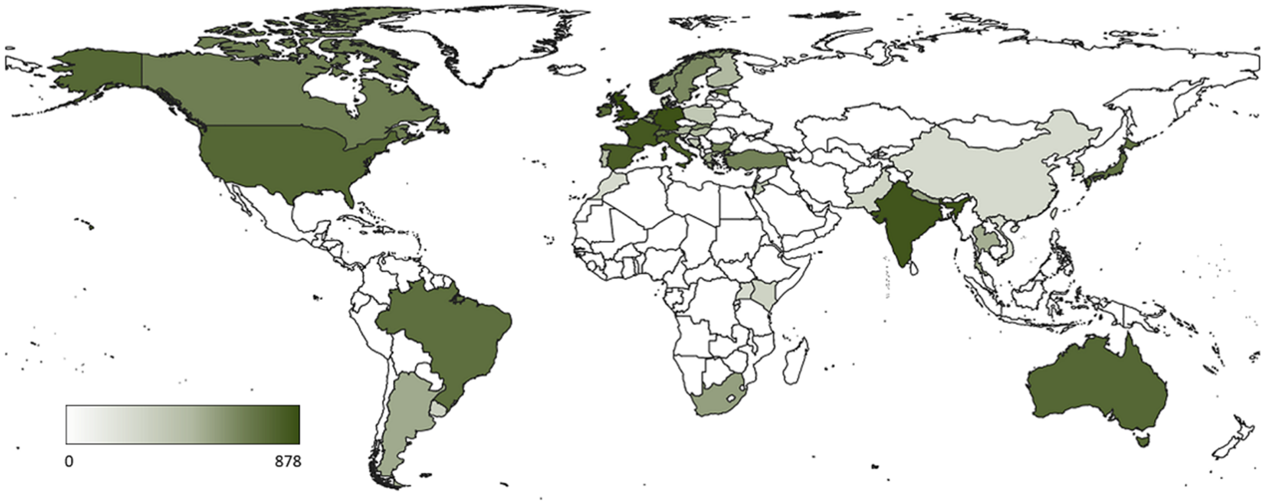

FIGURE 1 Map of the average global views of the workshop (over all 3 days of the workshop, 29 June to 1 July 2021, where darker shading indicates higher views). Attendance was widespread, with 49 countries represented

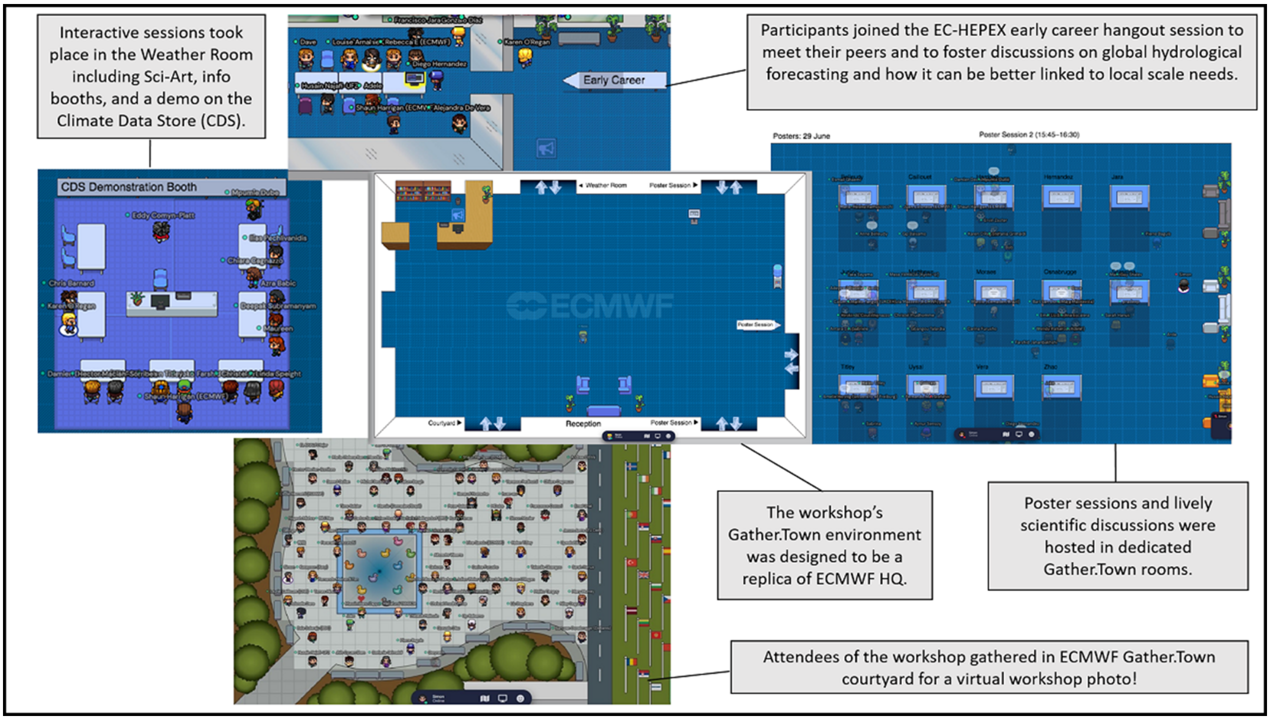

FIGURE 2 Layout of ECMWF's Gather.Town environment for the workshop. Participants joined the sessions to view posters, attend activities, and meet their peers to foster discussions on global hydrological forecasting and how it can be better linked to local scale needs

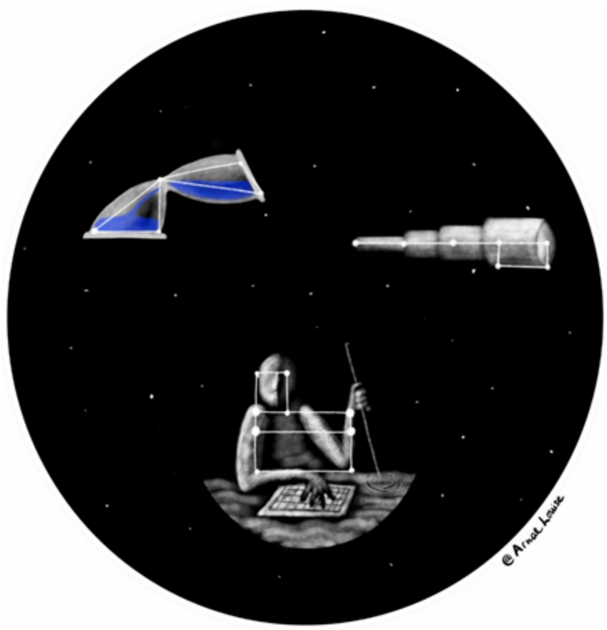

FIGURE 3 The final artwork piece, 'Hydrological Constellations', by Louise Arnal. This science and art piece is a metaphor for reading our destiny in the night sky constellations, and how far we have advanced as a community in terms of predicting future hydro-meteorological events. This art piece was created as part of the interactive virtual sessions of the workshop

In this article, we present the wide range of contributions to the workshop as a microcosm of the work being done by the wider hydrological community globally. The following sections provide a review of the work presented under each of the five key themes (acknowledging that, in many cases, one presentation may contribute to multiple themes). The presentations provide an overview of the challenges and advances in global hydrological modelling and forecasting, and of the research and applications that endeavour to effectively connect these global efforts to local scale decision-making. The sixth theme, 'Earth System Modelling', is woven throughout the five subsections. The final section of this article concludes with a discussion focussing around two questions:

1. How effective was the digital format in representing a broad view and bringing a global audience together?
2. In which direction is the field of global to local hydrological forecasting moving as a whole?

A full list of the contributions is provided in Table A1, detailing the authors of the work and indicating the citation codes used throughout this article. These citation codes follow a format providing the initials of the first author followed by a letter indicating whether the work was presented as a keynote talk [Author Initials-K] or a poster [Author Initials-P] within square brackets. Additionally, where something asserted by a presenter is directly referenced, the citation follows the format Author et al. [Author Initials-K/P]. Published work is cited in the usual way. The presentations and posters can be viewed online at https://events.ecmwf.int/event/222/timetable/.

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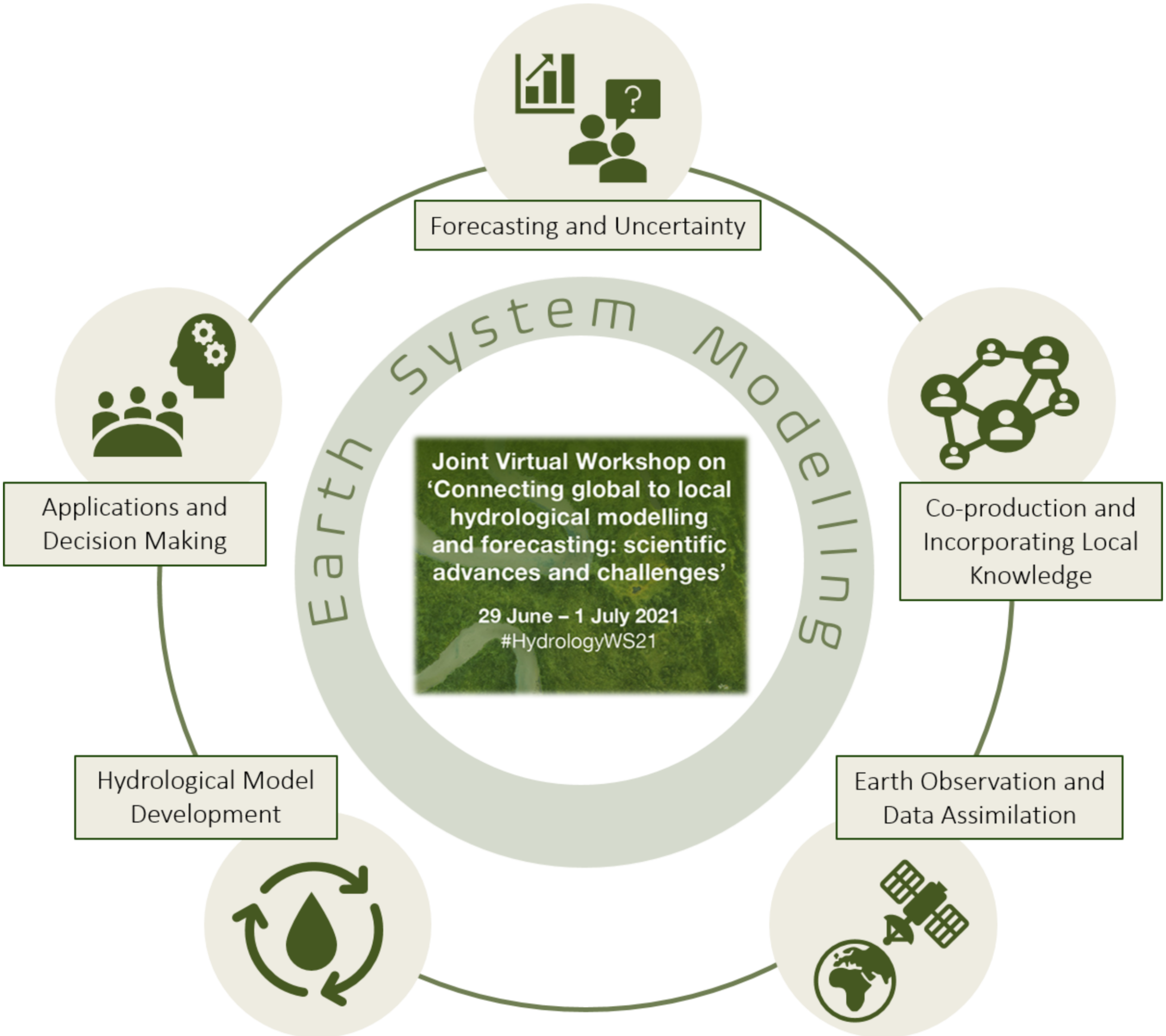

FIGURE 4 Schematic of the workshop's topical organisation. The five themes acted as the pillars of the workshop, while the sixth session, 'Earth System Modelling', was threaded throughout the five topics

2 | FORECASTING AND UNCERTAINTY

2.1 | Predictability and uncertainty

Hydrological forecasting assists many water-related applications in different horizons, helping society understand and mitigate the imminent threat posed by water cycle extremes (e.g., floods and droughts) and facilitating efficient water resources management. Uncertainty is an inherent part of forecasting and can, in hydrology, stem from meteorological forecasts and other input data, hydrological model structure and parameters, and the chaotic nature of our atmosphere (Lorenz, 1969) and Earth system. Uncertainties propagate through the forecasting chain and can degrade forecast quality, potentially leading to inadequate decisions if not quantified correctly (Schaake et al., 2007; Thiboult et al., 2016). However, as Stephens [ES-K] highlighted, accurately quantifying uncertainty is not sufficient if there is not an appropriate understanding and communication of its implications (Demeritt et al., 2013). Therefore, forecast products should be accompanied by systematic analysis of forecast uncertainty (Boelee et al., 2019; Troin et al., 2021). This comprises of identification, classification, quantification, propagation, and communication of uncertainty to users.

Epistemic uncertainty (lack of knowledge) was the most commonly addressed type of uncertainty in the workshop presentations (Figure 5, Table A2). The workshop presented different approaches (e.g., machine learning techniques, multi-model studies, and comparison of

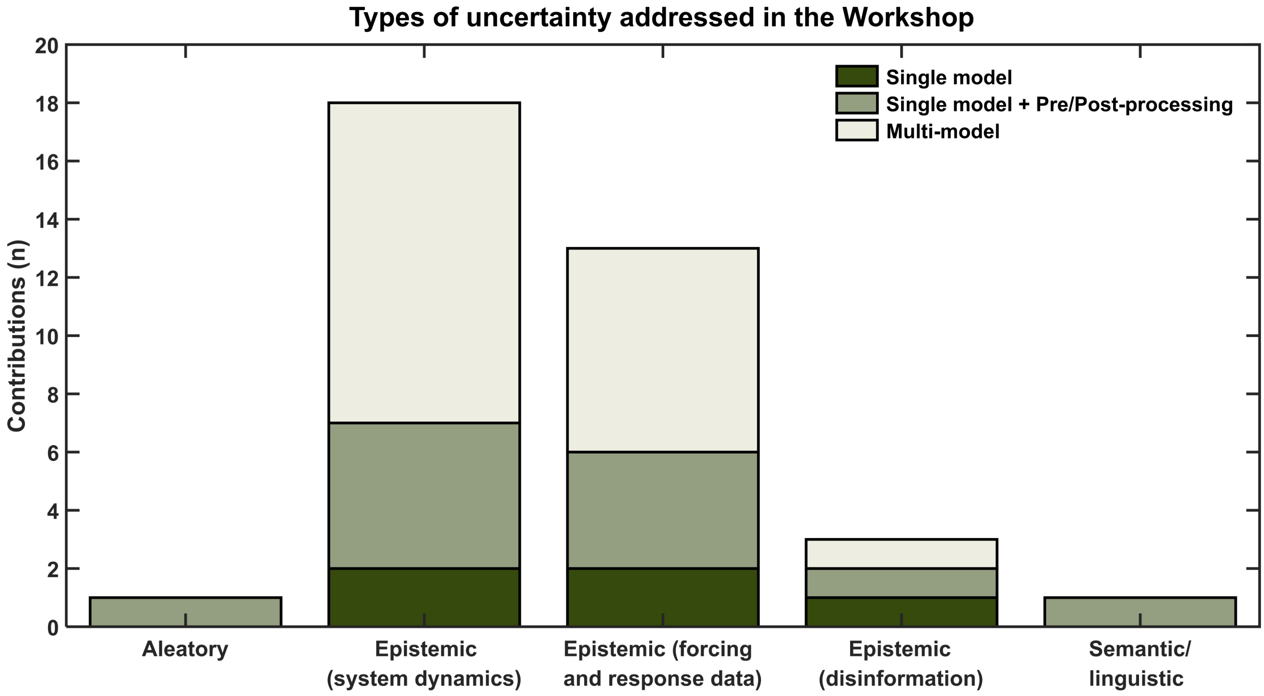

FIGURE 5 The main types of uncertainty tackled at the workshop (aleatory, epistemic, semantic/linguistic) linked to the applied model (single model, single model + pre-/post-processing, multi-model). A more detailed description of the types of uncertainty and the specific contributions linked to each type can be found in Table A2 in the Appendix.

deterministic and probabilistic models) to estimate predictive uncertainty, considering uncertainty sources either separately or holistically.

Understanding the predictive uncertainty of streamflow forecasts, and the sources of forecast skill allows forecasts to be benchmarked ([IP-P; FM-P]; Girons Lopez et al., 2021). This information provides clues about where and when efforts should be made to improve forecast quality and make it valuable for decision-makers ([LA-P]; Pechlivanidis et al., 2020). Several presentations contributed to the understanding of streamflow predictability through a focus on the hydrological-cycle processes [IP-P; LA-P; PD2-P]. Natural processes with high variability have lower predictability (larger uncertainty) and are challenging to simulate. For instance, precipitation has a higher variability than temperature (whose bias is relatively constant, Hagedorn et al., 2008) and was considered as one of the most difficult variables to predict in several studies [PD2-P; FJ-P; AB1-P; JSL-P2]. Therefore, it is crucial to identify the relationship between forecast quality, catchment descriptors, and hydrological signatures [GM-P; MB1-P]. Seasonal forecasts are commonly less skillful in flashy basins or when characterising extreme events [TS-P; IP-PA; B1-P]. In regions where hydrometeorological processes are less dominant (e.g., wet season in tropics) [HMS-P2] or are controlled by slow hydrological responses (e.g., snow and baseflow) [DR-P; TJ-P], forecasts were shown to have higher streamflow predictability. Therefore, given the spatial and temporal variability of streamflow predictability, it is challenging to identify a unique model or system that is applicable everywhere and at multiple temporal scales (see Sections 3 and 5). Nevertheless, operational large-scale models (e.g., GloFAS) attempt to provide globally consistent forecasts, which can be relevant as a tool for global and local decision-making (Section 6).

2.2 | The role of automation in fitness-for-purpose modelling

The usefulness of operational forecasting systems depends not only on the correct representation of hydrometeorological processes but also on cultural, social, and political factors (Pagano et al., 2014). Consequently, the need for operational forecasting services may vary across countries and applications. In her keynote talk, Parker [WP-K] explained the advantages of adopting a fitness-for-purpose approach to evaluation. In this approach, what matters is not how close a model comes to perfectly representing a real system, but whether the model represents the system sufficiently well in those respects that are relevant to the purpose at hand, as well as whether it has other required pragmatic features, such as being understandable by users or computationally efficient (Parker, 2020). This tailored approach suggests building forecast systems that are adaptable to individual circumstances and flexible enough to continuously incorporate newly developed techniques, especially for climate adaptation [AB2-P; LN-P; TB-P]. Moreover, a high degree of automation may enhance the fitness-for-purpose of a forecast system.

One of the highlights of the advances presented at the workshop is that operational systems are undergoing the ‘human over-the-loop’ approach [AW-P; BvO-P1], that is, the forecaster is manually less involved in some of the more technical forecast stages. This has facilitated the transition from deterministic to ensemble approaches [GU-P; DH-P; CPH-P; HN-P; AW-P], since automation allows incorporating more sophisticated pre/post-processing (Section 2.3) and data assimilation techniques (Section 4), running multiple high spatial resolution models (Section 5) and assisting in the verification process [BvO-P2]. Furthermore, automation for generating ensemble forecasts, whose dispersion comes from many sources of uncertainty, provides a more comprehensive estimate of uncertainty about future conditions, facilitating decision-making (Sharma et al., 2019; Valdez et al., 2022). For instance, ensemble systems for flood prediction [FF-P2; GU-P; RH-P; HH-P; HT-P; TS-P] were characterised by higher accuracy at longer lead times and by providing essential spatial information that deterministic approaches might not capture. However, it was also highlighted that combining deterministic and ensemble forecasts can provide complementary information that may facilitate both resilience to hydrological extremes and optimised flow management (e.g., agricultural activities adaptation under water stress conditions, short-term maintenance operations) [LC-P; AB2-P].

A high level of automation not only allows forecast verification to assess the system's ability to capture uncertainty, but also allows the forecaster to focus on tasks where their expertise is paramount—for example, incorporating local knowledge and adapting the system to the user's demands, interpreting model results, and communicating the forecasts with their uncertainties to users (Demeritt et al., 2014).

2.3 | Reducing uncertainty via hydrological pre-/post-processing

Statistical pre- and post-processing techniques characterise the frequency distribution of past prediction errors and apply this information to correct model outputs (Li et al., 2017). Their primary goal is to reduce the biases resulting from partial quantification of hydrometeorological uncertainty. We can differentiate between pre-processing (to reduce meteorological input uncertainty) and post-processing (to reduce the hydrologic model output uncertainty). Pre-/post-processing can result in powerful tools for data scarce studies, especially in mountainous regions [DH-P; FJ-P], for complex systems with multiple applications [HMS-P1; LC-P; CPH-P], for monitoring urban flooding and droughts [AG-P; HN-P], for reservoir operation [WG-P], and for flood risk assessment [AB1-P]. However, their performance is greatly dependent on data availability and hence can be constrained by limited data (in general observational data) for training the processing techniques [LF-P], especially when extreme events are of interest ([TK-P]; Hamill et al., 2015).

Presentations on the advances in pre-processing techniques were centred around increasing the skill of precipitation predictions (especially of intense and rare events) at subseasonal and seasonal scales [HN-P; YS-P; QY-P]. The main goals of the techniques were to reduce the number of model parameters to make them workable with short-term Numerical Weather Prediction (NWP) datasets and to preserve statistically significant observed trends for seasonal forecasts coming from Global Climate Models (GCMs). Concerning post-processing, new techniques were introduced for bias correction [JSL-P1] and error modelling [JB-P]. They provided local corrections of global hydrological models and produced statistically reliable long-range (annual) forecasts for ephemeral rivers [JB-P].

In conclusion, the improvements brought by pre/-post-processing techniques were conditioned on many factors: the catchments' characteristics ([GM-P]; Matthews et al., 2022), the hydrometeorological variable [AC-P], and the method implemented [FJ-P]. In fact, many presentations suggested that selecting suitable methods is rather application-dependent [WP-K; FT-P; WG-P; AB1-P]. In some cases, applying both pre- and post-processing techniques is not feasible in an operational context due to resource limitations; consequently, the selection of only one technique is not trivial (Tiwari et al., 2021; Valdez et al., 2022). Matthews et al. [GM-P] suggested that, at the medium-range time scale, it should be preferred to correct hydrological model errors rather than meteorological forcing errors, if a choice had to be made. However, other studies highlighted that seasonal streamflow forecast skill can be improved and extended by using pre-processing techniques, as climatology and precipitation biases can limit streamflow predictability [LA-P; IP-P; KB2-P]. Bogner et al. (2022) showed that using both pre- and post-processing techniques can extend the skill of streamflow forecasts (below, above, and under normal conditions) up to 1 week ahead, when compared to using pre-processing alone [KB2-P].

2.4 | Effective uncertainty communication

Effective communication of forecast uncertainty is needed in order to translate the technical improvements of the Hydrologic Ensemble Forecasting Systems (HEFS) into practical benefits ([ES-K; WP-K]; Spiegelhalter, 2017). The complexity lies in delivering user-specific information since users typically differ in their background and decision processes, thus requiring different types and amounts of information for decision-making [AG-P; ACER-P; AB2-P].

Uncertainty communication is effective when the information provided to users is simple, clear, relevant, and trustworthy (Thielen-del & Bruen, 2019). Interpreting unnecessary and complex information can be time-consuming, posing an obstacle when a quick response is required. Additionally, forecast literacy varies since different flood decision makers (e.g., farmers, local government officers, civil protection agents) will have different experience and exposure to forecasts. Therefore, products that simplify and summarise information may be more appropriate and preferred. Many interactive and user-tailored platforms were presented at the workshop. Some of them allow the user to choose between different forecast products [DDB-P; CP-P], and others provide quantitative forecasts with either verification [BvO-P2] or uncertainty classification [RH-P], preparing probabilistic forecasts for operational use. Other platforms are designed to train and educate users, representing a valuable tool for operators who lack experience with probabilistic forecasts [SH-P; LN-P].

The evaluation metrics and the visualisations used play an essential role in this aspect since the way in which the information is presented affects the perception of uncertainty ([ES-K]; Demeritt et al., 2019; Pappenberger et al., 2013). The choice of metrics used in emergency response and hazard warning can influence the decisions made [JSL-P1; DH-P; HH-P]. It is also important to use metrics that are appropriate to specific situations (e.g., evaluating event-based flash-flood and flood extent maps) [DPR-P; HHP; RH-P] and translating forecast improvement into monetary benefits ([HMS-P1; QJW-P; KH-P]; Cloke et al., 2017). However, when emergency actions involve the population's cooperation (e.g., evacuations), how uncertainty is addressed is more important than its visualisation [ES-K], since not the entire population has access to a web forecast or TV (e.g., remote areas or rural communities with only radio communication systems).

Creating a system in collaboration with end-users can narrow the forecast uncertainty and improve decision-making [HMS-P1; QJW-P; KH-P]. This exchange allows forecasters to know what information is relevant to users (e.g., data dimensionality, the amount of detail, etc.) and how to represent it to reflect the scientific confidence in the prediction without ambiguity (Stephens et al., 2012). Co-production seems to be pivotal to make the forecast quality-value relationship more direct and to tailor uncertainty communication to the decision needs (Barnhart et al., 2018).

3 | CO-PRODUCTION OF HYDROLOGICAL SERVICES AND INCORPORATION OF LOCAL KNOWLEDGE

3.1 | The hydrological services value chain

At the local level, decisions are made based on multiple knowledge sources (e.g., forecasts, monitoring information, local experiences and knowledge, and environmental signs). In his keynote, Werner [MW-K] argued that building an effective warning service, and providing data/information that is actually used, relies on in-depth understanding of users' knowledge, perceptions, motivations to act, and the options available to them.

The hydrological (climate) services value chain (Figure 6) shows the multiple actors that are involved in the service provision, from (global) data providers to local users. At each step, value is added through contextualising and tailoring data provided, which is purported to lead to better decisions for hazards, water resources, and sectoral information provision (see Section 6 for further discussion on applications and decision-making). The uptake of forecast information and warnings can, however, be limited by challenges in translating scientific information into actionable information that matches the local context and experience of intended users. Effective communication through translators of scientific information (service purveyors) is then a key element of the value chain. Such human-centred services, that is, communicating science-based warnings in the (visual) language that people speak (e.g., using environmental cues, signs that people see outside of their windows) could lead to more people taking action [MW-K], and ongoing research is exploring this, through the concept of Living Labs (Veeckman & Temmerman, 2021) and co-production of research and climate services with the decision-makers and communities using them (Contreras et al., 2020). This advances the current state-of-the-art to user-centred services that are both useful and usable (Vincent et al., 2018), and requires the integration of the knowledge and needs of the users in a reverse direction

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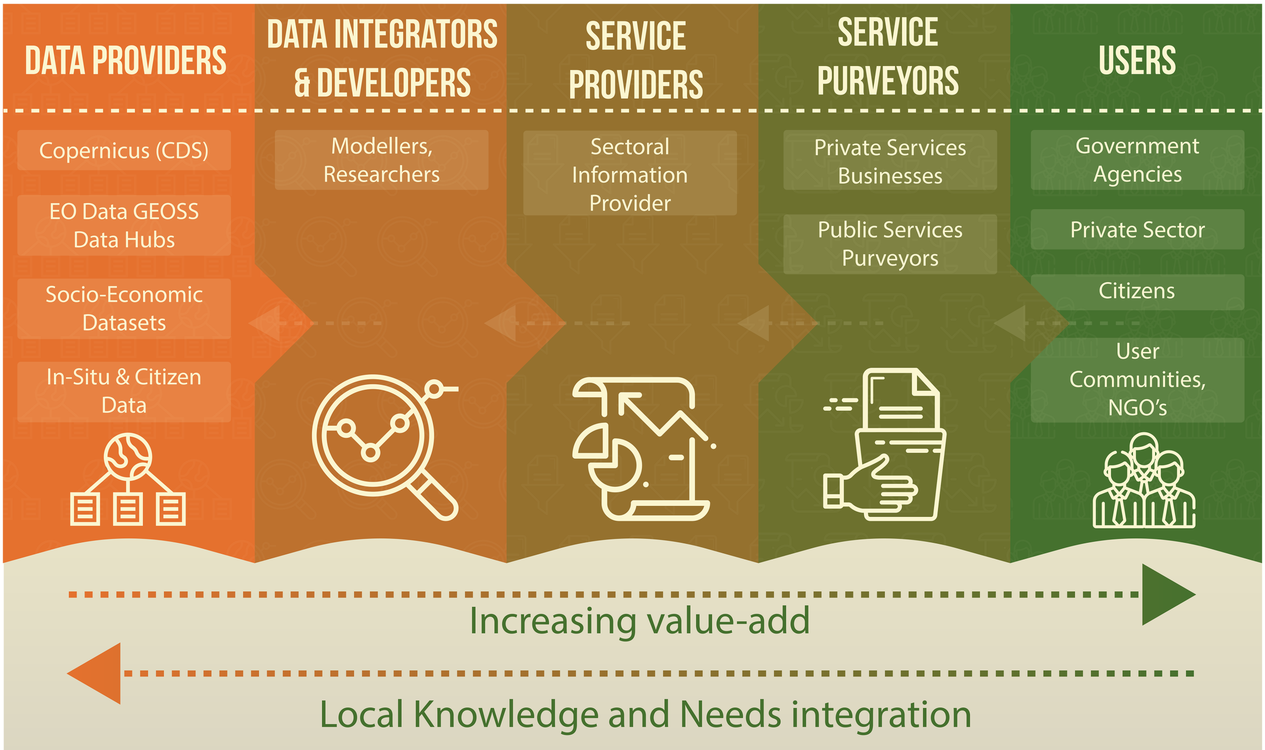

FIGURE 6 Workflow of the 'Climate Services Value Chain', from Werner's keynote presentation [MW-K] and at the core of the EU-H2020 project I-CISK (Innovating Climate services through Integrating Scientific and local Knowledge; https://icisk.eu)

(Figure 6), ultimately all the way through to the providers of climate and hydrological data.

Golding et al. (2019) argue that focussing on the entire weather-related hazard warning chain, and on its connectivity, is key toward implementing more effective warning systems. The chain includes sensor technology, atmospheric, environmental and socio-economic modelling, communication science and behavioural psychology. To develop an evidence-based bi-directional value-add decision-making chain that is fully integrated, multi-disciplinary research and trans-disciplinary research, tools, and data are necessary [MW-K]. This includes science, focus groups, stakeholder interviews, and creative methods such as serious games and storytelling workshops (Crochemore et al., 2021; Van Loon et al., 2020). These interdisciplinary tools can help establish jargon-free communication and effectively contribute to building community resilience to hazards, alongside more traditional methods (Van Loon et al., 2020).

A relevant example is the use of seasonal forecasts and drought warnings by farmers in Malawi ([MW-K]; Calvel et al., 2020; Mittal et al., 2021; Streefkerk et al., 2022). Through focus group discussions, researchers developed an understanding of the seasonal calendar of local farmers' activities. They show that seasonal forecasts are useful to local farmers when the information these forecasts contain focus on environmental cues the farmers recognise locally, such as wind and temperature patterns. Another example is the flash flood warning research by Bucherie et al. (2022). Through community engagement (i.e., community walks through the local area, drawing exercises, and focus group discussions), they demonstrate that local communities have a good understanding of where flash floods happen and their triggers, and that there is a complementarity between (global) scientific datasets and local knowledge that should be harnessed.

The following subsections give an overview of the various forms that co-production and incorporating local knowledge and information can take, exemplified by case studies presented during the workshop.

3.2 | Service co-development

As technical and scientific capabilities evolve, there are a growing number of large-domain forecasting systems available (e.g., the Global Flood Awareness System [GloFAS], the Global Flood Forecasting Information System [GLOFFIS], World-wide Hydrological Predictions for the Environment [HYPE] and the C3S hydrological prediction system; Emerton et al., 2016). Large-domain systems can provide information where there is limited existing capacity locally. Additionally, international centres have the computational power and resources to provide ensemble forecasts for longer lead times, as well as re-forecast and reanalysis datasets to support forecast evaluation. However, national/local forecasting agencies have a better understanding of the local context, the mandates to issue warnings, and links with other national and local agencies [ES-K]. In this context, global–local collaboration is vital. A successful example of a global–national collaboration is between GloFAS and the Bangladesh Flood Forecasting and Warning Centre (FFWC) to develop extended-range forecasting capacity on the Brahmaputra River. In a two-step process, 15-day GloFAS forecasts are used for pre-activation and FFWC forecasts are used for decision-making on shorter lead times of up to 3 days [ES-K].

To ensure that forecast products are useful locally, their design should be informed by users' needs and decision-making context, through regular consultations with users during the product design phase [CB-P; FW-P; WP-K]. Additionally, Baugh et al. [CB-P] argued that product dissemination should be user-tailored so that the most adequate dissemination method (e.g., operational web platform, direct integration into the users' systems) is used. To enhance users' uptake of co-developed products, forecasting centres should complement their operational systems with tools such as user guides, wikis, tutorials, FAQs, support portals, facts sheets, infographics, and visuals of forecast skill assessment [SH-P; LS-P]. Users with more resources may wish to actively participate in the service design. This can be enabled by sharing tools and methods to allow for easy experimentation and integration of developments by local users [BvO-P1].

Predicting usable information (e.g., available water for consumptive use) is a combination of (1) current information (e.g., water available in storage), (2) operational information (e.g., annual releases by a reservoir company), and (3) forecasts (e.g., seasonal forecast of inflows into storage) [MW-K]. While many operational systems provide (1) and (3), operational information (2) is not often incorporated. Several presentations demonstrated the added value of incorporating water management requirements into the development of a forecasting system:

- The use of water supply–demand curves for water allocation in the Murray Darling Basin (Australia) [KH-P].
- The prediction of inflows into storage to the end of season using seasonal forecasts to support decision-making on available water for consumptive use in the Murrumbidgee irrigation District, also in the Murray–Darling basin ([MW-K], Kaune et al., 2020)
- The development of a large-domain modelling framework for ensemble forecasting from which to tailor local to regional water management applications and develop risk-based strategies for operating reservoir systems in the USA [AW-P].
- An assessment of the economic impacts of the implementation of forecast-based allocation rules on the Jucar River system (Spain), using agricultural and hydropower impact measures and environmental status metrics [HMS-P1].
- The promotion of the integrated management of droughts and floods by bringing together various actors (e.g., water agencies, hydrometeorological institutes, energy and transport sectors, civil protection, water users, early warning institutes) in the Madeira River Crisis Room [MdM-P]. This was established in 2015 under the coordination of the Brazilian Water Agency (ANA), in the aftermath of the 2014 Madeira River Basin summer floods.

These presentations demonstrated the potential for improving forecasts by combining hydroclimatic forecasting expertise with local system knowledge. They also highlighted that forecasts are valuable and can lead to economic benefits (Cassagnole et al., 2021), but that there is still room for cooperation between water sectors.

Additionally to incorporating local knowledge, local data is a key element of larger-domain hydrometeorological systems, yet in many cases there are challenges due to confidentiality, lack of standardisation and quality control. Subsequent sections discuss the importance of incorporating local data through, for example, data assimilation (Section 4), model calibration and regionalization approaches to upscale local information (Section 5.2).

3.3 | Application and locally relevant evaluation

There are different perspectives when examining forecast quality (Anctil & Ramos, 2018; Troin et al., 2021; Werner et al., 2018). According to Werner [MW-K] and Stephens [ES-K], forecast evaluation should be user-defined to demonstrate applicability of the forecasts, based on variables of interest and for spatial and temporal scales of interest to users. Several studies presented evaluation results for and/or in collaboration with a specific user and are described in more detail in Section 6. In order to facilitate decision-making and forecast evaluation locally, more international and interdisciplinary data sharing is essential (e.g., through the Copernicus Climate Data Store, CDS 2022) [SH-P].

Local hydro-climatic conditions are important drivers of forecast performance, as shown by Pechlivanidis et al. [IP-P], discussed in Section 2.1. While the availability of global products is vital in data-scarce regions, their quality varies greatly locally. It is therefore important to assess their suitability over regions of interest (relevant presentations include [MW-P; MB1-P]). Bernhofen et al. [MB1-P] assessed the role of global datasets for flood risk management at national and catchment scales. They showed that national flood risk estimates calculated using different global datasets vary significantly, and encouraged the use of a combination of multiple global datasets to report flood risk in order to reduce the uncertainty associated with using a single dataset ([MB1-P]; Bernhofen et al., 2021, 2022). In addition, global datasets should be benchmarked against each other to better understand sources of model bias and uncertainties, and to support their informed application by end-users (Hoch & Trigg, 2019).

Several authors compared global with catchment-based models/systems for water sector applications in various parts of the world [DM2-P; DR-P; FF-P1]. In their comparison of GloFAS and a catchment-based model for flood forecasting in Uganda, Mulangwa et al. [DM2-P] showed that the catchment-based model works better overall for smaller basins, while GloFAS performs better in larger basins (see Section 5.4 for more information). This demonstrates that GloFAS can be used as an interim solution for countries without local forecasts, though only for basins above a certain size. Similarly, Robertson et al. [DR-P] compared catchment-scale forecasts from the Bureau of Meteorology against GloFAS seasonal forecasts for catchments across Australia. They showed that catchment-based forecasts tend to be more skillful and reliable for their specific application, while global forecasts are more skilful when hydrological processes are less important (e.g., wet season in the tropics), and are better at discriminating high and low flow seasons in comparison to actual flow volumes.

4 | EO AND DATA ASSIMILATION

EO provides scale-relevant measurements of hydrological variables, enabling streamflow modelling and forecasting even in data scarce regions [PD1-P]. Connecting EO-based temporally discrete snapshots of dynamic processes, however, requires assimilation into process-based models to characterise their temporal evolution (Figure 7). Hydrological data assimilation (DA) is rapidly evolving to match the unprecedented progress in observation capabilities. It has been frequently applied for state

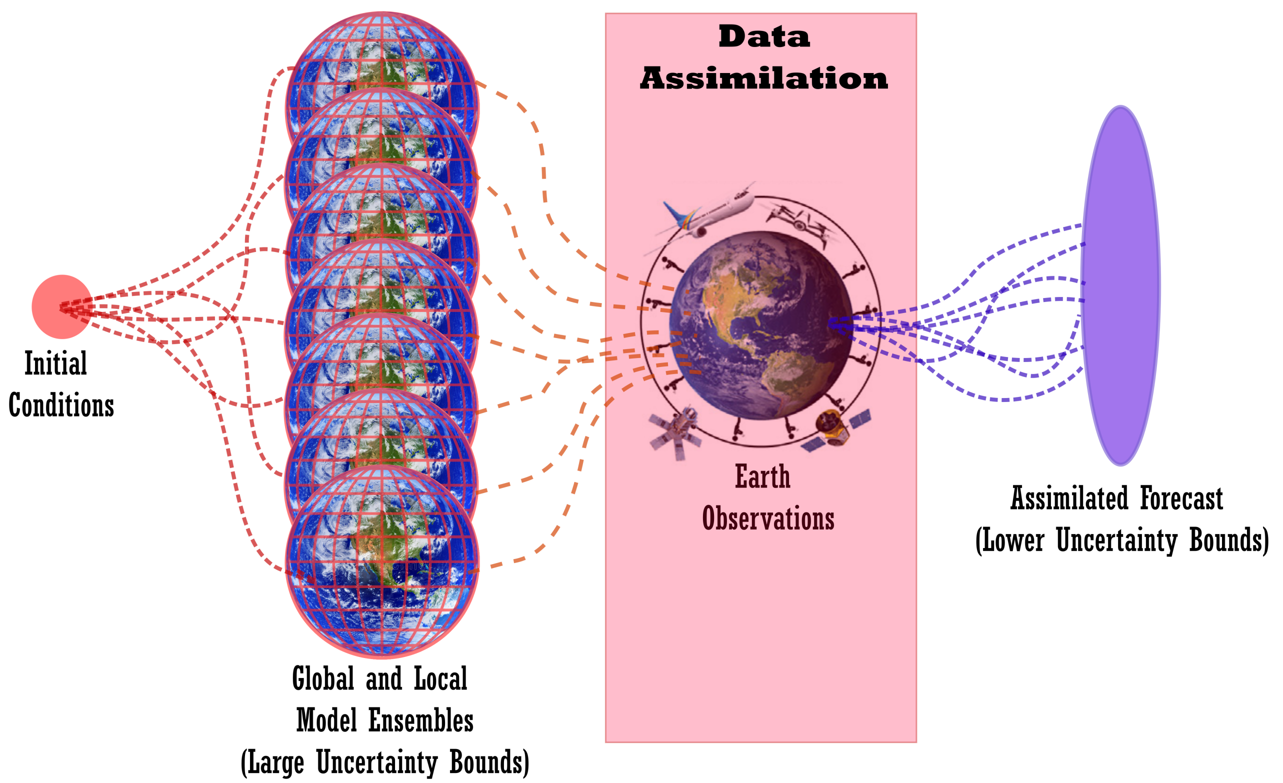

FIGURE 7 Schematic showing the role of Earth observations and data assimilation in the context of modelling and ensemble forecasting

estimation, dynamic parameter estimation, closing the water balance, and uncertainty estimation (Dasgupta et al. 2021). The rise of machine learning (ML), big EO data, and cloud computing, has unlocked new opportunities for the development of next-generation hybrid model-data integration methods (Geer, 2021). This section reviews the state-of-the-art in the field of EO-DA presented at the workshop.

4.1 | Advances in earth observations of the hydrosphere

Schumann [GS-K] introduced the state-of-the-art in the field of EO and DA, highlighting the potential of impact-level forecasting using emerging technologies in EO and big data processing. Satellite imagery is constantly improving in terms of spatial and temporal resolutions, making EO more useful for local-scale applications in hydrology. Rainfall measurement missions on board nanosatellites have recently been launched, leveraging novel sensor technology, which can improve weather forecasts through model-data-integration (Jales et al., 2020). Recent advances in ML have made on-board EO-based flood mapping (Mateo-Garcia et al., 2021), prediction of physically consistent flood observations (Lütjens et al., 2021), and real-time water level forecasting (Google HydroNets) operationally feasible, as shown in Shalev et al. ([GS-P]; Nevo et al., 2022). Lack of appropriate training data for ML and the incorporation of physical principles within ML networks were identified as open challenges, requiring routine evaluation, diagnosis, and domain-knowledge integration to deliver more skillful predictions globally. Furthermore, the large quantities of training data necessary for deep learning (DL) could additionally be sourced from smartphone camera pictures and videos, or from social media, along with leveraging generative models, such as Generalised Adversarial Networks or GANs, to produce synthetic data for data-scarce regions (Bentivoglio et al., 2022). Moreover, Physics Informed Neural Networks (PINNs) also hold promise for flood modelling in combination with methods from deep Gaussian processes or Bayesian neural networks to evaluate model and data uncertainties through probabilistic hazard mapping (Mahesh et al., 2022).

Jurlina et al. [TJ-P] used such domain-knowledge integration, where a Random Forest classifier was trained to predict climatological river flow percentiles. They used a variety of static and dynamic satellite-based inputs, with surface soil moisture (SSM) emerging as the most important feature for shorter lead times. Satellite remote sensing in combination with ML was also used for water budgeting using a variety of inputs (Adedeji et al., 2020), with geology and rainfall emerging as the dominant controls on groundwater recharge and distribution patterns (Orimoloye et al., 2021). EO satellites also enable large-scale observation of evapotranspiration (ET), which is important for closing the water balance in large basins and is challenging to measure in the field. Chen et al. (2021) showcased a new high-resolution multi-source merged satellite ET dataset, prepared by modifying the surface energy balance method, which outperformed existing datasets [XC-P].

EO also provides an invaluable resource for the spatial error assessment of ensemble forecasts, as shown by Hooker et al. [HH-P]. The authors used a normalised spatial map comparison metric to assess the spatial skill of GloFAS forecasts on the Brahmaputra river, providing a comprehensive measure of uncertainty at various scales (Hooker, Dance, et al., 2022b). The Fraction Skill Score, a domain averaged score, was then computed to determine the scale at which the forecast becomes useful, which could help in presenting model outcomes to end-users, or for model development and data assimilation (Hooker et al., 2022b). Such investigations will soon be supported by the CEMS Global Flood Monitoring (GFM; CEMS, 2021) product, as demonstrated by Hostache [RH-P], which provides near real-time and historical flood maps based on Sentinel-1 acquisitions. Unrestricted access to high-accuracy SAR-based flood extent maps alongside estimates of uncertainty will open up new opportunities for model error diagnosis, forecast evaluation, and data assimilation (Dasgupta et al. 2021). Previously, historical flood risk and discharge were calculated using much coarser optical (MODIS) and passive microwave data (AMSR-E/2, TRMM, GPM) by the Dartmouth Flood Observatory, which allowed the assessment of flood exposure over several decades (e.g., Tellman et al., 2021). Kettner et al. [AK-P] showed that the addition of high-resolution SAR and optical data, provided by the Copernicus Sentinel satellites, has further facilitated examining the relationship between flood extents for flow magnitudes corresponding to different return periods.

Despite significant advances in SAR-based flood detection algorithms, the problem of mapping inundation dynamics in urban areas, where most people and assets are located, still remains challenging due to complex scattering mechanisms (Shen et al., 2019). For instance, the GFM product masks these areas out due to the lack of appropriate globally applicable algorithms to detect urban inundation, as discussed in [RH-P]. However, [DM-P] developed a new method for detecting flooding in dense urban areas, using globally available datasets including Sentinel-1 (S1) SAR data, the WorldDEM Digital Surface Model (DSM) and the World Settlement

Footprint data, which could be promising for applications at local scales. The algorithm based on change detection uses pre- and post-flood S1 images to detect flooding in the vicinity of walls aligned within 30° of the satellite track. More details on the method can be found in Mason et al. (2021). While this approach resulted in useful flood extent detection in urban areas, the estimation of the corresponding inundation depths proved to be non-trivial, especially when street widths equalled or exceeded the DSM grid resolution, implying the need for higher resolution datasets.

4.2 | Optimising operational forecasting using EO-DA

It is now well understood that assimilation of satellite-based observations can help to reduce forecast spread and uncertainty when utilising ensemble forecasts (see extensive discussions in Beven, 2009; Cloke & Pappenberger, 2009; Lahoz et al., 2010; Walker & Houser, 2005). A prime example of progress in the field is the European Commission's DestinE programme presented in a keynote by Sandu. This programme aims to develop a highly precise digital model of the Earth (Digital Twin) to monitor and simulate natural and human activity [IS-K]. The possibility of a real-time Earth-system digital twin, which optimally combines simulations and near-real-time observations to monitor the evolution of the Earth system, was only made possible through advances in DA primarily pioneered by the field of meteorology (Bauer et al., 2021). The transition of hydraulic flood modelling from a data-poor to a data-rich science is relatively more recent compared to meteorology, and thus the development of the first flood DA algorithms has only emerged in the last decade. Dasgupta et al. in [AD-P] proposed the use of mutual information as a metric for the assimilation of EO-based flood extents into hydraulic models, and investigated the feasibility of targeted observation design for flood observations. The assimilation was shown to be keenly sensitive towards coverage with respect to reach morphology and timing relative to the flood peak, while the assimilation of one optimal image proved better than the assimilation of multiple suboptimal images.

In a similar effort to optimise EO-DA for operational forecasting in catchments facing persistent freshwater scarcity, Erlingis et al. [JE-P] proposed a novel land data assimilation system for drought monitoring in the Western United States. The assimilation of Leaf Area Index (LAI) was proposed to constrain the dynamic vegetation model within Noah-MP, which led to improved estimates of ET over agricultural regions, in addition to capturing drought severity. Similarly, the Australian Bureau of Meteorology assimilates SSM to forecast the surface water balance in Australia at a variety of spatiotemporal scales [CPH-P]. Comprehensive forecast evaluations showed positive skill scores for SSM and ET predictions with up to 2 months lead time and for runoff with 1 month lead time, resulting from the SSM assimilation. In Germany, the Terrestrial Systems Modelling Platform developed by the Forschungszentrum Jülich [HJHF-P] simulates the coupled terrestrial water and energy cycles using data assimilation of multi-source observations, through a scalable Parallel Data Assimilation Framework, allowing predictions across scales for different applications.

Despite the widespread application of SSM for data assimilation to improve the estimation and forecast of a variety of hydrometeorological variables, the resolution requirements cannot be met due to scale limitations in passive microwave remote sensing. Given the sensitivity of active microwave sensors towards SSM and vegetation water content, SAR backscatter provides a high-resolution alternative for assimilation into high-resolution Land Surface Models (LSMs) to improve state estimation. This novel technique was used for Sentinel-1 (at 1 km resolution) by Bechtold et al. [MB2-P], and ASCAT (at 25 km resolution) backscatter assimilation by Baguis et al. [PB-P]. Assimilation requires designing an observation operator which maps the simulated state variables (such as SSM and LAI) to the observation space (backscatter predictions). The Water Cloud Model was used as the observation operator in these studies, to simulate the backscatter as a function of the vegetation and soil backscatter. The backscatter assimilation resulted in both positive and negative impacts on forecast skill, especially deteriorating the forecast in areas where the LSM simulated erroneous LAI values. However, the approach holds promise for the future by providing methods to integrate high-resolution observations into LSMs. High-resolution observations of SSM and rainfall have long been identified as gaps in generating more accurate hydrological predictions (e.g., Alfieri et al., 2022), and the EO community is constantly working on improving the space–time granularity of satellite hydrology datasets (e.g., Filippucci et al., 2022; Peng, Albergel, et al., 2021; Peng, Tanguy, et al., 2021). The development of such high-resolution backscatter-based assimilation methods is necessary to ensure the quick uptake of these newly produced datasets.

For basins where snowmelt processes dominate runoff, operational forecasting presents substantial challenges due to the complex catchment response towards snow cover variability. To optimise operational streamflow forecasting for Quebec, Canada, Odry et al. [JO-P] proposed Bayesian multi-model forecast merging, but limited sensitivity to the prior distribution was observed and large differences in the skill of different models resulted in insignificant overall improvements from the merging. Yamada et al. [MY-P] showed improvements in water level prediction accuracy by incorporating river cross-section data into a high-resolution rainfall–runoff–inundation model for Japan. MODIS snow products were assimilated into the conceptual hydrological model HBV by Uysal et al. [GU-P] to improve forecasts and increase prediction horizons for the snow-dominated Karasu Basin in Turkey. Similarly, Casson et al. [DC-P] assimilated in situ and remotely sensed observations of fractional snow cover and albedo using perturbed observation Particle and Ensemble Kalman Filters in the North American Rocky Mountains. For Germany, Weier et al. [JW-P] showcased the soon-to-be operational HydPy unified modelling and data assimilation framework, based on OpenDA and Python, which is capable of assimilating multi-source observations and combines several conceptual models.

Altimetry assimilation for streamflow forecasting is set to be revolutionised by the imminent launch of the Surface Water and Ocean Topography (SWOT) satellite mission, which will provide 2D water surface elevation grids for all channels across the world >100 m in width. Pedinotti et al. [VP-P] demonstrated with an application to the Niger and the Congo river basins, the comparative performance assessment of water levels derived from SWOT discharge and water levels from the HydroWeb database, which contains water levels time series of large rivers based on altimetry data. The potential of DA to consistently improve simulated discharge estimates was demonstrated, and observation localization in space and time was shown to be critical for SWOT data.

4.3 | Limits to predictability of hydrological variables

Despite the best attempts to capture scale-dependent dynamic process variability in the current generation of hydrological models, the intrinsic uncertainty of natural processes nevertheless limits predictability. Dimitriadis et al. (2021; [PD2-P]) measured the scale-dependent variability of hydrological processes and found that fractal behaviour is exhibited at small-intermittent scales and long-range dependence is evident at large scales, which indicates low predictability. However, attempts to leverage advances in EO and ML to improve hydrologic predictability persist. For instance, Keppler et al. [RK-P] used a Convolutional Long Short Term Memory network (ConvLSTM) to assimilate streamflow into a distributed hydrological model. While the ConvLSTM improved the forecasts in the absence of input errors, it degraded the forecasts otherwise, due to the abridged input sequence and because the model could not capture long-term soil moisture and snow pack variability. Musuuza et al. [JLM-P] found that the assimilation of a variety of EO-based snow cover and ET products, along with in situ flow measurements, was unable to increase forecast skill during spring and summer due to incomplete snowmelt information and large flow errors. Bahramian et al. [KB1-P] similarly used data assimilation to improve SSM forecasts and found that the forecast improvements persisted for a maximum of 9 days for SSM and up to 16 weeks for the root zone soil moisture, but did not extend to seasonal scales.

5 | IMPROVING HYDROLOGICAL SIMULATIONS

A key tool for hydrologists is the hydrological model itself. However, no model perfectly replicates reality due to limited knowledge of the water cycles processes, and limited computational and data resources. The workshop presented a snapshot of the advances made and challenges faced in developing hydrological models.

5.1 | Physically based model development

Dynamical models are based on the physical laws dictating catchment processes. The increasing availability of data and computational resources has allowed for more complex models (Bates, 2022). Model choice should depend on several factors including intended use, spatio-temporal scale, and available computational resources (Horton et al., 2022; Pechlivanidis et al., 2011). Hence, several hydrological models were used in the presented studies. However, two separate but interlinked pathways for improving physically based model simulations were identified: increasing resolution and model coupling.

Model resolution has been increasing over the past several decades (Bierkens et al., 2015; Hoch et al., 2022; Melsen et al., 2016; Wood et al., 2011), largely facilitated by increases in computational resources (Bauer et al., 2021) and large observational datasets (Beven et al., 2015; Wilby, 2019). Overall, the skill of simulations has improved as a result (Beven et al., 2015; Habibi et al., 2019; Magnusson & Källén, 2013). In her keynote, Sandu [IS-K] outlined three key benefits of high-resolution (or hyper-resolution, $\lesssim$1 km) modelling: (1) more processes are resolved at these scales allowing for more realistic simulations, since some processes no longer need to be represented via parameterisation schemes (Roberts et al., 2018); (2) model resolution will be closer to the scale of observations, which can be both challenging and beneficial for processes such as data assimilation and verification (Crocker et al., 2020; Erlingis et al., 2021; Fiddes et al., 2019); and (3) simulations may be more useful for local decision making on a day to day basis (Habibi et al., 2019). Several presenters showed results from high-resolution models including Munier et al [SM-P], who presented the improved performance of a river routing model after an increase in resolution from 1/2° to 1/12°. Belleflamme et al [AB-P] showed the skill of 10-day and seasonal drought forecasts at a resolution of 600 m for use in the agricultural sector. Flash flood modelling [CB-P, MY-P, TS-P] is also a key area that benefits from (and requires) high-resolution models due to the ability to resolve convection and capture the variability in soil moisture (Hapuarachchi et al., 2011; Lovat et al., 2019). Sayama et al. [TS-P] showed that a 150 m resolution national rainfall-runoff model was able to predict two flash flood events reasonably well, although with large uncertainty in some locations due to the 5 km meteorological forecast being unable to confidently predict the location of the storm (Sayama et al., 2020).

Sandu [IS-K] noted how high-resolution models made scaling effects and computational efficiency key considerations for current and future projects ([GS-P], Bauer et al., 2021; Donahue & Caldwell, 2020; Yepes-Arbós et al., 2022). However, as also noted by Sandu [IS-K], higher resolution may not reduce uncertainty (Beven et al., 2015; Costanza & Maxwell, 1994; Wedi, 2014). On the other hand, technological advancements could allow for larger ensemble forecasting (Cloke & Pappenberger, 2009; Wu et al., 2020), providing valuable information regarding prediction uncertainty (Section 2). Thus, it may be best to focus on increasing ensemble size rather than model resolution in certain applications ([PZ-P]; Scaife et al., 2019).

Due to the complexity of the Earth system, the coupling of models that replicate different components of the water cycle is often required to make realistic simulations (Ning et al., 2019; Xu et al., 2005). Models can be coupled sequentially (one-way coupling) with the output of one model forcing a second model. For example, the outputs from NWP systems are often (both in practice and in many of the workshop presentations) used to drive hydrological models, allowing the forecast horizon to be extended (Bartholmes & Todini, 2005; Cloke & Pappenberger, 2009; Emerton et al., 2016). User-specific models can be coupled to hydrological models in this way to make bespoke forecasts. For example, De Vera et al. [ADV-P] coupled a rainfall-runoff model (GR4J), a routing model (Muskingum), and an electric system model (SimSEE) to produce 7-day forecasts of the optimal dispatch of the G. Terra reservoir (De Vera et al., 2021).

Alternatively, models can be fully coupled (two-way coupling) in an ESM approach, where all relevant aspects of the Earth system including atmospheric, ocean (including waves and sea ice), and terrestrial energy, water and biogeochemical dynamics are interactively coupled (Clark et al., 2015; Harrigan et al., 2020; Steffen et al., 2020). Ideally, human activities are also included in ESMs (Müller-Hansen et al., 2017; Pokhrel et al., 2016). Several presented studies focused on the implementation and evaluation of these fully coupled systems. These highlighted the increasing prominence of Earth system modelling at global ([LS-P; IS-K]; Flato, 2011; Prinn, 2013) and regional ([BN-P; HL-P; HJHF-P; CPH-P]; Giorgi & Gao, 2018; Elizalde et al., 2010) scales. For example, DestinE's 'Digital Twin' (Section 4.2) will combine all parts of the natural environment as well as related human activities in an attempt to capture the mutual feedback processes involved, and potentially to improve simulations [IS-K]. Additionally, it is expected that the hydrological components will be fully coupled to the atmospheric components, made feasible by the high resolution of the models. This will allow, for example, large rivers to impact the surface meteorology by feedback mechanisms ([IS-K]; Boussetta et al., 2021, Ning et al., 2019). Hendricks-Franssen et al. [HJHF-P] presented case studies of the coupled Terrestrial Systems Modelling Platform, which couples the atmospheric ICON model with the CLM land surface model, and the subsurface hydrological model ParFlow. By modelling the coupled terrestrial water and energy cycles, the system is able to predict crop yield, soil moisture, and flash floods with a higher accuracy. Lewis [HL-P] coupled the UK Met Office Unified Model with the land-surface model JULES, and with ocean and marine ecosystem models (NEMO, WWIII, and ERSEM). This resulted in an improved simulation of the vertical salinity and temperature profiles in near-coastal waters compared to climatology.

Coupled models are computationally expensive and their verification is complex (Grimaldi et al., 2019). Additionally, the optimal coupling method is not obvious particularly given the varying spatiotemporal scales at which different processes occur (Gentine et al., 2012). Several frameworks for coupling models have been developed in recent years (e.g., Hoch et al., 2019). Hendricks-Franssen et al. [HF-P] used OASIS-MCT, a model coupling library (Valcke, 2013), in their study allowing them to model all components of the terrestrial system and include a higher resolution sub-domain. Alternatively, Eilander et al. [DE-P] presented a new framework, HydroMT, for coupled modelling of compound flood simulations (Eilander et al., 2022). This open-access framework allows models to be set-up automatically given the appropriate datasets (Eilander & Boisgontier, 2022).

5.2 | Uncertainty in dynamical models

In this section, we discuss model structure and model parameter uncertainty (Moges et al., 2021). Model structure uncertainty may be reduced by increased fidelity of process representation (Section 5.1); however, this may not produce more useful forecasts (Section 2.1). An alternative method, used in several of the presented studies [LS-P; GU-P; FW-P; LN-P; CP-P], is to use a multi-model ensemble (Dion et al., 2021; Troin et al., 2021). In addition to improved forecasts (e.g., [LN-P]), multi-model systems offer opportunities for co-production leading to more usable forecasts ([FW-P], Section 3). However, construction of a multi-model system has many challenges, including the choice of models, communication (Section 2.3) and use of the output (Sections 3.2 and 6.1). The combination of multi-model forecasts is not trivial and is an active area of research (Wan et al., 2021).

Model calibration is used to reduce model parameter uncertainty (Moges et al., 2021; [TBTP-P]). Data scarcity hinders model calibration ([PD1-P]; Beven and Cloke, 2012) at the global [SG-P], continental [CM-P], and catchment scales [DH-P; MW-P]. One approach to overcome data scarcity is the use of alternative data sources, such as reanalysis [MW-P; DH-P], to calibrate the model of interest. However, Wanzala et al. [MW-P] showed that different reanalysis datasets resulted in large variation in predictive skill and affected the robustness of the estimated parameters. Alternatively, increasing EO data (Section 4) could provide the necessary observations for data sparse regions [GS-K].

In large-scale hydrological modelling, regionalisation methods can transfer knowledge from gauged to ungauged basins. Beck et al. (2020; [HB-P]) used transfer equations relating model parameters to catchment and climatic characteristics to yield global parameter maps for the LISFLOOD hydrological model. Alternatively, Seibert et al. ([JS-P]; Pool and Seibert, 2021) used calibrated model parameters of selected gauged catchments for ungauged catchments with similar characteristics. Mazzetti et al. [CM-P] overcame temporal data sparsity, where observations have different temporal resolution to the model, by aggregating the model output to match the daily resolution of the observations.

In some flood forecasting systems, model uncertainty can lead to inconsistencies between forecasts and observation-based flood thresholds. Therefore, some global flood forecasting systems, such as GloFAS, use reanalysis to define the flood threshold to account for these biases. However, Zsoter et al. (2020; [EZ-P]) showed that lead-time dependent ensemble reforecast-based thresholds provide even more reliable and skilful flood forecasts for longer lead-times since biases in the forecast due to the use of NWP models rather than meteorological observations are also accounted for.

5.3 | Data-driven and hybrid methods

Machine learning (ML) techniques have become increasingly common in hydrology over the past couple of decades (Lange & Sippel, 2020; Mosaffa et al., 2022; Mosavi et al., 2018; Shen et al., 2021; Shen & Lawson, 2021; Xu & Liang, 2021). This was accelerated by the progress made in developing deep learning algorithms as well as by an increase in the availability of large hydrological datasets (Shen et al., 2019). The long short-term memory (LSTM) was a popular choice of algorithm in the presented studies [YZ-P; GS-P; RK-P]. The LSTM is a type of neural network that allows the autocorrelation often seen in hydrological variables to be modelled. It is commonly used in hydrology for simulation, forecasting, and hydroclimate predictions (e.g., Kratzert et al., 2018; Le et al., 2019; Natel de Moura et al., 2022). Both Zhou et al. [YZ-P] and Shalev et al. [GS-P] used LSTM models to predict water level and flood inundation. Zhou et al. [YZ-P] found that their deep-learning water-level simulations showed only minor differences to the output from a 2D-hydrodynamic model although they were produced much faster with LSTM (Zhou et al., 2021a, 2021b). The LSTM-generated stage forecasts of Shalev et al. [GS-P] had a high median NSE ($\sim$0.97) across the tested basins. However, Keppler et al. [RK-P] had varying success using an LSTM approach within a data assimilation framework (see Section 4.3). Olusola et al. [AO-P] used the simpler, more computationally inexpensive random forest algorithm to predict the spatial variability of groundwater. They found that geology and rainfall were the variables with the greatest weight in the calculations. Additionally, Forouhar et al. [LF-P] used a Multi-Layer Perceptron Artificial Neural Network to forecast short-term irrigation water demand. They found that, although the forecasts had a skill comparable to previous studies, the lack of inclusion of physical understanding of the system limited the performance of the method. This is a common criticism of ML or statistical methods ([LS-K]; Gilpin et al., 2019; Schmidt et al., 2020; Nearing et al., 2021). Methods such as physics-informed ML (e.g., Bhasme et al., 2021; Herath et al., 2021) have been suggested as potential solutions, although it is acknowledged that more research is needed in this area to constrain ML predictions to physically plausible values ([LS-K]; Kratzert et al., 2019).

While some presentations discussed purely data-driven methods (e.g., [GS-P; AO-P]), there was a strong emphasis on hybrid data-driven and physics-based methods throughout the workshop. During a keynote talk, Slater [LS-K] discussed how the hybrid methods benefit from state-of-the-art developments in ML (e.g., increased speed) and physics-based modelling (e.g., physical understanding of the system). As discussed by Slater [LS-K], the combination of data-driven (particularly ML and deep learning methods) and physics-based methods has the potential to solve some of the outstanding challenges in hydrology, such as incorporating human activity into hydrological simulations and generating seamless predictions across time scales (Slater et al. 2022). Statistical methods can be introduced to dynamical systems throughout the forecasting chain (e.g., data assimilation [RK-P], ensembling [LS-K], post-processing [KB-P; AC-P], and evaluation [IP-P]) to reduce biases, for operational convenience, and to improve nonstationary modelling [LS-K]. However, as ML techniques are introduced into systems, they must be evaluated to ensure robust and plausible forecasts, and be benchmarked against traditional physics-based systems [LS-K].

An example of a hybrid system given by Slater [LS-K] is that of a seasonal streamflow forecast generated by driving a statistical model with the basin-average harvested corn and soybean acreage, and precipitation forecasts from a GCM (Slater et al., 2021). Due to the short training time of the statistical model, these models can be updated regularly to account for changes in land use. Driving ML algorithms with the output from physics-based models is a common hybrid approach (e.g., Frnda et al., 2022; Hauswirth et al., 2022; Hunt et al., 2022). Two other presentations demonstrated the skill of hybrid forecasts created in this way. Jurlina et al [TJ-P] created river flow forecasts for up to 10 days ahead by driving a random forest multiclass classifier with nine catchment characteristics, SMOS and in situ observations, and ECMWF forecasts. Golina et al [SG-P] compared forecasts of seasonal precipitation for the island of Ireland generated by driving a Multiple Linear Regression (MLR) and an Artificial Numerical Network (ANN) with predictors based on ECMWF seasonal hindcasts for mean sea level pressure. While the skill of these forecasts was season dependent, they consistently performed better than purely physics-based forecasts.

5.4 | Model development for forecasting across scales

There are currently several global- and continental-scale hydrological forecasting systems in operation (Emerton et al., 2016). Additionally, many regions are covered by basin or sub-basin scale systems. The benefits and challenges of using systems of both scales are discussed in Section 3.2. In particular, there are knowledge gaps in how forecasting systems at a range of scales can complement each other, and how global forecasting systems can address local needs [DR-P]. To overcome this gap, [BvO-P1] studied how a local forecasting system under development can be used with a global dataset that is designed to be executed on a global scale while supplemented by local information. Additionally, Eilander et al. [DE-P] presented a new framework (HydroMT) to automatically and rapidly set up a flood risk model for compound flooding anywhere around the globe. HydroMT is globally applicable and locally relevant as it is based on globally available data, with the inclusion of local data where available. Alternatively, Odry et al. [JO-P] used Bayesian merging to combine large and local-scale forecasts in Quebec, Canada. The resulting forecasts performed as well as or better than the individual forecasts, while removing the need to look at two separate forecasting systems.

Regardless of forecast accuracy, sufficient lead time is essential to facilitate effective decision-making and preparedness (Bradley et al. 2019). The workshop showcased various presentations aiming to improve both short- and long-term streamflow forecasts. For example, Uysal et al. [GU-P] provide perspectives on advances and developments in improving short-range streamflow forecasts. Arnal et al. [LA-P] presented preliminary results for the Bow River at Banff (Canada), using a workflow designed to quantify streamflow predictability on sub-seasonal to seasonal (S2S) timescales across North America. Both data-driven and process-based techniques are being investigated to produce continental-scale S2S hindcasts and quantify predictability [LA-P]. Such investigations can potentially provide useful science-based information for reservoir operations and water resource management (Section 6.5). Additionally, some studies showed progress in creating temporally seamless forecasts. Caillouet et al. [LC-P] combined deterministic short-range and probabilistic medium-range forecasts with expert knowledge to create a seamless forecast with the aim to optimise flow management decisions. Alternatively, post-processing (Section 2.2) was also utilised to extend the forecast horizon [DM3-P; KB-P].

6 | APPLICATIONS AND DECISION-MAKING

In this section, we summarise hydrological monitoring and forecasting applications and their use in decision making.

6.1 | Anticipatory humanitarian action

Stephens [ES-K] discussed the use of global flood forecasting for anticipatory humanitarian action in her keynote talk. Historically, humanitarian action has typically followed the occurrence of a disaster (Coughlan de Perez et al., 2015). Now, there is a move towards triggering actions based on forecast information at a range of lead times ('Forecast-based Financing' www.forecast-based-financing.org; Stephens et al., 2012; Coughlan de Perez et al., 2017). Stephens discussed a set of rationales for this shift, including the potential to reduce impacts by taking mitigating actions, a drive to better utilise state-of-the-art forecasting science and an increasing interest in bridging the gap between response and adaptation, while improving the cost-effectiveness of aid.

Taking action based on forecasts requires several considerations, including user-driven evaluation to understand forecast skill and reliability (Section 3.3). For example, which forecasting system should be used? While global models are available where no other forecasting system exists, and although they typically use probabilistic approaches, they may not be equally skilful everywhere. It is imperative that forecasts from national services are used first and foremost for disaster risk reduction. They can benefit from local knowledge, and typically hold the mandate to issue warnings (see also Section 3.2). A combination of models can also be beneficial, complementing detailed local forecasts with larger-scale context (e.g., transboundary information), and often longer lead times from global models (Emerton et al., 2016; Hirpa et al., 2018; see Section 5.4). Stephens highlighted the decision-led evaluation of GloFAS forecasts for the Brahmaputra river system, based on required lead times (e.g., 3 days for evacuation, 18 days for agriculture planning), as part of the combined use of GloFAS and local forecasts from the Bangladesh FFWC [ES-K].

Another example where a combination of models can provide complementary information is predicting flooding from tropical cyclones (TCs). Global NWP models can capture large-scale atmospheric flow patterns that influence TC movement, and other factors that influence flood severity (Titley et al., 2021, [HT-P]). Global flood models can add a hydrological perspective to complement the meteorological factors associated with flooding from TCs [HT-P]. There have been several cases where a combination of information from global, regional and national services, and local knowledge from decision-makers, have been used to take humanitarian action ahead of flooding from TCs, such as Idai and Kenneth in Mozambique in 2019 (Emerton et al., 2020). Flood extent maps can also be useful for rapid flood mapping during and following flood events, when humanitarian actors are required to make quick decisions based on knowledge of the areas most at risk.

6.2 | Impact, exposure and risk assessment

A key aspect of improving the application of forecasts across multiple sectors is the move towards impact-based forecasting and provision of risk information, which can assist decision-making by providing valuable context (e.g., number of people at risk or key infrastructure that may be vulnerable including hospitals, access roads, energy infrastructure). An example is the development of flash flood impact forecasts presented by Baugh and Hansford et al. [CB-P; EH-P]. Since flash flood hazard forecasts could highlight a wide area to be at risk of flooding, this work intersects flash flood hazard forecasts with exposure information [EH-P] to produce a risk matrix [CB-P]. A map is provided, colour coded according to the risk matrix, highlighting areas where the greatest impacts might be expected (Figure 8). To ensure applicability, the project engages regularly with forecast users on effective design and dissemination [CB-P] (Section 3.2), which also allowed identification of the most important exposure data to consider [EH-P]. Additionally, Teklesadik et al. [AT-P] combine GloFAS forecasts and flood reports with socio-economic vulnerability and population density data, demonstrating the ability of a global forecasting system to detect flood signals and activate local early action protocols.

While many studies have evaluated differences among global flood models, little research has been done to look at differences in the way population exposure is considered in the models. Hoch et al. [JH-P], combined flood maps with WorldPOP (www.worldpop.org) data on the delta of the Ganges-Brahmaputra river system. It was found that estimates of the number of people affected by flooding differ remarkably depending on the model applied. This was also highlighted by Bernhofen et al. (2022; [MB1-P]), who showed that global datasets can vary significantly at national levels, and the choice of model has a larger impact on population exposure estimates than the choice of the gridded population dataset. They advocate that further work is needed to incorporate locally sourced data and locally calibrated models to test global datasets, and to evaluate which data are most suitable for local use. This highlights a challenge of using global information for local decision-making, and the importance of model choice (Section 5).

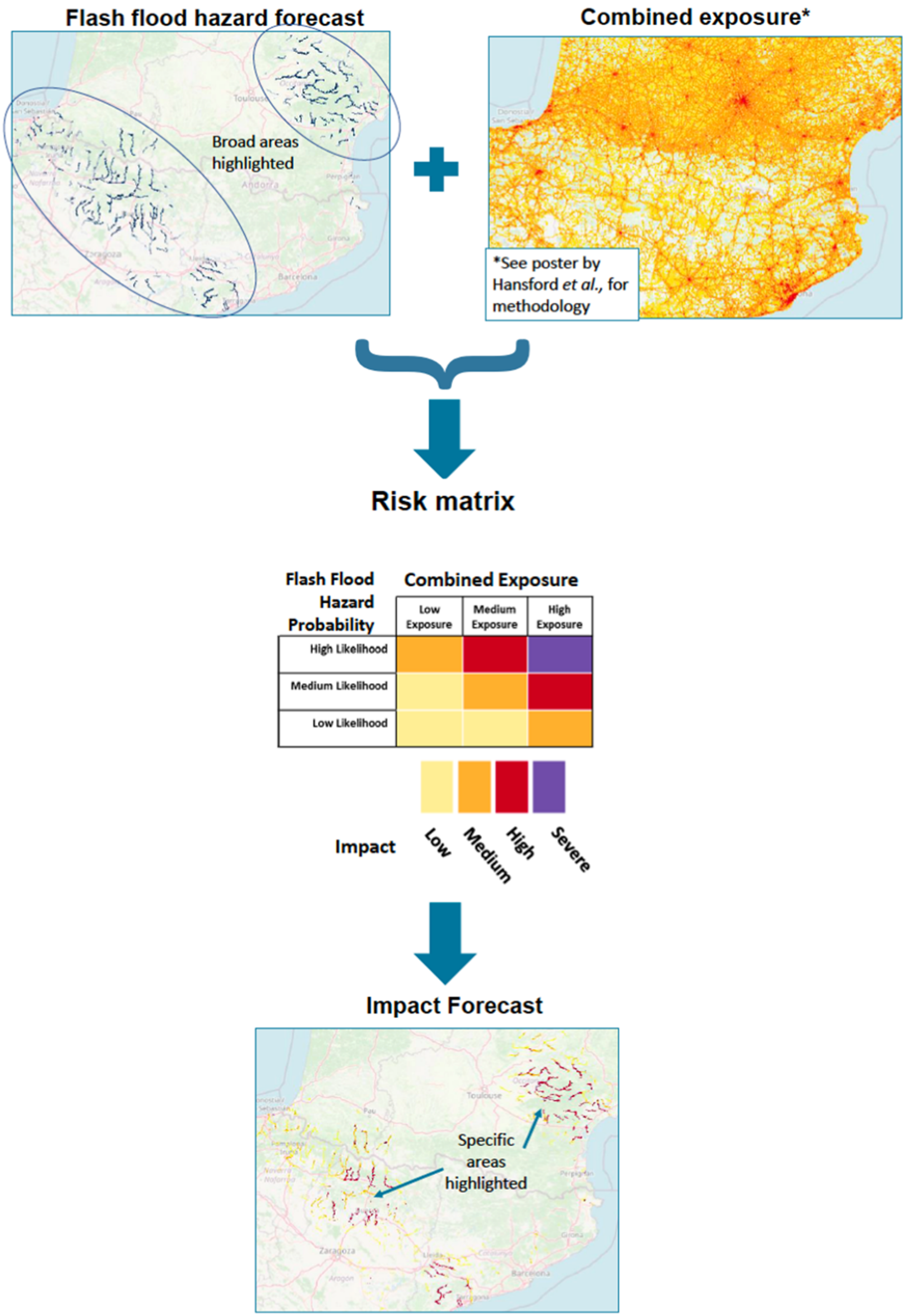

FIGURE 8 Schematic of the procedure for generating flash flood impact forecasts from flood hazard forecasts, exposure information and a risk matrix, as part of the TAMIR project (adapted from Baugh et al. [CB-P], Hansford et al. [EH-P]).

6.3 | Flood forecasting in challenging environments

Several presentations applied global and local data and models for flood forecasting in challenging environments, such as those with complex physiography, climatic conditions or human impact, for example, urban areas or fast-responding mountainous catchments. In such catchments, radar data is often applied for short-term forecasting. Imhoff et al. [RI-P], for instance, used Commercial Microwave Links (CMLs) as an alternative data source for nowcasting. The methods were tested in the Netherlands and it was found that, while radar is better for low rainfall intensities, CML data provided better estimates for more intense rainfall, with the advantage that CML could be used in fast-responding and urban catchments worldwide (Imhoff et al., 2020).

In Israel, a new forecasting system based on the GEO-GloWS streamflow service (GESS; ECMWF, 2020a, 2020b) is being used to predict urban flooding [AG-P]. In Tel Aviv, flooding can occur due to a combination of heavy rainfall, poor drainage, and high water levels in the city's two rivers. Givati et al. [AG-P] used GESS data to compute thresholds for different parts of the city. The approach has been applied successfully in several cities and is used by the Isreali Fire and Rescue Authority and Tel Aviv municipality drainage department, alongside local forecasts, for proactive decision-making. The Madeira Crisis Room [MdM-P] also uses global flood forecasts for decision-making in urban areas, bringing together a range of institutions and uses research with GloFAS to show the importance of a hydrological forecasting system alongside local data for contingency planning.

Another example is the work of ICIMOD (the International Centre for Integrated Mountain Development) in developing flood forecasts for the Chenab basin in Pakistan [PD1-P]. The Chenab is a transboundary tributary of the Indus in a mountainous area vulnerable to flooding and landslides, and with limited local data; it is, therefore, challenging to develop a well-calibrated model tuned to local information. As discussed in Section 4, Dangol et al. [PD1-P] used post-processing of satellite data for assimilation and calibration, exploring the potential of satellite rainfall data for flood prediction in transboundary and data sparse regions.

6.4 | Flood and drought monitoring

Several examples of recent developments using satellite data for flood monitoring were discussed during the workshop, highlighting different approaches. The Dartmouth Flood Observatory (Dartmouth Flood Observatory (DFO), n.d.) provides a range of publicly available maps, data, and information on ongoing and past flood events (see also Section 4.1). A variety of satellite data can be used to estimate flood extent and river flow, and Kettner et al. [AK-P] demonstrated the use of these data to produce flood extent maps for specific locations. These methodologies can be used worldwide, including in regions with a lack of observations or data sharing.

A different approach, implemented by the CEMS GFM products within GloFAS (CEMS, 2021), uses three flood mapping algorithms in parallel, alongside an ensemble algorithm, to create near-real-time maps of flood extent, including maps representing the uncertainty [RH-P]. This approach can also be used regardless of cloud cover or lack of daylight. The work of Mason et al. [DM1-P], also mentioned in Section 4.1, showcases the potential for use of global data for local applications, as their development of a state-of-the-art flood detection method uses data that are readily available worldwide to detect flooding in urban areas, addressing the issue that many remote sensing services are aimed at mapping rural floods due to complicated backscattering mechanisms in urban areas.

Two drought monitoring systems were also presented. The Western Land Data Assimilation System (WLDAS; Erlingis et al., 2021) aims to provide daily estimates of groundwater recharge, soil moisture, snow water equivalent and ET, for applications such as groundwater sustainability and agricultural decision-making in the western USA [JE-P]. An extension of the German Drought Monitor (UFZ, n.d.) was also developed to combine near-real-time observations with extended-range forecasts [HN-P]. This new hydroclimatic forecasting system (HS2S) provides soil moisture forecasts out to 3 weeks and is used for real-time drought monitoring and planning, and in impact assessments for agriculture and energy sectors (UFZ MOSES, n.d.).

6.5 | Modelling and forecasting for water-relevant sectors

An important application of hydrological forecasting is energy and water resource management. Several examples were presented at the workshop, using forecasts on a range of time scales. A coupled rainfall-runoff and electric system simulation approach for Uruguay's largest hydroelectric reservoir was developed to provide daily forecasts out to 7 days ahead [ADV-P]. In Turkey, a multi-model approach is being developed for the upper Euphrates basin, where streamflow forecasting is important for reservoir operations due to high upstream snow potential [GU-P]. Ensemble forecasting methods are utilised to represent the uncertainty and extend the lead time, while two hydrological models with different snow routines are used to reduce the uncertainty. A further example was presented for the Compagnie National du Rhône in France [LC-P], where two hydrological forecasting tools have been developed; an hourly deterministic forecast with a 4-day horizon, and a daily probabilistic forecast with a 14-day horizon. Discussions focussed around working towards coherence between the different tools. Implementing a seamless combined forecast helps to avoid duplication of expertise, eases the work of forecasters and optimises operations for river flow management.

For some applications, longer-range forecasts on the scale of months or seasons are essential. For example, the Requena-Utiel aquifer in Spain is used for vineyards and olive and nut trees, and suffers from overexploitation. A pumping cap is therefore set, based on the type of year (dry/normal/wet). There is a need to predict the type of year expected, to schedule pumping and crop production. Macian-Sorribes et al. [HMS-P2] investigated the skill of seasonal meteorological forecasts in anticipating the type of year. Similarly, several water management agencies in the Murray Darling basin (Australia) use seasonal forecasts for water demand forecasting [KH-P; QJW-P]. In Brazil, medium-range to seasonal forecasts are used operationally for the Brazilian National Interconnected System with more than 150 hydropower plants and reservoirs [FF-P2]. Water users in the Greater Mekong region utilise short and long-term streamflow, sediment and reservoir inflow forecasts [DDB-P]. Another example is the transboundary Yacyretá Hydropower Facility on the Paraná River, between Argentina and Paraguay. Working with the facility, Rodriguez et al. [ACER-P] identified that the main needs for seasonal forecasts are in energy generation planning and maintenance scheduling, with lead times up to 15 months required.

6.6 | Climate trends and adaptation

While most applications focussed on short-range to seasonal timescales, Busker et al. (2021; [TB-P]) presented a work that combines forecast and climate adaptation timescales. Green and blue infrastructure can decrease urban flood risk by increasing storage capacity (e.g., green roofs, permeable pavements, canals, floodplains). The work presented explores the use of blue-green roofs, where plant and water storage layers are combined, and the application of weather forecasts to trigger release of water from the blue layer ahead of extreme rainfall, or to retain water when a dry period is forecast. Such applications can be effective for urban climate adaptations to extreme precipitation and heat events (Busker et al., 2021). Kelder et al. (2020; [TK-P]) highlighted that relatively short precipitation records may not allow for robust detection of short-term (decades, rather than centuries) trends in climate extremes. They applied novel techniques pooling ensemble members of seasonal forecasts to increase the historical record and study decadal changes in precipitation extremes. Further, Kelder, Wanders, et al. (2022) also evaluated the feasibility of simulated climate extremes outside observed variability. They propose a workflow to study rare weather events using the C3S seasonal predictions (Kelder, Marjoribanks, et al., 2022). An example in Western Norway suggests a significant rise in 3-day precipitation extremes for Svalbard, 'such that the 100-year event estimated in 1981 occurs with a return period of around 40 years in 2015' (Kelder et al., 2020).

7 | DISCUSSION

This article has presented an outlook on current research related to hydrological modelling and forecasting from global to local scales. It provides a reflection on the keynotes and poster presentations from the Joint Virtual Workshop on 'Connecting global to local hydrological modelling and forecasting: challenges and scientific advances' from 29 June to 1 July 2021.

This section reflects on two points:

1. How effective was the digital format in representing a broad view and bringing a global audience together?
2. Where is the field of global to local hydrological forecasting moving as a whole?

7.1 | Discussing hydrological science with a virtual global audience

The number of contributions and participants set the stage for a successful event on paper. However, true success of a workshop is measured by engagement. Close to 60% of respondents to a follow-up survey of the event rated the Gather.Town platform as 'excellent', with one participant quoting it as the 'best online experience to date!'. It is this overwhelmingly positive feedback that shows that there is a future for virtual online workshops if designed well. The workshop success can also be quantified in terms of tangible post-workshop outputs. This article is an example of such output, written collaboratively by an international group of young professionals who met through this workshop. Additionally, this workshop allowed for hydro-meteorologists from all around the world to meet and discuss the latest scientific advances with no travel costs and related carbonfootprint, highlighting the viability and importance of virtual workshops to discuss science in the future.

Analysis of the contributions to the workshop shows how the study sites are spread over the globe, with Europe overrepresented and Africa clearly still underrepresented (Figure 9a). Most contributors were from universities and research institutes (Figure 9f), indicating that the outreach into the operational domain could be extended. The main application domain was floods (Figure 9d), showing that hydrological research is still disproportionately leaning towards forecasting floods, which may lead to increased drought vulnerability (Bressers et al., 2016), thus, demanding a conscious shift towards integrated flood and drought management. All different time scales of forecasting were strongly represented except for climate scales (Figure 9e). However, climate projections (forecasts on the climate scale) are not typically considered part of the operational forecasting time scales and therefore researchers may have been dissuaded from presenting by the workshop title. Last, it is notable that regional forecasting applications are still rare and most applications cover the basin scale (Figure 9b).

While the free-to-participate digital format lowers barriers to attendance and offers the inclusion of a much wider audience, some new barriers to communication are introduced (Shoshan & Wehrt, 2021). Our experience shows that these can be minimised through:

- Encouraging spontaneous meetings and the meeting of new people through platform design and by setting up dedicated activities. Here, the Gather.Town space was

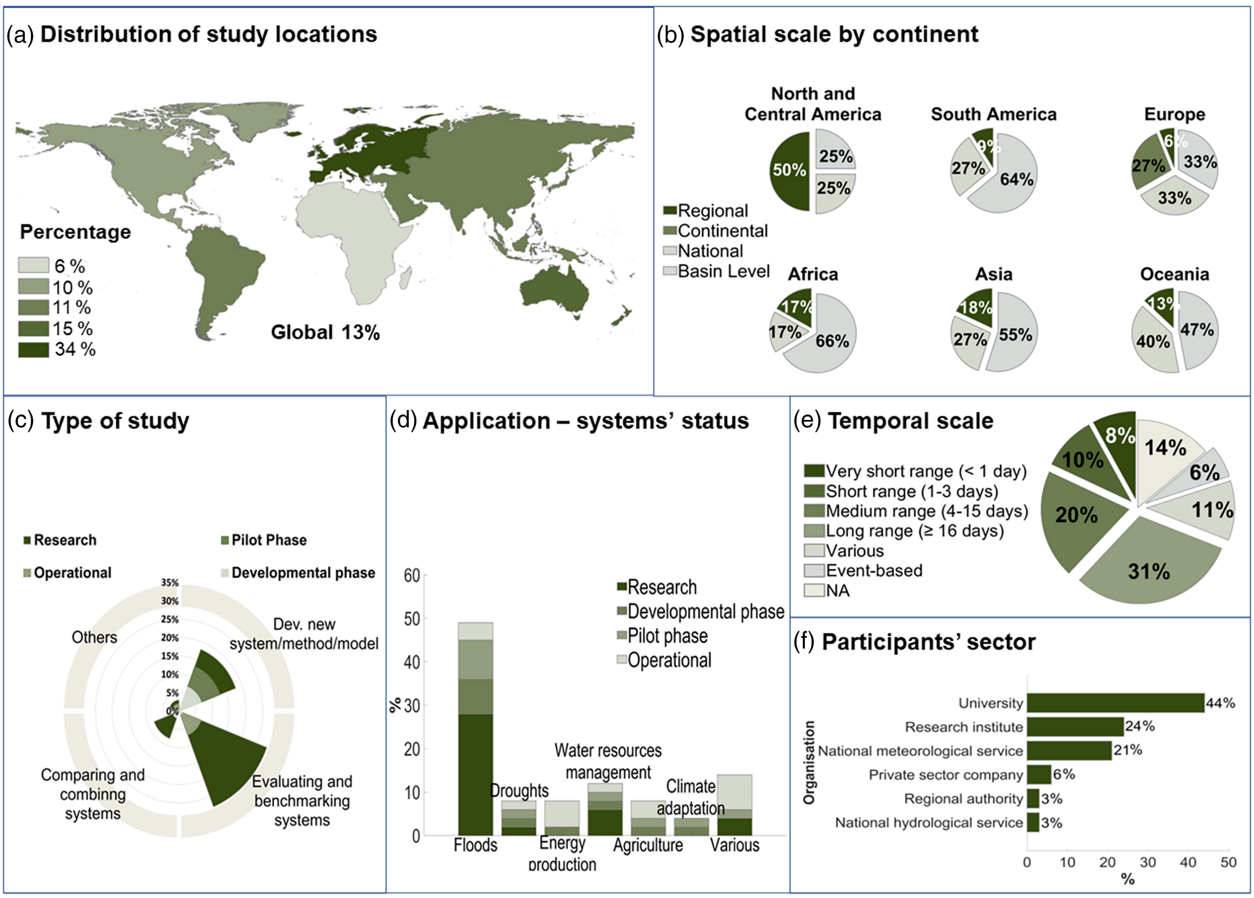

FIGURE 9 In-depth assessment of the research presented at the Workshop. (a) Distribution of study locations (location of study sites in the research presented); (b) Distribution of spatial scales by continent (Basin level: Studies conducted for each basin, Regional: Selection of basins within a country or a continent, National: for entire countries, Continental: for entire continents; (c) Type of study (Development of new system/method/model: Presents or explains a new forecasting system, correction method, or hydrological model, Evaluating and benchmarking: Evaluates the performance or relative value addition of a new system/database/model/technique, Comparing and combining: Combines systems, databases, techniques to improve forecasting performance, Others: studies that do not fit into these categories); (d) Application status in terms of operationalizability (Research: System/method developed without aiming for operational applications, Developmental: System development currently in progress, Pilot: Testing of fully developed systems in operational settings, Operational: System/technique/method operationally implemented); (e) Temporal scale; (f) The presenters' professional sector

designed to be a replica of the ECMWF headquarters located in Reading, UK, offering a sense of place to attendees. The activities included splinter meetings, art, walk-in demos and poster sessions, all of which could be accessed ad-lib and spontaneously.
- Creating entry points to existing networks, and promoting the creation of follow-up initiatives, such as EC-HEPEX for early careers.
- Ensuring that the technological barrier is as small as possible (e.g., stable internet connection and a web browser).
- Moderating the sessions for an efficient management of time during the presentations and an easy-to-follow format for the presentation of the content (e.g., proposing templates for slides or guidance for posters).
- Minimising the mental strain for attendants that comes with organising which link to click or where to follow up.
- Organising the workshop over a limited number of days (here 3 days) to limit 'Zoom fatigue' (Shoshan & Wehrt, 2021).
- Catering to different time zones, with morning and afternoon sessions to increase inclusiveness, making available recordings of presentations and offering several opportunities to meet the authors.
- Thinking about the follow-up: which is easier than ever before through the same set of virtual communication tools (e.g., Slack).
- Keeping attendance free of or with low costs.

Some further improvements were suggested by participants, including:

- The right to be forgotten: be clear on which information will be retained online forever, and to whom and why. There is a tendency in online events to record every session and publish online every contribution. This can raise barriers in openly discussing work that is often still work-in-progress.
- More dedicated emphasis on activities that generate new connections: possibly the success of this workshop owed to the pre-existing networks of attendees, but equally important is to offer room for new networks to be created, bringing new perspectives and topics to the community.

7.2 | Outlook on global to local hydrological modelling and forecasting research

There is a strong desire among the scientific community to contribute to current societal challenges associated with disaster risk reduction, climate change adaptation and changing societal needs. From discussions at the workshop about fit-for-purpose modelling, co-production, local applications and decision making, there seems to be a consensus that the added value of global to local forecasting research is in developing stronger interconnections between research institutes, forecast providers and local users. We expect that in the next decade, the portion of research that is directly related to this challenge will increase. This will make forecasting research more multidisciplinary as the research focus shifts from building new technical tools and techniques towards how those techniques, tools and products interact with the people who use them. Communities such as HEPEX and GFP are volunteer-based and non-funded, but have proved to be excellent places for networking and exchanging scientific ideas in combination with operational practices.

The importance of hydrology to solve societal challenges, and especially the integration of scientific endeavours into operational practice, was recently made clear in the recent efforts on hydrology by the WMO (WMO, World Meteorological Organisation, 2021). In October 2021, the WMO Extraordinary Congress adopted the WMO Water Declaration, which, among others, acknowledges the central role of the water cycle and hydrology in the water-climate-weather continuum and in the five long-term goals of the WMO Strategic Plan (2020–2023); it also endorsed the Water and Climate Coalition which, following also the recommendations of the 2021 WMO State of Climate Services: Water report, aims to provide tangible action, activities and policy support for an integrated water and climate agenda, and to accelerate the implementation of the water-related United Nations Sustainable Development Goals (SDGs). Last, it approved the WMO Vision and Strategy for Hydrology and its associated Action Plan, which target eight long-term ambitions for operational hydrology in support of the global water agenda: (1) No one is surprised by a flood, (2) Everyone is prepared for drought, (3) Hydro-climate and meteorological data support the food security agenda, (4) High-quality data supports science, (5) Science provides a sound basis for operational hydrology, (6) We have a thorough knowledge of the water resources of our world, (7) Sustainable development is supported by hydrological information, and (8) Water quality is known. Note that this action plan highlights societal needs that are directly related to operational hydrological forecasting and points out to the importance of the science-to-operations interface.

A key aspect of forecasting is communicating and ensuring understanding of the forecast and warning information (Budimir et al., 2020). A crucial part of this is understanding and communicating forecast uncertainty (Créton-Cazanave & Lutoff, 2013; Fundel et al., 2019; Pappenberger et al., 2013). There are well-established research paths such as forecast verification, benchmarking and pre- and post-processing tools, all of which are being explored simultaneously by the community. The greatest challenge that remains to operationalising the recently developed tools is that of uncertainty communication. Again this cannot be achieved by technological advancement alone, but through engagement with the end-user through system co-design and the use of creative methods (e.g., serious games, art).

Technical and scientific advances are enabling the development of global hydrological forecasting systems. New data (EO, citizen science, and CML) and data assimilation methods enable the continued push to create high-resolution forecasts relevant for a wide range of local users. It is now that the first systems are truly operational that the question arises: *Who can make use of these systems? To what extent can our still limited forecasts support decision-making now? Do better forecasts necessarily lead to better decisions?* Despite great advances, we still have difficulty in predicting extreme events. We argue that 'waiting for forecasts to be perfect' does not guarantee their use by decision-makers (Ramos et al., 2013) and that connections need to be made now between global systems and local users (see Becker et al., 2015).

Co-production and the incorporation of local knowledge have been identified as a research track that is crucial to study how global forecasting systems can be incorporated into local decision making, and how large-scale systems and data can better use local knowledge and experiences (see Arnal et al., 2020). Part of this process is to identify the 'user'. 'Local users' are a diverse group: *Are we talking about single farmers, or are we talking about national hydrometeorological services?* There is currently limited scope for users (sometimes including national hydrological services) to provide feedback and inform scientific developments of global forecasting systems. There is a need to:

- consider how national capacity can be supported with internationally developed forecasting systems (interim solutions, longer lead times and support ahead of major disasters);
- explore a seamless integration of local short-term and global longer-term forecasts;
- build community ownership of global forecasts;
- learn from and incorporate local knowledge and experiences in the development of large-scale forecasting systems.

The core engine of hydrological forecasting systems remains the hydrological model(s). The established research paths range from 'classic' single process-based or conceptual models and their calibration, to hybrid methods that combine data-driven methods (ML) to solve shortcomings of these classic models, and also multi-model approaches that capture model uncertainties. This large range of research pathways requires cooperation and FAIR (Findable, Accessible, Interoperable, Reusable) data/models exchange (Hutton et al., 2016; Wilkinson et al., 2016) between hydrological modelling groups, large-scale forecast providers and local forecasting agencies, who have to work closely together to build ensembles of multi-model forecasts. Breaking outside of the boundaries of hydrology, ESMs are a way forward not just in hydrology, but in many fields that would benefit from coupled ESMs that are born from collaborative efforts, and from the move towards less of a split between meteorology and hydrology.

The range of applications presented in the workshop and reported in this article showed how the current generation of hydrological forecasting systems is utilised. Forecasting only hydro-meteorological variables is not enough; the move towards impact-based and action-based forecasting (see Merz et al., 2020), complementing forecasts with impact estimates such as expected damage and human consequences, is essential (Merz et al., 2021). Hydrological forecasting becomes intertwined with water and energy management, humanitarian action and climate adaptation. A concern in the application of large-scale forecasting systems is the sustainability of training programs. What happens when a one-off funded project gets discontinued? Continuous connections are important for creating meaningful partnerships with local communities, as well as with local providers and purveyors of forecast services. A balance between continuing support and new initiatives is needed.

The common theme in all these developments is that the field of hydrological modelling and forecasting is becoming increasingly multidisciplinary. Many disciplines are increasingly collaborating as we move towards user-centred and/or Earth System modelling approaches (e.g., Irrgang et al., 2021). In the next decade, the core work of creating new methods and new products needs to be equally balanced by multidisciplinary studies. This includes fostering connections with social sciences to co-create and bring developed tools to practice and closer to users (Hall, 2019), as well as to optimise the positive impact that we as a hydrological forecasting community have on society (Lavers et al., 2020; Wesselink et al., 2017).

8 | CONCLUSIONS

This article reviewed and synthesised the contributions of the global hydrological prediction community to the Joint

Virtual Workshop on 'Connecting global to local hydrological modelling and forecasting: challenges and scientific advances'. Examining the diverse contributions through the lens of Early Career researchers, yielded the following conclusions which are conceptualised alongside the Workshop themes in Figure 10:

I. *Operationalising the Science*: The hydrological community is working actively to operationalise the science behind cutting-edge forecasts, well-aligned with the long-term goals of the WMO Strategic Plan (2020–2023), to improve global resilience towards water extremes.

II. (*Forecast*) *Communication is Key*: Helping decision-makers and end-users interpret forecasts is key in preventing impacts of hydrometeorological disasters, which requires creative solutions such as serious games or art to better engage users and effectively communicate forecast uncertainty.

III. *Users as the First Mile*: Co-production and co-designing forecasting systems with diverse local user groups is necessary to ensure that the forecasts will be used as intended, and will be useful to those relying on these for a variety of applications.

IV. *Data, data, everywhere*: The concurrent rise of Earth Observation, big data processing architectures, data assimilation, and deep learning, provide an opportunity to improve current prediction systems as well as investigate scale-relevant hydrological behaviours. Incorporating domain expertise and making training data/models available to the community by following the FAIR principles could accelerate the pace of advances in the field.

V. *Beyond hydrological forecasts*: Minimising damage from water extremes requires an understanding of expected socioeconomic impacts through impact forecasting, since damage depends only partially on hydrometeorological processes and hazards, and are strongly controlled by societal vulnerability to climate extremes.

VI. *Timing is everything*: Anticipatory action triggered based on impact forecasts is the way forward to effectively mitigate disaster risk, bridge the gap between forecasting science and adaptation, and improve the cost-effectiveness of humanitarian aid. Yet, subjectivity remains in choosing the scale and skill of models used for such applications, as well as the integration of local knowledge and dissemination

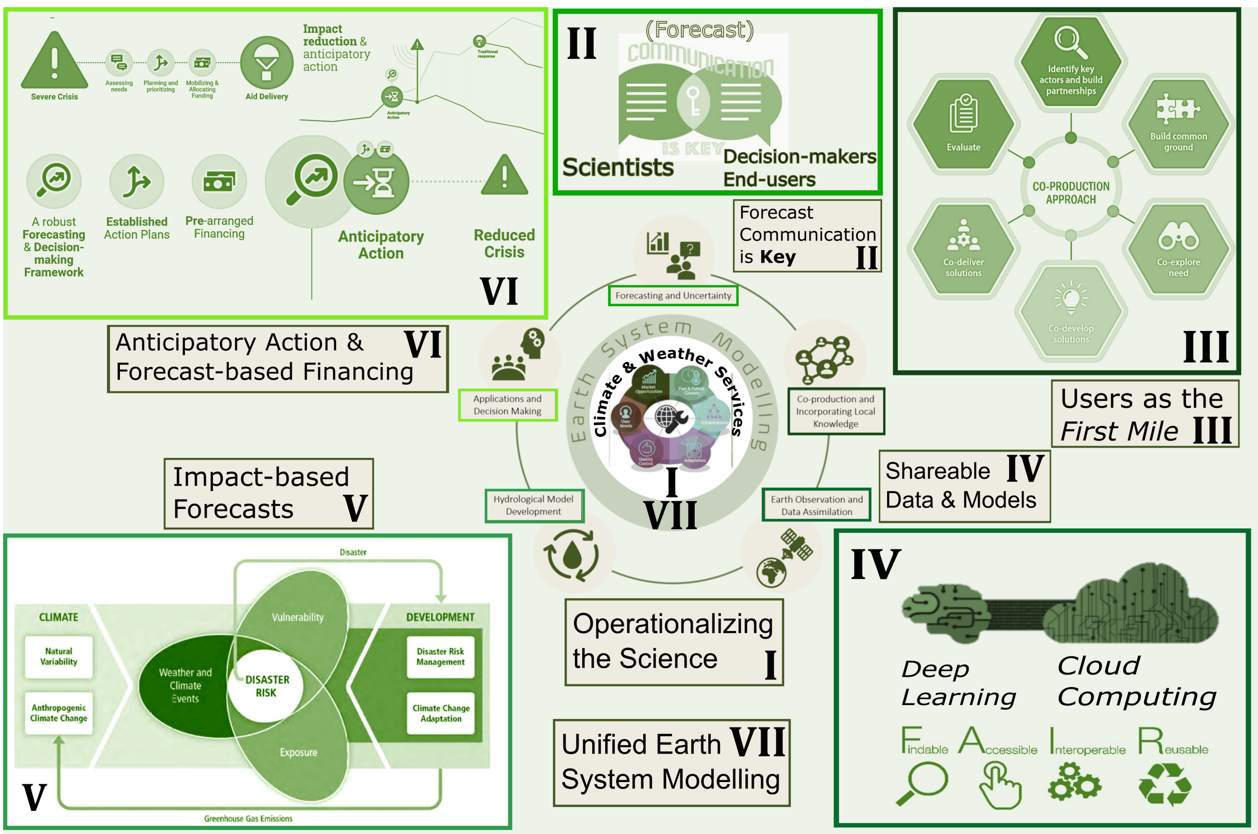

FIGURE 10 Conceptual diagram linking key conclusions with the Workshop themes in the context of Earth system modelling and predictions for weather/climate/hydrological services as outlined in Figure 4. The roman numbers in the figure correspond to similarly numbered conclusions, with key thematic advances pictorially represented, with each coloured box corresponding to a particular theme

systems. Further research on adapting global forecasting services for local-scale anticipatory action is necessary under the current scenario of worsening climate disasters.

VII. *Unified earth system modelling*: As compound disasters become the new normal in a changing climate, understanding their co-occurrence and predicting their unified impacts will be crucial to prepare for the unexpected extremes in the future. There is thus an urgent need for interdisciplinary collaboration and unification of modelling systems, in order to enable forecasting and societal preparedness for such compound and often unexpected events.

We expect that the new digital collaboration possibilities highlighted by the necessity of these during a global pandemic, as well as the rapidly changing landscape of big data computing will enable reaching these goals rapidly in the near future, leading to more skilful and useful hydrological predictions for everyone worldwide.

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DATA AVAILABILITY STATEMENT

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APPENDIX

TABLE A1 Abstracts presented at the workshop and cited in this article

Citation code	Authors	Title	Theme(s)
AB1-P	Anne Belleudy, Camille Debarre, Félicien Zuber	Flood risk assessment on small catchment with ECMWF ensemble forecasts in operational conditions	Forecasting and uncertainty
AB2-P	Alexandre Belleflamme, Niklas Wagner, Klaus Goergen, Stefan Kollet	Forecasting soil moisture at 600 m resolution over Germany using the hydrologic model ParFlow/CLM with ECMWF atmospheric forcing	Forecasting and uncertainty
ACER-P	Ana Cecilia Escalera Rodriguez, Micha Werner, Patricia Trambauer, Mark Hegnauer	Seasonal Hydrological Forecasts for the Yacyretá Hydropower Facility	Forecasting and uncertainty; applications and decision-making
AD-P	Antara Dasgupta, Renaud Hostache, Raaj Ramsankaran, Stefania Grimaldi, Guy Schumann, Valentijn Pauwels, Jeffrey P. Walker	Leveraging Earth Observation and Data Assimilation to Optimise Flood Inundation Forecasting	Earth observation and data assimilation
ADV-P	Alejandra De Vera, Guillermo Flieller, Ruben Chaer, Rafael Terra	Integrating hydrological ensemble forecasts into decision support tools for operation of the electric system in Uruguay	Applications and decision-making
AG-P	Amir Givati, Jorge Sanchez Lozano	Using the GEOGloWS ECMWF Streamflow Services for forecasting inundations and urban flooding in Israel	Forecasting and uncertainty; applications and decision-making
AK-P	Albert Kettner, Bob Brakenridge, Sagy Cohen	Utilising MODIS imagery and multi-platform microwave brightness temperature to constrain flood frequency	Applications and decision-making; Earth observation and data assimilation
AO-P	Adeyemi Olusola, Samuel Adelabu	Delineating groundwater occurrence and patterns within the Free State Province, South Africa	Hydrological model development
AT-P	Aklilu Teklesadik, Marc van den Homberg, Stefania Giodini, Aderajew Ferede, Henok Wondimu, Liz Stephens	Evaluating the forecast skill of GloFAS ensemble river discharge hindcasts for different lead times using impact data; a case study for Ethiopia	Applications and decision-making
AW-P	Andy Wood	Over-the-loop ensemble forecasting for risk-based reservoir operations in the US	Forecasting and uncertainty; co-production and incorporating local knowledge
BN-P	Bibi Naz, Wendy Sharples, Stefan Kollet, Klaus Goergen	A sensitivity analysis of hydrological states and fluxes to groundwater representation in pan-European multimodel simulations.	Hydrological model development
BvO-P1	Bart van Osnabrugge, Arianna Onate-Paladines, Jan Verkade, Albrecht Weerts, Matthijs den Toom	Deployment automation of hydrological forecasting systems on a global scale	Forecasting and uncertainty; co-production and incorporating local knowledge; hydrological model development

(Continues)

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
BvO-P2	Bart van Osnabrugge, Jan Verkade	Enabling hydrological (ensemble) verification as part of standard operational practice at operational centres around the world	Forecasting and uncertainty
CB-P	Calum Baugh, Eleanor Hansford, Christel Prudhomme, Corentin Carton de Wiart, Paolo Battino, Martin Blick, Marc Berenguer, Shinju Park	The challenges of making seamless pan-European flash flood impact forecasts useful for local decision making	Co-production and incorporating local knowledge; applications and decision-making
CM-P	Cinzia Mazzetti, Damien Decremer, Christel Prudhomme	Challenges of the European Flood Awareness System (EFAS) hydrological calibration	Hydrological model development
CP-P	Charles Perrin	Integrated chain for the hydrometeorological forecasting of low flows and droughts in France—The CIPRHES project	Forecasting and uncertainty; hydrological model development
CPH-P	Christopher Pickett-Heaps, Elisabeth Vogel, Julien Lerat, Zaved Khan, Andrew Frost, Chantal Donnelly, Katayoon Bahramian, Ashkan Shokri, Robert C Pipunic, Sean Loh, Aidan Griffiths, Kevin Plastow, Greg Kociuba, Vi Co Duong	Ensemble forecasts for soil moisture, evapotranspiration and runoff across Australia—verification and applications	Forecasting and uncertainty; Earth observation and data assimilation; hydrological model development
DC-P	Dave Casson, Martyn Clark, Louise Arnal, Wouter Knoben, Guoqiang Tang	Ensemble Snow Data Assimilation Methods for Streamflow Forecasting	Earth observation and data assimilation
DDB-P	Du Duong Bui, Tien Thuy Le Du, Patrick Willems, Thao Bui Thi Phuong, Son Do, Van Hung Hoang, Sheffield Justin, Ribbe Lars, Hyongki Lee, Salim Nidal, Shrestha Sangam, Darby Stephen, Sumi Tetsuya, Lakshmi Venkataraman, Phil Graham, Hong Van Pham, Pechlivanidis Ilias G., Quang Chien Nguyen	Development of a web-based decision support system (DSS) for water resources management in Vietnam and Mekong region	Forecasting & uncertainty; applications and decision-making
DE-P	Dirk Eilander, Anaïs Couasnon, Tim Leijnse, Hessel Winsemius, Philip Ward	Towards globally applicable and locally relevant compound flood simulations	Hydrological model development
DH-P	Diego Hernandez, Francisco Jara, Pablo Mendoza, María Ignacia Orell, James McPhee	Development of a medium-range ensemble streamflow forecasting system in a suite of Andean catchments	Forecasting and uncertainty; hydrological model development
DM1-P	David Mason, Sarah Dance, Hannah Cloke	Floodwater detection in urban areas using Sentinel-1 and WorldDEM data	Earth observation and data assimilation; applications and decision-making
DM2-P	Douglas Mulangwa, Andrea Ficchi, Philip Nyenje M., Jotham Sempewo, Linda Speight, Hannah Cloke, Shaun Harrigan, Benon Zaake T., Liz Stephens	Comparative Suitability of the Global Flood Awareness System and a Catchment-based Model to Simulate and Predict Floods in Uganda	Co-production and incorporating local knowledge

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
DM3-P	David McInerney	Multi-temporal Hydrological Residual Error Modelling for Seamless Subseasonal Streamflow Forecasting	Hydrological model development
DPR-P	Daniela Peredo-Ramirez, Maria-Helena Ramos, Hugo Marchal, François Bouttier	Challenges of event-based evaluation of flash floods: example of the October 2018 flood event in the Aude catchment in France	Forecasting and uncertainty
DR-P	David Robertson, Shaun Harrigan, Fitsum Woldemeskel, Urooj Khan, Ervin Zsoter, Narendra Tuteja	Understanding the current gaps between global and catchment scale seasonal and short-term streamflow forecasts	Forecasting and uncertainty; co-production and incorporating local knowledge; hydrological model development
EH-P	Eleanor Hansford, Calum Baugh, Christel Prudhomme	Combining pan-European flood hazard forecasts with exposure information to enhance local decision making	Applications and decision-making
ES-K	Liz Stephens	Global flood forecasting for anticipatory humanitarian action	Forecasting and uncertainty; co-production and incorporating local knowledge; applications and decision-making
EZ-P	Ervin Zsoter, Christel Prudhomme, Liz Stephens, Florian Pappenberger, Hannah Cloke	Using ensemble re-forecasts to generate flood thresholds for improved global flood forecasting	Hydrological model development
FF-P1	Fernando Fan, Alexandre Abdalla Araujo, Vinicius Siqueira, Ayan Fleischmann, Rodrigo Paiva, Maria Eduarda Alves, Gabriel Matte Rios, Leonardo Laipelt, João Paulo F. Breda	Continental versus regional scale flood inundation modelling estimates for southern South America	Co-production and incorporating local knowledge
FF-P2	Fernando Fan, Cassia Aver, Camila Freitas, Reinaldo Silveira, Walter Collischonn, André Campos, José Eduardo Gonçalves, Arlan Scortegagna, Rodrigo Paiva, Vinicius Siqueira, Ingrid Petry, Cleber Gama, Erik Quedi	Medium- to seasonal-range streamflow forecasting for the hydropower dams of the Brazilian National Interconnected System	Forecasting and uncertainty; applications and decision-making
FJ-P	Francisco Jara, Diego Hernandez, Pablo Mendoza, María Ignacia Orell, James McPhee	An assessment of raw and post-processed GEFS precipitation re-forecasts in the Maule River basin, Chile	Forecasting and uncertainty
FM-P	Francesca Moschini, Shaun Harrigan, Ervin Zsoter, Christel Prudhomme	Benchmarking hydrological model performance of GloFAS v3 against GloFAS v2	Forecasting and uncertainty
FT-P	Faranak Tootoonchi, Jan Olaf Mirko Haerter, Olle Raty, Thomas Grabs, Claudia Teutschbein	Advances and challenges in the past decade: from univariate to multivariate bias adjustment of climate models for impact studies	Forecasting and uncertainty
FW-P	Fredrik Wetterhall, Umberto Modigliani, Milan Dacic, Sari Lappi	Challenges in setting up a multi-model hydrometeorological forecasting system—lessons learned from the SEE-MHEWS-A project	Co-production and incorporating local knowledge; hydrological model development

(Continues)

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
GM-P	Gwyneth Matthews, Hannah Cloke, Sarah Dance, Christel Prudhomme	Evaluating the post-processing of the European Flood Awareness System's continental scale streamflow forecasts	Forecasting and uncertainty
GS-K	Guy Schumann	Advances in new EO technologies and computer modelling could soon enable better flood forecasting at impact-level scale	Earth observation and data assimilation; hydrological model development
GS-P	Guy Shalev, Morin Efrat, Grey Nearing, Sella Nevo	Google's Flood Forecasting Initiative: Globally-Scalable Models for Hyper-Local Information	Earth observation and data assimilation; hydrological model development
GU-P	Gokcen Uysal, Aynur Sensoy Sorman, Ali Arda Sorman, Mustafa Cansaran Ertas	Short-Range Streamflow Forecasting Using Multi-Models Over Snow Dominated Basin In Turkey	Forecasting and uncertainty; Earth observation and data assimilation; hydrological model development; applications and decision-making
HB-P	Hylke Beck, Stefania Grimaldi, Peter Salamon	Global high-resolution regionalized parameter maps for LISFLOOD based on observed streamflow from over 4000 headwater catchments	Forecasting and uncertainty; hydrological model development
HH-P	Helen Hooker, Sarah Dance, David Mason, John Bevington, Kay Shelton	An evaluation of ensemble flood inundation mapping spatial skill	Forecasting and uncertainty; co-production and incorporating local knowledge; Earth observation and data assimilation
HJHF-P	Harrie-Jan Hendricks-Franssen, Alexandre Belleflamme, Theresa Boas, Daniel Caviedes-Voullieme, Abouzar Ghasemi, Klaus Goergen, Johannes Keller, Stefan Kollet, Ulrich Löhnert, Silke Trömel, Niklas Wagner	Predicting the complete coupled terrestrial water and energy cycles	Earth observation and data assimilation; hydrological model development
HL-P	Huw Lewis	A regional coupled approach to water cycle prediction during winter 2013/2014 in the United Kingdom	Hydrological model development
HMS-P1	Hector Macian-Sorribes, Patricia Marcos-Garcia, Ilias Pechlivanidis, Louise Crochemore, Manuel Pulido-Velazquez	Estimating the benefits brought by seasonal forecasts on the management of the Water-Energy-Food nexus in the Jucar river system	Forecasting and uncertainty; co-production and incorporating local knowledge
HMS-P2	Hector Macian-Sorribes, Esther Lopez-Perez, Adria Rubio-Martin, Alberto Garcia-Prats, Manuel Pulido-Velazquez	Skill of seasonal meteorological forecasts from the Copernicus Climate Change Service to foresee groundwater pumping allocation in an overexploited Mediterranean aquifer	Forecasting and uncertainty; applications and decision-making
HN-P	Husain Najafi, Luis Samaniego, Stephan Thober, Oldrich Rakovec, Pallav Kumar Shrestha	Ensemble Forecasting of Drought over Germany at Sub-seasonal Time Scale	Forecasting and uncertainty; applications and decision-making
HT-P	Helen Titley, Hannah Cloke, Liz Stephens, Ervin Zsoter, Shaun Harrigan, Florian Pappenberger, Christel Prudhomme, Joanne Robbins	An ensemble-based method for investigating the predictability of fluvial flooding from tropical cyclones	Forecasting and uncertainty; applications and decision-making

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
IP-P	Ilias Pechlivanidis, Louise Crochemore, Marc Girons Lopez	Seasonal hydrological forecasting across scales: similarity patterns and attribution of forecast quality	Forecasting and uncertainty; co-production and incorporating local knowledge; hydrological model development
IS-K	Irina Sandu	The European Commission Destination Earth Programme	Earth observation and data assimilation; hydrological model development
JB-P	James Bennett	Error modelling for long-range ensemble forecasts of flow in highly ephemeral rivers	Forecasting and uncertainty
JE-P	Jessica Erlingis, Matthew Rodell, Christa Peters-Lidard, Bailing Li, Sujay Kumar	A High-Resolution Land Data Assimilation System Optimised for Drought Monitoring in the Western United States	Earth observation and data assimilation; applications and decision-making
JH-P	Jannis Hoch	Unravelling the interplay between flood model selection, simulations outcomes, and resulting flood risk—a case study in the Ganges–Brahmaputra delta	Applications and decision-making
JLM-P	Jude Lubega Musuuza, Louise Crochemore, Ilias Pechlivanidis	Does the assimilation of earth observations and in situ data affect the seasonal hydrological forecast quality?	Earth observation and data assimilation
JO-P	Jean Odry, Marie-Amélie Boucher, Vincent Fortin, Simon Lachance-Cloutier, Richard Turcotte, Dominic Roussel	Bayesian merging of large-scale and local hydrological forecasts	Earth observation and data assimilation; hydrological model development
JS-P	Jan Seibert and Marc Vis	A few hundred catchments later—lessons from modelling large samples of catchments around the globe	Hydrological model development
JSL-P1	Jorge Sanchez Lozano, Giovanni Romero Bustamante, Jim Nelson, Gustavious Williams, Alma Meyer, Riley Hales, Daniel Ames, Norm Jones	From Global to Local: Development of a Bias correction method for the GEOGloWS ECMWF Streamflow Services global model	Forecasting and uncertainty
JSL-P2	Jorge Sanchez Lozano, Angelica Gutierrez, Jim Nelson, Amir Givati, Manuel Conda, Alma Meyer	From Global to Local: Validating Forecast High Flow Events from GEOGloWS ECMWF Streamflow Services	Forecasting and uncertainty
JW-P	Julian Weier, Christoph Tyralla, Bastian Klein, Gernot Belger, Dennis Meißner	Applying the hydrological model framework HydPy for data assimilation in order to improve operational medium-range forecasts within the Rhine basin	Earth observation and data assimilation
KB1-P	Katayoon Bahramian, Ashkan Shokri, Elisabeth Vogel, Siyuan Tian, Luigi Renzullo, Robert C Pipunic, Julien Lerat, Wendy Sharples, Chantal Donnelly	Impacts of data assimilation on continental seasonal and short-term hydrological forecasts	Earth observation and data assimilation

(Continues)

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
KB2-P	Konrad Bogner, Massimiliano Zappa, Luzi Bernhard, Chang Yuan-Yuan	How can we extend the horizon of skilful hydrological predictions?	Forecasting and uncertainty
KH-P	Kirsti Hakala	Forecasting seasonal water demand across Australia's southern Murray Darling Basin	Forecasting and uncertainty; co-production and incorporating local knowledge; applications and decision-making
LA-P	Louise Arnal, Martyn Clark, Vincent Fortin, Alain Pietroniro, Vincent Vionnet, Andy Wood	Understanding streamflow predictability on seasonal timescales across North America	Forecasting and uncertainty; hydrological model development
LC-P	Laurie Caillouet, Olivier Vannier, Sabrina Celie	Seamless combination of short-term deterministic with mid-term probabilistic hydrological forecasts	Forecasting and uncertainty; hydrological model development; applications and decision-making
LF-P	Leila Forouhar, Wenjan Wu, Quan J. Wang, Kirsti Hakala Assendelft, Yating Tang	Evaluating the performance of a data-driven short-term irrigation demand forecasting model under different levels of data availability	Forecasting and uncertainty; hydrological model development
LN-P	Lisanne Nauta, Christiana Photiadou, Peter Berg, Denica Bozhinova, Anna Eronn, Fulco Ludwig, Ilias Pechlivanidis	Operational multi-model hydrological seasonal forecasts for Europe: development, skill and challenges	Forecasting and uncertainty; hydrological model development
LS-K	Louise Slater	Developments in hybrid hydrological forecasting	Hydrological model development
LS-P	Luis Samaniego, Kelbling Matthias, Edwin Sutanudjaja, Niko Wanders, Alberto Martinez-de la Torre, Oldrich Rakovec, Robert Schweppe, Stephan Thober	ULYSSES: a global multi-model hydrological prediction system	Co-production and incorporating local knowledge; hydrological model development
MB1-P	Mark Bernhofen, Mark Trigg, Sarah Cooper, Anna Mdee	Assessing the role of global datasets for flood risk management at national and catchment scales	Forecasting and uncertainty; co-production and incorporating local knowledge
MB2-P	Michel Bechtold	Updating soil moisture and vegetation by assimilating Sentinel-1 backscatter: Impact on streamflow simulations	Earth observations and data assimilation
MdM-P	Marcio Augusto Ernesto de Moraes, Peter Salamon, Jerusa Peixoto, Rodolfo Moreda Mendes, Eduardo Fávero Pacheco da Luz	GloFAS as fundamental tool in the Madeira River Crisis Room	Co-production and incorporating local knowledge; applications and decision-making
MW-K	Micha Werner, Marc van den Homberg, Agathe Bucherie, Alexia Calvel, Ileen Streefkerk, Alexander Kaune	Connecting large-scale climate services to the local context? Look out of the window	Co-production and incorporating local knowledge
MW-P	Maureen Wanzala, Andrea Ficchì, Hannah Cloke, Liz Stephens	Assessment of Global Reanalysis Datasets for Catchment modelling Across Kenya	Co-production and incorporating local knowledge; hydrological model development
MY-P	Masafumi Yamada, Takahiro Sayama, Dai Yamazaki	Development of nationwide 150 m high-resolution Rainfall–Runoff–Inundation model	Earth observations and data assimilation

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
		for flood forecasting: Integration of 26,000 cross-section data to improve flood predictions	
PB-P	Pierre Baguis, Emmanuel Roulin, Joris Van den Bergh, Stéphane Vannitsem, Alberto Carrassi, Gabrielle De Lannoy, Hans Lievens	Assimilation of backscatter radar observations in a hydrological model: a study for two catchments in Belgium	Earth observations and data assimilation
PD1-P	Pradeep Dangol, Mandira Singh Shrestha	Real-time flood forecasting in the Chenab basin in Pakistan	Earth observations and data assimilation; hydrological model development; applications and decision-making
PD2-P	Panayiotis Dimitriadis, Demetris Koutsoyiannis, Theano Iliopoulou, Panos Papanicolaou	Limits of predictability: a global-scale investigation of the distribution and stochastic structure of key hydrological-cycle processes	Forecasting and uncertainty
PZ-P	Pengcheng Zhao, Quan J. Wang, Wenjan Wu, Quichun Yang	Which precipitation forecasts to use? Deterministic versus coarser-resolution ensemble NWP models	Hydrological model development
QJW-P	QJ Wang, Yating Tang, Kirsti Hakala, Guy Ortlipp, Mark Bailey, Andrew Western, Senlin Zhou, Wenyan Wu, Yiliang Du	Improving irrigation water availability forecasting: A case study involving Australia's largest rural water corporation	Forecasting and uncertainty; applications and decision-making
QY-P	Quichun Yang, Quan Wang, Kirsti Hakala Assendelft	Effective calibration of precipitation forecasts across Australia using the Seasonally Coherent Calibration (SCC) model	Forecasting and uncertainty
RH-P	Renaud Hostache, Sandro Martinis, Bernhard Bauer-Marschallinger, Marco Chini, Candace Chow, Senmao Cao, Ramona Pelich, Yu Li, Christian Boehnke, Lisa Knopp, Marc Wieland, Florian Roth, Wolfgang Wagner, Patrick Matgen, Peter Salamon	A first evaluation of the future CEMS systematic global flood monitoring product.	Forecasting and uncertainty; Earth observation and data assimilation; applications and decision-making
RI-P	Ruben Imhoff, Aart Overeem, Claudia Brauer, Hidde Leijnse, Albrecht Weerts, Remko Uijlenhoet	Rainfall nowcasting using commercial microwave links from cellular communication networks	Applications and decision-making
RK-P	Robert Keppler, Lieke Melsen, Albrecht Weerts	Assimilation of streamflow into a distributed hydrological model using ConvLSTM	Earth observations and data assimilation; hydrological model development
SG-P	Saeed Golian, Conor Murphy, Robert L. Wilby, Seán Donegan, Dáire Foran Quinn, Shaun Harrigan	Seasonal forecasts of winter and summer precipitation for the Island of Ireland from dynamical–statistical methods	Hydrological model development
SH-P	Shaun Harrigan, Iacopo Ferrario, Ervin Zsoter, Christopher Barnard, Fredrik Wetterhall, Christel Prudhomme	Delivering Global Flood Awareness System (GloFAS) data operationally to the hydrological community	Forecasting and uncertainty; co-production and incorporating local knowledge

(Continues)

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
TB-P	Tim Busker	Forecast-based operation of blue-green roofs as a new solution to decrease the impact of extreme weather in cities	Forecasting and uncertainty; applications and decision-making
TBTP-P	Thao Bui Thi Phuong, Kawamura Akira, Thi Nuong Bui, Tien Thuy Le du, Du Duong Bui, René Capell, Amaguchi Hideo, Leyland Julian, Mang Hung Le, Thi Ngoc Nguyen, Kantoush SamehAhmed, Darby Stephen, Johan Strömqvist	Application of HYPE Model in Simulating Streamflow and Suspended Sediment Concentration at Upper Srepok River Basin in Vietnam	Forecasting and uncertainty; hydrological model development
TJ-P	Toni Jurlina, Calum Baugh, Hannah Cloke, Claudia Vitolo, Ruth Coughlan, Christopher Barnard, Florian Pappenberger, Matthias Drusch, Christel Prudhomme	Predicting river flow level categories using SMOS soil moisture within a machine learning approach	Forecasting and uncertainty; Earth observations and data assimilation; hydrological model development
TK-P	Timo Kelder, Louise Slater, Christel Prudhomme, Tim Marjoribank, Rob Wilby, Julia Wagemann	Exploiting SEAS5 (re-)forecasts to support risk-based decision making (UNSEEN)	Forecasting and uncertainty; applications and decision-making
TS-P	Takahiro Sayama, Masafumi Yamada, Yoshito Sugawara, Dai Yamazaki	Ensemble Flash Flood Predictions Using a High-Resolution Nationwide Distributed Rainfall-Runoff Model: Case Study of the Heavy Rain Event of July 2018 and Typhoon Hagibis in 2019	Forecasting and uncertainty
VP-P	Vanessa Pedinotti, Rémi Jugier, Marielle Gosset, Adrien Paris, Nicolas Picot, Gilles Larnicol, Laetitia Gal, Bachir Tanimoun, Kounge Soungalo	Towards an operational forecasting system using altimetry assimilation: two case studies on the Niger and the Congo river basins.	Earth observations and data assimilation
WG-P	Wouter Greuell, Ronald Hutjes	The effects of post-processing on the performance of reservoir inflow at Itaipu (Brazil/Paraguay)	Forecasting and uncertainty
WP-K	Wendy Parker	From ensembles to uncertainty in hydrological prediction	Forecasting and uncertainty; co-production and incorporating local knowledge
XC-P	Xuelong Chen	Remote Sensing of Global Daily Evapotranspiration based on Surface Energy Balance Method and Reanalysis data	Earth observations and data assimilation
AC-P	Annie Y.-Y. Chang, Konrad Bogner, Daniela Domeisen, Massimiliano Zappa, Christian M. Grams, Samuel Monhart	Post-processing hydro-meteorological tercile forecasts with weather regime data using machine learning	Forecasting and uncertainty; hydrological model development
YS-P	Yawen Shao	An improved trend-aware post-processing method for GCM seasonal precipitation forecasts	Forecasting and uncertainty

TABLE A1 (Continued)

Citation code	Authors	Title	Theme(s)
YZ-P	Yuerong Zhou, Wenjan Wu, Quan Wang, Rory Nathan	Emulation of 2D hydrodynamic flood inundation model using deep learning with spatial reduction and reconstruction	Hydrological model development

Note: Abstracts have been given a citation code based on the initials of the first author, and are listed alphabetically according to their first initial (and therefore citation code). -P indicates the abstract was presented as a lightning talk and poster, -K indicates the abstract was a keynote talk. Numbers are introduced to distinguish between topics when an author presented more than one poster, or in instances of multiple authors with the same initials. The theme(s) that each abstract relates to is also noted and indicates the section(s) under which the abstract is discussed in this article. The talks and posters presented at the workshop can be viewed here indefinitely: https://events.ecmwf.int/event/222/timetable/.

TABLE A2 Classification of different types of uncertainty (based on Beven (2016), and workshop contributions that specifically address those types of uncertainty.

Type of uncertainty	Description	Models	Workshop contributions
Aleatory	Uncertainty with stationary statistical characteristics. It may be structured (bias, autocorrelation, long-term persistence), but can be reduced to a stationary random distribution	Single model	
		Single model + PP	DM3-P
		Multi-model	
Epistemic (system dynamics)	Uncertainty arising from a lack of knowledge about how to represent the catchment system in terms of both model structure and parameters	Single model	TS-P, FF-P2
		Single model + PP/+ML	PD-P, TJ-P, DC-P, HT-P, CPH-P,
		Multi-model	BN-P, LS-P, GU-P, LC-P (deterministic + probabilistic), JO-P, AW-P, PZ-P (deterministic w/PP + probabilistic), FW-P, LA-P, FJ-P, GM-P
Epistemic (forcing and response data)	Uncertainty arising from lack of knowledge about the forcing data or the response data with which model outputs can be evaluated. This may be because of proportionality or interpolation issues when not enough information is provided by the observational techniques to adequately describe variables required in the modelling process	Single model	TS-P, FF-P2,
		Single model + PP	PD-P, TJ-P, DC-P, DH-P,
		Multi-model	BN-P, GU-P, JO-P, LN-P, FW-P, LA-P, GM-P
Epistemic (disinformation)	Uncertainties in either system representation or forcing data that are known to be inconsistent or wrong.	Single model	TS-P,
		Single model + PP	HT-P,
		Multi-model	JO-P
Semantic/ linguistic	Uncertainty about what statements or quantities in the relevant domain actually mean depending on the contexts or scale (e.g., storm runoff, baseflow, hydraulic conductivity, stationarity, etc.)		HT-P
Ontological	Uncertainty associated with different belief systems, including what are considered the appropriate assumptions		