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Uncertainty in hydrological modelling: A review

Syeda Zehan Farzana

Department of Civil Engineering, Leading University, Sylhet, Bangladesh.
Email: zehan_farzana@lus.ac.bd

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ABSTRACT

Availability of hydrological data and various soft wares for developing models make easy way to answer frequently asked questions to hydrologists. A great deal of concentration has given to the development of models in the last decades. But the thorough study regarding uncertainty of simulations has not carried out in comparison with the development of models. Uncertainty in models emanates from input data, calibrated data, parameters and from the structure of models. The sources of uncertainty, cause of generation and how these can be dealt with are reviewed here. This also comprises a review about five different methods viz. Monte Carlo sampling, Bayesian approach, Generalized Likelihood Uncertainty Estimation, Bootstrap Approach and Machine learning methods which were applied in the estimation of the model and parameter uncertainty. This will indicate the comparison between the methods which were applied to measure the uncertainty of hydrological models and highlight the strengths and weaknesses of the methods in identifying the usefulness of the models. By the comparison of the methods the improvement of the model reliability, slackening of the prediction error of the hydrological models can be suggested. By a proper quantification of uncertainty of data applied for the building up and evaluation of models, model performance can be improved, cost can be reduced and unambiguous results can lead the proper water resources management.

Contribution/Originality: In this paper, details on Uncertainty and types, how it is generated and the methods to dealt with this is extensively reviewed. And the comparison between the methods is done by mentioning their strengths and weaknesses which may give direction on how to apply the methods.

1. INTRODUCTION

Hydrological models provide simple representation of real world system, predicts system deportment and used to understand various hydrological processes. But the measurement and evaluation of the processes are often become nearly impossible due to high catchment heterogeneity and limitations of measurement techniques. The commencement of the application of hydrological models is started due to these limitations and for the necessity of deduce the information from the available measurements in both space and time. The applicability and confidence in the application of hydrological models reduces as a consequence of uncertainty in their predictions [1].

Hydrological models have wide range of applications which includes planning, development and management of water resources, flood forecasting and design, and water quality, hydro-ecology and climate modelling. Enhancement of the knowledge about the processes occurring in hydro systems and understanding the ramifications of physicochemical changes have been accomplished by enormous efforts. The level of uncertainty associated with it is a result of the relationship among various entities, and fortuitousness in the procedure of the system and is proportional to the system complexity [2].

A complex hydrological cycle system model comprises of input and output parameter, model structure and equations, initial and boundary conditions [3]. In recent decades, availability of distributed hydrological data and fast improvement of computational power enhance the building up of complex and sophisticated hydrological models which elaborate the understanding of the physics and dynamics of water systems. Complex distributed model with many parametric data inputs often depicts inaccuracy in results. This elicits extensive studies into the model uncertainty [4].

Model errors results due to mismatch between the behavior of observed and simulated system. They are undeniable because of the inherent uncertainties in the process in the context of hydrological modelling. Nevertheless, the recognition of the necessity of complementing point forecasts of decision variables by the uncertainty measures is moved forward by the efforts of the research community [4]. Therefore, there is an importance of identification and conception of uncertainty sources, estimation of uncertainty, dissemination of uncertainty through the model and the proper way to reduce it. In this paper, different methods of measuring uncertainty in hydrological modelling is discussed with their strengths and weaknesses.

2. UNCERTAINTY AND TYPES

To put it simply, uncertainty is lack of sureness of an event. In hydrology, uncertainty can be considered as an attribute of information and dealt with by the application of probability theory. The practical meaning of 'uncertainty' can be better understood by the interest of hydrologists focusing on the related questions they are willing to find answers [5].

The uncertainty in the parameter estimations can be reflected in parameter distributions and interactions on account of different optimum parameter sets [6]. Numerous studies are carried out by calibrating the model for different sub periods of all available data to assess the impact of input data on parameter uncertainty Padiyedath Gopalan, et al. [7]. Poulin, et al. [8] analyzed the hydrological model simulation uncertainty due to climate change impacts on model structure and parameter equality. For proper planning, design and decision-making process in water resources management, it is predominant to know the total model uncertainty arising from all sources than the individual ones. However, the major concern is which are the sources of uncertainty arising from different data quality, how much confidence bound can be placed on calibration for a given period, how do these affect the simulations and model parameterization [7].

Diverse attempts are found in literature to classify uncertainty in rainfall runoff modelling. Burges and Lettenmaier [9] determined two types of uncertainties like type I and type II. Type I associated with correct parameters embedded in an inadequate model and type II get to grisp with the exquisite model with parameter uncertainty.

Klir and Folger [10] in consistent with Ayyub and Chao [11] categorized two types of uncertainty that is to say ambiguity and vagueness. Ambiguity arises due to non-cognitive sources like lack of knowledge, physical randomness, use of sampled information in statistical uncertainty, modeling uncertainty. Cognitive sources affect vagueness uncertainty which includes definition of parameters, human factors, interrelationship among the parameters of the problems. Conflict in information, human and organizational errors also create uncertainty.

Uncertainty is two types in case of hydrodynamic modelling like epistemic uncertainty and inherent uncertainty [12]. Lack of knowledge about a phenomenon of interest is associated with epistemic uncertainty and changes with one level of knowledge. Inherent uncertainty refer to any uncertainty immanent in the concordance of models. Fuzzy, probabilistic , set based information are inherent uncertainty [12].

2.1. Sources of Uncertainty in Hydrological Models

There are three main sources of uncertainty in hydrological models [13].

2.1.1. Data Uncertainty

Hydro-meteorological, catchment and subsurface data are applied as input in hydrological models. In running out the analysis in building up a model, the data is subjected to gaps, exaggeration and uncertainties. The improvement in data acquisition cannot affect positively in most cases because of the involvement of interpolations, scaling and derivation from other measurements [14]. As a result, biased parameter estimation and wrong water balance calculations can occur [15]. The measurement of predictive uncertainty is restrained by input uncertainty. Simultaneous analysis of both input and parameter uncertainty can execute better result [16]. Figure 1 illustrates the types of data uncertainty in hydrological models, how these are generated and related examples.

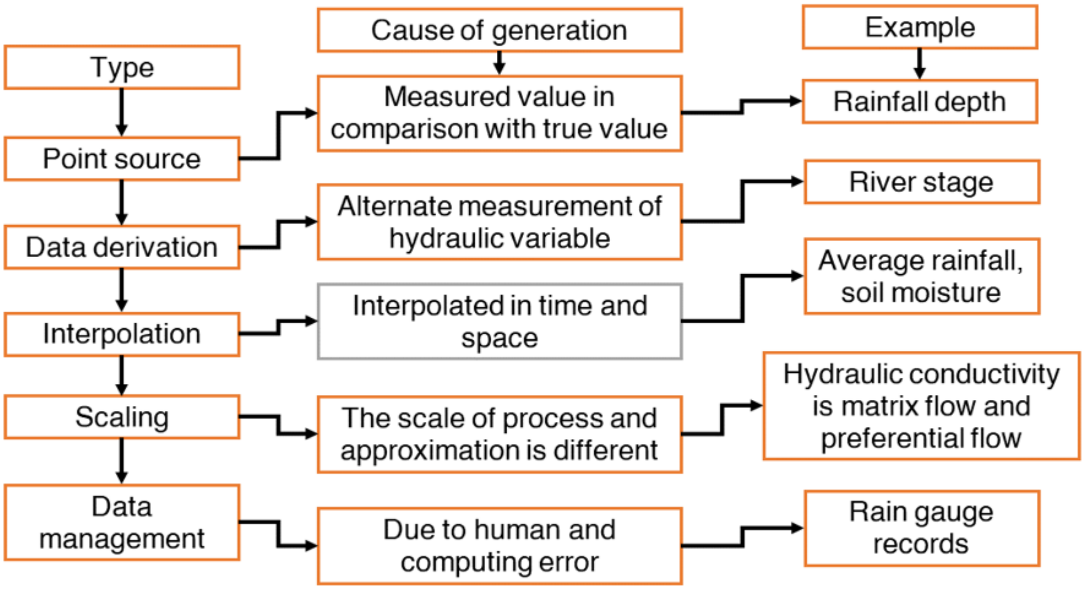

Figure 1. Different types of data uncertainty.

Source: McMillan, et al.[14].

2.1.2. Non-Experimental/Observational Uncertainty

Non-experimental or sampling uncertainty describes the ability to obtain a precise data measurement. In ecological data, sampling uncertainty is common where fidelity of repeated surveys can be affected by various factors like effects of process and observation uncertainty on data measurements. The magnitude of both can be calculated separately. Observation is the measurement of input and output data and sometimes states of the data. The observational uncertainty usually consists of two components e.g measurement errors and inadequate representation of data. Both instrumental and human errors create measurement errors and on the other hand scale adjustment or difference in time and space between the variable result inadequate representativeness of a data [13].

2.1.3. Parameter Uncertainty

Conceptual simplifications which often results discretization in hydrological models, known as effective parameters [17]. In integrating and conceptualizing processes, the estimation or measure of these effective parameters results parameter uncertainty [18]. Parameter uncertainty also results from natural process variability and observation errors. Conversely, parameter uncertainty can be encountered due to errors in the calibration data even if a model is an exact representation of the hydrologic system. Hence, inaccurate estimation of effective parameters, natural process variability measuring problems, and the existence of observation errors induce parameter uncertainty [17].

3. QUANTIFICATION OF UNCERTAINTY

Assessment of uncertainty is a quantitative characterization and to reduce it in implementation and trying to determine how anticipated are the outcomes if some aspects of the system are not known exactly. Research and development efforts in the quantification of uncertainty in incorporated in three ways: (a) Identification of uncertainty in system parameters and extraneous environment ;(b) dissemination of uncertainty through the large computational model; (c) verification and validation of the developed models and assimilate the uncertainty of the model into the global evaluation of uncertainty.

Either the differentiation of model equations and solution of a set of auxiliary sensitivity equations, or the reformulation of the original model using stochastic algebraic/differential equations are involved in analytical methods. Drastic assumptions and as well as access to the underlying model equations and formulation are required in analytical methods, but the results are computationally efficient [1].

Sampling based strategies require only model outputs associated to a set of input parameters combinations and there is no access of model equations and code. Uncertainty is performed by executing the model repeatedly for sets of parameter values sampled from a probability distribution; however, these methods are computationally expensive [19].

Three ways are reviewed to assess the uncertainty in hydrological models:

3.1. Replication

Replication is the standard method for the estimation of point uncertainty. Where any small changes in a variable can be result due to the change of another variable, cloning or replication is useful such as the effect of change of water movement in the change of water level. The mean and standard deviations of a normal distribution can be estimated by the replicates.

Epistemic uncertainty can also be assessed by replication process. Quantification of lab instruments precision, covering whole analysis chain for water quality and water isotope samples. The accurate particulars from occasional replicate runs is interpolated over the remaining data points of a dataset. Uncertainty associated with the selection of measurement method can be captured further by replicates, for example, by applying two different types of soil moisture sensors, or by measuring river flow using both the velocity-area and dye tracer methods. Areal average rainfall in which case interpolation uncertainty can occur, different replicate interpolation techniques can be applied to deal with it [14].

3.2. Fixed Scaling

When uncertainty change with scale and there is spatial data variation, fixed scaling approach can be applied. It is the extension of replication [14]. Diverging or converging topography influence the sub surface flow. Multiple clusters of measurements locations are embedded in fixed scaling which aids in estimation of uncertainty in both within clusters and between cluster scales. Multiple clusters of tensiometer can be used in the estimation of watershed-scale uncertainty in depth to water table [20]. Regions of similar behavior can be deployed in one cluster per region in a watershed , uncertainty from each cluster is gathered in the entire watershed leading to the estimation of total uncertainty [14].

3.3. Parameter Optimization

Model parameter are decisive constituent of a model structure and a representation of model structure. The model parameters in the abstract watershed characteristics should be analyzed through trial and error process or optimization algorithms which adjust the parameter values in such a way that the structure of model match the input-output data [21]. The outcomes of optimization algorithms are dependent on several factors like quality of input and output parameters, distribution and their initial values, optimization levels. When comprehensive assessment running on the model structure, the process requires extra time.

Multiple parameters sets explain the hydrological processes unsystematically [22]. Monte Carlo simulations differentiate between rational and non-rational parameters by behavioral threshold measures. This concept define uncertainties which reflect input and output observational uncertainties applied as a measure of acceptability than the subjective behavioral thresholds [23]. But this measurement does not represent the extent of uncertainties and their interactions.

In the line of Generalized Likelihood Uncertainty Estimation (GLUE), formal Bayesian statistics not only quantify the parameter uncertainty but also reduce. Reduction is done through the involvement of prior knowledge. Differential Evolution Adaptive Metropolis (DREAM) is the updated formal approach of Bayesian statistics [24]. It has the capability of merging differential evolution algorithms with Markov Chain Monte Carlo (MCMC) approach [25]. DREAM explore non-linear parameter spaces by differential evolution. The main challenge in DREAM is the use of strong assumption for a formal likelihood function that results in homoscedastic residuals [22].

When it is found that the optimized parameter uncertainty substantially decreased from the prior uncertainty get around to a reduced model uncertainty prediction, the analysis is justified.

Multi objective optimization (MOO) recover information from increasingly available data. Parameter uncertainty is estimated by acclimating model calibration through multiple objective functions. Matrices that measures the matching segments of hydrographs, soil moisture, evapotranspiration are the examples of this functions. The solutions which cannot succeed through the validation are rejected to optimize the uncertainty [26].

4. REVIEW OF EXISTING METHODS

After the number of papers reviewed, among various methods of uncertainty quantification, five recent methods are discussed in this paper.

4.1. Monte Carlo Sampling

Monte Carlo (MC) simulation is an extensively flexible method and elaborately used for uncertainty problems in hydrological applications. It is a numerical extension of Taylor series classical error propagation method. Monte Carlo can accommodate the distributed and differentiable models while classical error propagation showed limitations to proceed [27]. But when more samples are indispensable for complex models to process through longer running model codes, it may be limited by computational power.

The uncertain parameters are described by probability distributions and the model parameters are assumed independent in the absence of information on joint probabilities. According to the probability distributions the random values of each of the uncertain parameters are generated and the model is run using each random sample. Statistical outputs like mean, standard deviation, skewness are engendered and model output can be determined by the estimated probability distribution [28].

In the context of rainfall runoff model uncertainty analysis, uniform random parameter values are generated from the known upper and lower limit of the parameter. The parameter which are sensitive are taken into account and other are kept constant [29]. Combination of all parameters are done with the generated random numbers. After running the rainfall runoff model, model efficiency can be measured by Nash & Sutcliffe formula, Root Mean Square Error (RMSE), index of agreement, co efficient of determination. Model efficiency is termed as the objective function which is to be maximized in case of Nash Sutcliff and is to be minimized in case of RMSE.

4.2. Bayesian Approach

Most traditional methods in hydrological modelling do not explicitly account for model and parameter uncertainty. Comparison of the models are done without changing the methodology and model structure are not imposed with any limit. Allowance of prior knowledge about the models are proposed in Bayesian approach which enable the hydrologists in executing the results. Measurement of Bayes factor is the requirement in Bayesian model selection. Bayes factor is the ratio of posterior probability of the model on the assumption of equal prior probabilities [30]. Bayes factor indicate the probability of one model relative to another. It is the probabilistic approach to the model selection problem. Prior model probability, prior distributions are specified by model parameters.

An optimum value of a parameters within a model which indicate the catchment behavior is difficult to identify. Pre-existing knowledge about the parameters of a model conceivably combined with observed data and the model output in the framework provided by the Bayesian Methods. Summary of uncertainty about the parameters based on the combination of pre-existing (or prior) knowledge and the sampled data values are expressed in the probability distribution on the parameter space (named the posterior distribution). The development of schemes for assessment of parameter uncertainty in a Bayesian framework [30] have been led by the complications and uncertainties in accurately determining the parameters in conceptual rainfall-runoff models.

Sequential Bayesian Estimation or data assimilation is a type of method aim for measuring input-state-output uncertainty. Ensemble Kalman Filter (EnKF), Particle filter (PF) are widely used throughout the literature of hydrology. PF is applied in cases where the underlying assumptions are violated in EnKF [31]. But the feasibility of using PF in certain cases are questioned in broader data assimilation [32]. PFs are based on the Sequential Importance Sampling(SIS) algorithm [23]. Weight degeneration may result in PF. Resampling or replication is effective for building posterior density. Sampling of posterior with Markov Chain Monte Carlo (MCMC) create the most representative posterior distribution. MCMC is based on ergodic theory [32]. Metropolis Hastings algorithms [30] is the general and commonly used form among many MCMC sampling algorithms. Fundamental and sophisticated way around the computational difficulties are solved by the Markov chain Monte Carlo (MCMC) sampling which is a current development of Bayesian approach. The aim of MCMC sampling is to generate samples of the parameter values from the posterior distribution by simulating a random process that has the posterior distribution as its stationary distribution. Literature on MCMC methods suggests that it improves the diversity of each sample by restoring particle at each observation time step heading to more complete characterization of posterior distribution.

4.3. Generalized Likelihood Uncertainty Estimation (GLUE Method)

Uniformly divided sample parameter provide the most reported applications of probability distribution [33]. Various randomly chosen parameter values from prior probability distributions are applied to run large number of models [34]. Each parameter set is used to produce model output; the acceptability of each model run is then assessed using a goodness of-fit criterion which compares the predicted values to observed values over some calibration period [35].

GLUE method is a Monte Carlo approach and it is an extension of Generalized Sensitivity Analysis (GSA) which was introduced by Spear and Hornberger [36]. Recently, the reliability assessment in rainfall runoff modeling (R-R) has stimulated the concentration of researchers to do intensive research on this subject. GLUE method is based on the assumptions that, prior to input of data into a model, all model structures and parameter sets have an equal likelihood and this method rejects the concept of an optimum model and parameter set. The parameters which most affect the output is firstly identified for each model. Then, a high number of parameter sets is generated via uniform sampling or incorporating prior knowledge about the distribution of parameters. The R-R models are then run for each of the sets and the model output is compared to a record of observed data e.g., observed hydrographs or annual maximum peak flows [37]. The performance of each trial is assessed by likelihood measures [38].

Mainly five major steps are followed in GLUE approach [39]. These are as follows:

1. Definition of likelihood measures: This is based on objective function to identify the model performance as example RMSE, R^2.

2. A prior distribution must be defined for each of the parameters.

3. Using Monte Carlo Technique, a number of parameter sets are sampled originating from prior parameter distributions.

4. Removal of parameter sets for further analysis based on the performance below pre-selected threshold.

5. Remaining parameter sets are weighted based on likelihood value of the parameter. These are used in the successive model runs. The weighted mean and uncertainty bounds may be derived from this package. Using the likelihood weights, uncertainty intervals of model predictions are gained, the model outputs are ranked such that a cumulative distribution for the output variable can be formed.

4.4. Bootstrap Approach

Bootstrap approach developed by Efron [40] may be the most simplest non parametric method of time series analysis. In this method, the distribution of statistic like mean, variance, correlation is estimated by resampling the original time series with replacement. The original time series is resampled to spawn B bootstrap samples from which B estimates of the given statistic can be estimated to do the experiential probability distribution of the statistic [41]. This approach can subscribe to the development of stinting hydrological models with authentic approximation of parameter uncertainty [42].

This type of replication technique is applied in variegated fields of hydrology like developing Artificial Neural Network (ANN) model, estimating the sampling diversity of reconstructed runoff, designing storms from overrunning series by using non time series data etc [43-45]. Nonetheless, bootstrap approach is applying in limited scale to estimate and calibrate parameter uncertainty of rainfall runoff models [7]. Parameter uncertainty associated with forcing data and its impact on streamflow simulations are estimated by nonparametric block bootstrapping approach coupled with global optimization by Ebtehaj, et al. [46]. The effect of parameter uncertainty on Soil Water Assessment Tool (SWAT) model simulation vary from catchment to catchment [47].

Evaluation of the impact of different available data scenarios in calibration parameter uncertainty on the model simulation of the discharge in the upper Kanda river basin was done by residual based bootstrap technique in 2019 by Padiyedath Gopalan, et al. [7]. The study is based on the assumption of an independent and identically distributed model residual series. In that study, Bootstrap approach was employed to the individual flood events. Two indices were proposed to identify the parameter with highest and lowest uncertainty based on the width of confidence interval and median value and the characteristics of urban specific rainfall runoff model was described elaborately.

4.5. Hybrid Machine Learning Methods

Conventional machine learning algorithms are evolving at a fast rate and continuously improving by applying hybridization and techniques. By reason of an increase in the quantity of data in hydrology, machine learning is becoming important as it utilizes algorithm that detects patterns and relationships of input and output parameters of model, changes in different features of the models etc.

The M5 algorithm constructs hierarchical models where the input space is divided to relate the input data to the corresponding output values. The standard deviation of the output values which reach a node as a measure of the error, the expected reduction in error is calculated at that node [4].

Table 1. Summary of the methods representing their applicability, positive points and limitations in analysis.

Sl. No	Methods reviewed	Applicable to uncertainty sources	Positive points	Limitations
1.	Monte Carlo sampling	Input, parameter, structural uncertainty	• Beneficial in analyzing the combined effects of multitudinous uncertainty sources. • Uncertainty distribution of derived value using each sample can be determined from large sample size. • Lodge any distributional form and any complex model.	• Complex process and can be runned through the use of softwares. • Error in data and process may provide wrong results. • Substantial number of runs are required to get authentic approximation of uncertainty.
2.	Bayesian approach	Input, parameter, structural uncertainty	• First method possessing the ability to systematically account for input uncertainty. • Turn directly to input and output errors in hydrological models. • Detailed information about the data accuracy can be known by a consistent framework provided by this approach and in this systematic framework competing catchment and data uncertainty models can be compared.	• Long computational demand. • There is a strong influence of prior distribution but selection procedure of choosing the prior is not suggested.
3.	GLUE	Parameter and structural uncertainty	• Scrutinize the domains in the parameter space where the model predictions are consistent with the observations. • Conceptually simple and less vulnerable to model discontinuity. • Without taking strong assumptions regarding the nature of modelling errors, uncertainty assumptions improved by reckon with the new information.	• If the number of parameters is large, the sample size of respective parameter distributions must be too large to get a well-grounded estimate. • The number of expendable model runs may be large based on prior parameter distributions.
4.	Bootstrap	Parameter uncertainty	• Requires no distributional assumptions about parameters • Auto correlated model errors, common in the application of dynamic hydrological models at catchment scales are managed by this approach.	• Data are considered independent and identically distributed in classical bootstrap. • Resampling is carried from each prior data point with equal probability.
5.	Machine learning	Predictive uncertainty	• Able to encapsulate indistinct functional relationship between the input and the output variables, even if the underlying mechanism producing data is unknown or difficult to explain. • A multidisciplinary field enriched with the concepts drawn from many fields such as statistics, information technology, artificial intelligence, neurobiology, physiology, control theory etc.	• Required large amount of structural data for training and testing. • As data are usually correlated in time and space, the problem of bias-variance tradeoff arises.

In Cluster analysis, the data is partitioned into subsets on clusters. Exclusive, Overlapping and Hierarchical are the basic types of clustering algorithms. K means clustering is exclusive type where data are grouped in a way where each data point belongs to a specific clusters. Fuzzy sets are used as an overlapping cluster. Here, each data point belongs to several clusters with the degree in the range 0 to 1. Successive clusters dividing the established clusters are identified by hierarchical clustering algorithm [4].

Below in the Table 1, a summary of the methods reviewed are given:

5. UNCERTAINTY ANALYSIS OF FLOOD FREQUENCY AND STREAM FLOW

In the case study of climate change impact on flood frequency in Karun river Iran, the effect of different sources of uncertainty with respect to total uncertainty in climate change modelling was evaluated. The sources of uncertainty were hydrological models, climate change scenarios and combination of different effects on global climate models. Analysis of Variance (ANOVA) quantified uncertainty in downscaling methods, hydrological models. Fuzzy method was also used in the quantification of uncertainty in flood frequency study. A triangular membership function was applied with minimum, median and maximum elements. In the result, predicted data with maximum width of membership function shows the higher uncertainty [48].

Among the availability of numerous models, scientists are often got a challenge about the applicability of best model to a catchment for a particular modelling exercise. Marshall, et al. [49] applied a method alternative to conventional model for assessing both parameter and model uncertainty with the available catchment data. The analysis was carried out through Bayesian Statistical inference with computations carried out via Markov Chain Monte Carlo (MCMC) method. The developed model was a version of the Australian Water Balance Model (AWBM) [50] reformulated here by using flexible number of soil moisture storages . Stream flow variation often strongly depend on season and this dependence causes hydrological model errors and predictive uncertainty. In Australian Water Balance Model (AWBM), soil moisture variability was represented by three surface stores and in this study the model was developed to include two, four on ten surface stores. Model and parameter uncertainty was identified by analyzing eleven years of streamflow data by Bayesian methodology. The relative convenience of modelling data error was identified by comparing eight main models. The finding of the study concluded that if there is lack of data or insufficient data, the use of BIC (Bayesian Information Criterion) may cause risk in the measurement of likelihood [49].

Seasonally variant, seasonally invariant and hierarchical error model were developed by Li, et al. [51] to explain errors from a rainfall runoff model. Seasonally invariant models were applied to same parameter sets of all months whereas seasonally invariant model utilizes month specific error model parameters. The hierarchical model derived from seasonally variant model and assumed common prior of seasonally varying model parameters and deduced seasonal influence on errors from the data [51]. The models were applied to five catchments in Victoria, Australia and comparison was done through performance scores and diagnostic plots. Each verification score was calculated for every month with the aim of exemplify the seasonal performance for the period of 12 months. The error models updated the streamflow predictions of the Water Partition and Balance (WABAPA) model based on the particulars from the antecedent months [51]. In the results, it was noticed that streamflow predictions from cross validation analysis are biased in predictions than the calibration. The hierarchical error model showed the best ability to predict events that had been used in the estimation of parameters [51].

6. CONCLUSION

Proper quantification and representation of uncertainty in hydrological modelling is essential for decision making in water resources management. It is paramount to consider all types of errors in a comprehensive, explicit and cohesive way to reduce bias and uncertainty in the final prediction because any single source of uncertainty may cause the wrong way to predictions in the model output. According to Gupta, et al. [52], uncertainty in hydrological predictions could be reduced by collection of more informative and higher quality data, better quantification of the physical processes and improve their representation in the hydrological models, and applying robust techniques to uproot and ingest information from the available data.

Sampling based methods such as Monte Carlo, GLUE and Markov Chain Monte Carlo in theory allow robust analysis of the complexity of a response surface. MCMC method is suitable where distributions must be partially defined or restricted by output data. These methods can be prohibitively computationally expensive. GLUE is usually combined with an informal likelihood measure to condition the parameter space attaining to ensure that parameter uncertainty reflects total uncertainty. Recent research highlights the identification of the place where the model fails and where improvement is necessary by the model calibration and evaluation [52]. Multi-objective optimization algorithms highlight trade-offs between different objectives which may be considered as symptoms of model inadequacy and point in the direction of model improvement.

On the whole, this paper reviews current methodologies in uncertainty analysis in hydrological modelling. New predictive approaches based on a combination of current and new data assimilation and modelling ideas, using existing and new remote-sensed data sets, are required to assess the uncertainty properly.

7. FUTURE PERSPECTIVE

An outlook about the future perspective of uncertainty analysis can be attained by bringing back of the fundamental premise discussed above. Any type of useful information must be taken into account by the measuring methods. This contention will open the door to a pertinent approach of extensive research. This generalized theory may help to gain from divergent types of information either possibilistic or probabilistic Langley [53]. Zadeh [54] showed how different types of constraints on uncertainty estimation (such constraints may be probabilistic, possibilistic, veristic, fuzzy-graph, bimodal and many others) can be combined within a Generalized Theory of Uncertainty (GTU). By combining the strengths of different methods for uncertainty estimation in hydrology would allow the researches to move forward to a significant step [55].

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