

Forecasting and Prediction of Seasonal Rainfall in Drought and Flood Affected Zones of Karnataka Using Artificial Neural Network (ANN)

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Abstract

Rainfall prediction plays a pivotal role in managing climate-sensitive sectors such as agriculture, water resource planning, disaster mitigation, and infrastructure development. In regions with high climatic variability, such as Karnataka, accurate and timely forecasting is essential for decision-making. Karnataka has many different types of land and landscapes, few districts often face droughts, while others experience floods. Traditional statistical models often fall short in capturing the complex, non-linear dynamics of seasonal rainfall. This study explores the application of Artificial Neural Network (ANN) techniques to forecast rainfall across two categories of high-risk zones in Karnataka. The drought-prone such as Bagalkote, Chitradurga, Koppala, Raichur and flood-prone such as Dakshina Kannada, Udupi, Uttara Kannada, Chikkamagalur, Kodagu, Shivamogga districts. The model predicts rainfall for three key monsoon seasons such as Pre-monsoon (PRM), Southwest monsoon (SWM), and Northeast monsoon (NEM).

Keywords: Rainfall Prediction, pre-monsoon, monsoon, post-monsoon, ANN Modelling, Flood, Drought.

1. Introduction

Rainfall is a vital climate factor that greatly affects agriculture, water management, city planning, and disaster response. In areas where the weather is highly unpredictable, accurate rainfall forecasting becomes essential for making informed decisions. Karnataka, a state in southern India, has a wide range of landscapes from coastal regions to dry inland areas which causes major differences in rainfall across the state. Some districts often face drought due to low rainfall, while others suffer from flooding during heavy rains. This makes predicting rainfall in Karnataka especially challenging. Traditional methods used to forecast rainfall often struggle to deal with the complex and irregular patterns found in such data. These models are usually based on linear relationships and may not handle sudden or non-uniform changes well. Rainfall prediction has evolved from simple statistical models to sophisticated machine learning

techniques, aimed at addressing the highly non-linear and variable nature of precipitation patterns. Early studies, such as by G. Appa Rao and D.A. Mooley (1970), established the utility of the Gamma distribution in modeling rainfall, emphasizing its ability to capture skewness in precipitation data. This model has since been validated across various meteorological subdivisions in India (Parthasarathy & Mooley, 1984). To incorporate time-based patterns, Parthasarathy and Mooley (1984) applied correlograms and spectral analysis, identifying cycles of 2.8 and 14 years in Indian monsoon rainfall. Such findings underscored the need for time-dependent models to capture seasonal and inter-annual variations. Later, Parida (1999) introduced the four-parameter Kappa distribution for modeling monsoon thunderstorms, outperforming earlier methods like Singh's (1998) power transformation model. The adoption of **Artificial Neural Networks (ANN)** in hydrological forecasting marked a significant shift. D. Nagesh Kumar (2004)

pioneered ANN for temporal disaggregation of rainfall, capturing non-linear relationships in historical data. Radha Gupta (2019) further demonstrated that a simple ANN model could explain over 80% of inter-annual variability in monsoon rainfall. Seetharaman (2009) validated the ARIMA (3,0,3) model for Gangtok, showing the strength of ARIMA in time-series prediction. Recent research has increasingly emphasized machine learning (ML) methods. Mishra and Kushwaha (2019) reported a 95.4% accuracy using Gaussian Process Regression (GPR) for rainfall prediction, while Subrahmanyam et al. (2021) demonstrated the utility of GPR for heavy rainfall prediction over peninsular India. These models effectively manage the complex, nonlinear behavior of precipitation data, enhancing disaster preparedness and climate resilience. In terms of regional rainfall modeling, Kokila Ramesh and Iyengar (2017) designed an ANN model to incorporate both intra-seasonal and inter-annual variability. Extending this, Kumudha H.R. and Kokila Ramesh (2023) developed an ANN model for Karnataka's three meteorological subdivisions—Coastal, North Interior, and South Interior Karnataka—predicting rainfall across pre-monsoon, southwest monsoon, and northeast monsoon seasons. Their model, trained on 1960–2010 data and tested on 2011–2016 data, explained up to 98% of variance in several seasons, validating ANN's robustness in handling spatial and temporal complexity. In flood-prone districts of Karnataka, rainfall behavior is notably complex due to multimodal characteristics and non-Gaussian distributions. To address this, Kumudha et al. (2025) introduced a Gaussian and Gamma Mixture Model (GGM) to analyze 57 years of southwest monsoon rainfall in Dakshina Kannada, Udupi, Uttara Kannada, Chikkamagalur, Kodagu, and Shivamogga. The study found that GGM outperformed traditional Gaussian models in capturing bimodal rainfall patterns and extreme events. It offered significant improvements in flood risk assessment, resource allocation, and climate adaptation planning.

Furthermore, studies such as Rajeevan et al. (1998) employed Canonical Correlation Analysis (CCA) to link large-scale atmospheric parameters with monsoon rainfall, contributing to long-range forecasting models. Their models were integrated into operational forecasting by the Indian Meteorological Department (IMD) post-2002 drought, improving accuracy and policy trust (Rajeevan et al., 2004). Additionally,

studies have explored the of rainfall (Parthasarathy et al., 1985), showing that neighbouring meteorological subdivisions often experience similar anomalies. Pai et al. (2002) linked monsoon rainfall patterns to global climatic indices, revealing the influence of phenomena such as sea surface temperature anomalies and spatial coherences. Overall, the literature underscores a transition from purely statistical to hybrid and machine learning-based approaches. Techniques such as ANN, ARIMA, CCA, GPR, and GGM have each contributed to enhancing the accuracy of rainfall forecasts. These advancements support more informed decisions in climate-sensitive sectors, particularly in regions like Karnataka where rainfall variability poses significant socio-economic challenges. To overcome these challenges, more advanced techniques like Artificial Neural Networks (ANNs) are used. ANNs are powerful tools that can learn from large sets of data and capture non-linear patterns, making them suitable for forecasting in areas with high rainfall variation.

2. Materials & Methods

The study explores the use of ANN models to forecast seasonal rainfall in selected high-risk districts of Karnataka. It focuses on drought-prone districts such as Bagalkote, Chitradurga, Koppala, and Raichur. The flood-prone districts such as Dakshina Kannada, Udupi, Uttara Kannada, Chikkamagalur, Kodagu, and Shivamogga. The ANN model is designed to predict rainfall for three important monsoon seasons Pre-monsoon (PRM), Southwest monsoon (SWM), and Northeast monsoon (NEM). The model uses a three-layer structure with 15 input nodes representing seasonal rainfall from the previous five years, 5 hidden neurons with a tansigmoidal activation function, and 3 output nodes for predicting rainfall for the current year's three monsoon seasons. Historical rainfall data from 1960 to 2016, sourced from the Indian Institute of Tropical Meteorology (IITM) and the Karnataka State Natural Disaster Monitoring Centre (KSNDMC), is used to train and test the model. The training period spans 1960 to 2010, while data from 2011 to 2016 is used for testing and validation. After validating the model's accuracy, rainfall forecasts were generated for the period 2017 to 2026 for all selected drought-prone and flood-prone districts. The statistical indicators, – derived for each subdivision as well as for the entire state of Karnataka, are presented in Table 1.

Table 1: Basic statistics of SWM Rainfall Data of Drought & Flood Prone Regions – IITM (1960-2016)

Regions	Season	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z	Regions	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z
Bagalkote	PRM	4.38	2.07	0.72	3.28	Koppala	3.07	1.6	1.13	3.47
	SWM	18.15	6.01	0.62	3.05		15.17	5.01	0.18	2.7
	NEM	7.04	3.8	0.56	2.97		5.53	3.36	0.74	3.89
Chitradurga	PRM	7.09	3.18	0.53	2.24	Raichur	3.35	2.04	1.52	2.82
	SWM	18.01	5.93	0.16	2.17		22.69	6.21	0.37	2.67
	NEM	9.86	4.47	0.20	2.35		7.06	5.06	0.79	6.76
Dakshina Kannada	PRM	11.64	6.24	0.72	3.51	Chikkamagalur	12.23	4.45	0.57	2.89
	SWM	158.06	31.13	0.53	3.33		101.25	19.96	0.47	3.42
	NEM	17.19	5.54	0.95	3.51		14.97	6.77	0.64	2.94
Udupi	PRM	6.56	5.27	0.57	3.4	Kodagu	6.72	3.21	1.7	6.29
	SWM	107.15	17.19	0.24	2.66		63.05	15.1	0.86	4.15
	NEM	9.51	3.86	1.66	3.53		7.93	3.08	0.69	3.45
Uttara Kannada	PRM	14.52	10.28	1.05	4.81	Shivamogga	4.38	2.07	0.72	3.28
	SWM	270.8	35.91	0.44	3.47		18.15	6.01	0.62	3.05
	NEM	22.26	8.46	0.47	3.65		7.04	3.8	0.56	2.97

3. Data Analysis

The rainfall data for Pre-Monsoon (PRM), Southwest Monsoon (SWM), and Northeast Monsoon (NEM) seasons were normalized using season-specific mean and standard deviation values to improve the ANN model's learning and convergence. This normalization enabled consistent evaluation of the data's structure, highlighting its non-Gaussian nature through skewness and kurtosis analysis as shown in Tables 2. The

normalization process used season-specific mean and standard deviation values, and was performed using the following transformations. Due to the data's non-linearity and deviation from normal distribution, the ANN model was designed to process all three seasonal components collectively as both inputs and outputs to enhance prediction accuracy.

$$P_i = \frac{p_i - m_p}{s_{p_i}}, S_i = \frac{s_i - m_s}{s_{s_i}} \text{ \& } N_i = \frac{n_i - m_n}{s_{n_i}} \text{ respectively.}$$

Table 2: Statistical Overview of PRM, SWM, and NEM Normalized Rainfall Data for Drought & Flood Prone Regions (1960 - 2010)

Regions	Season	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z	Regions	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z
Bagalkote	PRM	0.00	1.00	3.63	0.8	Koppala	0.00	1.00	3.62	0.76
	SWM	0.00	1.00	2.8	0.52		0.00	1.00	2.57	0.5
	NEM	0.00	1.00	2.79	0.49		0.00	1.00	3.77	0.95
Chitradurga	PRM	0.00	1.00	2.51	0.65	Raichur	0.00	1.00	2.98	0.66
	SWM	0.00	1.00	2.17	0.2		0.00	1.00	2.64	0.2
	NEM	0.00	1.00	2.35	0.22		0.00	1.00	6.39	1.58
Dakshina Kannada	PRM	0.00	1.00	3.18	0.91	Chikkamagalur	0.00	1.00	3.09	0.70
	SWM	0.00	1.00	3.51	0.61		0.00	1.00	3.57	0.55
	NEM	0.00	1.00	3.32	0.64		0.00	1.00	2.82	0.62

Regions	Season	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z	Regions	LTA (m_z) (in cm)	LTD (σ_z) (in cm)	S_z	K_z
Udupi	PRM	0.00	1.00	3.07	1.03	Kodagu	0.00	1.00	6.04	1.69
	SWM	0.00	1.00	2.72	0.14		0.00	1.00	4.26	0.90
	NEM	0.00	1.00	3.47	0.86		0.00	1.00	3.31	0.64
Uttara Kannada	PRM	0.00	1.00	4.29	1.38	Shivamogga	0.00	1.00	3.63	0.81
	SWM	0.00	1.00	3.57	0.36		0.00	1.00	2.80	0.52
	NEM	0.00	1.00	3.34	0.67		0.00	1.00	2.79	0.49

4. Model Design and Architecture

Kokila Ramesh and R. N. Iyengar (2017) applied ANN models for monsoon rainfall prediction in India, focusing mainly on the core monsoon period. However, their studies lacked analysis of pre-monsoon and post-monsoon rainfall and did not address region-specific risks like drought or floods. This study fills that gap by developing an enhanced ANN framework focused on Karnataka’s drought- and flood-prone districts, covering all three major seasons such as Pre-Monsoon (PRM), Southwest Monsoon (SWM), and Northeast Monsoon (NEM). The ANN model captures both inter- and intra-seasonal variability, enabling better understanding of complex regional rainfall behaviors. It features 15 input nodes representing five years of seasonal rainfall data, a hidden layer with 5 neurons using a tansigmoidal activation function, and 3 output nodes predicting rainfall for PRM, SWM, and NEM of the target year. The model architecture is depicted in Fig 5.1. The input sequence to the model is constructed as follows:

$$P_{n-5}, S_{n-5}, N_{n-5}, P_{n-4}, S_{n-4}, N_{n-4}, P_{n-3}, S_{n-3}, N_{n-3}, P_{n-2}, S_{n-2}, N_{n-2}, P_{n-1}, S_{n-1}, N_{n-1}$$

Here, each symbol represents the rainfall value in a specific season and year, with n being the target prediction year. This structure allows the model to capture temporal dependencies and evolving trends in rainfall distribution. Training is conducted using the

backpropagation algorithm with Mean Squared Error (MSE) as the loss function, continuing until the error drops below 10^{-6} . This design effectively handles non-linear, non-stationary rainfall data, particularly in areas prone to climate extremes. Developed and tested in MATLAB, the model’s performance is evaluated using RMSE, Correlation Coefficient (CC), and Performance Parameter (PP). While CC measures prediction strength, PP provides a more comprehensive view of model accuracy across both training (1960–2010) and testing phases. Results across ten selected regions are presented in Tables 5.3.

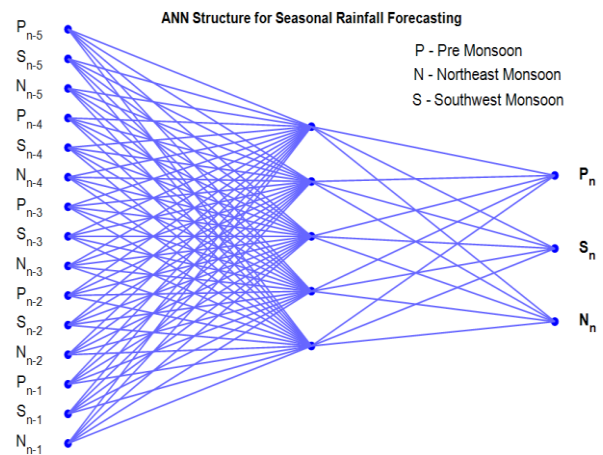


Figure 1: Structure of the ANN model comprising 15 input nodes, a hidden layer with 5 neurons, and 3 output nodes representing seasonal rainfall forecasts.

Table 3: Evaluation of ANN model performance for drought prone region data during training period

Regions	Season	RMSE	CC	PP	Regions	RMSE	CC	PP
Bagalkote	PRM	0.10	0.99	0.86	Koppala	0.14	0.99	0.95
	SWM	0.16	0.99	0.91		0.18	0.99	0.91
	NEM	0.08	0.99	0.92		0.19	0.98	0.92

Regions	Season	RMSE	CC	PP	Regions	RMSE	CC	PP
Chitradurga	PRM	0.12	0.99	0.96	Raichur	0.18	0.99	0.94
	SWM	0.12	0.99	0.96		0.19	0.99	0.93
	NEM	0.06	0.99	0.99		0.21	0.98	0.92
Dakshina Kannada	PRM	0.10	0.99	0.97	Chikkamagalur	0.12	0.99	0.96
	SWM	0.13	0.99	0.97		0.12	0.99	0.96
	NEM	0.06	0.99	0.98		0.06	1.00	0.99
Udupi	PRM	0.88	0.85	0.81	Kodagu	0.16	0.98	0.91
	SWM	0.89	0.90	0.85		0.18	0.98	0.92
	NEM	0.83	0.82	0.88		0.15	0.99	0.96
Uttara Kannada	PRM	0.13	0.99	0.94	Shivamogga	0.10	0.99	0.97
	SWM	0.13	0.99	0.95		0.16	0.99	0.93
	NEM	0.15	0.99	0.93		0.13	0.99	0.95

To validate the ANN model, observed and predicted rainfall data (1960–2005) were visually compared across Karnataka’s drought- and flood-prone districts for PRM, SWM, and NEM seasons. The model consistently captured seasonal trends and variations accurately. In heavy rainfall areas like Chikkamagalur, Udupi, and Uttara Kannada, the model effectively mirrored the variability. In drought regions like Chitradurga, Koppala, and Raichur, it tracked smooth and irregular trends well. Transitional zones like Shivamogga and fluctuating regions like Kodagu and Dakshina Kannada also showed strong model alignment with actual data. Figures 2 illustrate the model’s accuracy across all seasons, confirming its robustness and adaptability for rainfall prediction, aiding in hydrological planning and disaster preparedness.

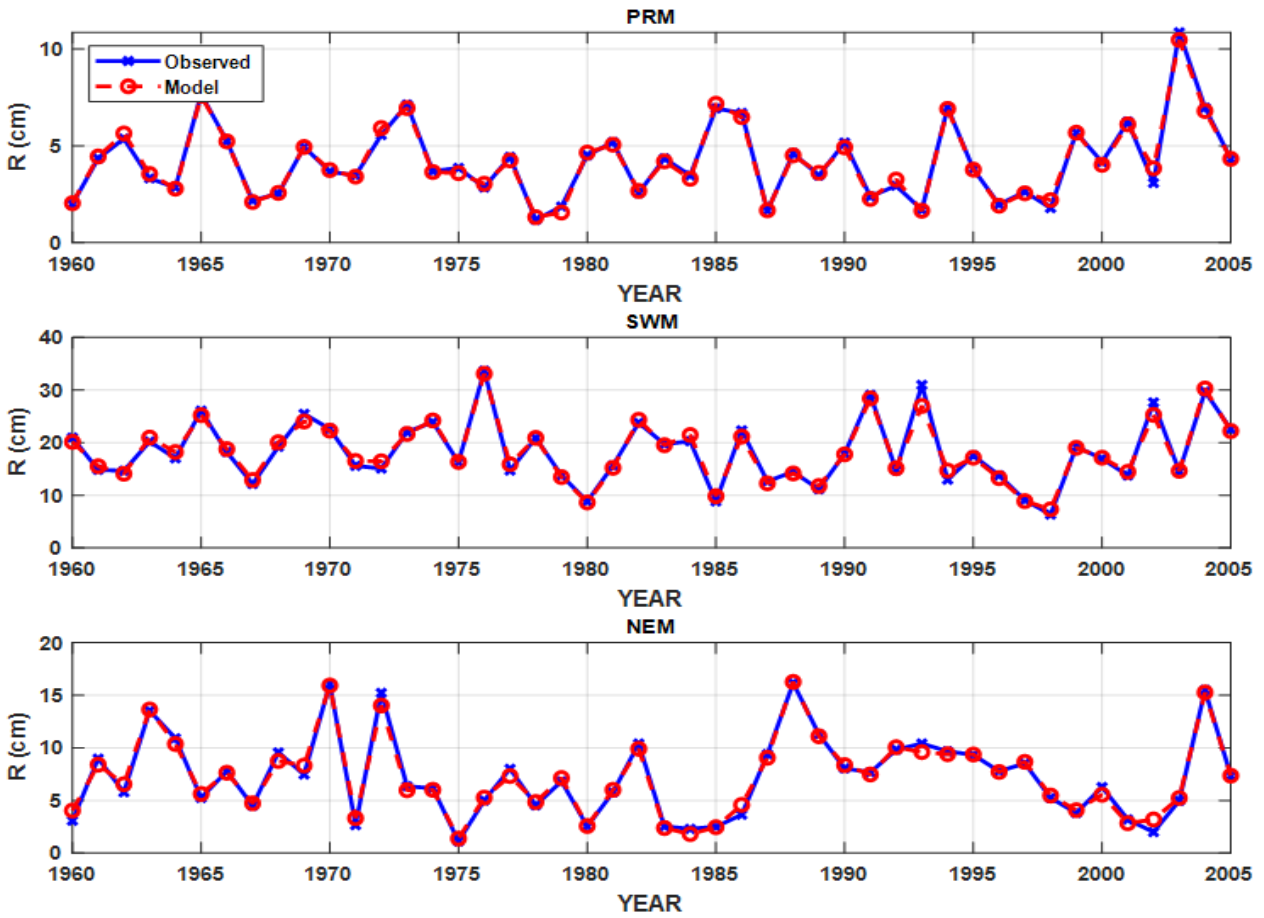
5. Statistical Overview of Training Rainfall Data (1960–2010)

The model closely matches observed mean rainfall, showing high accuracy. It effectively captures rainfall variability in both drought and flood prone regions of Karnataka. Tables 7 and 8 present statistical comparisons between observed and ANN-predicted rainfall data (1960–2010) for drought- and flood-prone districts in Karnataka across PRM, SWM, and NEM seasons. Key metrics such as mean, standard deviation, skewness, and kurtosis highlights how well the model replicates actual rainfall patterns. Skewness values indicate asymmetry in rainfall, particularly in

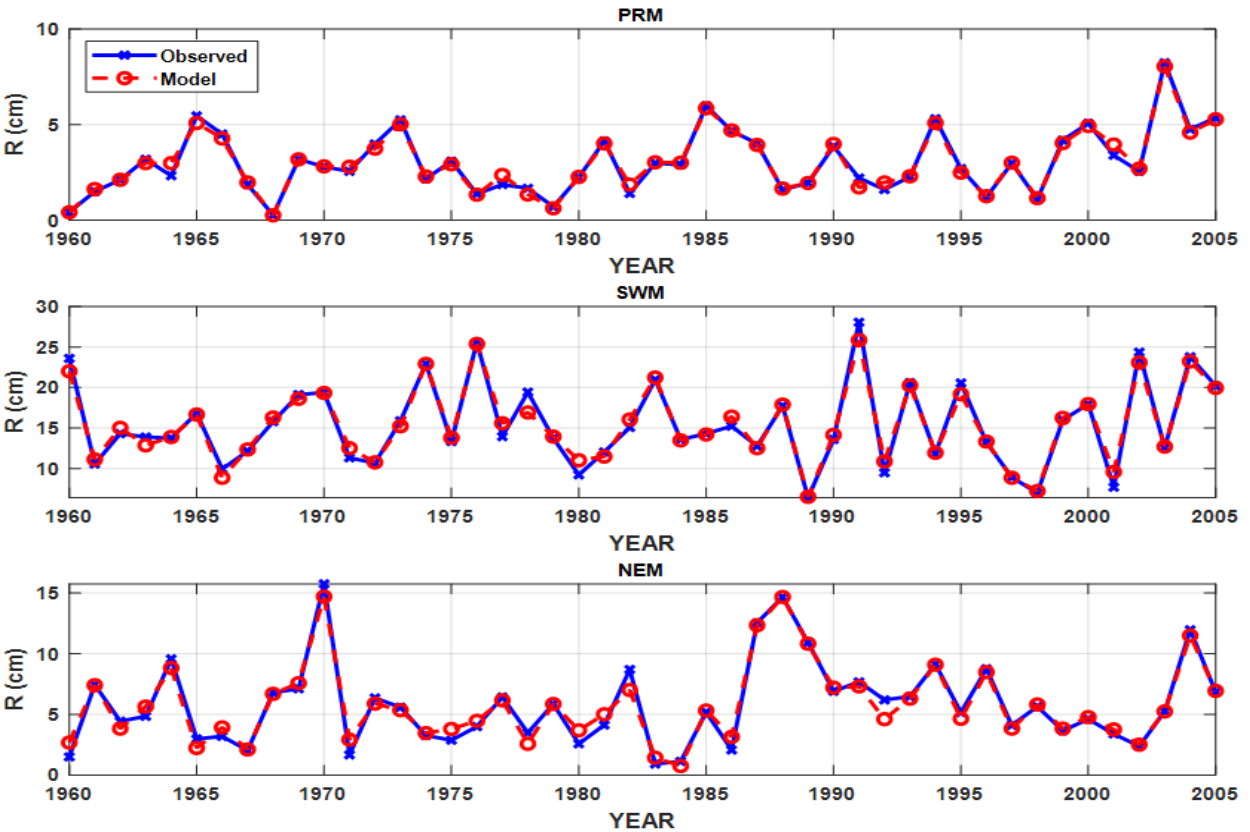
Kodagu and Shivamogga, which the model tracks well. Kurtosis values confirm non-Gaussian rainfall distribution, justifying the use of a non-linear ANN. The strong alignment between observed and forecasted statistics demonstrates the ANN model's reliability and adaptability, making it a robust tool for seasonal rainfall prediction in diverse climatic zones of Karnataka.

After training the ANN model using rainfall data from 1960 to 2010, its performance was tested using unseen data from 2011 to 2016. This testing phase assessed the model’s ability to predict rainfall accurately across Karnataka’s drought- and flood-prone districts for the key seasons—Pre-Monsoon (PRM), Southwest Monsoon (SWM), and Northeast Monsoon (NEM)—which are crucial for agriculture and water resources. To ensure realistic evaluation, the 2011–2016 data were excluded from training. The model used rainfall data from the previous five years to forecast the next year's rainfall for each year in the testing period. This method tested the model's generalization ability, reflecting real-life forecasting conditions. Given Karnataka's non-stationary rainfall behavior, the ANN model’s ability to learn from both linear and non-linear patterns made it well-suited for adapting to irregular trends in both dry and wet regions. Statistical summaries of both training and testing phase, including mean, standard deviation, skewness, and kurtosis, are presented in Tables 4 and 5 respectively to illustrate rainfall variation across districts and seasons.

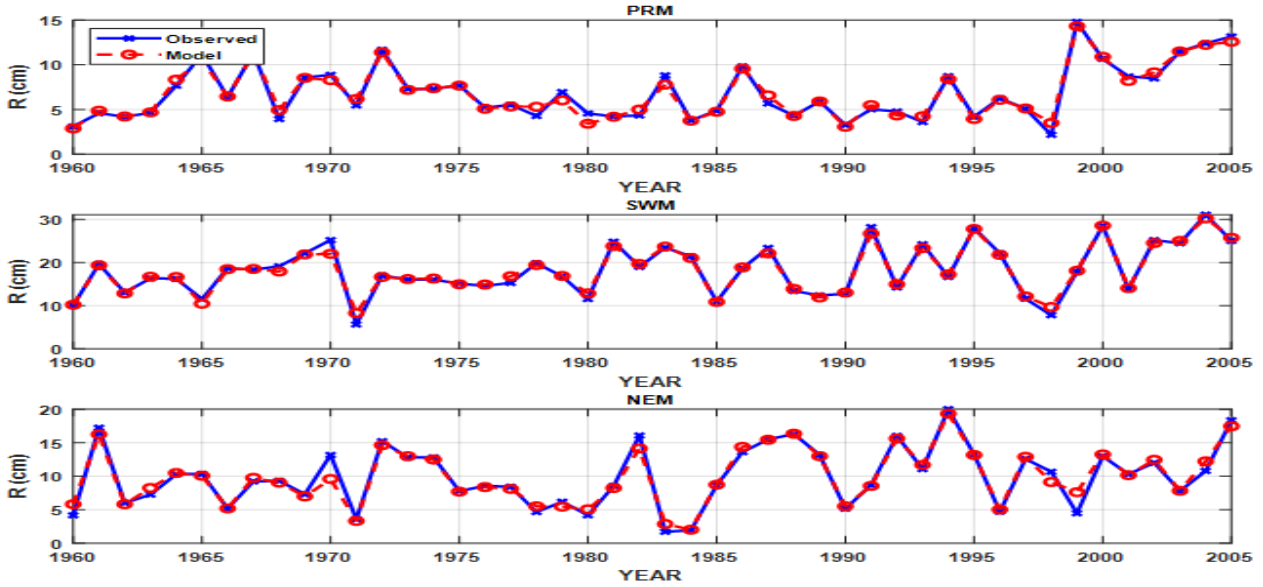
Bagalkote Rainfall: Observed Data vs Modelled Data(1960 -2005)



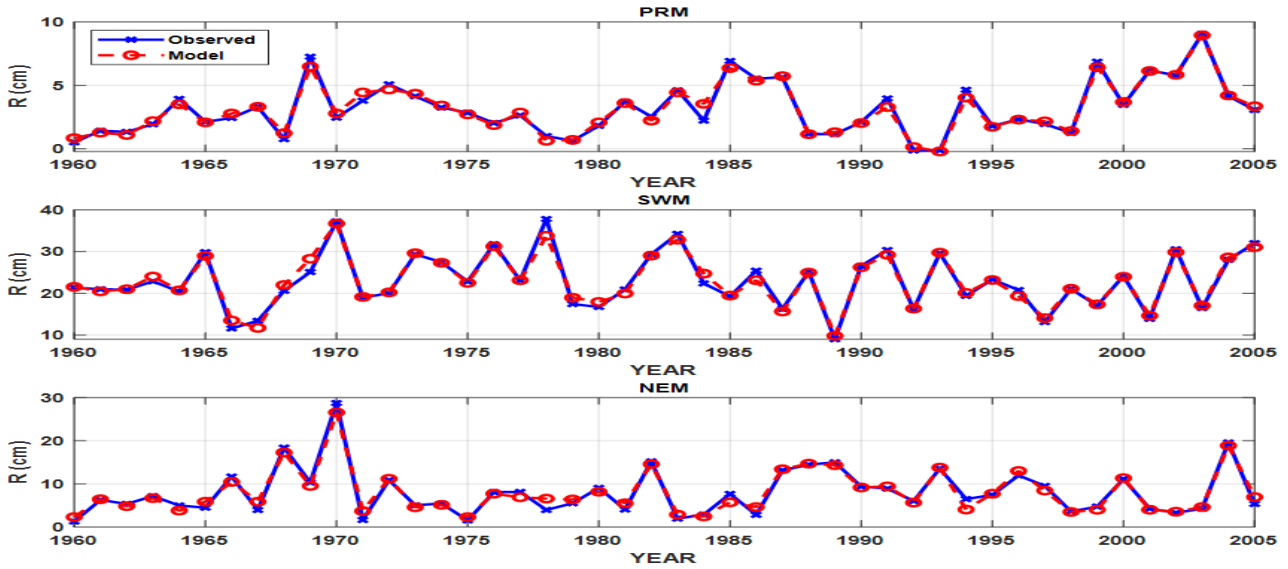
Koppala Rainfall: Observed Data vs Modelled Data(1960 -2005)



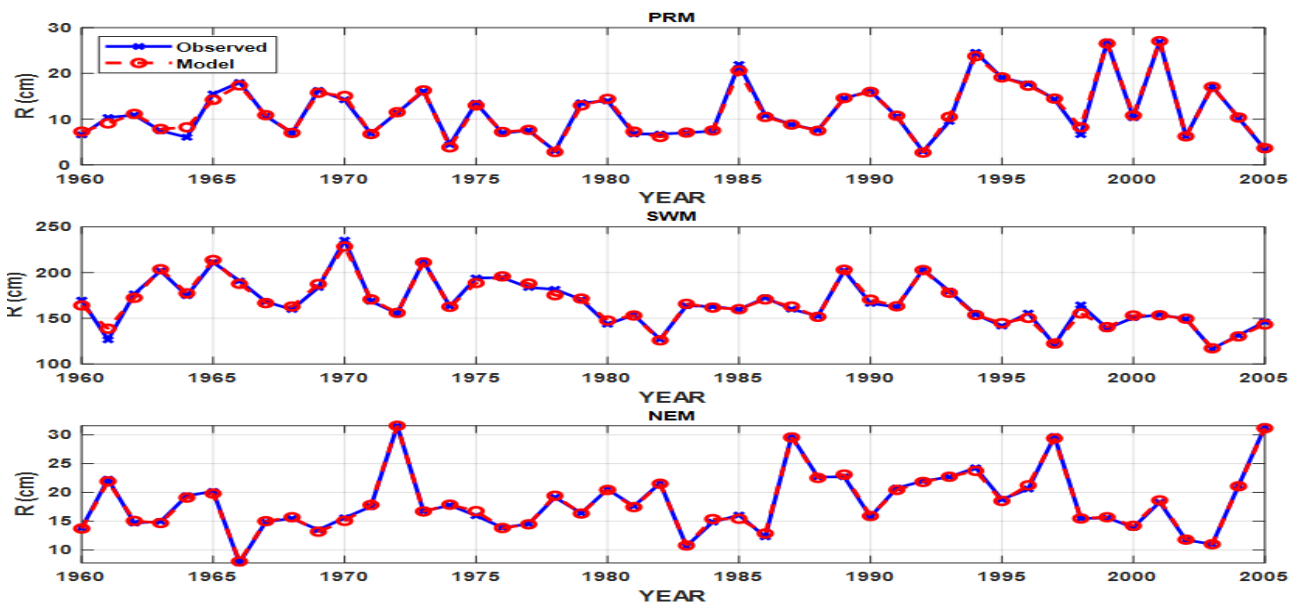
Chithradurga Rainfall: Observed Data vs Modelled Data(1960 -2005)



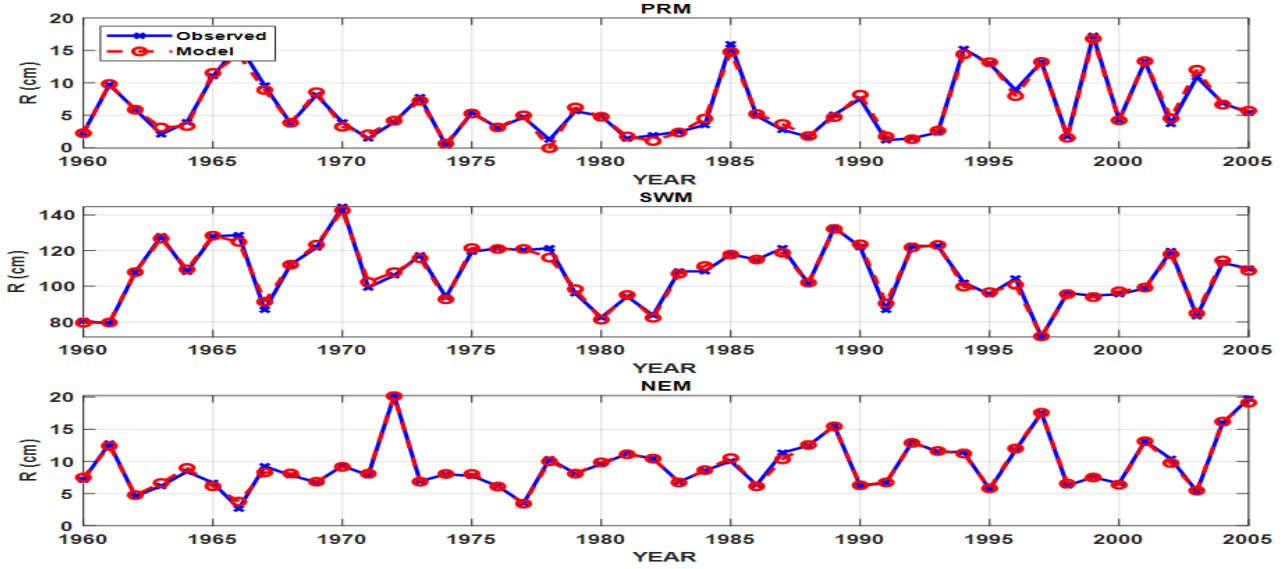
Raichur Rainfall: Observed Data vs Modelled Data(1960-2005)



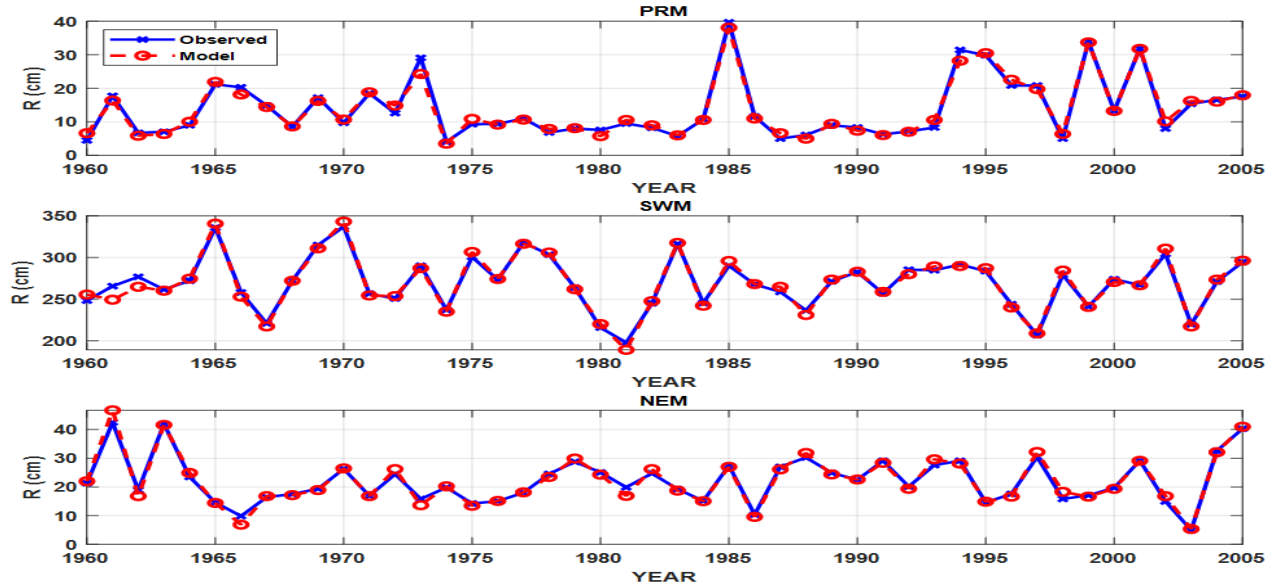
Dakshina Kannada Rainfall: Observed Data vs Modelled Data(1960 -2005)



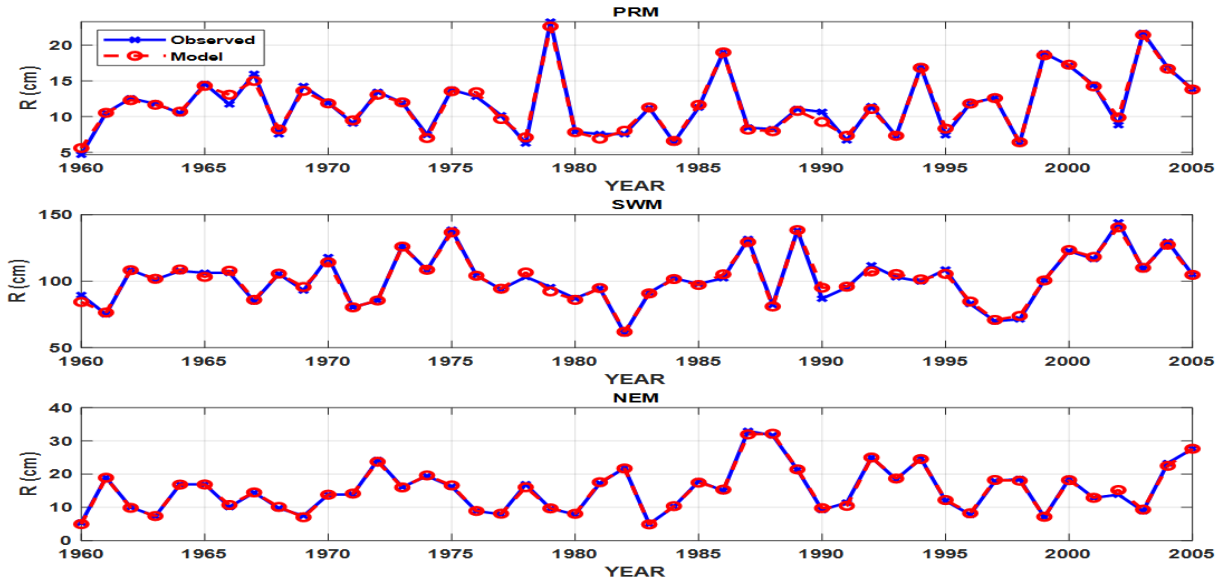
Udupi Rainfall: Observed Data vs Modelled Data(1960-2005)



Uttara kannada Rainfall: Observed Data vs Modelled Data(1960-2005)



Chikkamagalur Rainfall: Observed Data vs Modelled Data(1960 - 2005)



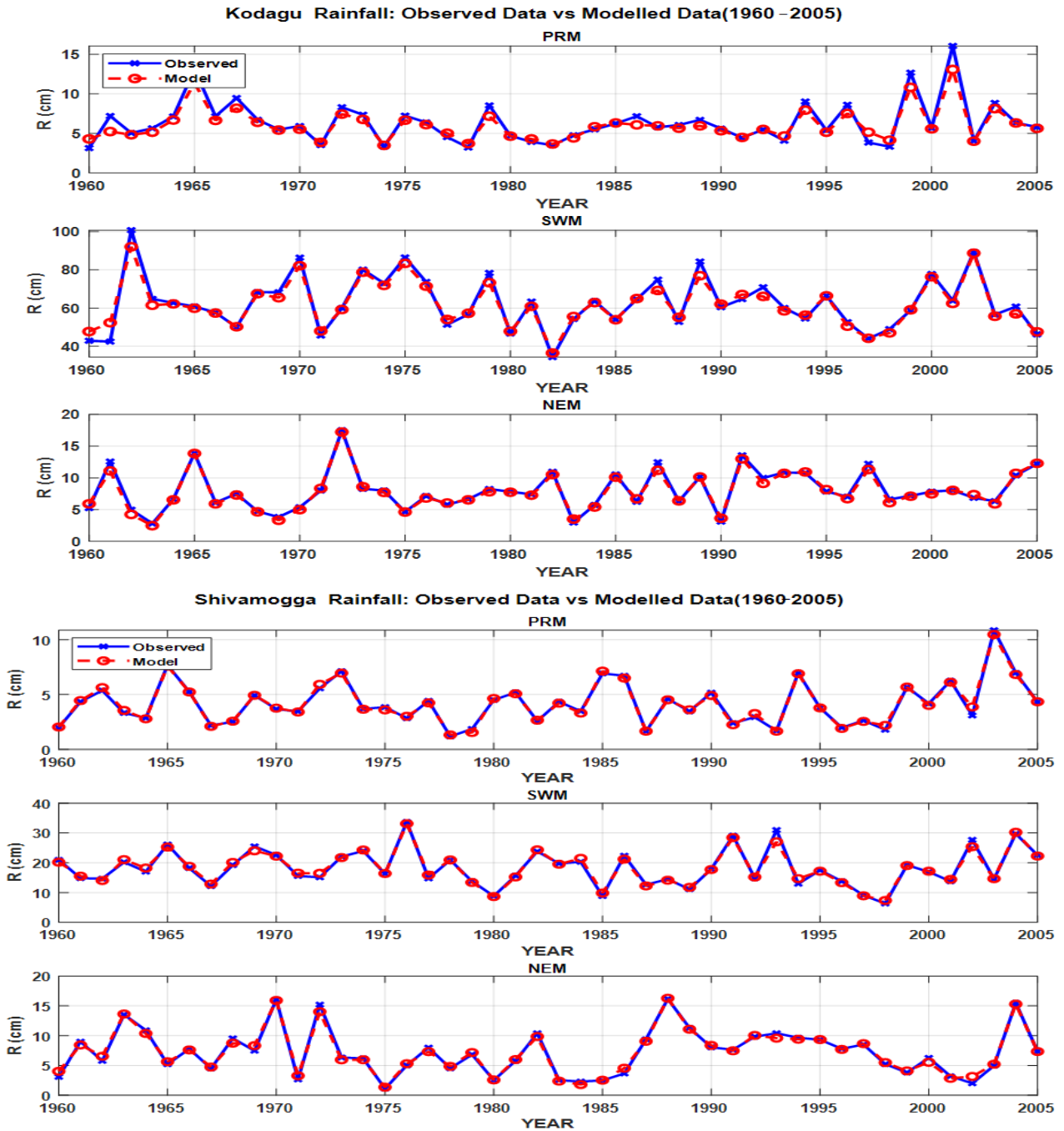


Figure 2: Comparison between observed and ANN-predicted rainfall values for Shivamogga district during PRM, SWM, and NEM seasons (1960–2005).

Table 4: Statistical Overview Training Rainfall Data (1960-2010) - Drought & Flood Prone Districts of Karnataka

	Bagalkote						Chithradurga					
	PRM		SWM		NEM		PRM		SWM		NEM	
	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred
μ	4.31	4.18	18.15	18.31	7.32	7.28	6.85	6.85	18.22	18.21	9.97	9.97
σ	2.05	1.9	6.01	5.73	3.86	3.71	3.06	2.89	5.89	5.41	4.52	4.13
K_z	0.98	0.88	0.48	0.4	0.65	0.7	2.66	2.64	2.4	2.36	2.28	2.27
S_z	1.45	1.1	0.08	0.01	0.07	0.2	0.76	0.76	0.17	0.27	0.17	0.18

Bagalkote							Chithradurga					
PRM		SWM		NEM		PRM		SWM		NEM		
Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	
Koppala							Raichur					
μ	3.02	3.02	15.42	15.42	5.79	5.79	3.15	3.15	22.92	22.93	8.03	8.01
σ	1.66	1.58	5.17	4.71	3.45	3.19	2.09	1.97	6.65	6.17	5.46	5.01
K_z	3.53	3.66	2.59	2.53	3.79	4.03	3.1	3.18	2.6	2.42	5.95	5.54
S_z	0.76	0.68	0.47	0.37	1.02	1.1	0.74	0.67	0.23	0.09	1.51	1.49
Dakshina Kannada							Udupi					
μ	11.8	11.8	166.8	166.8	17.9	17.9	6.09	6.1	107.1	107.1	9.39	9.39
σ	5.95	5.75	25.49	24.62	4.99	4.91	4.63	4.46	16.54	16.03	3.93	3.82
K_z	3.21	3.38	3.08	2.93	3.67	3.71	2.77	2.56	2.33	2.39	3.73	3.75
S_z	0.86	0.84	0.32	0.33	0.74	0.75	0.93	0.82	-0.13	-0.19	0.98	1.04
Uttara Kannada							Chikkamagalur					
μ	13.8	13.8	269.4	269.3	22.2	22.2	11.7	11.7	101.7	101.7	15.3	15.3
σ	8.89	8.38	31.56	33.22	8.01	8.58		4.04	18.34	17.64	6.81	6.71
K_z	3.69	3.75	2.87	2.93	3.41	3.61	3.18	3.17	2.99	2.93	2.91	2.92
S_z	1.25	1.22	-0.04	-0.01	0.6	0.68	0.73	0.77	0.25	0.2	0.65	0.62
Kodagu							Shivamogga					
μ	6.35	6.01	62.58	61.82	8.03	7.86	4.18	4.18	18.31	18.31	7.28	7.28
σ	2.66	2.42	14.05	12.96	3.16	3.02	1.98	1.92	6.21	5.74	3.91	3.71
K_z	6.13	6.32	3.02	3.05	3.37	3.6	4.17	3.86	2.79	2.86	2.81	3.06
S_z	1.59	1.68	0.5	0.51	0.71	0.72	0.95	0.85	0.47	0.38	0.63	0.68

The ANN model showed strong performance during testing, with most districts recording high accuracy indicators, CC above 0.85, PP above 0.80, and low RMSE values. These results confirm the model's

reliability and ability to make accurate rainfall predictions across Karnataka's diverse climatic regions. The model's testing performance is summarized in Tables 6.

Table 5: Statistical overview Testing Rainfall Data (2011 - 2016) Drought & Flood Prone Districts of Karnataka

Bagalkote							Chithradurga					
PRM		SWM		NEM		PRM		SWM		NEM		
Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	
μ	5.01	3.8	15.94	16.48	4.66	5.62	9.27	10.14	17.61	19.29	8.28	8.65
σ	2.38	1.91	2.61	3.1	2.31	2.71	3.19	4.18	5.54	5.84	4.52	3.37
K_z	1.53	1.37	0.73	1.28	1.23	1.56	1.11	1.06	1.26	1.54	1.46	0.45
S_z	0.08	0.54	0.37	0.24	1.3	0.78	0.49	0.14	0.58	1.04	0.06	0.94

Bagalkote							Chithradurga						
PRM		SWM		NEM			PRM		SWM		NEM		
	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	Obs	Pred	
Koppala							Raichur						
μ	3.06	2.92	13.43	13.44	3.36	4.22	4.09	5.1	21.1	23.19	3.49	2.54	
σ	1.52	1.49	3.75	3.84	2.47	2.22	1.83	1.46	5.18	5.07	1.91	1.01	
K_z	1.02	1.08	3.2	4.61	2.04	1.73	1.62	1.66	2.16	1.69	1.53	2.19	
S_z	0.89	0.42	-0.15	-2.08	0.18	-0.01	-0.01	-0.03	0.47	0.27	-0.1	0.07	
Dakshina Kannada							Udupi						
μ	8.17	10.86	117.87	112.09	11.97	10.83	5.03	5.94	103.52	100.32	9.2	10.48	
σ	2.18	3.62	18.27	17.69	4.71	3.11	2.41	2.35	16.85	14.65	3.6	2.61	
K_z	2.82	3.69	1.65	2.87	2.54	1.52	1.32	1.49	1.88	1.91	3.08	2.91	
S_z	0.92	1.48	0.02	-0.97	-0.73	-0.6	0.19	0.34	0.43	-0.13	-1.15	0.23	
Uttara Kannada							Chikkamagalur						
μ	9.95	11.5	259.49	265.42	18.6	20.05	14.14	14.5	88.65	96.9	10.54	12.87	
σ	3.1	2.91	36.2	35.62	3.29	3.02	3.62	2.05	20.4	28.94	5.03	4.36	
K_z	1.65	1.66	2.48	1.56	1.98	2.23	2.27	1.34	1.52	1.75	1.46	2.24	
S_z	-0.26	-0.41	0.48	0.47	0.06	-0.49	-0.6	0	0.27	0.1	-0.08	0.05	
Kodagu							Shivamogga						
μ	6.21	7.16	58.31	56.36	5.78	4.82	5.01	3.72	15.94	16.49	4.66	5.44	
σ	2.31	2.47	14.86	11.17	1.87	1.51	2.38	2.81	2.61	2.72	2.31	1.94	
K_z	2.28	2.02	1.89	1.83	2	1.38	1.62	1.3	1.89	1.68	2.57	2.43	
S_z	0.23	-0.06	0.38	0.15	-0.44	-0.21	0.06	-0.01	-0.27	0.28	-0.95	0.39	

Table 6: ANN model performance during 2011–2016 for the drought and flood prone districts

Drought Prone Regions									
Regions	Season	RMSE	CC	PP	Regions	Season	RMSE	CC	PP
Bagalkote	PRM	1.68	0.84	0.8	Koppala	PRM	0.77	0.96	0.98
	SWM	1.34	0.9	0.84		SWM	0.54	0.87	0.98
	NEM	1.56	0.87	0.85		NEM	0.81	0.9	0.9
Chithradurga	PRM	1.9	0.84	0.76	Raichur	PRM	0.88	0.85	0.8
	SWM	0.79	0.87	0.95		SWM	1.15	0.86	0.98
	NEM	1.22	0.85	0.75		NEM	1.47	0.88	0.88
Flood Prone Regions									
Dakshina Kannada	PRM	0.88	0.85	0.81	Chikkamagalur	PRM	1.29	0.92	0.76
	SWM	1.15	0.9	0.85		SWM	1	0.82	0.7
	NEM	1.47	0.82	0.88		NEM	0.88	0.76	0.87

Drought Prone Regions									
Regions	Season	RMSE	CC	PP	Regions	Season	RMSE	CC	PP
Udupi	PRM	1.41	0.83	0.88	Kodagu	PRM	1.48	0.89	0.94
	SWM	1.29	0.86	0.87		SWM	1.13	0.85	0.75
	NEM	2.06	0.89	0.72		NEM	2.42	0.85	0.81
Uttara Kannada	PRM	0.55	0.84	0.94	Shivamogga	PRM	1.78	0.88	0.85
	SWM	1.64	0.81	0.9		SWM	1.49	0.84	0.96
	NEM	1.74	0.84	0.92		NEM	1.45	0.81	0.84

To make the analysis more meaningful, Tables 7 and 8 present a detailed year-wise comparison of actual and predicted rainfall values for each district. These tables clearly show that the ANN model was able to follow the ups and downs of rainfall each year, even in difficult cases. The match between predicted and observed values is quite close in most years and seasons. In conclusion, the ANN model has shown good ability to predict rainfall during the testing period. Hence the model is accurate, flexible, and suitable for practical use in agriculture planning, water management, and disaster preparedness. This makes it a valuable tool for future climate-based decision-making in Karnataka.

6. Prediction

To analyzing historical rainfall data, this study incorporates a two-step forecasting approach to

predict seasonal rainfall for the upcoming years 2025 and 2026. The forecasted rainfall values for each season, pre-monsoon, south-west monsoon, post-monsoon, during these two years are compiled and presented in a detailed table in 9. This allows for a clear understanding of expected seasonal rainfall patterns in the near future. To enhance interpretability, a graphical representation of these predicted values is included in Figure 3. This visual aid illustrates the projected rainfall trends over time, helping to identify any noticeable patterns for drought-prone and flood-prone districts of Karnataka. Overall, the combined use of tabular and graphical data, along with targeted regional analysis, strengthens the utility of this study in supporting climate-resilient planning and resource allocation across Karnataka.

Table 7: Comparison of predicted and actual rainfall values (in cm) for the testing period (2011–2016) for the drought prone districts

Bagalkote							Koppala					
Season	PRM		SWM		NEM		PRM		SWM		NEM	
Year	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data
2011	6.81	4.23	18.59	19.76	5.54	5.76	3.14	3.45	13.01	14.26	1.67	1.76
2012	2.06	2.71	12.03	12.43	6.75	9.05	1.46	1.7	7.81	5.88	6.04	6.24
2013	5.87	3.5	16.3	14.41	6.43	5.3	2.08	1.2	13.7	14.91	3.95	3.99
2014	8.23	6.95	18.85	20.46	5.25	7.45	5.54	5.15	18.67	15.88	6.3	7.04
2015	4.24	4.19	15.68	15.81	3.4	5.16	4.02	3.87	16.02	16.2	1.83	4.61
2016	2.84	1.2	14.21	15.98	0.59	1.02	2.12	2.17	11.39	13.49	0.33	1.71
Chithradurga							Raichur					
2011	6.29	4.69	9.23	9.16	8.3	7.65	6.33	5.55	17.35	20.03	1.59	1.1
2012	11.22	15.86	15.92	16.8	8.83	8.53	1.69	3.54	14.87	16.51	5.4	3.01
2013	9.5	10.13	22.98	26.15	3.69	5.35	3.71	4.97	29.36	27.47	5.69	4.04

Bagalkote							Koppala					
Season	PRM		SWM		NEM		PRM		SWM		NEM	
Year	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data
2014	13.15	13.76	22.44	20.49	14.15	10.53	5.92	7.06	21.36	22.25	3.88	2.91
2015	10.76	9.61	21.3	22.73	12.09	14.29	4.36	6.14	19.37	22.33	3.29	2.21
2016	4.71	6.77	13.79	20.4	2.64	5.56	2.55	3.36	24.27	30.53	1.07	1.97

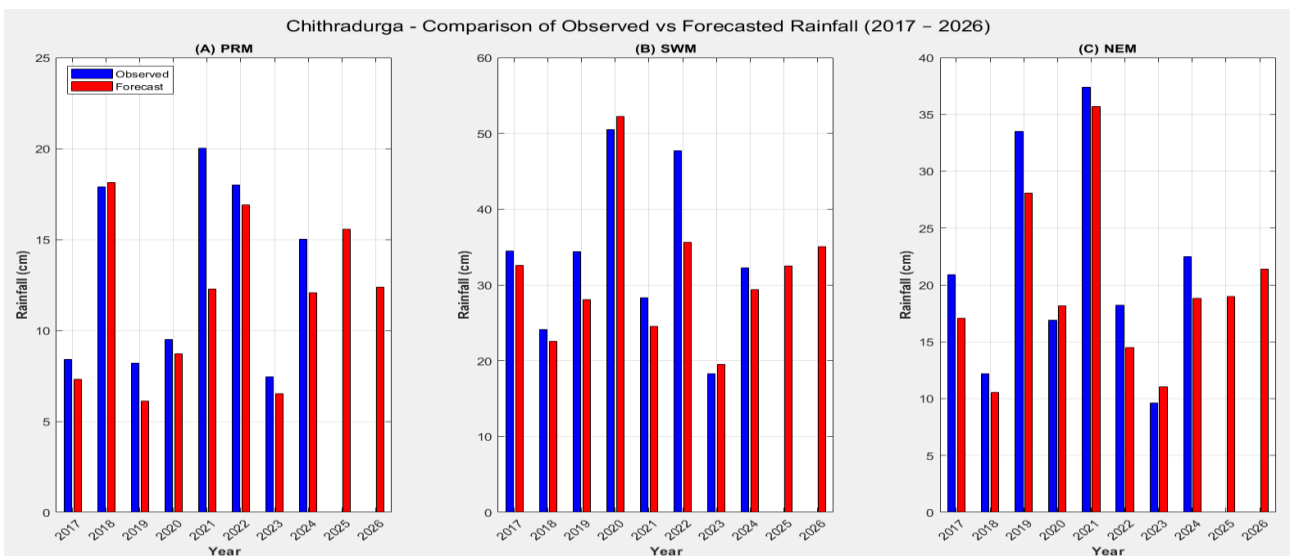
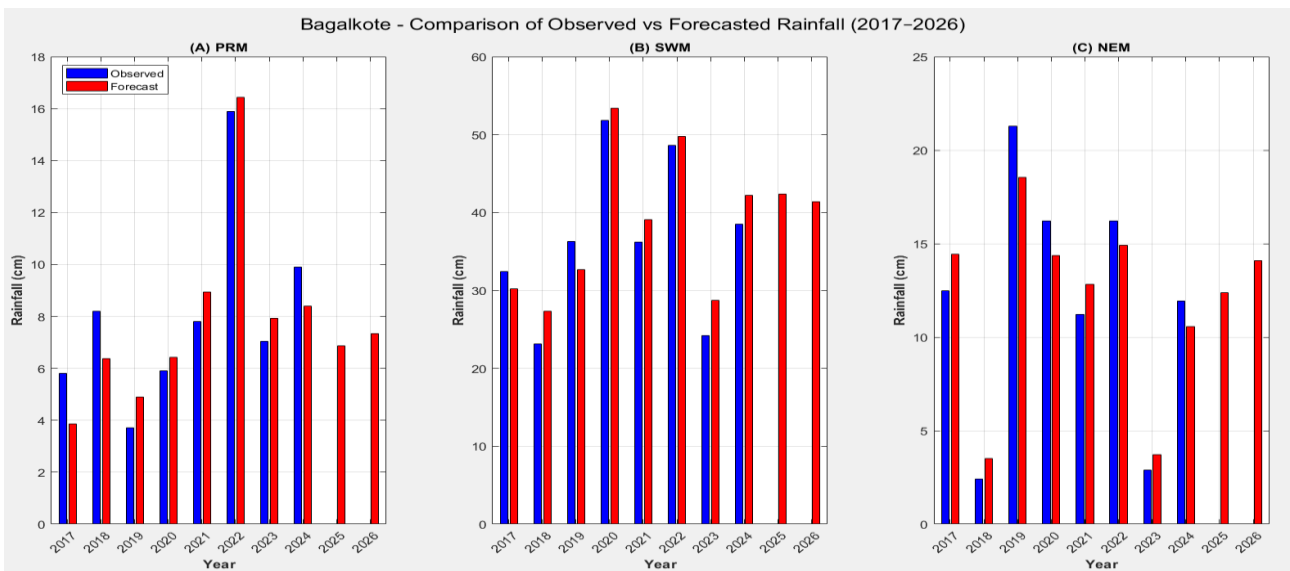
Table 7: Comparison of predicted and actual rainfall values (in cm) for the testing period (2011–2016) for the flood prone districts

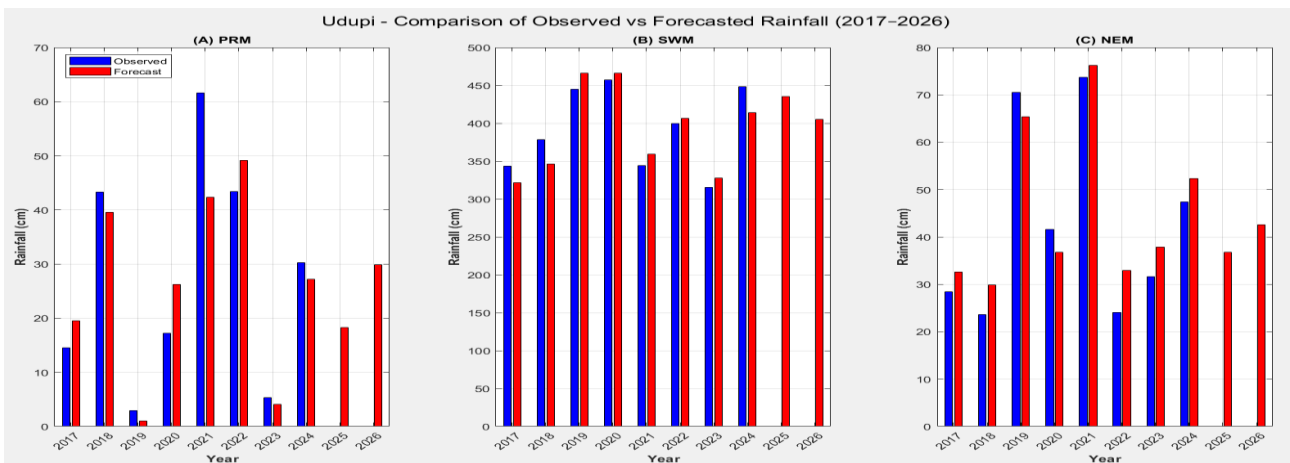
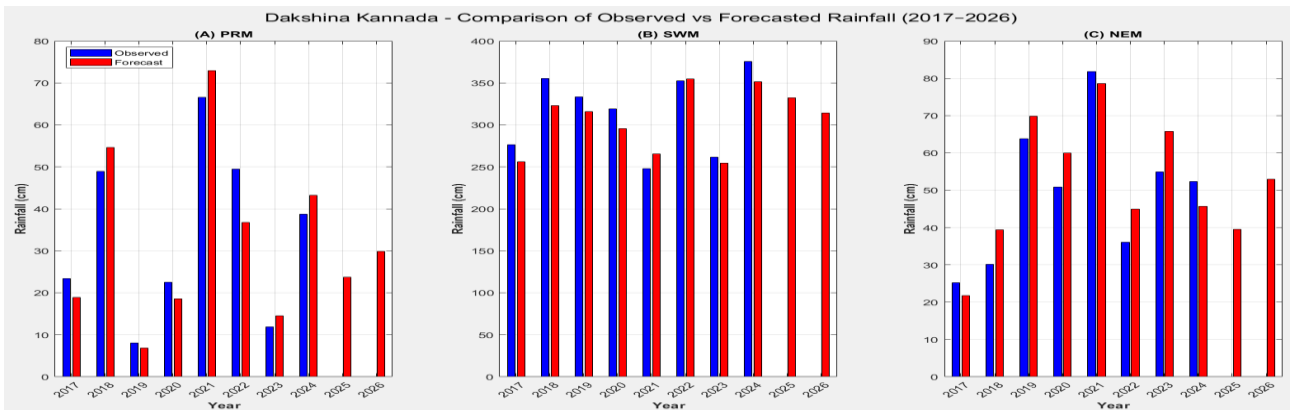
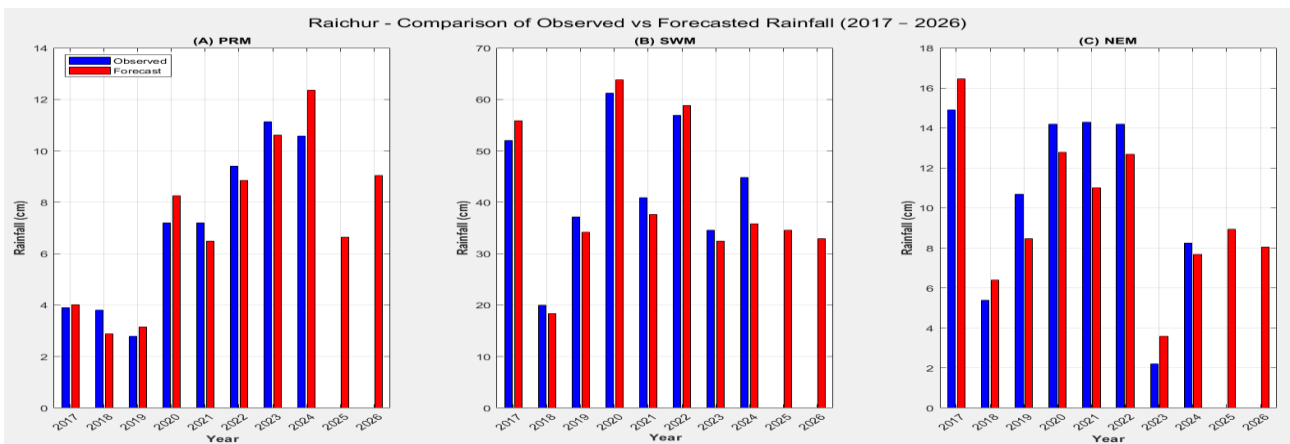
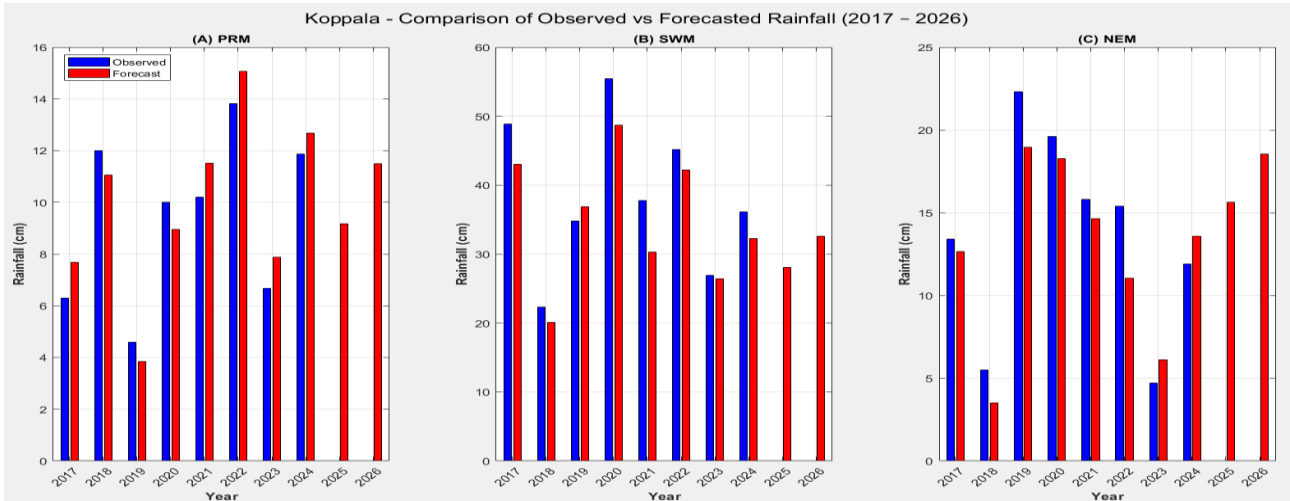
Dakshina Kannada							Udupi					
Season	PRM		SWM		NEM		PRM		SWM		NEM	
Year	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data	Obs data	Pred data
2011	6.46	7.9	137.22	120.31	12.88	12.8	2.61	5.9	129.27	119.47	12.51	14.75
2012	5.94	10.45	115.06	115.15	10.37	6.79	2.68	3.33	116.07	111.97	8.24	9.97
2013	7.95	8.72	139.89	121.52	16.45	12.31	7.54	8.62	105.42	104.47	9.72	10.37
2014	12.07	17.96	118.22	110.8	11.64	12.25	5.77	4.74	93.54	91.97	10.46	10.18
2015	8.82	9.66	93.67	94.22	16.6	13.84	7.97	8.93	84.01	95.1	11.74	11.03
2016	7.77	10.46	103.18	110.56	3.85	6.96	3.58	4.11	92.81	78.94	2.51	6.59
Uttara Kannada							Chikkamagalur					
2011	13.51	14.91	319.36	304.58	17.86	19.9	12.92	12.43	94.37	95.5	16.32	15.79
2012	7.63	12.1	270.25	313.98	20.65	20.87	12.99	13.67	77.17	58.09	9.38	12.06
2013	8.97	8.43	267.86	254.45	23.33	22.32	15.5	15.32	117.03	125.75	5.53	12.91
2014	11.54	13.32	250.56	255.5	14.11	15.16	17.93	16.63	106.03	134.6	12.14	12.27
2015	12.53	12.75	213.34	232.52	19.48	23.67	17.38	16.82	70.61	77.41	15.55	14.26
2016	5.49	7.48	235.58	231.48	16.16	18.36	8.14	12.15	66.68	90.02	4.31	3.33
Kodagu							Shivamogga					
2011	4.64	5.78	60.14	47.63	7.88	6.84	6.81	5.73	18.59	20.11	5.54	6.17
2012	5.76	7.09	48.99	57.46	6.5	6.2	2.06	0.46	12.03	14.89	6.75	5.9
2013	6.78	7.01	80.78	72.17	5.44	4.18	5.87	7.14	16.3	15.31	6.43	8.59
2014	7.19	10.29	69.35	65.31	4.64	3.04	8.23	5.68	18.85	19.35	5.25	4.58
2015	9.81	9.12	50.15	53.7	7.38	5.85	4.24	2.28	15.68	16.2	3.4	4.54
2016	3.07	3.76	40.42	41.91	2.85	3.81	2.84	1.04	14.21	13.08	0.59	2.86

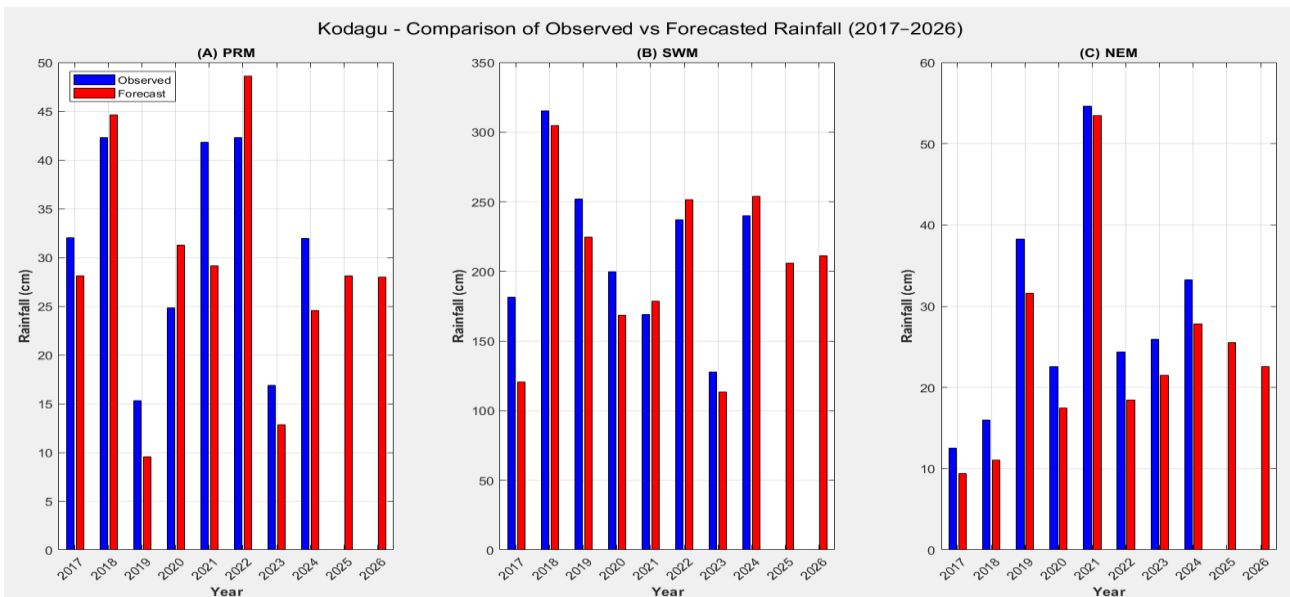
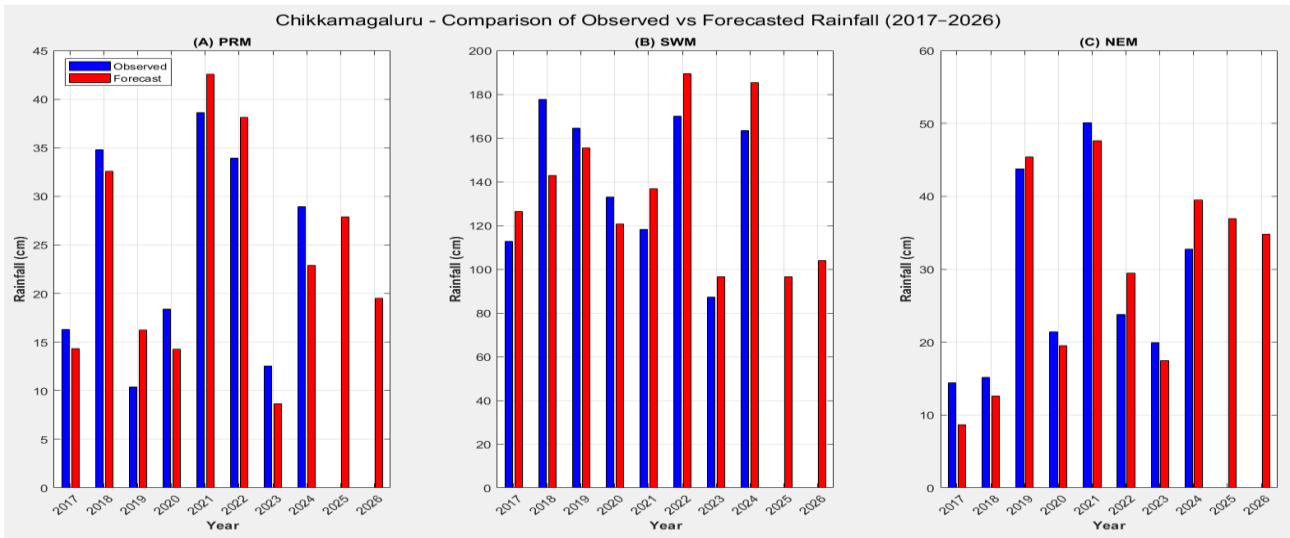
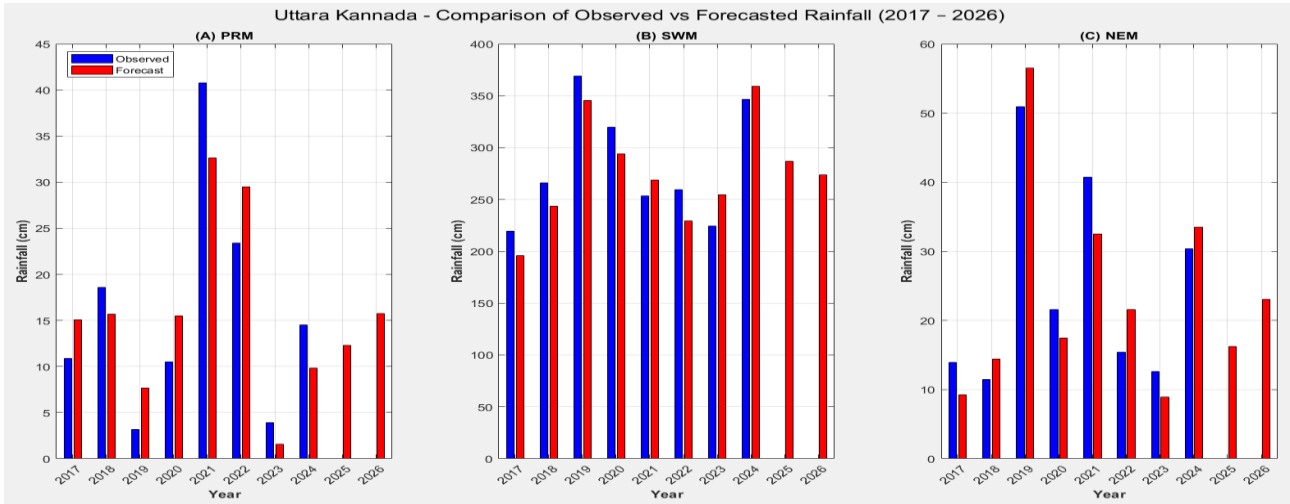
Table 9: Predicted Rainfall Data during 2025 – 2026

Drought Prone Districts						
Bagalkote				Koppala		
Year	PRM	SWM	NEM	PRM	SWM	NEM
2025	6.86	42.35	12.37	9.18	28.05	15.63
2026	7.34	41.38	14.1	11.49	32.56	18.56

Drought Prone Districts						
Chithradurga				Raichur		
2025	15.58	32.53	18.96	6.65	34.59	8.95
2026	12.38	35.06	21.38	9.05	32.91	8.06
Flood Prone Districts						
Dakshina Kannada				Uttara Kannada		
2025	23.76	332.56	39.56	12.29	286.59	16.23
2026	29.86	314.07	52.93	15.76	273.74	23.05
Udupi				Chikkamagaluru		
2025	18.26	435.49	46.78	27.89	96.48	36.98
2026	29.87	405.29	51.59	19.53	103.89	34.83
Kodagu				Shivamogga		
2025	28.09	205.89	25.48	18.63	192.56	24.56
2026	27.98	210.98	22.6	15.98	181.45	27.81







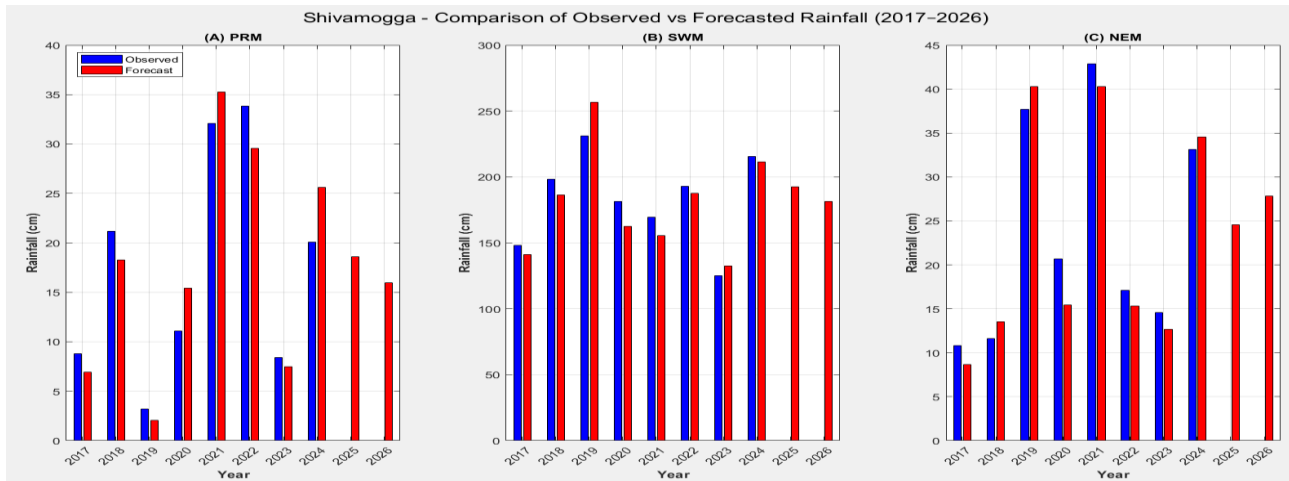


Figure 3: Comparison plot between the observed rainfall data and the modeled rainfall data along with predicted data during 2017 – 2026 – Flood Prone Districts of Karnataka

7. Discussion

Rainfall patterns in Karnataka varies differently depending on the location. Some districts like Bagalkote, Chitradurga, Koppala, and Raichur often suffer from drought due to very low and irregular rainfall pattern. In contrast, districts like Dakshina Kannada, Udupi, Uttara Kannada, Chikkamagaluru, Kodagu, and Shivamogga experience floods because of heavy and consistent rainfall, especially during the Southwest Monsoon (SWM). This sharp contrast creates a big challenge for predicting rainfall accurately because the rainfall is not steady, it changes in amount and timing from year to year. To deal with this problem, the study used an Artificial Neural Network (ANN) model that could learn from past rainfall data and predict future rainfall for three seasons such as Pre-Monsoon (PRM), Southwest Monsoon (SWM), and Northeast Monsoon (NEM). The model was designed with 15 input nodes (five years of seasonal data), 5 hidden nodes to process the information, and 3 output nodes to give predictions for the three monsoon seasons. The model was trained using data from 1960 to 2010, and tested using new data from 2011 to 2016. The testing results showed that the model was very accurate and it could explain about 85% to 94% of the variation in rainfall. The model worked well in drought-prone areas with low rainfall and also in flood-prone areas with very high rainfall. In places like Shivamogga and Kodagu, where rainfall patterns are more complex and change a lot, the model still gave very good results. This shows that the ANN model is strong, flexible, and dependable for predicting seasonal rainfall in all types of regions in Karnataka.

8. Conclusion

This study showed that the Artificial Neural Network (ANN) model is effective in predicting seasonal rainfall in different parts of Karnataka. The model used rainfall data from the past five years to predict the rainfall for the next year, for all three major monsoon seasons: Pre-Monsoon (PRM), Southwest Monsoon (SWM), and Northeast Monsoon (NEM). The architecture, with 15 inputs, 5 hidden processing units, and 3 outputs. The model was trained with a large amount of historical data (1960–2010) and then tested with more recent data (2011–2016). During training, the model could explain about 88% to 95% of the rainfall variation. During testing, it still performed well, explaining 74% to 95% of the variation, depending on the district and the season. Because the model worked well in both drought and flood regions, it proves to be a useful and reliable tool for predicting rainfall. This can help people and governments make better plans for farming, water storage, flood control, and drought management. The predictions for future years like 2025 and 2026 also show that this method can be used for long-term planning. In summary, the ANN model is a helpful to support climate-based decisions in Karnataka.

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