Automatika

Journal for Control, Measurement, Electronics, Computing and Communications

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/taut20

Analysis of shift in Indian monsoon and prediction of accumulated cyclone energy in Indian subcontinent using deep learning

S. Manoj & C. Valliyammai

To cite this article: S. Manoj & C. Valliyammai (2023) Analysis of shift in Indian monsoon and prediction of accumulated cyclone energy in Indian subcontinent using deep learning, Automatika, 64:4, 1116-1127, DOI: 10.1080/00051144.2023.2250640

To link to this article: https://doi.org/10.1080/00051144.2023.2250640

Published online: 26 Aug 2023.

AUTOMATIKA
2023, VOL. 64, NO. 4, 1116–1127
https://doi.org/10.1080/00051144.2023.2250640

Analysis of shift in Indian monsoon and prediction of accumulated cyclone energy in Indian subcontinent using deep learning

S. Manoj[a] and C. Valliyammai[b]

[a]Dept. of CSE, Vel Tech Rangarajan Dr Sagunthala R & D Institute of Science and Technology, Chennai, India; [b]Department of Computer Technology, MIT Campus, Anna University, Chennai, India

ABSTRACT
Every year India faces many cyclones and erratic monsoon seasons are common in recent times. Cyclones destroy the infrastructure and lead to loss of life and damage property in coastal areas. The agriculture sector is also affected by random and unexpected rainfall. In recent years, India gets rainfall during the harvest season which leads to financial loss. Also, the number of drought events is on the rise in the Indian subcontinent as the rainwater is not managed properly. Farmers need to know whether the monsoon rainfall pattern has been shifted or not and need to shift their agricultural activity accordingly to handle the impacts of climate change. From the rainfall and accumulated cyclone energy (ACE) data analysis, it is found that monsoon seasons in India are not shifted, but, rainfall is intense during the initial months of each monsoon season. ACE values are predicted using techniques such as ARIMA, LSTM, Prophet, and stacked ensemble with multi-layer perceptron. Based on the experimental results, the proposed stacked ensemble model achieves 91% accuracy.

ARTICLE HISTORY
Received 3 June 2023
Accepted 16 August 2023

KEYWORDS
ARIMA; prophet; LSTM; rainfall shift analysis; accumulated cyclone energy; ensemble

1. Introduction

Indian agriculture depends on rainfall from two monsoon seasons namely South West Monsoon (SWM) which is occurring in the summer months namely June, July, August, and September (JJAS). The North East Monsoon (NEM) is occurring in the winter months namely October, November, and December. During NEM, low-pressure systems, depressions, and cyclones cause the associated rainfall in India. In the recent past, India faced erratic monsoon seasons, unexpected city floods, and coastal flooding. The agricultural industry is impacted by irregular rainfall, and in particular, if heavy rainfall occurs during the harvest season, it results in a loss of production. Even worse, it causes a food crisis and financial loss. For example, southern states in India saw significant rain in January 2021, and as a result, thousands of acres of land that were ready for harvest were drowned in water. For the past 100 years, January month has never seen such amount of rainfall in Tamil Nadu state as in the year 2021. Additionally, many coastal cities in India had experienced unprecedented flood conditions in the past ten years. For instance, Chennai city, in the Tamil Nadu state of India, experienced a city flood in the year 2015. Floods had affected the Maharashtra state in India. Kerala state in India experienced very heavy rainfall in the year 2018, which caused landslides, property damage, and loss of life. Drought is defined as a moisture deficit state relative to the average water availability at a given location and season. The number of drought events is surging and heatwave events are also increasing. There is a need to find out if major rainfall seasons in India have gone through any changes in the recent past due to global warming and climate change. If such changes are real, it has to be communicated to the people and in particular to the agriculture sector so as to plan accordingly. For example, if SWM or NWM is delayed by one month, then, all agricultural activities during SWM or NWM season have to be delayed by one month. Otherwise, the farmers will face a loss of production during the respective harvest season. Hence, there arises a need to analyze the rainfall and cyclone-related events in the Indian region. The paper is organized as follows: Section 2 comprises of literature survey. Section 3 includes an analysis of Indian rainfall and the prediction of ACE using various algorithms. Section 4 describes the results obtained. Section 5 explains the conclusion and future enhancements.

2. Literature survey

Extreme weather, including erratic rainfall and unexpected drought, is affecting almost all countries. And all over the world, daily temperature is on the rise [1]. The Sherma Formula for calculating yearly rainfall was established after taking into account the annual

CONTACT C Valliyammai cva@mitindia.edu Department of Computer Technology, MIT Campus, Anna University, Chennai, India

rainfall data of China, Korea, and the Philippines. Sharma Formula is more accurate at predicting short-duration rainfall [2]. It is discovered that Kerala's rainfall had fluctuated throughout the seasons, which has a significant impact on the output of rubber in 14 districts of Kerala state. In SWM and NEM, the pattern of daily, weekly, and monthly rainfall had increased [3].

Sea Surface Temperature (SST) variations influence the heat budget of the atmosphere-ocean system, leading to changes in atmospheric circulation patterns. Warmer SSTs over the Indian Ocean and the Arabian Sea (AS) provide a source of moisture, leading to increased evaporation. The moisture-laden air mass interacts with prevailing winds and triggers convection, contributing to the monsoon rainfall. The strength of the coastal upwelling was significantly impacted, according to the analysis of El Nino southern oscillation (ENSO) and Indian Ocean Dipole (IOD) events' effects on the south of Java islands. Partial correlation results showed that IOD had a bigger impact than ENSO. Between June and November, the impact of coastal upwelling was stronger. The outcomes were provided by the upwelling index anomaly [4]. An extreme rainfall that affected Guangzhou in China was analyzed using integrated multiplatform observations and a four-dimensional variation [5]. A cutting-edge flood forecasting model was developed and machine learning techniques, such as decision trees, Random Forest (RF), Naive Bayes, MLP, Support Vector Machine (SVM), and fuzzy logic were used for the prediction. Flood events were accurately predicted, and the top three Machine learning (ML) algorithms were documented [6]. It was evident that neural network techniques outperformed downscaling in experiments employing the techniques such as statistical downscaling, learning vector quantization, and backpropagation in terms of accuracy and 9-month lead time in predicting the Pakistan's monsoon rainfall. For training, data from 1960 to 2004 and for testing, data from years 2005 to 2009 were used [7]. Recurrent Neural Network (RNN) can detect non-linearity that exists in the data. RNN was used to predict the Indian rainfall at the start of a season that utilized the data from 1948 to 2015 for the months of JJAS. RNN-based model forecasted the Indian summer monsoon with low Mean Absolute Error (MAE) with a three-month lead using the ideal model parameters. Indian Meteorological Department (IMD) ensemble model used ensemble multiple linear regression as a prediction model which used the North-East Pacific Ocean to North-West Atlantic Ocean SST gradient, South-East Equatorial Indian Ocean SST, East Asia Sea Level Pressure (SLP), Central Pacific Ocean SST, and North Atlantic Ocean SLP [8]. Anthropogenic heat and moisture from all sources had a major impact on cloud microphysics. The first case examined how heat affected local weather without considering moisture, and the second case examined how heat and moisture affected local weather. It was found that close to the industrial location where much heat was released, the rate at which water and vapor mixed was increasing [9]. Levenberg Marquardt and MLP algorithms were applied and precipitation over the Tawau region had been calculated. It was reported that the Outgoing Longwave Radiation reaches its maximum value on clear sunny days in the middle of July. The Artificial Neural Network (ANN) method was the most accurate for estimating precipitation and the accuracy improved when Adaptive Neuro Fuzzy Inference System was employed [10].

Auto Regressive Integrated Moving Average (ARIMA) models are a class of time series models used for forecasting and analyzing time-dependent data. Autoregressive (AR), differencing (I), and moving average (MA) components are combined to capture the underlying patterns and dynamics in the data. Seasonal ARIMA models (SARIMA) extend the basic ARIMA model to handle seasonal patterns in the data. By incorporating seasonal differencing and seasonal autoregressive and moving average terms, SARIMA can effectively capture and forecast seasonal variations. The ARIMA model is one of the popular techniques for analyzing time series data (TSD) [11]. Neural networks aim to simulate how the human brain makes decisions. Neurons are the fundamental units in the brain and similarly in neural networks, nodes with computing facilities are the fundamental units. In neural networks, the following layers exist: the input layer, which receives the input followed by hidden layers with computation capability. These layers are well connected. Finally, there is the output layer that displays the output. Long Short-Term Memory (LSTM) is a variation of RNN that can remember key information for a long time due to the usage of memory cells in the hidden layer and it gives more weightage to important features in data and assigns low weights to non-important features and hence useful for TSD [12]. LSTM gives more weightage to important features in data and assigns low weights to non-important features and hence useful for TSD.

Prophet is an open-source library for time series forecasting that employs an additive model, combining multiple seasonal components such as yearly, weekly, and daily patterns, along with user-provided holidays and custom seasonality. It gracefully handles missing data and outliers and can also automatically detect change points, identifying shifts in the time series. The prophet is suitable for detecting the trends and seasons hidden in the data [13]. A Multi-Layer Perceptron (MLP) is a type of ANN that consists of multiple layers of interconnected neurons. It is a feedforward neural network, meaning that information flows in one direction, from the input layer to the output layer, without any cycles. MLP is a feed-forward neural network that is well-suited for predicting climate-related time series data [14]. LSTM, SARIMA, and Prophet were used to predict monthly rainfall in the Jakarta region. Prophet displayed low MAE and Root Mean Square Error (RMSE) [15]. A sustainable marine environment was developed which was used for a multilayer LSTM for weather forecasting. It was observed that MLP-based high-speed model combined with LSTM was better at time series prediction [16]. Rainfall data from the year 1951 to 2007 were used and it was found that the frequency of monsoon rainfall gaps during July and August months significantly increases in recent decades. It was also reported that moisture convergence over the eastern Indian Ocean had intensified due to SST warming trends [17]. It was reported that the Bharathapuzha river basin in Kerala experienced many droughts in the past. The temperature and precipitation from Bharathapuzha, from 1971 to 2005 were analyzed. Standard precipitation index and modified evapotranspiration index were used for the analysis [18]. A new kind of probability-based mean square error was applied, and the best fit was obtained for precipitation data. It was reported that heavy-tailed distributions dominate over light-tailed Gamma and Weibull distributions. An increase in extreme precipitation was also reported [19]. One of India's arid regions is Vidarbha and Marathwada region. Data from the years 1871–2016 were used. Sen's slope test, Mann-Kendall test, and innovative trend analysis were performed. The Marathwada and Vidarbha regions had a negative trend in annual rainfall, while the central Maharashtra region revealed an overall increasing trend in rainfall [20]. The Coupled Model Inter comparison Project phase 6 model simulation used mean temperature and precipitation data in Thailand, Myanmar, Vietnam, and Laos. It is found that the temperature over northern Vietnam, Laos, and Myanmar increases drastically [21]. An analysis of how the Chenab River basin's hydrological system was impacted by rainfall, snow, and water from ice melt was done and it was found that while the overall rainfall will decrease over the course of the current century, temperature will increase. It is also found that increased discharge of water as a result of higher temperature has an impact on the basin's ecosystem [22]. Fifty years of climatic data and wheat crop production data from year 1966–2015 were analyzed and it was found that the seasonal temperature had risen significantly in 29 Indian states, which impacted wheat production among 21 states. It was shown that temperature in the month of February had a significant effect on wheat yield in the majority of Indian states [23].

Three models, namely CNTL, Global Telecommunication System, and the INSAT3DR were compared with respect to the route of cyclone Titli. INSAT-3D/3DR radiance data provided more accurate weather predictions with low mean track error [24]. When the four-dimensional data over India was used to test the weather research and forecasting model's predictive ability, it performed better. If the model was initialized with 4DVar data, satellite radiance, and satellite-derived winds, then it captured the features of all the cyclones and performed better with low error compared to 3DVar data [25]. The prediction of cyclogenesis using the ocean wind vectors generated from the sea-winds scatterometer was described. The probability of detection was high, as 26 out of 28 low-pressure systems that developed in the past were identified successfully [26]. An analysis of ocean aerosol variability before the occurrence of supercyclones, namely GONU and SIDR, was performed and it was found that aerosol low existed in cyclone formation areas roughly two weeks before the actual cyclonic event. The strong vertical and horizontal wind fields were reported as the reasons for the formation of the aerosol low [27]. The trends of tropical cyclones (TC) were analyzed using the velocity flux, ACE, and power dissipation index. Based on data from 1990 to 2013, the inter-seasonal and inter-annual variations of the above three parameters for AS, Bay of Bengal (BOB), and North Indian Ocean (NIO) were examined. IOD and ENSO effects were also considered and shown that the impacts over BOB during the post-monsoon season (October to December) of El Nino years were lower than in La Nina and normal years [28].

RMSE is a measure of prediction errors which is used in numerical prediction and it is defined as:

$$RMSE = \sqrt[2]{\Sigma((\mathrm{Ei} - \mathrm{Ai})^2)/\ \mathrm{n}} \tag{1}$$

where n is the sample size, Σ denotes a summation symbol, E_i is the expected value for the i^{th} observation in the dataset, A_i is the actual value for the i^{th} observation in the dataset. Mean absolute error (MAE) is derived by dividing the sum of absolute errors by number of observations and it is defined as:

$$\mathrm{MAE} = ([\Sigma\ |X_i - Y_i|])\ /\ \mathrm{n} \tag{2}$$

where X_i is the i^{th} predicted value, Y_i is the i^{th} actual data, $|X_i - Y_i|$ is the absolute error and n is the number of observations.

3. Proposed ACE prediction system

The coastal region is more affected by TC that originate in the AS, BOB, and NIO. The disaster management teams will get beneficial if government organizations provide accurate forecasts of the path, location, severity, and amount of heavy rainfall that TC would deliver. In this research, the ACE of several cyclones that crossed the Indian region is analyzed. The components of the proposed model are illustrated in Figure 1. IMD had published ACE values for three seasons namely pre-monsoon, annual and post-monsoon seasons in all three coastal regions of India, namely BOB,

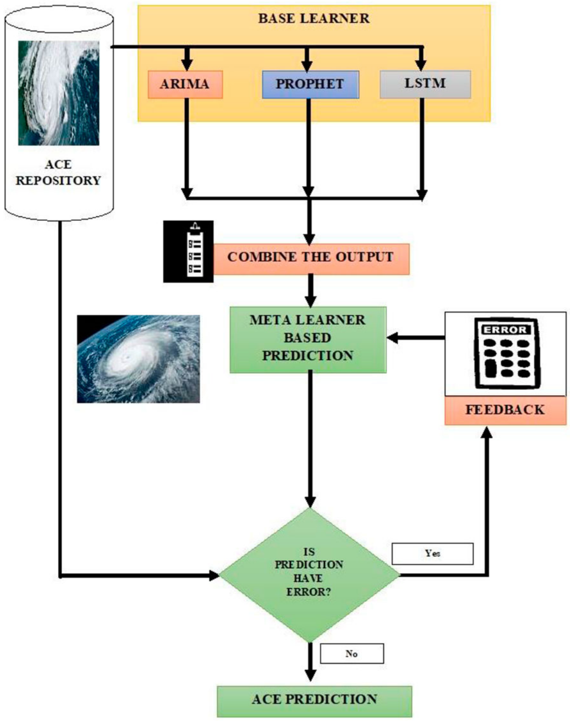

Figure 1. Workflow of the proposed ACE prediction model.

AS, and NIO [29] which are fed into the proposed system. ACE data is given to ARIMA, Prophet, and LSTM models. Similarly, ACE data for AS, BOB, and NIO is used as input for the proposed Stacked Ensemble Model (SEM) to predict the ACE values. The rainfall data from the year 1901 to 2011 was obtained from [30].

An ensemble refers to a technique where multiple models are combined to make predictions or decisions. The idea behind ensembles is that combining the predictions or decisions of multiple models can often result in better performance than any individual model on its own. The ensemble is particularly effective in reducing the impact of bias or overfitting, capturing different aspects of the data. Some popular ensemble methods include bagging, boosting, random forests, and stacking. An ensemble-based rainfall prediction system has been developed that included K-Nearest Neighbor (KNN), support vector classifier, decision tree classifier, binary logistic regression, and stacked generalization [31]. Linear regression, random forest, logistic regression, extreme gradient boosting, and support vector regression are used as base models. As a second-layer learner, the weighting algorithm combines the results from the base models to make predictions [32].

4. Results and discussion

The various packages in Python including tsa, fbpro phet, sci-kit learn, tensor flow, and keras packages are used for implementation. A stacked ensemble model (SEM) is constructed that uses ARIMA, Prophet, and LSTM as base learners and MLP as meta learners. The k-fold cross validation is used. The overall accuracy is

Table 1. Accumulated monthly rainfall over India during the year 1901–2011.

Month	Overall Rainfall %	Month	Overall Rainfall %
July	24.51	April	3.05
August	20.5	November	2.81
June	16.26	March	1.93
September	13.94	February	1.54
October	6.74	January	1.34
May	6.05	December	1.33

improved while using the ensemble approach. India has different mean rainfall rates and each state in India has different mean rainfall rates. Rainfall shift analysis is done for Tamil Nadu state level as well as India level.

4.1. SWM season – mean rainfall trend for Tamil Nadu using the last 30-year data

Figure 2 illustrates that, in Tamil Nadu, during the SWM season, September month has recorded more rainfall than all other months, which contrasts with the overall Indian rainfall trend, where July month has more rainfall during the season. In Tamil Nadu, during the SVM season June and July month has a higher coefficient of variation (CV) for a few districts which is shown in Figure 3.

4.2. Indian monsoon rainfall analysis

It is clear that July month receives the highest rainfall during the entire SWM season accounting for approximately 25% of total rainfall in past seasons as shown in Figure 4. The analysis shows that the rainfall is decreasing in all months of the SWM season except August, with respect to the last few decades.

Figure 5 depicts more rainfall during the NEM season. Approximately 7% of total rainfall occurred in that month. It is clear that July month has the highest rainfall and December month has the lowest rainfall in a given rainfall season as tabulated in Table 1. The two monsoon seasons of India, namely NEM and SWM are analyzed and the following observations are made.

4.2.1. Intense period of monsoon season in India

During SWM and NEM, the initial months of the respective season have seen more rainfall. The information is useful for farmers to plan their agricultural activity. It is found that there are no major changes in the beginning and end of the SWM as well as the NEM monsoon rainfall season in India. But in a few years, the season-ending time has been extended by a few weeks. Based on the analysis, it is clear that the rainfall season has not been shifted.

4.2.2. Intense period of the monsoon season in Tamil Nadu state, India

NEM brings more rainfall than SWM to Tamil Nadu state and it is found that the mean rainfall in the last

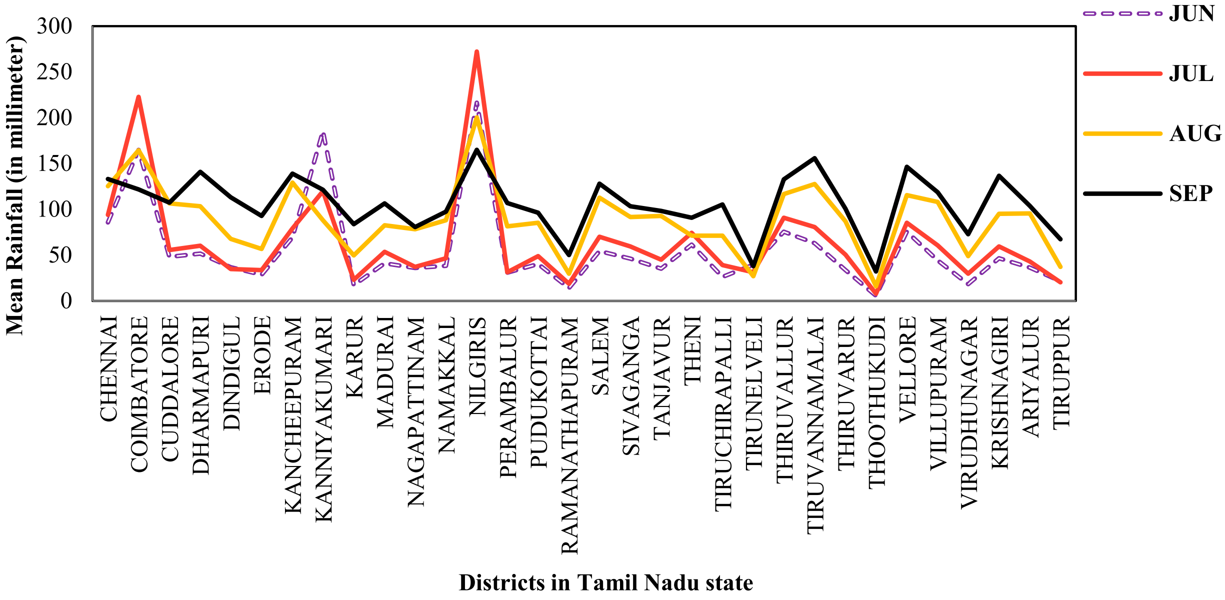

Figure 2. SWM mean rainfall analysis for Tamil Nadu using data during the year 1970–2000.

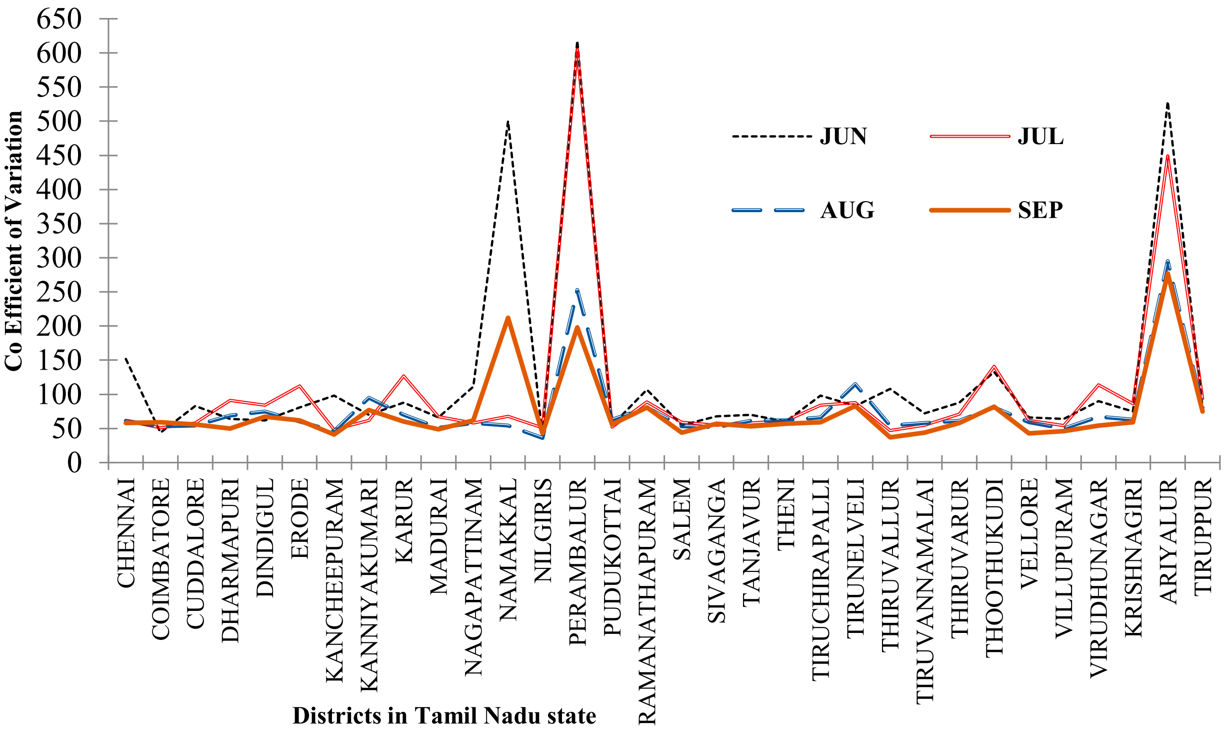

Figure 3. Co-efficient of Variation analysis using data during the year 1970–2000 for SWM data for Tamil Nadu state in India.

30 years is higher in August and September months than in other months. It is to be noted that, the August and September months mark the harvest season for a few crops including rice, in Tamil Nadu, and in some other districts, agricultural activities are started during these months [33]. Also, October month also receives more rain due to the NEM season. That is, with respect to Tamil Nadu state, August, September, and October have heavy rainfall in a given calendar year. The above information is useful for Tamil Nadu state farmers because the agricultural production will be submerged in water due to excessive rainfall in August, September, and October months. So, the farmers need to plan accordingly to avoid a loss in production.

4.3. Drought events trend over India

Drought events are on the rise in the Indian subcontinent even though more than average rainfall recorded in a few years. The rainwater harvesting and proper usage of available water are the need of the hour to handle drought-like situation. In the last sixty years, that

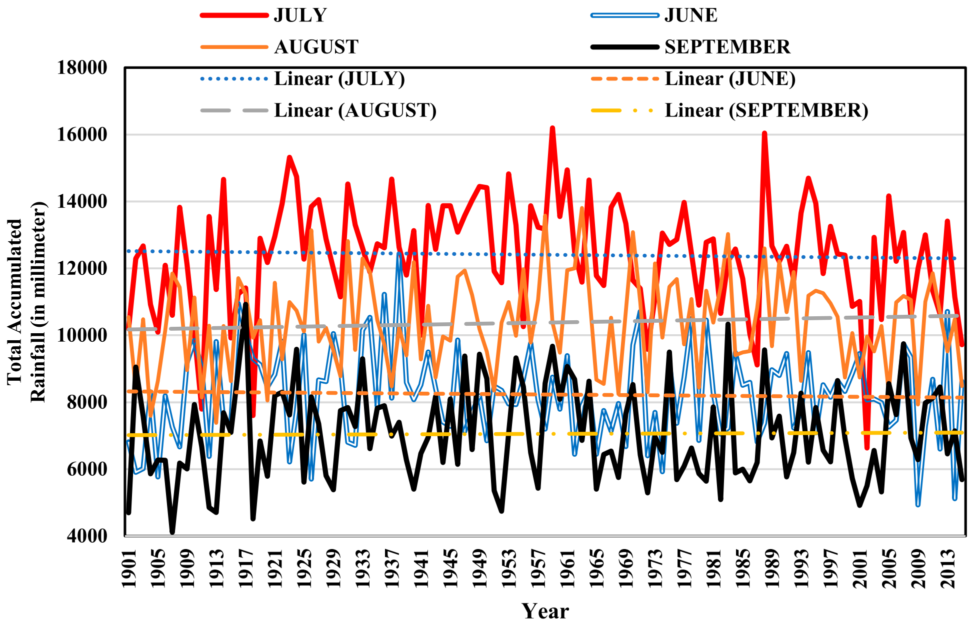

Figure 4. Total accumulated rainfall during 1901–2013 for Indian SWM rainfall.

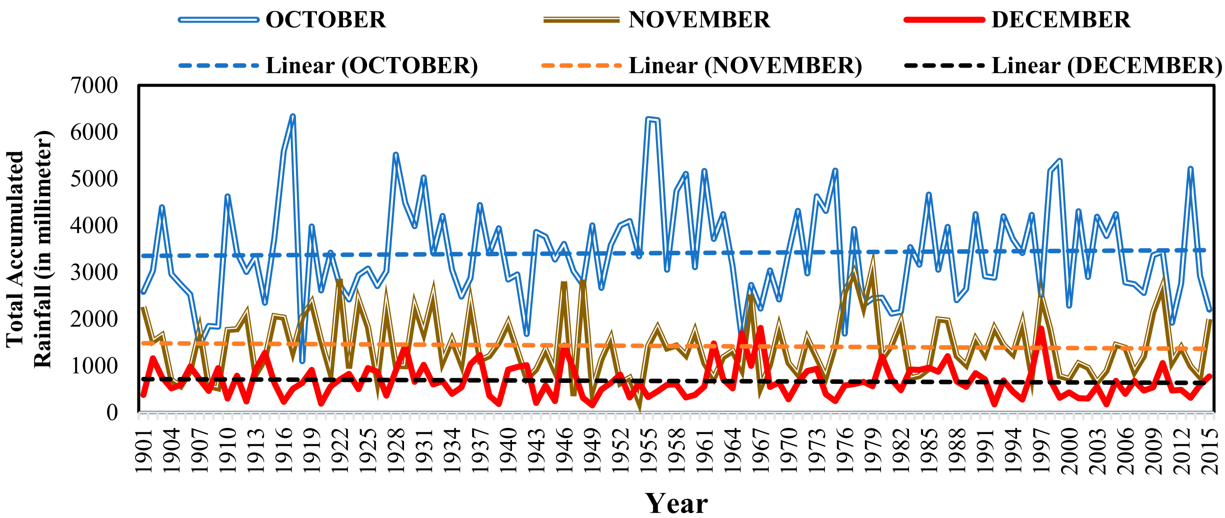

Figure 5. Indian NEM rainfall analysis for total accumulated rainfall during 1901–2015.

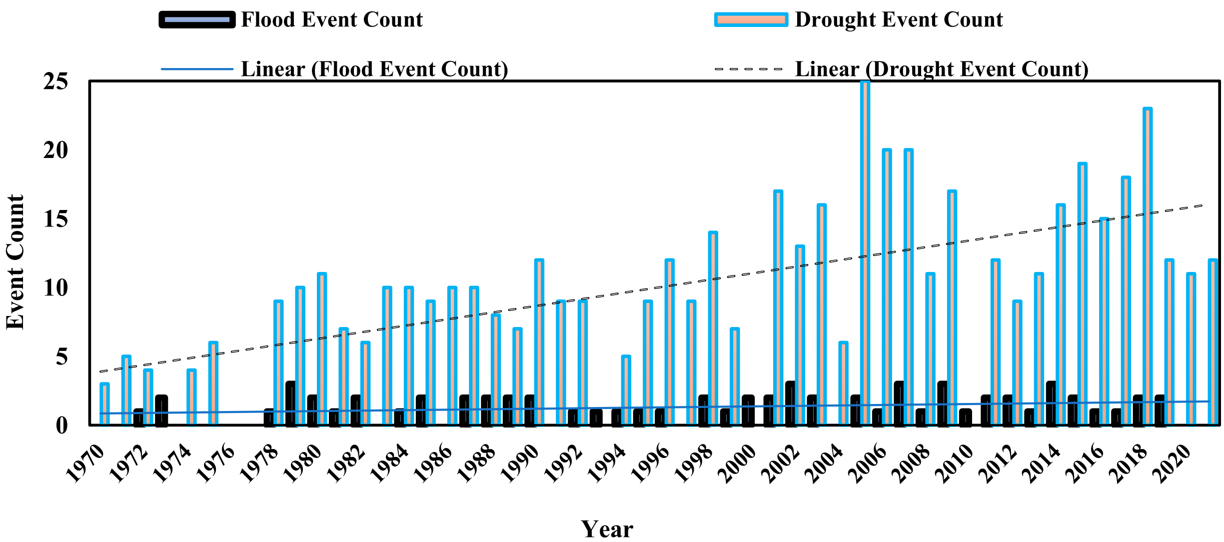

Figure 6. Number of flood and drought events in India from the year 1970–2020.

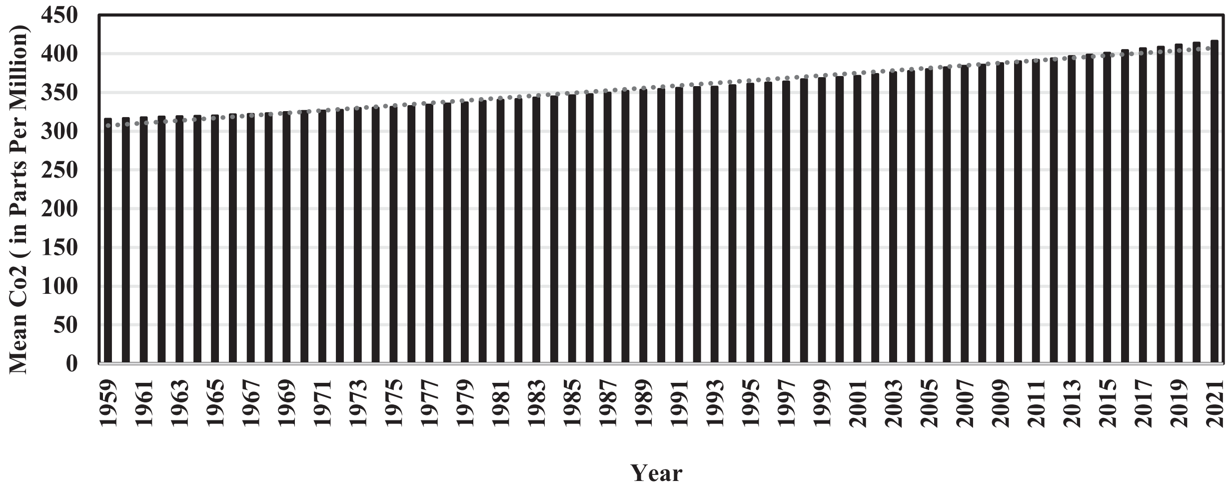

Figure 7. Mean CO_2 in atmosphere (also known as Keeling curve).

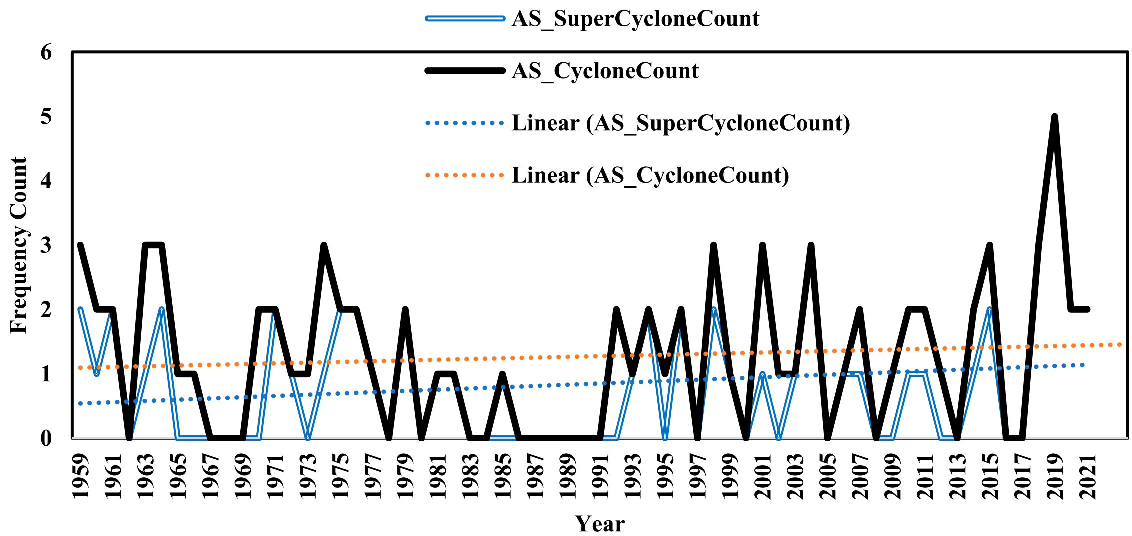

Figure 8. Analysis of cyclone and severe cyclones frequency count in AS.

is from the year 1970 to 2020, more drought events have occurred than flood events in India as shown in Figure 6.

4.4. Relationship between green house gases (GHG) and the increased number of cyclones in India

It is obvious that CO_2 content is clearly increasing in the atmosphere as shown in Figure 7. Other GHG like N_2O, and CH_4 are also increasing every year [34]. It is found that there is a positive correlation between the amount of GHG in the atmosphere and the increase in the frequency of cyclones in India.

The number of cyclones and severe cyclones is on the rise in AS region, as it is evident from Figure 8. The number of cyclones formed in the BOB region is decreasing, but it is increasing in AS region during recent years, particularly from the year 1991, as shown in Figure 9. The linear trend lines are also confirming the same. A similar trend continues in the case of severe cyclones in the respective regions, as illustrated in Figure 10. The linear trend lines are also confirming the same. Figure 11 shows that, in recent decades, the number of cyclogenesis events in AS is increasing but it is decreasing in the BOB region, particularly from the year 2009. The BOB region got more cyclogenesis, as shown in Table 2 when the frequency count is considered.

Table 2. Count of cyclone and severe cyclone hazards in India during 1891 – 2021.

Event	Count of events in Bay of Bengal (BOB)	Count of events in Arabian Sea (AS)
Cyclone	526	136
Severe Cyclone	237	084

4.5. ACE prediction using ARIMA, prophet, LSTM and ensemble

It is observed that in recent years, during the pre-monsoon season, very high-energy cyclones crossed the Indian landmass as shown in Figure 12. The linear trend line shows that it may continue to increase in

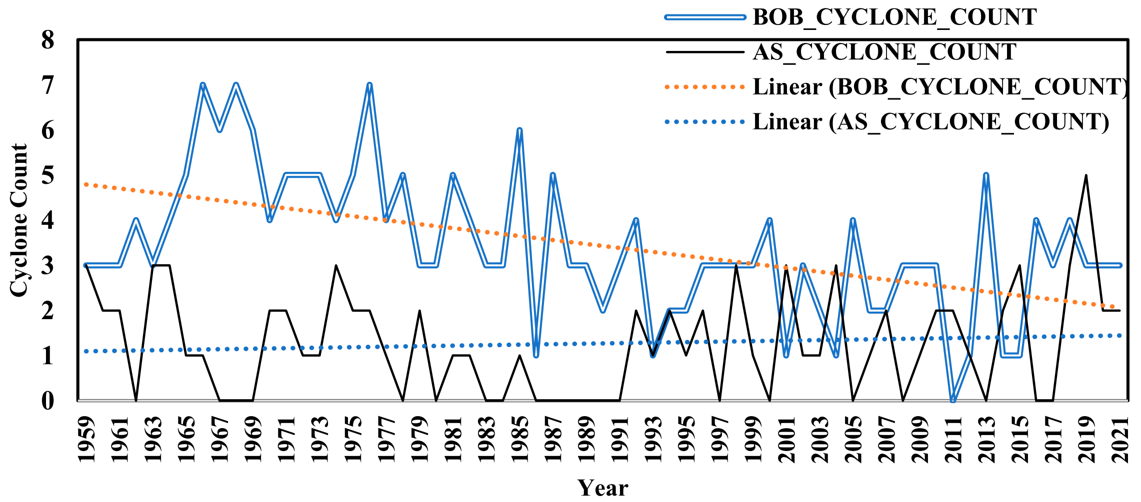

Figure 9. Analysis of cyclone frequency count in BOB and AS.

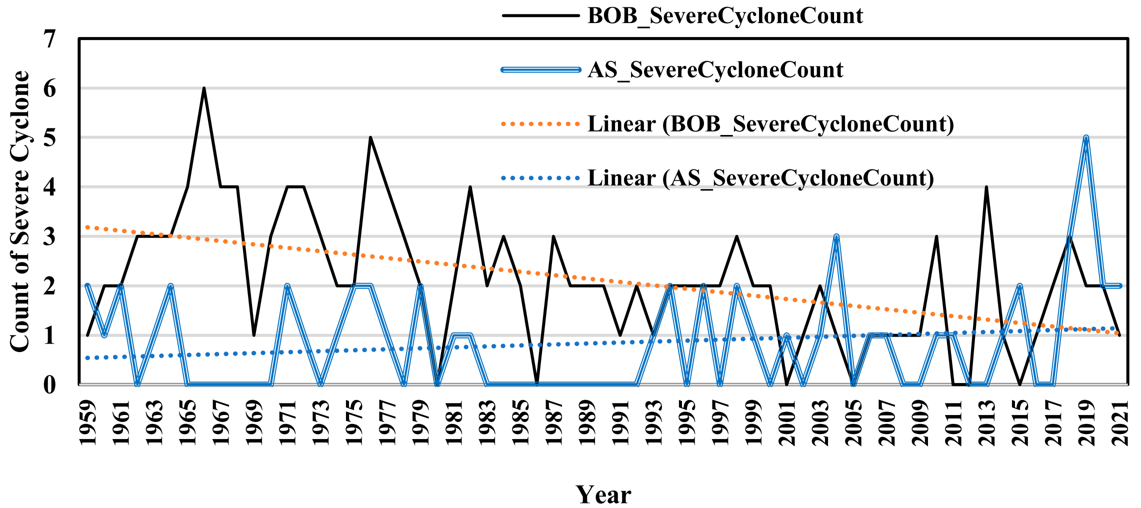

Figure 10. Analysis of severe cyclone frequency count in BOB and AS.

the near future for all three coastal areas of India. The number of cyclones and severe cyclones that crossed the Indian region during the year 1891–2021 has been listed in Table 2 and it is evident that the BOB region had seen more cyclones and supercyclones but as per the recent year data, it is getting decreased. Figure 13 illustrates that, during the post-monsoon season, very high-energy cyclones occurred in the recent past, particularly from the year 2012. As per the trend line, in the NIO region, ACE may decrease while in other regions,

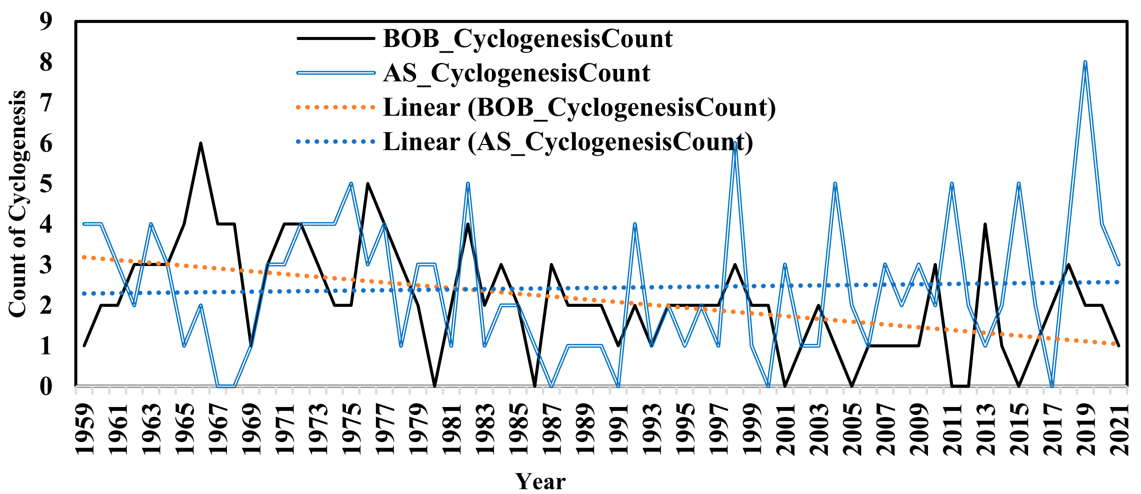

Figure 11. Analysis of cyclogenesis frequency count in BOB and AS.

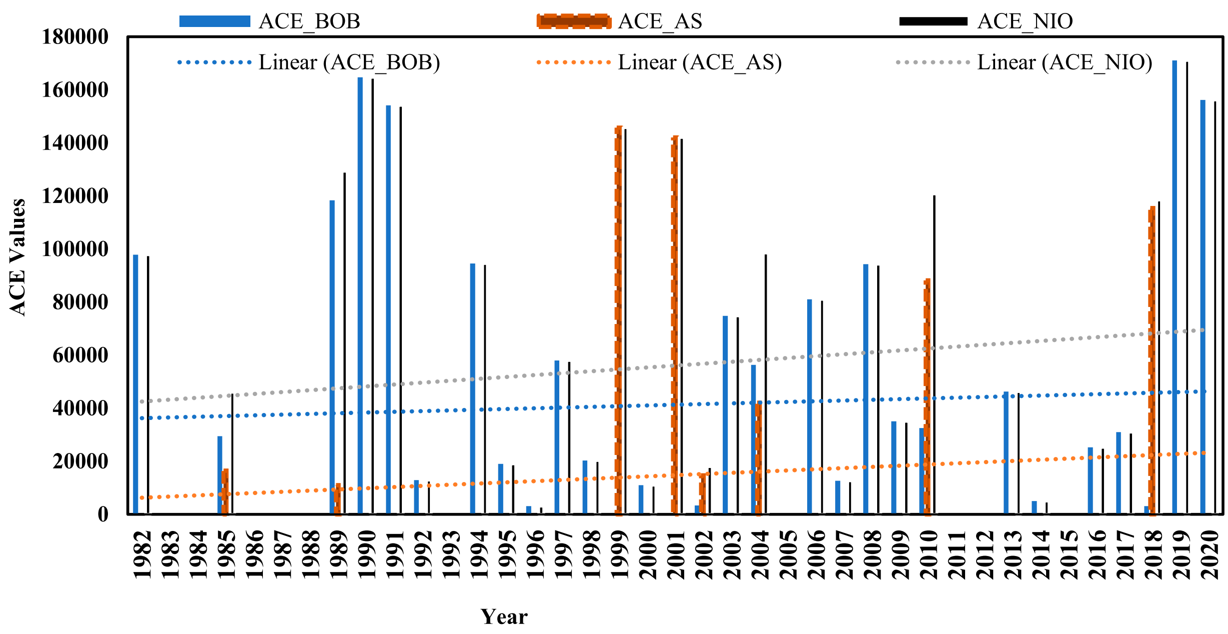

Figure 12. ACE trend over BOB, AS and NIO during pre-monsoon season.

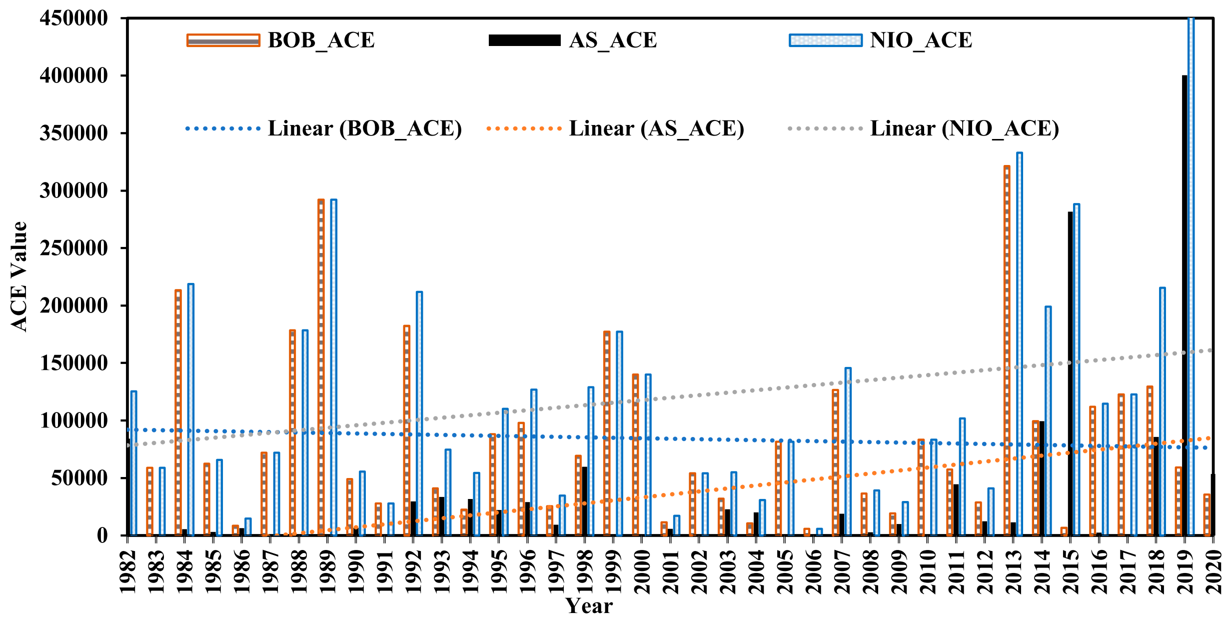

Figure 13. ACE trend over BOB, AS and NIO during post-monsoon season.

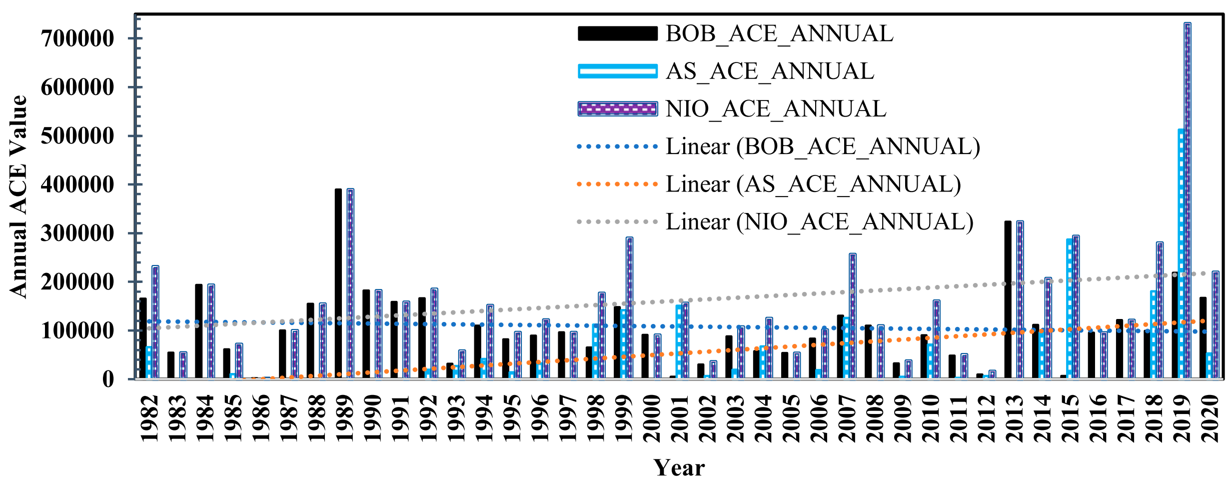

Figure 14. Annual ACE trend over BOB, AS and NIO.

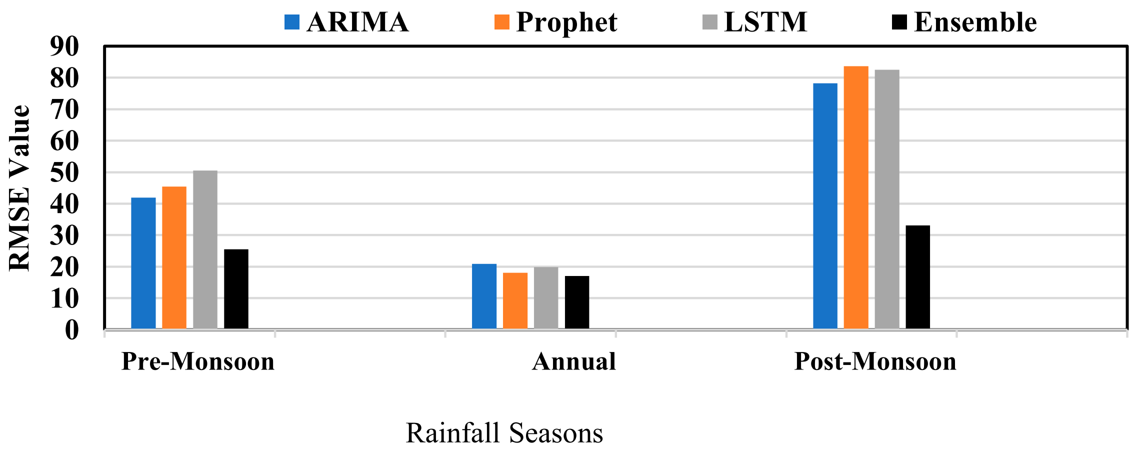

Figure 15. RMSE for ACE prediction.

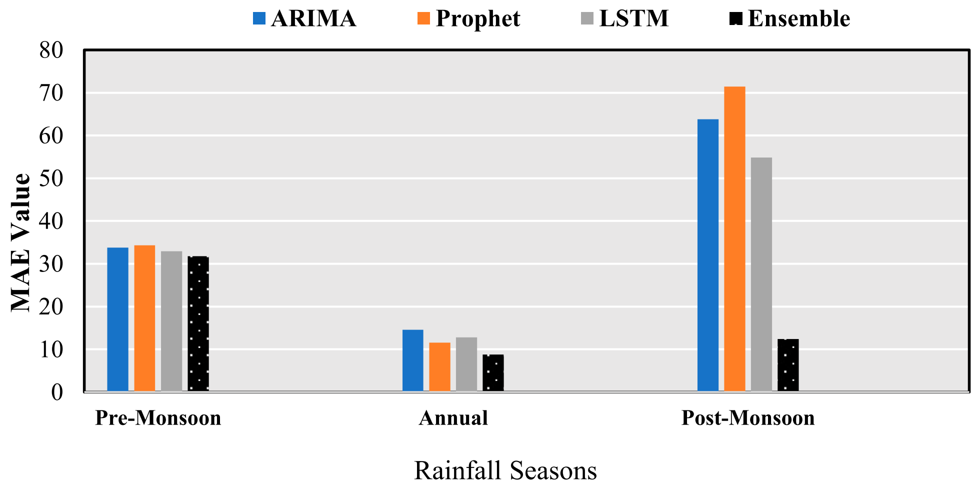

Figure 16. MAE for ACE prediction.

it may increase in the near future. As shown in Figure 14, it is observed that annual ACE values are high in the BOB region. The trend line shows that BOB-related ACE may continue to decrease while in other regions, it may increase in the near future.

The ACE value is predicted using ARIMA, prophet, LSTM, and ensemble. It is found that ensemble has the best prediction with low RMSE values for all three seasons. The RMSE and MAE are shown in Figures 15 and 16 respectively. The experimental analysis proves that the ensemble approach has reduced the error in prediction.

5. Conclusion and future work

The ACE during the northeast monsoon and southwest monsoon and the rainfall intensity changes are analyzed over the Indian subcontinent. It is observed that rainfall in India is increasing during the beginning months of the monsoon season and is comparatively weaker during the ending months of the season. It is found that there are no significant changes in the beginning and end dates of both monsoon seasons but the season's start date and end dates have been delayed by a few days in some years in the past. The intensity of rainfall is high in the first few months of the SWM season in India, but in contrast, in Tamil Nadu state, rainfall is intense during the last few months of the SWM season. It is found that August, September, and October months experience heavy rainfall, and hence agricultural production may be affected due to excessive rainfall. The key observation is continuous rainfall season with no break in between is possible during August, September, and October months in Tamil Nadu state. In recent decades, drought events are on the rise in India. These observations help the farmers to plan agricultural activities efficiently. ACE values are predicted for various monsoon seasons using ARIMA, LSTM, Prophet, and stacked ensemble. The experimental results reveal that the stacked ensemble provides 91% accuracy. The overall frequency count reveals that the BOB region got more cyclogenesis and cyclone activities than AS region in the past, but it is decreasing in the BOB region and increasing in AS region in recent decades.

The limitation of the work is that the other external parameters, sea level pressure and sea surface temperature which influence the rainfall may be taken into consideration. The proposed work can be extended to send early warning alerts to many sectors when heavy and extreme rainfall happens.

Acknowledgements

S Manoj and C Valliyammai thank the Big Data Analytics Research and Development laboratory, Department of Computer Technology, MIT Campus, Anna University for the infrastructure support for carrying out the research. One of the authors C. Valliyammai is thankful to the Science and Engineering Research Board, Department of Science Technology, Government of India for the award of SERB–POWER (Promoting Opportunities for Women in Exploratory Research) Fellowship (File No. SPF/2021/000068) and providing technical support to carry out this work.

Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data that support the findings of this study are openly available. RSMC, Cyclone energy matrix at https://rsmcnewdelhi.imd.gov.in/uploads/climatology/tcenergymatrix.pdf, Open Data initiative, Rainfall and Drought data at https://data.gov.in/catalog/rainfall-india, Global Monitoring laboratory, Greenhouse gas data at https://gml.noaa.gov/aftp/data.

References

[1] Sadhukhan B, Mukherjee S, Samanta RK. A study of global temperature anomalies and their changing trends due to global warming. 14th International conference on computational intelligence and communication networks (CICN); 2022 Dec 4-6; Al-Khobar, Saudi Arabia: IEEE; 2023. p. 660-666.

[2] Huang Q, Chen Y, Xu S, et al. Scaling models of a rainfall intensity-duration-frequency relationship. Proc. of the sixth international conference on natural computation; 2010 Aug 10-12; Yantai, China: IEEE; 2010. p. 3415-3419.

[3] Varghese LR, Vanitha K. A time-series based prediction analysis of rainfall detection. Proc. of the international conference on inventive computation technologies (ICICT); 2020 Jul 20-22; Lalitpur, Nepal: 2022, IEEE; 2020. p. 513-518.

[4] Rachman H, Lumban-Gaol J, Fadli S. Remote sensing of coastal upwelling dynamics in the eastern Indian ocean off Java. Role of ENSO and IOD. 2020;10:1–6.

[5] Li M, Luo Y, Zhang D-L, et al. Analysis of a record-breaking rainfall event associated with a monsoon coastal megacity of south China using multisource data. IEEE Trans Geosci Remote Sens. 2021;59:6404–6414. doi:10.1109/TGRS.2020.3029831

[6] Puttinaovarat S, Horkaew P. Flood forecasting system based on integrated big and crowdsource data by using machine learning techniques. IEEE Access. 2020;8:5885–5905. doi:10.1109/ACCESS.2019.2963819

[7] Jehangir A, Onaiza M. Application of artificial neural networks for monsoon rainfall prediction. Proc. 6th international conference on emerging technologies; 2010 Oct. 18-19; Islamabad, Pakistan: IEEE; 2010; p. 27-32.

[8] Saha M, Mitra P. Recurrent neural network based prediction of Indian summer monsoon using global climatic predictors. Proc. of the international joint conference on neural networks (IJCNN); 2016 Jul 24-29; Vancouver, BC, Canada: IEEE; 2016; p. 1523-1529.

[9] Mishra PS, Kannan SR. A numerical experiment to study the effect of anthropogenic heat and moisture on local weather. IEEE international India geosci remote sens symposium (InGARSS); 2021 Dec 20-21; Ahmedabad, India: IEEE; 2022; p. 401-404.

[10] Suparta W, Putro WS, Singh MSJ, et al. The estimation of rainfall and precipitation variation during 2011 convective system using an artificial neural network over Tawau, Sabah. Proc. of the international conference on space science and communication (IconSpace); 2015 Aug 10-12; Langkawi, Malaysia: IEEE; 2015. p. 479-484.

[11] Ariyo A, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. Proc. of the UKSim-AMSS 16th international conference on computer modelling and simulation; 2014 Mar 26-28; Cambridge, UK: IEEE; 2014. p. 106-112.

[12] Maktala P, Hashemi M. Global land temperature forecasting using long short-term memory network. IEEE 21st international conference on information reuse and integration for data science (IRI); 2020 Aug 11-13; Las Vegas, NV, USA: IEEE; 2020. p. 216-223.

[13] Jha K, Pande S. Time series forecasting model for supermarket sales using fb-prophet. Proc. of the 5th international conference on computing methodologies and communication (ICCMC); 2021 Apr 8-10; Erode, India: IEEE; 2021. p. 547-554.

[14] Chen Q, Zhang W, Lou Y. Forecasting stock prices using a hybrid deep learning model integrating attention mechanism, multi-layer perceptron, and bidirectional long-short term memory neural network. IEEE Access. 2020;8:117365–117376. doi:10.1109/ACCESS.2020.3004284

[15] Sulasikin A, Nugraha Y, Kanggrawan JI, et al. Monthly rainfall prediction using the Facebook prophet model for flood mitigation in central Jakarta. Proc. of the international conference on ICT for smart society (ICISS); 2021 Aug. 2-4; Bandung, Indonesia: IEEE; 2021. p. 1-5.

[16] Menaka D, Gauni S. Prediction of dominant ocean parameters for sustainable marine environment. IEEE Access. 2021;9:146578–146591. doi:10.1109/ACCESS.2021.3122237

[17] Kumar R, Krishnan R, Sankar S, et al. Increasing trend of break-monsoon conditions over India—role of ocean–atmosphere processes in the Indian ocean. IEEE Trans Geosci Remote Sens Letters. 2009;6:332–336. doi:10.1109/LGRS.2009.2013366

[18] Rose J, Chithra NR. Evaluation of temporal drought variation and projection in a tropical river basin of Kerala. J. Water Clim. Chang. 2020;11:115–132. doi:10.2166/wcc.2020.240

[19] Gupta N, Sagar C. Assessment of temporal change in the tails of probability distribution of daily precipitation over India due to climatic shift in 1970s. J. Water Clim. Chang. 2021;12(6):2753–2773. doi:10.2166/wcc.2021.008

[20] Aher MC, Yadav SM. Assessment of rainfall trend and variability of semi-arid regions of upper and middle Godavari basin, India. J. Water Clim. Chang. 2021;12:3992–4006. doi:10.2166/wcc.2021.044

[21] Supharatid S, Nafung J, Aribarg T. Projected changes in temperature and precipitation over mainland Southeast

Asia by CMIP6 models. J. Water Clim. Chang. 2022;13: 337–356. doi:10.2166/wcc.2021.015

[22] Grover S, Tayal S, Sharma R, et al. Effect of changes in climate variables on hydrological regime of Chenab basin, Western Himalaya. J. Water Clim. Chang. 2022;13:357–371. doi:10.2166/wcc.2021.003

[23] Madhukar A, Kumar V, Dashora K. Temperature and precipitation are adversely affecting wheat yield in India. J. Water Clim. Chang. 2022;13:1631–1656. doi:10.2166/wcc.2022.443

[24] Nadimpalli R, Srivastava A, Prasad VS, et al. Impact of INSAT-3D/3DR radiance data assimilation in predicting tropical cyclone Titli over the Bay of Bengal. IEEE Trans Geosci Remote Sens. 2020;58:6945–6957. doi:10.1109/TGRS.2020.2978211

[25] Gopala Krishnan D, Chandrasekhar A. On the impro ved predictive skill of WRF model with regional 4dvar initialization: A study with north Indian ocean tropical cyclones. IEEE Trans Geosci Remote Sens. 2018;56(6):3350–3357. doi:10.1109/TGRS.2018.2798623

[26] Jaiswal N, Kishtawal CM, Pal PK. Prediction of tropical cyclogenesis in North Indian Ocean using Oceansat-2 scatterometer (OSCAT) winds. Meteorol Atmos Phys. 2013;119:137–149. doi:10.1007/s00703-012-0230-8

[27] Rahul PRC, Salvekar PS, Devara PCS. Super cyclones induce variability in the aerosol optical depth prior to their formation over the oceans. IEEE Trans Geosci Remote Sens Letters. 2012;9:985–988. doi:10.1109/LGRS.2011.2170551

[28] Mohapatra M, Kumar V. Interannual variation of tropical cyclone energy metrics over North Indian Ocean. Climate Dynamics. 2017;48:5–6. doi:10.1007/s00382-016-3150-3

[29] Mohapatra M, Vijay Kumar V. Interannual variation of tropical cyclone energy matrix over north Indian ocean. Clim Dyn. 2016;48(5-6):1431–1445. doi:10.1007/s00382-016-3150-3

[30] Open Data Initiative Rainfall and Drought data [Internet], Delhi, Government of India [cited 2023 Apr 29]. Available from: https://data.gov.in/catalog/rainfall-india.

[31] Rahman T, et al. Flood prediction using ensemble machine learning model. 5th International congress on human-computer interaction, optimization and robotic applications (HORA); Istanbul, Turkiye; 2023. p. 1-6.

[32] Jaiswal PPG, et al. A stacking ensemble learning model for rainfall prediction based on Indian climate. 6th International conference on information systems and computer networks (ISCON); Mathura, India; 2023. p. 1-6.

[33] Rice Seasons of Tamil Nadu, Coimbatore, Tamil Nadu Agricultural University. [cited 2023 Apr 29]. Available from: https://agritech.tnau.ac.in/agriculture/agri_seasonandvarieties_rice.html.

[34] Anderson TR, Hawkins E, Jones PD. CO_2: the greenhouse effect and global warming from the pioneering work of Arrhenius and Calendar to today's Earth System Models. Endeavour. 2016;40(3):178–187. doi:10.1016/j.endeavour.2016.07.002