INNOVARE JOURNAL OF AGRICULTURAL SCIENCE

Vol 12, Issue 4, 2024 ISSN - 2321-6832

Review Article

CRITICAL ANALYSIS OF INDIAN MONSOON RAINFALL FORECASTING

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Received: 12 April 2024, Revised and Accepted: 26 May 2024

ABSTRACT

Extensive study has been undertaken in recent years to comprehend climate changes and their potential impacts, aiming to mitigate natural disasters such as droughts, snowfall, floods, and more. This paper provides a comprehensive literature review focusing on the variability in rains during the Indian monsoon, employing statistical analysis, modeling, and forecasting techniques applied by various researchers over the years. The findings of this study reveal that the variability in Indian rainfall time series can be attributed to a range of tools and methodologies. This variability plays a key part in the development and prediction of future rainfall forecasting models. Notably, Data on historical rainfall time series have predominantly centered on broad regional scales in India and its subdivisions. To better serve the needs of farmers and bolster the Indian economy, there is an urgent need to develop new statistical models at smaller spatial and temporal scales. Throughout this review, it becomes clear that there exists an average monsoon rainfall level in India, which functions as a benchmark. Rainfall below this threshold is considered a poor monsoon, while rainfall exceeding it is regarded as a good monsoon. It is worth noting that a substantial 70% of the annual rainfall occurs in India during the monsoon season, encompassing the period from June to September. The average monsoon rainfall in India, calculated based on data spanning a century from 1901 to 2000, stands at 85 cm. Notably, specific years such as 2002, 2004, 2009, 2014, 2015, and 2016 have witnessed below-average rainfall. This comprehensive review serves as a wonderful resource for readers interested in learning more about the intricacies of monsoon rainfall variability in India and its potential modeling through appropriate methodologies.

Keywords: Review, Rainfall, Time Series, Modeling, Drought.

 DOI: http://dx.doi.org/10.22159/ijags.2024v12i4.50801. Journal homepage: https://innovareacademics.in/journals/index.php/ijags

INTRODUCTION

Agriculture and farmers are frequently referred to as the backbone of a nation, and their subsistence is mainly reliant on the monsoon season. India receives an annual rainfall of approximately 110 cm, making it one of the regions with the highest precipitation levels in the world. This rainfall is distributed unevenly throughout the year, with nearly 78% of it occurring during the southwest monsoon (SWM) season, typically from June to September. The remaining 11% is divided between the pre-monsoon (PRM) and post-monsoon or northeast monsoon (NEM), which mainly transpire from January to May and October to December, respectively. Given the significant variability in rainfall patterns, there is an urgent need to analyze historical data to simulate future conditions and develop mathematical models with forecasting capabilities. Atmospheric scientists and engineers continue to express keen interest in data analysis and modeling to better understand and predict these intricate patterns. This chapter intends to provide a high-level overview of the major research available in the existing literature, identifying areas for additional research warranted. While the review primarily focuses based on rainfall data from India, it also incorporates a few relevant cases from other regions. Models found in the literature can be broadly categorized into two main types: General circulation models and empirical models. General circulation models are rooted in the physics of atmospheric processes, often expressed as partial differential equations requiring extensive computational resources. These models utilize various parameters derived from available data on factors such as temperature, pressure, and wind patterns. In contrast, empirical models are primarily constructed based on observed data related to precipitation and other atmospheric variables. The emphasis of this paper is on empirical models. Empirical models, grounded in historical data, have gained prominence due to their practicality and ability to capture real-world rainfall patterns. These models are required for providing insights into monsoon behavior, enabling more accurate forecasting, and ultimately supporting the vital agricultural sector and the broader Indian economy. Future studies in this area should continue to refine and enhance empirical models to better serve the needs of farmers and decision-makers, ensuring sustainable agriculture and food security in India.

EXPLORING RANDOM VARIABLE MODELS: UNDERSTANDING AND APPLICATIONS

Empirical models in the realm of rainfall analysis can be classified into two main categories: Time-independent models and time-variable models. Both of these models are rooted in data analysis. Time-independent models disregard temporal variations, such as year-to-year fluctuations, treating all data points as independent samples. These are frequently called as random variable models, as they characterize rainfall across different time and spatial scales using probability density functions (PDFs). However, when it comes to accurately representing extreme occurrences such as droughts and floods, the Gaussian PDF may not be suitable. In contrast, time-variable models incorporate temporal variations in their analysis and simulation. These models, often addressed as random process models, utilize historical rainfall time series data to uncover internal correlations that can aid in forecasting exercises. The efficacy of a model in explaining past events is referred to as its descriptive ability. This metric assesses how well statistical models can capture random or extreme events. For instance, Parthasarathy and Mooley (1978) examined the statistical properties of Indian southwest monsoon (SWM) data from 1866 to 1970. Their analysis, using the Chi-square statistic, indicated that the data followed a normal distribution, albeit with a dominant 2–3-year cycle. However, since rainfall data is strictly positive, the normal distribution is not universally applicable, especially when dealing with values far from the mean. Continuing this research, Parthasarathy *et al.* (1992) analyzed Indian SWM rainfall data for the period 1871–1990. They found that decadal averages of Indian SWM rainfall were consistently below the long-term average for three decades. Reeves (1996) focused on modeling Indian monsoon rainfall using maximum likelihood estimation and various distributions. He concluded that the general extreme value distribution and Waybill distributions provided a better fit for the data in contrast to the normal distribution. Singh (1998) used a general power transformation to approximate a near-normal distribution for data from 50 different stations across India, facilitating the estimation of quintiles.

Parida (1999) attempted to model the random behavior of summer monsoon rainfall in India using a generalized four-parameter Kappa distribution, with parameters estimated through moment estimation. This strategy produced superior outcomes in predicting quintiles compared to previous work by Singh (1998). Dietz and Chatterjee (2014) proposed the use of a generalized linear mixed model, specifically the lognormal mixed model, to describe the underlying structure of Indian monsoon precipitation. They applied this model to light, moderate, and extreme rainfall events, estimating parameters using moment estimation.

EXPLORING STATISTICAL MODELS WITH PRECURSORS FOR MONSOON RAINFALL PREDICTION

Statistical models that incorporate precursors, based on historical rainfall data and statistical correlations among selected atmospheric variables, play a crucial role in long-range monsoon rainfall prediction. These models can be classified based on spatial scales (global, regional, subdivision) and temporal scales (annual, seasonal, monthly, and weekly). They rely on the idea that rainfall is linked to antecedent local and global parameters, and the statistical correlation between these parameters and rainfall is tested for significance to facilitate long-range forecasting. Blanford (1884) was one of the pioneers in suggesting the use of surface boundary conditions, such as snowfall over the Himalayas in the preceding winter, to predict summer monsoon rainfall in India. Walker (1923, 1924) developed a simple linear regression model based on statistical correlations between southwest monsoon (SWM) rainfall, May snow accumulation over the Himalayas, and South American atmospheric pressure parameters during spring. However, Jagannathan's comprehensive review in 1960 revealed varying correlations over decades, rendering these models inconsistent. Banerjee et al. (1978) introduced the mean latitudinal position of the subtropical ridge at 500 hPa in April over India as a predictor for monsoon rainfall. They developed a regression equation that incorporated this parameter along with others used by Walker. Several subsequent studies identified parameters such as the Southern Oscillation Index (SOI), mean meridional wind at various locations, April subtropical ridge position at 500 hPa along 75°E over India, and Darwin pressure tendency from winter to spring as strong predictors for Indian summer monsoon rainfall. These studies emphasized the importance of monitoring the El Niño and Southern Oscillation (ENSO) for long-range forecasting. Inspired by these findings, various linear and non-linear regression models utilizing multiple precursors were proposed. However, some of these models suffered from having more undetermined parameters than available data, leading to poor forecasts. Attempts were made to reduce the number of predictors through transformation, but challenges persisted. Rajeevan et al. (2000, 2001) and Thapliyal et al. (2003) introduced models with reduced parameters, which performed reasonably well for certain years. However, these models faced limitations, particularly during extreme monsoon years like 2002 and 2004, as highlighted by Guhathakurta (2006). Sahai et al. (2003) developed a model based solely on global sea surface temperature data for long-lead prediction of Indian monsoon rainfall, achieving significant performance efficiency. Nonetheless, this model also struggled to forecast droughts like those in 2002 and 2004, as noted by Gadgil et al. (2005). Gadgil et al. (2004) identified a strong relationship between Indian monsoon rainfall and the indices of ENSO and Equatorial Indian Ocean oscillation (EQUINOO), recommending the inclusion of EQUINOO as a predictor to enhance rainfall predictions.

Forecast accuracy has been significantly improved by recent developments of statistical models predicting rainfall in the monsoon. Rajeevan *et al.* (2005) introduced a two-stage forecasting system at the Indian Meteorological Department (IMD). The first stage, utilizing precursor predictor data up to March, and the second stage up to May with six predictors, aimed to enhance operational forecasting. Among the models tested, the artificial neural network (ANN) model demonstrated slightly better performance with an efficiency of 0.68 compared to other regression models with an efficiency of 0.65. These models proved capable of replicating drought years such as 2002 and 2004. In subsequent work by Rajeevan *et al.* (2007), new statistical models based on ensemble multiple linear regression and projection pursuit regression techniques were employed for generating seasonal forecasts of southwest monsoon (SWM) rainfall in India. These models exhibited high correlations ranging from 0.78 to 0.88 with SWM rainfall index predictions.

Guhathakurta (1998 and 1999) acknowledged the complexity of weather prediction in high-resolution geographical regions and noted the increasing interest in neural network techniques since 1986. Neural networks are known for their ability to handle complex non-linear problems effectively, outperforming conventional statistical techniques. Ashok et al. (2012) aimed to improve forecasting by combining stepwise linear regression and non-linear ANN techniques for a three-stage forecasting process (April, June, and July) of SWM rainfall. These models, trained from 1958 to 2000, achieved skill scores of 0.60, 0.65, and 0.62, respectively, during validation from 2001 to 2011. Joseph et al. (2013) highlighted the correlation between deficient monsoon rainfall in India and warm sea surface temperature anomalies in the tropical Indian Ocean, along with cold sea surface temperature anomalies in the western Pacific Ocean. They proposed incorporating these parameters into the precursors list for long-range forecasting. Wang et al. (2014) introduced new predictors, such as Central Pacific-ENSO and spring atmospheric conditions, for seasonal prediction of Indian monsoon rainfall. Their model achieved a retrospective forecast skill of 0.64 for 92 years and an independent forecast skill of 0.51 for 1921–2012, successfully capturing the rainfall patterns in 2013 and 2014. Gadgil et al. (2015) emphasized the strong influence of ENSO and EQUINOO on Indian SWM rainfall prediction, with July–September and August–September rainfall being particularly dependent on these indices. Kakade and Kulkarni (2016) employed clustering techniques and multiple regressions to identify coherent regions for various atmospheric parameters and their relation to SWM rainfall. Their approach achieved high skill scores of 0.75 to 0.8 and successfully replicated drought years such as 2002 and 2009. Moumita et al. (2017) proposed a deep neural network-based predictor identification method to improve regional monsoon prediction accuracy. They analyzed global climatic variables to identify new monsoon predictors and used ensemble regression tree models for prediction across different Indian regions.

Despite these advancements, selecting the right predictors remains a challenge due to the time-varying and non-Gaussian nature of atmospheric parameters, leading to evolving correlations with SWM rainfall over time.

RAINFALL-DRIVEN STATISTICAL MODELS FOR MONSOON PREDICTION

An alternative approach which does not involve additional climate parameters focuses on rainfall data as a time series with the sole aim of understanding and forecasting monsoon rains. In the last few years, there have been some attempts to analyze and model the timing series of rainfalls at different temporalities, such as each week, month, season, or year. Mooley and Parthasarathy (1984) conducted a detailed analysis of all India southwest monsoon (SWM) data spanning from 1871 to 1978. They identified 13 years with large-scale deficient rainfall and 9 years with excess rainfall during this 108-year period. In addition, they detected two cycles in the data, one with a 14-year period and the other with a 2.80-year period. Building on this work, Parthasarathy (1984) analyzed SWM rainfall time series for 29 subdivisions, each covering 108 years, to investigate inter-annual and long-term rainfall variability. Standard statistical tests confirmed the homogeneity and Gaussian distribution of data in all subdivisions. Some subdivisions exhibited a 14-year cycle, which was revealed through correlogram and spectrum analysis. Rupa Kumar *et al.* (1992) performed a comprehensive analysis of monthly rainfall data from 306 rain gauge stations across India for a period of 114 years (1871–1984). Their study focused on identifying long-term trends in both monthly and seasonal rainfall. The analysis revealed increasing trends in certain regions, such as north Andhra Pradesh and northwest India along the west coast, while other areas, including east Madhya Pradesh, northeast India, and parts of Gujarat and Kerala, exhibited decreasing trends. Kripalani *et al.* (2003) delved into the variability of Indian monsoon rainfall and its teleconnections on inter-annual and decadal time scales, utilizing a dataset spanning 130 years. Their findings indicated that inter-annual variability displayed random fluctuations, whereas decadal variability exhibited alternating epochs of above-normal and below-normal rainfall. These studies demonstrate the importance of analyzing rainfall time series data to uncover patterns and trends, which can contribute to a deeper understanding of monsoon variability and improve forecasting capabilities.

Analyzing and forecasting rainfall data at various time scales presents several challenges due to the often weak linear correlations between past and present data. Even at weekly time scales, the linear correlations tend to be small. Nonetheless, there are indications that there may be some connections from one time step to the next, particularly in time series data. Traditional linear time series models such as autoregressive (AR) and moving average (MA) models have been explored but often yield unsatisfactory results. These models rely on linear correlations between present data points and their past values, which may not adequately capture the complex dynamics of rainfall data. Autoregressive integrated moving average (ARIMA) models have also been applied to southwest monsoon (SWM) data for India and its regions. While they showed slightly improved forecast skill compared to multiple regression models, the autocorrelations in all India SWM data during the period 1871–2000 were statistically insignificant, highlighting the limitations of linear approaches.

Efforts have been made to transform non-Gaussian rainfall data into Gaussian processes using techniques such as log-normal transformations, power transformations, and alternate-year transformations. These transformations can make the data more amenable to modeling, but they require the determination of joint probability density functions, which can be complex. Nonetheless, non-linear models like artificial neural networks (ANNs) have emerged as valuable tools for modeling rainfall time series data. ANNs are capable of handling unstructured data and capturing complex relationships. Guhathakurta (1999) developed a hybrid principle component neural network model for long-range forecasting of Indian SWM data. This model demonstrated a skill of 0.76 and outperformed other ANN-based models. Sahai *et al*. (2000) proposed ANN techniques for monsoon rainfall forecasting using only past data. They considered spatial averages of monsoon months (June to September) and their sum as time series data for the period 1871–1960. Five antecedent values for each of the five-time series were used to train a multilayer ANN to model and predict the subsequent year's rainfall components. While the modeling efficiency was high (0.8), it is worth noting that the large number of model parameters (276) was due to the relatively small effective sample size (335) and the high dimensionality of the input data. These studies demonstrate the potential of non-linear models like ANNs to capture the complex dynamics of rainfall time series data and improve forecasting accuracy, even when linear correlations are weak or statistically insignificant.

Iyengar and Raghukanth (2003) made an innovative attempt to develop a non-linear time series model for Indian monsoon rainfall in three stages. In the first stage, they considered the climatic mean behavior, while in the second and third stages, they incorporated important connections from previous years and periodic modulating terms into the model. Collectively, these stages allowed the model to explain 50% of the inter-annual variability. The model's year-to-year forecasts were validated against observed data for an independent dataset. A novel approach to studying southwest monsoon (SWM) rainfall was introduced by Iyengar and Raghukanth (2004). They decomposed the SWM data series into a finite number of uncorrelated components called intrinsic mode functions (IMFs). Their analysis revealed that the SWM data for the period 1901–2000 could be split into a strongly non-Gaussian short-period component and a nearly Gaussian long-period component. The non-Gaussian component was modeled using artificial neural network (ANN) methods, while the Gaussian part was modeled as a linear five-step autoregression. This approach resulted in a relatively low number of unknown parameters (42) for a sample size of 100. The modeling efficiency for the non-Gaussian component through ANN was 0.84, and the overall variance explained by the model was as high as 0.83. However, one limitation of the empirical mode decomposition (EMD) approach, as mentioned, is its sensitivity to endpoint approximations, particularly when used for forecasting. Guhathakurta (2008) proposed an ANN model for each of the 36 divisions of India, which included 11–12 antecedent rainfall values in the input layer with three neurons in the hidden layer and an output. This model had 40–43 parameters, which was more than half the length of the sample size of 51 used in the training period (1941–1991). The modeling efficiency during the training period for the all-India time series was 0.7, and for the subdivisions, it was 0.8. Another example of an ANN model was presented by Pritpal and Bhogeswar (2013) for all-India rainfall data. They proposed five different three-layered ANN architectures with varying numbers of parameters. The efficiency of this ensemble model throughout the training phase of 84 years was found to be 0.65. It is worth noting that some of the ANN approaches discussed may not be skillful, as increasing the number of parameters to match the sample size can result in a polynomial function that fits the data exactly. Recently, a new ANN model was developed by Kokila and Iyengar (2017) that considered all seasons' variability to forecast the 2017 monsoon rainfall for all of India and its broad regions while optimizing the number of parameters. This approach likely aimed to strike a balance between modeling complexity and forecasting accuracy.

DISCUSSION

The review you provided emphasizes the two main categories of models used for rainfall data analysis, which are random variable models and random process model.

Random Variable Models (Univariate Models)

The distribution of rainfall data is characterized by these models, and they are appropriate for understanding the statistical properties of the data. Constructing joint probabilities for prediction is a complex task, making them less effective for forecasting.

Random Process Models (Linear and Non-linear Models)

Random process models include both linear and non-linear approaches, making them more versatile for analyzing, and forecasting rainfall data. Linear time series models, which rely on linear correlations between past and present data, tend to be inefficient for forecasting in the case of rainfall data due to weak linear correlations. Statistical models with precursors, which use various climate parameters as predictors, offer some promise for long-range forecasting. However, the selection of precursors can vary from year to year, which is a significant limitation. Artificial neural network (ANN) techniques have shown promise for modeling non-Gaussian rainfall data. ANN models can capture complex, non-linear relationships in the data, making them suitable for forecasting. While ANN techniques offer promise, they also have their challenges and limitations. The selection of ANN architecture is subjective, and there is no one-size-fits-all solution. Many existing ANN models have a high number of parameters relative to the sample size, which can lead to overfitting. Most models assume stationary, which means that identical values for the model parameters are used throughout the forecasting period. This assumption may not hold in practice, as rainfall patterns can change over time. Overall, capturing the non-linearity present in rainfall data is crucial for accurate modeling and forecasting.

CONCLUSION

The limitations you have identified in the existing methods for modeling and forecasting rainfall data are important considerations in advancing the area of hydroclimatology and improving the accuracy of rainfall predictions. Here's a summary of these limitations:

Random Variable Models and Stationary

Random variable models typically provide basic statistics such as mean and standard deviation over long time periods, assuming that the random variable is stationary. However, rainfall data are frequently not constant, which means its statistical properties change over time. Research continues to focus on the issue of scarcity, as well as how these models can best be used for short-term and long-term forecasts.

Empirical Models and Precursor Selection

Empirical models often establish statistical relationships between rainfall and various atmospheric and oceanic parameters. The importance of these parameters may change over time, making it challenging to select fixed precursors for forecasting. There is a need for dynamic precursor selection methods that adapt to changing climate patterns.

Modeling with Only Past Data

Much of the literature focuses on using external parameters alongside rainfall data. However, there is limited work on modeling rainfall using only past rainfall data. Developing models that rely solely on historical rainfall data could be valuable, especially for practical applications like agriculture.

Overfitting in Neural Network Models

Many neural network models in the literature employ a high number of parameters relative to the data length, which can lead to overfitting. Overfit models may produce high correlations and spurious performance metrics, making it crucial to minimize the quantity of variables to improve model reliability.

Shorter Time Scale Models

Most existing neural network models focus on longer time scales, such as annual or seasonal forecasting. There is a need for more sophisticated neural network models tailored to shorter time scales, like monthly or seasonal predictions, that rely solely on past data relationships.

Addressing these limitations will likely require innovative approaches, including improved model selection techniques, more robust methods for handling non-stationarity, and the development of models that can capture both short-term and long-term rainfall patterns effectively. Advances in data science, machine learning, and climate modeling will be valuable in overcoming these challenges and enhancing our ability to predict rainfall accurately.

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