

Article

Enhanced Spatio-Temporal Modeling for Rainfall Forecasting: A High-Resolution Grid Analysis

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Abstract: Rainfall serves as a lifeline for crop cultivation in many agriculture-dependent countries including India. Being spatio-temporal data, the forecasting of rainfall becomes a more complex and tedious process. Application of conventional time series models and machine learning techniques will not be a suitable choice as they may not adequately account for the complex spatial and temporal dependencies integrated within the data. This demands some data-driven techniques that can handle the intrinsic patterns such as non-linearity, non-stationarity, and non-normality. Space-Time Autoregressive Moving Average (STARMA) models were highly known for its ability to capture both spatial and temporal dependencies, offering a comprehensive framework for analyzing complex datasets. Spatial Weight Matrix (SWM) developed by the STARMA model helps in integrating the spatial effects of the neighboring sites. The study employed a novel dataset consisting of annual rainfall measurements spanning over 50 (1970–2019) years from 119 different locations (grid of 0.25×0.25 degree resolution) of West Bengal, a state of India. These extensive datasets were split into testing and training groups that enable the better understanding of the rainfall patterns at a granular level. The study findings demonstrated a notable improvement in forecasting accuracy by the STARMA model that can exhibit promising implications for agricultural management and planning, particularly in regions vulnerable to climate variability.

Keywords: ARIMA; error metrics; non-linearity; rainfall forecasting; STARMA; spatial weight matrix



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1. Introduction

Rainfall pattern in India is largely influenced by the monsoon system, which serves as the primary source of precipitation across the country. The agricultural sector, which directly sustains a significant portion of the population, relies heavily on rainfall for irrigation and crop cultivation [1,2]. The timely distribution and adequate quantity of rainfall are crucial factors that directly influence crop yields and the livelihoods of millions of farmers [3]. Inconsistent rainfall can lead to droughts, crop failures, and economic distress in rural areas [4,5]. Fluctuations in rainfall are becoming increasingly common due to current environmental changes influenced by factors such as climate change, land use alterations, urbanization, and natural variability [6,7]. These fluctuations complicate the forecasting process, leading to economic uncertainties and social challenges. Consequently, accurate rainfall forecasting has emerged as a pivotal scientific challenge, crucial for effective resource management and disaster preparedness across the country [8–10]. Accurate rainfall forecasts play a critical role in agricultural management, providing valuable insights into optimal planting, irrigation, and harvesting schedules for farmers. By aligning farming practices with forecasted rainfall patterns, farmers can optimize crop yields, conserve water

resources, and mitigate risks associated with extreme weather conditions like droughts or excessive rainfall [11]. Therefore, reliable rainfall forecasting is essential for planning and economic stability across various sectors.

Rainfall data exhibit significant spatial and temporal variability, which can vary greatly over short distances and time periods [12,13]. This inherent variability, shaped by complex climatic interactions, presents formidable challenges for conventional forecasting approaches. This variability requires models that can capture local and regional nuances to provide accurate predictions. Traditional methods often struggle with accuracy and reliability due to these complexities [14].

Autoregressive Integrated Moving Average (ARIMA) models are conventional linear time series models extensively utilized for predicting hydrological and meteorological phenomena over the past few decades [15–17]. However, the ARIMA model operates under constraints that limit its effectiveness in complex environmental applications [18]. Primarily, it is a univariate model that does not account for spatial interdependencies and is inadequate for handling the non-linear and spatially interrelated data [19,20]. Machine learning techniques, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forest (RF), have gained prominence in handling complex time series data [21–23]. These methods offer substantial improvements in modeling capabilities due to their data-driven nature, which does not necessarily require prior assumptions about the data's distribution or structure [24]. However, these models often do not account for spatial interactions, which are crucial for accurately forecasting rainfall distribution across different regions [25–27].

Given the limitations of existing models and the complexity of rainfall data, which embody temporal, spatial, linear, and non-linear dynamics, Space–Time Autoregressive Moving Average (STARMA) models have been introduced as new alternatives. STARMA models incorporate both lagged effects and neighborhood influences of adjacent regions, offering an improved framework over univariate conventional and machine learning models [28,29]. The development of the spatial weight matrix is key to building these models. This approach promises to be a pivotal tool in enhancing agricultural planning, water management, and disaster preparedness strategies across climatically diverse and sensitive regions like India through efficient rainfall forecasting.

2. Background

Conventional time series models and machine learning models are widely used for univariate time series data, with extensive applications in environmental and weather modeling. Conventional models, such as ARIMA, typically address linear patterns, while machine learning models are adept at handling non-linearities within datasets. Basha et al. combined the ARIMA model with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to predict the summer monsoon rainfall of India [30]. Dotse et al. conducted a comprehensive review on hybrid machine learning models used to enhance rainfall prediction accuracy [9]. Garai et al. explored various machine learning techniques, including Neural Networks (NNs), Support Vector Regression (SVR), and kernel ridge regression, for rainfall forecasting [31]. Sekhar et al. employed both ARIMA and ANN models to forecast rainfall in the coastal Andhra region [32]. Bommala et al. provided an overview of ensemble-based models integrating machine learning and deep learning techniques for rainfall prediction [33]. The integration of Autoregressive (AR) models with Neural Networks (NNs) was explored to enhance monthly rainfall forecasts in the watershed regions of Cuba [34]. This study involved the application of Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) neural networks, ARIMA models, and a hybrid model (ANN + ARIMA) for rainfall prediction. Kaur et al. offered a comprehensive review on the use of AR models in forecasting environmental variables [35]. Zhang et al. explored the forecasting capabilities of ARIMA, Wavelet Neural Network (WNN), and Support Vector Machine (SVM) for drought forecasting [36]. A comparison of various time series models, such as LSTM, Stacked-LSTM, Bidirectional-

LSTM Networks, XGBoost, and an ensemble consisting of Gradient Boosting Regressor, Linear Support Vector Regression, and Extra-Trees Regressor, was conducted to forecast hourly rainfall volumes in five major cities of the United Kingdom [37]. Ridwan et al. demonstrated the superiority of Boosted Decision Tree Regression (BDTR) over other models in predicting rainfall in the Terengganu region of Malaysia [38]. Praveen et al. utilized non-parametric models and ANN-MLP to analyze trends and forecast rainfall changes in India [39]. However, these models often fall short when dealing with spatio-temporal data. Handling spatio-temporal data poses significant challenges for conventional and machine learning models due to the inherent complexity of patterns within the data, necessitating the need for alternative models.

The Space–Time Autoregressive Moving Average (STARMA) model stands as a well-established methodology specifically designed for handling such data. Various studies have showcased the efficacy of the STARMA model in effectively managing climatological data, which inherently exhibits spatio-temporal characteristics. Pfeifer and Deutrch proposed a three-stage iterative procedure known as STARIMA models, which integrates ARIMA modeling in the absence of spatial correlation [40]. Subsequently, they extended their work to include Seasonal Space–Time ARIMA modeling [41], along with providing techniques for the identification and interpretation of first-order space–time ARMA models [42]. Pfeifer and Bodily applied space–time ARMA modeling to obtain data from hotels in eight different locations in a major US city [43]. The application of STARMA models extends to comparing monthly mean temperatures from nine meteorological stations across the United Kingdom [44] and studying timber prices [45]. Saha et al. utilized a hybrid spatio-temporal modeling approach by integrating STARMA with ANN and SVM to predict annual precipitation data across six districts in the northern part of West Bengal, India [46]. Rathod et al. applied the Two-Stage Spatio-temporal Time Series model to forecast rice yield [29]. Kumar et al. employed a Hybrid Space–Time modeling approach to forecast the monthly temperatures [47]. Rathod et al. introduced an improved STARMA model for modeling and forecasting the spatio-temporal time series data [48]. Saha et al. employed fuzzy rule-based weighted Space–Time Autoregressive Moving Average models for temperature forecasting [28]. Additionally, the performance of a STARIMA model was compared with a Seasonal ARIMA (SARIMA) model for predicting infectious diseases [49].

3. Materials and Methods

3.1. Data Description

Daily rainfall data of West Bengal, India, were obtained from India Meteorological Department (IMD) web portal (<https://www.imdpune.gov.in/lrfindex.php>, accessed on 5 December 2022). The dataset consisted of yearly gridded rainfall data of a high-resolution grid ($0.25^\circ \times 0.25^\circ$), encompassing 119 grid points across 23 districts of West Bengal over a period of 50 years (1970–2019) [50]. For each grid, daily data have been converted to annual data using standard procedure. Hence, at each grid point, the spatio-temporal data series included 50 observations. Out of these, data from 45 years were utilized to develop the model, while the remaining observations were reserved for validation purposes. Figure 1 presents the location map of the study region along with the grid points. After calculating the observed and predicted values for each point, these values were interpolated using the Inverse Distance Weighted (IDW) technique to generate comprehensive rainfall maps for the entire state of West Bengal.

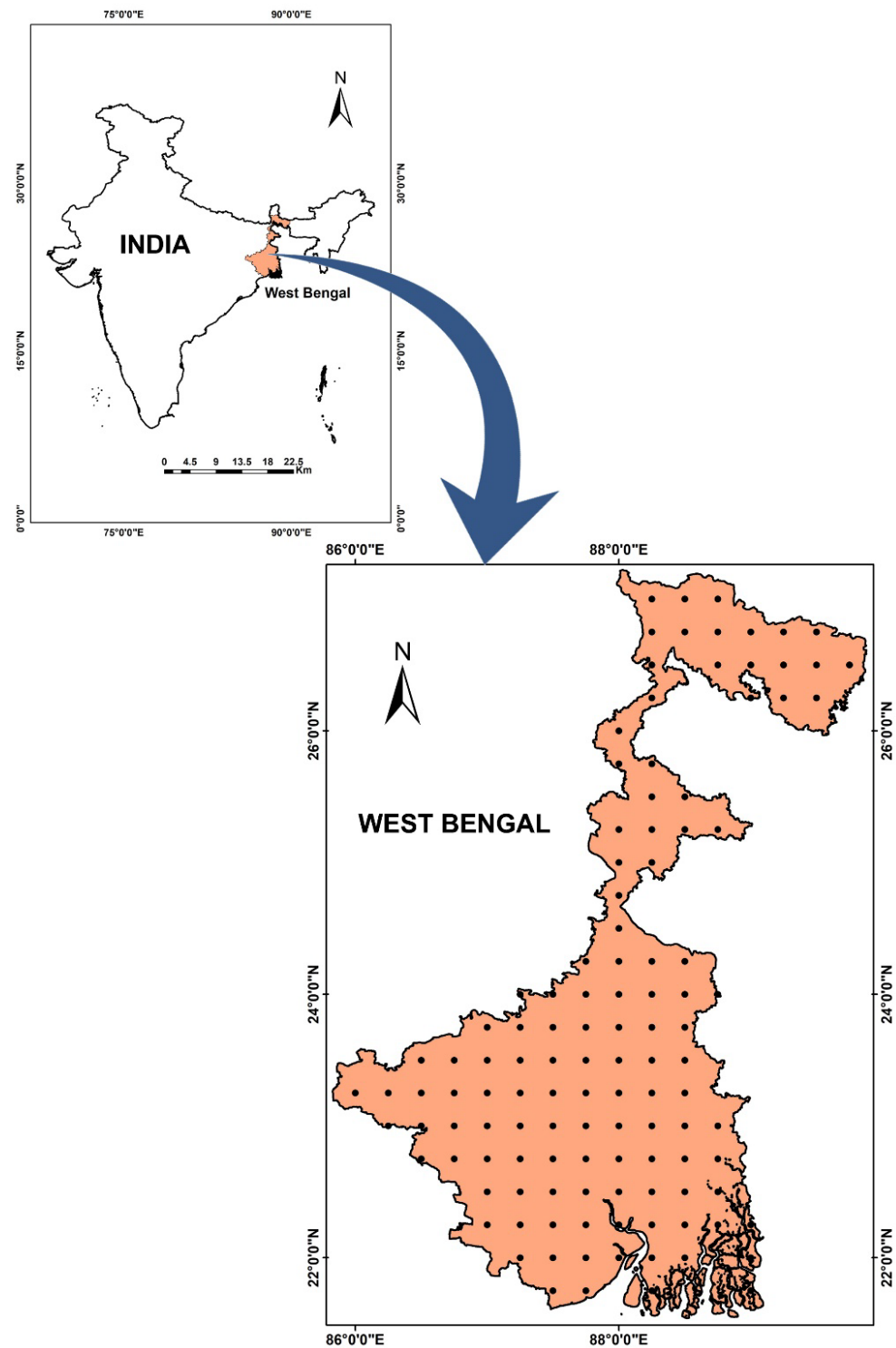


Figure 1. Location map depicting the 119 grids of data points.

3.2. Spatio-Temporal Data

Spatio-temporal time series data are the observations that are recorded with systematic dependencies across different spatial locations over various temporal intervals. Unlike traditional data, the analysis of spatio-temporal data provides comprehensive insights into the subject matter due to its rich and multi-dimensional nature. However, handling such data presents several formidable challenges. These datasets often comprise a massive volume of observations collected across numerous spatial locations and time intervals, necessitating efficient preprocessing and analysis techniques to manage the sheer scale

of the data. Furthermore, spatio-temporal datasets exhibit intricate relationships and dependencies across space and time, requiring sophisticated modeling approaches capable of capturing and interpreting these complex interactions accurately. Addressing these challenges is essential for unlocking valuable insights and deriving meaningful information across the domains.

3.3. ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) is a widely used conventional linear time series model [51,52]. There are three parameters of the ARIMA model: autoregressive (p) refers to the information from the past values of the series, order of differencing (d) refers to the number of times the data are differenced to convert them into stationarity, and moving average (q) refers to the information from the past forecast errors. The general equation and working procedure of the ARIMA model are given below.

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q}$$

where y_t is the time series, ϕ_i and θ_j are model parameters, ε_t is a random error, p is the number of lags of autoregressive terms, and q is the number of lags of moving terms.

The stationarity of the data can be checked either by ADF test or graphically observed by using the plots of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). If the time series is not stationary, it can be transformed by appropriately differencing the series. The number of lags of autoregression (p) and moving average (q) can be determined by examining the plots of PACF and ACF [53,54]. If the ACF plot shows a significant autocorrelation at lag k_1 , and the PACF plot shows a significant partial autocorrelation at lag k_2 ; then, the order of the AR component will be $p = k_2$, and the order of the MA component will be $q = k_1$, respectively. After finding the values of p , d , and q , the ARIMA model is fitted by estimating the parameters of each component using Maximum Likelihood Estimation (MLE). The ARIMA model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values is usually selected. After fitting a tentative ARIMA model, the adequacy of the model is checked. Confirmation of white noise is performed by examining the residual of the fitted model using Ljung–Box test, which examines the presence of autocorrelation in the residuals. If the model is not white noise, then the procedure is repeated until an adequate model is fitted.

3.4. STARMA Model

The STARMA (Space–Time Autoregressive Moving Average) model is a statistical model used for analyzing and forecasting spatio-temporal data. It is an extension of the traditional ARMA (Autoregressive Moving Average) model, adapted to handle univariate time series data across different locations considering both spatial and temporal dependencies [22,39,42]. It considers how observations at different spatial locations influence each other over time and how observations at the same location evolve over time. The model works by estimating parameters that describe the spatial and temporal dependencies within the data. These parameters include coefficients for autoregressive and moving average terms, as well as parameters that describe the spatial structure of the data. Spatial weight matrix with spatial weights helps in considering the neighboring effect. In addition, first, second, third, or higher order may be chosen depending on the neighboring areas. The STARMA model [35,37] is expressed as follows:

$$z(t) = \sum_{k=1}^p \sum_{l=0}^{\lambda_k} \Phi_{kl} W^l z(t-k) + \varepsilon(t) - \sum_{k=1}^q \sum_{l=0}^{m_k} \Theta_{kl} W^{(l)} \varepsilon(t-k)$$

where $z_i(t)$ is the observation at site i ($i = 1, 2, \dots, N$) and time t ($t \in Z$);

- $z(t)$ is a $N \times 1$ vector of observations at time t ($t = 1, \dots, T$);
- p is the autoregressive order (AR), and q is the MA order;

- λ_k represents the spatial order of the k^{th} AR term, and m_k represents the spatial order of the k^{th} MA term;
- ϕ_{kl} is the AR parameter at temporal lag k and spatial lag l (scalar), and θ_{kl} is the MA parameter at temporal lag k and spatial lag l (scalar);
- $W^{(l)}$ is the $N \times N$ matrix of weights for spatial order l ;
- $\epsilon(t)$ is normally distributed random error at time t with

$$E[\epsilon(t)] = 0 \text{ and } E[\epsilon(t)\epsilon(t+s)] = \begin{cases} G, & s = 0 \\ 0, & s \neq 0 \end{cases}$$

The STARMA (Space–Time Autoregressive Moving Average) model can be simplified into two distinct forms based on the absence of certain components. Firstly, in the absence of the moving average component, the STARMA model transforms into the Space–Time Autoregressive (STAR) model. This configuration captures the autoregressive relationships between observations at different spatial locations over various time intervals. It delineates how past observations at different locations influence the current observation at a given location, considering both spatial and temporal dependencies. Conversely, when the autoregressive term is absent, the STARMA model becomes the Space–Time Moving Average (STMA) model [40]. In this rendition, the model solely focuses on capturing the moving average relationships between observations at different spatial locations over time. It elucidates how past error terms at different locations contribute to the current observation at a specific location, accounting for both spatial and temporal dependencies. The goodness of the fitted model is examined by checking the white noise in the residual. Multivariate Box–Pierce test is used for checking the autocorrelation of residuals, i.e., the residuals are normally distributed with mean zero and constant variance [23]. This evaluates the model's ability in capturing the temporal dependencies in the data.

3.5. Model Evaluation Criterion

A comparative modeling and forecasting performance of the proposed hybrid model with the other existing model was assessed by estimating the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). RMSE, MAPE, and MAE were calculated using the following formula:

$$\begin{aligned} \text{RMSE} &= \left(\sqrt{\frac{\sum_{t=1}^n \left\{ \frac{Y_t - \hat{Y}_t}{Y_t} \right\}^2}{n}} \right) \\ \text{MAPE} &= \left(\sqrt{\frac{\sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|^2}{n}} \right) * 100 \\ \text{MAE} &= \frac{1}{n} \sum_{t=1}^n |Y_t - \hat{Y}_t| \end{aligned}$$

where n represents the total number of modeled or forecasted values, Y_t represents the actual value at time t , and $\hat{Y}_t$ represents the corresponding modeled or forecasted value.

4. Results and Discussion

The intensity of the rainfall across the 119 locations of the West Bengal region is depicted in Figure 2, which reveals that the northern region experienced abundant rainfall ranging from 3250 to 3750 mm. Conversely, the southern region exhibited lower rainfall levels, with precipitation ranging between 1500 and 1750 mm. The collected rainfall data were analyzed using two different time series models: ARIMA and STARMA. Both the time series models were compared, and the best model was selected using the error metrics.

All the prior statistical assumptions are satisfied before proceeding with the statistical techniques.

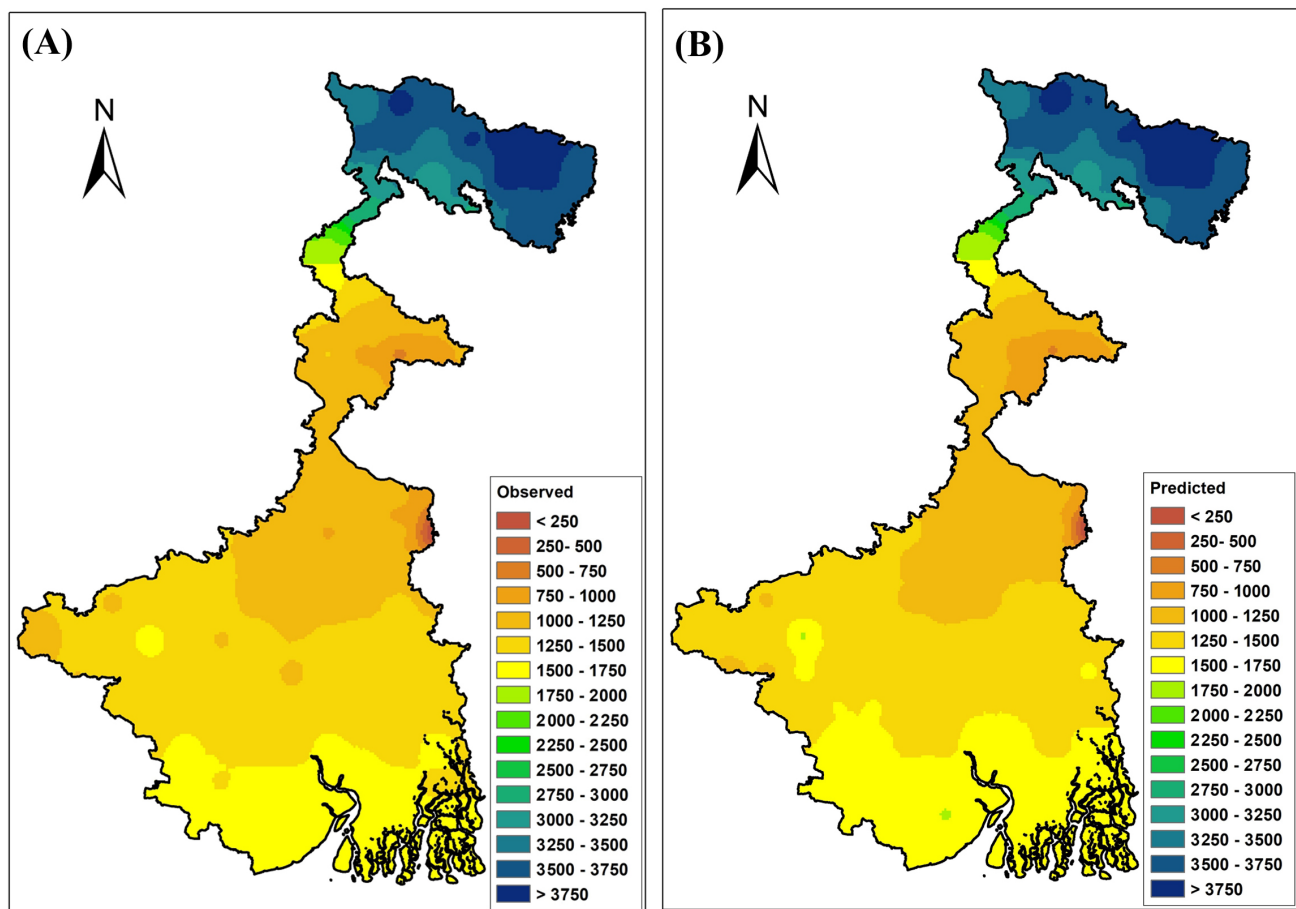


Figure 2. Average (A) observed (B) predicted annual rainfall for the period (2015–2019) in West Bengal.

4.1. ARIMA Fitting

The study begins with fitting the ARIMA model to the rainfall data. Initially, the Augmented Dickey–Fuller (ADF) test was conducted to check the stationarity of the series. The series exhibiting non-stationarity were differenced to achieve stationarity, while some series were stationary in their base form. The ARIMA models were fitted using parameters estimated through Maximum Likelihood Estimation (MLE). Diagnostic checks using the Ljung–Box test confirmed that all fitted models exhibited white noise, indicating a good fit. The ARCH-LM test also showed the absence of volatility in all models, ensuring that the selected models effectively capture the underlying patterns in the rainfall data. Table 1 lists the ARIMA models fitted for the 119 locations.

Table 1. Candidate ARIMA models fitted for the data.

Locations	Model	Locations	Model	Locations	Model	Locations	Model	Locations	Model
WB1	ARIMA(0,1,1)	WB26	ARIMA(0,1,2)	WB51	ARIMA(0,1,1)	WB76	ARIMA(1,2,0)	WB101	ARIMA(1,1,0)
WB2	ARIMA(1,1,0)	WB27	ARIMA(0,1,2)	WB52	ARIMA(0,1,1)	WB77	ARIMA(1,3,2)	WB102	ARIMA(0,1,1)
WB3	ARIMA(1,1,1)	WB28	ARIMA(0,1,2)	WB53	ARIMA(0,1,1)	WB78	ARIMA(1,2,0)	WB103	ARIMA(2,1,0)
WB4	ARIMA(3,2,1)	WB29	ARIMA(1,1,2)	WB54	ARIMA(1,1,0)	WB79	ARIMA(1,0,0)	WB104	ARIMA(1,1,0)
WB5	ARIMA(0,1,1)	WB30	ARIMA(1,1,0)	WB55	ARIMA(1,3,2)	WB80	ARIMA(0,1,1)	WB105	ARIMA(0,1,1)
WB6	ARIMA(0,1,1)	WB31	ARIMA(2,1,0)	WB56	ARIMA(2,2,2)	WB81	ARIMA(2,2,0)	WB106	ARIMA(1,3,2)

Table 1. Cont.

Locations	Model	Locations	Model	Locations	Model	Locations	Model	Locations	Model
WB7	ARIMA(2,1,0)	WB32	ARIMA(0,1,1)	WB57	ARIMA(2,2,0)	WB82	ARIMA(1,2,0)	WB107	ARIMA(4,2,0)
WB8	ARIMA(1,1,1)	WB33	ARIMA(0,1,1)	WB58	ARIMA(2,2,2)	WB83	ARIMA(1,1,0)	WB108	ARIMA(2,2,0)
WB9	ARIMA(1,1,1)	WB34	ARIMA(0,1,1)	WB59	ARIMA(2,2,0)	WB84	ARIMA(0,1,1)	WB109	ARIMA(0,1,1)
WB10	ARIMA(3,2,0)	WB35	ARIMA(3,2,1)	WB60	ARIMA(2,2,0)	WB85	ARIMA(0,1,1)	WB110	ARIMA(0,1,1)
WB11	ARIMA(0,1,2)	WB36	ARIMA(3,2,2)	WB61	ARIMA(0,1,2)	WB86	ARIMA(0,1,1)	WB111	ARIMA(1,1,0)
WB12	ARIMA(1,1,0)	WB37	ARIMA(0,1,1)	WB62	ARIMA(0,1,2)	WB87	ARIMA(2,2,0)	WB112	ARIMA(2,2,0)
WB13	ARIMA(1,1,0)	WB38	ARIMA(0,1,1)	WB63	ARIMA(1,1,0)	WB88	ARIMA(2,2,0)	WB113	ARIMA(1,3,2)
WB14	ARIMA(1,1,1)	WB39	ARIMA(1,1,0)	WB64	ARIMA(1,3,2)	WB89	ARIMA(2,2,2)	WB114	ARIMA(1,3,2)
WB15	ARIMA(2,1,0)	WB40	ARIMA(1,1,1)	WB65	ARIMA(0,1,1)	WB90	ARIMA(3,2,0)	WB115	ARIMA(1,3,2)
WB16	ARIMA(1,1,1)	WB41	ARIMA(1,1,0)	WB66	ARIMA(2,2,0)	WB91	ARIMA(1,2,0)	WB116	ARIMA(0,1,1)
WB17	ARIMA(3,2,0)	WB42	ARIMA(1,1,0)	WB67	ARIMA(2,2,0)	WB92	ARIMA(1,3,2)	WB117	ARIMA(2,2,0)
WB18	ARIMA(3,2,1)	WB43	ARIMA(1,2,0)	WB68	ARIMA(2,2,0)	WB93	ARIMA(1,2,0)	WB118	ARIMA(0,1,1)
WB19	ARIMA(3,2,1)	WB44	ARIMA(0,1,1)	WB69	ARIMA(2,2,0)	WB94	ARIMA(1,2,0)	WB119	ARIMA(2,3,0)
WB20	ARIMA(3,2,1)	WB45	ARIMA(0,1,1)	WB70	ARIMA(4,2,0)	WB95	ARIMA(1,2,0)		
WB21	ARIMA(3,1,0)	WB46	ARIMA(2,2,0)	WB71	ARIMA(2,2,2)	WB96	ARIMA(1,2,0)		
WB22	ARIMA(1,1,0)	WB47	ARIMA(2,2,0)	WB72	ARIMA(1,1,0)	WB97	ARIMA(1,2,0)		
WB23	ARIMA(1,1,0)	WB48	ARIMA(2,2,0)	WB73	ARIMA(1,0,0)	WB98	ARIMA(2,2,0)		
WB24	ARIMA(1,1,0)	WB49	ARIMA(2,2,0)	WB74	ARIMA(3,2,0)	WB99	ARIMA(1,2,0)		
WB25	ARIMA(0,1,1)	WB50	ARIMA(0,1,1)	WB75	ARIMA(2,2,0)	WB100	ARIMA(0,1,1)		

4.2. STARMA Fitting

The primary step in fitting the STARMA model involves constructing weight matrices for the data. This study utilized spatial weight matrices up to the first order. The zero-order spatial weight matrix ($W^{(0)}$) was treated as an identity matrix to incorporate the temporal pattern within the STARMA model. The first-order spatial weight matrix ($W^{(1)}$) was constructed by considering the percentage sharing of borders between specific districts and their neighbors. This integration of spatial data from neighboring districts into each district is achieved through a row-normalized first-order weight matrix. The zero-order ($W^{(0)}$) and first-order ($W^{(1)}$) spatial weight matrices developed for the study location were represented in the Supplementary Tables S1 and S2. The Multivariate Box–Pierce non-correlation test confirmed significant spatio-temporal correlations within the rainfall data, with a chi-squared value of 69,668.64 and a p -value of <0.01 (Table 2), indicating significant spatio-temporal correlation within the rainfall data. Following the assessment of spatio-temporal correlations, the suitable STARMA model was identified, and its parameters were estimated using Maximum Likelihood Estimation methods. The results of the fitted STARMA model are summarized in Table 2, presenting the estimated parameters alongside their standard errors and probability values. The ϕ of AR and θ of MA components were derived for both spatial lags 0 and 1. All estimated parameters were statistically significant at the 5% level. The equational form of the STARMA model is given by the following:

$$Z(t) = 0.87 (W^{(0)}) z(t-1) + 0.13 (W^{(1)}) z(t-1) - 0.48 (W^{(0)}) \varepsilon(t-1) - 0.23(W^{(1)}) \varepsilon(t-1)$$

A comparison was conducted between the performance of ARIMA and STARMA models in fitting rainfall data across 119 locations in West Bengal. The best-performing model was determined based on error metrics such as RMSE, MAPE, and MAE. Table 3 displays the error metrics calculated from the observed and predicted values for both models. The results revealed that the STARMA model exhibited lower error rates in predicting rainfall across 119 locations compared to the ARIMA model. Five-year (2015–2019) mean observed and predicted rainfall obtained from the STARMA model was mapped,

and it can be seen that the STARMA model predicted rainfall is almost at par with the average observed rainfall for the period 2015–2019 (Figure 2). Thus, the STARMA model consistently outperformed the ARIMA model across all error metrics and locations.

Table 2. Parameters of STARMA model.

Spatial Lag	Slag 0		Slag 1	
	AR	MA	AR	MA
	φ_{10}	θ_{10}	φ_{11}	θ_{11}
Model				
Estimate	0.87	−0.48	0.13	−0.23
Standard error	0.04	0.06	0.05	0.06
t-value	19.47	−8.33	2.83	−3.71
p-value	<0.01	<0.01	<0.01	<0.01
Multivariate Box–Pierce Non-Correlation Test	69,668.64(<0.01)			

Table 3. Comparison of models based on error metrics.

Model		ARIMA			STARMA		
Locations	RMSE	MAPE	MAE		RMSE	MAPE	MAE
WB1	110.73	5.24	85.21		0.14	0.01	0.12
WB2	452.04	25.92	446.37		0.13	0.01	0.10
WB3	156.62	8.56	147.48		0.20	0.01	0.17
WB4	245.18	11.71	212.98		0.26	0.01	0.25
WB5	182.00	11.42	171.00		0.18	0.01	0.15
WB6	89.08	3.97	69.34		0.11	0.00	0.09
WB7	201.98	9.38	169.36		0.24	0.01	0.16
WB8	204.10	10.68	147.50		0.24	0.01	0.17
WB9	273.24	12.83	242.49		0.30	0.01	0.25
WB10	603.58	31.72	524.65		0.33	0.02	0.28
WB11	342.30	17.26	303.93		0.26	0.01	0.24
WB12	262.95	12.80	218.26		0.29	0.01	0.24
WB13	233.20	13.96	216.39		0.28	0.02	0.25
WB14	257.98	14.20	186.96		0.29	0.02	0.26
WB15	200.33	10.52	151.21		0.21	0.01	0.19
WB16	121.49	5.88	94.70		0.22	0.01	0.18
WB17	592.71	27.07	484.05		0.34	0.02	0.31
WB18	431.62	21.05	402.87		0.33	0.02	0.31
WB19	463.20	24.51	421.66		0.29	0.02	0.27
WB20	392.58	17.62	342.82		0.28	0.28	0.26
WB21	166.69	9.69	143.33		0.23	0.01	0.21
WB22	224.03	10.06	170.91		0.25	0.01	0.20
WB23	205.84	11.09	133.20		0.26	0.02	0.24
WB24	329.54	21.44	254.30		0.33	0.02	0.28

Table 3. Cont.

Model		ARIMA			STARMA	
WB25	230.52	11.81	211.36	0.27	0.01	0.25
WB26	607.10	28.76	483.53	0.66	0.04	0.58
WB27	419.00	21.52	358.86	0.29	0.02	0.26
WB28	445.18	22.80	382.42	0.29	0.02	0.27
WB29	274.34	16.77	205.86	0.19	0.01	0.15
WB30	260.13	14.53	186.70	0.15	0.01	0.11
WB31	148.10	9.66	142.89	0.15	0.01	0.13
WB32	202.41	11.09	172.93	0.26	0.01	0.23
WB33	199.19	12.74	167.20	0.26	0.02	0.21
WB34	127.60	8.10	117.35	0.18	0.01	0.16
WB35	446.59	25.55	417.08	0.21	0.01	0.17
WB36	639.31	33.70	591.39	0.37	0.02	0.29
WB37	274.62	16.49	259.48	0.30	0.02	0.28
WB38	281.15	16.31	260.49	0.29	0.02	0.27
WB39	236.82	18.96	198.95	0.27	0.02	0.21
WB40	301.88	22.74	252.60	0.22	0.02	0.20
WB41	425.80	22.53	351.54	0.48	0.02	0.34
WB42	201.45	11.72	174.05	0.19	0.01	0.14
WB43	838.06	63.28	808.37	0.21	0.01	0.19
WB44	326.47	20.50	282.52	0.41	0.03	0.33
WB45	199.56	11.23	152.79	0.23	0.01	0.16
WB46	988.25	69.62	851.29	0.30	0.02	0.25
WB47	998.14	68.86	860.95	0.32	0.02	0.25
WB48	809.57	49.31	665.16	0.34	0.02	0.30
WB49	995.17	61.59	860.78	0.31	0.02	0.29
WB50	247.30	14.34	198.49	0.21	0.01	0.19
WB51	231.13	13.49	163.22	0.25	0.02	0.23
WB52	295.40	17.60	232.51	0.37	0.02	0.31
WB53	685.51	23.57	486.69	0.80	0.03	0.59
WB54	282.14	12.45	201.75	0.29	0.01	0.20
WB55	314.43	19.94	268.14	0.27	0.02	0.25
WB56	379.05	19.22	307.62	0.42	0.03	0.37
WB57	621.46	53.50	529.94	0.45	0.03	0.32
WB58	295.81	18.20	250.27	0.41	0.02	0.30
WB59	861.01	55.38	726.71	0.31	0.02	0.30
WB60	836.47	52.33	695.29	0.32	0.02	0.28
WB61	277.35	20.11	226.56	0.24	0.02	0.20
WB62	286.11	15.59	235.35	0.31	0.02	0.25
WB63	343.69	16.12	248.14	0.43	0.02	0.33
WB64	431.27	18.49	304.67	0.48	0.04	0.42
WB65	374.59	26.64	334.10	0.46	0.03	0.38

Table 3. Cont.

Model		ARIMA			STARMA	
WB66	1120.06	116.75	986.04	0.47	0.04	0.37
WB67	1011.03	85.23	894.89	0.35	0.02	0.28
WB68	499.40	35.72	455.68	0.26	0.01	0.16
WB69	789.89	53.21	639.64	0.31	0.02	0.25
WB70	258.82	15.18	222.45	0.25	0.02	0.23
WB71	334.03	15.48	245.82	0.23	0.02	0.27
WB72	434.99	37.31	390.53	0.46	0.03	0.36
WB73	445.33	42.24	395.77	0.48	0.04	0.39
WB74	890.25	93.81	828.40	0.49	0.04	0.37
WB75	982.28	82.60	867.87	0.35	0.02	0.26
WB76	1192.55	94.77	1045.35	0.32	0.02	0.22
WB77	374.38	23.03	338.14	0.28	0.02	0.23
WB78	412.41	30.12	364.46	0.31	0.02	0.23
WB79	489.57	48.92	469.72	0.49	0.04	0.43
WB80	330.71	22.40	240.09	0.41	0.03	0.36
WB81	1206.94	114.07	1043.41	0.40	0.03	0.33
WB82	1358.38	120.81	1198.15	0.35	0.02	0.28
WB83	273.13	18.18	209.61	0.36	0.02	0.27
WB84	320.81	20.10	257.39	0.38	0.02	0.27
WB85	312.06	23.19	256.50	0.39	0.03	0.32
WB86	326.07	22.03	244.67	0.40	0.03	0.32
WB87	1135.30	108.46	984.01	0.40	0.03	0.32
WB88	640.17	58.30	559.74	0.39	0.03	0.31
WB89	226.79	17.38	197.19	0.24	0.02	0.20
WB90	455.38	33.49	393.61	0.18	0.01	0.16
WB91	1425.33	162.05	1323.24	0.33	0.03	0.26
WB92	211.71	14.69	155.16	0.23	0.02	0.18
WB93	1477.81	170.73	1366.80	0.36	0.04	0.30
WB94	1591.61	232.69	1501.94	0.45	0.06	0.38
WB95	746.77	84.91	665.01	0.40	0.04	0.35
WB96	792.67	79.47	694.53	0.39	0.04	0.33
WB97	402.56	40.17	348.08	0.45	0.04	0.37
WB98	395.73	18.60	310.42	0.27	0.01	0.23
WB99	1282.43	92.15	1184.96	0.39	0.03	0.35
WB100	495.02	28.93	478.99	0.31	0.02	0.27
WB101	132.29	3.37	99.33	0.18	0.00	0.13
WB102	196.47	5.25	149.01	0.30	0.01	0.22
WB103	409.13	9.19	274.92	0.48	0.01	0.40
WB104	436.67	10.94	385.79	0.50	0.01	0.38
WB105	314.99	9.11	264.53	0.28	0.01	0.27
WB106	1641.20	52.22	1578.99	0.47	0.01	0.38

Table 3. Cont.

Model		ARIMA			STARMA	
WB107	516.44	13.49	449.97	0.18	0.00	0.16
WB108	1104.70	23.48	981.12	0.66	0.01	0.58
WB109	412.80	8.69	354.59	0.39	0.01	0.33
WB110	463.29	10.46	413.25	0.53	0.01	0.52
WB111	493.46	8.04	324.20	0.46	0.01	0.35
WB112	1491.95	39.28	1445.75	0.56	0.01	0.52
WB113	487.46	12.53	443.59	0.39	0.01	0.33
WB114	346.72	8.46	323.85	0.25	0.01	0.22
WB115	1067.61	26.13	1045.75	0.33	0.01	0.29
WB116	363.95	6.87	286.08	0.57	0.01	0.49
WB117	2285.05	60.29	2100.02	0.73	0.02	0.64
WB118	521.00	11.49	473.18	0.66	0.01	0.59
WB119	1887.67	38.06	1385.06	0.47	0.01	0.40

Rainfall data always present a multifaceted challenge for modeling due to their intricate and dynamic nature. One primary complexity lies in its temporal dependency, where rainfall patterns exhibit seasonality, trends, and periodic fluctuations over time. These temporal variations necessitate the models to capture and accommodate such dynamic changes effectively [28,48]. Additionally, rainfall data also possess significant spatial variability, with precipitation levels varying widely across different geographical locations. This variability is influenced by diverse factors that can account for these spatial intricacies. To address these challenges, the study used a sophisticated modeling approach that was capable of capturing the complex interplay of temporal and spatial dynamics inherent to rainfall data. The study initially applied the ARIMA model to all 119 locations, and the candidate ARIMA model was chosen for each dataset. Next, the STARMA model that is highly known for its efficacy in handling spatio-temporal datasets was applied. Prior to fitting the STARMA model, the presence of spatial relationships between the selected locations was confirmed, ensuring the suitability of the model for the study. The construction of spatial weight matrices is a critical step that can influence model accuracy. This study used the first-order weight matrices. STARMA (ϕ_{10} , θ_{10} , ϕ_{11} , θ_{11}) model was identified as the best-fitted model for the data. Error metrics such RMSE, MAPE, and MAE were used to compare the performance of the fitted mode. The results show that the univariate ARIMA models fall short in capturing the spatial dependencies. In contrast, the STARMA model that is specifically designed to handle spatio-temporal datasets was found to be more suitable for this study. The STARMA model provides a robust framework for modeling and predicting rainfall in West Bengal. Its superior performance was compared to the ARIMA model, which highlights the importance of considering spatio-temporal dependencies in rainfall data [28,29]. Thus, the STARMA model outperformed all ARIMA models for all study locations, i.e., the grid points. Future research could further explore the application of STARMA models in different regions and climates to validate and extend these findings. Integrating variables like temperature and humidity could enhance predictive power, providing a more comprehensive understanding of rainfall patterns. This has significant implications for agriculture, water management, and disaster preparedness.

5. Conclusions

Every time series model has its own limitations and strong assumptions. Some models excel in handling linear datasets, while others are better suited for non-linear datasets. Therefore, it is crucial to carefully consider the nature of the data under study before

selecting a time series model. This study serves as a prime example where the primary objective is to model the rainfall patterns across 119 different locations in West Bengal, India. Rainfall data are highly known for their spatio-temporal variability, which requires some data-driven time series models rather than conventional time series models. This study employed ARIMA and STARMA models where the performance of the fitted model was compared using error metrics such as RMSE, MAPE, and MAE. The results showed that the fitted STARMA ($\phi_{10}, \theta_{10}, \phi_{11}, \theta_{11}$) model consistently yielded lower errors compared to ARIMA across all 119 locations. This provides strong evidence that STARMA models perform well in handling spatio-temporal data by capturing the complex temporal and spatial dynamics inherent in the rainfall data across diverse geographical locations. This helps in efficiently forecasting the rainfall, which ensures the efficient allocation of water resources and the minimization of the potential risks to agriculture. Future studies could enhance forecasting precision by developing hybrid space–time hybrid models integrated with machine learning and deep learning techniques.

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