Open Access
Volume 7 Issue 2
Research Article

Journal of Water Engineering and Management
ISSN: 2582-6298

Adaptation of Seasonal Forecasting Techniques for Water Management in India

Manjeet Singh Dhillon[1]*, Saad Asghar Moeeni[2], Shazhad Asghar Moeeni[3], Mohammed Sharif[4]
[1]Ex-Chairman, Ganga Flood Control Commission, Sinchai Bhavan, Government of Bihar, Patna, Bihar, India.
[2]Assistant Professor, Aryabhatta Knowledge University, Patna, Bihar, India
[3]Research Scholar, BIT Sindri, Dhanbad
[4]Professor, Department of Civil Engineering, Faculty of Engineering and Technology, Jamia Millia Islamia Central University, New Delhi. India.

Article Info

Article History:
Received on: December 25, 2025
Revised on: June 14, 2026
Accepted on: May 2, 2026
Published on: August 31, 2026
Published by Academic Hope
Corresponding author:* **Manjeet Singh Dhillon, Email msdcwc62@gmail.com
How to Cite:
Dhillon, M. S., Moeeni, S. A., Moeeni, S. A. and Sharif, M. 2026. Adaptation of Seasonal Forecasting Techniques for Water Management in India, Journal of Water Engineering and Management 7(2): 1-11
DOI:
https://doi.org/10.47884/jweam.v7i2pp1-11

Abstract

Seasonal forecasting techniques are in vogue all over the world and are applied depending upon the region of interest and the type of problem. Many methodologies varying between statistical approach, dynamic approach and hybrid approach are adopted. In India, the Indian Meteorological Department (IMD) issues seasonal forecasting bulletins on the national and regional scales for the monsoon season. However, there is no large-scale seasonal model available at the basin level, which is the scale for water management issues like those in storage strategies for reservoirs, reservoir sedimentation and contingency planning for floods and drought. In the present paper, many techniques applied all over the world in the realm of Seasonal forecasting for water management are reviewed for adaptation towards the Indian context, along with a hint at their process of operationalisation.
Keywords: Seasonal forecasting: Dynamical modelling: Ensemble streamflow prediction: Statistical modelling: Machine learning algorithms.

Introduction

Water management faces multiple issues covering all or part of a river basin and on different time-scales, as shown in Fig. 1. The issues include, but are not limited to: Flood, including monsoon, flash, rain-fed, and storm surge floods. The time scales of these flood types differ from hours to weeks for flash-, rain-fed-, and storm surge floods, increasing to weeks to months for monsoon floods. Drought is divided into meteorological, hydraulic and agricultural drought (it may be noted that these three drought types all have limitations in their practical applications, and it is preferable instead to state water scarcity for specific uses and users). The time scale is weeks to months. Navigation includes low water depths during the dry season and sedimentation of rivers. The time scale is weeks to months. Climate change can impact most of the other issues. The time scale is years or longer. Prediction of hazards and/or available water resources. A longer and longer lead time is required by water resources managers. Water sharing among users (at the local level), states (at the national scale) and countries (at the international scale). Groundwater includes over-exploitation, falling groundwater table, salinity intrusion and groundwater pollution. The time scale is years. Institutional and human capacity, which includes unclear or overlapping responsibilities between departments and a lack of staff. (time scale is months to years).

Fig. 1 Overview of major challenges in water management

The water availability and its needs are variable across time and space, making water allocation and management a more challenging problem for the decision makers, solving which is imperative. This problem of optimal management of water resource allocations and reservoir operations can be solved if a reliable inflow forecast is known in advance. That is, we don't need precise forecasts on a daily basis, but we require reliable forecasts of inflow volumes weeks to months in advance, so that water management can be effectively done. River flow forecasting has been routinely done for various rivers across the world and across various temporal scales, depending upon the issue that needs to be resolved (Fig. 2). The flow forecasting is done on time-scales of hours to weeks, mainly for flood forecasting and on time-scales of years to decades for water planning and climate change adaptation. Fig. 3 shows the decision-making process for seasonal forecasting in water resource systems.

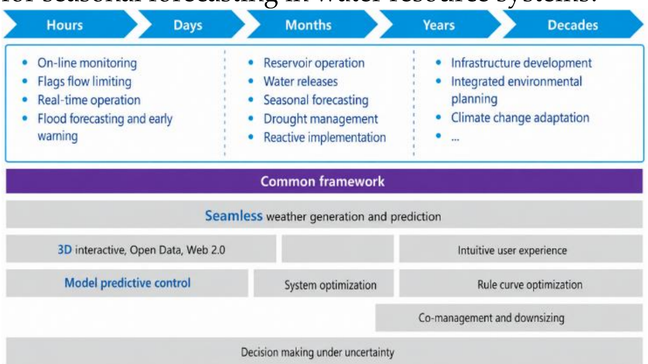

Fig. 2 Different forecasting time-scales and methods to address water resources issues

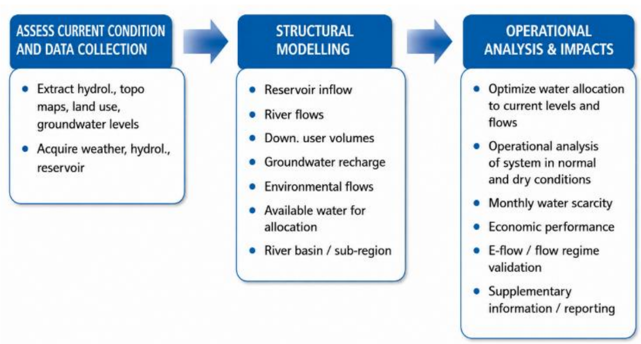

Fig. 3 Schematic of the decision-making process for seasonal forecasting in water resource systems

A reliable forecast with a lead time of a few weeks to slightly over one year has applications in efficient water management, agricultural planning and effective strategies for storage. It also has great potential for advanced flood warning, as it gives an estimate of high floods in a river month ahead. Thus, giving ample time to the stakeholders to plan the mitigation and rescue activities for the affected area. On the other hand, hydrology has undergone tremendous advances during the last few decades, such as the use of powerful computers and the application of remote sensing. Nevertheless, the seasonal hydrological forecasting is often termed a predictability desert due to the difficulty in providing skilful forecasts in the desired range. In a country like India, a multiplicity of water management issues coexists, thus highlighting the immediate need for seasonal forecasting.

Conceptual Approach and Methodology

There is a large spectrum of potential methodologies for seasonal predictions, which can vary from being based on pure-dynamical modelling to pure-data-driven (Fig. 4). These approaches are broadly classified as process-driven, data-driven and hybrid approaches. A few of the major tools, techniques and recent advances under these classifications are presented below.

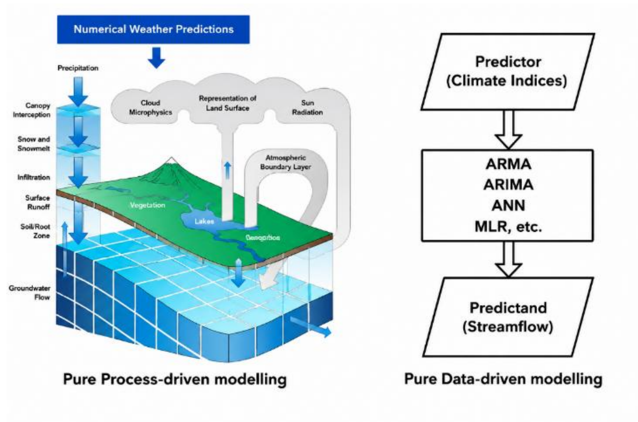

Fig. 4 Two ends of streamflow forecasting approaches

Dynamical Modelling Approaches

Conventionally, seasonal hydrological predictions have depended upon the dynamical modelling approach, i.e. based on the concepts of system dynamics with various hydrological processes in the catchment along with the initial hydrological conditions of soil moisture, groundwater and the streamflow. The initial hydrological conditions (IHC) were one of the prime sources of seasonal hydrological predictions, which was the starting point for the development of the ensemble streamflow prediction approach in the 1970s (Wood and Lettenmaier, 2006).

Ensemble streamflow prediction

Ensemble Streamflow Prediction (ESP) approach provides probabilistic streamflow predictions using various calibrated conceptual or physically based hydrological models or time series models or models based on soft-computing techniques, considering the long-term historical records of observed meteorological forcing variables (such as precipitation and temperature) to simulate a possible set of river flows that are dependent both upon the current hydrological conditions and future climatic conditions in the catchment.

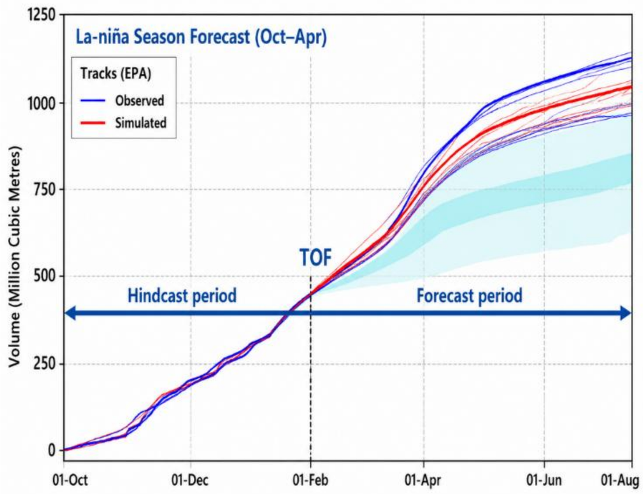

Fig. 5 ESP forecast showing the time of forecast (TOF), hindcast period and the forecast period

The reliability of the ESP forecasts depends on how well the hydrological model represents the catchment, especially the storages (snow cover, reservoir levels, etc.), the quality of the calibration and the representativeness of the historical climate data.

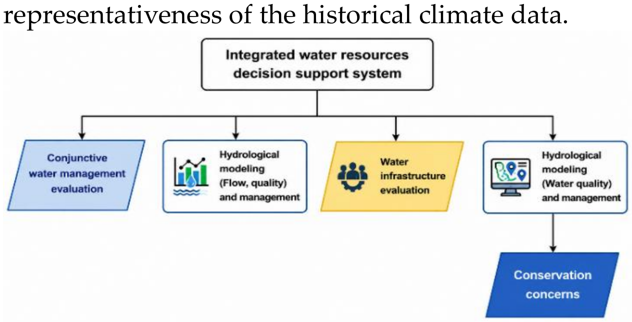

Fig. 6 Schematic representation of ensemble stream flow prediction methodology

For operational forecasting, the uncertainties in the IHC can be reduced in several ways. Firstly, by ensuring high-quality hydrological modelling to capture the hydrological conditions and behaviour. Secondly, by including a sufficiently long hindcast period (Fig. 5) to ensure that the effects of any long-term storage are accounted for. Thirdly, methods used for assimilating observed hydrological data (streamflow, reservoir level, snow cover) (Madsen and Skotner, 2005; Wood and Lettenmaier, 2006; Shukla and Lettenmaier, 2011; Rasmussen et al., 2015; Butts et al., 2017). One of the advantages of this approach is that it can be used in both the wet season and the dry season. Fig. 5 shows an example of such a forecast during the austral dry season. The success of one such ESP forecast in Bangladesh during the time period 2007-08, which had skills between 10 and 15 days, helped people living in the Brahmaputra River to get evacuated much before the floods struck (Webster et al., 2010). However, the ESP skill for seasonal forecasts diminishes sharply after 1 month for most parts of the world (Shukla et al., 2013).

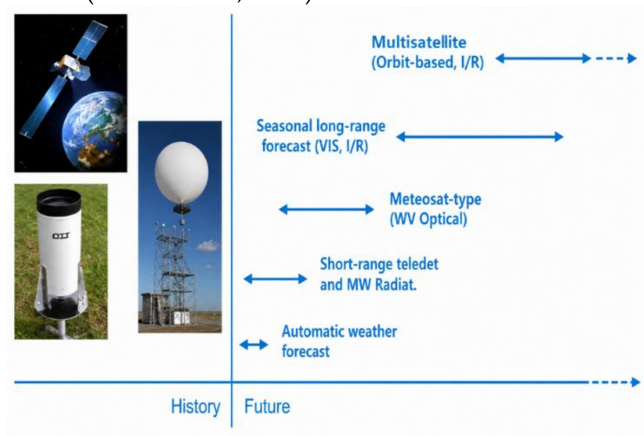

Fig. 7 Overview of methods of weather forecasting

Climate model-based ensemble methods

A climate model-based ensemble approach provides probabilistic streamflow predictions by running hydrological models, like the ESP. However, Climate model-based ensemble methods use seasonal forecasts of meteorological variables from numerical climate models as forcing for the hydrological models, whereas in ESP, the historic meteorological observations are used. A detailed review of climate-model-based seasonal hydrologic forecasting is presented by Yuan et al. (2015). The climate-model-based ensemble prediction is explained in Fig. 8.

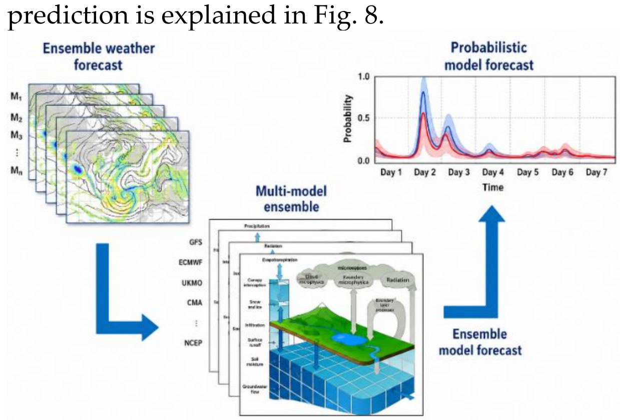

Fig. 8 Representation of ensemble streamflow predictions using ensemble weather forecasts

Coupled ocean-atmosphere general circulation models

(CGCMs) are the main sources of seasonal meteorological forecasts. Coupling of the ocean and atmosphere models means that sea surface temperature (SST) processes, which change more slowly than atmospheric conditions, are captured. This long- term memory is likely to increase the overall forecast skill of these models in India. India Meteorological Department's (IMD) National Weather Prediction (NWP) system provides high-resolution, 10-day probabilistic weather forecasts. One of the most important challenges that remains is relating this ensemble-based estimate of the model prediction uncertainty to the actual prediction uncertainty, as these ensembles represent the model sensitivity to initial conditions and parameterisations rather than a prediction uncertainty. It can be expected that these will underestimate the actual uncertainty. Apart from the CGCMs' limitations such as computational demands, limited observational data for initial conditions and approximation of physical processes, they also provide forecasts of meteorological variables at relatively large spatial scales as compared to the smaller catchment scales that are often of interest. These limitations can lead to systematic biases in the ensemble spread of model outputs (Molteni et al., 2011).

Multiple statistical bias-correction and downscaling techniques have been developed to overcome such model biases, and there is an extensive literature on the subject. Two important points to note are that many of these methods are similar to methods used in climate change, like the delta change method (additive or multiplicative bias correction) and quantile mapping (Ines and Hansen, 2006; Piani et al., 2010; Butts et al., 2017). However, for seasonal prediction, the corrections are not only a function of month or season as used in climate change modelling but also a function of lead time (Fig. 9). The ensemble of forecasts is based on the System 4 model of ECMWF and the historical reference based on the flow ensembles from Butts et al. (2017).

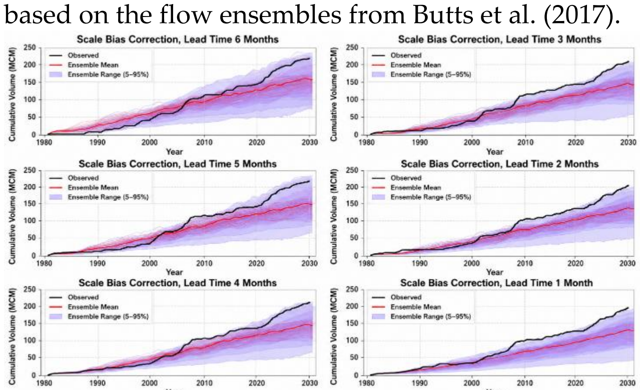

Fig. 9 Flow forecasts for lead times of 1-6 months showing the actual accumulated flow in black

Hydrological Modelling Systems

Both the ESP and the Climate model-based ensemble method provide streamflow forecasts using the hydrological models. Hydrological modelling is a wide, evolving field with many approaches available, many numerical models developed and have been in practice for decades. These models capture the real-world catchment responses and attribute features of the response correctly to the underlying processes, which are even more difficult to quantify. The available hydrological models can be broadly classified as follows:

Lumped models: These are sub-catchment-based hydrological models, in which the response of the entire sub-catchment is computed as a flow hydrograph at its outflow location. Any flow details within the sub-catchment are lost.

Distributed models ("rain-on-grid" model): These are based on modelling of overland flows. The model determines the infiltration and other losses at each cell, and the remaining rainfall becomes runoff subject to the overland flow equations. Many different hydrological models exist in the modelling domain, applicable to different situations and giving differing solutions. The modellers select the appropriate modelling software based on their experience and an understanding of the physical processes of the system.

Statistical/ Stochastics Inferential Modelling

Statistical/Stochastic models take advantage of empirical (often lagged) links between the predictand of interest (like precipitation or flow in rivers) and one or several predictors (for instance, sea surface temperature, sea surface pressure or indices of the global climate system). These models use past data, and therefore, these models require the presence, amount, and quality of the past oceanic, atmospheric and hydrological data (Anderson et al., 1999; Lavers, 2010).

$$predictand = f(predictors) \quad \ldots \quad (1)$$

The function f can either be (1) a statistical or empirical approach or (2) a dynamical approach. In the former, statistical approaches employ past observations to develop a model relationship between the predictor and the predictand, while dynamical approaches use GCMs to integrate physically based equations governing the process dynamics of atmosphere-land-ocean systems to project the future state of the system. Models using statistical approaches are less expensive to develop and operate than dynamical models. In addition, statistical/stochastics models can be viewed as benchmarks for evaluating the performance of computationally demanding dynamical models (Barnston et al., 1994; Bierkens and van Beek, 2009; Kuo et al., 2010). Linear regression, correlation analysis, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and multiple linear regression (MLR) are the most commonly used statistical methods (Fig. 10).

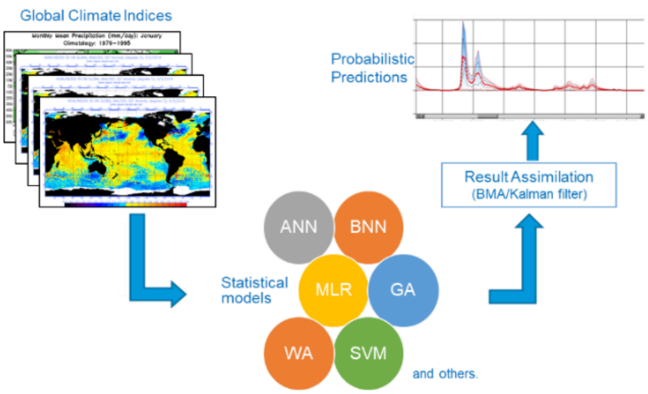

Fig. 10 Schematic representation of statistics-based streamflow prediction modelling

Table 1 Statistical/ Stochastics approaches used for streamflow prediction based on global climate indices

Authors	**Geographical Region**	**Method Used**
Eldaw et al. (2003)	Africa (Nile)	Correlation/linear regression
Wang and Eltahir (1999)	Africa (Nile)	Bayesian theorem
Barlow and Tippett (2008)	Asia	Correlation/CCA
Chiew et al. (1998, 2003)	Australia	Serial streamflow/ENSO streamflow correlation
Chowdhury and Sharma (2009)	Australia	Combination of three statistical models
Kiem and Franks (2001)	Australia	Classification approach
Ruiz et al. (2007)	Australia	Linear regression
Kirono et al. (2010)	Australia	Correlation
Wang et al. (2009)	Australia	Bayesian approach
Webster and Hoyos (2004)	Brahmaputra and Ganga river	Wavelet/ Regression
Rasouli et al. (2012)	Canada	Bayesian neural network (BNN), support vector regression (SVR) and Gaussian process(GP) – and compared with multiple linear regression (MLR).
Bierkens and Van Beek (2009)	Europe	Lagged SVD NAO forecast
Gámiz-Fortis et al. (2008, 2010)	Europe	ARMA/linear regression
Ionita et al. (2008)	Europe	Correlation
Kumar and Maity (2008)	India/Mahanadi	Artificial neural network (ANN)
McKerchar et al. (1998)	New Zealand	Classification approach
Purdie and Bardsley (2009)	New Zealand	Linear regression
Archer and Fowler (2008)	Pakistan	Linear regression
Cardoso and Silva Dias (2006)	South America	Linear regression
Gutiérrez and Dracup (2001)	South America	Correlation
Hastenrath (1990)	South America	Correlation /Linear regression
Chandimala and Zubair (2007)	Sri Lanka	Principal component
Zubair (2003)	Sri Lanka	Correlation
Kuo et al. (2010)	Taiwan	Wavelet-based ANN-GM model
Wedgbrow et al. (2002)	UK	Correlation
Wedgbrow et al. (2005)	UK	Expert System

Authors	Geographical Region	Method Used
Svensson and Prudhomme (2005); Wilby (2001); Wilby et al. (2004)	UK	Linear regression
Devineni et al. (2008)	USA	Regression approach
Bracken et al. (2010); Grantz et al. (2005); Opitz-Stapleton et al. (2007)	USA	K-nearest neighbour (KNN), locally weighted polynomial (LWP) regression

Generally, river flow variations in many regions of the world are influenced by ENSO. Because of such ENSO – streamflow association, many studies have considered one of the ENSO measures in their analysis to predict river flows on a seasonal basis through correlation or regression techniques. From Table 1, more than half of the studies (20 out of 36) have utilized a measure of ENSO as the predictor variable (these studies were primarily found in the low-latitude zones). But there are many indices which have been designed to determine the state of ENSO in different zones of the world.

Flow (Discharge) Ensembles

This is the simplest method for deriving ensemble streamflow forecasts based on the use of resampled observed river flow records under the assumption that the range of historical river flow events is representative of possible future conditions. This approach uses historical river flow observations to determine a possible range of future accumulated river flows. Figure11 shows an example of such a discharge flow ensemble based on 21 years of resampled observed flow data. In this example, all the available data is used to generate the range of future flows. A variation of this is to use a subset of these 21 years, selecting those that are similar to current hydrological conditions and/or climate conditions, where climate conditions can be based on, for example, historical or forecasted rainfall or climatic indices like SST or ENSO status.

The main advantage of this approach is simplicity, but it requires several years of reliable historical flow data to reflect the likely range of variation of future flows. Furthermore, it does not reflect varying catchment conditions before or during the forecast period, such as changes in groundwater and surface water storage. However, this method can be used as a reference to interpret the severity of the forecast in relation to normal conditions and to evaluate other methods (Butts et al., 2017). This is achieved by grouping the accumulated flows into terciles, dividing the distribution of flows into three parts using 0.333 and 0.667 probabilities. This creates three categories which can be viewed as representing below-normal, normal and above-normal accumulated flow ranges, each containing 7 ensemble members per category (Fig. 12).

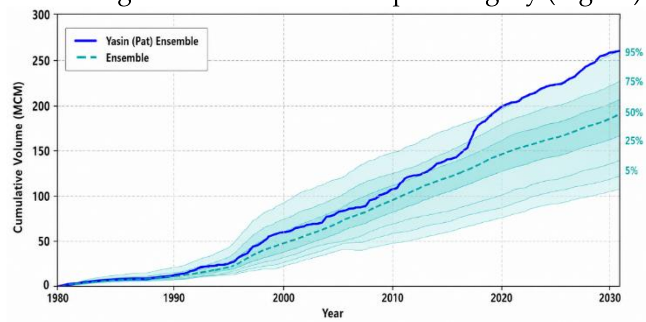

Fig. 11 Ensemble of historical discharges for a 7-month river flow forecast

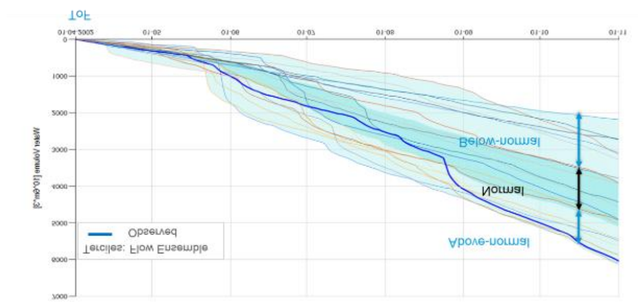

Fig. 12 Using the flow ensembles to define normal, above normal or below normal conditions

Hydro-Climatic Teleconnections

The extensive review of studies on extended-range streamflow prediction based on a direct statistical relationship with climate indices suggests that there is a large scope for advancement in capturing the nonlinear scale-specific interactions between global climate patterns and streamflow at basin or sub-basin scale. In general, the following shortcomings were found in the prevalent practices of Statistical Inferential Modelling. The selection procedure of global climate indices as predictors of a statistical model was very subjective and based on a preconceived understanding of their influence at a regional or continental scale. Different phases of climate indices (negative, positive and neutral), spatiotemporal variability, interdependence, nonlinear and nonstationary behaviour were overlooked. It was inherently assumed that all global climate indices contribute equally to the variability of streamflow. Therefore, it is pertinent to have a critical selection of global climate indices (or even proposing new indices) accounting for their different phases, spatiotemporal variability, weights, interdependence, nonlinearity and non-stationarity.

Seasonal forecasts in the monsoon season

For seasonal streamflow forecast modelling during the monsoon season, the following methodologies have been recognized as leading approaches:
Approach I: Ensemble streamflow prediction method using NWP weather forecasts of IMD
Approach II: Statistical Inferential modelling
Approach III: Hybrid modelling

Hybrid modelling

Precipitation is the most important forcing when it comes to streamflow predictions in pure-dynamical approaches. A rainfall-related issue might be caused by limited or excessive rainfall, unusual geographical distribution of rainfall, early or late arrival of rainfall and long or short duration of rainfall. In a nutshell, the predicted precipitation is uncertain, and the longer the lead time, the more uncertain the predicted precipitation is. Hence, a methodology to skilfully forecast the monsoon progression and strength could be an added advantage to the EHP study. Few recent studies have used a hybrid approach for streamflow forecasting that combines a statistical model and a dynamical model (Bierkens and van Beek, 2009; Kuo et al., 2010). This statistical method is based on direct relationships which have been developed through empirical data and derived indices for the predictors. There are several climate indices that are based on anomalies in the atmospheric pressure and SSTs, which have been associated with future rainfall. The forecasts of rainfall as well as other climate variables are then used in hydrological models to generate streamflow forecasts. The accuracy of the existing statistical as well as new dynamic streamflow forecasts depends on the location and period of forecasting. For example, the Australian Bureau of Meteorology has recently introduced a new Seasonal Streamflow Forecasting (SSF) service using the hybrid modeling approach in December 2010.All three approaches can be explained using the schematic diagram given in Fig. 13.

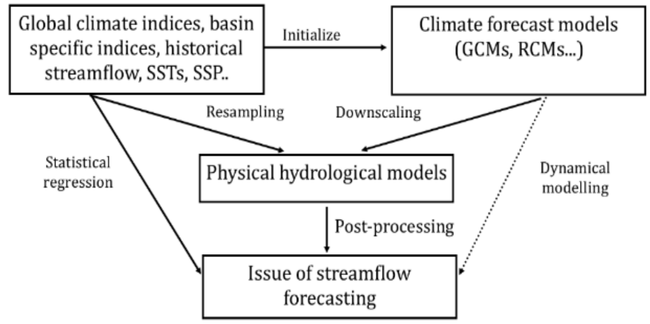

Fig. 13 Diagram for different seasonal hydrologic forecasting approaches (Yuan et al., 2015)

Seasonal Forecasts in Non-Monsoon Season

Streamflow forecasting for the low-flow season is not actively performed presently in India. However, the necessity of low-flow season forecasts for improved and efficient decision-making of water resources cannot be ignored. A reliable, accurate and advanced forecast of streamflow in the non-monsoon season is imperative for optimal management of reservoirs, water allocation for irrigation and other users, navigation and environmental health of the riverine systems. Although methods such as ESP and Statistical inferential models are promising for the objective of flow forecast modelling for the low-flow season, the recession curve fitting and regression approaches have been routinely used in the past for the low-season forecasting.

The recession curve is the falling limb of the hydrograph, which is developed due to the gradual depletion of flow in the river during the non-monsoon period. The recession period lasts until the flows begin to increase due to the contribution from significant rainfall. The river hydrograph is the reflection of the dynamics of its watershed processes and storage. Hence, flow in the recession limb is dominated by the water contribution from the natural storages, like groundwater storage and snow cover. The shape of this recession curve can be studied and analysed to understand the catchment characteristics and source of flow during this period. For example, slow and gradual recession of flows represents the contribution from groundwater. The quantification of this recession curve has been widely used as a technique of low-flow forecasting. An analytical expression or a mathematical model is developed that adequately fits the recession curve. The characteristic features of all the recessions are computed, and then the fitting model is chosen. The fitting models are broadly categorized into linear regression and nonlinear regression. The power law recession fitting is also widely used for event-scale recession fitting (Dralle et al., 2017). Major limitations of this approach are that the reliability of the forecasts is low and skilful forecasts are possible only for shorter forecasting periods.

Regression analysis is a more reliable approach. The techniques model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to the data points. The major limitation of this technique is the assumption of independence requirements, which is difficult to validate due to serial dependence in the data. The recession curve analysis and linear regression are traditional approaches that have been widely used for non-monsoon season forecasts. In the low flow season, the stream flow is mainly generated by the stream aquifer interactions and snowmelt. Groundwater movement is geologically a slow process that is of low frequency and thus can be modelled using Wavelet Analysis (WA) techniques coupled with non-linear techniques (ANN, SVM) (Adamowski and Sun, 2010; Rathinasamy et al., 2013). The wavelet-based techniques have proven to be more reliable and accurate in the hydrological forecasting of non-stationary systems. Climate model-based ESP is one of the methods for low-flow season forecasting. In this purely dynamical approach for seasonal water forecasting, the dynamical climate models produce forecasts of rainfall and other climate variables, which are then fed into hydrological models to produce predictions of streamflow forecasts. The flows during the non-monsoon season are mainly driven by stream-aquifer interaction and also by snowmelt. The complex dynamics of the subsurface-surface flow interaction and snowmelt runoff generation can be better captured by deterministic hydrological modelling than by statistical inferential modelling using climate indices. As precipitation is the major meteorological variable which is influenced by the climate indices, it is not a dominant source of low-flow season flows.

Machine Learning Algorithms

Dynamic or process-driven and statistical seasonal forecasting approaches have their limitations, and fast developments have taken place in the recent past in areas like Machine Learning and Artificial Intelligence. With the availability of more and more data, data-intensive analysis has come to stay at present and for the future. Machine learning involves adaptive learning by machines without any explicit programming. Many studies have been undertaken all over the world using machine learning techniques. An artificial neural network was used to forecast summer rainfall in the Yangtze River basin, using LSCPs including SOI and the Scandinavia Pattern by Hartmann et al. (2008). Genetic programming was used to predict ISMR using LSCPs from both the tropical Indian Ocean and the tropical Pacific Ocean. A study was conducted in Australia and focused on developing an ML-based probabilistic seasonal rainfall forecasting model using multiple LSCPs from the Pacific, Indian and Southern Oceans. The ML algorithms used in this study were compared with other Statistical and Dynamic models in practice in Australia, and Random Forest (RF), a tree-based ensemble learning algorithm, was adopted.

Performance of seven machine learning algorithms, namely Logistic Regression, Naïve Bayes, KNN, Decision Tree, Random Forest, Gradient Boosting and Support Vector Machine, was evaluated in the study by Dhillon et al. (2023) for seasonal precipitation forecasting for the Kosi basin in India. Logistic regression was found to have the best accuracy (Fig. 14). A total of 14 Large Scale Climate Predictors have been considered for the seasonal forecast of precipitation with lead times of 1, 2, and 3 months. Historical data of precipitation were divided on a tercile basis into three categories, namely Above Normal (AN), Normal (N) and Below Normal (BN), and compared with output from the Seasonal Prediction Model (SPM) for a period of 20 years from 2000 to 2020 and for lead times of 1,2 and 3 months. The overall accuracy was found to be 81 % for a lead time of one month and 71% for lead times of 2 and 3 months (Table 2).

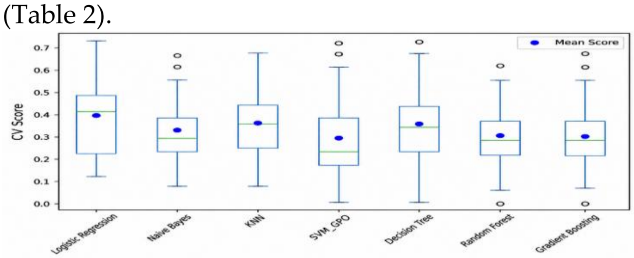

Fig. 14 Machine learning models' performance based on random split train/test analysis.

Table 2 Probabilistic model output of SPM vis-a-vis actual category

Year	Lead Time 1 Month BN	N	AN	Lead Time 2 & 3 Months BN	N	AN	Actual Category
2000	6.4	16.1	78.5	4.2	16.7	79.1	AN
2001	2.5	56.3	18.7	44.1	51.4	4.5	N

2002	7.8	4.0	88.2	5.8	22.2	72.0	AN
2003	13.6	4.7	81.8	6.8	17.1	76.1	AN
2004	10.6	20.2	69.2	14.6	9.4	37.8	AN
2005	97.9	36.6	25.5	67.5	13.2	19.3	BN
2006	90.7	4.8	4.5	76.2	22.5	1.3	BN
2007	0.8	6.1	93.2	12.5	34.1	53.4	AN
2008	28.7	50.8	20.5	65.4	40.0	14.4	N
2009	76.7	21.7	1.6	21.9	59.8	26.8	BN
2010	7.2	88.5	24.3	3.9	99.0	46.2	N
2011	28.8	80.0	31.0	1.3	26.9	71.8	AN
2012	24.4	65.7	9.9	70.0	2.8	1.3	BN
2013	18.4	20.8	60.8	52.1	47.4	0.5	BN
2014	88.0	24.1	32.3	41.7	99.8	8.5	N
2015	9.6	47.9	2.6	90.0	12.2	21.8	BN
2016	20.6	72.6	6.7	20.0	55.0	34.4	N
2017	73.5	23.6	2.9	41.2	55.8	3.3	BN
2018	99.0	4.6	4.6	71.1	28.8	0.1	BN
2019	3.1	26.0	6.3	14.7	29.7	76.0	AN
2020	13.7	85.0	38.1	20.5	18.3	61.1	AN

Conclusions

A country like India has a multitude of water management issues with varying time scales and complexities. Whereas floods create havoc, especially during the monsoon season, drought affects many parts of the country. Being an agrarian economy, agricultural planning and irrigation management of water assume importance. Scarcity of drinking water is assuming more and more importance with time. Similarly, industrial water supply and energy requirements require better planning to conserve and manage the precious water resources. It is in the context of the macro-scale planning that seasonal forecasting assumes great importance. Yet the challenges inherent in seasonal forecasting are many, which are required to be confronted for more efficient water management in India. Seasonal forecasting has applicability both in monsoon and non-monsoon seasons, though different methodologies are apt for both scenarios. Extant methodologies are reviewed based on a brief review of the literature and experience. In developing a hydrological forecasting model, the choice of approach depends upon the nature of the application, desired outcomes of the model, the lead-time requirement, the spatial scale of interest, available computational facilities, availability of real-time data and a range of other factors. A flexible technical approach with an assortment of modelling strategies: (i) one pure dynamical; (ii) one pure statistical; and (iii) one that is a hybrid of both could be considered in practice. The following general guidelines may be kept in view while attempting seasonal forecasting at a basin scale:

- Basin-specific selection/creation of indices: critical selection of global climate indices (considering their interdependence, nonlinearity and non-stationarity) and creation of new basin-specific indices using nonlinear geophysical modelling techniques to identify the predictors of the statistical models.
- Range of statistical models: A rigorous mathematical framework for multi-week streamflow forecasting based on multiscale statistical inferential models could be developed, which may have an ensemble of different statistical models ranging from linear stochastic models (ARMA, ARIMA), nonlinear models (NARMAX), to artificial intelligence models (ANN, SVM).
- Hybrid model: The hybrid model could be a coupled system having (i) a statistical modelling framework to forecast meteorological variables (such as precipitation) using global climate indices and (ii) a dynamic framework to model the basin hydrology to generate the streamflow forecasts under weather forecasts from the pre-developed model as forcing. Apart from covering the entire spectrum of modelling approaches, the implementation of hybrid modelling will also result in a skilful, reliable

forecast model for precipitation.

- Whereas many studies have been undertaken for seasonal forecasting on a country and regional scale, yet not much work has been undertaken at the basin scale in India. Needless to mention here that a basin is a basic unit for water management. There are numerous challenges to be overcome till seasonal forecasting is effectively utilized and operationalized for water management, especially at a basin scale in India.

Data Availability Statement

The datasets generated during the current study are available from the corresponding author on reasonable request.

Conflict of Interest

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

Funding

No funding has been received.

References

Adamowski, J. and Sun, J. K. 2010. Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds. Journal of Hydrology, 390(1–2): 85–91. https://doi.org/10.1016/j.jhydrol.2010.06.033

Anderson, S. R., Aziz, O., Tootle, G., Grissino-Mayer, H. and Barnett, A. 1999. Using Pacific Ocean climatic variability to improve hydrologic reconstructions. Journal of Hydrology, 434-435: 69-77, doi:10.1016/j.jhydrol.2012.02.037

Archer, D. R. and Fowler, H. J. 2008. Using meteorological data to forecast seasonal runoff on the River Jhelum, Pakistan. Journal of Hydrology, 361(1–2): 10–23 https://doi.org/10.1016/j.jhydrol.2008.07.017

Barlow, M. A. and Tippett, M. K. 2008. Variability and predictability of Central Asia river flows. Journal of Hydrometeorology, 9(6):1334–1349.

Barnston, A. G., van den Dool, H. M., Rodenhuis, D. R., Ropelewski, C. R., Kousky, V. E., O'Lenic, E. A., Livezey, R. E., Zebiak, S. E., Cane, M. A., Barnett, T. P., Graham, N. E., Ji, M. and Leetmaa, A. 1994. Long-lead seasonal forecasts—Where do we stand? Bulletin of the American Meteorological Society, 75(11): 2097–2114.

Bierkens, M. F. P. and van Beek, L. P. H. 2009. Seasonal predictability of European discharge. Journal of Hydrometeorology, 10(4): 953–968.

Bracken, C., Rajagopalan, B. and Prairie, J. 2010. A multisite seasonal ensemble streamflow forecasting technique. Water Resources Research, 46(3), https://doi.org/10.1029/2009WR007965

Breiman, L. 2001. Random forests. Machine Learning, 45: 5–32, https://doi.org/10.1023/A:1010933404324

Butts, M., Jensen, R., Larsen, J., Mueller, H., Richaud, B., Larsen, P., Corcuera Barrera, M. Á. and Lasart, A. E. 2017. Seasonal forecasting of reservoir inflows and their uncertainties. Proceedings of the 37th IAHR World Congress, Kuala Lumpur, Malaysia.

Cardoso, A. O. and Silva Dias, P. L. 2006. The relationship between ENSO and Paraná River flow. Advances in Geosciences, 6:189–193.

Chandimala, L. and Zubair, L. 2007. Predictability of stream flow and rainfall based on ENSO for water resources management in Sri Lanka. Journal of Hydrology, 335(3–4):303–312.

Chiew, F. H. S., Piechota, T. C., Dracup, J. A. and McMahon, T. A. 1998. El Niño/Southern Oscillation and Australian rainfall, streamflow and drought. Journal of Hydrology, 204(1–4):138–149.

Chiew, F. H. S., Zhou, S. L. and McMahon, T. A. 2003. Use of seasonal streamflow forecasts in water resources management. Journal of Hydrology, 270(1–2):135–144.

Chowdhury, S. and Sharma, A. 2009. Multisite seasonal forecast of arid river flows. Water Resources Research, 45(10), https://doi.org/10.1029/2008WR007510

Devineni, N., Sankarasubramanian, A. and Ghosh, S. 2008. Multimodel ensembles of streamflow forecasts. Water Resources Research, 44(9), https://doi.org/10.1029/2006WR005855

Dhillon, M. S., Sharif, M., Madsen, H. and Jacobsen, F. 2023. Precipitation forecasting for water management in Kosi Basin, India using large scale climate predictors. Journal of Water and Climate Change, 14(6):1868.

Dralle, D. N., Karst, N. J., Charalampous, K., Veenstra, A. and Thompson, S. E. 2017. Event-scale power law recession analysis.

Hydrology and Earth System Sciences, 21:65–81.

Eldaw, A. K., Salas, J. D. and Garcia, L. A. 2003. Long-range forecasting of the Nile River flows. Journal of Applied Meteorology, 42(7):890–904.

Feng, P., Wang, B., Liu, D. L., Ji, F., Niu, X., Ruan, H., Shi, L. and Yu, Q. 2020. Machine learning-based integration of large-scale climate drivers. Environmental Research Letters, 15, 084051.

Gámiz-Fortis, S. R., Castro-Díez, Y., Esteban-Parra, M. J. and Trigo, R. M. 2008. Statistical forecasting of winter streamflow in Europe using atmospheric circulation indices and ARMA/linear regression approaches. (Please verify the exact journal name, volume and page numbers before use.)

Hartmann, H., Becker, S. and King, L. 2008. Predicting summer rainfall in the Yangtze River basin with neural networks. International Journal of Climatology, 28(7):925–936.

Ines, A. V. M. and Hansen, J. W. 2006. Bias correction of daily GCM rainfall. Agricultural and Forest Meteorology, 138:44–53.

Ionita, M., Lohmann, G., Rimbu, N., Chelcea, S. and Dima, M. 2008. Interannual variability of Danube River flow and its relation to the North Atlantic Oscillation. International Journal of Climatology, 28(13):1819–1831.

Kashid, S. S. and Maity, R. 2012. Prediction of monthly rainfall using genetic programming. Journal of Hydrology, 454:26–41.

Kuo, C.-C., Gan, T. Y. and Yu, P.S. 2010. Seasonal streamflow prediction. Journal of Hydrology, 387(3–4):292–303.

Lavers, D. A. 2010. Seasonal hydrological prediction in Great Britain – An assessment. Ph.D Thesis, University of Birmingham.

Madsen, H. and Skotner, C. 2005. Adaptive state updating in river flow forecasting. Journal of Hydrology, 308:302–312.

Molteni, F., Stockdale, T., Balmaseda, M., Balsamo, G., Buizza, R., Ferranti, L. and Vitart, F. 2011. The new ECMWF seasonal forecast system (System 4). European Centre for Medium-Range Weather Forecasts.

Piani, C., Haerter, J. O. and Coppola, E. 2010. Statistical bias correction for daily precipitation. Theoretical and Applied Climatology, 99:187–192.

Rasmussen, J., Madsen, H., Jensen, K. H. and Refsgaard, J. C. 2015. Data assimilation in integrated hydrological modeling. Hydrology and Earth System Sciences, 19:2999–3013.

Rasouli, K., Hsieh, W. W. and Cannon, A. J. 2012. Daily streamflow forecasting by machine learning methods with weather and climate inputs. Journal of Hydrology, 414–415:284–293.

Rathinasamy, M. and Khosa, R. 2012. Multiscale hydrological forecasting using wavelet–Volterra coupled models. LAP Lambert Academic Publishing.

Shukla, S. and Lettenmaier, D. P. 2011. Seasonal hydrologic prediction in the United States. Hydrology and Earth System Sciences, 15:3529–3538.

Shukla, S., Sheffield, J., Wood, E. and Lettenmaier, D. 2013. Sources of global land surface hydrological predictability. Hydrology and Earth System Sciences, 17:2781–2796.

Wang, Q. J., Robertson, D. E. and Chiew, F. H. S. 2009. A Bayesian joint probability modeling approach for seasonal forecasting of streamflows at multiple sites. Water Resources Research, 45(5):W05407.

Webster, P. J. and Hoyos, C. D. 2004. Prediction of monsoon rainfall and river discharge on 15–30-day time scales. Bulletin of the American Meteorological Society, 85(11):1745–1765.

Webster, P. J., Jian, J., Hopson, T. M., Hoyos, C. D., Agudelo, P. A., Chang, H.-R., Curry, J. A., Grossman, R. L., Palmer, T. N. and Subbiah, A. R. 2010. Extended-range probabilistic forecasts. Bulletin of the American Meteorological Society, 91:1493–1514.

Wood, A. W. and Lettenmaier, D. P. 2006. A test bed for new seasonal hydrologic forecasting approaches. Bulletin of the American Meteorological Society, 87(12):1699–1712.

Yuan, X., Wood, E. F. and Ma, Z. 2015. Climate-model-based seasonal hydrologic forecasting. Wiley Interdisciplinary Reviews: Water, 2(5):523–536.

Zubair, L. 2003. Sensitivity of Kelani streamflow to ENSO. Hydrological Processes, 17(12): 2439–2448.