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Generating Ensemble Streamflow Forecasts: A Review of Methods and Approaches Over the Past 40 Years

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Key Points:

- This work summarizes the 40 years of research in the generation of streamflow forecasts based on an exhaustive review of studies
- Ensemble prediction systems are categorized into three classes: statistics-based, climatology-based and numerical weather prediction-based hydrological ensemble prediction systems
- For each ensemble forecasting system, thorough technical information is provided

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Ensemble forecasting applied to the field of hydrology is currently an established area of research embracing a broad spectrum of operational situations. This work catalogs the various pathways of ensemble streamflow forecasting based on an exhaustive review of more than 700 studies over the last 40 years. We focus on the advanced state of the art in the model-based (dynamical) ensemble forecasting approaches. Ensemble streamflow prediction systems are categorized into three leading classes: statistics-based streamflow prediction systems, climatology-based ensemble streamflow prediction systems and numerical weather prediction-based hydrological ensemble prediction systems. For each ensemble approach, technical information, as well as details about its strengths and weaknesses, are provided based on a critical review of the studies listed. Through this literature review, the performance and uncertainty associated with the ensemble forecasting systems are underlined from both operational and scientific viewpoints. Finally, the remaining key challenges and prospective future research directions are presented, notably through hybrid dynamical - statistical learning approaches, which obviously present new challenges to be overcome in order to allow the successful employment of ensemble streamflow forecasting systems in the next decades. Targeting students, researchers and practitioners, this review provides a detailed perspective on the major features of an increasingly important area of hydrological forecasting.

1. Introduction

Many water planning and management decisions require an understanding of the future states of hydrological systems for a wide range of conditions. In the operational water resource sector, skillful and reliable hydrological forecasting constitutes a critical input for the operation and management of infrastructures in various future time periods (Pagano et al., 2014; Werner et al., 2009). For example, hydropower operators in snowmelt-dominated regions often must commit to reservoir storage drawdown rates in early winter to maximize their potential revenues. However, the optimal drawdown rate is conditional on unknown future inflows and their timing. Too much water drawn too quickly, coupled with lower-than-expected inflows, carries a risk of water shortages, which could have serious consequences for energy generation and present other constraints. On the other hand, a drawdown rate that is too conservative may miss opportunities to generate revenues and could ultimately lead to flooding on the reservoir banks or downstream. Water management agencies face similarly complex dilemmas on a regular basis. In these contexts, river flow forecasting is widely used to help water managers and users improve their decision-making capabilities by providing timely and effective information about current extreme hydrological conditions and their potential near-term evolution (Bayazit, 2015; Georgakakos et al., 1998; Roundy et al., 2019).

The significance of hydrological forecasting for both natural disaster mitigation and water resource management was recognized by the World Meteorological Organization as early as 1975 (WMO, 1975). Since the mid-1970s, the WMO has undertaken several projects to encourage the development of streamflow forecasting systems and to provide information regarding the choice of methods and approaches (WMO, 1986, 1987, 1990; Serban & Askew, 1991). Over time, collaborative initiatives between researchers and forecasters have grown stronger, narrowing the gap between state-of-the-art research and operational practices. Much progress has been made in forecasting research, and additional efforts introduced toward communicating and delivering forecasting information in a useful form to real-world decision-making that meets the needs of a diverse water user community (e.g., Arnal et al., 2016; Demeritt et al., 2010; 2013; Morss, 2010; Pielke Jr., 1999). Forecasting agencies have thus emerged, and work in close collaboration with research centers and organizations, providing their own streamflow forecasting system at the:

- Global level (Alfieri et al., 2013; Arheimer et al., 2020; Pappenberger et al., 2010)
- Continental level (Arduino et al., 2005; Emerton et al., 2016) (e.g., the European Flood Forecasting System (EFFS) and the European Flood Awareness System (EFAS; Alfieri et al., 2014; Bartholmes et al., 2009; Demeritt et al., 2013; Thielen et al., 2009); the Cooperation in Science and Technology (COST-731 actions), which was a European initiative for the quantification of uncertainty in hydrometeorological forecasting systems (Bruen et al., 2010; Rossa et al., 2011; Zappa et al., 2010); the EUROflood research project (Parker & Fordham, 1996); the Mesoscale Alpine Program Demonstration of Probabilistic Hydrological and Atmospheric Simulation of flood Events in the Alpine region (MAP D-PHASE; Zappa et al., 2008)
- National level (e.g., the United States Adams, 2016; the River Forecast Centers—RFCs: Demargne et al., 2009; the NOAA/NWS Hydrologic Ensemble Forecast Service—HEPS: Brown et al., 2014; Great Britain Bell et al., 2013, 2017; Pilling et al., 2016; Werner et al, 2009, 2013; France Thirel et al., 2010; Australia Pagano, Elliot et al., 2016; the national ensemble seasonal streamflow forecasting system—Feikema et al., 2018; Wang & Robertson 2011; Zhao et al., 2016; the ensemble 7-days streamflow forecasting service— Bennett et al., 2014; Li et al., 2020; Shrestha et al., 2015); China Liu, 2016; Brazil Fan et al., 2016, Israel Givati et al., 2016, and Russia Borsch & Simonov, 2016)
- Regional level (e.g., Germany: Demuth and Rademacher, 2016)
- Basin level (trans-boundary) (e.g., Amarnath et al., 2016; Artinyan et al., 2016; Awwad et al., 1994; Chang et al., 2004; Khavich & Ben-Zvi, 1995; Lin et al., 2010; Plate, 2007; Renner et al., 2009; Shi et al., 2015; Tshimanga et al., 2016; Werner et al., 2005; Younis et al., 2008; Yuan et al., 2016).

Of particular note, since 2004, the Hydrologic Ensemble Prediction Experiment (HEPEX; www.hepex.org) initiative has provided a collaborative context for advancement by bringing together international and inter-agency researchers, forecasters, and forecast user communities to work toward improving ensemble streamflow predictions and illustrating their utility in decision-making relating to water management (Schaake et al, 2006, Schaake, Hamill et al., 2007; Thielen et al., 2008). HEPEX participants have recently produced a reference work entitled *Handbook of Hydrometeorological Ensemble Forecasting*, which describes key features of hydrometeorological ensemble forecasting, from fundamental theories to particular steps for developing ensemble forecasting components, as well as operational ensemble forecast applications and case studies (Duan et al., 2019).

Ensemble forecasting applied to the field of hydrology is currently a well-established area of research boasting key achieved milestones, as evidenced by the large array of associated specific review articles, such as the combination of streamflow forecasts (Jeong & Kim, 2009), the use of ensemble quantitative precipitation forecasts for short- and medium-range streamflow forecasting (Cuo et al., 2011), ensemble systems based on large-scale climate precursors for seasonal hydrologic predictions (Yuan et al., 2015), statistical post-processing hydrometeorological ensemble forecasting methods (Li et al., 2017), and snow data assimilation methods (Helmert et al., 2018). The major underlying benefit of ensemble forecasting is that it allows the quantification of forecast uncertainty by generating a range (*ensemble*) of future streamflow forecast possibilities (Demargne et al., 2014). Therefore, new hydrological ensemble forecasting systems and approaches have emerged to account for more sources of uncertainty with the aim of increasing more confidence in the ensemble approaches, specifically for their operational use in water management. Among the various areas of hydrological prediction, (flash) flood (ensemble) forecasting has aroused the most interest over the last decade, generating associated review articles (e.g., Cloke & Pappenberger, 2009; Han & Coulibaly, 2017; Hapuarachchi et al., 2011). Cloke and Pappenberger (2009) laid the foundation for the ensemble approach in flood forecasting by investigating the scientific drivers of the evolution of deterministic (*single value*) forecasting systems toward probabilistic (*ensemble*) forecasting systems based on numerical weather prediction (NWP)-forced hydrological model, known as ensemble prediction systems (EPSs). The authors also pointed out seven technical challenges posed by the EPSs related to flood forecasting, which were subsequently taken up and discussed at the continental and global scale in Emerton et al. (2016). More recently, Wu et al. (2020) provided insights on the status and future opportunities in ensemble forecasting for flood

Figure 1. Diagram illustrating the key aspects of the ensemble streamflow forecasting systems explored in this review. For each aspect, some examples of attribut are given which are thereafter analyzed in more details in the corresponding section.

management given the latest relevant advances in EPS. However, EPSs represent only one of the possible development trajectories of hydrological model-based (dynamical) ensemble forecasting systems to predict streamflow or other discrete hydrological variables.

The intent of this review is to catalog and contrast hydrological ensemble forecasting systems (EFSs) at all time horizons by providing a critical analysis of existing methods and approaches for generating ensemble forecasts of streamflow. We present an extensive literature review, covering the past 40 years, with more than 700 references, to depict a comprehensive overview of the leading EFSs, including details about their strengths and weaknesses, as well as the key aspects of the forecast systems (i.e., uncertainty analysis, data assimilation, multi-model combination, post-processing, verification and communication; Figure 1). The emphasis is placed on the current state of the art in hydrological model-based (dynamical) ensemble forecasting techniques, with the goal of clarifying the underlying notions and concepts. The challenges faced by the operational community in terms of determining the relevance of EFSs in water resource management are considered, in addition to those of the research community in reducing uncertainty in streamflow forecasts. Besides sharing current knowledge on ensemble forecasting, this review examines current operational challenges and future aspirations in the field of streamflow prediction, while providing a valuable reference to those wishing to forecast river flows by drawing on the best existing techniques for their application. The overarching motivation for this review is to provide perspective to students, researchers, and practitioners on the accomplishments to date within this growing field, and to highlight current challenges and opportunities for advancement. The following section provides an overview of ensemble streamflow forecasting, after which a literature review of EFSs is given, and then the successes, challenges, and future aspirations of EFSs are depicted. We then conclude with some final remarks.

2. Ensemble Streamflow Forecasting: An Overview

After the preamble, the overview that follows classifies EFSs into three major types and summarizes the key literature on the topic, before describing the main features of the forecast systems, including uncertainty analysis, data assimilation, multi-model combination, post-processing, and verification (Figure 1).

2.1. Preamble

Forecasting streamflows is a challenging endeavor that entails predicting the behavior of a river basin using current hydrometeorological knowledge and tools while grappling with substantial uncertainty in the trajectory of future weather conditions, imperfect watershed models and significant observational limitations (Pagano et al., 2014). The typical procedure for producing dynamical streamflow forecasts is as follows: (a) a hydrological model is run with historical data up to the beginning of the forecast to estimate current hydrologic conditions of the basin, and observational data can potentially be used to update and correct the resulting model state variables; and (b) the hydrological model then uses these hydrologic state estimates to initialize a forecast simulation driven by weather forecasts to produce streamflow forecasts. Weather forecasts may be used as forcings to one or more hydrological models, and corresponding hydrological forecasts may be either single-valued or ensemble-based. Additional specific information can also be required, depending on:

- The purpose of the forecast—e.g., droughts with the need to have information on soil moisture and flood warnings, where extreme storm rainfall data are required
- The basin characteristics—e.g., urban, with the need for operational data to support the control of flow in the drainage network (pump discharge and location, gate locations), mountainous or snow-dominated basins, where snow observation data and accurate estimation of snow water equivalent are critical
- The type of forecasting model—e.g., statistical models such as artificial neural networks with high-quality training data requirements, dynamical distributed models with the need for information on soil type and land-use/cover and probabilistic models that require sets of predictors such as antecedent streamflows and climate indicators
- The desired time horizons of the forecasts—e.g., very short-/short-range which often relies on satellite-based precipitation estimates to supplement numerical weather forecasts, and medium-/long-range where resampling of forcings from historical data based on climate indicators can improve the forecast skill; and
- The extent to which ancillary supporting strategies such as hydrologic data assimilation (e.g., where both the hydrologic process knowledge, as embodied in a hydrological model, and information that can be gained from observation are combined) or post-processing (e.g., when ensemble hydrological forecasts are post-processed) are applied.

Streamflow forecasting relies on adequate historical input data to generate high quality initial hydrologic conditions (state variables), as well as on the hydrological model's ability to simulate streamflow and on the skill of weather forecasts (Mazrooei et al., 2015; Montanari & Grossi, 2008; Paiva et al., 2012; Schaake, Demargne et al, 2007; Schaake, Hamill et al., 2007). Each stage of the forecasting process introduces uncertainties which can degrade the quality and limit the operational utility of streamflow forecasts (Bogner & Kalas, 2008; Demirel et al., 2013; Pappenberger et al., 2005). Information about uncertainty is not conveyed in a deterministic or single-valued forecast, as such forecasts do not reflect the full range of future streamflow possibilities (Demargne et al., 2014). By generating an ensemble of possible streamflow forecasts, the ensemble (*probabilistic*) approach illustrates the likelihood of different forecasts in the desired horizon and serves as a pragmatic means of quantifying forecast uncertainty—mostly related to weather forecast uncertainty (Devineni et al., 2008; Komma et al., 2007; Nester et al., 2012; Seo et al., 2006).

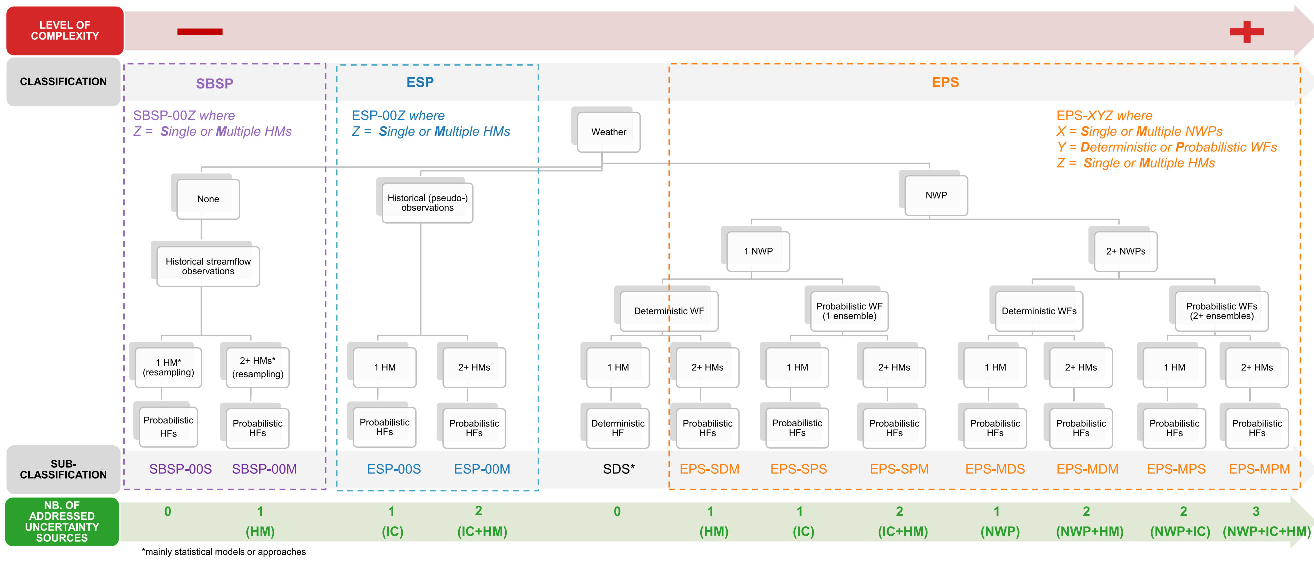

Figure 2. Schematic view of the various ensemble forecast systems used to produce probabilistic hydrological forecasts (HFs), except for the SDS sub-classification leading to deterministic hydrological forecast (not addressed in this study). The referenced sources of uncertainty are related to the initial conditions (IC) of the atmosphere, the numerical weather prediction (NWP) models, and the hydrological models (HMs). SBSP, statistical-based streamflow prediction; ESP, ensemble streamflow prediction; EPS, ensemble prediction systems; WF, weather forecast.

2.2. Classification

To communicate the full range of EFSs applied in hydrological forecasting, it is useful to classify model-based (dynamical) ensemble forecasting approaches. To this end, we consider the forcing type as the initial determinant to which successive modeling steps are added to generate the EFSs. The choice of using the forcing as initial determinant of the classification—rather than the application field or the time horizon of the forecast—is motivated by the fact of conducting an organized and structured EFSs overview through the availability of data, models and sources of uncertainty that follows the chronology of the scientific development. This classification can support practitioners and experts at selecting the most appropriate approach regarding the priorities for their application. With respect to the forcing type, we distinguish (a) no weather observations (e.g., historical streamflow observations only) (b) observations (e.g., in situ meteorological measurement stations), and pseudo-observations (e.g., reanalysis, reforecast of past weather data, weather satellites and radars) of historical climate, and (c) the weather forecasts from the NWP models (Figure 2). This results in three main categories of EFSs with different sub-classes representing the different possible levels of complexity at each step of the forecasting system. The three hydrological EFSs above illustrate the entire evolution of development trajectories with a view to embracing (even more) uncertainties on streamfow forecasts; they are briefly presented below and explored in more detail in Section 3.

The first EFS approach relies on the climatology of observed streamflow, which is predicted using statistics-based hydrological models (or data-driven models, such as artificial neural networks and autoregressive models), using only observed streamflows as predictors. Note that the statistics-based models based on both climate and hydrological predictors are out of the scope of this review. Although this pathway accounts for certain degrees of randomness or unpredictability, this EFS is, by definition, suitable as it produces a variety of likely synthetic streamflow outcomes based on observed streamflows, coupled with historical statistics (e.g., Fortin et al., 2004; Karunanithi et al., 1994; Maier & Dandy, 2000; Ramos et al., 2012). More complex statistics-based streamflow prediction (SBSP) forms can be obtained by using single (SBSP-00S sub-class) or multiple (SBSP-00M sub-class) statistics-based hydrological models (Figure 2).

In the second EFS, historical weather (pseudo-)observations are assumed as plausible representations of future conditions and are used as inputs to dynamic-based hydrological models (or process-driven models), ranging from lumped-conceptual to physically-based distributed models. An ensemble of streamflow time series (or traces) is produced as a function of the current hydroclimatic state. This straightforward alternative encompasses the extended streamflow prediction approach initially proposed by Jay Day in 1974, and published 10 years later (Day, 1985), as well as all approaches using (pseudo-)observations of historical climate. This is hereafter referred to as an ensemble streamflow prediction (ESP) system, with two sub-classes according to whether a single (ESP-00S) or several (ESP-00M) hydrological models are used (Figure 2). Ensembles of streamflow forecasts based on historical weather (pseudo-) observations are considered the most reliable for long-range forecasting, where weather uncertainty dominates the other sources of uncertainty and NWP or climate forecasting systems often fail to provide usable skills in terms of predictability beyond the long-term climatology (Demargne et al., 2014).

Over the years, the concept of ensemble forecasting has evolved toward the generation of shorter predictions for operational purposes (Connelly et al., 1999). To generate shorter-range predictions, forecasters have actively worked on the integration of weather forecasts from NWP models into dynamical hydrological models, known as ensemble prediction systems (EPS; Figure 2; Demeritt et al., 2007; Pappenberger, Thielen et al., 2011). In its simplest form, the forecasting system driven by an NWP model consists of a combination of a deterministic weather forecast with a hydrological model (SDS sub-class; Figure 2). Given that this system leads to single-value (deterministic) - and not probabilistic - hydrological forecasts, it is not addressed here in any detail. Based on the EPS, several sub-classes can be distinguished according to the added complexity level during the development steps of the forecasting system: the combination of a deterministic weather forecast into multiple hydrological models (EPS-SDM sub-class; Figure 2); the combination of single or multiple NWP ensembles with single or multiple hydrological models (EPS-SPS to EPS-MPS sub-classes; Figure 2); toward to a completely full-blown system through the combination of multiple NWP ensembles with multiple hydrological models, leading to the multi-model multi-ensemble concept (multi-model refers to multiple hydrological models and multi-ensemble to multiple NWP ensembles) and the EPS-MPM sub-class (Figure 2). As the primary motivation for generating ensemble forecasts is the quantification of forecast uncertainty, EPS hold great potential for optimizing the confidence level of predictions for risk management (Arduiro et al., 2005; Davolio et al., 2013) by sampling uncertainty related to the initial conditions (IC) of atmosphere and/or NWP and/or hydrological model formulations (See Section 2.3).

2.3. Uncertainty

Uncertainty analysis is an important factor in hydrology in terms of both simulations and predictions (Pappenberger & Beven, 2006). The uncertainty involved in the EFSs constitutes an emerging research field which has attracted intense research interest over the last 20 years, as illustrated in the *Water* Special Issue 2016 "*Uncertainty Analysis and Modeling in Hydrological Forecasting*." This research focus has naturally led to the emergence of specific uncertainty typologies. The most widely used among these are epistemic and aleatoric uncertainties. Epistemic uncertainty refers to the lack of knowledge (or the presence of incomplete knowledge) of underlying processes and phenomena (e.g., the constantly changing river geometry or short historical records). Aleatoric (random) uncertainty relates to the inherent unknowns of the system that vary each time a same experiment is run (e.g., the chaotic nature of the atmosphere or the measurement error in water levels). Both uncertainties are present in all development stages of an operational EFS. Since aleatoric uncertainty cannot be reduced, it must therefore be quantified, accepted, and accounted for in decision making. For its part, epistemic uncertainty can be quantified and reduced through additional information during the EFS design (e.g., additional water level measurements or data assimilation). From an operational point of view, we must know how the uncertainty estimates are produced and what these estimates contain (e.g., aleatoric uncertainty and/or epistemic uncertainty).

Epistemic uncertainties in ensemble streamflow forecasts originate from three sources (Figure 2):

(1) Initial conditions of the atmosphere (weather uncertainty) derived from (pseudo-) observations and numerical weather forecasts (e.g., Ceppi et al., 2010; Li et al., 2009; Sun et al., 2018)
(2) NWP uncertainty (weather predictive uncertainty): errors in NWP model structure and parameters (e.g., Zappa et al., 2010), since they are (mostly) uncalibrated as well as chaotic at reasonably short lead times
(3) HM uncertainty (hydrological predictive uncertainty): errors in hydrological model structure, parameters, initial conditions and calibration (e.g., Bourgin et al., 2014; Demirel et al., 2013; Wagener & Gupta, 2005; Zappa et al., 2011)

These epistemic uncertainties can be reduced by:

(1) Data assimilation (See Section 2.4): methods used to assimilate (pseudo-)observations in the EFSs (Liu et al., 2012)
(2) Aggregation (See Section 2.5): techniques used to merge weather and/or streamflow ensemble forecasts (e.g., Leandro et al., 2019); and
(3) Post-processing (See Section 2.6): methods used to bias-correct weather and/or streamflow ensemble forecasts as well as to reduce model errors and quantify uncertainty (e.g., Abaza et al., 2017; Brown & Seo, 2013; Yuan & Wood, 2012).

Weather forecasts are inherently uncertain, but forecasters have no alternative to their use. Furthermore, even with precise meteorological inputs, streamflow forecasts would still be uncertain because of the inherent limitations of hydrological models, data assimilation and post-processing techniques. Carrying out a systematic analysis of forecast uncertainty remains, however, a necessary step for providing accurate and actionable guidance from forecasts (e.g., Demeritt et al., 2007; Pappenberger et al., 2008; Weerts et al., 2011). Systematic uncertainty analysis proceeds in five steps: identification, classification, quantification, propagation, and communication to users. There are many ways an estimate of predictive uncertainty can be provided, including, for instance, autoregressive error model (Pianosi & Raso, 2012), particle filters (DeChant & Moradkhani, 2011), ensemble Kalman filters (Maxwell et al., 2018), generalized likelihood uncertainty estimation frameworks (Demirel et al., 2013), hindcast reverse ESP frameworks (Li et al., 2009; Wood & Lettenmaier, 2008), ensemble dressing (Verkade et al., 2017) and copula-based models (Chen et al., 2016). Communication regarding hydrological predictive uncertainty is strongly encouraged, as it allows forecasters to transmit their confidence in forecasts and to help users make informed decisions (Demeritt et al., 2013; Pappenberger et al., 2013). However, although some forecasters find it challenging to provide intelligibly communications with respect to hydrological predictive uncertainty (Ramos et al., 2010; Thielen & Bruen, 2019), others are adept at using uncertainty with decision makers (e.g., hydropower operators).

2.4. Data Assimilation and Ensemble Forecasting

Data assimilation (DA) is a powerful technique which was initially applied in the fields of weather modeling and forecasting. The purpose of DA is to combine many (pseudo-)observations of atmospheric variables (e.g., atmospheric moisture and pressure, sea surface temperature, etc.) with the underlying dynamical principles governing the atmosphere and oceans to provide a better estimate of the state of the system and, by extension, an improvement of the forecasting skills of the NWP models. DA is thus a cornerstone in weather forecasting. Its success is notably attributed to the three/four-dimensional variational (3D/4D-VAR) methods, Kalman filters and other assimilation methods (Bauer et al., 2015).

In hydrological forecasting, DA allows (a) the routine integration of various past (pseudo-)observations (weather forcings, streamflow, soil moisture, snow cover) from in situ measurements and remotely sensed sensors and (b) the sequential state updating of the hydrological models in time (called *filtering*) for keeping the model forecasts in line with the current observed streamflows and other hydrologic variables through an assimilation window. This step, which is less critical than in NWP models, is often characterized as a "salient bottleneck" in the operationalization of hydrological EFS because of the complex nature of hydrologic processes and memory issues, in addition to the under-determinedness of many hydrological models (Noh et al., 2019; Seo et al., 2014). Therefore, very few operational hydrological EFS use DA in their hydrological models (e.g., Emerton et al., 2016), particularly those which are wholly automated, and when DA is used, it is to assimilate streamflow and snow observations. These are due mainly to the scarcity, the non-existence, and the heterogeneity of hydrological (state) observations (e.g., subsurface soil moisture or groundwater/subsurface fluxes); in that sense, satellite measurements offer a great avenue to improve hydrological DA (See Section 4.2). However, probabilistic, and ensemble-based DA hold considerable potential as relevant methods for increasing the skills of streamflow forecasts by improving initial model states (DeChant & Moradkhani, 2011), model parameters (Abbaszadeh et al., 2018) and even structures (Nearing & Gupta, 2015), while quantifying predictive uncertainty (Moradkhani et al., 2019). The success of DA application in the field of meteorology (Pu and Kalnay, 2019) contributed to its success in hydrology (Liu et al., 2012; Noh et al., 2019) over the past two decades, leading to a special dedicated issue in *Journal of Hydrology* (2014) and numerous related publications.

Table 1
List of Popular (Ensemble) DA Methods[a] *(Not Exhaustive)*

Methods	Reference for streamflow DA	Reference for soil moisture DA	Reference for snow water equivalent DA
Dimensional variational data assimilation (1D- to 4D-VAR)	Seo et al. (2003; 2009)	Seo et al. (2009)	N.A.
Particle filter and variants			
Lagged particle filtering (LPF)	Noh et al. (2013; 2014)	N.A.	N.A.
Sequential importance resampling (SIR)	Noh et al. (2011; 2014); DeChant and Moradkhani (2012)	N.A.	DeChant and Moradkhani (2011)
Particle filtering and Sequential Bayesian Combination (PF-SBC)	DeChant and Moradkhani (2014)	N.A.	N.A.
Particle Filter-Markov Chain Monte Carlo (PF-MCMC)	Moradkhani et al. (2012)	N.A.	N.A.
Evolutionary PF-MCMC (EPFM)	Abbaszadeh et al. (2018)	N.A.	N.A.
Kalman filter and variants			
Extended Kalman filter (EKf)	Shamir et al. (2010)	Reichle et al. (2002)	N.A.
Ensemble Kalman filter (EnKf)	DeChant and Moradkhani (2012); Noh et al. (2013); Jiménez et al. (2019)	Han et al. (2012); Patil and Ramsankaran (2017)	Slater and Clark (2006)
Asynchronous EnKf (AEnKf)	Rakovec et al. (2015)	N.A.	N.A.
Recursive ensemble Kalman Filter (REnKf)	McMillan et al. (2013)	N.A.	N.A.
Maximum likelihood ensemble filter (MLEf)	Rafieeinasab et al. (2014)	Tran et al. (2013)	N.A.
Hybrid Kalman filter (HKf)	Pauwels et al. (2013)	N.A.	N.A.
Other			
H-infinity filters	Wang and Cai (2008)	N.A.	N.A.
Bayesian approaches	Reggiani and Weerts (2008); Reggiani et al. (2009)	N.A.	N.A.

[a]Partly based on the classification of Liu et al. (2012) and Moradkhani et al. (2019).

There are many different methods for assimilating (pseudo-)observations into the EFS; they range from simple rule-based, direct insertion methods to advanced methods usually derived from the Bayes' theorem for probabilistically conditioning the model states on (pseudo-)observations (Liu et al., 2012). The advanced DA methods differ from the set of tractability approximations (Moradkhani et al., 2019): smoothers (e.g., variational [VAR] DA method) versus filters (e.g., particle filter [PF]), linear (e.g., Kalman filter [Kf]) versus nonlinear (e.g., Extended Kalman filter [EKf]), and deterministic (e.g., Kf and EKf) versus ensemble (e.g., ensemble Kalman filter [EnKf], PF and maximum likelihood ensemble filter) DA (Moradkhani et al., 2019). The most popular advanced DA methods are listed in Table 1. Besides the classical distinction between smoothing and filtering methods, DA can also be pooled into synchronous and asynchronous approaches (Noh et al., 2019): the synchronous DA assimilates (pseudo-)observations only valid at the forecasting time (e.g., 3D-VAR DA method, PF and EnKf), while the asynchronous DA assimilates (pseudo-)observations into the EFS valid at times other than the forecasting time (e.g., 4D-VAR and Asynchronous EnKf). (See Noh et al. (2019)) and De Lannoy et al. (2019) for two recent comparative studies of DA methods applied on streamflow and soil moisture, respectively). An application of Kf and its variants for assimilating streamflow data in an operational forecasting testbed is provided in Tao et al. (2016). As for the interactions between DA and post-processing (See Section 2.4) in the EFS, the reader is invited to refer to Bourgin et al. (2014).

2.5. Combining Multiple Weather and Hydrological Model Predictions to Generate Consensus for Short- and Medium/Long-Term Forecasts

To better quantify uncertainty in ensemble forecasting, forecasts from multiple weather and hydrological models are merged together to account for structural model deficiencies. The rationale behind the multi-model combination is based on the fact that models inevitably include errors, which can be reduced with optimal multi-model combinations (Ajami et al., 2007). By merging individual forecasts, a more reliable assessment of the "ground truth" can be obtained by allowing the models to reinforce (or compensate for) each other through partially complementary strength biases (Devineni et al., 2008; Duan et al., 2007). The merged forecasts may be more realistic, as the features each model performs well are implicitly strengthened through the combinations. Some studies have demonstrated that the fusion of competing hydrological models leads to overall improved streamflow predictions (e.g., Arsenault & Brissette, 2015; Georgakakos et al., 2004; Li & Sankarasubramanian, 2012; Vrugt & Robinson, 2007), even though, for practical applications, this inevitably increases the computation time (Jiang et al., 2014).

Fusing is typically achieved by pooling the predictions from the multiple models (weather and/or hydrological models) and extracting a single prediction value corresponding to the "best" forecast from the multi-model ensemble. The multi-model combination can be performed by fusing individual streamflow forecasts from multiple hydrological models (e.g., Brochero et al., 2011; Demirel et al., 2015; Mahanama et al., 2012), combining multiple NWP model ensembles of weather forecasts (e.g., Bao et al., 2011; Bogner et al., 2011; Kim et al., 2017), and ultimately, merging the different approaches (e.g., Bourdin & Stull, 2013; Dutta et al., 2012; Slater et al., 2017). However, even though the combination methods can improve some of the statistical properties of the forecasts, they are little used in operational EFSs, where they are put into practice in a decision-making context. In operational EFSs based on multiple models, decision rules are often based on the output of individual forecasting models, where weights are assigned to them to create a decision tree.

The most popular methods for multi-model (ensemble) combinations applied on hydrometeorological forecasts are listed in Table 2. The studies involving the steps in which forecasts are aggregated into the EFS are summarized in Figures 2–5 and are detailed in Tables S1–S3. The multi-model aggregation techniques are categorized into two groups according to the approach used for weighting the weather and streamflow forecasts.

In the first group, multi-model forecasts are combined using a set of deterministic weights, which can vary in time (dynamic weighting) or not vary at all (static weighting). The simple average (Georgakakos et al., 2004) and weighted average (Granger & Ramanathan, 1984) methods are the simplest of the ad-hoc static-weighting methods. Dynamic weighting methods can contain the switching mechanism, where various single modeling solutions are switched at different streamflow levels (e.g., Deutsch et al., 1994; Hu et al., 2001) or at each time step (e.g., Abrahart & See, 2002; See & Openshaw, 2000). Jeong and Kim (2009) argue that the time-varying-weight merging approaches lead to better results than do the constant-weight approaches when forecasts depict non-stationary errors. However, these techniques provide consensus deterministic forecasts, with a lack of physical interpretations in the attributed weights (negative weight values are possible) and the inability to evaluate the model uncertainty (Ajami et al., 2007). The studies by Xiong et al. (2001), Ajami et al. (2006), Diks and Vrugt (2010) and Arsenault et al. (2015) provide a comparison of the static-weight methods in terms of accuracy of point forecasts and simulations.

While the first category of combination techniques focuses on point predictors (deterministic forecasts), the second group is concerned with density forecasts (i.e., probability density of possible future values of streamflow). Among the well-established probabilistic combination techniques, Bayesian model averaging (BMA in the finite mixture model; Neuman, 2003) is the most prevalent. These methods respond to the issue of multi-model aggregation by calculating a predictive probability density function (PDF) as a weighted average of various model PDFs. The weights are derived from a statistical analysis of each individual forecast's historic performance and uniqueness. For instance, the BMA accounts for conceptual model uncertainty by conditioning both on a single "best" model and on the entire ensemble (Raftery et al., 2005). Here, the BMA produces not only the traditional point forecast (mean PDF value), but also a quantitative assessment of predictive uncertainties (Liang et al., 2013). The BMA and its variants have gained in popularity by providing efficient and seamless predictions (e.g., Duan et al., 2007; Hemri, 2019; Vrugt & Robinson, 2007). However,

Table 2
List of Popular Methods for Combining Multiple (Ensemble) Hydrological Models (Not Exhaustive)

Type	Method	Reference for model combinations
Deterministic with static weighting	Simple average (equal weights)	Georgakakos et al. (2004)
	Weighted average method	Granger and Ramanathan (1984)
	Multi-model super ensemble	Krishnamurti et al. (2000)
	Multiple linear regression	Krishnamurti et al. (1999)
	Modified Multi-model super ensemble	Ajami et al. (2006)
	Akaike information criterion averaging	Akaike (1974)
	Bayes information criterion averaging	Schwarz (1978)
	Bates-Granger averaging	Bates and Granger (1969)
	Granger-Ramanathan averaging	Granger and Ramanathan (1984)
	Bayesian model averaging (linear regression model)	Raftery et al. (1997)
	Neural network averaging	Shamseldin et al. (1997, 2007)
	Fuzzy logic model	See and Openshaw (1999)
Deterministic with dynamic weighting	Linear time-varying sum of squared error	Granger and Newbold (1977)
	Geometric time-varying sum of squared error	Clemen and Winkler (1986)
	Switching mechanisms	Deutsch et al. (1994); See and Openshaw (2000); Hu et al. (2001); Abrahart and See (2002)
	Pairwise dynamic combination method	Chowdhury and Sharma (2009)
Probabilistic with density forecast	Mallows model averaging	Mallows (1973)
	Ensemble model output statistic (non-homogeneous Gaussian regression)	Gneiting et al. (2005)
	Beta-transformed linear pooling approach	Gneiting and Ranjan (2013)
	Quantile model averaging	Schepen and Wang (2015)
	Bayesian model averaging (finite mixture model)	Neuman (2003); Raftery et al. (2005)

there are concerns about the mechanisms used to estimate the weights of the individual forecasts and their complexity levels (Diks & Vrugt, 2010; Graefe et al., 2015). The other probabilistic techniques are suitable alternatives for pooling multi-model ensemble forecasts due to their more straightforward applications and to the fact that they are less time consuming (Bogner et al., 2017; Schepen & Wang, 2015).

2.6. A Need for Post-Processing Ensemble Streamflow Forecasts

Statistical post-processing of both weather and streamflow forecasts is typically required to compensate for errors in model structure or initial conditions, and to correct biases and improve dispersion issues within ensembles. Many hydrological EFSs integrate post-processing techniques in the form of a "weather post-processor" and/or a "hydrological post-processor" (e.g., Demargne et al., 2014). The weather post-processor produces bias-corrected forcing ensemble forecasts of precipitation and temperature, which preserve the spatio-temporal relevance and the consistency between variables at the scale of the hydrological models (Wetterhall & Smith, 2019); for its part, the hydrological post-processor produces bias-corrected streamflow ensembles that meet user requirements, such as temporal covariability in the ensemble time series while ensuring that over-fitting does not occur (Hopson et al., 2019). However, both weather and hydrological post-processors can ultimatively have an impact on the quality of hydrological ensemble forecasts (See Section 2.7 for the definition of forecast quality) and must be selected with care according to the attribute of the forecast quality to be improved (Abaza et al., 2017).

The widely used statistical post-processing methods applied on weather and hydrological forecasts are illustrated in Table 3. The statistical post-processing methods range in complexity from univariate ensemble post-processing methods encompassing regression-based approaches, ensemble dressing, fully Bayesian

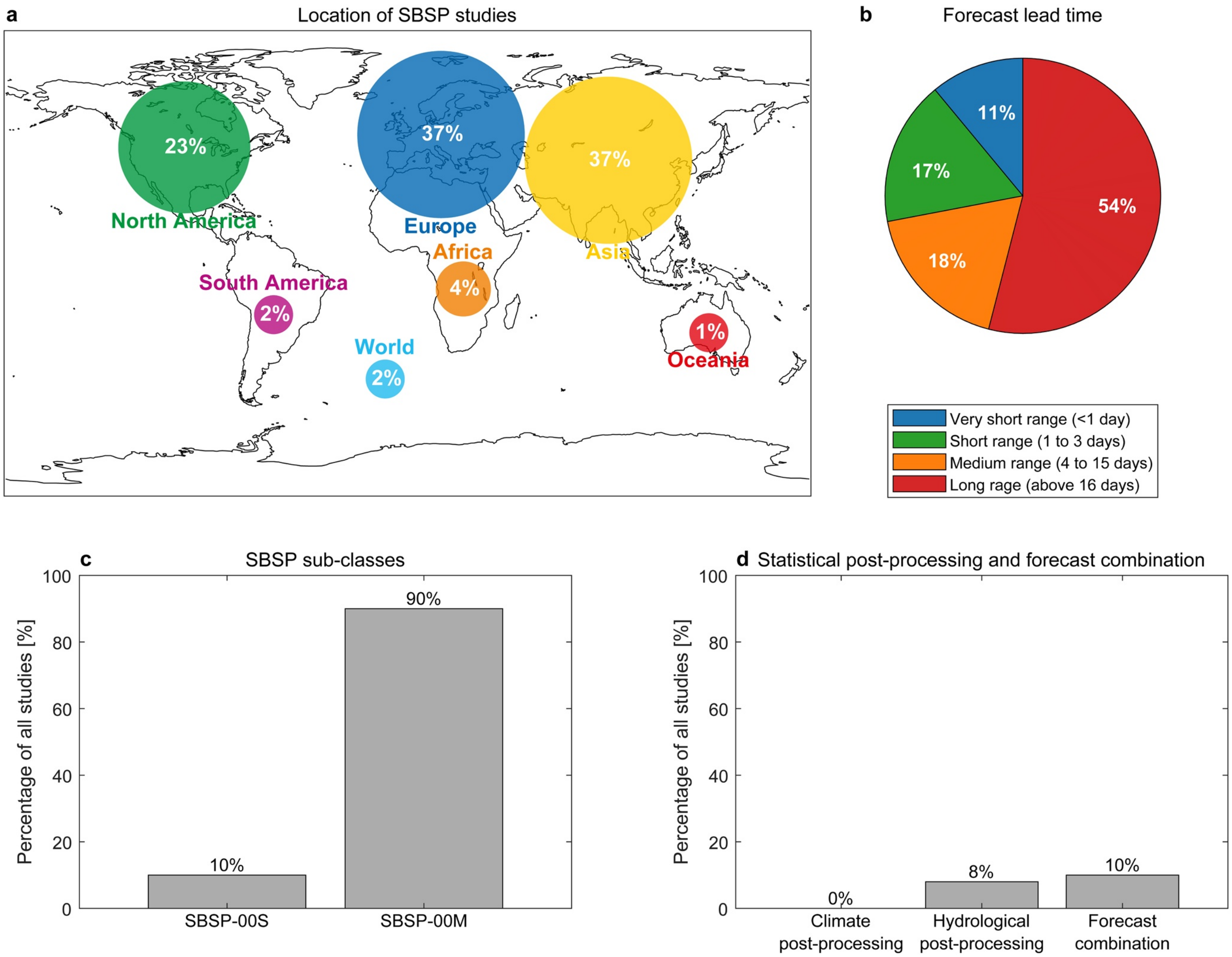

Figure 3. Synthesis of the 52 SBSP studies: (a) location of the SBSP studies investigated by region; (b) types of SBSP sub-classes (SBSP-00S or SBSP-00M); (c) Percentage of the SBSP studies including statistical post-processing and forecast combination; and (d) forecast lead time considered in the SBSP studies. *Note*. that the total percentage of the location of SBSP studies exceeds 100% because some studies have several study areas over several continents. SBSP, statistics-based streamflow prediction.

methods to multivariate ensemble post-processing of temporal, spatial, and spatio-temporal dependencies (Boucher et al., 2019; Hemri; 2018; Wilks; 2018; Wood & Schaake, 2008). Works, including a post-processing of weather and/or hydrological forecasts in the EFS, are listed similarly as for the combination techniques in Figures 2–5 and detailed in Tables S1–S3 (indicated by Yes/No). The meteorological community has long recognized the importance of statistical post-processing for objective weather forecasts, initially using the perfect prognosis method (Klein et al., 1959). Statistical post-processing techniques are now flourishing in both the weather and hydrological communities and share some theoretical similarities. The only substantial difference between weather and hydrological post-processing techniques lies in the strong autocorrelation in streamflow forecasts, which requires the use of historical observations or forecasts as predictors through statistical post-processing (Li et al., 2017). There is a fundamental conceptual difference between post-processing techniques which break the temporal/spatial relationships of the input data, such as model output statistics (Wilks, 2006) traditionally applied on the NWPs to remove epistemic biases (See Section 2.3) but requiring additional methods to "reassemble" temporal/spatial relationships, and those which correct ensemble traces while trying to work with the temporal properties of the hydrological model, such as error models (Demargne et al., 2014), but can not ensure reliable ensembles at long lead times. This means that the weather post-processing techniques (usually a form of model output statistics post-processing combined

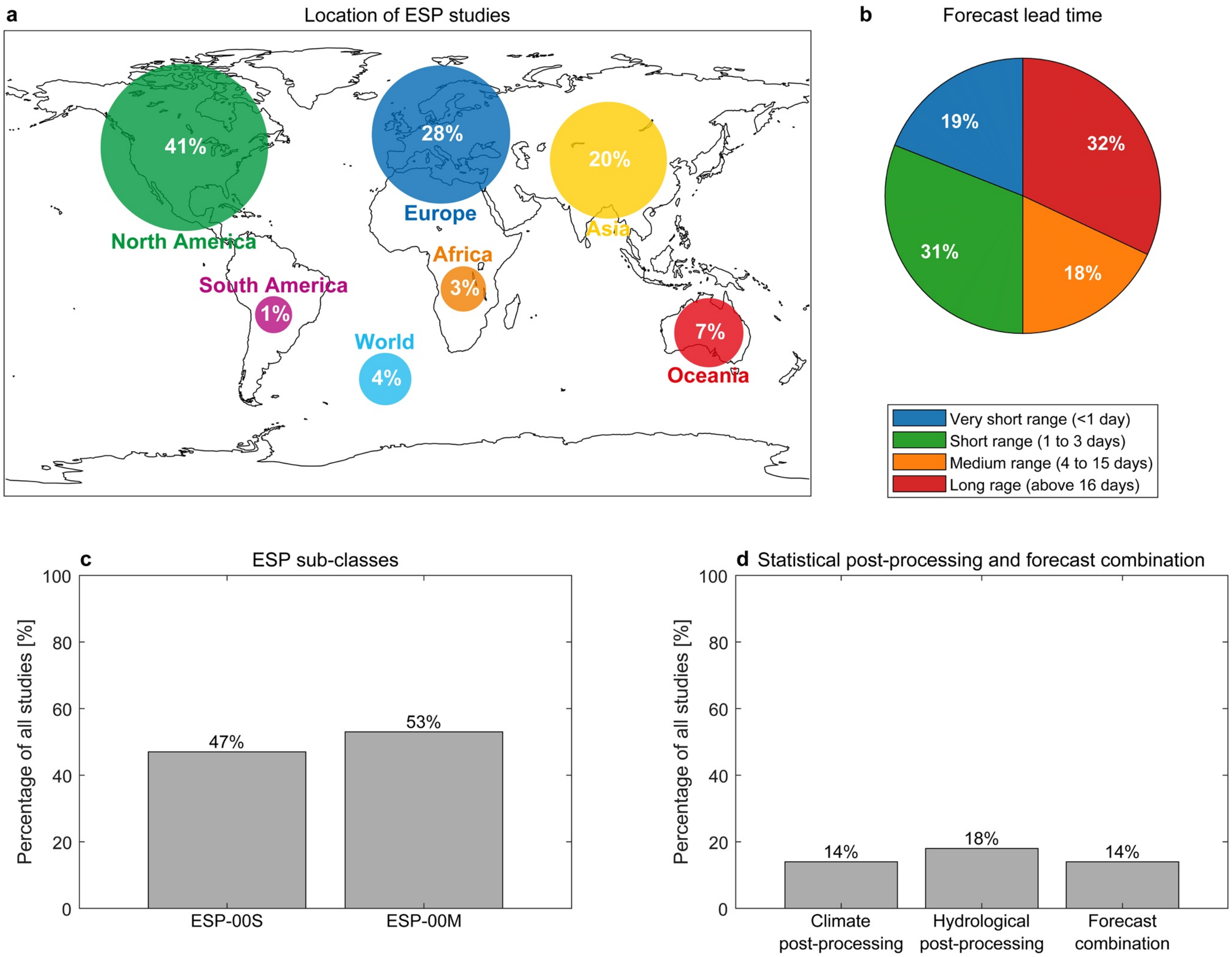

Figure 4. Synthesis of the 147 ESP studies: (a) location of the ESP studies investigated by region; (b) types of ESP sub-classes (ESP-00S or ESP-00M); (c) Percentage of the ESP studies including statistical post-processing and forecast combination; and (d) forecast lead time considered in the ESP studies. *Note.* that the total percentage of the location of ESP studies exceeds 100% because some studies have several study areas over several continents. ESP, ensemble streamflow prediction.

with a reordering method such as in the Schaake Shuffle; Clark et al., 2004; Bellier, Bontron, & Zin, 2017; Scheuerer et al., 2017; Wu et al., 2018) may or may not be appropriate for streamflow forecasts as they are largely untested.

2.7. Verification of Ensemble Streamflow Forecasts

Streamflow forecast quality verification procedures (or *benchmarking* since the forecasts are, by definition, only verified or evaluated against observations (Oreskes et al., 1994) during hindcasting; see below) constitute a final and necessary step to properly achieve EFS implementation. Because errors occur throughout the EFS development process—from the input of the (ensemble) weather forecasts to the production of (ensemble) streamflow forecasts (e.g., with/without a weather-hydrological DA scheme, before/after post-processing, hydrological models) for different flow aspects (e.g., discharges or streamflow volumes at a critical threshold, single-valued or probabilistic forecasts)—verification of streamflow forecasts is needed in order to monitor and improve the forecast quality and to compare the quality of different EFSs for a large range of spatio-temporal scales (Anctil and Ramos, 2019). Forecast verification is thus becoming more and

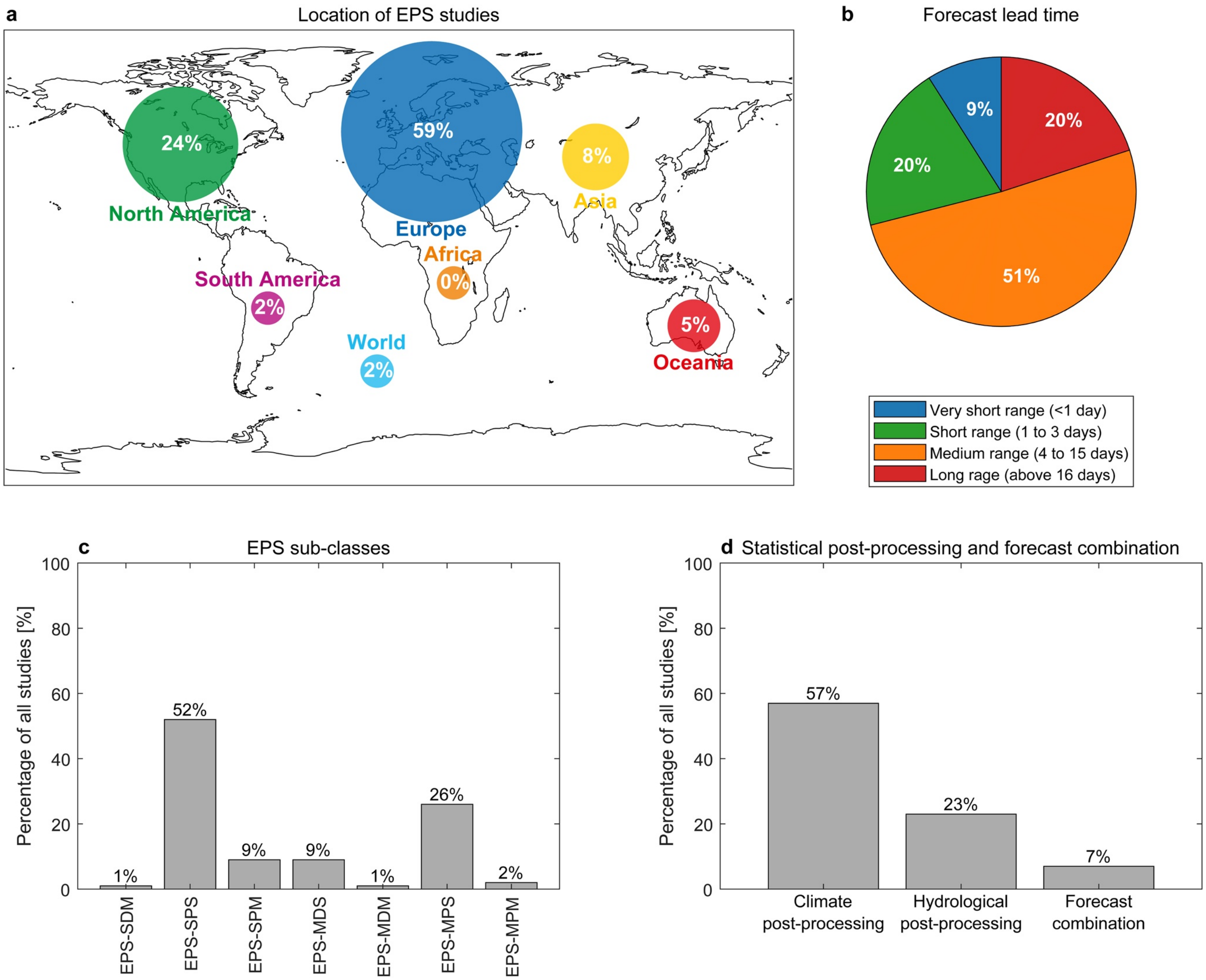

Figure 5. Synthesis of the 127 EPS studies: (a) location of the EPS studies investigated by region; (b) types of EPS sub-classes (ESP-SDM; EPS-SPS, EPS-SPM, EPS-MDS, EPS-MDM, EPS-MPS or ESP-MPM); (c) Percentage of the EPS studies including statistical post-processing and forecast combination; and (d) forecast lead time considered in the EPS studies. ESP, ensemble streamflow prediction; EPS, ensemble prediction systems.

more present in the hydrological EFSs, as it allows forecasters to have confidence in their forecast tools and products, while supporting operational decision-making (Demargne et al., 2009; Werner et al., 2019; Zappa et al., 2013).

To evaluate the quality of the ensemble streamflow forecasts, forcing input weather ensembles and hydrological ensembles are commonly verified by using retrospective forecasts, or *hindcasts*, generated by an ensemble hindcast system (EHS) for an extended time period (Demargne et al., 2007). The following are the three steps of the EHS: (a) generation of retrospective weather ensembles from deterministic forecasts or routinely using an EFS initialized from NWP reanalysis (as is done in the ECMWF reforecast system) for the first few lead days, coupled with resampled climatological ensembles for longer lead times; (b) generation of retrospective initial conditions (IC) of hydrological models from a set of existing ICs and historical weather observations; (c) generation of streamflow hindcasts based on retrospective ICs and weather ensemble hindcasts. These hindcasts are compared with a reference simulation to determine the prediction consistency of the EHS; the reference simulation is carried out with the same hydrological models and retrospective ICs as the hindcasts, but the forcing inputs are taken

Table 3
List of Popular Statistical Post-Processing Methods Applied on Weather and Hydrological Forecasts[a] *(Not Exhaustive)*

Category	Method	Reference for weather post-processing	Reference for hydrological post-processing
	Analog method	Lorenz (1969); Hamill and Whitaker (2006); Marty et al. (2012)	N.A.
Regression	Perfect prognosis	Klein et al. (1959)	N.A.
	Model output statistics	Glahn et al. (1972)	N.A.
	Ensemble model output statistics (EMOS)	Gneiting et al. (2005); Scheuerer (2014)	Analog-based EMOS: Hemri and Klein (2017) EMOS with the copula approach: Hemri et al. (2015)
	Linear scaling	Crochemore et al. (2016)	N.A.
	Logistic regression	Wilks (2009); Messner and Mayr (2014)	N.A.
	Extended logistic regression	Messner and Mayr (2014)	Fundel and Zappa (2011)
	Member-by-member regression	Van Schaeybroeck and Vannitsem (2015)	N.A.
	Rank histograms	Hamill (2001)	N.A.
	Quantile regression (QR)	Taillardat et al. (2016)	QR: Muthusamy et al. (2016) QR with neural networks: Bogner et al. (2017)
	General linear model post-processor	N.A.	Zhao et al. (2011); Ye et al. (2015)
	Leave-out-cross validation	N.A.	Li et al. (2017a)
	Ensemble Kalman filter	N.A.	Vrugt et al. (2006); Vrugt and Robinson (2007)
	Autoregressive models (ARM)	N.A.	ARM: Seo et al. (2006); Hopson and Webster (2010) ARM with wavelet transform: Bogner et al. (2016)
Distribution transform	Distribution mapping	Crochemore et al. (2016)	N.A.
	Quantile mapping	Wood et al. (2002); Zhao et al. (2017); Li et al. (2017a)	Wood and Schaake (2008)
	Quantile model averaging	N.A.	Schepen and Wang (2015)
Bayes' Theorem/conditional distribution	Bayesian processor of output	Krzysztofowicz (2004); Marty et al. (2015)	N.A.
	Bayesian processor of ensemble	Wang et al. (2019)	N.A.
	Ensemble pre-processor	Schaake, Demargne et al. (2007); Wu et al. (2011)	N.A.
	Bayesian joint probability	Robertson et al. (2013)	Wang et al. (2009); Zhao et al. (2015)
	Hydrological uncertainty processor	N.A.	Krzysztofowicz and Kelly (2000); Krzysztofowicz and Herr (2001); Krzysztofowicz (2001a, 2001b); Reggiani et al. (2009); Herr and Krzysztofowicz (2015)
	Model conditional processor	N.A.	Todini (2013)
Ensemble dressing	Best-member dressing method	Roulston and Smith (2003); Hamill and Scheuerer (2018)	Raftery et al. (2005)
	Dressing kernels	Wang and Bishop (2005); Fortin et al. (2006)	N.A.

[a]Partly based on the classification of Li et al. (2017a).

from historical weather observations. This verification procedure is quite common in short-, medium- and long-range hydrological forecasting (Alfieri et al., 2014; Brown et al., 2014; Greuell et al., 2018; He et al., 2016).

Assessing forecast quality involves examining aspects or *attributes* of hindcasts (Bradley et al., 2019). Murphy (1993) defines key attributes contributing to forecast quality: bias, skill, accuracy, correlation, reliability, resolution, discrimination, sharpness and uncertainty. These are briefly presented in Table 4. Traditionally, forecast verification focuses on skill and accuracy. However, other attributes of forecast quality have an impact on the forecast *value*, for example, the level to which the forecast supports operational decision-making (Murphy, 1993). For each forecast quality attribute, there are many approaches available for its evaluation. Some include conventional graphical representations of statistical verification data (e.g., rank histogram or reliability diagram), while others include statistical forecast quality metrics (e.g., brier skill score or mean continuous rank probability score), contingency tables (i.e., tables constructed by testing hits, misses, false alarms and correct negatives in a forecasting framework) and cost-loss scenarios. The latter can be applied to ensemble mean (single-valued forecasts) or ensemble (probabilistic) forecasts for a discrete (e.g., streamflow exceeding a threshold) or continuous (e.g., streamflow) variable; they are particularly relevant in determining the usefulness of the forecast for decision making (See Table 4 for an illustration of the common metrics used to evaluate forecast quality in operational systems).

A common conclusion of the forecast verification literature is that there is no best verification approach combining all attributes sought in assessing a forecast. However, in the theoretical literature, there is clear guidance on what properties to assess (Gneiting et al., 2007): “to maximize sharpness subject to calibration” (in this case, “calibration” means “reliability”); in other words, make sure your forecasts are reliable, and then make them as sharp as possible (whatever the metrics chosen to measure these properties). If these two criteria are met, forecasts will become more accurate (as they become sharper). In many hydrological forecasting studies, reliability is often considered as an afterthought. Some forecasting systems are proposed and executed even though they can't lead to reliable ensembles. Selecting at least one approach for key forecast attribute of interest and then proceeding to a step-by-step process for assessing its relevance is highly suggested (See Cloke a Pappenberger (2008) for an illustration of a six-step process for selecting, comparing, and assessing performance metrics, focusing on extreme weather forecasts for hydrological forecasting). For a description of the Ensemble Verification System (EVS), which is a flexible software tool devised to verify weather ensembles (temperature, precipitation) and streamflow forecasts, the reader is referred to Brown et al. (2010).

3. Ensemble Streamflow Forecasting: Literature Review of Systems

The following literature review describes the three EFSs: statistics-based streamflow prediction (SBSP) systems, climatology-based ensemble streamflow prediction (ESP) systems and numerical weather prediction-based hydrological ensemble prediction systems (EPS) (Figure 2). For each EFS, a synthesis of the representative studies is given to provide an understanding of the development of such systems through four main aspects: location of studies, the types of EFS sub-classes, the use of statistical post-processing and forecast combination, and the lead time of these ensemble forecasts. In total, 326 studies from 73 journals up to 2018 are identified by using keywords search on web of science and science direct; the first paper is published in 1980. The following keywords “ensemble forecasting/prediction and streamflow/hydrology” are selected in the title or in the abstract to include all studies related to water management instead of focusing on specific forecasting studies based on key aspects of the hydro-meteorological ensemble systems (i.e., [flash] floods, operational systems or process-oriented studies). The list of the selected studies and the related information for each EFS are included in Tables S1–S3.

3.1. Statistics-Based Streamflow Prediction Systems

In this section, the SBSP systems are reviewed through 52 representative studies over the last 25 years (See Table S1). The primary justification for the existence of SBSP systems based on observed streamflow as the

Table 4
Description of the Nine Key Forecast Quality Attributes

Attribute	Definition	Metric	Type of forecast	Type of variable
Bias	The difference between mean forecast and mean observation	Frequency bias	Probabilistic	Discrete and continuous
Skill	The accuracy of a forecast relative to a reference forecast	Brier skill score	Probabilistic	Discrete and continuous
Accuracy	The mean difference between the individual forecasts and observations	Continuous ranked probability score	Probabilistic	Discrete
Correlation	The strength of the linear relationship between the forecasts and observations	Pearson correlation coefficient	Ensemble mean	Continuous
Reliability	How well the forecast agrees with the observed outcome on average when a specific forecast is issued	Probability integral transform	Probabilistic	Discrete and continuous
Resolution	If the outcomes are different for different forecasts issued	Brier score resolution	Probabilistic	Discrete and continuous
Discrimination	If the forecasts are different for different outcomes	Brier score discrimination	Probabilistic	Discrete and continuous
Sharpness	The degree of variability of the forecasts	Average width of prediction intervals	Probabilistic	Continuous
Uncertainty	The degree of variability in the observations	Variance of the observations	N.A.	Continuous

Note. An example of common verification metrics used in operational forecasting for each attribute is given; the type of forecast (ensemble mean or probabilistic forecasts) is also mentioned (Partly based on Anctil & Ramos, 2019).

only predictor is the need to deal with the absence of quantitative precipitation forecast scenarios, built either statistically or from a dynamical model (Goswami & O'Connor, 2007). When available information consists solely of observed streamflow data, statistical streamflow data-driven models are used, with abstraction of other variables or predictors. The conventional data-driven approach encompasses stochastic models such as autoregression, autoregression moving average and (multiple) linear regression (Rajagopalan et al., 2010). The models have been applied to streamflow forecasting since 1970 (Table S1). More sophisticated data-driven models were subsequently developed to account for non-linearity and non-stationarity in river flow processes and to capture the noise complexity in prediction datasets (Yaseen et al., 2015). The latter are artificial intelligence data-driven methods. More specifically, this category includes machine learning techniques, including the commonly used artificial neural networks (Coulibaly et al., 1999; Maier & Dandy, 2000; Maier et al., 2010; ~65% of the referenced studies), fuzzy inference systems (Özger, 2009), evolutionary computation with genetic programming (Charhat et al., 2009) and other techniques, such as wavelet-based artificial intelligence techniques, hidden Markov chain models and chaos theory (Cui & Singh, 2015; Fortin et al., 2004; Liu et al., 2014).

As can be seen in Figure 3a, SBSP-related studies dominate the northern hemisphere as follows: Europe (37%), Asia (37%) and North America (23%); only 7% are conducted in the southern hemisphere (South America, Africa, and Oceania). There are also some global-scale SBSP studies (2%). Statistical hydrological data-driven models, such as artificial neural networks and autoregressive models, require a lot of input data because of the lack of the physics to constrain them; such input data are usually hard to access in South America and Africa which probably explain the limited number of studies conducted over those regions. However, for other statistical models, such as the Bayesian Joint Probability model used operationally in Australia few input data are needed to implement them. On the other hand, the statistical hydrological data-driven models are generally well-suited for improving predictions in ungauged catchments (Kratzert et al., 2019).

Most of the SBSP studies use more than one statistical hydrological data-driven models, as shown in Figure 3b, with the SBSP-00M sub-class accounting for 90% of the referenced studies. Eight percent of the SBSP studies make the use of a post-processing in addition to their stochastic models to get hydrological output statistics in better accordance with observations or to form a direct bridge between predictors and streamflow (Figure 3c). However, very few SBSP studies perform a combination of streamflow forecasts (10%; Figure 3c).

The long-range (i.e., with lead time above 16 days) ensemble streamflow forecasts are the focus of SBSP systems (58%; Figure 3d). They follow the short- (i.e., lead time of 1–3 days; 21%) and medium- (i.e., lead time of 4–15 days; 18%) range ensemble streamflow forecasts. Only 10% of the referenced studies consider a forecast lead time less than 1 day. An example of long-range operational ensemble streamflow forecasting systems based on statistical methods can be seen at http://www.bom.gov.au/water/ssf/index.shtml, in addition to the regression techniques that have long been used in the United States to produce long-range predictions (Pagano et al., 2014).

3.2. Ensemble Streamflow Prediction

While the aforementioned EFSs are established based only on historical streamflow data, the ESP systems use historical weather observations or pseudo-observations (essentially, precipitation from reanalysis/reforecast of past weather data, weather satellites and radars) as inputs to hydrological models (Figure 2), whose state variables are initialized for the time of the forecast inputs. An assessment of 147 studies over the last 40 years with respect to the use of ESP systems (See Table S2) is presented below.

The geographical location of the ESP studies is different from that of the SBSP studies, since the former are mainly conducted in North America (41%), followed by Europe (28%) and Asia (21%) (Figure 4a). 12% of the ESP studies are from the southern hemisphere, mostly in Oceania (7%). There are also a few global-scale ESP studies (4%).

The ESP systems are most commonly created using multiple hydrological models leading to the ESP-00M sub-class majority (53%; Figure 4b). Most of the ESP studies reviewed use an ensemble of dynamical hydrological models (45%) rather than statistical hydrological models (39%), with a maximum of 8-model ensembles. Dynamical hydrological models, which require specific sets of input information, are more appropriate for medium-to long-term forecasting, where knowledge of rainfall-runoff interactions is expected to generate adequate forecasts (Humphrey et al., 2016; Rezaeianzadeh et al., 2013). 16% of the studies listed are based on an amalgamation of data-driven and process-driven models. The weather (14%; Figure 4c) and hydrological (18%; Figure 4c) post-processing steps as well as those for ensemble forecast combinations (14%; Figure 4c) are not extensively included in the ESP studies.

Almost one-third of ESP systems are applied to generate short- and long-range ensemble streamflow forecasts, while less than 20% of the ESP studies focus on very short- and medium-range ensemble forecasting (Figure 4d). These studies exploit multiple sources of weather information (stations, satellites, and radars) as inputs to the ESP systems. As for the traditional ESP system, which uses weather information from stations (Day, 1985), it is usually used to forecast streamflows and reservoir inflows over longer horizons, with monthly to seasonal forecasting lead times.

A complement to the ESP approach is given by a technique called "reverse ESP" (See Wood & Lettenmaier, 2008), which was developed not as an operational forecast approach, but as a method for testing new forecasting systems, understanding sources of skill and error, as well as assessing the uncertainty from the observations, initial hydrological conditions and weather forcings on the reliability of streamflow forecasts (Yuan et al., 2016; Zhu et al., 2019). Reverse ESP was later expanded into an approach for estimating streamflow forecast skill elasticities, termed the Variable Ensemble Streamflow Prediction Analysis (VESPA; Wood et al., 2016), a technique that was then streamlined by Arnal et al. (2017).

It should be noted that large-scale climate precursors can be included in the ESP (and EPS) frameworks as a weighting scheme for improving the ensemble spread of streamflow forecasts at seasonal scales (e.g., Beckers et al., 2016; Delorit et al., 2017; Gobena & Gan, 2010; Mendoza et al., 2017; Najafi et al., 2012).

3.3. Ensemble Prediction System

The attractiveness of streamflow EPS based on NWP model outputs cannot be overlooked owing to their strong scientific consideration over the past 20 years. The rigorous critique of Cloke and Pappenberger (2009), the special issue in *Hydrological Processes* (2013), and the growing HEPEX community worldwide are but a few examples of this consideration. A synthesis of the 127 EPS-related studies (See Table S3) is presented below.

Most of the EPS studies reviewed cover Europe (59%) followed by North America (24%) (Figure 5a). There are few case studies of EPS in Asia (8%) and Oceania (5%), and very few in South America (2%); none has been conducted in Africa to date (Figure 5a).

Regarding the EPSs, the two major sub-classes are: the EPS-SPS (52%), which uses one NWP ensemble prediction system (an ensemble of weather forecasts initiated from perturbed initial conditions known as probabilistic forecasts) as input to one (dynamical) hydrological model; and the EPS-MPS sub-class (26%) with up to 7 NWP ensemble prediction system-forced hydrological models (Figure 5b). These are followed by the EPS-MDS sub-class (9%) where multiple (up to 7) high-resolution NWP deterministic runs are used as inputs to a hydrological model (Figure 5b and Table S3) and the EPS-SPM sub-class (9%) where one NWP ensemble prediction system drives multiple hydrological models, with a maximum of a 16-dynamical hydrological model ensembles (Table S3). To a lesser extent, they are the EPS-MDM (2%), EPS-MPM (2%) and the EPS-SDM (1%) sub-classes (Figure 5b).

To our knowledge, only three studies have used the EPS-MPM sub-class (Bourdin & Stull, 2013; Slater et al., 2017; Wanders et al., 2019), the "Super EPS," that is, multiple ensembles of NWP models forcing multiple hydrological models. The EPS-MPM sub-class represents the outcome of a long technological process and scientific cooperation between the weather and hydrological forecasting communities. Its main advantage is that it provides a quantification of all major sources of uncertainty in streamflow forecasts. Note, however, that the interactions between uncertainties are complex, even though many studies implicitly assume that the sources of uncertainty are simply additive (e.g., Pagano et al., 2013; Roulin & Vannitsem, 2015). Although most of the studies reviewed have argued for the potential benefits of EPS-MPMs, they are, by definition, complex systems, as *m* ensembles of NWP models are used to drive *n* hydrological models (with post-processing); *m* by *n* runs must be completed to forecast streamflow. This means that small values of *n* and *m* or powerful computing resources are needed, even though efficient machine learning methods for uncertainty analysis exist. This is especially a critical issue when the system has a short time to execute in an operational environment, and it is presently unclear that this EPS will find broad operational acceptance given the amount of probabilistic information that needs to be processed, especially in the context of decision making.

As mentioned above, the use of multiple hydrological models in the EPSs does not fall within a common framework (EPS-SDM: 1%; EPS-SPM: 9%; EPS-MDM: 2%; EPS-MPM: 2%; Figures 2 and 5b). One possible explanation is that hydrological model parameters are usually calibrated, and variations in outputs from multiple hydrological models often explain only a small part of the hydrological predictive uncertainty (See Section 2.3). Multiple hydrological models may be more justified when using uncalibrated physically based hydrological models, even though these can be computationally expensive.

The use of global NWP models in hydrological EPSs has some technical implications due to their typical coarse-scale grid, which leads to errors and introduces biases at the scale of the hydrological model (Crochemore et al., 2016). Weather post-processing is usually held to be a required first step prior to using NWP model outputs to forecast streamflows (see Section 2.6). The weather post-processing step is very broadly included in the 127 EPS-related studies (53%) as compared to the hydrological post-processing step (23%; Figure 5c).

Note that there are some statistical methods which are applied to link dynamical NWP models and HMs together. These techniques include, for instance, model conditional processors (Todini, 2008), model output statistics methods (Schick et al., 2018), analogs sorting approaches (Obled et al., 2002) and ensemble Bayesian forecasting systems (e.g., Biondi & Luca, 2013; Herr & Krzysztofowicz, 2015; 2019; Seo et al., 2006; Wang & Robertson, 2011; Weerts et al., 2011). However, only 7% of EPS studies perform a combination of post-processed ensemble streamflow forecasts (Figure 5c). The Meteorological Model-based Ensemble Forecasting System (MMEFS) does not apply this step (Adams, 2016). An alternative approach consists in using regional or limited area (mesoscale) NWP systems (Wood et al., 2005), as they are more suited to capture specific regional climate features (e.g., extremes in meteorological events and complex orography)

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due to their higher horizontal resolution (e.g., up to 1.3 km resolution for AROME-France-EPS; Raynaud and Bouttier, 2017) at the time of the forecast (usually for very short horizons). Approximately a quarter of the EPS studies reviewed use regional or limited area NWP systems. However, the ensemble size of the regional NWP systems is often greatly reduced, as compared to that of the global NWP systems. According to Raynaud and Bouttier (2017), the ensemble size should have a stronger effect over long forecasting ranges, as the predictability decreases, and additional members are needed to better sample uncertainty in those cases. Some EPS studies use variable resolution NWP systems (VAREPS), which offer the combinatorial benefits of short lead time resolution and longer lead time probabilities (e.g., Alfieri et al., 2013 in Table S3).

An important aspect of dynamical hydrological models is that they integrate over space and time. This means that the spatial and temporal resolution of NWP models do not need to be as high as might be assumed since the resolution of the NWP models needs only match that of the hydrological models. Of course, in some cases, such as in mountainous basins, a high-resolution hydrological model combined with high-resolution limited area NWP models with very steep rainfall gradients is required. In other words, an increase in resolution of the NWP model is not axiomatically good since higher resolution weather forecasts—especially convection enabled NWPs—can sometimes produce more erroneous weather forecasts over larger areas than coarser NWP models. Although high-resolution weather forecasts are similarly accurate, there is no need to force coarser scale hydrological models with them, especially since an improvement of the reliability of the hydrological forecasts is not assured.

Although hydrological EPS studies based on NWP systems are promoted as constituting the current state of the art in ensemble forecasting, they do have some drawbacks.

One possible drawback of the EPSs is to produce unreliable probabilistic forecasts. Poor reliability of the ensemble can happen conditionally, for instance, even though an EPS is generally reliable, its reliability can be challenged for large floods ensembles (See Bellier, Zin, & Bontron, 2017; Hamill, 2001). Conditional reliability is very seldom measured since it requires very long hindcast experiments; this aspect maybe merits further consideration because of the expanding application of the EPSs. The most important such drawback is often related to a lack of understanding how to translate a probabilistic forecast from an EPS into a decision. Exceedance thresholds can be set to optimize the decision, i.e., the degree of uncertainty a decision maker can accept before deciding (risk acceptance), often connected to expected losses. A low threshold risks producing too many false alarms, but reduces misses, while a high threshold reduces false alarms but increases the risk of missed events. In addition, the EPS can take a very long time to implement, depending on the numerical weather component (e.g., development of a new NWP model which is very costly and time consuming, or the purchase of NWP forecasts from a meteorological agency which is less costly and quick access) and the hydrological component (e.g., development of a statistical model with very few input data, without a calibration step or a physical-based model that is very demanding in terms of input data and the need to perform a calibration/validation of outputs) chosen. The key to the success of EPSs likely lies in training on how to interpret these complex systems and in finding better ways of presenting them to decision makers.

Nonetheless, medium-range ensemble streamflow forecasts constitute the dominant temporal resolution of the EPSs (51%), and to a lesser extent, short/long-term forecasting (20%) and very short forecasting (9%; Figure 5d).

4. Ensemble Streamflow Forecasting: Success, Challenges and Future Aspirations

In the following section, we first question the relevance of multi-model EFSs whose application has significantly increased over the last decade. We then discuss four key operational challenges associated with the EFSs, such as the implementation of effective DA techniques and optimal post-processing, the assurance of forecast quality for decision-making and the critical issue of an effective communication in ensemble forecasting. An attempt is made to contextualize the EFSs in the perspective of climate change, in particular for seasonal and longer-duration streamflow forecasts. Finally, some prospective future developments of EFSs are considered in order to move both the hydrology and meteorology communities forward.

4.1. Do Multi-Model Ensemble Forecast Systems Offer a Strategic Path Forward?

The use of EPS for operational purposes (such as flood forecasting, warning and civil protection) intensified over the past decades (Wetterhall et al., 2013). This was driven by the demonstration of the added value of NWP models, with increasing forecast lead times up to 45 h (e.g., Cloke & Pappenberger, 2009; Cuo et al., 2011; He et al., 2009; Pappenberger et al., 2005; Raynaud & Bouttier, 2017). A number of studies have illustrated the ability of EPS in forecasting streamflow (e.g., Chiang et al., 2017; DeChant & Moradkhani, 2014; Jaun & Ahrens, 2009; McEnery et al., 2005; Velazquez et al., 2011).

The multi-model ensembles of deterministic forecasts (SBSP-00M, ESP-00M, EPS-SDM, EPS-MDS, and EPS-MDM sub-classes; Figure 2) have proven to be beneficial, as compared to single deterministic forecasts for short- and medium-range forecasting, by providing a spectrum of plausible answers, particularly in the tails of extreme event distributions (Fritsch et al., 2000; Pappenberger et al., 2008). However, using multiple-model ensembles addresses only one of the main sources of uncertainty in forecasting. Probabilistic information generates more interest than deterministic information for many users. The multi-NWP-hydrological model ensembles approach (EPS-MPS and EPS-MPM sub-classes; Figure 2) is particularly attractive, as it produces greater consistency and reliability in the description of the true probability distribution of forecasts, as compared to the single-model ensembles (EPS-SPS and EPS-SPM sub-classes; Figure 2) (Hagedorn et al., 2005). However, the multi-model ensembles introduce a non-predictable degree of uncertainty inherent in the NWP-hydrological models into the forecasts (Goswami & O'Connor, 2007; Roulin, 2007). Some studies have shown that multi-model ensemble averages perform better than the best calibrated single-model simulations (Ajami et al., 2006; 2007; Arsenault et al., 2015). Georgakakos et al. (2004) attributed the superior skill of multi-model ensembles to the fact that they at least partly account for model structural uncertainty. Kirtman et al. (2014) illustrate the fact that fusing grand ensembles of individual weather forecasts provides equal or higher performance, as compared to the ensemble mean of individual models.

The added value of multi-model ensembles remains to be explored through these questions (Hagedorn et al., 2005; Li & Sankarasubramanian, 2012; Mo & Lettenmaier 2014; Silvestro & Rebora, 2014; Weigel et al., 2008):

- Can the average performance of deterministic forecast ensembles (SBSP-00M, ESP-00M, EPS-SDM, EPS-MDS, and EPS-MDM sub-classes; Figure 2) improve the average single-model ensemble (EPS-SPS and EPS-SPM sub-classes; Figure 2) performance?
- Can multiple models outperform the best participating single model to a degree that warrants the added cost of running a multi-model system?
- What is the benefit of merging multi-model ensemble forecasts?
- How does post-processing (weather/streamflow) modify the characteristics of the ensemble forecast (derived from single-model and multi-model ensembles)?

Answering these questions will help remove the concerns of the scientific community, on the validity of the multi-model concept, and of the operational community, on their utility in real-time forecasting.

4.2. Current Operational Challenges

Besides the well-established issue with capturing the full uncertainty in EFSs, there are additional operational challenges that need to be addressed. The main such challenges fall into four major areas, which are discussed next.

4.2.1. Implementation of Effective DA Techniques

How do DA techniques can effectively be implemented in the operational EFSs (See Section 2.4), regarding the aspects of state/error updating, timing errors, multi-observational and large-scale DA, and remote sensing data? DA requires knowledge of model states and observation functions for mapping model states to forecasted data. In operational hydrological forecasting, automated DA has seen limited application to date, and it is currently more common for forecasters to manually correct the model states (e.g., apply DA) to improve the agreement of the model with observations (Seo et al., 2009). The efficiency of filtering methods relies on a perfect awareness of the observation function, and for the model exhibiting minimal bias; in many cases, the observation function is unknown and the observational data display significant errors (e.g., instrumental, gap, and resolution), leading to suboptimal state estimates (Hamilton et al., 2019). Systematic errors must be eliminated by using, for instance, stochastic model errors (Hu & Franzke, 2017) or Bayesian approaches (Krzysztofowicz & Maranzano, 2004). However, this remains challenging for extreme events (Liu et al., 2012; Rakesh & Goswami, 2015).

Streamflow timing errors are not explicitly considered in many DA methods; rather, they must be estimated and corrected prior to the assimilation (Noh et al., 2019). The estimation of flow timing errors can be achieved through visual analysis or wavelet-based approaches, and corrections can be made by modifying the objective function in the DA methods or by shifting the predicted hydrographs according to the estimated timing error (Liu et al., 2011).

Assimilating multiple sources of observational data is challenging in operational forecasting, because of biases and unknown errors in observations and models, in addition to the multiple spatio-temporal resolutions of data and model setups (Bergeron et al., 2016; Liu et al., 2012; Noh et al., 2019). While many works have looked at regional-scale operational applications of streamflow DA using Kf-based methods (e.g., Bourgin et al., 2014; Randrianasolo et al., 2014), there are few DA applications at large scale due to (a) the lack of data to perform this efficiently over large areas, (b) the expensive computation cost of ensemble forecasting and (c) the relevance of DA approaches in high-dimensional domains (Noh et al., 2019).

The addition of remote sensing data to operational EFS is becoming an active field of research, with the potential for new observations and their use in DA to improve streamflow forecasts (Helmert et al., 2018; Liu et al., 2012; Revilla-Romero et al., 2016). However, even though DA appears particularly useful for certain parameters, for others (e.g., soil moisture), it can lead to negative effects on streamflow if not implemented correctly. DA can distort the physics of the model, and unless the tuning or calibration of the EFS is done with the same DA techniques as used in the forecast mode, it can introduce unwanted biases. DA should therefore be applied with care as its advantage in hydrological forecasting is far from clear-cut.

4.2.2. Implementation of Optimal Forecast Post-Processing

The issue of implementing optimal forecast post-processing (See Section 2.6) is challenging when considering the issues of sample size and stationarity assumption as well as of the performance on extreme events.

Does the sample contain enough data for reliable parameter estimation in post-processing methods? This is a primary concern in the application of complex EFSs with numerous variables (degrees of freedom), but also for the forecasting of extreme and seasonal events, where data availability is limited. Caution must be taken with the empiric rule of the 100 samples is an adequate size in post-processing methods, since various factors must be accounted for (e.g., number of explanatory variables used) (Hopson et al., 2019). Cross-validation strategies can be a good and rigorous avenue to ensure that over-fitting of the post-processing methods does not occur, while avoiding overconfident solutions (Wood et al., 2019).

Statistical post-processing methods rely on a strong assumption of stationarity in the weather or hydrological forecasts. In situations of limited observational sample data (e.g., seasonal forecasting), the independence and non-stationarity of observations and/or forecasts in post-processing are often assumed in the forecasting systems (Hopson et al., 2019). This can lead to systematic errors in the post-processed streamflow forecasts, and even potentially to suboptimal operational decision-making (Wood et al., 2019).

Hydrological extreme events (e.g., floods) occur on various time scales and thus require specific demands in post-processing. Both simulation and prediction of heavy-to-intense precipitation inducing flash floods are challenging, because the NWPs are not able to accurately simulate the magnitude and location of convective storms as well as the rapid development of the thunderstorms (Wetterhall & Smith, 2019). Multivariate statistical post-processing of weather forecast ensembles with a particular view to extreme events might bridge the gap.

4.2.3. Forecast Quality

An assurance of forecast quality can be undertaken by verification tools and identification of suitable metrics for diagnostic verification of (ensemble) forecasts (See Section 2.7).

Efforts are still required to propose verification tools for streamflow forecasts to support decision-making (Werner et al., 2019) by providing up-to-date verification of (ensemble) forecasts (e.g (flash)floods; Brown et al., 2010; Liechti & Zappa, 2019; Renner et al., 2009; Weijs et al., 2010). Verification tools should also provide formal guidance for evaluating medium- and long-range (ensemble) streamflow forecasts in a decisional perspective such as water resource planning, hydroelectricity production optimization and risk management (Perreault et al., 2019).

Metrics for the diagnostic verification of (ensemble) weather forecasts should focus on key hydrological forecasting aspects, such as point precipitation forecasts and extreme events (e.g., Franz et al., 2003; Gilleland et al., 2019; Wilks, 2016); in that perspective, developing new methods to assess weather forecasts over all horizons for seamlessly considering the short and long-range forecasting is an additional challenge (Ebert et al., 2013). As for the diagnostic verification of (ensemble) streamflow forecasts, suitable metrics are required at pertinent spatio-temporal scales of hydrological processes (e.g., hourly to seasonal flows; extreme events), which target operational water-related decisional contexts (e.g., Anctil & Ramos, 2019; Franz & Hogue, 2011; Laio & Tamea, 2007; Olsson & Lindström, 2008; Demargne et al., 2009; Pappenberger et al., 2015, Pappenberger, Begner, et al., 2011).

Other areas of concern in forecast verification include the shortness of observation time series (which interfere in forecast verification or performance, leading to improper decisions; Perreault et al., 2019), extreme events, in which some metrics are unsuitable for assessing extreme value predictions (Gneiting & Ranjan 2011; Naveau et al., 2014; Taillardat, 2017 for a new approach based on random forests algorithms with applications in real cases), and multisite-multivariate hydrological forecasting (Gneiting et al., 2008; Perreault et al., 2019 for recommendation of a metric preserving the dependence structure and the spatial coherence between variables and catchments).

4.2.4. Effective Communication in Ensemble Forecasting

Even though there is a general understanding of the potential benefits of hydrological EFSs in the operational sector, there is a need for effective communication about ensemble forecasting and its use in decision-making (Pagano et al., 2014). This includes clear and simple information through (better) interactive visualization methods, as well as relevant and trustworthy information (Thielen & Bruen, 2019).

Among conventional interactive visualization methods, we can cite spaghetti-style hydrographs, plume charts or matrix forms (e.g., Bogner & Pappenberger, 2011; Bruen et al., 2010; Cloke & Pappenberger 2009), but they provide no spatial information that can be useful for end users. For instance, the EFAS has designed a hybrid visualization approach, combining threshold exceedance maps and clickable tabular information, for use in depicting early flood warnings for any pixel of the river catchment (Demeritt et al., 2013). However, there is no one-size-fits-all method because each end user has specific decision-making needs that require that information be visualized in a specific way in order to satisfy their operational requirements (Pappenberger et al., 2013).

It is important to transfer relevant and trustworthy information from the EFSs that meet end user expectations and seeking their feedbacks of the accordingly decisions made (Demeritt et al., 2013, 2019). Among the communication challenges posed by ensemble forecasting is the appropriate conveyance of information regarding predictive uncertainty (See Section 2.3) (Pegram et al., 2019). Hartman (2019) provides four methods to convey uncertainty information associated with streamflow forecasts and emphasizes the need to assess forecast reliability through the hindcasting process. Pegram et al. (2019) suggest that any information communicated to end users must be accompanied by confidence intervals, which translate the predictive uncertainty and the forecast reliability (See the reliability matrix for flood decision support in Pegram et al., 2019). It is, however, difficult for institutions involved in flood risk management to accept and embrace predictive uncertainty (Demeritt et al., 2019).

To increase end users' understanding of ensemble forecasting, the emphasis is (and must be) on training and better visualization tools (Demeritt et al., 2019; Hartman, 2019; Hirpa et al., 2019; Tuteja et al., 2019). Even though demonstration EFS projects arouse interest (Zappa et al., 2008), dialogue and tailored training seem to be more suitable (Pappenberger et al., 2019; Wetterhall et al., 2013). For instance, continuous training sessions at the national hydrological services, a strong connection between international initiatives and research projects (such as HEPEX), an active participation of the operational forecasters (such as operational French and Italian teams) guarantee that the EFAS provides forecast products in agreement with the needs of decision makers, while maintaining the EFAS platform in the state of the art of ensemble forecasting (Thielen & Brunen, 2019; Wittwer et al., 2019).

4.3. How About Climate Change?

Short-term weather and streamflow forecasting are an "initial conditions" problem, therefore little affected by the climate. For seasonal and longer-duration forecasts, the influence of initial conditions wanes at long lead times and the climate becomes the main driving factor. All boundary conditions affecting the energy balance must therefore be considered. Climate change is the result of unforced and forced variability (Flato et al., 2013; Ribes et al., 2017; Solomon et al., 2011). Unforced variability (also called internal or natural variability) is the result of the inherent chaotic nature of the climate system, which manifests itself naturally at the seasonal, annual, and multidecadal scales (Solomon et al., 2011). Artic ice extent and seas surface temperature (SST) anomalies are the most important manifestations of internal variability. Various SST-based indices and atmospheric pressure anomalies were used to characterize the state of internal variability (e.g., ENSO, AMO), and their impacts on weather patterns (Bengtsson and Hodges, 2019; Haustein et al., 2019; Hegerl et al., 2018). Forced variability can in turn be characterized as natural (e.g., volcanic eruptions) or anthropogenic (increase in greenhouse gases emissions [GHE]).

With the expected magnitude of climate change, the ESP assumption of past hydrometerological events being representative of possible future events is questionable - and depends on the size of the historical period sampled and the forcing variable (e.g., regional precipitation may or may not closely follow climate-change related trends). This has been acknowledged in many studies incorporating weights in ESP pre-processing and post-processing schemes (e.g., Hopson et al., 2019; Najafi et al., 2012; Seo et al., 2019). The bulk of the work has however been targeted at the internal variability component of climate change by using climate indices as covariates (e.g., Caillouet et al., 2018; Ouarda & Charron, 2019; Shams et al., 2018). For temperatures, the forcing due to GHE is now larger than that due to internal variability in many parts of the world (Lehner et al., 2017), and both components should therefore be accounted for avoiding biased streamflow forecasts. Weighing past hydroclimatological series should be considered necessary but not sufficient to properly account for climate change. For precipitation, the time of emergence is expected later in this century (Martel et al., 2018) and only taking internal variability into account may be sufficient at the present time. There are also issues with sub-seasonal to seasonal weather forecasts, since many dynamical NWP models are gradually nudged toward climatological values (Sigmond et al., 2016), which are borne to be biased to some extent due to the anthropogenic forcing component of climate change. Some systems, known as Earth System Models (ESMs; Leung et al., 2020), incorporate aerosols and radiative active gases as well as vegetation dynamics, and simulate the evolution of these components over time in response to anthropogenic land use, land cover changes and changing climate conditions. An emerging field of climate model development involves the use of an ESM in NWP mode (Simmons et al., 2016). There is much work remaining in this regard, and many challenges to overcome before climate change can be properly incorporated into long-term streamflow forecasts. However, initiatives emerge to add climate trends (i.e., variability and climate change) into seasonal weather forecasts by the means of statistical post-processing (See Shao et al., 2021).

4.4. Prospective Future Developments

Following the literature review and discussion, we will now examine prospective future developments in operational forecasting as well as future prospects of the EFS type systems. Below are some of the latest examples of development interests.

- The challenges for flash flood forecasting and early warning (Braud et al., 2018) with these developments
  1. The extension of forecast lead times beyond the catchment response time (Blöschl et al., 2008). This is crucial for small and medium size catchments, where the response times are short, and more time is needed for local actions in an operational context;
  2. The improvement of heavy rainfall prediction into the NWP models to better predict flash floods (e.g., the international HyMeX project: https://www.hymex.org/). This is closely related to the higher resolution of the NWP models, which should translate into a better description of orographic

effects and non-hydrostatic formulations (already implemented in some NWP models and many limited-area models);

(3) The improvement of flash flood forecasting in ungauged basins (e.g., the HYDRATE project; Borga et al., 2011);

(4) The implementation of higher resolution EFSs over mountainous and coastal areas (e.g., Cloke & Pappenberger, 2009; Werner et al., 2009; Zappa et al., 2008);

(5) Overall, future developments of flood forecasting will involve the improvement of some technical aspects, such as DA (See Section 4.2), and ensemble forecasting for additional discrete variables (e.g., flood inundation) with the potential application of AI algorithms (e.g., machine learning), along with an effective communication of probabilistic ensemble forecasts (See Section 4.2) for operational flood management (Wu et al., 2020).

- From the traditional map analysis made by human operators only to the modern practices with further automation of the forecasting systems (The Over-The-Loop Streamflow Forecast Demonstration Project; http://hydro.rap.ucar.edu/hydrofcst/info.html), the operational streamflow forecasting has evolved over the past three decades. Nowadays, the EFSs deal with many weather and hydrological models through objective data assimilation, post-processing and combination techniques with a repeatability of the processing toward a robust execution. Consequently, the "active" role of the human operator can be called into question, leading to doubts as to whether human operators are still needed in forecasting systems. Some hydrological forecasting domains, such as flash flood forecasting, which requires rapid response times (Hapuarachchi et al., 2011), and seasonal streamflow forecasting, which requires a quantification of uncertainty (Pagano et al., 2004), already employ high levels of automation. However, short-term streamflow forecasting requires a more prudent approach toward automation, due to practices and interfaces between meteorologists and operators, and the issues associated with the effects of humans on the water cycle (Blöschl, 2008). Pagano, Pappenberger et al. (2016) provide seven technical recommendations derived from the success of weather forecasting, to lead automation and human-machine interactions to more efficient hydrological forecasts.
- Today, millions of people check their smart phones to get the latest weather forecasts. Knowing what the weather will be for the next few hours and the next five days has opened great opportunities for society and decision makers working the areas of risk management, industry planning, and protection. What if that there were hydrological forecasts could be used in a similar fashion, and be provided through an application on a smart phone? What about hydrological forecasts for two weeks or three months ahead? We can imagine the added value of two-week to 12 months hydrological forecasts for certain industrial sectors (e.g., energy, agriculture, insurance/reinsurance, and water resource management). Although such forecasts will never match the confidence level associated with truly short time weather forecasts, they could be particularly useful to individuals, businesses, and governments for planning and decision making. The National Academies of Sciences, Engineering, and Medicine Committee (2016) provides an overview of sub-seasonal/seasonal forecasting (two weeks to 12 months), which, a decade from now, could become as widely used as very short-term forecasts are today.
- The future prospects of hydrological ensemble forecasting certainly lie in *innovative approaches with a hybrid modeling between the three EFS type systems*. The purpose of hybrid modeling is to take advantage of the complementary strengths of the SBSP systems and ESP/EPS systems. The knowledge encapsulated within an ESP/EPS system enables forecasts to be made with confidence for extreme events and significant changes of the operating parameters. The SBSP systems, in essence, adapt themselves better to the nuances of historical data (hydrological and/or climate predictors) than an ESP/EPS system. The following hybrid modeling approaches between the three EFS type systems can be proposed: (1) mixed EFS systems - the physical systems are simulated by using different types of EFS systems. For instance, low flows are simulated by using a process-driven model (ESP/EPS systems) whereas high flows are simulated by using a data-driven model (SBSP system); (2) committee EFS systems where both types of systems are used for the whole time horizon, and then the forecasts from both systems are merged; (3) complementary EFS systems—the idea here is on the mismatch between an ESP/EPS system and the observations. A SBSP system is used to estimate the measured mismatch and to update the results of the original forecasting system.
- The future prospects of weather ensemble forecasting lie in the development of *hybrid dynamical—statistical learning approaches and crossovers based on new generation ESMs*—complex systems that

simulate the individual components of the climate system (atmosphere, ocean, land, and sea ice) and the exchange of energy and mass between these components; these components are all solved for a number of locations in space forming a three-dimensional grid over the earth's surface and below the ocean surface. ESMs can be distinguished from global climate models by their ability to simulate the carbon cycle and by the sophistication of their atmospheric and oceanic chemistry (Heavens et al., 2013), in an NWP mode (See Section 4.3). The rationale is that climate can be considered as the long-term statistical average of weather, and therefore, a good climate model must also manifest good NWP properties (Folini, 2018). As the atmospheric component of the ESM is validated against detailed (pseudo-) observational data, there is more confidence in the physical ground. It is also an opportunity to bridge the lead time gap between NWP and climate toward seamless forecasts (Palmer et al., 2008; Simmons et al., 2016). Recent trends show a growing interest among the NWP community in using AI algorithms and statistics in combination with ESMs with a view to improving (or *learning*) ESMs directly from observations (Geer, 2020); for instance, machine learning can be used to extend weather station networks and build new stations (Chen & Huang, 2020); deep learning-based methods might provide short-range point forecasts (1–3 days ahead) of the 10-m wind speed for complex terrains (Papazek & Schicker, 2020); AI algorithms can capture the state of multiple ESM signals and contribute to improving seasonal forecasts based on large-scale climate precursors (Giuliani et al., 2019)—all in a bid to supplement weather forecasts from ESMs. Some processes can be mimicked by AI algorithms, and so it is likely that hybrid AI-dynamical weather forecasting approaches might be seen in the future. Today, both the hydrology and meteorology communities are working more closely to bridge the gap between their two research fields; ESMs increasingly embrace the whole water cycle, where components become more connected with important feedbacks. Connecting streamflow dynamically to oceans and better representing groundwater in land surface schemes are two examples. We can envisage that in the next decades, the new generation of ESMs might provide hydrological forecasts for variables such as runoff with a confidence level close to what is achieved by current hydrological EPSs.

- What is the target complexity level for the end user? This final point concerns the operationalization of forecasting systems and converges with two issues often mentioned in the literature: the difference of perception between the scientific and operational communities and the balance between research progress and operational tradition. Ensemble forecasting methods may not always coincide with the needs of operators, and where they do, given the complexity level, how should decision makers implement solutions without a clear guidance? Connecting the scientific and operational communities more effectively is a key motivation for advancing research and quasi-operational EFSs into full operational mode. Ensuring that the best scientific results lead to operational use of the EFSs and allowing researchers to learn from the experiences of the operational centers are ongoing challenges for both the weather and hydrological forecasting communities.

5. Conclusions

Ensemble approaches applied to the field of hydrological forecasting have become an established area of research, which encompasses a broad spectrum of operational situations, ranging from real-time forecasting with flash floods to seasonal streamflow forecasts for optimizing hydropower energy generation and other objectives. While it is hardly a fully mature research field, it has nonetheless made significant contributions in the evolution to better hydrological forecasts.

This work provides a detailed summary of the past 40 years of research in the generation of streamflow forecasts based on an exhaustive review of studies and projects worldwide. In terms of EFS applications, it is evident that ESP systems constitute the most common and popular system currently used for streamflow forecasting. The review finds that the EPS are the most advanced systems for predicting streamflow, with the infusion of new technology and science, and their strong added value in the quantification of the total uncertainty, into forecasts. Based on published research, SBSP systems appear to be rank third, with artificial neural networks being the most popular methods used for streamflow forecasting, while stochastic methods and support vector machine models are two other attractive choices.

This article also relates findings from the recent success of the multi-model ensemble forecasting system, where the merging of multiple forecasts can improve skills in predicting streamflow, in addition to representing the leading sources of uncertainty through the EFSs, which need to be effectively communicated between forecasters and users. Regarding key challenges and prospective developments, a final comment before we conclude this review is that forecasters and water resource managers must learn to be comfortable with the multiple implicit deficiencies of EFSs, and to opt for a collaborative process of co-construction through real cases, with a conscious mix of human-machine interactions in the field of river flow forecasting.

Data Availability Statement

This works is a literature review study and does not use data; this study compiles pre-existing information from published works in a new analysis.

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