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An overview of approaches for reducing uncertainties in hydrological forecasting: Progress and challenges

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ABSTRACT

Uncertainty plays a key role in hydrological modeling and forecasting, which can have tremendous environmental, economic, and social impacts. Therefore, it is crucial to comprehend the nature of this uncertainty and identify its scope and effects in a way that enhances hydrological modeling and forecasting. During recent decades, hydrological researchers investigated several approaches for reducing inherent uncertainty considering the limitations of sensor measurement, calibration, parameter setting, model conceptualization, and validation. Nevertheless, the scope and diversity of applications and methodologies, sometimes brought from other disciplines, call for an extensive review of the state-of-the-art in this field in a way that promotes a holistic view of the proposed concepts and provides textbook-like guidelines to hydrology researchers and the community. This paper contributes to this goal where a systematic review of the last decade's research (2010 onward) is carried out. It aims to synthesize the theories and tools for uncertainty reduction in surface hydrological forecasting, providing insights into the limitations of the current state-of-the-art and laying down foundations for future research. A special focus on remote sensing and multi-criteria-based approaches has been considered. In addition, the paper reviews the current state of uncertainty ontology in hydrological studies and provides new categorizations of the reviewed techniques. Finally, a set of freely accessible remotely sensed data and tools useful for uncertainty handling and hydrological forecasting are reviewed and pointed out.

1. Introduction

Climate change and anthropogenic activities are influencing the rise in global temperature and altering precipitation occurrences. Consequently, the intensity and frequency of floods and droughts are increasing (IPCC, 2021). Besides, the global water demand is also growing due to rapid population growth, urbanization, and industrialization. Supplying water and diminishing the consequences of hydrological extremes are major tasks for decision-makers in this modern era. This requires a clear assessment of current and future water resource availability and an understanding of the impacts of environmental changes such as climate (Krysanova et al., 2018), land use, and land cover (Chawla and Mujumdar, 2018) on hydrological systems. In these regard, hydrological modeling and forecasting are widely used to investigate, understand, and predict various natural processes of hydrology (Todini, 2007; Papacharalampous et al., 2020; Lakshmi and Sudheer, 2021; Moges et al., 2021; Horton et al., 2022).

Hydrological modeling techniques (HMTs) are found useful in various hydrological forecasting applications such as streamflow (e.g., Abbasi et al., 2021; Althoff et al., 2021; De Santis et al., 2021; Hassan and Hassan, 2021; Lee et al., 2021; Liang et al., 2021) and floods (e.g., Adams and Dymond, 2019; Anandharuban et al., 2019; Bhola et al., 2019; Rajib et al., 2020; Tran et al., 2020; Silvestro et al., 2021; Xu et al., 2021). Similarly, HMTs are also applied to watershed assessment applications such as water balance, rainfall-runoff process, water availability, streamflow (e.g., Ashraf et al., 2019; Huang et al., 2020; Hui et al., 2020; Lilhare et al., 2020; Papacharalampous et al., 2020; Papacharalampous et al., 2020b), and snow melt modeling (e.g., Di Marco

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et al., 2021; Dion et al., 2021; Thornton et al., 2021; Zaremehrjardy et al., 2021). Other applications of HMTs include understanding, prediction, and management of reservoir inflow, soil moisture, and groundwater (e.g., Wu and Zeng, 2013; Fraga et al., 2019; Mustafa et al., 2019; Amanambu et al., 2020; Chen et al., 2020; Kasiviswanathan et al., 2020; Fathololoumi et al., 2021; Klotz et al., 2021; Valdez et al., 2021). Overall, HMTs are used in various applications of water resources management such as irrigation and drainage management, flood management and adaptation, reservoir inflow predictions and operations, framing short-term and long-term water supply strategies, and mitigating the negative impacts of floods and droughts.

The hydrological models that are in use can be classified into two major types: (i) data-driven and (ii) process-driven (conceptual models and physically based models) (Papacharalampous et al., 2020; Lakshmi and Sudheer, 2021). These models vary in providing solutions at different levels of complexity (Horton et al., 2022; Moges et al., 2021; Papacharalampous et al., 2020), e.g., data-type (Hassan and Hassan, 2021), conceptual-level (Thiboult et al., 2015; Humphrey et al., 2016), physically-based (e.g., Fraga et al., 2019; Her et al., 2019a, 2019b), semi-distributed level (Huang et al., 2020), fully distributed-level (Abbott et al., 1986), and process integration-level (Van Steenbergen et al., 2012; Habert et al., 2016). Although advancements have been seen in hydrological modeling for the past four decades, handling uncertainty in hydrological models is still pertinent to address new developments (Blöschl et al., 2019), for example, the development of management scenarios in hydrological modeling.

These developments require at least three prerequisites: (1) objective definition and input preparation, (2) parameter definition and model conceptualization, and (3) model calibration and validation. All these stages of development contain uncertainty in connection with the measurement (e.g., Das Bhowmik et al., 2020; Piazzi et al., 2021; Yang et al., 2020), the scope of inputs (e.g., Althoff et al., 2021; De Santis et al., 2021; Hassan and Hassan, 2021), model parameters (e.g., Liu et al., 2020; Tran et al., 2020; Liang et al., 2021), conceptualization (e.g., Bhola et al., 2019; Lee et al., 2021; McInerney et al., 2021), and simulation/forecasting platform employed (e.g., Siqueira et al., 2021; Mazrooei et al., 2021; Xu et al., 2021). Therefore, efforts must be undertaken to address these uncertainties and produce reliable hydrological forecasting that can be communicated to decision-makers and the public (Krzysztofowicz, 2001; Blöschl et al., 2019). Since the early work in hydrological forecasting, several researchers have tried to account for various facets of uncertainty using various techniques and tools (Moradkhani et al., 2005; Pappenberger and Beven, 2006; Montanari, 2007). However, the site-specific nature and complexities involved in developing such models have kept studies on uncertainty handling as one of the unsolved problems in hydrology (Moges et al., 2021; Papacharalampous et al., 2020). Strictly speaking, there are inherent challenges in handling uncertainty linked to its nature, scope, and perception when associated with the model under consideration (e.g., scale: spatial-temporal scales; lumped and distributed) and its expected outcome. It is, for instance, open to debate whether this uncertainty is static or dynamic.

In this respect, uncertainty in hydrological forecasting may evolve due to one or more of the following reasons: (1) measurement error (Tauro et al., 2018; Vema et al., 2020), (2) input error (Hrachowitz et al., 2013; Tauro et al., 2018; Blöschl et al., 2019), (3) errors in model conceptualization (McInerney et al., 2021), (4) initial setting of the parameters (Vema et al., 2020), (5) simulation error (Tran et al., 2020; Wang et al., 2017; Vema et al., 2020), (6) techniques and assumptions used in calibration procedures (Sivapalan et al., 2003), (7) assumptions used in the hydrological projections (Brigode et al., 2013), and (8) modeler's experience (Moges et al., 2021). Evaluation of recent studies suggests that much progress has been made in addressing the measurements, input, and conceptual uncertainties. This has been achieved with the awareness of increased data availability, the arrival of remote sensing and digital recording, the development of non-invasive measurement systems, new tracer-based methods (Tauro et al., 2018), and applications of Machine Learning and Artificial Intelligence in hydrological modeling. Advancements in hydrological modeling, such as physically based and fully integrated models, require many parameters depending on the assessed hydrological process. These parameters must be adjusted compared to the measured data, e.g., for calibration purposes (Shafii et al., 2015). However, parameter uncertainty also occurs because of the initial setting and approximations that are part of the employed modeling approach (Khoi and Thom, 2015). For this purpose, many studies have attempted to reduce the parameter uncertainties in hydrological forecasting while addressing the measurement, input, and conceptual uncertainties (Chawla and Mujumdar, 2018; Lafaysse et al., 2017; Meng et al., 2017; Mustafa et al., 2020; McInerney et al., 2021).

Although considerable progress has been accomplished in addressing various uncertainties of hydrological modeling, model uncertainty (or structural uncertainty) is still a major challenge in hydrology (Pappenberger and Beven, 2006; Montanari, 2007; Mustafa et al., 2020) and is more elusive than other uncertainties, e.g., parameter uncertainty (Kirchner, 2006). Hence, a more consistent framework for addressing different types of uncertainty is required while considering the context (Bennett et al., 2013) and uniqueness of the study (Beven, 2000) in hydrological forecasting despite developing a range of alternative models (e.g., Clark et al., 2015; Blöschl et al., 2019).

In the past four decades, studies related to uncertainties in hydrological forecasting have evolved in terms of methods of uncertainty quantification, impacts of these uncertainties in hydrological forecasting, and sources involved in hydrological forecasting (Beck, 1987; Morgan, 1994; Beven, 2009; Beven, 2002; Paul et al., 2021; Beven and Lane, 2022; Gupta and Govindaraju, 2023; Beven, 2023). Because of the importance of hydrological forecasting which supports irrigation and drainage management, flood early warning, drought monitoring, snow accumulation, and melting, recent studies related to uncertainty handling have shifted towards improving hydrological forecasting by devising methods for reducing uncertainty levels and improving the model structure for reliable forecasts.

1.1. Motivation for this study

Our initial literature search in terms of existing review papers in this field identified eleven survey papers investigating the aspects of uncertainty in hydrological modeling and forecasting. These reviews can be classified into three major classes: (1) data and input (Dong, 2018; Maggioni and Massari, 2018; McMillan et al., 2018; Jose and Dwarakish, 2020), (2) developments on models and methodology for hydrological forecasting (Rossa et al., 2011; Wu and Zeng, 2013; Li et al., 2017; Guo et al., 2021; Moges et al., 2021; Troin et al., 2021), and (3) methodological developments in quantification and reduction of these uncertainties in hydrological forecasting (Wu et al., 2020). However, our scrutiny of these reviews also revealed the lack of global scope and comprehensive analysis of alternative methods in dealing with uncertainty, which calls for further research and updated reviews in this field. To our knowledge, no review has focused on reducing uncertainty for improving hydrological forecasting, which motivates our current work in this paper.

1.2. Objectives

The main objective of this study is to compile the current progress and challenges while categorizing existing solutions for reducing uncertainty involved in hydrological forecasting by replying to the following research questions:

Q1. What are the latest developments in reducing uncertainty in hydrological forecasting?

Q2. How do various methods of hydrological forecasting address the various uncertainties, and what are their advantages and disadvantages?

Q3. How does remotely sensed data impact uncertainty in hydrological forecasting?

Q4. What are the criteria for selecting a model to reduce the uncertainties in hydrological forecasting?

1.3. Contributions and organization of the manuscript

The significant contributions from this review are threefold. First, it synthesizes the methods and tools for reducing uncertainties in hydrological forecasting. Second, it provides insights into the advantages and limitations of the current developments/solutions for reducing uncertainty in hydrological forecasting. Third, the role of remote sensing in reducing uncertainties of hydrological forecasting is elucidated. Finally, an extensive review of existing hydrological models has been carried out with an emphasis on multi-criteria approaches for uncertainty handling and open-source data sources in a way to simulate further studies in this field. A high-level graphical summary of the paper content is depicted in Fig. 1, while a concise list of abbreviations employed in this paper is shown in Table 1 (a complete and extended list of abbreviations is reported as a supplementary file to this paper in Table S1). The

Table 1
List of main abbreviations.

Sl. No	Abbreviations	Expansion
1	DA	Data Assimilation
2	ET	Evapotranspiration
3	GCMs	Global Climate Models
4	GWR	Groundwater Recharge
5	HMTs	Hydrological modeling techniques
6	IPCC	Intergovernmental Panel on Climate Change
7	LAI	Leaf Area Index
8	LST	Land Surface Temperature
9	LULC	Land Use Land Cover
10	NDVI	Normalized Difference Vegetation Index
11	RCMs	Regional Climate Models
12	RMSE	Root Mean Square Error
13	SCE	Snow Cover Extent
14	SM	Soil Moisture
15	SWE	Snow Water Equivalent

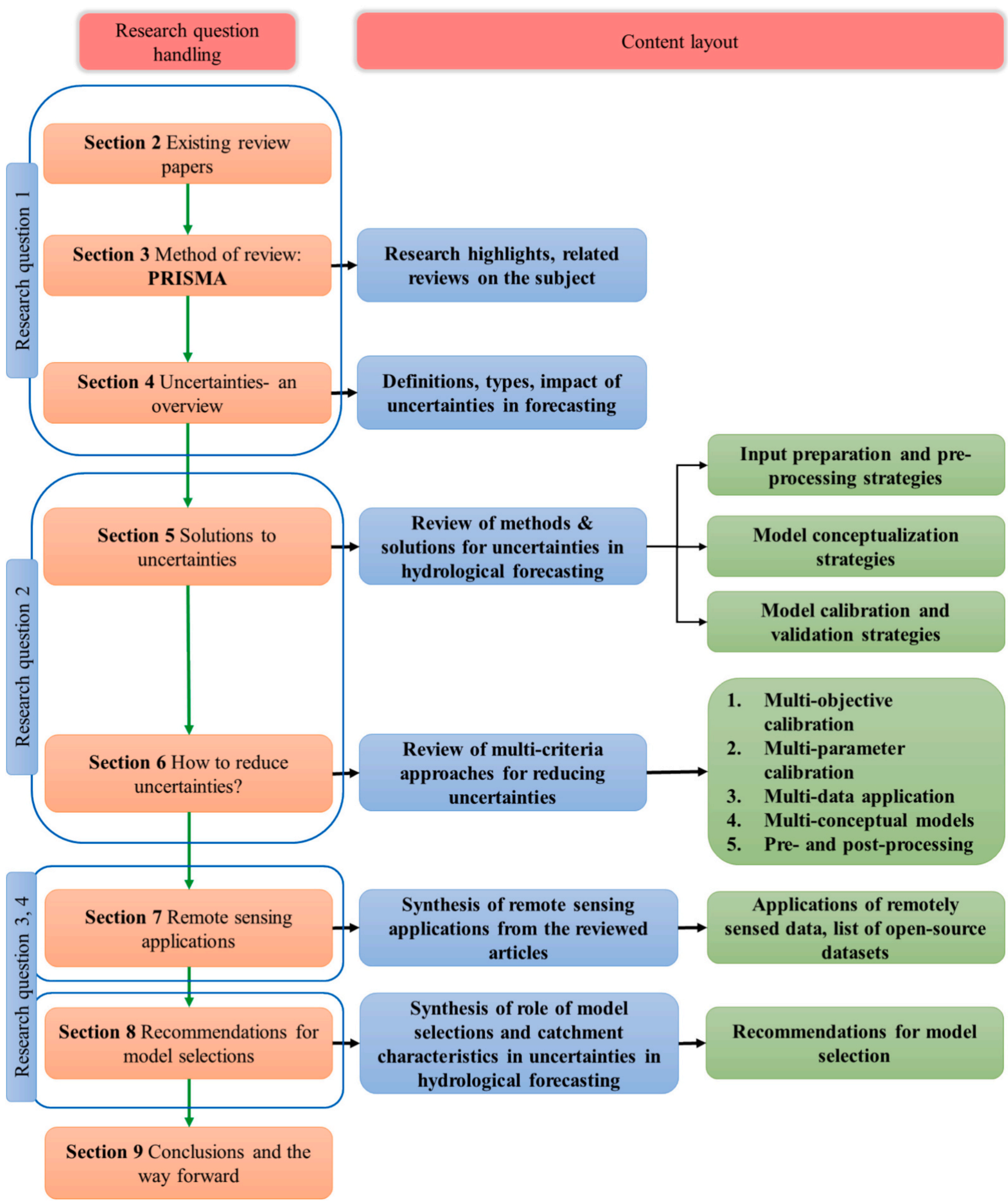

Fig. 1. Summary of the present review (Three columns represent the manuscript organization from Sections (Red) to sub-sections (Blue) and its content organization (Green)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

organization of the paper is as follows. Section 2 reviews existing review papers in the field. Section 3 outlines the review methodology employed in this review. In Section 4, an overview of uncertainty handling in hydrological forecasting is discussed. Subsequently, Section 5 shifts the focus to various methods used for uncertainty reduction. Following this, Section 6 delves into multi-criteria approaches for uncertainty handling and provides insightful comments on both current practices and potential future directions. Advancing further, Section 7 discusses the applications of remote sensing in reducing uncertainties. Thereafter, Section 8 provides a comprehensive summary of the criteria for choosing hydrological models. Finally, the paper concludes with Section 9, which draws conclusive statements and recommendations.

2. Existing review papers

The synthesis of scientific progress and challenges in managing uncertainties within hydrological forecasting, spanning various facets of captured processes as discussed in several review papers, is detailed in Table 2.

McMillan et al. (2018) examined the use of hydrometeorological data in model conceptualization and calibration, and the uncertainties that arise from these processes. These uncertainties, which contribute to 10–40 % of the total uncertainties in hydrological forecasting, are categorized into measurement, derived data, interpolation, scaling, and data management-based uncertainty. Recent advancements in the applications of Global Climate Models (GCMs) have provided a fresh perspective on forecasting uncertainties. Jose and Dwarakish (2020) outlined these uncertainties, which involve scenario uncertainty, climate scenario selection, and model uncertainty. The advent of new sensor systems in hydrological modeling has opened new avenues for exploration in terms of uncertainty handling and modeling. For example, the applications of remotely sensed data products carry inherent uncertainty due to variations in spatial and temporal coverage as well as scale. Maggioni and Massari (2018) surveyed these factors for satellite precipitation products (SPPs), while Dong (2018) examined the impact of temperature data products, snow cover, soil moisture, evapotranspiration (ET), and various environmentally related indices (e.g., Leaf Area Index (LAI)), and their derived products. These products are used in a range of tasks, from modeling data-scarce situations to streamflow and flood modeling, paving the way for a detailed examination of these uncertainties. In particular, data scarcity and the regionalization of model parameters have been found to significantly impact input and model uncertainty, which in turn, affect forecasting uncertainty. Ensemble forecast techniques, recognized for their ability to utilize multiple sources and datasets in the forecasting process, can positively impact the reduction of uncertainty. Troin et al. (2021) surveyed this trend in streamflow forecasting over the past four decades. They categorized streamflow ensemble forecast techniques into three categories: statistics-based systems, climatology-based ensemble systems, and numerical weather prediction-based systems.

Similarly, Wu et al. (2020) reviewed ensemble prediction for flood forecasting, and Li et al. (2017) reviewed statistical postprocessing methods for hydrometeorological ensemble forecasting, distinguishing between methods for single model forecasting and those for multiple model forecasting. Moges et al. (2021) identified various levels of addressing hydrological forecasting uncertainty, which stem from model parameters, model structure, calibration, and input data, each requiring special attention. However, these authors focused on optimization and probabilistic-based uncertainty analysis, leaving qualitative and ill-known factors unaccounted for. In their review, Guo et al. (2021) focused on urban surface water flood modeling, highlighting four distinct categories: drainage network models, shallow-water-based models, hydrogeomorphic models, and other models. They emphasized the lack of reliable modeling of urban surface water flooding as the main source of uncertainty. Rossa et al. (2011) reviewed the outcomes and guidelines of the European Cost Action 731, which dealt with the quantification of uncertainty in hydro-meteorological forecast systems. For this purpose, the action promoted three development-based methodologies: combining meteorological and hydrological models, chain-based uncertainty propagation, and advancements in high-resolution weather prediction precipitation forecasts. Wu and Zeng (2013) focused on groundwater systems, employing numerical simulations to

Table 2
List of review papers and their advantages and limitations.

Sl. No	Review paper	Advantages	Limitations
1	McMillan et al., 2018	The uncertainties associated with hydrological data are examined and categorized into five types: measurement, derived data, interpolation, scaling, and data management-based uncertainty.	Other sources of uncertainty in hydrological modeling have not been addressed. Furthermore, the methods to mitigate these additional sources of uncertainty have not been discussed.
2	Jose and Dwarakish, 2020	Uncertainties associated with GCMs are discussed in detail.	The study focuses solely on General Circulation Models (GCMs) and the uncertainties associated with hydrological modeling.
3	Maggioni and Massari, 2018	A summary of common satellite products, along with their associated errors and uncertainties is provided.	This review is restricted to the remotely sensed precipitation products in flood forecasting applications.
4	Dong, 2018	The study focuses on uncertainties associated with the application of remote sensing, hydrological modeling, and in situ measurements in snow cover research. It also provides a list of the pros and cons of remote sensing.	This research work is focused on snow cover studies. The uncertainties are discussed in the context of remote-sensing products.
5	Troin et al., 2021	40 years of ensemble streamflow forecast research studies are summarized in this review.	Uncertainties discussed in this review are restricted to the ensemble streamflow forecast.
6	Moges et al., 2021	This review summarizes the different methods of uncertainty analysis used in hydrological modeling.	The discussion did not cover the computational efficiency of the uncertainty analysis. Furthermore, it did not provide details on how to address the uncertainties in hydrological forecasting.
7	Guo et al., 2021	Focus on improvement in the regionalization of the parameters and application of remote sensing in this field.	It has not brought the broad spectrum of uncertainties involved in the hydrological modeling.
8	Li et al., 2017	A comprehensive review of post-processing techniques aimed at reducing uncertainties is provided.	Other methods for reducing uncertainties in hydrological forecasting have not been discussed.
9	Rossa et al., 2011	Concise review of EU Cost Action on hydrological systems and uncertainties is provided.	The review does not include recent studies. Limited to the groundwater system.
10	Wu and Zeng, 2013	The uncertainties about the groundwater systems are summarized.	The review, which is limited to the groundwater system, does not include recent studies.
11	Wu et al., 2020	A comprehensive review of ensemble flood forecasting method is provided.	The discussion is restricted to ensemble flood forecasting. However, methods for overcoming hydrological forecasting uncertainties have not been discussed.

model and distinguish uncertainty pervading groundwater model parameters, groundwater conceptual model uncertainty, and observation-related uncertainty. In summary, previous review papers, lack a holistic view on the issue of uncertainty handling in hydrological forecasting systems and do not adequately address RQ1-RQ3. This gap calls for further research in this field to assist both researchers and practitioners in hydrology with state-of-the-art research and findings. Finally, the review papers revealed the potential of a multicriteria approach to reduce uncertainty, as well as the constraints imposed by the nature of the hydrological forecast employed, model structure, and environmental variables. These aspects will be further considered in the categorization of the literature search in the following section.

3. Method of review

We have utilized the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Page et al., 2021) protocol for a systematic literature search for our review, as shown in Fig. 2. The proposed research theme was to collect, organize, and categorize the latest developments in uncertainty handling in hydrological forecasting and comprehend how different approaches were used. The keywords used as search terms are given in Table 3.

The search starts by crawling the results from three academic research databases: Scopus, Web of Science, and Google Scholar whenever the keywords appear in the title, abstract, or keyword list of the papers. The choice of these databases is justified by our desire to restrict the search to peer-reviewed papers. Besides, we restricted our search to papers published in the last decade (from 2010 to 2023). Research works contributing to reducing uncertainty are then taken further for a full screening and review. The scope of this review is narrowed down to forecasting streamflow, flooding, snow, and other applications such as rainfall-runoff processes and soil moisture. The groundwater modeling and forecasting were not considered due to their high volume, which would require a separate review by itself. Based on the selected criteria, 96 pieces of literature were chosen for conducting this review research. The selection of literature is limited to provide an overview of latest developments in reducing uncertainties. See Table 3 and Fig. 2 for a high-level description of the review method carried out in this study.

Building on the findings from the review papers investigated in the previous section, the reviewed literature is organized according to the hydrological model used, the forecasting model, the multi-criteria approach employed for uncertainty reduction, and the type of uncertainty handled, along with a description of the study. Especially, the classification of uncertainties involved in hydrological forecasting was assessed according to methods and data used for reducing this uncertainty. The outcome of this categorization is described in Tables S1 in the supplementary file of this paper. The following section delves into various aspects of handling uncertainty in hydrological forecasting. This includes definitions of uncertainty, levels of analysis (such as initial conditions, input, model structure, model parameters, calibration, observation, and forecasting), applications related to hydrology, and statistical analysis of the number of studies in each category or field. Lastly, based on the results of this review, numerous resources and freely accessible remotely sensed data have been prepared to aid future hydrological studies and guide subsequent research.

Table 3
Characteristics list of review method employed in this study.

Overall aim	Uncertainty handling in hydrological forecasting
Key Question	How to classify the uncertainties and reduce uncertainties using multi-source data?
Source	Google Scholar, Web of Science, Scopus
Keywords &/ search terms	"Uncertainties in hydrological modeling", "hydrological forecasting", "uncertainty quantification in hydrological modeling", "multi-source data in hydrological modeling", "conceptual uncertainty in hydrological forecasting", "reducing uncertainties", "improving hydrological forecasting"
Evaluation method	Comparative, critical evaluation
Synthesis	Qualitative and quantitative in certain aspects
Inferences	Evidence-based

4. A comprehensive outlook of the uncertainty handling in hydrological modeling

In hydrological modeling and forecasting, the term 'uncertainty' deals with the reliability of the data utilized, the accuracy of the conceptualized model employed, the quality of the calibration and the validation, and the accuracy of the predicted results (Montanari, 2007).

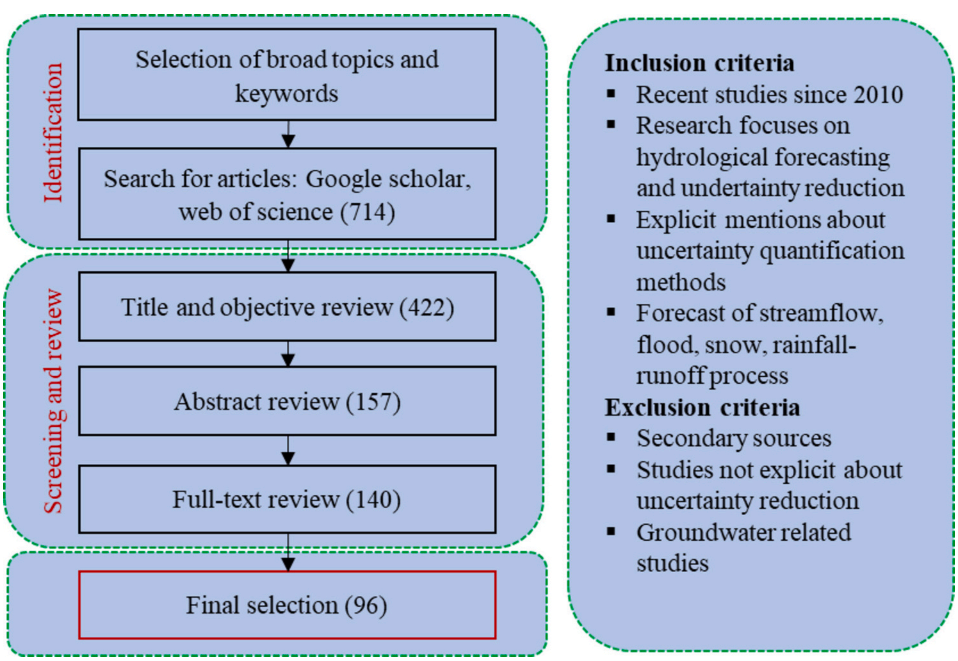

Fig. 2. PRISMA Literature screening process followed in this study.

In other words, the uncertainty term is mainly used to quantify the extent to which a particular input, model, or result matches or genuinely represents reality (McMillan et al., 2018; Moges et al., 2021; Troin et al., 2021). Indeed, a key difference between real-world data and measured data manifests in the corresponding input uncertainty; a faithful representation of a given hydrological system depends on the quality of the various natural processes involved in the description of the hydrological system, known as conceptual model uncertainty; parameter- related uncertainty arises from an inherent conceptual simplification of the model (Moges et al., 2021); finally, the difference between the simulated hydrological model and the reality corresponds to predictive uncertainties. The types of uncertainties, their sources, and examples are given in Table 4.

4.1. Impacts of uncertainties on hydrological forecasting

Hydrological forecasting is the process of translating hydro-meteorological inputs into useful hydrological parameters such as discharge, runoff, and flood depth (Huang et al., 2020; Penny et al., 2020; Lee et al., 2021; Adams and Dymond, 2019; Lee et al., 2019). This process involves the application of different hydrological models at various temporal scales from a few hours (i.e., flood forecasting) to daily forecasts (i.e., streamflow predictions) or seasonal forecasting (e.g., snow and streamflow seasonal forecasting) (Poulin et al., 2011; Che et al., 2014; Zarzar et al., 2018; Huang et al., 2020; Di Marco et al., 2021). Depending upon the hydrological forecasting used, uncertainty in the forecast does impact the decision-making process and can yield catastrophic consequences. For example, a flood forecasting model with high uncertainty may have severe social, economic, and human losses (Habert et al., 2016; Lee et al., 2019). Similarly, unreliable streamflow predictions for reservoir operations may have different impacts on operational decisions (Di Marco et al., 2021). Hence, the uncertainties involved in hydrological forecasting systems should be considered to avoid severe negative consequences. Recently, different approaches have been used and highlighted to address these issues and communicate the uncertainties to decision-makers and stakeholders.

The conventional framework of a hydrological modeling and forecasting system is being improved with numerous advancements to address these uncertainties and enhance the reliability of forecasting (McMillan et al., 2023). These improvements contribute to enhance the accuracy of input data as well as devising new methodological developments for the uncertainty quantification and integration of various workflows associated with model calibration, and remote sensing data, among others. These improvements provide effective decision-making tools that can assist in real-time applications (De Santis et al., 2021; Silvestro et al., 2021; Lee et al., 2019). Improved hydrological forecasting systems can provide fundamental support to deal with climate change, especially for managing frequent hydrological extremes. Apart from these improvements in hydrological forecasting, other factors such as forecasting skill, assessment of water system services, risks involved in finance, stakeholder's level of risk aversion, availability of tools and data to test the forecast-informed operations, and legacy guidance of local issues may influence the decision-making results as well.

However, the hydrological community is continuously working towards improving the hydrological forecasting systems at different stages of the forecasting processes (Rajib et al., 2020; Thiboult et al., 2017). Fig. 3 outlines these potential improvements in the hydrological forecasting systems to address uncertainty issues.

4.2. Uncertainties in hydrological forecasting

Since the early development of hydrological modeling, the reliability of the simulated results is open to debate. Conventionally, the streamflow at the basin outlet was used as a reliable method for determining the performances of hydrologic models. Meanwhile, the fine-tuning development of the various forecasting stages not only increases the

Table 4
Types and definitions of uncertainties in hydrological forecasting.

Sl. No	Types	Source	Definition	Examples
1	Initial conditions uncertainty	The auxiliary conditions required at the start of a run of a model to define all initial model states (Beven, 2009)	Uncertainties arise from the variations in both the initial and boundary conditions within a modeling framework	Uncertainties arise due to the initial conditions specified in a forecast. For instance, the initial soil moisture conditions provided in flood forecasting can significantly impact the final results (Meng et al., 2017).
2	Measurement uncertainty	Errors in the manual or instruments during the measurements	Uncertainty in the value of the measured hydro-climatological data, compared to the true quantity at the same scale of measurement (McMillan et al., 2018).	Uncertainties in the precipitation, temperature, discharge, soil moisture at a given location
3	Input uncertainty	Data that are interpolated, data that are scaled up/down, derived data	Inaccuracies in the model inputs cause input uncertainties (Moges et al., 2021). Often inputs in the measurement lead to greater input uncertainties.	Uncertainties due to the application of derived data such as interpolated rainfall data.
4	Parameter uncertainty	Model calibration, parameterizations, conceptual simplifications, observation errors	Uncertainties due to the failure or inability of the model to capture the hydrological process using a set of parameters.	Equifinality is an example of parameter uncertainty
5	Conceptual model uncertainty	Numerical simplification, process simplifications, limitations of theories, model structure	Uncertainties that are cascade into the results of the hydrological forecasting due to the deficient representation of the hydrological process in the model.	Inaccurate representation of the hydrological system or processes.
7	Forecast uncertainty	All other sources of uncertainties in the hydrological forecasting	Forecast uncertainties are the results of the combinations of the above-said uncertainties reflected in the	Uncertainties in the different forecasts such as streamflow, flood depth, and snow cover.

(*continued on next page*)

Table 4 (*continued*)

Sl. No	Types	Source	Definition	Examples
			hydrological forecasts (Moges et al., 2021).	
8	Unknown uncertainty	Uncertainties remain inherent even after the quantification of all uncertainties.	Unknown uncertainties are the results of the lack of a 'true' model due to natural complexities and limitations of data (Moges et al., 2021)	Uncertainties remained in the forecasts.

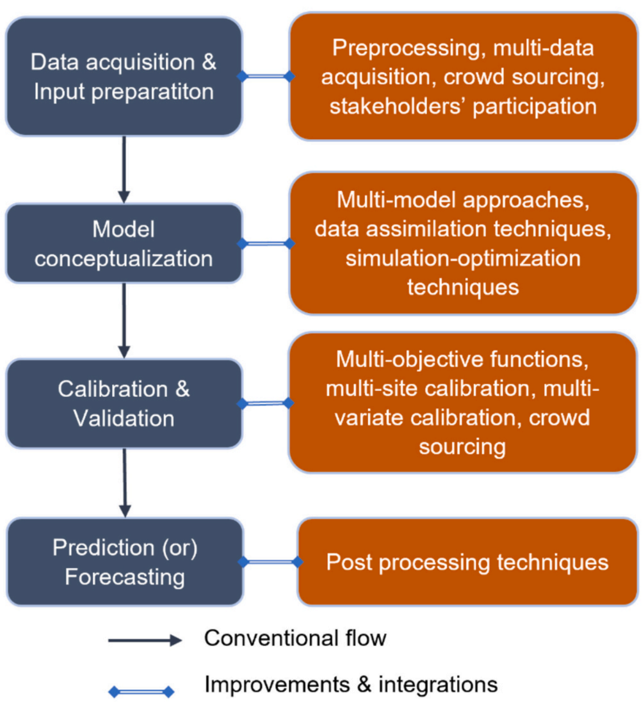

Fig. 3. Modern improvements in the hydrological forecasting system.

model reliability but also the process complexity. Nevertheless, increasing the complexity or using a multi-criteria-like approach is not always in favor of uncertainty reduction. Therefore, there is a need to select suitable combinations of modeling tools and approaches for a specific case that will likely yield uncertainty reduction. A systematic uncertainty analysis is required to find the sources of uncertainties and their reduction in the forecasting processes (Demirel et al., 2013). Ultimately, this section should account for the various types of uncertainty pointed out previously involved in hydrological forecasting tasks and the aim of the research work. Fig. 4 shows the number of studies of hydrological forecasting and uncertainties reviewed in this work. For more details on the list of reviewed studies with various models, methods, and techniques used in hydrological forecasting to reduce uncertainties at different stages of modeling, refer to Table S2.

4.2.1. *Measurements and inputs*

Hydrological modeling and forecasting mainly depend on the measurements of various catchment inputs such as hydrology, meteorology, and topography. A developmental time frame for the measurements of hydrological data is shown in Fig. 5. These inputs are used for model conceptualization, calibration of the model parameters, and validation of the results. The development of the basic datasets for hydrological modeling is encouraged through different research agendas and outreach activities of hydrological communities. Meanwhile, the global hydrological system changes must be accounted for the modeling, as highlighted in the water cycle diagram by USGS, 2022 (USGS, 2022). Hydrological community is working towards developing process-based approaches to accommodate the changes, and relevant processes and address the data scarcity issues. The success of this task depends on the improvements and integration of field measurements (Penny et al., 2020). Continuous monitoring of the fields is made possible through advancements in remotely sensed applications, developments of automatic sensors, modern equipment, and multiple field investigations. Through this continuous acquisition of data, it becomes possible to improve the forecast (Brigode et al., 2013) and to explain the changes in the catchment system.

The second important aspect of measurement acquisition is data accuracy and availability. A degradation in accuracy and availability can occur in modern sensor systems such as remote observation or complex Internet of Things (IoT) sensor networks and the usage of sensors. In such cases, any prior knowledge about measurement accuracy can be integrated into a qualitative /quantitative estimation of errors (Das Bhowmik et al., 2020). This knowledge of measurement error can help reduce measurement uncertainty, thereby, increasing the forecasts' reliability.

Reducing measurement uncertainty plays a significant role in improving the forecasting task, especially in streamflow, where it directly impacts the model conceptualization, calibration, and validation processes. The impact of initial conditions has been acknowledged in several hydrological systems, e.g., flood forecasting (Meng et al., 2017), snow-dominated hydrological processes (Leisenring and Moradkhani, 2011; Singh and Sankarasubramanian, 2014), and soil moisture studies. In this case, uncertainty on initial conditions in input variables plays a major role in the quality of the forecasts, which stresses the importance of appropriate handling of initial condition-related uncertainty to improve the overall system accuracy.

The classification of types of data that are being used in hydrological forecasting in recent times, ranging from conventional data sources (e.g., streamflow measurements) to modern-day data sources (e.g., remote sensing systems and, crowdsourcing), is outlined in Fig. 6. Uncertainty in hydro-meteorological data input can cause a higher error in the forecast estimate than uncertainties in model structure or parameters (Singh and Sankarasubramanian, 2014; Xue et al., 2018; Thornton et al., 2021; Zaremehrjardy et al., 2021). In this context, uncertainties are mainly due to the lack of spatial coverage (Dechant and Moradkhani, 2011; Zappa et al., 2011) and higher data gap frequency in the temporal scale (Thornton et al., 2021). In addition, the uncertainty in climate change projection is found to be more significant than the parameter uncertainty (Her et al., 2019a, 2019b). Topographical data sources such as land use and land cover, soil information, slope, and elevation information must be cautiously chosen based on the forecasting application. The non-stationarity nature of topographical data is an important factor in reducing forecasting uncertainty. Similarly, remotely sensed products are beneficial in data-scarce regions (Panchanathan et al., 2023); nonetheless, accounting for such sources in hydrological applications requires ground verification for the reliabilities and application to real-time forecasting. As listed in Fig. 6, the application of local knowledge is new to the hydrological community. It has been successfully applied in recent studies due to the growing field of data acquisition.

Nevertheless, it is essential to mention that comprehensive accounting for all physical processes is almost impossible, and measurement uncertainty is likely to prevail in all three types of sources (Gan et al., 2018a, 2018b). This can be attributed to the complexity of the hydrological processes and the inherent challenges in representing the various facets of these processes (Helfricht et al., 2014). However, the

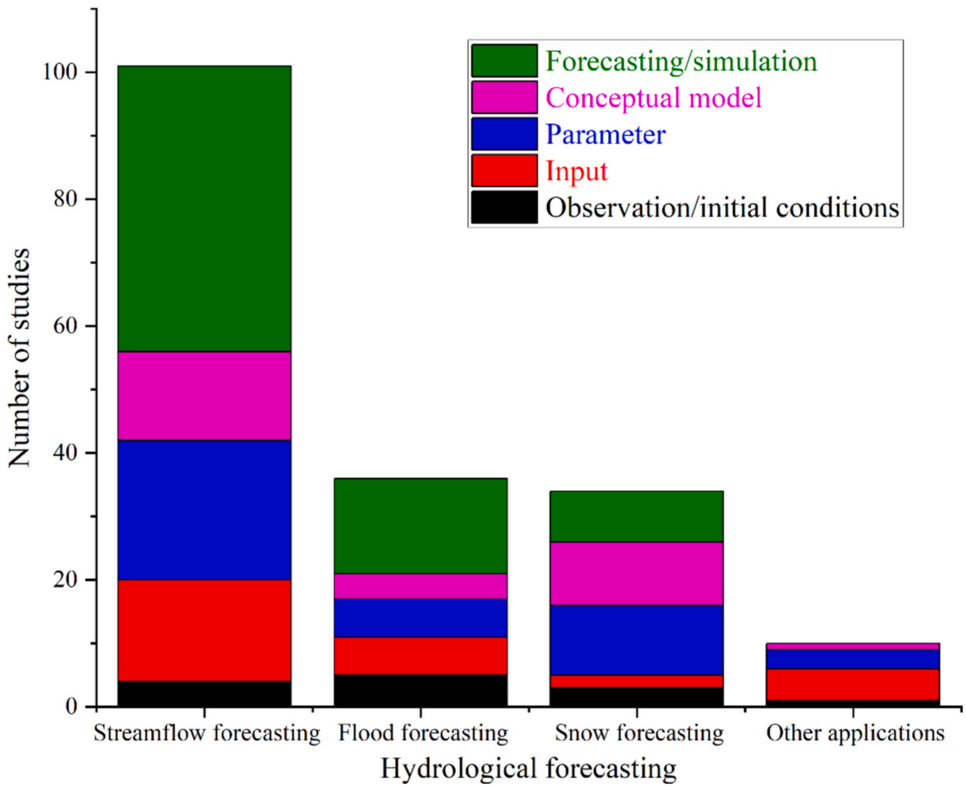

Fig. 4. Number of studies reviewed concerning their applications

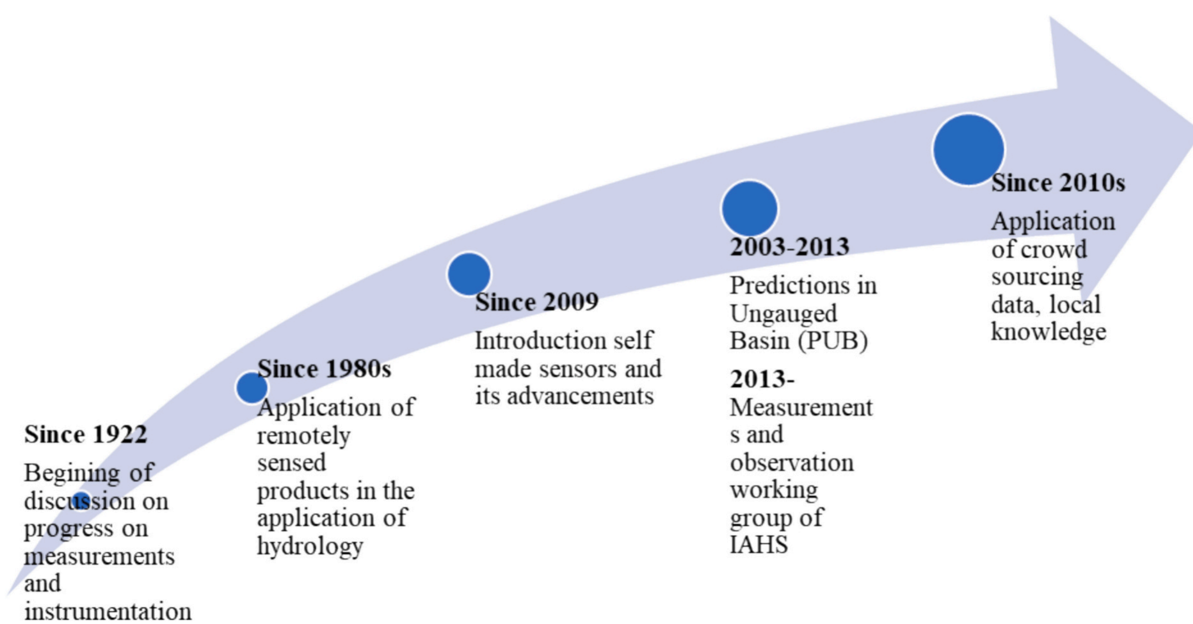

Fig. 5. Evolution of instrumentation and measurements used in hydrological forecasting (Adapted from Tauro et al., 2018).

hydrologic community is working towards synthesizing multiple data sources to address measurement uncertainty. Recent studies built on the foundation of multiple evidence to bring reliable forecasts demonstrate such improvements (Helfricht et al., 2014; Hassan and Hassan, 2020; Penny et al., 2020). Therefore, there is potential to further reduce such uncertainty by enhancing our understanding of related challenges and applying the right combination of datasets and models. For example, hydro-meteorological data and its influence on uncertainty can be tackled by considering meteorological bias and dispersion thresholds (Klotz et al., 2021). The uncertainties sustained in the input dataset and calibration data would influence the parameter uncertainties and the results.

4.2.2. Parameter uncertainty

Parameter uncertainties are considered important due to their nature in the hydrological modeling setup and their influence on the forecasts (Vema et al., 2020). For instance, although the inputs are likely to change according to spatial-temporal coverage, the model parameters

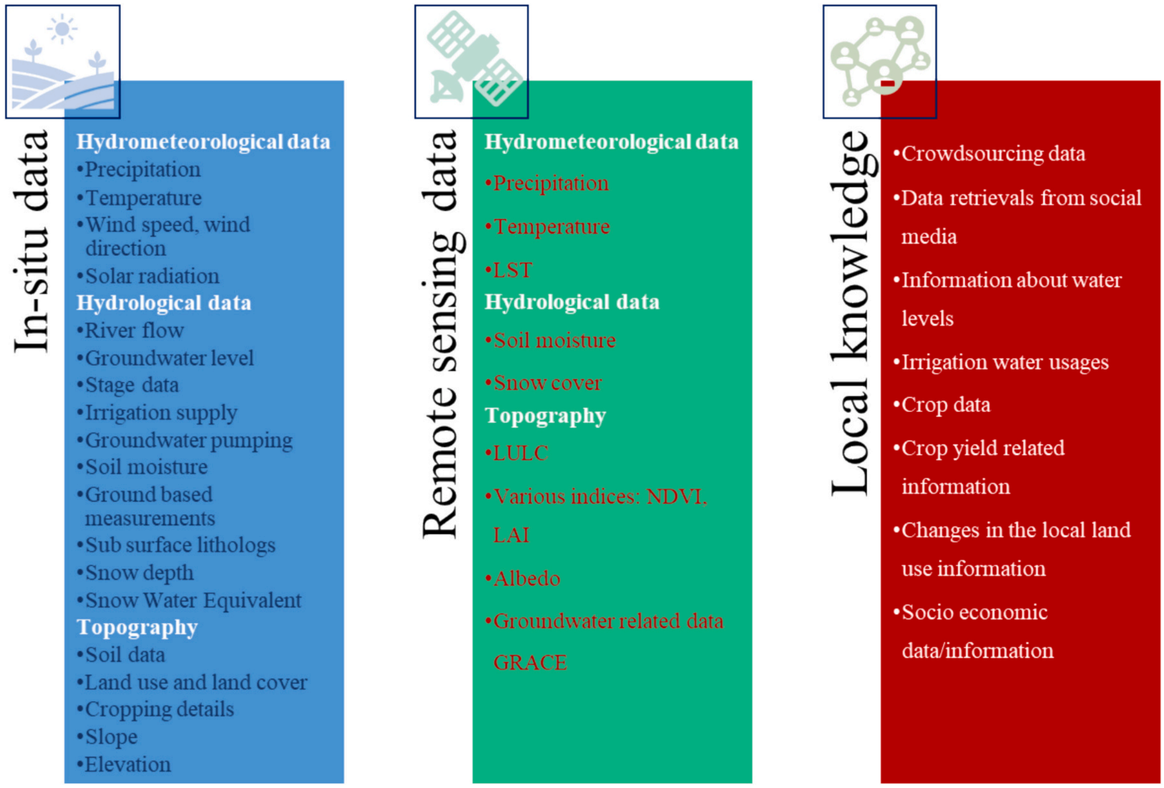

Fig. 6. Types of data used in hydrological forecasting.

are often applied uniformly over the simulation period (Thornton et al., 2021). So, the choice of model parameters is critical, as any distortion of these parameters may lead to a misrepresentation of the hydrological system (Piazzi et al., 2021). Trivially, this depends on the type of datasets used (Montanari and Grossi, 2008), the model employed (conceptual or physical model), and the forecast task (short term or long-term forecast) being applied in the study (Sun et al., 2018). Especially for short-term forecasting, model parameters play a more vital role (Tran et al., 2020). The parameters' uncertainty has two main implications: parameter equifinality (Beven and Freer, 2001; Beven, 2006; Xue et al., 2018; Ashraf et al., 2019), and dimensionality of the optimization process (Lilhare et al., 2020). In some cases, increasing the number of calibration parameters reduces the performance of the forecasts (Poulin et al., 2011) and reduces the forecast quality due to equifinality (Demirel et al., 2013). To overcome the parameter uncertainties and equifinality, recent studies suggest limiting the number of parameters that control the major processes in the catchment (Lilhare et al., 2020). This process requires experience, consideration of the hydrological model structure, and understanding of the hydrological processes within the basin (Zappa et al., 2011; Xue et al., 2018). However, sufficient observations can regulate major parameters in the calibration process, but special attention needs to be given to larger catchments with varying landscape properties. It is also important to understand the sensitivity of these parameters concerning each catchment scenario (He et al., 2011).

4.2.3. Conceptualization of models

The conceptualization of complex models plays an important role, and the associated uncertainties depend on the type of chosen models for the specific problem at hand and the prior knowledge in the specific field of hydrological forecasting. Typically, hydrological models have to be assessed for their suitability by selecting the best-suited model that represents the specific site or catchment. So, a comprehensive assessment of the models is needed before the model selection (Paul et al., 2021). The uncertainty of hydrological predictions from hydrological modeling generally originates from the model structure and its inherent parameters (Yuan et al., 2017). However, hydrological model structure uncertainty is more significant than parameter uncertainty (Poulin et al., 2011). Forecast skill is also closely linked to the hydrological model performance (Siqueira et al., 2021). Errors in model structure can be compensated by calibration, thus, parameter uncertainty and structural uncertainty can be linked to concept model uncertainty as well (Essery et al., 2013).

In general, the conceptual model uncertainty arises due to the conflicts in the representation of the hydrological processes. This uncertainty is more significant than other types of uncertainties because misrepresentation may lead to completely different forecasting. Most studies on forecasting uncertainties highlight the fact that the conceptualization of hydrological models is closely associated with forecasting skills (Siqueira et al., 2021). Specifically, the hydrological modeling uncertainties occur due to the following reasons: (a) propagation of input uncertainties; (b) less suitable chosen model and its limitations on the requirements (Patil and Ramsankaran, 2017); (c) parameterization of the models; (d) the representation of stationarity or non-stationarity (Chawla and Mujumdar, 2018); (e) complexities and catchment characteristics; (f) initial conditions, model parameterizations, and numerical limitations (Zarzar et al., 2018); (g) spatial and temporal evaluation of the modeling parameters; (h) modeler's experience; (i) usage of "one model fits all".

To overcome the model structural uncertainties, recent studies have shown the inherent link between model complexity and uncertainty. However, this idea of increasing complexity led to both positive and negative feedback (Ashraf et al., 2019). Indeed, increasing model complexity increases the number of parameters as well, which, in turn, calls for support from ground truth for the validation of the process. Contrastingly, the usage of different hydrological models for the same catchment would bring different results, which may influence the forecasts (Her et al., 2019a, 2019b), but in a few other studies, this has helped to reduce the model errors effectively (DeChant and Moradkhani, 2014). This approach of multi-modal approach can be useful as it captures the impact of models on reliability (Singh and Sankarasubramanian, 2014). However, choosing the right processing flow and supporting techniques such as data assimilation, calibration method, ensemble methods, and post-processing methods would influence the model performance in addition to the model structure (Krysanova et al., 2018; Her et al., 2019a, 2019b; De Santis et al., 2021).

5. How are the uncertainties being handled in hydrological forecasting?

The uncertainties in hydrological forecasting are handled in three stages, as shown in Fig. 7. Initially, the measurement and input uncertainties can be addressed at stage I with the help of preprocessing and improving the data quality. Stage II is a model conceptualization and setup. At this level, the uncertainties generated due to the model conceptualization, model selection, and model setup will be dealt with using multi-model approaches. Stage III consists of calibration and validation strategies. At this level, the parameter uncertainties are mainly handled by incorporating different strategies like applying multi-objective calibration, multi-site calibration, data assimilation (DA) techniques, and applications of remote sensing techniques.

5.1. *Stage I: input preparation and pre-processing*

The uncertainties involved in the measurements and inputs can be reduced at this stage. This can be possible with the help of an understanding of measurement errors and pre-processing techniques employed. The estimation of measurement errors within the modeling framework will help to reduce these uncertainties (Das Bhowmik et al., 2020). The accuracy level of the measurement error does matter in influencing the outcomes according to the employed modeling framework and type of measurement inputs. For example, gauge-specific measurements can be accurate for the estimation of measurement errors. However, the forecast variance may increase due to the consideration of measurement errors. This can be tackled by a suitable model structure to assess the tradeoff between measurement errors and forecast performance. High frequent data collection can also support the measurement and input uncertainties, as exemplified in the measurement of the rating curve (Das et al., 2018).

Ensemble techniques such as Kalman filtering with nonlinear gain and variance updating, extended & ensemble Kalman filter, and sequential Monte Carlo methods are useful in reducing uncertainties in real-time forecasting systems (Beven, 2009). Few studies found that soil moisture, streamflow, and flood forecasting are sensitive to the initial conditions, which calls for a model adjustment strategy before the forecasting task to reduce such uncertainties (Meng et al., 2017). In this case, ensemble techniques can be used to correct the model's initial states through the assimilation of additional data. For instance, applying ensemble streamflow prediction would help enhance operational capacity (Muhammad et al., 2018). Similarly, hydrometeorological ensembles can help to reduce the uncertainties in modeler subjectivity and improve flood inundation maps (Zarzar et al., 2018). Also, this depends on the type of hydrologic model and the required hydrologic forecasting (Mazrooei and Sankarasubramanian, 2019). However, the assimilation of additional data and its positive influence may change the model structure and type of forecasts (e.g., a seasonal forecast of streamflow has shown a trade-off with model errors than the initial state) (DeChant and Moradkhani, 2014).

Providing additional data and improving measurements' temporal and spatial resolution would help reduce these uncertainties. For example, improvements in the additional bathymetry have improved the performance of water level simulation (Habert et al., 2016), and systematic errors in the spatial resolution of the Digital Elevation Model were assessed for Ground Penetrating Radar techniques that assisted in improving the measurement errors (Helfricht et al., 2014), snow DA has shown improvements in snow modeling, such as assimilation of snow cover area (Che et al., 2014). The application of suitable input data has a greater impact on precipitation products. For example, the application of global precipitation products and remotely sensed precipitation products needs prior assessment and preprocessing of the data (Sun et al., 2018). Similarly, the application of various GCMs, RCMs, and climate change projections needs proper downscaling and prior estimation of errors concerning ground observation for the suitability of the catchments.

Preprocessing techniques can be chosen based on the linear and nonlinear characteristics of the hydrologic variables (Abbasi et al., 2021). The catchment-specific requirements also need to be considered to reduce the measurements and input errors in hydrological forecasting (Zaremehrjardy et al., 2021). For example, mountainous regions require higher spatial resolution information for modeling, application of gridded data needs more ground observation for the validation of the model for the now simulation, and the inclusion of snow water equivalent has improved the snow simulation in alpine areas (Schöber et al., 2014a, 2014b). Hence, improvements in historical data can enhance the reliability of the model by reducing uncertainties.

Empirical correction factors can be applied to correct the biases in the solid precipitation and other measurement deficiencies (Thornton et al., 2021). The model's performance can be evaluated with the

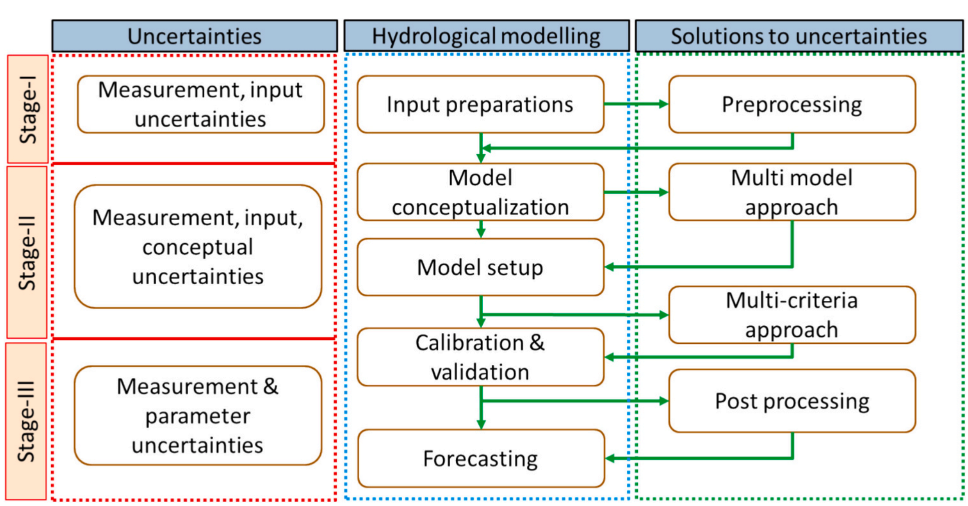

Fig. 7. Various uncertainties addressed in hydrological forecasting.

provision of well-measured catchments. However, the model structure plays a vital role in deciding its performance (Essery et al., 2013). Therefore, reducing the input uncertainty first is critical before reducing hydrologic model uncertainty (Singh and Sankarasubramanian, 2014). Thiboult et al., 2015 showed that meteorological forecast and its deficiencies can be solved by applying appropriate pre-processing techniques.

5.2. Stage II: model conceptualization uncertainty

The model structural uncertainties are compensated or solved at this stage. The selection of appropriate model structure and model flow provides insights to solve the parameter uncertainty to a greater extent. Applying multi-model approaches may help reduce the model structural uncertainties depending upon the chosen models (Butts et al., 2004). It must be chosen in a way that should comprehend the overall modeling uncertainties. In this case, the extent of structural uncertainty captured is more important than the number of models chosen for the study (Dion et al., 2021). The importance of the model selection task is because distributed or semi-distributed models can provide more insights into the system's functioning details than a lumped model. Data assimilation in a multi-model approach helps to reduce uncertainties by reducing the errors in the initial states (DeChant and Moradkhani, 2014). Hydrological model structure largely influences the forecasting skill; however, the forecast skill is also influenced by various other factors such as process spatial representation, model calibration, and the application of inputs especially the precipitation forecast used for the initial conditions, which can potentially yield a complex model (Siqueira et al., 2021).

One of the arguments that were extensively discussed in the hydrology community to produce reliable forecasts is model complexity. Nevertheless, it is open to debate whether increased model complexity always leads to an increase in forecast performance. For instance, Tran et al. (2020) advocated the use of model complexity to deal with real-time and ensemble flood forecasts. Whereas Essery et al. (2013) claimed there is a limit beyond which we cannot expect higher model complexity would help to increase the model performance. Appropriate representations of the error components in the modeling flow can help in improving the reliability of the hydrological forecasts (McInerney et al., 2021). For instance, Liu et al. (2020) showed that temporally varied error statistics with finer error models helped to improve forecasting accuracy. Similarly, any additional information about the hydrological processes within the catchment would reduce the model structural uncertainties in the hydrological forecasts, e.g., the application of multi-source data (Hassan and Hassan, 2020). Therefore, it is important to prioritize model structure to fine-tune input measurement in the study area (De Santis et al., 2021).

Model structures for snow modeling need a detailed energy balance method for snow representation (Mazrooei and Sankarasubramanian, 2019). Forecast reliability depends on spatial resolution (DeChant and Moradkhani, 2014), while ensemble streamflow prediction with DA is found to help improve the forecasts (Dechant and Moradkhani, 2011). Energy balance modules and temperature index modules share a large portion of uncertainties in the snow modeling of the Hilly region (Zaremehrjardy et al., 2021). The initial state of the model structure plays a vital role and implementing an appropriate error reduction scheme of this initial state is found to help reduce the uncertainties and improve the forecasts (Mazrooei and Sankarasubramanian, 2019).

5.3. Stage III: calibration and validation strategies

Calibration and validation strategies at this stage of the hydrological modeling setup are used to adjust the model parameters according to the measured data. Eventually, this helps improve the model's performance (Moriasi et al., 2007). Especially, this procedure helps to resolve structural uncertainties to a reasonable extent, so that the parameters and model structural uncertainties are connected (Essery et al., 2013). However, care should be given to the potential problem of overfitting the parameters through calibration procedures.

The conventional calibration procedure of streamflow calibration at the outlet of the basin can provide significant information on the streamflow pattern, but there are chances to misrepresent another important hydrological phenomenon, which may lead to parameter and prediction uncertainties. Eventually, this causes a bias towards estimating hydrological components in the simulation. For example, a biased estimation of evapotranspiration is reported by Rajib et al. (2018). The equifinality can be reduced by reducing the number of parameters or increasing the number of observed variables in the calibration procedure (Rajib et al., 2018). Calibration of additional parameters helps to improve the forecast. For example, calibrating soil moisture sensors and the corresponding spatial measurement sensors are found to improve streamflow forecasts (Wang et al., 2017).

Calibrating hydrological parameters in multi-sites and constraining the related parameters with different climatic conditions are found to improve the model performance (Huang et al., 2020). However, studies need further assessment to evaluate the extent of the uncertainty reduction due to the improvements in the calibration procedures. On the other hand, the spatial dependency of the hydrological parameters can be resolved using spatial validation of multi-objective parameters and uncertainty assessments. For example, constraining snow parameters with snow ground measurements improves the parameters in snow modeling (Di Marco et al., 2021). Historical evaluation of model performance is necessary; however, it is not sufficient when looking into future aspects of hydrological changes such as the prediction of climate change, land use, and land cover changes (Krysanova et al., 2018).

Another aspect that impacts the calibration method is the period during which this calibration is carried out. For instance, the selection of calibration and validation time-periods in a catchment case study should represent both the dry and wet climatic conditions for better model performances (Brigode et al., 2013). The calibration performance also depends on the method used, the objective function employed, and the inherent constraints in the catchment area. Baseline information may be used for the verification of model results in the case of no ground truth information, as used by Zarzar et al. (2018) for the flood inundation maps. However, this is subject to uncertainty in the forecast. Besides, parameter sensitivity is highly variable from site to site, and parameter uncertainties are higher than the input uncertainties (He et al., 2011; Demirel et al., 2013). Therefore, the choice of calibration methods straightforwardly influences the prediction uncertainty bounds (Brigode et al., 2013).

In this respect, combinations of multimodal approaches with DA and post-processing techniques are found to reduce uncertainties and improve forecasts (Dion et al., 2021; Siqueira et al., 2021). For post-processing or updating the forecasts, finer temporal granularity is recommended for better quantification of uncertainties. Coarser temporal granularities are recommended in the case of a lower computational cost (Liu et al., 2020). Bayes theorem-based ensemble streamflow prediction models are used to produce a posterior mean which helps to update the forecast (Seo et al., 2019).

Statistical post-processing can improve the forecasting accuracy in some studies, although this should be subject to testing the post-processing techniques across multiple catchments, lead times, multiple hydrological models, and various sample sizes. The accuracy of post-processing techniques depends on the models used, ensemble size, the complexity of the basin, and the time used for analysis. Regarding the phase of the post-processing task, in contrast to calibration, the post-processing task can generate relatively good quality results with a relatively stationary hydrologic period for model training (Muhammad et al., 2018).

The usage of post-processing techniques should be investigated thoroughly before the application of multi-model approaches for better forecast results. Among post-processing techniques, probabilistic approaches and ensemble predictions are increasingly popular in practice. An important aspect of post-processing includes communication of uncertainties that may occur at different stages of the hydrological forecasting pipeline. Indeed, communication uncertainty in hydrological forecasting is equally important as the quantification of these uncertainties, as it directly affects the lives of individuals, e.g., flood forecasting. Uncertainty communication in different ways, such as linguistic, graphical, numeric, or combinations of these (Van Steenbergen et al., 2012).

5.4. Practical applications of reducing uncertainties in hydrological forecasting

In practice, various organizations utilize different models, rules of thumb, and recommendations for their hydrological forecasting applications (WMO, 2009). In the present review, 96 studies were reviewed and more than 100 combinations of models, methods of uncertainty quantifications, and uncertainty reductions were reported (Table 5). These selections and the availability of data, instruments, and funds can influence the forecasting results. However, following guidelines such as the International Association of Hydrological Sciences, WMO, 2009, and national hydrological institutions' recommendations can be beneficial in practical applications. As directed by the World Meteorological Organization in Report 168 (WMO, 2009), the randomness of the hydrological phenomena should be accounted for in hydrological forecasting as a probability distribution and estimation of parameters for the transparency in the reliability of the results. In addition, it is recommended to use one or more independent estimation methods to quantify the uncertainties in hydrological forecasting. A more detailed analysis of the types of uncertainties, models, and calibration techniques used is summarized in Table 5. The taxonomy shown in Table 5 is based on the decision tree for choosing uncertainty estimation method highlighted in Beven (2009). The 96 reviewed studies are categorized into three main groups: (i) real-time DA methods, which include the Kalman filter, Kalman filtering with nonlinear gain and variance updating, the extended Kalman filter, the ensemble Kalman filter, and sequential Monte Carlo methods; (ii) methods for conditioning uncertainty on data, which encompass nonlinear regression methods, Bayesian dynamic methods, and GLUE methods; and (iii) forward uncertainty propagation methods, which consist of fuzzy methods, error propagation methods, and Monte Carlo methods (Fig. 8).

6. Multi-criteria approach for reducing the uncertainties in hydrological forecasting

In this section, the multi-criteria approach or supporting techniques used for reducing the uncertainties in the reviewed literature are summarized. Figs. 9 and 10 show the list of approaches found in the literature as a measure of reducing uncertainties in hydrological forecasting. Multi-site calibration and multi-objective calibration for the streamflow have been increasingly in use since the last decade (Table S2). Knowing the type of forecasts and the interconnections between the process representation and the uncertainties will help to alleviate the uncertainties. The process representation improvements through random error components will help reduce the total hydrological uncertainties in short forecast leads (McInerney et al., 2021). As discussed in the earlier sections, the criteria followed in the reviewed studies are interrelated; for example, when we apply multi-source data for improving model conceptualization, the model parameters must be calibrated for better performances of the hydrological model. Likewise, this section will summarize the requirements for the multi-criteria used to reduce the uncertainties and their applications and limitations. The advantages and disadvantages can be found in Table S2.

6.1. Multi-data applications in reducing uncertainties

In multi-data applications, DA techniques are used to assimilate additional data sources before the model conceptualization and update the output variables using the real-time measured data during the forecast period (Barbetta et al., 2017; Zarzar et al., 2018; De Santis et al., 2021). Model performance and the forecast horizon (e.g., short-term, or long-term forecasts like a 1-day forecast) are intrinsically connected, and the forecast horizon can influence model performance (Krysanova et al., 2018; Papacharalampous et al., 2020). For such cases, assimilation of real-time measurements would assist in maintaining the standard of the model performance (Mazrooei and Sankarasubramanian, 2019; De Santis et al., 2021). Nonetheless, additional information on the hydrological process through supporting techniques is recommended to reduce such uncertainties. For example, in contrast to conventional outlet calibration, multi-site evaluation of parameters is one of the ways employed to reduce the uncertainties (Lin et al., 2014), while accounting for spatial variation in the hydrological processes. Krysanova et al. (2018) showed that conventional modeling and validation of the hydrological modeling using historical data perform better than the multi-model ensemble approach for the projections of the climate change data. Wang et al., 2017 demonstrated that DA along with the uncertainty quantification method can provide a robust hydroclimatic forecasting framework. Thiboult et al. (2017) showed that different qualities of the forecast system are intrinsically connected, and one should first attempt to improve forecast accuracy to yield improvement in forecast reliability. Table 6 shows a summary of the advantages and limitations of multi-criteria approaches used for reducing uncertainties. Refer to Table S2 for the detailed advantages and limitations of the reviewed studies.

DA of additional data can be used to enhance the performance of low (resp. high) flow simulations using the assimilation of streamflow (resp. soil moisture) (Mazrooei and Sankarasubramanian, 2019). This is found to be helpful in ungauged catchments (Meng et al., 2017). The authors also showed that any minor improvement in deep soil layer representation improves the streamflow prediction after applying vertical error correlation for soil moisture. Patil and Ramsankaran (2017) found that the ensemble propagation method, along with ensemble generation methods, can handle some types of uncertainty due to weak model structure.

Data assimilation-based forecast estimations provide a comprehensive representation of system uncertainties, although the predictive accuracy is influenced by the choice of the DA method and modeling scheme (Piazzi et al., 2021). Often additional information is required to successfully perform the DA task depending on dominant hydrological processes in the catchment. For example, a snow-dominated catchment needs different Ensemble Kalman Filter implementations to combine the streamflow and snow information (Abaza et al., 2014), while for flood forecasting, the performance depends on the initial soil moisture (Meng et al., 2017).

The effect of DA of Soil Moisture (SM) on hydrological models depends on the model structure, and calibration practices (De Santis et al., 2021). Also, the effect of DA may have different impacts on different seasons. So, special care should be given to aspects of the 'one model fits all' paradigm. The application of specific remotely sensed products and their accuracy trivially have effects on DA techniques and outcomes (De Santis et al., 2021; Piazzi et al., 2021; Rajib et al., 2018; Koster et al., 2018). The accuracy of the products is influenced by factors such as the local efficiency of satellite observations due to climatic factors such as snow, and humid conditions (De Santis et al., 2021). The integration of this additional information about the catchment in the modeling scheme yields better outcomes than enforcing high NSE (Nash-Sutcliffe efficiency) values or low statistical errors. The satellite-derived snow cover area can serve as one of the predictors for streamflow estimation in the snow-dominated region (Hassan and Hassan, 2020).

Ensemble Kalman Filter at the DA stage can reduce the difference

Table. 5
Comparative Analysis of Uncertainty Assessment Methods in Hydrological Forecasting.

Types of Uncertainty Assessment Method	Hydrological forecasting	Uncertainties addressed	Multi-criteria approach used to reduce uncertainties	Studies
Conditioning uncertainty on data methods-Bayesian dynamic methods	Flood forecasting	Forecasting	Multi-data	Seo et al., 2019
	Snow forecasting	Parameter, conceptual model	Multi-data, multi-model	Poulin et al., 2011
			Multi-model	Franz et al., 2010
			Multi-data	Chawla and Mujumdar, 2018
	Streamflow forecasting	Conceptual model, forecasting	Multi-model, multi objective function	Arsenault et al., 2015
		Observation and forecast	Multi-data	Yang et al., 2020
		Observation, Input, Forecasting	Multi-data	Das Bhowmik et al., 2020
		Parameter, conceptual model, forecasting	Multi-data, multi-model	Humphrey et al., 2016
		Parameter, forecasting	Multi-model, post processing	Muhammad et al., 2018
Conditioning uncertainty on data methods-GLUE method	Flood forecasting	Forecasting	Multi-data, multi-site calibration	Rajib et al., 2020
	Rainfall-runoff process	Input	Multi-data	Fraga et al., 2019
	Runoff, snow	Parameter, conceptual model	Multi-data	Xue et al., 2018
	Snow forecasting	Parameter, conceptual model, forecasting	Multi-data, multi-objective function	Di Marco et al., 2021
		Parameter, forecasting	Multi-data, multi-model	Zaremehrjardy et al., 2021
			Multi-data, Posterior function	He et al., 2011
		Conceptual model	Multi-data	Lee et al., 2021
		Forecasting	Multi-data	Herman et al., 2018
		Input	Multi-model, multi objective function	Lerat et al., 2020
		Input, Parameter	Multi-data, multi-variate calibration strategies	Dembélé et al., 2020
				Demirel et al., 2013
		Input, parameter, forecasting	Multi-model	Rajib et al., 2018
		Parameter	Multi-data, multi-optimization	Hui et al., 2020
			Multi-data	Panchanathan et al., 2023
		Parameter, conceptual model, forecasting	Multi-model	Brigode et al., 2013
				Huang et al., 2020
			Multi-data	Uniyal et al., 2015
			Multi-model	Li et al., 2015
				Yuan et al., 2017
			Multi-model, multi objective function	Gan et al., 2018a, 2018b
			Multi-objective function	Liang et al., 2021
			Multi-parameter, multi-GCM ensemble	Her et al., 2019a, 2019b
	Streamflow forecasting	Parameter, forecasting	Multi-site evaluation, posterior functions	Lin et al., 2014
		Parameter, simulation	Multi-model	Vema et al., 2020
		Parameter, forecasting	Multi-data	Sun et al., 2018
	Streamflow forecasting, Water budgets	Input, forecasting	Multi-data	Ashraf et al., 2019
	Water budget	Input, parameter	Multi-objective function	Lilhare et al., 2020
		Forecasting	Post processing, wisdom of crowd	Van Steenbergen et al., 2012
Conditioning uncertainty on data methods-Nonlinear regression	Flood forecasting	Observation, parameter, conceptual model, forecasting	Multi-data	Bhola et al., 2019
		Parameter, forecasting	Multi-data, multi-model	Bonakdari et al., 2019
	Rainfall-runoff process	Parameter	Multi-data	Klotz et al., 2021
	Reservoir inflow	Input, parameter	Multi-data	Kasiviswanathan et al., 2020
		Conceptual model	Multi-data	Helfricht et al., 2014
		Conceptual model, forecasting	Multi-data	Thackeray et al., 2016
		Forecasting	Multi-data	Rittger et al., 2013
	Snow forecasting	Input	Multi-data	Brown and Robinson, 2011
		Observation, input, conceptual model	Multi-data	Lafaysse et al., 2017
		Observation, parameter, conceptual model	Multi-data, multi-objective function	Schöber et al., 2014a, 2014b
		Parameter, conceptual model	Multi-data	Slater et al., 2013
		Parameter, forecasting	Multi-data, multi-objective function	Thornton et al., 2021
	Soil moisture	Input	Multi-data	Fathololoumi et al., 2021
	Streamflow forecasting	Conceptual model	Multi-data	Nayak et al., 2021
		Forecasting	Multi-model, Preprocessing	Abbasi et al., 2021
			Multi-data	Liu et al., 2018
		Input	Preprocessing	Hassan and Hassan, 2021
		Input, Conceptual model	Multi-data	Althoff et al., 2021
		Parameter	Post processing	Liu et al., 2020

(continued on next page)

Table. 5 (*continued*)

Types of Uncertainty Assessment Method	Hydrological forecasting	Uncertainties addressed	Multi-criteria approach used to reduce uncertainties	Studies
Forward uncertainty propagation method	Flood forecasting	Forecasting	Multi-data	Hu et al., 2019
		Input, forecasting	Multi-data	Xu et al., 2021
		Input	Multi-data	Penny et al., 2020
	Streamflow forecasting	Parameter, forecasting	Post processing, Posterior function	Wang et al., 2017
		Conceptual model, forecasting	Multi-data	Lee et al., 2019
	Flood forecasting	Forecasting	Multi-model	Barbetta et al., 2017
		Input, forecasting	Multi-data	Adams and Dymond, 2019
		Input, parameter, forecasting	Multi-data, multi-model	Zappa et al., 2011
		Observation, Input	Multi-data	Silvestro et al., 2021
		Observation, input, conceptual model, forecasting	Multi-data	Meng et al., 2017
		Observation, parameter	Multi-data, Post processing	Habert et al., 2016
		Observation, parameter, forecasting	Multi-data, Post processing	Zarzar et al., 2018
		Parameter, conceptual model, forecasting	Multi-data, multi-model	Thiboult et al., 2017
		Parameter, forecasting	Multi-data, Posterior function	Tran et al., 2020
	Precipitation forecast	Input, forecasting	Pre and post processing	Chen et al., 2020
		Observation, conceptual model	Multi-model	Valdez et al., 2021
		Forecasting	Multi-data	Che et al., 2014
	Snow forecasting		Multi-model	Dion et al., 2021
		Observation, parameter	Multi-data	Leisenring and Moradkhani, 2011
		Parameter, conceptual model	Multi-model	Essery et al., 2013
				Abaza et al., 2014
			Multi-data	DeChant and Moradkhani, 2014
		Conceptual model, forecasting		McInerney et al., 2021
Real time data assimilation methods	Streamflow forecasting		Multi-data, multi-model	Thiboult et al., 2015
			Multi-data	Chen et al., 2016
				De Santis et al., 2021
				Dechant and Moradkhani, 2011
		Forecasting		Mazrooei et al., 2021
			Multi-data, Post processing	Papacharalampous et al., 2020b
			Post processing	Siqueira et al., 2021
				Das et al., 2018
			Multi-data	Massari et al., 2015
		Input, forecasting		Mazrooei and Sankarasubramanian, 2019
			Multi-data, multi-model	Singh and Sankarasubramanian, 2014
			Multi-data, multi-objective function	Budhathoki et al., 2020
		Input, forecasting	Multi-data	Hassan and Hassan, 2020
		Observation, Input, Forecasting	Multi-data	Piazzi et al., 2021
		Observation, parameter, conceptual model, forecasting	Multi-data	Patil and Ramsankaran, 2017
		Parameter, forecasting	Post processing, wisdom of crowd	Papacharalampous et al., 2020
	Streamflow, water balance parameters	Forecasting	Multi-model	Krysanova et al., 2018

between the measurement and the ensemble streamflow predictions by accounting for uncertainties in hydrometeorological measurements (Dion et al., 2021). DA may not be able to reduce the model structural deficiencies, and it may even in certain cases reduce the model performances. So, care should be given to the selection of DA methods (De Santis et al., 2021). Di Marco et al. (2021) found that remotely sensed MODIS products for snow cover areas improve the identifiability of combined melt factor parameters. Mazrooei and Sankarasubramanian (2019) claimed that streamflow accuracy can be enhanced by using DA of groundwater storage and soil moisture observations before the model iterations using EnKF. Application of global satellite-gauge merged precipitation products, and their ensembles have also been found to improve decision-making through the reduction of the parameter and model structural uncertainties (Sun et al., 2018). Model structural uncertainty has been reduced by updating the soil water routing through perturbed soil water storages (Patil and Ramsankaran, 2017). Additional bathymetry data has helped to improve the floodplain friction coefficient. This procedure improves the relationship between water level discharge and reduces the uncertainties concerning the time-dependent friction coefficient (Habert et al., 2016).

Additional field data and multi-temporal airborne laser scanning data have improved hydrologic simulations of snow-dominated catchments (Schöber et al., 2014a, 2014b). Especially, it enhanced the estimation of snow density, which depends on various factors such as elevation, terrain features, parameterization, precipitation gradients, and accumulation pattern. Overall, it is stressed that in most DA techniques, it is essential to know the uncertainty contribution before applying any measurement data. If the uncertainties are larger in quantity, they must be reconstructed with the following information: (1) the final date of seasonal snow cover, (2) the potential snowmelt model, (3) appropriate parameterization, and (4) the selection of relevant data (Slater et al., 2013). Especially, DA methods showed significant

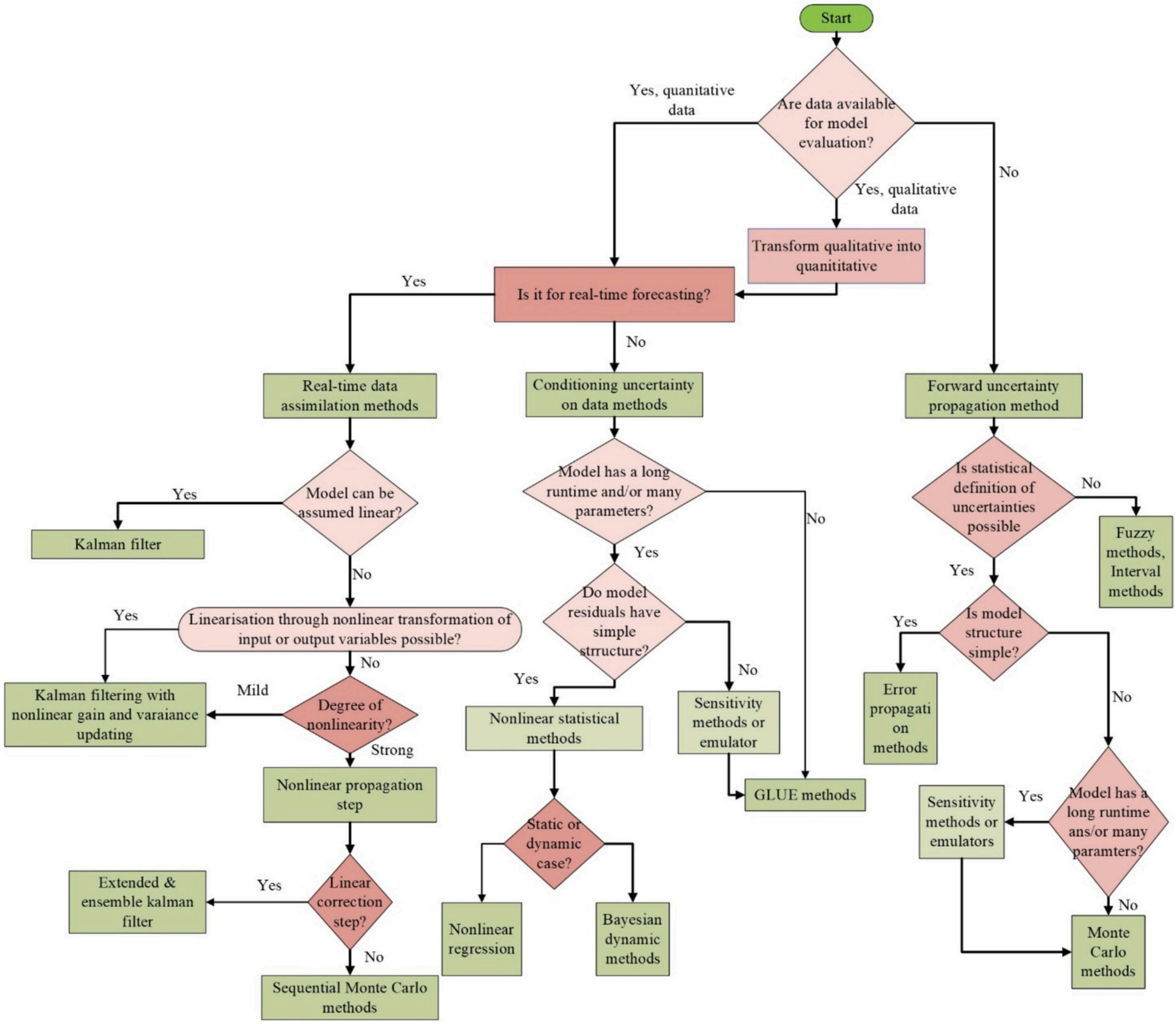

Fig. 8. A decision tree for choosing an uncertainty estimation method (Source: Beven, 2009).

improvements in seasonal accumulation and ablation of SWE predictions in the SNOW-17 model (Leisenring and Moradkhani, 2011).

6.2. Multi-model applications in reducing uncertainties

To deal with the conceptual deficiencies in a single model, it has recently been proposed to have a multi-model approach. This can be carried out using different complexities of the same model and the application of different hydrologic models for the same studies using, for instance, ensemble techniques. This helps to enhance the performance of the forecasts by reducing model error. Multi-model ensembles are useful for large basins for the applications of climate change on streamflow. For communication, the ensemble results must be verified and compared with the individual performance of the models (Krysanova et al., 2018). In the forecasting context, the economic values of using multi-model approaches instead of a single model should be transparent. The choice of models and selection of the best model to deliver the forecast not only depends on model performance criteria but also on the reliability and accuracy of the forecast. For this purpose, Thiboult et al. (2015) advocate the use of ensemble methods for a probabilistic meteorological forecast to reduce the accumulation of errors in the initial conditions.

6.3. Other applications in reducing uncertainties

The multi-objective approach helps to enhance the identification of the hydrological model (Gupta et al., 1998; Gupta et al., 2009). It also helps identify the best choice in a multi-model approach to streamflow forecast (Arsenault et al., 2015). It essentially helps to reduce the biases in the simulation of streamflow. For example, in snow-dominated catchments, streamflow measurements can be simultaneously used with the measurements of snow or remotely sensed data (Di Marco et al., 2021). Multi-variate calibration can reveal the interconnection between the variables, possibly providing insights regarding whether the uncertainty originated from input, model structure, or lack of knowledge about the hydrological system.

The objective functions or the model performance indicators are subject to the modeler's choice. However, numerous available indices /tools can assist in this task. This includes Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) Root Mean Square Error (RMSE) (Willmott

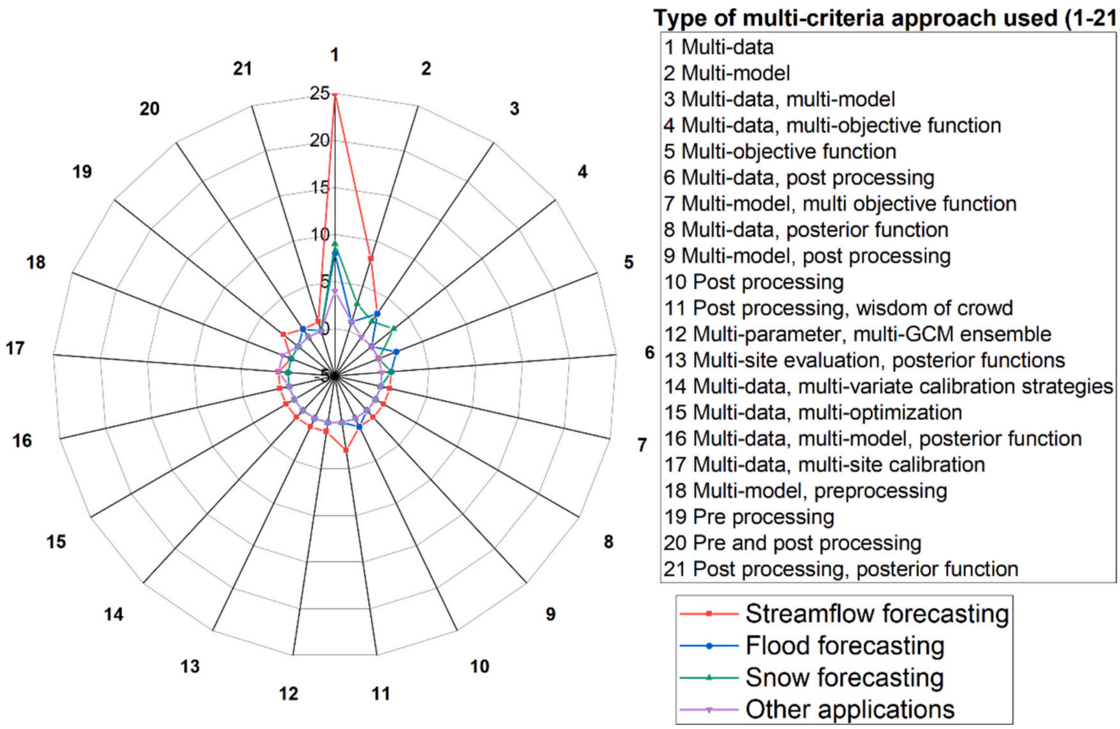

Fig. 9. Synthesis of various techniques used to reduce uncertainties in hydrological forecasting (clockwise indexed numbers from 1 to 21 indicate the types of multi-criteria approach studied, the counts from 0 to 25 along the 0 deg-line refer to the number of studies about types of multi-criteria approach employed per types of forecasting).

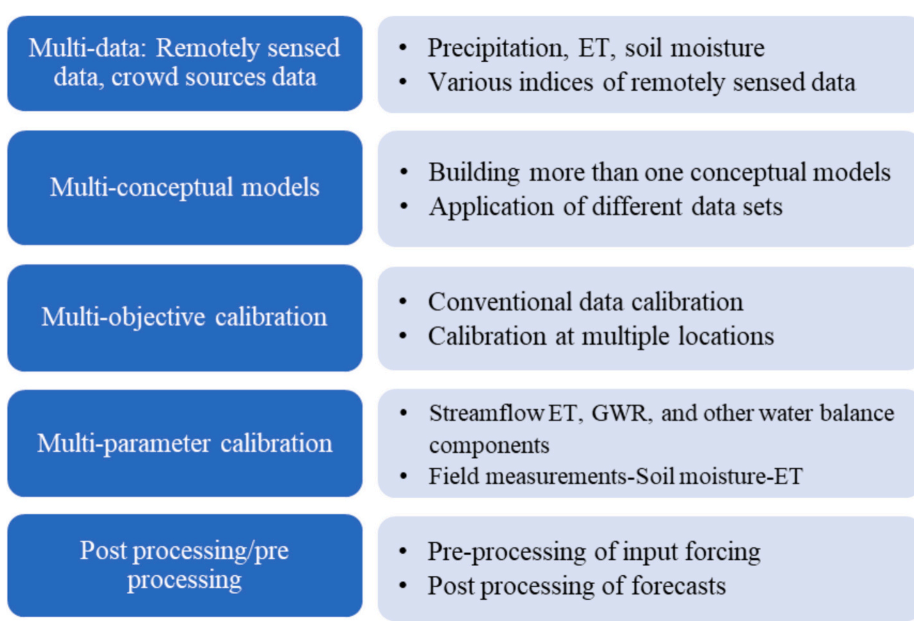

Fig. 10. Multi-criteria approaches involved in the hydrological forecasting.

and Matsuura, 2005; Willmott et al., 2009), and Klinge-Gupta efficiency index (Gupta et al., 2009; Kling et al., 2012). These indices can be chosen based on the literature and the subject of interest (streamflow, snow, flood forecast), the types of models used, and the application constraints for the selected process of hydrological modeling (Di Marco et al., 2021). Applying a combination of these indicators helps alleviate the deficiencies in other indices and enhances the parameter selection and predictive performance (Wang et al., 2017). In a multi-model framework, the identified best models can benefit from applying the multi-objective function. Sometimes for a high value of Nash-Sutcliffe efficiency, the representation of high and low flows may not be captured, and the biases may be higher than 10 %. This is due to the limitations of a single index score. The application of a multi-objective function can overcome this (Brigode et al., 2013).

Multi-site observation and calibration of streamflow have revealed unique responses to climate change (Chien et al., 2013). Accounting for other variables, such as ET, soil moisture, and groundwater, can be added to model calibration, yielding improved representation of the

Table 6
A summary of multi-criteria approaches used for reducing the uncertainties its advantages and limitations/challenges.

Sl. No	Multi-criteria approach employed	Uncertainty addressed	Advantages	Limitations/ challenges
1	Multi-data	Observation, Input, Conceptual, Forecasting	Helps to reduce equifinality and input uncertainties. Additional data increases the forecasting skill/ accuracy. In general model performance is increasing. Real-time updating of multi-data compensates for the time delay in data assimilation techniques. Considering non-stationarity in data helps to reduce parameter uncertainties.	Potential cost increase. The application of open-source data sources may overfit the test data. Uncertainties in the inputs may influence the model performance. The selection of remotely sensed products needs initial assessment before application. Many of the studies using multi-data approaches are tailored to catchment. It needs more analysis for the wider applications.
2	Multi-models	Input, Parameter, Conceptual, Forecasting	Different combinations of uncertainties can be accounted for and tested in the case of a multi-model approach to select the best model. It improves the forecast by reducing uncertainties in the forecast. Multi-model combined with multi-data, posterior function helps to reduce Input, parameter, and forecast uncertainties. Multi-model using hybrid models helps to improve the representation of the system. The economic value of the hydro-meteorological forecast can be increased.	More expensive than conventional modeling. Increasing the complexity of the models needs careful consideration of uncertainties. It may reduce the performance in some cases. The application of different models may bring differences in results which need further evaluation. Different catchments may also bring differences in results due to changes in climatic regions. Selecting the single best model for increasing the forecast value is challenging
3	Multi-objective function/ multi-parameter calibration	Observation, Parameter, Conceptual, Forecasting	Calibrating more than one parameter or calibration of parameters at multiple locations improves the spatial accuracy of representations. This improves the model's performance. It reduces the number of parameters and parameter uncertainty. The multi-objective function may be useful in case of lack of data e.g., in case of lack of daily flow data, monthly analysis can be used to understand the catchment processes. Uncertainties in the prediction or forecast is reduced.	A lack of field observations may need reliability analysis. Trying to improve the model accuracy only using parameter calibration is challenging. The lack of accurate parameters regionalized using multi-objective function may influence the model performance. Applicability of the studies is limited to the tested case, and it needs to be verified for other catchments. The accuracy of this approach depends on the data used for the calibration. Inherent uncertainties in the data may affect the overall performance of the model.
4	Pre-processing, Post-processing	Observation, Input, Forecast	Post-processing helps to improve the forecast accuracy in real-time forecasting systems. Pre-processing helps to reduce the input uncertainties and improve the model performance. The combination of post-processing with the application of multi-data helps to reduce the uncertainties. It is used in flood forecasting systems. The combination of post-processing and additional crowd-sourcing information is simple, and it helps to communicate uncertainties easily.	Post-processing techniques in real-time forecasts are subject to the limitations of several models, ensemble sample size, basin complexity, and study period. The performance of the combination of pre- and post-processing may vary in different regions of study. Computational costs may be higher, and procedures are intensive. Usage of crowd-sourcing information can't be used in the decision-making system.

system and model performance. Rajib et al. (2018) found that the application of Moderate-resolution Imaging Spectroradiometer (MODIS) ET data in the calibration has improved the simulation performance. Similarly, introducing groundwater storage in the calibration has helped to improve the model performance (Qiao et al., 2013). Researchers also showed that the predictability of hydrological models can be significantly improved when jointly calibrating with streamflow and satellite-based ET data (Rajib et al., 2018; Panchanathan et al., 2023).

Pre-processing helps to reduce the uncertainties accumulated in the datasets before the conceptualizations (Abbasi et al., 2021). Depending upon the type of forecast, models used, and variable of interest, the input uncertainties shall be addressed using pre-processing techniques, utilizing, e.g., precipitation data for streamflow prediction (Abbasi et al., 2021), bathymetry for flood studies (Meng et al., 2017), and snow density for the snow modeling (Dion et al., 2021). A combination of pre-processing methods and non-linear models has improved the prediction accuracy to a significant extent (Abbasi et al., 2021). Typically, pre-processing helps to reduce the number of predictor variables. For instance, dimensionality reduction and variable selections contribute to improving the accuracy of prediction (Her et al., 2019a, 2019b).

7. Role of remote sensing applications in reducing uncertainties of hydrological forecasting

The development of remote sensing data such as Landsat products, soil moisture data, evapotranspiration data, and various products of snow data such as snow cover data, snow water equivalent, and snow water estimation are used widely to improve hydrological forecasting. Table S3 shows the list of studies reviewed that apply remotely sensed data and relevant derived products to reduce uncertainties in hydrological forecasting. The application of remotely sensed data is reported to help address input uncertainty (Dembélé et al., 2020; Hassan and Hassan, 2020), parameter uncertainty (Gan et al., 2018a, 2018b; Dembélé et al., 2020; Liu et al., 2020; Papacharalampous et al., 2020), forecast uncertainty (Gan et al., 2018a, 2018b; Hassan and Hassan, 2020; Papacharalampous et al., 2020; Abbasi et al., 2021; De Santis et al., 2021; Mazrooei et al., 2021), conceptual model uncertainty (Lee et al., 2021; Nayak et al., 2021). The availability of remotely sensed data makes this application feasible even in data-scarce conditions for improving hydrological modeling. For detailed information on the applications, and limitations of remotely sensed data products, we illustrated in Table S3 the detailed review of the studies. Table S4 shows the list of open-source data available in vegetation, soil, evapotranspiration, and climate that can contribute to this task. The web addresses provide more information on the availability, usage, and limitations of the data products.

8. Recommendations for the model selections and reducing uncertainties in hydrological forecasting

Selecting a suitable hydrological model and understanding the catchment play a vital role in reducing uncertainties (Wagener and Gupta, 2005). These two factors are interconnected and influence each other in forecasting results. This section will discuss the key aspects of hydrological models and catchment characteristics that have been highlighted in the reviewed studies.

8.1. Choice of models

One of the key aspects is the selection of models for hydrological forecasting. As the choices are plenty, choosing a model needs to be given careful consideration. Here we summarize some of the key points for choosing a model. The models utilized in the reviewed studies are organized into Tables 7 and 8. Table 7 presents the frequency of model usage across various regions, while Table 8 provides a comprehensive list of the models, the uncertainties they address, and the number of catchments investigated.

1. Recent studies suggest that devising different combinations of model structures can effectively reduce model errors and forecast uncertainty (DeChant and Moradkhani, 2014).
2. Knowing the watershed characteristics is important to select a hydrological model, for example, to choose a simple ABCD model, the watershed's hydrological response could be reproduced concerning a given rainfall and temperature (Her et al., 2019a, 2019b).
3. The performance can degrade when we have not chosen an appropriate hydrological model or model structure. This situation cannot be considered uncertain; rather, it can be the result of model selection in some cases (Lin et al., 2014). Low flows were not able to be simulated well in this study due to the selection of the model or model structure (Lin et al., 2014).

Table. 7
The frequency of models used across different regions of the world.

Sl. No	Region	Model used (Number of studies used the same model)
1	Australia	GR4J (1)
2	Asia (China, India, Iran, Japan, Pakistan, India, Tibet, South Korea, Vietnam)	ANN-based (5), VIC (3), SWAT (3), CREST (1), CUE model (1), TOPMODEL (1), XAJ (1), Conceptual hydrological model (1), Remote sensing data (1), Tank model (1), NAM (1), Common Land Model (CoLM) (1)
3	Europe (Austria, Belgium, France, Germany, Italy, Norway, Spain, Switzerland)	HBV (2), GR4J (2), MISDc (2), Remote sensing data (1), Snow and ice melt model (SES) (1), MIKE 11 (1), NAM (1), MASCARET (1), Data-driven model (1), GR5J (1), SnowMIP (1), SURFEX/ISBA (1), TOPMo (1), TOPMODEL (1), HEC-RAS 2D (1), ICHYMOD (1), STAFOM-RCM (1), TOPMELT (1), Hydrological Model Continuum (HMC) (1), HEC-HMS (1), PREVAH (1), WaSiM (1)
4	North America (Canada, USA)	SWAT (4), GR4J (2), VIC (2), Hydrotel (2), HYMOD (2), SAC-SMA (2), HSAMI (1), MOHYSE (1), BUCKET (1), CEQUEAU (1), CREC (1), DFM (1), GARDENIA (1), HBV (1),, IHACRES (1), MARTINE (1), MESH (1), MOHYSE (1), MORDOR (1), NAM (1), SACRAMENTO (1), SIMHYD (1), SMAR (1), Tank model (1), TOPMODEL (1), WAGENINGEN (1), WATFLOOD (1), XAJ (1), HOOPLA (1), Dynamic Budyko (1), abcd model (1), ANN based (1), BDHM (1), GR2M (1), HEC-RAS 2D (1), LISFLOOD-FP, Probability Distributed Model (1), Snow cover retrieval models (1), SNOW-17(1), SNOW-18 (1), Remote sensing data (1), SWIM (1),
5	South America (Brazil, Continental-scale study)	ANN-based (1), MGB (1)

4. Care should be given when we use any model for extreme rainfall events. A few models cannot capture those events well, e.g., VIC (Chawla and Mujumdar, 2018).
5. Similarly, for low flows, the GR4J model overestimates, whereas HBV is prone to underestimate low flows (Demirel et al., 2013).

8.2. Model complexity

Secondly, for a selected model how much we can increase the model complexity to improve the performance of the model is a key question. Some of the important aspects of choosing the model complexities are listed as follows,

1. The application of multi-level complex model implementation can be considered for a given study to identify the suitable model structure and improve forecasting (He et al., 2011; Huang et al., 2020). However, we cannot assume that model performance will improve if we only increase the model complexity. For example, well-known empirical parameterizations can perform as well as physically based models (Essery et al., 2013).
2. So, the selection of model structure in terms of complexity, model structure, and parameters may influence the results of the supporting applications such as data assimilation, and remote sensing (De Santis et al., 2021).
3. The explicit assessment of the influence of data errors (Franz et al., 2010), modeling structures, and parameters (He et al., 2011) is required for a more comprehensive understanding of the total uncertainty.
4. The field data should support increasing the model complexity to reduce these uncertainties.

Table. 8
The comprehensive list of models used, uncertainties addressed, and the number of catchments investigated.

Sl. No	Hydrological forecasting	The model used (Number of studies used)	Combinations of Uncertainties addressed	Studies (Sum of Number of catchments investigated)
1	Streamflow forecasting	Dynamic Budyko (1), SWIM (1), abcd model (3), ANN based (8), BDHM (1), BUCKET (1), CEQUEAU (1), Conceptual hydrological model (1), CREC (1), CREST (1), CUE model (1), DFM (1), GARDENIA (1), GR2M (2), GR4J (8), GR5J (1), HBV (3), Hydrotel (1), HYMOD(1), IHACRES (1), MARTINE (1), MESH (1), mesoscale Hydrologic Model (mHM) (1), MGB (1), MISDc (1), MOHYSE (1), MORDOR (1), NAM (1), Probability Distributed Model (1), SACRAMENTO (1), SAC-SMA (2), SIMHYD (1), SMAR (1), SNOW-17 (1), SNOW-18 (1), SWAT (9), Tank model (1), TOPMo (1), TOPMODEL (2), VIC (7), WAGENINGEN (1), WATFLOOD (1), XAJ (3)	(Input), (Input, forecasting), (Input, conceptual model), (Input, parameter), (Input, parameter, forecasting), (Conceptual model), (Conceptual model, forecasting), (Forecasting), (Parameter, conceptual model, forecasting), (Parameter, forecasting)	De Santis et al., 2021 (700), Lerat et al., 2020 (508), Arsenault et al.,2015 (429), Mazrooei and Sankarasubramanian, 2019 (340), Papacharalampous et al., 2020b (270), Her et al., 2019a, 2019b (156), Brigode et al., 2013 (89), Nayak et al., 2021 (43), Thiboult et al., 2015 (20), McInerney et al., 2021 (11), Gan et al., 2018a, 2018b (10), Massari et al., 2015 (5), Das Bhowmik et al., 2020 (4), Huang et al., 2020 (3), Humphrey et al., 2016 (3), DeChant and Moradkhani, 2014 (3), Singh and Sankarasubramanian, 2014 (2), Yuan et al., 2018 (2), Abbasi et al., 2021 (1), Liu et al., 2018 (1), Hassan and Hassan, 2021 (1), Althoff et al., 2021 (1), Hassan and Hassan, 2020 (1), Yang et al., 2020 (1), Wang et al., 2017 (1), Vema et al., 2020 (1), Penny et al., 2020 (1), Chen et al., 2016 (1), Papacharalampous et al., 2020, Demirel et al., 2013 (1), Demirel et al., 2013 (1), Li et al., 2015 (1), Abaza et al., 2014 (1), Budhathoki et al., 2020 (1), Dembélé et al., 2020 (1), Siqueira et al., 2021 (1), Dechant and Moradkhani, 2011 (1), Lee et al., 2021 (1), Herman et al., 2018 (1), Rajib et al., 2018 (1), Patil and Ramsankaran, 2017 (1), Hui et al., 2020 (1), Panchanathan et al., 2023 (1), Liang et al., 2021 (1), Uniyal et al., 2015 (1), Muhammad et al., 2018 (1), Chawla and Mujumdar, 2018 (1), Mazrooei et al., 2021 (1), Das et al., 2018 (1), Liu et al., 2020 (1), Yuan et al., 2017 (1), Sun et al., 2018 (1), Muhammad et al., 2018 (1), Lin et al., 2014 (1)
2	Flood forecasting	MASCARET (1), MIKE 11 (1), ANN-based (4), BUCKET (1), CEQUEAU (1), CREC (1), Data-driven model (1), DFM (1), GARDENIA (1), GR4J (1), HBV (1), HEC-RAS 2D (2), Hydrological Model Continuum (HMC) (1), HYMOD (1), IHACRES (1), LISFLOOD-FP (1), MARTINE (1), MISDc (1), MOHYSE (1), MORDOR (1), NAM (3), PREVAH (1), SACRAMENTO (1), SAC-SMA model (1), SIMHYD (1), SMAR (1), STAFOM-RCM (1), SWAT (1), Tank model (2), TOPMODEL (1), WAGENINGEN (1), XAJ (2)	(Input, parameter), (Input, parameter, forecasting), (Input, conceptual model, forecasting), (Observation, parameter), (Parameter, conceptual model, forecasting), (Parameter, forecasting), (Observation, parameter, conceptual model, forecasting), (Forecasting)	Adams and Dymond, 2019 (796), Seo et al., 2019 (35), Thiboult et al., 2017(20), Lee et al., 2019 (10), Bonakdari et al., 2019 (6), Van Steenbergen et al., 2012 (3), Meng et al., 2017 (2), Habert et al., 2016 (1), Hu et al., 2019 (1), Xu et al., 2021 (1), Bhola et al., 2019(1), Zarzar et al., 2018(1), Silvestro et al., 2021(1), Rajib et al., 2020 (1), Barbetta et al., 2017 (1),), Tran et al., 2020 (1), Zappa et al., 2011 (1), Barbetta et al., 2017(1), Rajib et al., 2020 (1)
3	Snow forecasting	HSAMI (1), HYMOD (1), MOHYSE (1), CEQUEAU (1), Common Land Model (CoLM) (1), GR4J (1), HBV (1), Hydrotel (1), ICHYMOD (1), IHACRES (1), Remote sensing data (4), SIMHYD (1), Snow and ice melt model (SES) (1), Snow cover retrieval models (1), SNOW-17 (3), SnowMIP (1), URFEX/ISBA (1), SWAT (1), TOPMELT(1), TOPMODEL(1), WaSiM (1)	(Input), (Forecasting), (Parameter, conceptual model, forecasting), (Parameter, conceptual model), (Observation, parameter), (Observation, input, conceptual model), (Parameter, forecasting),	Che et al., 2014 (9), He et al., 2011 (8), Franz et al., 2010 (6), Dion et al., 2021 (5), Poulin et al., 2011 (1), Di Marco et al., 2021 (1), Helfricht et al., 2014 (1), Thackeray et al., 2016 (1), Brown and Robinson, 2011 (1), Slater et al., 2013 (1), Schöber et al., 2014a, 2014b (1), Rittger et al., 2013 (1), Leisenring and Moradkhani, 2011 (1), Essery et al., 2013 (1), Lafaysse et al., 2017 (1), Zaremehrjardy et al., 2021 (1), Di Marco et al., 2021 (1), Thornton et al., 2021 (1)
4	Other applications (Soil moisture, water budget, water, rainfall runoff, reservoir inflow, Precipitation forecast)	SWAT, VIC, Global and regional hydrological models, Remote sensing data, Ann based,	(Input), (Observation, conceptual model) (Parameter), (Input, parameter), (Parameter, conceptual model), (Input, forecasting), (Forecasting)	Klotz et al., 2021 (531) Valdez et al., 2021 (30) Ashraf et al., 2019 (17) Krysanova et al., 2018 (1) Lilhare et al., 2020 (1), Fathololoumi et al., 2021 (1), Chen et al., 2020 (1) Fraga et al., 2019 (1) Kasiviswanathan et al., 2020 (1) Xue et al., 2018 (1)

5. It is crucial to meet the balancing hydrological model structure that can represent the near real-time complexity as well as to meet the computational requirements (Di Marco et al., 2021).
6. Hydrological modeling and its reliability in snow-dominated catchments depend on the capability of simulating snow accumulation and melting as it affects the runoff and streamflow.

8.3. Supporting techniques

Thirdly, the developments in supporting techniques for reducing uncertainties needed a comparative evaluation for the selection. Some of the key points are listed below, for a detailed comparison, refer to Tables 5, 6, and S2.

1. Hydrological models tend to have lower efficiency in representing both low and high flows because of climate change (Brigode et al., 2013). This is also rooted back to various infelicitous parameters resulting from the calibration processes (Lin et al., 2014). The alternative option to avoid parameter equifinality can be the application of multi-criteria approaches.
2. Selection of appropriate processing flow such as pre-processing, model structure, parameter selections, calibration techniques, and post-processing enhances hydrological forecasting performance (Abbasi et al., 2021; Patil and Ramsankaran, 2017).
3. In some cases, an individual model can produce better performance than ensemble models of streamflow. In this case, it is important to select an appropriate forecasting model (Thiboult et al., 2015; Thiboult et al., 2017).
4. In addition, reducing various uncertainties requires the application of allied techniques such as sampling distributions, ensemble means, and probabilistic approaches in the prediction task together with multi-criteria-based approaches as discussed in Klotz et al. (2021).
5. The accuracy of remotely sensed products in data assimilation plays a vital role in the quantification and reduction of uncertainties in the forecasted results. Depending on the model structure used, the impact of application remotely sensed data can have a different outcome (Loizu et al., 2018).

8.4. Model calibration

Choosing a method of calibration plays a vital role in terms of parameterization, equifinality, and the performance of the calibrations. Hence, it is important to analyze the previously used techniques, and some of the key aspects are listed as follows:

1. Any developed technique or methodology to reduce the uncertainties in one study cannot be directly assumed to provide similar results. In some cases, it may downgrade the accuracy of the models (Seo et al., 2019).
2. For any modeling structure, flow, techniques, tools, and established methodology, the application of the same technique to a new study or region requires detailed investigations and understanding before the selection of processes (Klotz et al., 2021).
3. Previously published works are always cautious about the final recommendation of their work, highlighting the factors involved in the study and the replication of the same method can produce different results for different requirements. For example, high-performing lower lead-time forecasts may not be suitable for the higher lead-time forecast requirements. However, the developed approaches can be considered as the base of the specific problem we are trying to address (Habert et al., 2016; Seo et al., 2019; Tran et al., 2020; Dion et al., 2021).
4. Care should be undertaken for using the specific published techniques: ensemble methods, and DA techniques (Seo et al., 2019). All individual techniques contain different challenges, which should be considered before the selection.
5. Spatial analysis of uncertainties is a more sophisticated process to consider. However, recent studies suggest promising results for the enhancement of hydrological model performances when using the appropriate spatial dataset (Zaremehrjardy et al., 2021).

8.5. Characteristics of the basins in the uncertainty studies

For a hydrologic modeling framework, characteristics of the catchments being investigated may influence the performance. Here we list the identified key aspects in this regard,

1. Hydrological forecast skill depends on the catchment characteristics such as the area of the basin, geography, topography, hydro-climatic features, and flow regimes. With larger catchments, the complexity of the catchment increases. Thereby, the forecast skill is expected to be lower (Krysanova et al., 2018; Siqueira et al., 2021).
2. The role of the catchment characteristics has to be well evaluated for hydrological forecasting. Depending upon the applications of the forecast, influencing factors should be emphasized as follows:

- Streamflow forecasting should include the size of the catchments and dominant catchment processes.
- Snow-based catchments should be given importance in the aspects of snow accumulation and melt, liquid water storage, and refreezing (Essery et al., 2013) (Di Marco et al., 2021). Additionally, the snow accumulation and melting abilities of a hydrological model contribute largely to modeling the snow-dominated catchments.
- For flood forecasting, sensitive parameters should be adjusted prior to forecasting such as initial soil moisture to reduce the uncertainty in the forecast (Bonakdari et al., 2019; Bhola et al., 2019; Thiboult et al., 2017).
- Forest thickness may affect the land surface state information derived from remotely sensed data for the DA techniques, in which case ground observation data are important to improve the modeling (DeChant and Moradkhani, 2014).
- Non-stationarity should be considered in hydrological modeling, such as land use and land cover (Chawla and Mujumdar, 2018).

3. A catchment's dominant process identification is a key factor in conceptualizing the right combination of the model (Paiva et al., 2012). This helps to identify the uncertainties potentially involved in the modeling framework (Chawla and Mujumdar, 2018). This procedure requires various analyses at different stages of the hydrological modeling.
4. For rainfall-runoff-dominated basins, the accuracy of the high flow events influences the performances of the streamflow predictions (Wang et al., 2017). For such basins, reducing the uncertainties in seasonal climate forecasts requires more care for the higher rainfall seasons (Singh and Sankarasubramanian, 2014).
5. The catchments responding to floods quickly need to be studied in finer spatial and temporal scales to reduce the uncertainty of flood forecasting (Thiboult et al., 2017).
6. The applications of GCMs, RCMs, downscaling methods, and their interactions influence the uncertainty of hydrological modeling. Since meteorological factors influence these, the regions with less temperature variability e.g., colder seasons in mountainous regions have less impact on snow formation (Zaremehrjardy et al., 2021), whereas the impact of wind is higher (Thornton et al., 2021).
7. The estimation of air temperature at higher elevations may produce biases if it contains any incorrect assumptions with lapse rate (Zaremehrjardy et al., 2021).
8. The uncertainty evaluation also should be categorized in terms of the hydroclimatic conditions (Brigode et al., 2013), as it influences a specific hydrological process according to the seasons of the considered catchment. For example, monsoon-based catchments have higher rainfall in a shorter duration, while snow-based catchments (Brigode et al., 2013) should be considered more carefully in winter months (Essery et al., 2013).

9. In special cases like high-elevation areas, climate data inputs are likely to be more important than the model selection and process representation (Zaremehrjardy et al., 2021).
10. It is suggested that for regions with an intensive distribution of topographical index, high runoff accumulations and improved temperature indicators would help to improve the snow melt process (Xue et al., 2018).
11. The number of catchments studied in a particular study and the region of those catchments influence the results of any developed methodology (KlemeŠ, 1986) (Table 8). Different regions and even the area of the catchments in some cases can influence hydrological forecasting (Dion et al., 2021). The parameter uncertainties in hydrological forecasting cannot be justified or generalized in the case of larger catchments with a variety of landscape properties.
12. Various studies suggest that techniques should be tested, validated, and standardized against multiple catchments (Table 8) (e.g., see (Liu et al., 2020) for statistical post-processing techniques; (Essery et al.,2013; Meng et al.,2017; Huang et al., 2020; De Santis et al., 2021) for now-based studies; (Patil and Ramsankaran, 2017) for soil-water routing; (Humphrey et al., 2016) for soil-moisture driven).
13. Seasonal flow predictions should consider the region of highly changing weather patterns in the catchment from summer to snowfall in the winter (Abbasi et al., 2021).

To our best understanding from this review work, we would like to suggest that the application and the usage of more than one hydrological model structure or models with different levels of complexities in combination with the application of different catchments are needed to develop a unified methodology for reducing uncertainties. This approach requires widespread cooperation among the hydrologic communities.

9. Conclusions and the way forward

This study reviewed 96 representative studies to explore the latest developments in reducing uncertainty in hydrological forecasting. Applications of multi-criteria-based approaches in hydrological forecasting studies have seen a wide share of the collected studies, as evidenced by the fact that 73 studies advocate a combination of multiple data with multi-parameter calibration and objective functions. On the other hand, 27 studies utilized more than one model, and 35 studies utilized more than one catchment to test their hypotheses for the improvement in hydrological forecasting. These applications helped to reduce uncertainties at different levels to enhance the reliability of the forecast. We have listed the advantages and disadvantages of each reviewed study. We have summarized the application of remotely sensed data in reducing these uncertainties. Based on the reviewed literature, we have summarized the criteria for selecting a hydrological model to reduce uncertainty in hydrological forecasting. Thus, our review work provides a comprehensive understanding of the current state-of-the-art techniques for handling uncertainty in hydrological forecasting together with their associated advantages and limitations in a way to guides both researcher and practitioner.

Finally, it is also worth asking, “Is it essential to address all the uncertainties in hydrological forecasting?” Without claiming a full answer to this question, it is worth pointing out that this depends on the context and study requirement. This review highlights various classes of uncertainty associated with hydrological forecasting, including input, model parameter, structural, model conceptual, calibration, and validation uncertainty. Besides, the interlink between these uncertainties cannot be neglected. Therefore, estimating a single type of uncertainty may not be suitable in many real-world case studies. On the other hand, the link between the system’s complexity and uncertainty has also been highlighted. This complexity explains the challenge of replication in the hydrological forecast due to its large-scale temporal horizon, emerging constraints related to study area and its specificities. Because “unknown factors” are the key elements to explore in a way that improves our understanding regarding hydrological process forecast. For instance, the debate over the selection of methods for quantifying uncertainties remains unresolved, as the true uncertainties are still unknown (Gupta and Govindaraju, 2023). In this regard, we support Blöschl et al. (2019)’s note regarding “the importance of local or regional works to be done effectively for reducing uncertainties in hydrological predictions or forecasting”.

9.1. The way forward

Understanding uncertainties in the process-based hydrological models during hydrological forecasting is essential. These understandings and quantification of uncertainties in the process should evolve together with the advancements in modeling techniques, such as machine learning (ML), Artificial Intelligence (AI), for the better use of the available datasets. In addition to the techniques and technological developments, international associations such as IAHS (International Association for Hydrological Sciences) are engaging researchers and stakeholders across the globe in developing various solutions for global water issues through digital water globe, and science for solutions initiatives, such as Hydrology Engaging Local People IN one Global world (HELPING). These developments are encouraging the participation of stakeholders in developing the solutions. Engaging in such developments will likely improve the quality of hydrological forecasting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

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References

Abaza, M., Anctil, F., Fortin, V., Turcotte, R., 2014. Sequential streamflow assimilation for short-term hydrological ensemble forecasting. J. Hydrol. 519, 2692–2706. https://doi.org/10.1016/j.jhydrol.2014.08.038.

Abbasi, M., Farokhnia, A., Bahreinimotlagh, M., Roozbahani, R., 2021. A hybrid of Random Forest and Deep Auto-Encoder with support vector regression methods for accuracy improvement and uncertainty reduction of long-term streamflow prediction. J. Hydrol. 597, 125717. https://doi.org/10.1016/j.jhydrol.2020.125717.

Abbott, M.B., Bathurst, J.C., Cunge, J.A., O’Connell, P.E., Rasmussen, J., 1986. An introduction to the European hydrological system-systeme hyrdrologique europeen, “SHE”, 2: structure of a physically-based, distributed modelling system. J. Hydrol. 87, 61–77. https://doi.org/10.1016/0022-1694(86)90115-0.

Adams, T.E., Dymond, R.L., 2019. Possible hydrologic forecasting improvements resulting from advancements in precipitation estimation and forecasting for a real-time flood forecast system in the Ohio River Valley, USA. J. Hydrol. 579, 124138. https://doi.org/10.1016/j.jhydrol.2019.124138.

Althoff, D., Rodrigues, L.N., Bazame, C.H., 2021. Uncertainty quantification for hydrological models based on neural networks: the dropout ensemble. Stoch. Env. Res. Risk A. 35, 1051–1067. https://doi.org/10.1007/s00477-021-01980-8.

Amanambu, A.C., Obarein, O.A., Mossa, J., Li, L., Ayeni, S.S., Balogun, O., Ochege, F.U., 2020. Groundwater system and climate change: present status and future considerations. J. Hydrol. 589, 125163.
Anandharuban, P., La Rocca, M., Elango, L., 2019. A box-model approach for reservoir operation during extreme rainfall events: a case study. J. Earth Syst. Sci. 128. https://doi.org/10.1007/s12040-019-1258-7.
Arsenault, R., Gatien, P., Renaud, B., Brissette, F., Martel, J.L., 2015. A comparative analysis of 9 multi-model averaging approaches in hydrological continuous streamflow simulation. J. Hydrol. 529, 754–767. https://doi.org/10.1016/j.jhydrol.2015.09.001.
Ashraf, S., Majid, V., David, I., Yuliya, S., Greg, A., Monireh, G., 2019. Regionalization and parameterization of a hydrologic model significantly affect the cascade of uncertainty in climate-impact projections. Clim. Dyn. 53, 2861–2886. https://doi.org/10.1007/s00382-019-04664-w.
Barbetta, S., Coccia, G., Moramarco, T., Brocca, L., Todini, E., 2017. The multi temporal/multi-model approach to predictive uncertainty assessment in real-time flood forecasting. J. Hydrol. 551, 555–576. https://doi.org/10.1016/j.jhydrol.2017.06.030.
Beck, M.B., 1987. Water quality modelling: a review of the analysis of uncertainty. Water Resour. Res. 23 (8), 1393–1442.
Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S. A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environ. Model. Softw. 40, 1–20. https://doi.org/10.1016/j.envsoft.2012.09.011.
Beven, K.J., 2000. Uniqueness of place and process representations in hydrological modelling. Hydrol. Earth Syst. Sci. 4, 203–213.
Beven, K., 2002. Towards a coherent philosophy for modelling the environment. Proc. Roy. Soc. A 458 (2026), 2465–2484. https://doi.org/10.1098/rspa.2002.0986.
Beven, K., 2006. A manifesto for the equifinality thesis. J. Hydrol. 320 (1–2), 18–36. https://doi.org/10.1016/j.jhydrol.2005.07.007.
Beven, K.J., 2009. Environmental Modelling: An Uncertain Future? Routledge, London.
Beven, K., 2023. Benchmarking hydrological models for an uncertain future. In: Hydrological Processes, vol. 37, Issue 5. John Wiley and Sons Ltd. https://doi.org/10.1002/hyp.14882
Beven, K., Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. J. Hydrol. 249, 11–29. https://doi.org/10.1016/S0022-1694(01)00421-8.
Beven, K., Lane, S., 2022. On (in)validating environmental models. 1. Principles for formulating a Turing-like Test for determining when a model is fit-for purpose. Hydrol. Process. 36 (10). https://doi.org/10.1002/hyp.14704.
Bhola, P.K., Leandro, J., Disse, M., 2019. Reducing uncertainties in flood inundation outputs of a two-dimensional hydrodynamic model by constraining roughness. Nat. Hazards Earth Syst. Sci. 19, 1445–1457. https://doi.org/10.5194/nhess-19-1445-2019.
Blöschl, G., Bierkens, M.F.P., Chambel, A., Cudennec, C., Destouni, G., Fiori, A., et al., 2019. Twenty-three unsolved problems in hydrology (UPH)–a community perspective. Hydrol. Sci. J. 64, 1141–1158. https://doi.org/10.1080/02626667.2019.1620507.
Bonakdari, H., Zaji, A.H., Binns, A.D., Gharabaghi, B., 2019. Integrated Markov chains and uncertainty analysis techniques to more accurately forecast floods using satellite signals. J. Hydrol. 572, 75–95. https://doi.org/10.1016/j.jhydrol.2019.02.027.
Brigode, P., Oudin, L., Perrin, C., 2013. Hydrological model parameter instability: a source of additional uncertainty in estimating the hydrological impacts of climate change? J. Hydrol. 476, 410–425. https://doi.org/10.1016/j.jhydrol.2012.11.012.
Brown, R.D., Robinson, D.A., 2011. Northern Hemisphere spring snow cover variability and change over 1922-2010 including an assessment of uncertainty. Cryosphere 5, 219–229. https://doi.org/10.5194/tc-5-219-2011.
Budhathoki, S., Rokaya, P., Lindenschmidt, K.E., Davison, B., 2020. A multi-objective calibration approach using in-situ soil moisture data for improved hydrological simulation of the Prairies. Hydrol. Sci. J. 65, 638–649. https://doi.org/10.1080/02626667.2020.1715982.
Butts, M.B., Payne, J.T., Kristensen, M., Madsen, H., 2004. An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. J. Hydrol. 298 (1–4), 242–266. https://doi.org/10.1016/j.jhydrol.2004.03.042.
Chawla, I., Mujumdar, P.P., 2018. Partitioning uncertainty in streamflow projections under nonstationary model conditions. Adv. Water Resour. 112, 266–282. https://doi.org/10.1016/j.advwatres.2017.10.013.
Che, T., Li, X., Jin, R., Huang, C., 2014. Assimilating passive microwave remote sensing data into a land surface model to improve the estimation of snow depth. Remote Sens. Environ. 143, 54–63. https://doi.org/10.1016/j.rse.2013.12.009.
Chen, L., Singh, V.P., Lu, W., Zhang, J., Zhou, J., Guo, S., 2016. Streamflow forecast uncertainty evolution and its effect on real-time reservoir operation. J. Hydrol. 540, 712–726. https://doi.org/10.1016/j.jhydrol.2016.06.015.
Chen, Xinchi, Chen, Xiaohong, Huang, D., Liu, H., 2020. Post-processing and evaluation of precipitation ensemble forecast under multiple schemes in beijiang river basin. Water (Switzerland) 12. https://doi.org/10.3390/w12092631.
Chien, H., Yeh, P.J.F., Knouft, J.H., 2013. Modeling the potential impacts of climate change on streamflow in agricultural watersheds of the Midwestern United States. J. Hydrol. 491, 73–88. https://doi.org/10.1016/j.jhydrol.2013.03.026.
Clark, M.P., Nijssen, B., Lundquist, J.D., Kavetski, D., Rupp, D.E., Woods, R.A., Freer, J. E., Gutmann, E.D., Wood, A.W., Brekke, L.D., Arnold, J.R., Gochis, D.J., Rasmussen, R.M., 2015. A unified approach for process-based hydrologic modeling: 1. Modeling concept. Water Resour. Res. 2498–2514. https://doi.org/10.1002/2015WR017200.A.
Das Bhowmik, R., Ng, T.L., Wang, J.P., 2020. Understanding the impact of observation data uncertainty on probabilistic streamflow forecasts using a dynamic hierarchical model. Water Resour. Res. 56, 1–20. https://doi.org/10.1029/2019WR025463.
Das, J., Treesa, A., Umamahesh, N.V., 2018. Modelling impacts of climate change on a River Basin : analysis of uncertainty using REA & possibilistic approach. Water Resour. Manag. 32, 4833–4852.
De Santis, D., Biondi, D., Crow, W.T., Camici, S., Modanesi, S., Brocca, L., Massari, C., 2021. Assimilation of satellite soil moisture products for river flow prediction: an extensive experiment in over 700 catchments throughout europe. Water Resour. Res. 57, 1–21. https://doi.org/10.1029/2021WR029643.
Dechant, C.M., Moradkhani, H., 2011. Improving the characterization of initial condition for ensemble streamflow prediction using data assimilation. Hydrol. Earth Syst. Sci. 15, 3399–3410. https://doi.org/10.5194/hess-15-3399-2011.
DeChant, C.M., Moradkhani, H., 2014. Toward a reliable prediction of seasonal forecast uncertainty: addressing model and initial condition uncertainty with ensemble data assimilation and Sequential Bayesian Combination. J. Hydrol. 519, 2967–2977. https://doi.org/10.1016/j.jhydrol.2014.05.045.
Dembélé, M., Hrachowitz, M., Savenije, H.H.G., 2020. Improving the predictive skill of a distributed hydrological model by calibration on spatial patterns with multiple satellite data sets. Water Resour. Res. 1–26. https://doi.org/10.1029/2019WR026085.
Demirel, M.C., Booij, M.J., Hoekstra, A.Y., 2013. Effect of different uncertainty sources on the skill of 10 day ensemble low flow forecasts for two hydrological models. Water Resour. Res. 49, 4035–4053. https://doi.org/10.1002/wrcr.20294.
Di Marco, N., Avesani, D., Righetti, M., Zaramella, M., Majone, B., Borga, M., 2021. Reducing hydrological modelling uncertainty by using MODIS snow cover data and a topography-based distribution function snowmelt model. J. Hydrol. 599, 126020. https://doi.org/10.1016/j.jhydrol.2021.126020.
Dion, P., Martel, J.L., Arsenault, R., 2021. Hydrological ensemble forecasting using a multi-model framework. J. Hydrol. 600, 126537. https://doi.org/10.1016/j.jhydrol.2021.126537.
Dong, C., 2018. Remote sensing, hydrological modeling and in situ observations in snow cover research: a review. J. Hydrol. 561, 573–583. https://doi.org/10.1016/j.jhydrol.2018.04.027.
Essery, R., Morin, S., Lejeune, Y., B Ménard, C., 2013. A comparison of 1701 snow models using observations from an alpine site. Adv. Water Resour. 55, 131–148. https://doi.org/10.1016/j.advwatres.2012.07.013.
Fathololoumi, S., Vaezi, A.R., Firozjaei, M.K., Biswas, A., 2021. Quantifying the effect of surface heterogeneity on soil moisture across regions and surface characteristic. J. Hydrol. 596, 126132. https://doi.org/10.1016/j.jhydrol.2021.126132.
Fraga, I., Cea, L., Puertas, J., 2019. Effect of rainfall uncertainty on the performance of physically based rainfall–runoff models. Hydrol. Process. 33, 160–173. https://doi.org/10.1002/hyp.13319.
Franz, K.J., Butcher, P., Ajami, N.K., 2010. Addressing snow model uncertainty for hydrologic prediction. Adv. Water Resour. 33, 820–832. https://doi.org/10.1016/j.advwatres.2010.05.004.
Gan, Y., Liang, X.Z., Duan, Q., Ye, A., Di, Z., Hong, Y., Li, J., 2018a. A systematic assessment and reduction of parametric uncertainties for a distributed hydrological model. J. Hydrol. 564, 697–711. https://doi.org/10.1016/j.jhydrol.2018.07.055.
Gan, Y., Liang, X.Z., Duan, Q., Ye, A., Di, Z., Hong, Y., Li, J., 2018b. A systematic assessment and reduction of parametric uncertainties for a distributed hydrological model. J. Hydrol. 564, 697–711. https://doi.org/10.1016/j.jhydrol.2018.07.055.
Guo, K., Guan, M., Yu, D., 2021. Urban surface water flood modelling-a comprehensive review of current models and future challenges. Hydrol. Earth Syst. Sci. 25, 2843–2860. https://doi.org/10.5194/hess-25-2843-2021.
Gupta, A., Govindaraju, R.S., 2023. Uncertainty quantification in watershed hydrology: which method to use? J. Hydrol. 616, 128749. https://doi.org/10.1016/j.jhydrol.2022.128749.
Gupta, H.V., Sorooshian, S., Yapo, P.O., 1998. Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information. Water Resour. Res. 34 (4), 751–763. https://doi.org/10.1029/97WR03495.
Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J. Hydrol. 377, 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.
Habert, J., Ricci, S., Le Pape, E., Thual, O., Piacentini, A., Goutal, N., Jonville, G., Rochoux, M., 2016. Reduction of the uncertainties in the water level-discharge relation of a 1D hydraulic model in the context of operational flood forecasting. J. Hydrol. 532, 52–64. https://doi.org/10.1016/j.jhydrol.2015.11.023.
Hassan, M., Hassan, I., 2020. Improving ANN-based streamflow estimation models for the Upper Indus Basin using satellite-derived snow cover area. Acta Geophys. 68, 1791–1801. https://doi.org/10.1007/s11600-020-00491-4.
Hassan, M., Hassan, I., 2021. Improving artificial neural network based streamflow forecasting models through data preprocessing. KSCE J. Civ. Eng. 25, 3583–3595. https://doi.org/10.1007/s12205-021-1859-y.
He, M., Hogue, T.S., Franz, K.J., Margulis, S.A., Vrugt, J.A., 2011. Characterizing parameter sensitivity and uncertainty for a snow model across hydroclimatic regimes. Adv. Water Resour. 34, 114–127. https://doi.org/10.1016/j.advwatres.2010.10.002.
Helfricht, K., Kuhn, M., Keuschnig, M., Heilig, A., 2014. Lidar snow cover studies on glaciers in the Ötztal Alps (Austria): comparison with snow depths calculated from GPR measurements. Cryosphere 8, 41–57. https://doi.org/10.5194/tc-8-41-2014.
Her, Y., Yoo, S.H., Cho, J., Hwang, S., Jeong, J., Seong, C., 2019a. Uncertainty in hydrological analysis of climate change: multi-parameter vs. multi-GCM ensemble predictions. Sci. Rep. 9, 1–22. https://doi.org/10.1038/s41598-019-41334-7.

Her, Y., Yoo, S.H., Cho, J., Hwang, S., Jeong, J., Seong, C., 2019b. Uncertainty in hydrological analysis of climate change: multi-parameter vs. multi-GCM ensemble predictions. Sci. Rep. 9, 1–22. https://doi.org/10.1038/s41598-019-41334-7.

Herman, M.R., Nejadhashemi, A.P., Abouali, M., Hernandez-Suarez, J.S., Daneshvar, F., Zhang, Z., Anderson, M.C., Sadeghi, A.M., Hain, C.R., Sharifi, A., 2018. Evaluating the role of evapotranspiration remote sensing data in improving hydrological modeling predictability. J. Hydrol. 556, 39–49. https://doi.org/10.1016/j.jhydrol.2017.11.009.

Horton, P., Schaefli, B., Kauzlaric, M., 2022. Why do we have so many different hydrological models? A review based on the case of Switzerland. Wiley Interdiscip. Rev. Water 9. https://doi.org/10.1002/wat2.1574.

Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., Freer, J. E., Gelfan, A., Gupta, H.V., Hughes, D.A., Hut, R.W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P.A., Uhlenbrook, S., Wagener, T., Winsemius, H.C., Woods, R.A., Zehe, E., Cudennec, C., 2013. A decade of Predictions in Ungauged Basins (PUB)-a review. Hydrol. Sci. J. 58, 1198–1255. https://doi.org/10.1080/02626667.2013.803183.

Hu, R., Fang, F., Pain, C.C., Navon, I.M., 2019. Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. J. Hydrol. 575, 911–920. https://doi.org/10.1016/j.jhydrol.2019.05.087.

Huang, S., Shah, H., Naz, B.S., Shrestha, N., Mishra, V., Daggupati, P., Ghimire, U., Vetter, T., 2020. Impacts of hydrological model calibration on projected hydrological changes under climate change—a multi-model assessment in three large river basins. Clim. Chang. 163, 1143–1164. https://doi.org/10.1007/s10584-020-02872-6.

Hui, J., Wu, Y., Zhao, F., Lei, X., Sun, P., Singh, S.K., Liao, W., Qiu, L., Li, J., 2020. Parameter optimization for uncertainty reduction and simulation improvement of hydrological modeling. Remote Sens. 12, 1–23. https://doi.org/10.3390/rs12244069.

Humphrey, G.B., Gibbs, M.S., Dandy, G.C., Maier, H.R., 2016. A hybrid approach to monthly streamflow forecasting: integrating hydrological model outputs into a Bayesian artificial neural network. J. Hydrol. 540, 623–640. https://doi.org/10.1016/j.jhydrol.2016.06.026.

IPCC, 2021. In: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B. (Eds.), Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://doi.org/10.1017/9781009157896, 2391 pp.

Jose, D.M., Dwarakish, G.S., 2020. Uncertainties in predicting impacts of climate change on hydrology in basin scale: a review. Arab. J. Geosci. 13. https://doi.org/10.1007/s12517-020-06071-6.

Kasiviswanathan, K.S., Sudheer, K.P., Soundharajan, B.S., Adeloye, A.J., 2020. Implications of uncertainty in inflow forecasting on reservoir operation for irrigation. Paddy Water Environ. https://doi.org/10.1007/s10333-020-00822-7.

Khoi, D.N., Thom, V.T., 2015. Parameter uncertainty analysis for simulating streamflow in a river catchment of Vietnam. Glob. Ecol. Conserv. 4, 538–548. https://doi.org/10.1016/j.gecco.2015.10.007.

Kirchner, J.W., 2006. Getting the right answers for the right reasons: linking measurements, analyses, and models to advance the science of hydrology. Water Resour. Res. 42, 1–5. https://doi.org/10.1029/2005WR004362.

KlemeŠ, V., 1986. Operational testing of hydrological simulation models. Hydrol. Sci. J. 31 (1), 13–24. https://doi.org/10.1080/02626668609491024.

Kling, H., Fuchs, M., Paulin, M., 2012. Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. J. Hydrol. 424, 264–277. https://doi.org/10.1016/j.jhydrol.2012.01.011.

Klotz, D., Kratzert, F., Gauch, M., Sampson, A.K., Brandstetter, J., Klambauer, G., Hochreiter, S., Nearing, G., 2021. Uncertainty estimation with deep learning for rainfall–runoff modelling. Hydrol. Earth Syst. Sci. Discuss. 1–32.

Koster, R.D., Liu, Q., Mahanama, S.P.P., Reichle, R.H., 2018. Improved hydrological simulation using SMAP data: relative impacts of model calibration and data assimilation. J. Hydrometeorol. 19, 727–741. https://doi.org/10.1175/JHM-D-17-0228.1.

Krysanova, V., Donnelly, C., Gelfan, A., Gerten, D., Arheimer, B., Hattermann, F., Kundzewicz, Z.W., 2018. How the performance of hydrological models relates to credibility of projections under climate change. Hydrol. Sci. J. 63, 696–720. https://doi.org/10.1080/02626667.2018.1446214.

Krzysztofowicz, R., 2001. The case for probabilistic forecasting in hydrology. J. Hydrol. 249 (2001), 2–9. https://doi.org/10.1016/S0022-1694(01)00420-6.

Lafaysse, M., Cluzet, B., Dumont, M., Lejeune, Y., Vionnet, V., Morin, S., 2017. A multiphysical ensemble system of numerical snow modelling. Cryosphere 11, 1173–1198. https://doi.org/10.5194/tc-11-1173-2017.

Lakshmi, G., Sudheer, K.P., 2021. Parameterization in hydrological models through clustering of the simulation time period and multi-objective optimization based calibration. Environ. Model Softw. 138, 104981. https://doi.org/10.1016/j.envsoft.2021.104981.

Lee, H., Shen, H., Noh, S.J., Kim, S., Seo, D.J., Zhang, Y., 2019. Improving flood forecasting using conditional bias-penalized ensemble Kalman filter. J. Hydrol. 575, 596–611. https://doi.org/10.1016/j.jhydrol.2019.05.072.

Lee, S., Qi, J., Kim, H., McCarty, G.W., Moglen, G.E., Anderson, M., Zhang, X., Du, L., 2021. Utility of remotely sensed evapotranspiration products to assess an improved model structure. Sustain 13, 1–18. https://doi.org/10.3390/su13042375.

Leisenring, M., Moradkhani, H., 2011. Snow water equivalent prediction using Bayesian data assimilation methods. Stoch. Env. Res. Risk A. 25, 253–270. https://doi.org/10.1007/s00477-010-0445-5.

Lerat, J., Thyer, M., McInerney, D., Kavetski, D., Woldemeskel, F., Pickett-Heaps, C., Shin, D., Feikema, P., 2020. A robust approach for calibrating a daily rainfall-runoff model to monthly streamflow data. J. Hydrol. 591, 125129. https://doi.org/10.1016/j.jhydrol.2020.125129.

Li, H., Xu, C.Y., Beldring, S., 2015. How much can we gain with increasing model complexity with the same model concepts? J. Hydrol. 527, 858–871. https://doi.org/10.1016/j.jhydrol.2015.05.044.

Li, W., Duan, Q., Miao, C., Ye, A., Gong, W., Di, Z., 2017. A review on statistical postprocessing methods for hydrometeorological ensemble forecasting. Wiley Interdiscip. Rev. Water 4. https://doi.org/10.1002/wat2.1246.

Liang, Y., Cai, Y., Sun, L., Wang, X., Li, C., Liu, Q., 2021. Sensitivity and uncertainty analysis for streamflow prediction based on multiple optimization algorithms in Yalong River Basin of southwestern China. J. Hydrol. 601, 126598. https://doi.org/10.1016/j.jhydrol.2021.126598.

Lilhare, R., Stadnyk, T.A., Pokorny, S., Déry, S.J., Koenig, K.A., 2020. Sensitivity Analysis and Uncertainty Assessment in Water Budgets Simulated by the Variable Infiltration Capacity Model for Canadian Subarctic Watersheds 2057–2075. https://doi.org/10.1002/hyp.13711.

Lin, K., Liu, P., He, Y., Guo, S., 2014. Multi-site evaluation to reduce parameter uncertainty in a conceptual hydrological modeling within the glue framework. J. Hydroinf. 16, 60–73. https://doi.org/10.2166/hydro.2013.204.

Liu, Z., Guo, S., Xiong, L., Xu, C.Y., 2018. Hydrological uncertainty processor based on a copula function. Hydrol. Sci. J. 63, 74–86. https://doi.org/10.1080/02626667.2017.1410278.

Liu, L., Wang, Q.J., Xu, Y.P., 2020. Temporally varied error modelling for improving simulations and quantifying uncertainty. J. Hydrol. 586, 124914. https://doi.org/10.1016/j.jhydrol.2020.124914.

Loizu, J., Massari, C., Álvarez-Mozos, J., Tarpanelli, A., Brocca, L., Casalí, J., 2018. On the assimilation set-up of ASCAT soil moisture data for improving streamflow catchment simulation. Adv. Water Resour. 111, 86–104. https://doi.org/10.1016/j.advwatres.2017.10.034.

Maggioni, V., Massari, C., 2018. On the performance of satellite precipitation products in riverine flood modeling: a review. J. Hydrol. 558, 214–224. https://doi.org/10.1016/j.jhydrol.2018.01.039.

Massari, C., Brocca, L., Tarpanelli, A., Moramarco, T., 2015. Data assimilation of satellite soil moisture into rainfall-runoff modelling: a complex recipe? Remote Sens. 7, 11403–11433. https://doi.org/10.3390/rs70911403.

Mazrooei, A., Sankarasubramanian, A., 2019. Improving monthly streamflow forecasts through assimilation of observed streamflow for rainfall-dominated basins across the CONUS. J. Hydrol. 575, 704–715. https://doi.org/10.1016/j.jhydrol.2019.05.071.

Mazrooei, A., Sankarasubramanian, A., Wood, A.W., 2021. Potential in improving monthly streamflow forecasting through variational assimilation of observed streamflow. J. Hydrol. 600, 126559. https://doi.org/10.1016/j.jhydrol.2021.126559.

McInerney, D., Thyer, M., Kavetski, D., Laugesen, R., Woldemeskel, F., Tuteja, N., Kuczera, G., 2021. Improving the reliability of sub-seasonal forecasts of high and low flows by using a flow-dependent nonparametric model. Water Resour. Res. 57, 1–16. https://doi.org/10.1029/2020WR029317.

McMillan, H.K., Westerberg, I.K., Krueger, T., 2018. Hydrological data uncertainty and its implications. WIREs Water 5, 1–14. https://doi.org/10.1002/wat2.1319.

McMillan, H., Araki, R., Gnann, S., Woods, R., Wagener, T., 2023. How do hydrologists perceive watersheds? A survey and analysis of perceptual model figures for experimental watersheds. Hydrol. Process. 37 (3). https://doi.org/10.1002/hyp.14845.

Meng, S., Xie, X., Liang, S., 2017. Assimilation of soil moisture and streamflow observations to improve flood forecasting with considering runoff routing lags. J. Hydrol. 550, 568–579. https://doi.org/10.1016/j.jhydrol.2017.05.024.

Moges, E., Demissie, Y., Larsen, L., Yassin, F., 2021. Review: sources of hydrological model uncertainties and advances in their analysis. Water (Switzerland) 13, 1–23. https://doi.org/10.3390/w13010028.

Montanari, A., 2007. What do we mean by 'uncertainty'? The need for a consistent wording about uncertainty assessment in hydrology. Hydrol. Process. 21, 841–845. https://doi.org/10.1002/hyp.6623.

Montanari, A., Grossi, G., 2008. Estimating the uncertainty of hydrological forecasts: a statistical approach. Water Resour. Res. 44 (12). https://doi.org/10.1029/2008WR006897. W00B08.

Moradkhani, H., Hsu, K.L., Gupta, H., Sorooshian, S., 2005. Uncertainty assessment of hydrologic model states and parameters: sequential data assimilation using the particle filter. Water Resour. Res. 41 (5), 1–17. https://doi.org/10.1029/2004WR003604.

Morgan, R.P., 1994. A predictive model for the assessment of soil erosion risk. J. Agric. Eng. Res. 30, 245–253.

Moriasi, D.N., Arnold, J.G., van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.

Muhammad, A., Stadnyk, T.A., Unduche, F., Coulibaly, P., 2018. Multi-model approaches for improving seasonal ensemble streamflow prediction scheme with various statistical post-processing techniques in the Canadian Prairie Region. Water (Switzerland) 10. https://doi.org/10.3390/w10111604.

Mustafa, S.M.T., Hasan, M.M., Saha, A.K., Rannu, R.P., Van Uytven, E., Willems, P., Huysmans, M., 2019. Multi-model approach to quantify groundwater-level prediction uncertainty using an ensemble of global climate models and multiple abstraction scenarios. Hydrol. Earth Syst. Sci. 23 (5), 2279–2303.

Mustafa, S.M.T., Nossent, J., Ghysels, G., Huysmans, M., 2020. Integrated Bayesian Multi-model approach to quantify input, parameter and conceptual model structure uncertainty in groundwater modeling. Environ. Model Softw. 126, 104654. https://doi.org/10.1016/j.envsoft.2020.104654.

Nash, J.E., Sutcliffe, J., 1970. V.: River flow forecasting through conceptual models part I – a discussion of principles. J. Hydrol. 10, 282–290. https://doi.org/10.1016/0022-1694(70)90255-6.

Nayak, A.K., Biswal, B., Sudheer, K.P., 2021. Role of hydrological model structure in the assimilation of soil moisture for streamflow prediction. J. Hydrol. 598, 126465. https://doi.org/10.1016/j.jhydrol.2021.126465.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., et al., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Syst. Rev. 10 (1), 89. https://doi.org/10.1186/s13643-021-01626-4.

Paiva, R.C.D., Collischonn, W., Bonnet, M.P., De Gonçalves, L.G.G., 2012. On the sources of hydrological prediction uncertainty in the Amazon. Hydrol. Earth Syst. Sci. 16, 3127–3137. https://doi.org/10.5194/hess-16-3127-2012.

Panchanathan, A., Torabi Haghighi, A., Oussalah, M., 2023. A multi-criteria approach for improving streamflow prediction in a rapidly urbanizing data scarce catchment. Int. J. River Basin Manag. 1–14. https://doi.org/10.1080/15715124.2023.2188597.

Papacharalampous, G., Koutsoyiannis, D., Montanari, A., 2020. Advances in Water Resources Quantification of predictive uncertainty in hydrological modelling by harnessing the wisdom of the crowd: Methodology development and investigation using toy models. Adv. Water Resour. 136, 103471. https://doi.org/10.1016/j.advwatres.2019.103471.

Papacharalampous, G., Tyralis, H., Koutsoyiannis, D., Montanari, A., 2020b. Quantification of predictive uncertainty in hydrological modelling by harnessing the wisdom of the crowd: a large-sample experiment at monthly timescale. Adv. Water Resour. 136, 103470. https://doi.org/10.1016/j.advwatres.2019.103470.

Pappenberger, F., Beven, K.J., 2006. Ignorance is bliss: or seven reasons not to use uncertainty analysis. Water Resour. Res. 42, 1–8. https://doi.org/10.1029/2005WR004820.

Patil, A., Ramsankaran, R.A.A.J., 2017. Improving streamflow simulations and forecasting performance of SWAT model by assimilating remotely sensed soil moisture observations. J. Hydrol. 555, 683–696. https://doi.org/10.1016/j.jhydrol.2017.10.058.

Paul, P.K., Zhang, Y., Ma, N., Mishra, A., Panigrahy, N., Singh, R., 2021. Selecting hydrological models for developing countries: perspective of global, continental, and country scale models over catchment scale models. J. Hydrol. 600, 126561. https://doi.org/10.1016/j.jhydrol.2021.126561.

Penny, G., Peschel, J., Jeremiah, K., Thompson, S., 2020. Research Article A Process-Based Approach to Attribution of Historical Streamflow Decline in a Data-Scarce and Human-Dominated Watershed 1981–1995. https://doi.org/10.1002/hyp.13707.

Piazzi, G., Thirel, G., Perrin, C., Delaigue, O., 2021. Sequential data assimilation for streamflow forecasting: assessing the sensitivity to uncertainties and updated variables of a conceptual hydrological model at basin scale. Water Resour. Res. 57, e2020WR028390. https://doi.org/10.1029/2020WR028390.

Poulin, A., Brissette, F., Leconte, R., Arsenault, R., Malo, J.S., 2011. Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin. J. Hydrol. 409, 626–636. https://doi.org/10.1016/j.jhydrol.2011.08.057.

Qiao, L., Herrmann, R.B., Pan, Z., 2013. Parameter uncertainty reduction for SWAT using grace, streamflow, and groundwater table data for lower Missouri River Basin. J. Am. Water Resour. Assoc. 49, 343–358. https://doi.org/10.1111/jawr.12021.

Rajib, A., Evenson, G.R., Golden, H.E., Lane, C.R., 2018. Hydrologic model predictability improves with spatially explicit calibration using remotely sensed evapotranspiration and biophysical parameters. J. Hydrol. 567, 668–683. https://doi.org/10.1016/j.jhydrol.2018.10.024.

Rajib, A., Liu, Z., Merwade, V., Tavakoly, A.A., Follum, M.L., 2020. Towards a large-scale locally relevant flood inundation modeling framework using SWAT and LISFLOOD-FP. J. Hydrol. 581, 124406. https://doi.org/10.1016/j.jhydrol.2019.124406.

Rittger, K., Painter, T.H., Dozier, J., 2013. Assessment of methods for mapping snow cover from MODIS. Adv. Water Resour. 51, 367–380. https://doi.org/10.1016/j.advwatres.2012.03.002.

Rossa, A., Liechti, K., Zappa, M., Bruen, M., Germann, U., Haase, G., Keil, C., Krahe, P., 2011. The COST 731 action: a review on uncertainty propagation in advanced hydro-meteorological forecast systems. Atmos. Res. 100, 150–167. https://doi.org/10.1016/j.atmosres.2010.11.016.

Schöber, J., Schneider, K., Helfricht, K., Schattan, P., Achleitner, S., Schöberl, F., Kirnbauer, R., 2014a. Snow cover characteristics in a glacierized catchment in the Tyrolean Alps - improved spatially distributed modelling by usage of Lidar data. J. Hydrol. 519, 3492–3510. https://doi.org/10.1016/j.jhydrol.2013.12.054.

Schöber, J., Schneider, K., Helfricht, K., Schattan, P., Achleitner, S., Schöberl, F., Kirnbauer, R., 2014b. Snow cover characteristics in a glacierized catchment in the Tyrolean Alps - improved spatially distributed modelling by usage of Lidar data. J. Hydrol. 519, 3492–3510. https://doi.org/10.1016/j.jhydrol.2013.12.054.

Seo, S.B., Kim, Y.O., Kang, S.U., Il Chun, G., 2019. Improvement in long-range streamflow forecasting accuracy using the Bayes' theorem. Hydrol. Res. 50, 616–632. https://doi.org/10.2166/nh.2019.098.

Shafii, M., Tolson, B., Shawn Matott, L., 2015. Addressing subjective decision-making inherent in GLUE-based multi-criteria rainfall-runoff model calibration. J. Hydrol. 523, 693–705. https://doi.org/10.1016/j.jhydrol.2015.01.051.

Silvestro, F., Ercolani, G., Gabellani, S., Giordano, P., Falzacappa, M., 2021. Improving real-time operational streamflow simulations using discharge data to update state variables of a distributed hydrological model. Hydrol. Res. 52, 1239–1260. https://doi.org/10.2166/NH.2021.162.

Singh, H., Sankarasubramanian, A., 2014. Systematic uncertainty reduction strategies for developing stream- flow forecasts utilizing multiple climate models and hydrologic models. Water Resour. Res. 50, 1288–1307. https://doi.org/10.1002/2013WR013855.

Siqueira, V.A., Weerts, A., Klein, B., Fan, F.M., de Paiva, R.C.D., Collischonn, W., 2021. Postprocessing continental-scale, medium-range ensemble streamflow forecasts in South America using ensemble model output statistics and ensemble copula coupling. J. Hydrol. 600, 126520. https://doi.org/10.1016/j.jhydrol.2021.126520.

Sivapalan, M., Blöschl, G., Zhang, L., Vertessy, R., 2003. Downward approach to hydrological prediction. Hydrol. Process. 17, 2101–2111. https://doi.org/10.1002/hyp.1425.

Slater, A.G., Barrett, A.P., Clark, M.P., Lundquist, J.D., Raleigh, M.S., 2013. Uncertainty in seasonal snow reconstruction: relative impacts of model forcing and image availability. Adv. Water Resour. 55, 165–177. https://doi.org/10.1016/j.advwatres.2012.07.006.

Sun, R., Yuan, H., Yang, Y., 2018. Using multiple satellite-gauge merged precipitation products ensemble for hydrologic uncertainty analysis over the Huaihe River basin. J. Hydrol. 566, 406–420. https://doi.org/10.1016/j.jhydrol.2018.09.024.

Tauro, F., Selker, J., Van De Giesen, N., Abrate, T., Uijlenhoet, R., Porfiri, M., Manfreda, S., Caylor, K., Moramarco, T., Benveniste, J., Ciraolo, G., Estes, L., Domeneghetti, A., Perks, M.T., Corbari, C., Rabiei, E., Ravazzani, G., Bogena, H., Harfouche, A., Broccai, L., Maltese, A., Wickert, A., Tarpanelli, A., Good, S., Lopez Alcala, J.M., Petroselli, A., Cudennec, C., Blume, T., Hut, R., Grimaldia, S., 2018. Measurements and observations in the XXI century (MOXXI): innovation and multi-disciplinarity to sense the hydrological cycle. Hydrol. Sci. J. 63, 169–196. https://doi.org/10.1080/02626667.2017.1420191.

Thackeray, C.W., Fletcher, C.G., Mudryk, L.R., Derksen, C., 2016. Quantifying the uncertainty in historical and future simulations of Northern Hemisphere spring snow cover. J. Clim. 29, 8647–8663. https://doi.org/10.1175/JCLI-D-16-0341.1.

Thiboult, A., Anctil, F., Boucher, M.-A., 2015. Accounting for three sources of uncertainty in ensemble hydrological forecasting. Hydrol. Earth Syst. Sci. Discuss. 12, 7179–7223. https://doi.org/10.5194/hessd-12-7179-2015.

Thiboult, A., Anctil, F., Ramos, M.H., 2017. How does the quantification of uncertainties affect the quality and value of flood early warning systems? J. Hydrol. 551, 365–373. https://doi.org/10.1016/j.jhydrol.2017.05.014.

Thornton, J.M., Brauchli, T., Mariethoz, G., Brunner, P., 2021. Efficient multi-objective calibration and uncertainty analysis of distributed snow simulations in rugged alpine terrain. J. Hydrol. 598, 126241. https://doi.org/10.1016/j.jhydrol.2021.126241.

Todini, E., 2007. Hydrological catchment modelling: past, present and future. Hydrol. Earth Syst. Sci. 11 (1), 468–482. https://doi.org/10.5194/hess-11-468-2007.

Tran, V.N., Dwelle, M.C., Sargsyan, K., Ivanov, V.Y., Kim, J., 2020. A novel modeling framework for computationally efficient and accurate real-time ensemble flood forecasting with uncertainty quantification. Water Resour. Res. 56, 1–31. https://doi.org/10.1029/2019WR025727.

Troin, M., Arsenault, R., Wood, A.W., Brissette, F., Martel, J.L., 2021. Generating ensemble streamflow forecasts: a review of methods and approaches over the past 40 years. Water Resour. Res. 57, 1–48. https://doi.org/10.1029/2020WR028392.

Uniyal, B., Jha, M.K., Verma, A.K., 2015. Parameter identification and uncertainty analysis for simulating streamflow in a river basin of Eastern India. Hydrol. Process. 29, 3744–3766. https://doi.org/10.1002/hyp.10446.

USGS, 2022. https://labs.waterdata.usgs.gov/visualizations/water-cycle/index.html#/ (Accessed on 08-12-2022).

Valdez, E.S., Anctil, F., Ramos, M., 2021. Choosing between post-processing precipitation forecasts or chaining several uncertainty quantification tools in hydrological forecasting systems. Hydrol. Earth Syst. Sci. Discuss. 1–40.

Van Steenbergen, N., Ronsyn, J., Willems, P., 2012. A non-parametric data-based approach for probabilistic flood forecasting in support of uncertainty communication. Environ. Model Softw. 33, 92–105. https://doi.org/10.1016/j.envsoft.2012.01.013.

Vema, V.K., Sudheer, K.P., Chaubey, I., 2020. Uncertainty of hydrologic simulation, and its impact on the design and the effectiveness of water conservation structures. Stoch. Env. Res. Risk A. 34, 973–991. https://doi.org/10.1007/s00477-020-01814-z.

Wagener, T., Gupta, H.V., 2005. Model identification for hydrological forecasting under uncertainty. Stoch. Env. Res. Risk A. 19 (6), 378–387. https://doi.org/10.1007/s00477-005-0006-5.

Wang, S., Huang, G.H., Baetz, B.W., Ancell, B.C., 2017. Towards robust quantification and reduction of uncertainty in hydrologic predictions: integration of particle Markov chain Monte Carlo and factorial polynomial chaos expansion. J. Hydrol. 548, 484–497. https://doi.org/10.1016/j.jhydrol.2017.03.027.

Willmott, C.J., Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Clim. Res. 30, 79–82. https://doi.org/10.3354/cr030079.

Willmott, C.J., Matsuura, K., Robeson, S.M., 2009. Ambiguities inherent in sums-of-squares-based error statistics. Atmos. Environ. 43, 749–752. https://doi.org/10.1016/j.atmosenv.2008.10.005.

Wu, J., Zeng, X., 2013. Review of the uncertainty analysis of groundwater numerical simulation. Chin. Sci. Bull. 58, 3044–3052. https://doi.org/10.1007/s11434-013-5950-8.

WMO, 2009. Guide to hydrological practices, Volume II, Management of Water Resources and Application of Hydrological practices. World Meteorological Organization WMO-No., 168.

Wu, W., Emerton, R., Duan, Q., Wood, A.W., Wetterhall, F., Robertson, D.E., 2020. Ensemble flood forecasting: current status and future opportunities. WIREs Water 7. https://doi.org/10.1002/wat2.1432.

Xu, B., Huang, X., Mo, R., Zhong, P. An, Lu, Q., Zhang, H., Si, W., Xiao, J., Sun, Y., 2021. Integrated real-time flood risk identification, analysis, and diagnosis model framework for a multireservoir system considering temporally and spatially dependent forecast uncertainties. J. Hydrol. 600, 126679. https://doi.org/10.1016/j.jhydrol.2021.126679.

Xue, L., Yang, F., Yang, C., Wei, G., Li, W., He, X., 2018. Hydrological simulation and uncertainty analysis using the improved TOPMODEL in the arid Manas River basin, China. Sci. Rep. 1–12. https://doi.org/10.1038/s41598-017-18982-8.

Yang, X., Zhou, J., Fang, W., Wang, Y., 2020. An ensemble flow forecast method based on autoregressive model and hydrological uncertainty processor. Water 12, 3138. https://doi.org/10.3390/w12113138.

Yuan, F., Zhao, C., Jiang, Y., Ren, L., Shan, H., Zhang, L., Zhu, Y., Chen, T., Jiang, S., Yang, X., Shen, H., 2017. Evaluation on uncertainty sources in projecting hydrological changes over the Xijiang River basin in South China. J. Hydrol. 554, 434–450. https://doi.org/10.1016/j.jhydrol.2017.08.034.

Zappa, M., Jaun, S., Germann, U., Walser, A., Fundel, F., 2011. Superposition of three sources of uncertainties in operational flood forecasting chains. Atmos. Res. 100, 246–262. https://doi.org/10.1016/j.atmosres.2010.12.005.

Zaremehrjardy, M., Razavi, S., Faramarzi, M., 2021. Assessment of the cascade of uncertainty in future snow depth projections across watersheds of mountainous, foothill, and plain areas in northern latitudes. J. Hydrol. 598, 125735. https://doi.org/10.1016/j.jhydrol.2020.125735.

Zarzar, C.M., Hosseiny, H., Siddique, R., Gomez, M., Smith, V., Mejia, A., Dyer, J., 2018. A hydraulic multimodel ensemble framework for visualizing flood inundation uncertainty. J. Am. Water Resour. Assoc. 54, 807–819. https://doi.org/10.1111/1752-1688.12656.