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Prediction of Monthly Rainfall in Togo Using Artificial Neural Networks (ANN)

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Abstract

This study evaluates the performance of a feed-forward Artificial Neural Network (ANN) model in simulating historical monthly rainfall in Togo (1981-1985, 1986-1990, 1991-1996, and 1996-2000) and projecting rainfall patterns for 2026-2030. The model reliably captures the seasonal progression and north-south gradient, with low RMSE and high R^2 values in most periods. Historical results reveal early-season overestimation in northern and central regions (+15% to +45%), mid-season peak biases in southern and central zones (+25% to +50%), and late-season underestimation in the north (up to −75%). Projected rainfall for 2026-2030 indicates a relatively dry scenario in northern Togo, an irregular minor rainy season in the south, and notable spatial variations across regions. These findings demonstrate the model's capacity to reproduce both historical and future rainfall dynamics, while highlighting uncertainties related to ITCZ positioning, coastal monsoon influence, and localized convective events, supporting its application in regional rainfall simulation, water resource management, and climate adaptation planning.

Keywords

Artificial Neural Network (ANN), Monthly Rainfall, Rainfall Projection, Togo, Seasonal Variability

1. Introduction

Rainfall is a complex, non-linear, and highly dynamic process that is not yet fully understood. It is influenced by numerous climatic and environmental factors, including temperature, relative humidity, wind speed and direction, atmospheric pressure, and historical rainfall records. These variables interact in intricate and often unpredictable ways, making accurate rainfall prediction a challenging task [1]. Reliable rainfall forecasts are essential for agriculture, water resource management, flood mitigation, and urban infrastructure planning, such as traffic control and sewer management [2]. Accurate predictions enable timely decisions for disaster prevention, efficient reservoir operation, and strategic scheduling of agricultural activities.

Despite significant advances in meteorology and computational modeling, consistently accurate rainfall forecasting remains difficult due to the inherent uncertainty and variability of atmospheric processes [3]. Traditional statistical and time series models often rely on assumptions about linearity or fixed functional forms, which can limit their ability to capture the non-linear and chaotic nature of rainfall dynamics.

In recent years, there has been significant interest among various research groups in developing high-resolution gridded rainfall datasets. Artificial neural network (ANN) activity mostly mimics that of the human brain. An ANN does calculations, recognizes patterns, and performs other tasks. Artificial Neural Networks (ANNs) have emerged as a promising alternative for rainfall prediction. Their advantages include the ability to model complex, non-linear relationships between input and output variables, the capability to learn patterns from historical data without requiring restrictive assumptions, and the efficiency in handling large datasets through parallel processing [4]. Furthermore, ANNs can generalize learned patterns to predict unseen events, making them particularly suitable for modeling rainfall in regions with high spatial and temporal variability.

The primary objective of this study is to evaluate the performance of ANN models in simulating historical monthly rainfall in Togo and to project future seasonal rainfall for the period 2026-2030. The analysis considers regional differences across northern, central, and southern Togo to capture the spatial variability of rainfall patterns. By integrating historical data with ANN-based modeling, this study aims to provide more accurate forecasts, supporting water resource management, agricultural planning, and climate adaptation strategies. Ultimately, this research contributes to improving rainfall prediction in semi-arid regions, enhancing preparedness for extreme weather events, and informing sustainable development planning.

2. Study Area, Methods, Data, and Materials

In this section, Study area, Methods, and Data Collection, Site Selection, Optimization and Simulation Tools are described.

2.1. Study Area

The Republic of Togo is situated in West Africa, along the Gulf of Guinea, between latitudes 6˚N and 11˚N (**Figure 1**). It is bordered by Ghana to the west, Benin to the east, and Burkina Faso to the north, with a coastline of approximately 56 km along the Gulf of Guinea [5]. The country covers an area of 54,600 km^2 and exhibits a diverse geography that includes rolling hills in the north, a central plateau, and a low-lying coastal plain with lagoons and marshes.

Figure 1. Study area.

Togo faces significant socio-economic and environmental challenges. Nearly 69% of rural households live below the poverty line, and the majority of the population depends directly on rain-fed agriculture for their livelihoods. This heavy reliance on agriculture makes rainfall variability a critical factor for food security, water resource management, and energy production. The climate ranges from tropical in the south to savanna in the north, with distinct rainfall regimes. In the southern regions, rainfall follows a bimodal pattern (March-July and September-November), while the northern part of the country is characterized by a unimodal regime, strongly influenced by the West African monsoon system.

The choice of Togo as the study area is motivated by the country's high vulnerability to climate variability and extreme weather events, particularly droughts and floods, which frequently disrupt agricultural productivity and threaten rural livelihoods. Accurate prediction of monthly rainfall is therefore essential to improve early warning systems, guide agricultural planning, and support policy decisions on water and energy management.

2.2. Data Sources, Methods and Materials

This study draws upon three primary data sources. The first consists of observed rainfall records obtained from the National Meteorological Agency of Togo (Météo Togo) covering the period 1980-2024. These records originate from stations distributed across the country and were regridded onto a common 50 km spatial resolution to ensure consistency with model outputs. To strengthen spatial coverage, these observations were supplemented with meteorological station data from neighboring countries, including Benin, Ghana, and Burkina Faso.

Given the limited number of stations, their uneven spatial distribution, data gaps, and relatively short observation periods, a second dataset was incorporated: the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), which provides high-resolution reanalysis data freely accessible at https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/ [6]. These data proved essential for complementing observed values, particularly at finer temporal scales (e.g., hourly). Missing observational records were further reconstructed using a cross-validation approach, following the methodology outlined in Celestin (2019) [7].

2.2.1. Development of ANN

Artificial Neural Networks (ANNs) are computational models inspired by the architecture of the human brain. The brain consists of numerous neurons interconnected by synapses. Neural networks, inspired by these biological structures, are composed of such interconnected neurons. A mathematically simplified representation of a biological neural network is referred to as an ANN. In this representation, a neuron is depicted as a node in a directed graph, and a synapse as a connecting edge. Since the 1940s, numerous ANN models have been proposed, with the most widely used being the Radial Basis Function (RBF) network and the Multi-Layer Perceptron Neural Network (MLPNN) [8].

In this study, a feed-forward MLPNN was developed for rainfall prediction. The network architecture consisted of:

- **Input layer:** corresponding to the predictor variables (e.g., past rainfall data, temperature, humidity, or climate indices, depending on the dataset).
- **Hidden layers:** two hidden layers were implemented. The first hidden layer contained N1N_1N1 neurons and the second contained N2N_2N2 neurons. The number of neurons was optimized through a trial-and-error process to balance accuracy and computational efficiency.
- **Activation functions:** the ReLU (Rectified Linear Unit) activation function was applied in the hidden layers to capture non-linear relationships, while the sigmoid function was used in the output layer to generate bounded predictions.
- **Output layer:** produced the forecasted rainfall values.

The ANN was trained using the backpropagation algorithm with the Adam optimizer, which adapts the learning rate during training to improve convergence. The performance of the model was evaluated using standard statistical metrics, including the correlation coefficient (Equation (1)) and mean squared error (MSE, Equation (2)), which are commonly used indicators of predictive accuracy [9].

Although rainfall forecasting is essentially a time series problem, a feed-forward ANN was chosen instead of more complex architectures such as Recurrent Neural

Networks (RNNs) or Long Short-Term Memory (LSTM) networks. This decision was motivated by several factors: the available rainfall dataset is relatively small, limiting the efficient training of data-hungry models like LSTM; feed-forward ANNs are simpler, faster to train, and robust in contexts with constrained computational resources; and previous studies have shown that feed-forward ANNs can provide reliable performance for climate variable prediction, especially when data are properly pre-processed and relevant features extracted.

The selection of ANN as the predictive algorithm also considered its accuracy, computational efficiency, and robustness. The model is suitable for handling specific data types, including NetCDF formats, and can be applied to large datasets and real-time forecasting applications.

The square of the correlation coefficient (R^2) and root mean square error analysis (RMSE) are used to evaluate the performances of numerical methods. These parameters are calculated by equation below:

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{n}\left(y_i - x_i\right)^2\right)} \tag{1}$$

The square of the correlation coefficient (R^2) and root mean square error analysis (RMSE) are used to evaluate the performances of the model.

$$\mathrm{R}^2 = \frac{\sum_{i=1}^{n}\left(y_i - v_i\right)^2 - \sum_{i=1}^{n}\left(y_i - x_i\right)^2}{\sum_{i=1}^{n}\left(y_i - x_i\right)^2} \tag{2}$$

The mean percentage error (MPE) is also used for measuring the error in the predicting value. It is defined as:

$$\mathrm{MPE} = \frac{\text{Actual Value} - \text{Predicted Value}}{\text{Actual Value}} \cdot 100 \tag{3}$$

2.2.2. ANN-Based Spatial Prediction of Monthly Precipitation from NetCDF Data

This study aims to develop an Artificial Neural Network (ANN) model to spatially predict monthly precipitation in the Mono River Basin using historical data stored in NetCDF forma. Daily precipitation data are ingested and harmonized onto a common grid with xarray and pandas, then aggregated into monthly totals and quality-checked using numpy. A basin-specific mask, derived from a shapefile and rasterized with regionmask or rasterio, isolates precipitation within the basin boundary. Spatial coordinates and optional temporal descriptors are extracted and standardized with scikit-learn to serve as features. A feed-forward ANN, implemented in TensorFlow/Keras, is trained using the Adam optimizer to minimize MSE. The dataset is split chronologically, with the first 75% of months for training and the remaining 25% for testing. Model performance is evaluated using RMSE and R^2. The trained ANN is then used to predict precipitation across all basin grid cells, reshaped with numpy/xarray, and exported as NetCDF or GeoTIFF via xarray and rasterio. The workflow for ANN-based spatial prediction of monthly precipitation in the Togo is summarized in Figure 2. The workflow for generating predicted precipitation maps using an artificial neural network (ANN) involves six main steps. **1)** It begins with the ingestion of daily precipitation data from NetCDF files. **2)** these daily values are then aggregated into monthly totals to facilitate long-term pattern analysis. **3)** a spatial mask corresponding to the target area (e.g., Togo) is applied to isolate relevant precipitation data. **4)** the masked and aggregated data are subsequently prepared and formatted as inputs for model training. **5)** the ANN model is then trained and validated using historical precipitation records to ensure robust predictive performance. **6)** finally, the trained model is used to generate precipitation forecasts, which are visualized as spatially explicit prediction maps for the study basin.

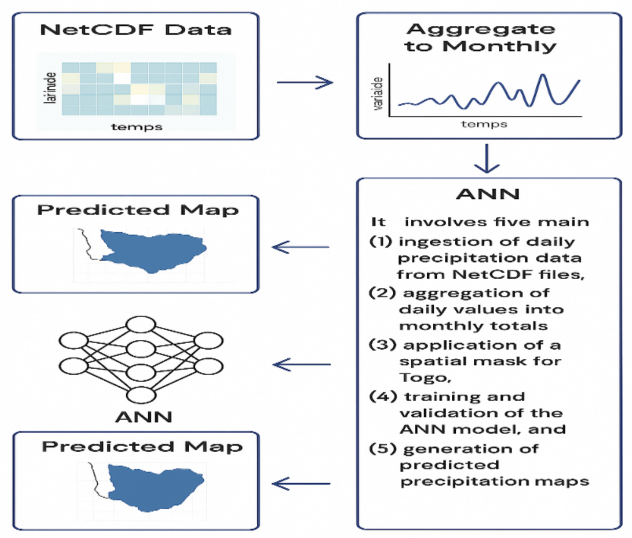

Figure 2. Workflow for generating predicted precipitation maps using ANN from NetCDF data.

3. Results and Discussion

3.1. Results

3.1.1. ANN Model Performance and Rainfall Simulation across Togo (1981-2000)

The following four figures (Figures 1-4) summarize the ANN model performance across the four periods, highlighting spatial variations in rainfall simulation from May to October from northern to southern Togo. During 1981-1985 (Figure 3), May is dominated by overestimation, particularly in the north and center (+30% to +40%) and slightly less in the south (+20% to +25%), indicating that the model anticipated the onset of the rainy season but overstated its intensity in northern areas. By June, the north aligns closely with observations, while the south and center show slight underestimations (−10% to −15%). From July onward, underestimations emerge almost nationwide, with the south and center experiencing substantial deficits (−25% to −35%) and the north moderate underestimation (−10% to −15%). August and September sustain this pattern (−30% to −40%), before errors diminish toward zero in October, reflecting improved end-of-season accuracy.

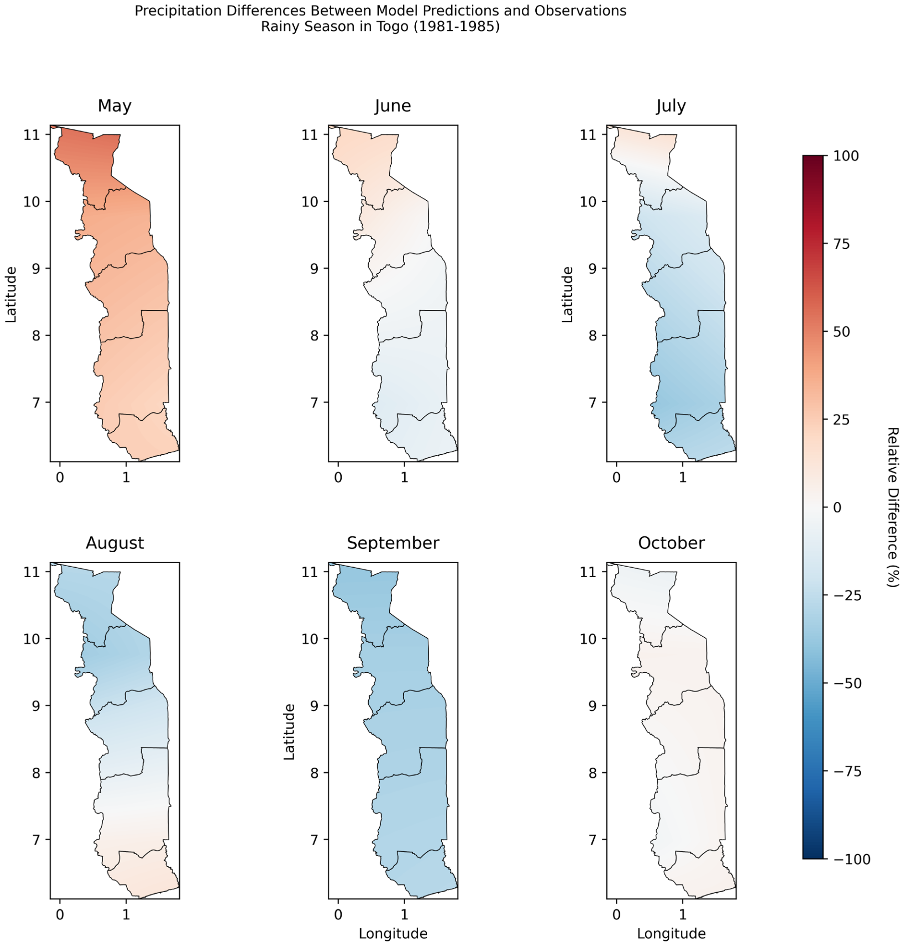

Figure 3. Comparison of observed and ANN-predicted 5-year rainfall deviations (%) in Togo during 1981-1986.

Transitioning to 1986-1990, early May deviations are generally small but slightly negative in the south (−20% to −30%), suggesting a delayed capture of rainfall onset (**Figure 4**). However, June quickly shifts to strong overestimation, with the south at +40% to +45%, the center at +30% to +35%, and the north at +15% to +20%. By July, overestimation becomes nearly universal, with the south and center near +40% and the north at +20%. August and September maintain this excess (+25% to +40% across regions), indicating that the model exaggerated the seasonal rainfall maximum, particularly in the south. By October, biases weaken, showing near-zero deviations and a slight north-south contrast.

During 1991-1996, May shows notable overestimation in the north and center (+25% to +35%), while the south aligns with observations (**Figure 5**). In June, this intensifies (+40% to +45% in the south and center, +20% to +25% in the north). By July, the north shifts to slight underestimation (−10% to −15%), while the south and center retain moderate overestimation (+15% to +25%). August and September exhibit minimal errors (−5% to +10%), reflecting accurate modelling during the seasonal peak. In October, a strong spatial divergence occurs: overestimation rises in the north and center (+35% to +45%), whereas the south records a moderate deficit (−20% to −25%), highlighting ongoing challenges in simulating the gradual cessation of rains across climatic zones.

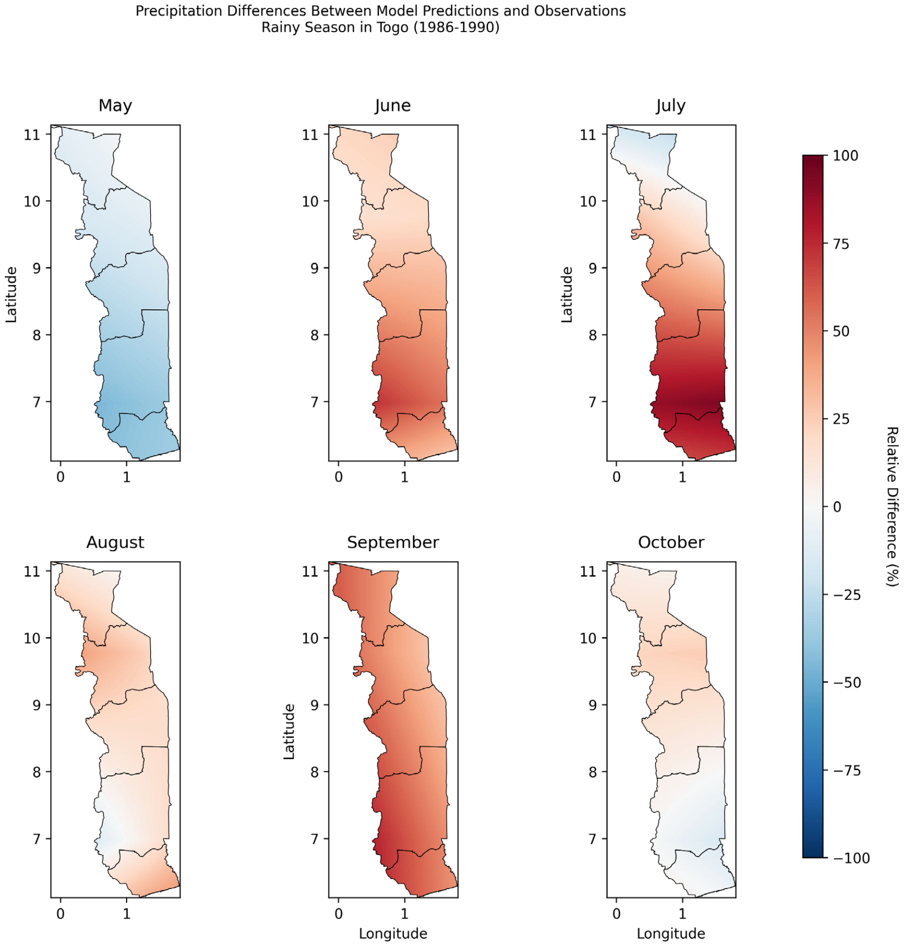

Figure 4. Comparison of observed and ANN-predicted 5-year rainfall deviations (%) in Togo during 1986-1990.

Finally, in 1996-2000, regional analysis illustrates of **Figure 6** pronounced spatial variability. In the south (coastal zone), June and August show pronounced overestimation (>+50%), while July exhibits strong agreement with observations. The central region experiences moderate overestimation from June to August (+25% to +50%), aligning closely with observations by September. The north (Sahelian zone) shows persistent underestimation from July to October (−50% to −75%), indicating difficulties in capturing sporadic rainfall events and the late-season position and intensity of the ITCZ. This period underscores the importance of regional differentiation when evaluating ANN model outputs.

Across all four periods (1981-1985, 1986-1990, 1991-1996, and 1996-2000), the ANN model demonstrates a generally good ability to capture the temporal evolution of rainfall in Togo, particularly the onset and cessation of the rainy season. Early-season months, especially May and June, often show overestimations in the north and center (+25% to +45%) and variable performance in the south (−30% to +45%), reflecting the model's sensitivity to the initial rainfall intensification. Mid-season months (July to September) reveal contrasting biases depending on region and period: the south and center frequently experience overestimation (+25% to +50%) or underestimation (−25% to −35%), while the north shows moderate underestimation (−10% to −60%), particularly in the later periods. By October, errors generally decrease toward zero, although spatial divergences persist in some periods, highlighting challenges in simulating the end of the rainy season.

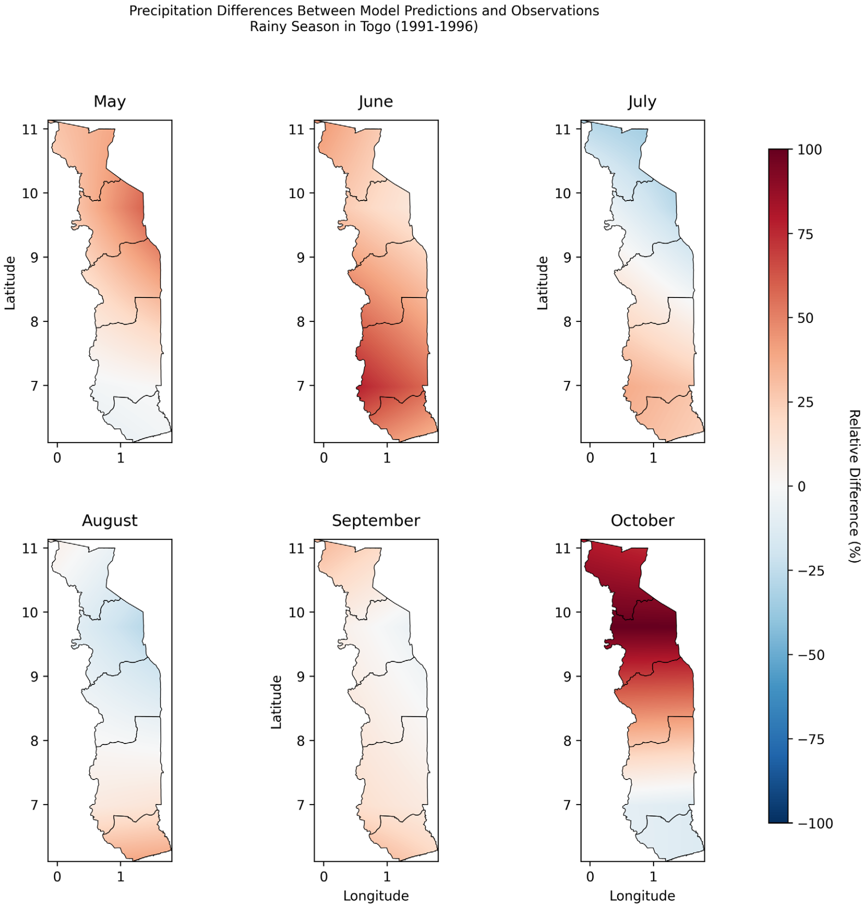

Figure 5. Comparison of observed and ANN-predicted 5-year rainfall deviations (%) in Togo during 1991-1995.

Despite these deviations, the **ANN** outputs closely follow the observed seasonal dynamics, capturing the overall monthly progression and regional patterns with reasonable accuracy. Sources of uncertainty include the model's representation of the Intertropical Convergence Zone (ITCZ), which drives rainfall distribution, regional orographic effects, sporadic convective events, and the complex coastal monsoon influence in the south.

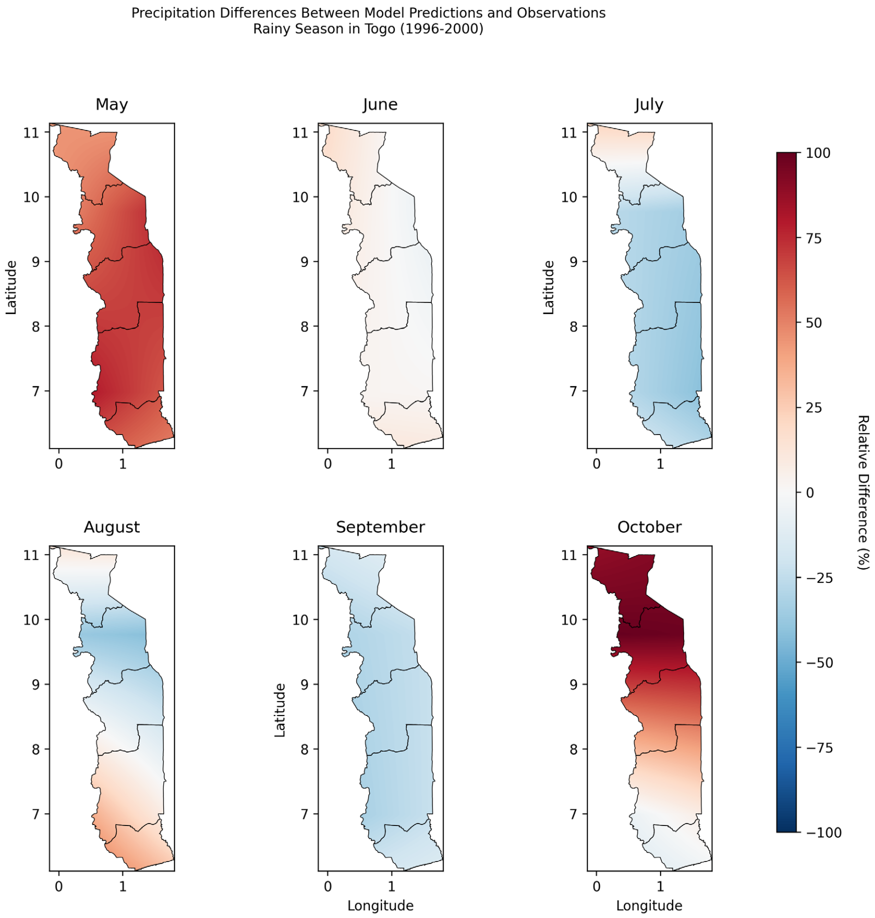

Figure 6. Comparison of observed and ANN-predicted 5-year rainfall deviations (%) in Togo during 1996-2000.

Overall, the ANN model provides a reliable tool for simulating rainfall patterns in Togo, with remaining uncertainties mostly linked to the inherent complexity of regional climate processes rather than fundamental model deficiencies. This suggests that, with further refinement and higher-resolution inputs, predictive accuracy could improve, especially for late-season rainfall and extreme events.

3.1.2. Evaluation of ANN Model Performance Using RMSE and R² Criteria for Monthly Rainfall in Togo (1981-2000)

The performance metrics of the feed-forward ANN indicate that the model effectively captures the seasonal variability of monthly precipitation in Togo. The combined RMSE and R^2 values across the four periods (1981-1985, 1986-1990, 1991-1996, and 1996-2000) provide a comprehensive overview of the ANN model's ability to simulate monthly rainfall in Togo (Table 1). **Beginning with the early-season months (May-June),** the model demonstrates relatively low RMSE values (7.5 - 11.0 mm) and high R^2 (0.94 - 0.95) during 1981-1985 and 1991-1996, indicating a good representation of rainfall onset. By contrast, in 1986-1990 and 1996-2000, higher RMSE (9.5 - 18.0 mm) and lower R^2 (0.87 - 0.92) reveal overestimation in June (+15% to +45%) and a delayed or exaggerated rainfall onset in the southern region. **Transitioning into the mid-season months (July-August),** RMSE values peak in 1986-1990 (16.0 mm in July, 14.0 mm in August) and 1996-2000 (12.0 - 17.0 mm), consistent with strong overestimation observed in the south and center (+25% to +50%). In contrast, 1981-1985 and 1991-1996 maintain lower RMSE (6.0 - 12.0 mm) and high R^2 (0.95 - 0.97), reflecting better model performance and accurate capture of the seasonal peak. **As the season progresses to September and October,** the model generally improves, with RMSE decreasing to 5.0 - 8.0 mm and R^2 remaining above 0.90 for most periods. Nevertheless, 1996-2000 exhibits a higher RMSE of 14.0 mm in October, indicating ongoing difficulties in simulating the late cessation of rainfall, particularly in northern Togo.

Table 1. RMSE and R^2 of ANN-predicted monthly rainfall across four five-year periods in Togo.

Month	RMSE (mm) 1981-1985	R^2 1981-1985	RMSE (mm) 1986-1990	R^2 1986-1990	RMSE (mm) 1991-1996	R^2 1991-1996	RMSE (mm) 1996-2000	R^2 1996-2000
May	8.0	0.94	9.5	0.92	7.5	0.95	10.0	0.91
June	10.0	0.95	15.0	0.90	11.0	0.94	18.0	0.87
July	12.0	0.96	16.0	0.88	9.0	0.96	12.0	0.90
August	10.0	0.95	14.0	0.89	6.0	0.97	17.0	0.88
September	7.0	0.93	12.0	0.90	5.0	0.97	11.0	0.91
October	5.0	0.91	6.0	0.93	8.0	0.92	14.0	0.89

Overall, the analysis confirms that the ANN model reliably reproduces the general seasonal rainfall pattern and the north-south gradient, although performance varies by month and period. Periods with higher RMSE correspond to months and regions with strong over- or underestimation, reflecting sources of uncertainty such as the representation of the ITCZ, coastal monsoon influence, and sporadic convective events. Despite these biases, consistently high R^2 values indicate that the model explains a substantial proportion of rainfall variability, underscoring its usefulness for regional rainfall simulations.

3.1.3. Projected Monthly Rainfall Patterns in Togo (2026-2030) Using ANN Models

Figure 7 presents the projected monthly rainfall trends in Togo from May to October for the period 2026-2030, simulated with the ANN model. The ANN was trained and validated using historical rainfall observations (1980-2020) combined with bias-corrected and statistically downscaled outputs from the ERA5 reanalysis. These downscaled climate inputs provided the basis for generating the 2026-2030 rainfall projections. The results highlight clear regional variations between the north, center, and south. In May, rainfall reaches 110.52 mm across all regions, suggesting a simultaneous onset of the rainy season, although the north, usually drier at the start, may experience an early initiation, while the south begins its post-peak decline. By June, values decrease to 100 mm, reflecting a modest reduction that is more pronounced in the north, whereas the south, transitioning toward its short dry season, maintains a reasonable alignment with expected trends. In July, precipitation rises sharply to 250 mm; while the south enters the anticipated short dry season, the north shows unusually low values compared to typical expectations, indicating possible dry anomalies or limitations in model representation. This pattern continues in August, with rainfall remaining at 270 mm; the south stays in phase with the dry season, yet the north exhibits excess rainfall for this critical transitional period of the monsoon. In September, central Togo records 225 mm, slightly below the extreme north, signaling a gradual retreat of rains in northern areas, while the south, entering its minor rainy season, shows higher precipitation, reflecting a spatial shift in seasonal rainfall. By October, rainfall drops to 95 mm, marking the season's end; this reduction aligns with northern trends but appears underestimated for the south, where rains typically persist until November. Overall, these projections indicate a relatively dry scenario in the north and an irregular pattern in the south, emphasizing the importance of considering regional climatic variability and the inherent uncertainties in model-based rainfall forecasts during transitional monsoon periods.

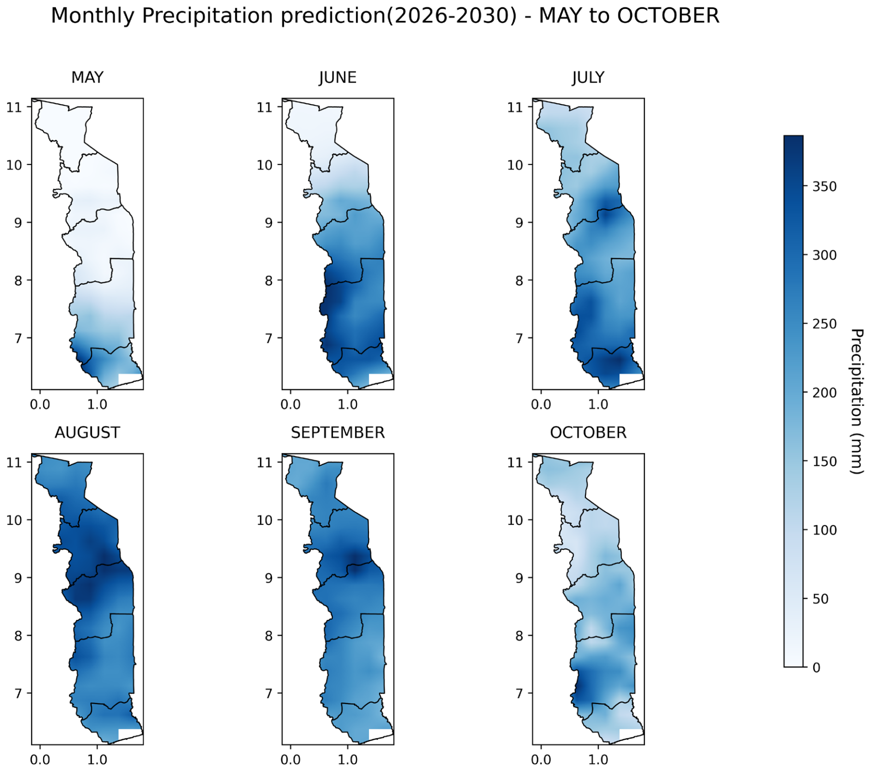

Figure 7. ANN-based projection of monthly rainfall (May-October) across northern, central, and southern Togo (2026-2030).

3.2. Discussion

The historical analysis confirms that the ANN model effectively captures general seasonal rainfall patterns in Togo, including the north-south gradient and the timing of onset, peak, and cessation of rains. Early-season months tend to be overestimated in northern and central Togo, while mid-season biases are most pronounced in southern and central regions, reflecting high convective activity and coastal monsoon influence. Late-season underestimations, particularly in the north, indicate challenges in representing transitional monsoon dynamics. Projections for 2026-2030 suggest a drier northern region and irregular rainfall patterns in the south, highlighting potential shifts in seasonal intensity and spatial distribution. These findings emphasize the importance of considering regional climatic variability and transitional periods when interpreting model outputs. Overall, the ANN model is robust for capturing broad seasonal trends but has limitations in representing localized anomalies, which should be carefully considered in water resource planning and agricultural management.

These results are consistent with previous studies in West Africa. For instance, Bodian and Ansoumana [10] noted that many climate models tend to overestimate early-season rainfall in northern Togo and underestimate late-season precipitation due to challenges in simulating the West African monsoon transition. Similarly, CORDEX-Africa simulations report irregular rainfall projections across the Mono and Oti basins, confirming the difficulties in capturing local convective dynamics) [11]-[13].

Comparative analyses in other regions further contextualize these findings. Ewona *et al.* (2016) [14] demonstrated that ANNs predict rainfall more accurately at higher latitudes in Nigeria, while Folorrunsho [15] achieved an 81% correlation coefficient for monthly rainfall forecasting in Zaria, Nigeria, using multiple meteorological inputs. Kashiwao *et al.* [16] compared multilayer perceptrons (MLP) with hybrid algorithms combining backpropagation and random optimization, as well as radial basis function networks (RBFN), for short-term rainfall prediction, highlighting both the strengths and limitations of ANN models in capturing extreme events.

Global applications of ANN models, including studies in China and India, show similar patterns. In South Asia, ANNs captured long-term monsoon trends but struggled with high intra-seasonal variability [17]. These parallels suggest that while ANNs are effective for detecting large-scale rainfall variability, they underperform during transitional periods and localized extremes, supporting the use of hybrid approaches such as combining ANNs with RNNs or LSTM networks to improve temporal dependency representation.

Methodologically, Cheng *et al.* (2020) [18] noted that the absence of long monthly datasets limits LSTM model performance at the monthly scale, although it performs better for daily predictions. Hybrid approaches combining neural networks with genetic algorithms have also shown improved performance [19]. Hung *et al.* (2009) demonstrated that generalized feed-forward ANNs using a hyperbolic tangent transfer function achieve superior generalization when incorporating multiple meteorological parameters [20]. Lin and Wu (2009) confirmed that these models outperform conventional neural network approaches [21].

In the Togolese context, these results demonstrate that ANNs are valuable tools for capturing broad seasonal rainfall patterns and projecting future trends. However, limitations in representing localized anomalies and transitional monsoon phases indicate the need for methodological improvements, particularly for informing water resource management, agriculture, and climate adaptation strategies in the Mono and Oti basins. The results also highlight the potential for hybrid models and expanded datasets to enhance prediction accuracy and support evidence-based decision-making for climate resilience planning.

4. Conclusion

The ANN model provides a robust framework for understanding rainfall dynamics in Togo. Regional differences in projected rainfall highlight the importance of tailored planning for water resource management and agricultural activities. While uncertainties remain particularly regarding ITCZ positioning, coastal monsoon influence, and localized convective events, the model offers valuable insights for climate risk assessment and regional adaptation strategies. Future work should focus on integrating larger datasets and exploring hybrid ANN architectures to enhance predictive accuracy.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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