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REVIEW ARTICLE

Global hydrological model: A comprehensive review of types, applications and uncertainties

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Abstract

The rapid growth of industrialization and urbanization has significantly impacted our natural resources, such as air, water and soil. Many problems have been brought about by these changes, such as drought, more frequent flooding, pollution, climate change, biodiversity loss, the extinction of numerous plant and animal species, changes in land cover and usage and deterioration of the land. Extensive research has been conducted to understand how these physical changes affect natural resources, particularly using the hydrological models. As a result, a trustworthy hydrological model that can provide outcomes in line with observable parameters is essential. This comprehensive analysis highlights the vital role of hydrological modelling plays in forecasting floods, managing water supplies and simulating ecosystems. This review explains the mathematical underpinnings and applicability of hydrological models for various system aspects by classifying them into empirical, conceptual and physically-based frameworks. To furnish details with a comprehensive understanding of model robustness and dependability, this study encompasses calibration methodologies and uncertainty analysis frameworks. Furthermore, it meticulously elucidates the diverse sources of uncertainty inherent in hydrological modelling, thereby providing a nuanced perspective on the subject. It also presents a summary of well-known global hydrological models, emphasising their goals, history and contributions to our knowledge of biogeochemical cycles, climate change effects and water shortage dynamics.

Keywords: empirical model; global models; hydrological model; sensitivity; uncertainty

Introduction

The field of hydrology encompasses a wide range of applications, including water resource planning, flood prediction and design and integrated modelling of hydrologic and environmental systems, such as climate-land surface interactions and water-energy nexus. These applications rely heavily on hydrological models, but are often limited by the availability of spatial-temporal data due to resource constraints and measurement techniques. As a result, it becomes essential to extrapolate data from current observations over time and location and to evaluate the possible hydrological effects of future system reactions, such as modifications to the climate and land management. Over the centuries, numerous attempts have been made to measure and forecast water flow and storage in hydrology, advancing our understanding of the dynamics of water systems. Regional and global climate patterns are significantly shaped by variations in soil moisture content and terrestrial evapotranspiration. Studies have demonstrated the important effects of changes in land use and climate on water systems (1-3). Furthermore, research has revealed the downstream effects of land use changes on water quality and hydrology across hundreds of kilometres, indicating that river discharge directly impacts marine features (4,5). Furthermore, there are ramifications for coastal eutrophication and climate due to the strong relationship between global hydrology and the carbon cycle (6,7).

These interconnected global cycles ultimately affect society and the economy, with globalization's influence on food security and the world water cycle leading to the growing significance of virtual water trading (8). The impact of climate on hydrology has been a topic of interest within the scientific community for a long time, but recently there has been a growing focus on the feedback mechanisms involved. This has led to the concept of a "Global Water System" (9,10), which considers the interconnectedness of water flow with other systems, including physical, institutional and economic aspects. Human actions like the storing and withdrawing of water further complicate this network (11). Although there have been reviews of hydrological modelling in the past, an updated examination of the capabilities and limits of modelling is currently required (12-14). This is a result of the field's fast evolution, which includes developments in distributed modelling, managing uncertainty, simulating ungauged basins and dealing with non-stationarity.

Hydrological modelling

This model is a simplified representation of a real-world system (15). The most effective model is one that uses the fewest parameters and model complexity while still producing results that closely resemble reality. Models are primarily used to understand various hydrological processes and predict system behaviour. A model is defined by various parameters, such as rainfall, soil type and vegetation cover, which determine its characteristics and behaviour. A runoff model comprises formulas that help estimate the runoff based on various factors describe the characteristics of a watershed. Critical inputs for all models include the drainage area and rainfall data. Additionally, watershed attributes such as soil composition, vegetation cover, geography, soil moisture content and groundwater aquifer features are also taken into consideration. Modern water and environmental resources management relies heavily on the use of hydrological models. Although hydrological models are useful resources for comprehending and forecasting the behaviour of water systems, it is critical to remember that they are not perfect representations of reality. This is because hydrological processes are dynamic and complicated, changing over time and in all three geographical dimensions. Consequently, one cannot confidently predict the actual system's responses, such as water levels, flow rates, or quality, to various environmental or human-induced factors (16). Studying all five sources of variation (randomness, time and the three spatial dimensions) simultaneously is difficult and has only been achieved under highly idealized conditions. Hydrological models usually consider only one or two causes of variations in real-world applications. Notwithstanding these drawbacks, hydrological models offer insightful information and are frequently expressed by particular equations that accurately reflect the fundamental dynamics of the system.

$$O = f(I, P, t) + \varepsilon \qquad \text{Eq. (1)}$$

Where,

O: n × k matrix of hydrologic responses to be modelled

f: collection of functional relationships

I: n × m matrix of inputs

P: vector of p parameters

t: n × k matrix of errors

ε: number of data points

k: number of responses

m: the number of inputs

The relationship between hydrological inputs, parameters, errors and responses as defined in Equation (1). The inputs and parameters influence the outputs of hydrological models, highlighting the sources of variability and errors in the modelling process (Fig. 1). Stand-alone hydrological models are typically utilized for smaller catchment areas and basins. These models possess specific characteristics that necessitate regional estimation or calibration. The stand-alone models include the Hydrological Simulation Program-Fortran (HSPF) (17), the Soil and Water Assessment Tool such as SWAT (18) and the Hydrologiska Byrans Vattenbalansavdelning, HBV (19). These models are designed to be used at a smaller scale and require careful estimation and calibration at the regional level to ensure accurate results.

Types of models

Scientists have made multiple attempts to classify hydrological models in the past, with various categorization systems proposed by different researchers. Hydrological models can be classified based on their input parameters and the extent to which they rely on physical representations of hydrological processes (20). Hydrological models are categorized into three types: joint stochastic-deterministic, which combines statistical and physical approaches to simulate hydrological processes; purely stochastic models, which rely on probabilistic methods; and deterministic models, which use physical laws and equations to describe processes in a defined system (21). Additionally, three other categories of deterministic models exist: conceptual, empirical and physically-based models. This classification system can be applied to both single-component models, such as groundwater models and watershed models. However, it is important to note that this categorization is not precise and certain model codes may not fit neatly into these classifications. Different categories of classification are represented in Fig. 2.

Empirical models (Metric models)

Metric models describe how a system behaves by using observable data. Sherman's unit hydrograph theory, which is applied to catchment-scale modelling based on events, serves as one illustration. Because of their simplicity, these empirical models may be used to apply regional analysis to ungauged catchments. They connect the simple properties of the model, such as "unit hydrograph," which is a graphical representation of the direct runoff response of a catchment to a unit of rainfall over a specific duration, as well as time to peak and percentage runoff, to the catchment's physical and meteorological variables. However, it is important to note that metric models heavily rely on the available data. While they are useful for predicting extreme situations or ungauged catchments, their findings often lack a clear statement of confidence bounds.

Recent advancements in metric modelling that have captured interest include Artificial Neural Networks (ANN) and Data Based Mechanistic (DBM) modelling. The ANN approach involves learning about the behaviour of rainfall-runoff systems by using existing rainfall and runoff data. Typically, an artificial neural network consists of three layers: the input layer (e.g., rainfall), the hidden layer of neurons and the output layer (e.g., stream flow). This type of model adjusts the network's link weights to ensure that the network response closely resembles the real response, a process known as "training," to understand the relationship between input and output.

Conceptual methods (Parametric models)

Conceptual models are constructed based on two key criteria (12). First, the structure of the model was established prior to

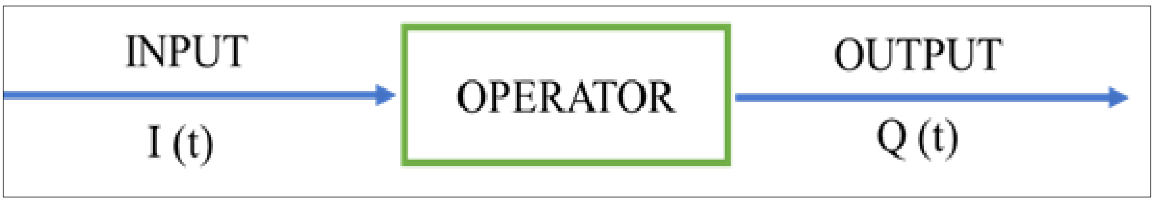

Fig. 1. Schematic representation of system operation

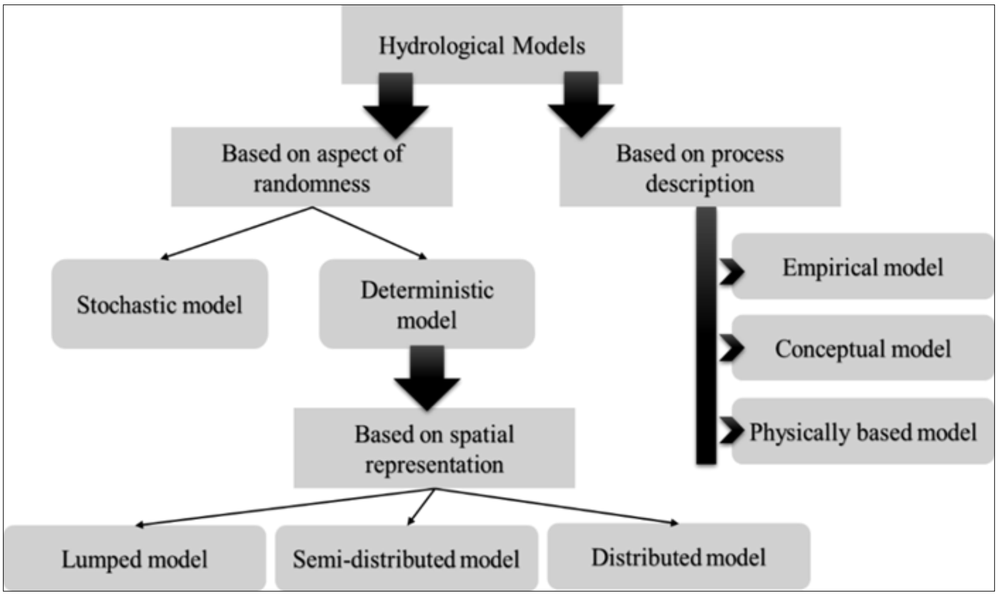

Fig. 2. Classification of the hydrologic model (16)

modelling activities. Second, not all of the parameters of the model can be directly interpreted physically, meaning they are not independently measurable. Consequently, it becomes necessary to estimate at least some conceptual model parameters by calibrating them against observable data. Conceptual models typically encompass every significant component of hydrological activity thought to be involved in input-output connections at the catchment scale (22). These models can vary greatly in complexity and often incorporate a framework centred on the extensive use of schematic storages, collectively providing a conceptual representation of the key hydrological aspects.

The structure of a model can vary from a simple representation with a few basic components to a highly intricate depiction. Using a complex model structure without sufficient data support or employing a simple model that fails to capture the complexity of the rainfall-runoff response can present challenges (22). To effectively develop a model, it is essential to strike a balance between the available knowledge and the model's complexity. Techniques such as identification statistics, sensitivity analysis, holding insensitive parameters constant, or formal model restructuring can be employed to appropriately reduce model complexity (23-27).

Physically based models

Physically based models capture different hydrological processes such as evapotranspiration, infiltration, overflow and flow in both saturated and unsaturated zones. This is achieved by using the fundamental equations of motion, often expressed as non-linear partial differential equations derived from continuum mechanics. These equations can have analytical solutions, but most often, finite difference or finite element spatial discretisation techniques are used to solve them numerically (12). Because they are characterised by completely observable properties, physics-based models have the ability to continually simulate runoff response without the need for calibration (27). Although these models are suitable to capture key hydrological processes, such as surface and subsurface flow and energy balance, they also come with significant challenges.

The use of simplified physics and mechanics is sometimes employed to represent complex physical processes in order to reduce computational burden and data requirements. However, this approach, such as using simplified St. Venant equations or the Green-Ampt equation, may lead to a departure from the true physical basis and introduce further ambiguity. Even when material qualities are parameterized, including variations across different geographic locations, they may not fully capture the heterogeneity of a catchment. While the NSRI database and calibration procedures can be utilized to estimate local-scale properties, the resulting uncertainties are significant and may lead to a wide range of potential process responses.

The characteristics of models based on process description have been shown in Table 1.

Table 1. Characteristics of three models (20)

S.No.	Particulars	Empirical Model	Conceptual Model	Physically Based Model
1.	Description	Data-driven or black-box model	A semi-empirical or hybrid model	A mechanistic or white-box model
2.	Mathematical Basis	Uses mathematical equations to derive values from accessible time series	Based on reservoir modeling and includes semi-empirical equations with a physical basis	Based on spatial distribution, analyzing criteria that describe physical attributes
3.	Consideration of System Features	Minimal attention to system functions and characteristics	Parameters are obtained through calibration and field data	Requires data on the catchment's morphology and initial state
4.	Model Characteristics	Low explanatory depth, high prediction power, not extendable to other catchments	Simple to incorporate into computer code, requires significant hydrological and meteorological data	Complex, requires computational power and expertise, faces scaling issues
6.	Domain	Limited to a specified domain	Calibration involves curve fitting for physical interpretation	Applicable to a wide range of situations

Deterministic model

A deterministic hydrological model generates consistent outputs for a given set of input values and does not consider randomness. (16). This type of model is used to make predictions and can be categorized into hydrological models that account for constant flow and those that accommodate unstable flow.

Stochastic model

Stochastic hydrological models can produce various output values for a given set of input parameters (16). These models exhibit a degree of randomness in their output. Forecasts generated by stochastic models can be categorized as space-correlated, space-independent, or time-independent. Based on geographic representation, the deterministic hydrological model is divided into two categories:

1) Lumped Model
2) Model of Semi-Distribution
3) Distributed Framework

The two main types of hydrological models are lumped and distributed models. Lumped models use average values for the whole catchment region and show the catchment as a single entity. They are often described by differential or empirical algebraic equations and do not take into account the spatial variability of inputs, processes, boundary conditions and geometric aspects of the system. Distributed models, on the other hand, compute state variables for each of the smaller pieces, or grid squares, that make up the catchment. With this method, predictions may be made that are dispersed spatially and take into consideration local differences in boundary conditions, watershed characteristics, processes and inputs. Consequently, the geographical variation within catchment regions can be partially addressed by distributed models.

In distributed models, data availability often leads to the averaging of parameters over numerous grid squares. These models utilize average variables and parameters at element or grid sizes. A proposed alternative, semi-distributed models, aims to combine the advantages of both spatial representations. Instead of trying to represent a continuous spatial distribution of state variables, this model type employs a series of lumped models to discretize the catchment to a relevant extent. A semi-distributed model can effectively capture the significant characteristics of a watershed while requiring fewer data and processing resources compared to distributed models (28). The characteristics of models based on geographic representation have been shown in Table 2.

Identification of hydrological models

Calibration of hydrological models

Calibrating hydrological models involves selecting appropriate parameter values to accurately simulate the hydrological processes of a specific catchment area (14, 29). These parameters generally fall into two categories: process parameters and physical parameters (30). Physical parameters, such as watershed size and surface slope, provide insights into the physical characteristics of the catchment and can be quantified. However, certain watershed characteristics, like the average depth of water storage capacity and the coefficient of nonlinearity governing discharge rates from different storage areas, are often challenging to measure directly (31). Although some physical properties, such as porosity and hydraulic conductivity, can be theoretically quantified, they are difficult to measure in practice and thus are often calibrated. This calibration can be automated, manual, or a combination of both.

Manual calibration

Manual calibration involves the modeller adjusting the parameters of the model by trial and error until the output closely matches the observed data. This process, known as manual calibration, can be time-consuming and may produce different results depending on the familiarity of the modeller with the model structure and the catchment being studied (22,30). Determining the "best fit" or the optimal calibration solution can

Table 2. Characteristics of lumped model, semi-distributed model, and distributed model (16)

S.No.	Lumped Model	Semi-Distributed Model	Distributed Model
1.	Input parameters are spatially constant within the basin	Allows for some spatial variation in input parameters	User can select the resolution for fully fluctuating input parameters
2.	Evaluates production or reaction based on outflow without considering sub-basin responses	Assesses response by dividing the basin into multiple sub-basins	Divides the basin into smaller sub-basins to evaluate response
3.	Not suitable for event-based processes		Suitable for event-based processes
4.	Parameters do not represent physical hydrologic features; uses area-weighted averages	Parameters lie between lumped and distributed models	Considers hydrologic processes at various spatial points, defining model variables based on spatial dimensions
5.	Requires fewer data	Less data-intensive than distributed models	Requires large amounts of data
6.	Easy to use		Requires expert use
7.	Predicts results only at the outlet		Predicts results at any location and time
8.	Simple, minimal computational time		Complex, high computational time
9.	Example: SCS-CN based models, IHACRES, WATBAL, etc.	Example: SWMM, HEC HMS, TOPMODEL, etc.	Example: HYDROTEL, MIKE11/SHE, WAIFLOOD, etc.
10.	Does not consider governing processes during predictions		Meticulously models every controlling physical mechanism
11.	Not very accurate		Highest accuracy achievable with adequate data

be challenging, leading to variability in the results produced by different modellers. Another drawback of this method is the extensive time required. Formally analysing uncertainty is particularly difficult, if not impossible, because the process may yield minimal or no information from prior parameter modifications.

Automatic calibration

The need to accelerate the calibration process and improve computational efficiency has led to the development of computer -based methods for automating hydrological model calibration. Automated calibration methods aim to reduce the subjective human judgment involved in manual techniques and provide consistent performance (32). These methods also strive to enhance impartiality and reduce the need for extensive model-specific knowledge (31). However, designing objective functions and optimization algorithms that accurately replicate human judgment remains a challenge, so automated techniques have not fully replaced manual methods. Therefore, combining automatic calibration with manual procedures is often most effective.

A typical automated parameter estimation methodology comprises four primary components: calibration data, the optimization technique, termination criteria and the selected objective function (or performance measure) (30). The aim of automated calibration is to identify the parameter values that optimize the objective function's numerical value, either by maximizing or minimizing it.

Objective functions

An objective function, or goodness of fit, is a numerical representation of the discrepancy between the model's simulated output and the actual catchment output (33). In hydrology, objective functions are often based on maximum likelihood and conventional least squares techniques. One popular objective function is the Nash-Sutcliffe Efficiency (NSE), which indicates the proportion of data variance explained by the model (34). While NSE captures the time to peak and linear correlation with measured flow well, it under-represents flow variability and mean (33, 35, 36). The Kling-Gupta Efficiency (KGE) was developed to address some of NSE's shortcomings, maintaining a good linear relationship between observed and modelled data while matching flow variability, peak and mean well in limited studies.

Multi objective analysis

The choice of objective functions is crucial for certain modelling tasks, such as flood predictions, irrigation system design and hydroelectric power generation. Using single-objective functions can skew the results towards specific hydrograph characteristics (37). Balancing conflicting objectives often requires compromising on several factors and a parameter set that meets one criterion is rarely the same as one that meets another (38). The multi-objective approach addresses this issue by considering multiple aspects of the performance of the model simultaneously. This approach helps identify the shortcomings of the model in achieving multiple performance objectives at once and aids the modeller in choosing the performance trade-off that best meets the requirements of the application (39). A common technique involves combining multiple objectives into a single criterion and optimizing for the best fit value, with the final result significantly influenced by how the objectives are weighted or combined (37).

Optimization algorithms

Hydrological modelling makes extensive use of random search techniques. A specific model parameter distribution is used to generate sets of random values. These values are then included into the model equations to produce corresponding sets of outputs. This distribution often makes the assumption that the parameters are independent when the joint probability is unknown in advance (40). Other methods for global optimisation include set coverage approaches, pure random search, adaptive and controller random search, multiple local searches, simulated annealing and tabu search. Shuffled Complex Evolution (SCE) (41), AMALGAM (42), DREAM (43), Multi-Objective complex evolution (MOCOM) (37) and Multi-Objective Shuffled Complex Evolution Metropolis (MOSCEM-UA) (44) are examples of genetic and evolutionary algorithms used in hydrological modelling.

Verification

Following calibration, the model is subjected to verification, often referred to as validation, in order to assess its performance on data that was not utilised in the calibration process. Model verification seeks to detect biases in the calibrated parameters and validates the model's capacity to precisely describe the watershed's hydrological response (39). Split sample studies, in which one set of data is used for model calibration and another set is used to confirm the model predictions, are frequently employed (45). Numerous tests have been proposed for split sampling, proxy catchment and proxy catchment split sample. A proxy catchment may have discharge data and other variables that may be used to assess the model's predictions, but during the model estimate phase, it is regarded as ungauged. The following tests were proposed in a previous study (46) and were also extended in another report (47):

- simple split-sample test
- different split-sample test
- proxy-catchment test and
- Different proxy-catchment test

Sensitivity analysis

Sensitivity analysis is the process of evaluating how modifications to a model's inputs, initial conditions, or parameters affect the its output (31). The region around the optimal parameter estimates, when the function value deviates from the optimal by a small amount, is known as the zone of indifference. The relationships between parameters can be found using sensitivity analysis when two or more are changed simultaneously. A sensitivity analysis entails examining the model parameter space and visually or numerically illustrating how sampled parameters affect the intended model output (48). Other examples are found in other studies (40, 49).

The nominal range and differential analysis approaches are two methods for performing local sensitivity studies (50). Conversely, global sensitivity analysis seeks to investigate the whole parameter space within predefined attainable parameter ranges (51). A statistic is used to quantify the total variability of the objective function over the space, or a sub-dimension of the space. For instance, the Kolmogorov-Smirnov test, can be used to gauge the extent to which the response surface deviates from the uniform value of the objective function. (52). The literature has identified a number of methods for performing global sensitivity analysis, such as variance-based approaches (53), regression-based approaches (54), regional sensitivity analysis (55) and Bayesian sensitivity analysis (56, 57).

Sources of hydrological model uncertainties

Uncertainties in hydrological models can arise from various factors, including parameters, model structure, input data, calibration (observation) and initial or boundary conditions. Additionally, initial and boundary conditions of the model can also contribute to uncertainty, although these are not considered in this assessment. Hydrological models often use effective parameters, which are simplifications of actual processes. The inability to accurately quantify or predict these effective parameters can lead to parameter uncertainty (27, 58). The accurate representation of a hydrological system is challenging due to the lack of a unifying theory, incomplete information and numerical and procedural simplifications. These limitations create structural uncertainty in the model.

Other conceptualizations, like subsurface hydro-stratigraphy or the discretization of surface and process characteristics, may also contribute to model structural uncertainty (59-61). Model architectures significantly influence model performance (62). Structural uncertainty is crucial because it has the potential to invalidate the model and the measurement of other uncertainties (63-65). A comparison of structural and parameter uncertainty revealed that structural uncertainty is more prevalent, particularly when the model is applied outside of its calibration range. Additionally, up to 30% of the prediction error might be attributed to structural uncertainty (66). The largest contributor to prediction uncertainty is model structure, as demonstrated using the variance decomposition of stream flow estimates (67).

Hydrological model uncertainty analysis

Six general classes of uncertainty analysis methods have been identified: (i) Monte Carlo sampling; (ii) response surface-based schemes, which include machine learning and polynomial chaos expansion; (iii) multi-modelling approaches; (iv)Bayesian statistics; (v) multi-objective analysis; and (vi) least square-based inverse modelling. The classification of hydrological model uncertainties into four major sources: parameter, input, structural and observation uncertainty. It highlights common techniques for addressing these uncertainties, such as Bayesian statistics, Monte Carlo analysis and multi-model approaches. Parameter uncertainty involves advanced methods such as inverse modelling and response surface schemes, while input and structural uncertainties rely on techniques, namely multipliers and multi-model analysis (Fig. 3).

Parameter uncertainty

Parameter uncertainty, unlike other types of uncertainty, is addressed using various strategies. One popular technique for dealing with parameter uncertainty is the Generalized Likelihood Uncertainty Estimation (GLUE), which takes into account the equifinality hypothesis. The equifinality hypothesis highlights the presence of numerous parameter settings that describe hydrological processes indiscriminately or lead to the same outcome. GLUE improves Monte Carlo simulations by adding a behavioural threshold measure that separates viable and unfeasible parameters and structures. However, GLUE has been criticized for its subjectivity in selecting a behavioural threshold and its lack of a rigorous statistical basis, despite its widespread usage due to its simple conceptualization and execution. Another method, although not as popular as GLUE, has been used in various studies. One factor limiting its implementation is the absence of measures that account for the degree of input and output uncertainty and their interactions (68).

Input uncertainty

Accurate hydro climatic input data is crucial for hydrological models, particularly for precipitation and associated uncertainty. Traditional methods involve using a multiplication factor to address input uncertainty, often determined by model parameters or expert judgment. However, there is a lack of formal processes for determining this multiplication factor. More robust options, such as Bayesian statistics and Monte Carlo methods like GLUE, offer better solutions. Isolating input uncertainty from model parameters can be achieved by adopting a distribution for "true" precipitation, thus reducing other uncertainties (68). Nevertheless, determining the "true" input distribution presents challenges. In order to deal with structural uncertainties, input uncertainty is simultaneously evaluated with model parameters using the Bayesian Total Error Analysis (BATEA) (69) and the Integrated Bayesian Uncertainty Estimator (IBUNE) (70). These methods can, however, be computationally taxing, especially for distributed models that need inputs that fluctuate across time and space and they may result in fluctuating input uncertainty as model topologies change.

Structural uncertainty

The use of ensemble approaches and multi-model averaging has helped to quantify and reduce structural uncertainty by combining several model structures. The effectiveness of multi-model averaging depends on dependability, consistency and error compensation (71). Statistical evidence and empirical large-sample data have demonstrated why a multi-model average outperforms a single model (72). Ensemble predictions are aggregated using weights that are either performance-based or equal. Equal weighting is advantageous as reported in a previous study (73). Performance-based weighted multimodel predictions have also been reported in several studies (62, 43, 74). A comparison of many alternative model averaging methods is provided in a study (75). When component models perform similarly and there is no model weighting or discriminating criteria, equal weighting is preferable. However, employing variable weights yields better forecasts when the models' performances differ noticeably and each model is focused on modelling a particular aspect of the hydrological processes.

Existing global hydrological models: Twelve global hydrological models developed between 1989 and 2010, focusing on their objectives, developers and key applications, are highlighted and summarised in Table 3. These models address critical challenges such as global water availability, climate change impacts and nutrient transport. They employ advanced techniques to enhance water balance, vegetation dynamics and energy modelling across diverse spatial and temporal scales.

Conclusion

The notable developments in hydrological modelling since the establishment of the initial Hydrological Research Unit (HRU) at Wallingford in the 1960s have not occurred in isolation. They have coincided with rapid technological advancement. Complex mathematical computations that take hours or days to complete on a PC or laptop can now be performed in seconds. New

Table 3. Existing Global Hydrological Models - Detail

S.No.	Year	Model	Developed by	Objectives	Applications
1	1989	HDTM 1.0 (HydroDynamic Model)/WBMplus / WBM-WTM (Water Balance Model - Water Transport Model)	University of New Hampshire, USA	Study global biogeochemical cycles; linked to Terrestrial Ecosystem Model and Trace Gas Model via soil moisture and evapotranspiration.	1. Comparison of PET methods on US watersheds-WBM (77) 2. Using GHM in an application of isotope tracers at the continental scale in hydrological modelling (78) 3. Calculation of variability and uncertainty in the global irrigation water demand-WBMplus (79) 4. Analysis of the effect of climate and hydrological alteration in the hydrological cycle to study nutrient transport (7) 5. Using GHM to calibrate remote sensing signal to discharge (80)
2	1998	MPI-HM (Max Planck Institute - Hydrology Model)	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology), Germany	Define lateral water flow from continents to oceans, linking with a GCM (ECHAM).	1. Validation of the weather forecasting models, European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA) and National Center for Environmental Prediction Re-Analysis (NRA) (81)
3	1999	GWAVA (Global Water Availability Assessment model)	Centre for Ecology & Hydrology (formerly Institute of Hydrology), UK	Study progression of global water scarcity due to population increase and climate change.	1. Estimation of water scarcity for eastern and southern Africa (82) 2. Measurement of the impact of climate and land use change (83)
4	1998	Macro-PDM (Macro Probability Distribution Model)	University of Reading, UK	Develop a macro-scale global model; initially, only WBM existed. Uses VIC principles on a global scale.	1. Measurement of uncertainty in an ensemble with 21 GCMs at a global scale using a campus-wide computer grid (84) 2. Study of the impact of climate change on river flow regimes (85)
5	2001	VIC (Variable Infiltration Capacity model)	University of Washington, Seattle, USA	Improve previous models by adding sub -grid heterogeneity for vegetation and multiple soil layers.	1. Estimation of global soil moisture content (86) 2. Prediction of discharge of the world's rivers (87) 3. Evaluation of the Atmospheric Model Intercomparison Project (AMIP II) (88)
6	2002	LAD (Land Dynamic model)	National Oceanic and Atmospheric Administration (NOAA) / Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey, USA	Enhance energy and water balance modeling of older models.	1. Illustrating an approach of land model evaluation with precipitation uncertainty (89) 2. Measurement of the inter-annual variation in river discharges (90)
7	2004	PCR-GLOBWB (PCRaster Global Water Balance model)	Utrecht University, The Netherlands	Add advanced routines for grid heterogeneity, surface runoff, inter-flow, groundwater, and lateral heat transport.	1. Measurement of the skill of seasonal predictability of river discharge for different European rivers (91) 2. Analysis of the depletion of global groundwater resources (92) 3. Modelling methane (CH4) emissions of boreal and arctic wetlands (93) 4. Analysis of future global runoff changes (94) 5. Calculation of global water stress (95, 96) 6. Study of the impact of human abstraction of surface water and groundwater on streamflow (97)
8	2007	LPJmL (Lund-Potsdam-Jena managed Land model)	Potsdam Institute for Climate Impact Research (PIK), Germany	Simulate spatial and temporal dynamics of global vegetation and its impact on hydrological and carbon cycles.	1. Calculation of green water flows-LPJ (98) 2. Measurement of global carbon fluxes and pools (99) 3. Checking the uncertainty of the terrestrial carbon and water cycle at different spatial resolutions using the LPJDynamic Global Vegetation Model (LPJ-DGVM) (100) 4. Studying human alteration of the terrestrial water cycle through land management (11) 5. Calculation of global-scale water withdrawal, allocations, and consumptive use for surface water and groundwate (101)
9	2007	WASMOD-M (Water And Snow balance Modelling system)	Department of Earth Sciences, Air, Water, and Landscape Sciences, Uppsala University, Sweden	Complement existing global models, and establish minimum parameters for gauged and ungauged river basins.	1. Comparison of two flow network-response functions to evaluate the improvement in runoff routing (102) 2. Comparison of two precipitation datasets (TRMM and WATCH Forcing Data) in southern Africa (103)
10	2008	H08 (H07)	National Institute of Environmental Studies, University of Tokyo, Japan	Assess global water availability at sub-annual time-scales.	1. Calculation of national agriculture water withdrawals and locating water-stressed regions (104) 2. Estimation of global virtual water flows (105) 3. Analysis of scenarios for different socio-economic conditions to calculate water availability and scarcity(106)
11	2003	WaterGAP (Water - Global Analysis and Prognosis model)	University of Kassel; University of Frankfurt, Germany	Combine water availability and usage based on structural and technological global changes.	1. Identification of regions in which water resourceshave higher sensitivity to global change-critical regions(107) 2. Global modelling of irrigation water requirements (108) 3. Calculation of water availability indicators (109) 4. Integration of Gravity Recovery and Climate Experiment (GRACE) data into global hydrological models (110) 5. Analysis of river flow alterations due to water withdrawals and reservoirs
12	2010	ISBA-TRIP (Interactions between Soil, Biosphere, and Atmosphere - Total Runoff Integrating Pathways)	Centre National de Recherchés Météorologiques, France	Measure continent-level terrestrial water storage and validate it with GRACE data.	1. Measurement of terrestrial water storage and its seasonal and inter-annual variability (111)

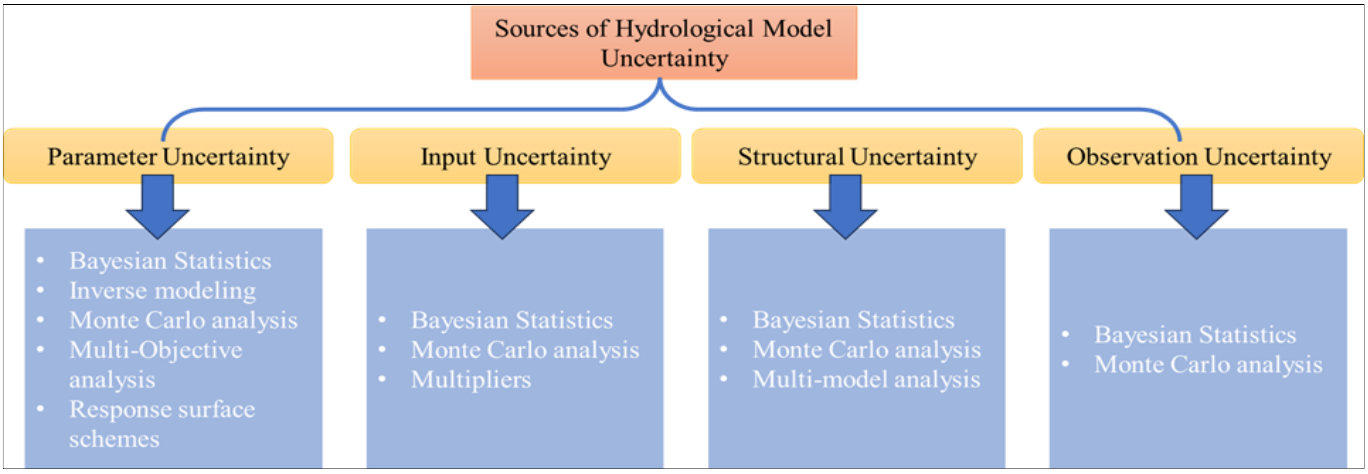

Fig. 3. Sources of hydrological model uncertainty and broad technique (76)

instruments and data recording tools allow for more precise and frequent observations. Recent significant flood occurrences have led to the development of real-time flood forecasting systems with sophisticated data processing algorithms, real-time updating of model parameters and the estimation of prediction uncertainty. These systems use data from multi-parameter weather radars. Hydrological models need to be part of a broader, multidisciplinary approach to flood management. This approach should involve planners, asset managers responsible for engineered infrastructure such as flood defences and barriers and stakeholders in flood-affected areas who possess valuable local knowledge. Additionally, software tools can facilitate the visualization and analysis of various flood risk assessment options, enabling more informed decision-making. This awareness has grown alongside more realistic expectations for the accuracy of model predictions.

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Authors' contributions

HM conducted an extensive literature review and contributed to drafting sections on hydrological model types and their mathematical frameworks, as well as assisting in the preparation of tables and figures. PS conceptualized and supervised the review, provided critical insights into the structure and scope of the manuscript and reviewed and edited all sections to ensure coherence and quality. MD focused on collecting and analysing data related to calibration and uncertainty analysis and contributed to drafting sections on global hydrological models and their applications. SS compiled information on global hydrological model applications, emphasizing case studies and contributed to revising and enhancing the technical content. SAP conducted a detailed review of uncertainty sources and methods and prepared illustrations and figures to visually represent classifications and uncertainties. RKP provided support in data visualization, prepared supplementary materials and assisted in the final proofreading of the manuscript.

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