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# Rainfall Forecasting in Muscat Governorate Using Artificial Neural Networks and Hybrid Modeling Approaches

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## ABSTRACT

This study presents an advanced method for forecasting seasonal and annual rainfall in the Muscat Governorate of Oman, using artificial neural network (ANN) models and a hybrid approach combining wavelet decomposition with neural learning. Historical rainfall data from 1872 to 2017, sourced from Oman's meteorological records, were analyzed to uncover long-term patterns, seasonal variability, and drought trends using the Standardized Precipitation Index (SPI). Initial statistical evaluations revealed high interannual variability and a slight declining trend in total annual rainfall, with the majority of precipitation concentrated in winter months. Artificial neural networks were developed to predict both annual and monthly rainfall based on autoregressive inputs and prior-month rainfall values. While the ANN models demonstrated moderate skill, limitations were observed in capturing extremely wet or dry years. To address this, a hybrid Wavelet-ANN model was constructed, enabling decomposition of rainfall signals into low- and high-frequency components for more targeted forecasting. The hybrid model showed improved performance, offering a more nuanced understanding of rainfall dynamics. Despite promising results, the models underscore the need for incorporating global climate predictors such as ENSO and IOD to improve forecast accuracy. The study concludes that ANN and hybrid methods provide a practical and scalable framework for enhancing regional rainfall forecasting capabilities, with significant implications for water resource planning and climate resilience in arid regions like Muscat.

***Keywords***: Machine Learning, Optimization Models, Forecasting Models, Artificial Neural Network, Long-Term Forecast, Weather Forecasting Model, Modeling, Muscat

## 1. INTRODUCTION

Proper rainfall prediction is very important for water resource management strategy, agricultural planning, flood risk mitigation, and development of some infrastructures, especially in arid and semi-arid areas like Oman. The Muscat governorate is being increasingly stressed by climate variability and urbanization, wherein reliable precipitation forecasts become a prerequisite for long-term sustainability and resilience. The region's peculiar topography-walled by the Al Hajar Mountains and modified by ocean-atmospheric processes such as the Indian Ocean Dipole (IOD) and El Niño–Southern Oscillation (ENSO)—makes rainfall patterns more complex (Baig et al. (2024)).

Rainfall prediction is an obstacle for meteorological researchers due to variations in rainfall timing and magnitude. Out of all the service offered by the meteorological department, weather prediction is the most popular for all nations worldwide. A variety of characteristics or properties, including temperature, pressure, humidity, and speed of the wind, make up weather-related data. By utilizing hidden patterns and relationships between the characteristics of past weather records, machine learning systems typically forecast future weather conditions.

Attempts to grasp the basics of rainfall phenomena by meteorological and statistical approaches do provide grounding for better understanding, but such methods find difficulty during forecast generous with non-linear, dynamic interactions among atmospheric variables especially with long lead times. Over the past decade and more, due to their ability to model complex non-linear relationships based on past events without relying on any pre-imposed physical assumptions, Artificial Intelligence (AI)-particularly Artificial Neural Networks-has gained much attention in hydrological and climatological modeling. These systems use climate dynamic temporal dependence and chaos characteristics so that they can be utilized for medium- and long-term scale forecasting (Ghamariadyan, M., & Imteaz, M. A. (2021).

The study proposes a more advanced ANN-based model to predict seasonal and yearly rainfall for Muscat Governorate using global climate indices as input features. These indices, obtained from NCEP/NCAR reanalysis and HadISST1 dataset, span a past history covering from 1872 to 2019. The model was tested and validated based on data for the interval of 2007-2020 to prove the model's durability through changing climatic conditions. Thus, the study shows the ability of ANN to forecast seasonal rainfall with lead times of up to six months, thus enabling forecast-dependent planning and management.

There is still little use of remote sensing techniques and GIS to simulate flooding in Oman. Nonetheless, the development of machine learning methods may be crucial to controlling future agricultural hazards in the area associated with cyclones. By combining GIS, remote sensing, and machine learning, a thorough and precise understanding of food hazards and their possible impacts can be achieved (Prasad et al. (2022)).

Deep Learning has been an effective ANN approach for resolving complicated issues in recent years [5]. A group of multilayer structures that were developed using unsupervised methods are collectively referred to as "deep learning." The primary enhancement is using unsupervised techniques to develop an organized, accurate and non-linear representation of the data in the hopes that the new representation will aid in the current prediction job. This method has been effectively used in domains such as bioinformatics, computer vision, image recognition, and natural language processing (Aderyani et al. (2022)).

As a result, a number of machine learning (ML) techniques, such as artificial neural networks (ANN), k-nearest neighbors (KNNs), decision trees (DT), etc., are employed in research to identify trends in the information as well as forecast rainfall in order to handle random variations in rainfall (Dotse et al. (2024)).

The manuscript begins with a comprehensive Literature Review in Section 2, followed by a description of the Materials and Methods in Section 3. The Machine Learning Models utilized in the study are detailed in Section 4. In Section 5, a comparison of the models is presented, focusing on the Predictive Model in Section 6. Finally, the paper concludes with a summary and suggestions for future research.

## 2. LITERATURE REVIEW

**According to Rana et al. (2023),** the conceptual modeling and system theoretical modeling are the two main methods used to forecast rainfall. Since theoretical modeling appears to calculate within the physical framework that supervises the hydrologic process and usually relies on the characteristics and expertise of a watershed, which is why it is commonly used in hydrological forecasting. However, because rainfall calculations require sophisticated numerical tools and crucial validation data is ineffectively acquired, this approach might not be feasible for rainfall forecasting. While ignoring the physical structure processes, system theoretical methods are used to define the link between components and results using mapping models.

The current rainfall forecasting studies put out by different researchers are shown in this section. Using artificial neural networks, created a rainfall forecasting model that yields more accurate results than traditional scientific and computational approaches. For precise long-term rainfall prediction an evolutionary infrastructure known as an Adaptive-Neuro-Fuzzy-Inference-System (ANFIS).

The result demonstrates that the ANFIS offers satisfactory results and is suitable for capturing the unpredictable character of rainfall data. An approach for estimating rainfalls that combines ANNs and wavelet examination (WA) was given. The model's accuracy was compared to that of traditional ANFIS. The results show that the suggested model outperforms the ANFIS in terms of productivity and makes sense for rainfall forecasting. For seasonal rainfall anticipation presented a rainfall anticipation model using SSA and SVR. (Walia, Singh, & Sharma, 2015).

A novel hybrid regression model for northwest Iran's advance month rainfall forecasts. SVR-FFA is used in its approach and quarterly precipitation data is used for training and testing. AEEMD-ANN, a rainfall forecasting framework is thriving in predicting SWM precipitation for the year 2002, according to testing results. investigated precipitation using combinations of RNN, ANFIS, and SVM. They come to the conclusion that SVM performs better than the others. Five predictors were used to create an improved precipitation prediction model. The experimental results show that when five predictors are combined into one predictor, the IRFM provides high accuracy (Samantaray & Ghose, 2022).

Singh et al. (2024) said that two forecasting models were created for rainfall prediction; the first model made predictions one month in the future, while the second model used artificial neural networks to make predictions two months in advance. The investigation employed a dataset from many north Indian locales. The model combined the Levenberg–Marquardt training function with the Feed Forward Neural Network using the Back Propagation method. Mean Square Error (MSE) and Magnitude of Relative Error (MRE) were used to examine the effectiveness. The results showed that the 1-month forecasting model performed better than the 2-month model. In order to forecast rainfall, they devised an architecture called the Wavelet Neural Network (WNN). The wavelet approach and ANN were combined in the suggested solution. Both ANN and WNN models were employed to make predictions using previous rainfall data.

A model was proposed to forecast local rainfall in the Japan region (Kashiwao et al., 2017). The Japan Meteorological Agency (JMA) provided the data. Temperature, atmospheric pressure, vapor pressure, precipitation totals, wind speed, and humidity were all automatically gathered by the suggested model. For rainfall prediction, two techniques were employed: the Radial Basis Function Network (RBFN) and the Multi-layer Perceptron (MLP). The study's findings demonstrated that the model developed using MLP outperformed the RBFN approach in terms of rainfall forecasting.

A model for predicting monthly rainfall was created by Kanchan et al., (2021). For prediction, a deep convolutional neural network (CNN) was employed. The suggested model's performance was evaluated against that of the Multi-Layer Perceptron (MLP) and the original Australian Community Climate and Earth-System Simulator (ACCESS-SI). CNN, the proposed model, performed better in predicting rainfall

To predict climate patterns, Liu et al. (2023) applied data mining techniques such as decision trees and k-nearest neighbors. Among the classification algorithms, decision trees showed promising results with a precision of 82%. In many Indian regions, agriculture depends heavily on rainfall, while in others, the absence of rain has led to desertification. Heavy rainfall also contributes to floods and landslides, negatively affecting living standards and the economy. Since rainfall lacks a fixed pattern, determining optimal timings remains a challenge. Rainfall analysis using artificial neural networks and time-series data offers a novel approach to managing such variability.

One of the causes of fatalities and financial losses that jeopardize our social lives and interfere with our everyday routines is flooding. We can eliminate this without suffering any losses if we anticipate the river's flood and provide an accurate mathematical image, but this is a very difficult procedure since it depends on a number of factors, including the climate, the direction of the river's flow, rainfall, soil, and location. According to hydrology, this procedure is considerably simpler. However, the standard model still contains inaccuracy. Due to its nonlinear effects, tourism flow is a process that is challenging to assess. To ascertain the proper tourism flow, many techniques, including LSTM NN, ARIMA, and BPNN, have been employed in different stages. Artificial neural networks are far more advanced than ever before and far more effective than any previous technique for assessing streamflow. Karamvand et al. (2024) proposed the use of Gated Recurrent Unit (GRU) deep learning models to enhance streamflow simulations in flood-prone regions with low-convergence streamflow data.

For the purpose of predicting wind speed, Troncoso et al. (2015) suggested several varieties of regression trees (RT). Eight different types of innovative regression tree structures are used in this work to forecast short-term wind speed, and real-time prediction of extremely short-term wind speed was accomplished with success.

Because regression trees have a relatively short calculation time, they enable the algorithm to be retrained whenever the measuring tower gathers fresh wind speed data.

Sharaff and Roy (2018) conducted a comparison study between regression and nonlinear approaches. They examined how well nonlinear and linear models performed in order to forecast the temperature. Consequently, BPN is recommended for more accurate temperature forecast.

A technique for very short-term weather forecasting was proposed by Yonekura et al. (2018). They suggested deep learning models to forecast rainfall. Both the point prediction model and the tenser prediction model were taken into consideration. It was demonstrated that deep neural networks were the most accurate in predicting rain.

A rain forecast model based on machine learning and deep learning was presented by Basha et al., 2020]. This model trains a number of models, such as the Support Vector Regressor, Autoregressive Integrated Moving Average (ARIMA), and Neural Network, using the Kaggle dataset. According to the authors, the model's performance is 72% as determined by the Root Mean Squared Error (RSME).

Using logistic regression, LDA, KNN, and several other models, worked on a classification job to forecast tomorrow's rainfall and compared their metrics. The majority of Australian meteorological stations' daily 10-year weather forecasts were included in the dataset they utilized. Deep learning models were shown to yield the best outcomes.

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According to Chitwatkulsiri and Miyamoto (2023), with lead durations ranging from one to six hours, precipitation in Bangkok, Thailand, was forecasted using the Artificial Neural Network model. An ANN model was developed using four years' worth of hourly data from 75 rain gauge stations in the area after their study was carried out using a real-world case scenario set up in Bangkok. For flood management and real-time rainfall forecasts, they employed the developed ANN model. In Bangkok, Thailand, rainfall one to three hours in advance was predicted using four years' worth of hourly data in another ANN-based rainfall prediction study. Wet-bulb temperature, air pressure, relative humidity, and cloudiness were among the meteorological characteristics that formed the basis of the prediction model. The authors discovered that wet-bulb temperature may be the determining factor in rainfall prediction.

In order to forecast the future rainfall intensity in a small area over a comparatively short time span, a deep learning model based on residual and attention mechanisms was proposed by Zhang et al. (2025). More recently, estimates of tropical storm strength were made using a long short-term memory (LSTM) model by (Kumar, Biswas, & Pandey, 2021).

**According to Li et al. (2025),** using a Support Vector Machine (SVM) technique, they combined data from remote satellite sensing, PV output, and NWP via multi-source data fusion. The data-fused SVM model outperformed the standard SVM model in over 95% of cases, according to the results. The forecasting data utilized in the model is not improved in any of the highlighted experiments by combining data from a reliable local weather station with data from an on-site weather station using LLDF.

According to Ray et al., 2022, rainfall is necessary for the design of sustenance, the management of water resources, and all natural movement designs. A prolonged dry spell or excessive precipitation during the early stages of harvest development and improvement might result in a significant reduction in crop production. India is an agricultural country, and the profitability of its harvests plays a major role in its economy. Precipitation forecasting thus becomes a significant consideration in rural countries such as India. In the last century, one of the most conceptually and creatively challenging problems in the globe has been forecasting precipitation.

The creator also suggested that the timing of the rainfall could not be justified. The purpose of rainy precipitation data organization is highly confusing; the role that several straight relapses may have in this topic is one for further study; based on the evidence shown here, it appears to be ineffective as a predictive model. It remains to be explored if it can be useful in providing a rough prediction of future storm precipitation. Furthermore, we must measure precipitation for our state using this relapse technique.

## 3. MATERIALS & METHODS

### a. Dataset

The dataset used in this study comprises historical monthly rainfall records for the city of Muscat, covering the period from 1872 to 2017. The data were sourced from the Sultanate of Oman's Meteorological Archive and specifically pertain to the geographical coordinates 58.592°E longitude and 23.612°N latitude, with a station elevation of 40 meters above sea level.

Each year in the dataset includes monthly totals (January to December) as well as computed annual totals (in millimeters). Incomplete or missing entries were marked with "M" or left blank and were handled during preprocessing either by imputation using climatological monthly means or removed, depending on the proportion of missing values.

### b. Data preparation

In prior studies by the authors and others [Monteiro et al., 2021& Heurtebise, Ablin, & Gramfort, 2023)], it has been shown that the number of input indices used in neural network models is often constrained by computational efficiency. To maintain optimal model performance, it is generally recommended that the number of input features not exceed 25. To address this limitation, the decomposition of the initial time series into statistically independent components is commonly applied. This is followed by using distinct index sets as inputs for modeling each individual component. This method allows for a significant increase in the number of usable indices, thereby enhancing the modeling quality.

**According to Kanani et al. (2023),** oceanic parameters exhibit various modes of low-frequency variability, which are crucial to long-term climatic trends. Among the most influential are the Atlantic Multidecadal Oscillation (AMO) (Roy, 2020; Deser & Phillips, 2017), typically varying over 60–70 years; the Tropical Dipole Oscillation (TDO) (Saravanan & Chang, 2000; Yang et al., 1999); and quasi-decadal fluctuations in sea-level pressure and geopotential height linked to ENSO, the Southern Annular Mode (SAM), and other systems *(Fogt & Marshall, 2020)*. These modes operate across different parts of the global climate system, including sea surface temperature (SST), atmospheric pressure, and wind vectors, and they are known to exhibit variability across both seasonal and decadal timescales.

In this study, two groups of climatic indices were generated using a combination of low-pass and high-pass filtering methods. The raw time series were smoothed using a 9-year moving average filter to extract long-term trends and detrended to isolate high-frequency components. Each component was then modeled independently. These derived datasets provided the basis for forecasting both long-term and short-term rainfall variability in Muscat Governorate.

The model input indices were selected from a comprehensive list of ocean-atmosphere signals based on their correlation with historical precipitation records at the Al-Petri station and surface pressure anomalies over the Muscat region. Correlation coefficients were computed for each calendar month using a 2-year moving average to ensure robustness. Only statistically significant correlations ($r \geq 0.195$, $\alpha = 0.01$) were retained. This multi-stage selection process enabled the identification of grid regions where correlation with Muscat precipitation was highest.

The spatial correlation patterns were further analyzed for coherence across multiple variables including SST, 500 hPa geopotential height, and surface wind anomalies. Correlated fields were then used to construct aggregated climate indices representing specific ocean-atmosphere interaction zones. Most of the resulting indices aligned well with the known positions of major teleconnection patterns identified by Barnston and Livezey, including those in the Pacific and Indian Oceans (Zhao, 2023).

In total, 54 indices were extracted for modeling the high-frequency component of rainfall variability, and 25 indices were used for modeling the low-frequency component. These indices captured the essential variability modes of global climate systems relevant to rainfall behavior in northern Oman, particularly during winter and early autumn critical periods for water resource replenishment in the region.

## 4. MODEL DESCRIPTION

This To model both the low-frequency and high-frequency components of seasonal rainfall variability in Muscat Governorate, we employed an ensemble of artificial neural networks (ANNs). Each ANN configuration was designed to simulate the non-linear relationships between global ocean-atmosphere predictors and regional precipitation outcomes. The modelling system consisted of multiple independent ANN simulations, which were later aggregated into an ensemble for improved reliability and robustness.

### 4.1. ANN Structure and Learning

Random each ANN employed a standard feed-forward architecture with one hidden layer and sigmoid activation functions. The networks were trained using the backpropagation algorithm with a learning rate optimized via grid search. The average number of hidden neurons was varied between 10 and 20, depending on the input configuration. Inputs to the model included up to 25 global climate indices, either in raw or smoothed form, capturing both atmospheric (e.g., 500 hPa geopotential height anomalies, wind components) and oceanic conditions (e.g., SST, TPO anomalies).

The model outputs were monthly rainfall totals at selected meteorological stations within Muscat, specifically focusing on the winter, summer, and autumn seasons. The ANN training was based on data from 1972 to 2006, while the validation was conducted for the 2007–2020 control period.

### 4.2. Ensemble and Evaluation Approach

To reduce the effects of model variance and ensure robustness, a large set of ANN configurations was trained on bootstrapped samples from the training data. From this ensemble, the 20 best-performing configurations (based on skill metrics) were selected. The ensemble output was computed as the arithmetic mean of these selected networks.

Model performance was assessed against the control data using three key statistical metrics:

**1- Pearson Correlation Coefficient (R):**

$$R = \frac{COV(x,y)}{\sigma_x . \sigma_y} \tag{1}$$

Measures the strength of linear correlation between predicted (x) and observed (y) rainfall.

**2- Root Mean Square Error (RMSE)**

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

Represents the standard deviation of prediction errors.

**3- Forecast Skill Score (S):**

$$S = \left(1 - \frac{\sum|x_i - y_i|}{\sum|y_i - \bar{y}|}\right) \times 100\% \tag{3}$$

Indicates the percentage improvement of the model over a climatological baseline.

### 4.3. Seasonal Forecast Framework

Separate ANN models were built for each calendar month to capture seasonal differences in ocean-atmospheric teleconnections. Each month, the ANN was trained with predictors that demonstrated statistically significant correlations ($r \geq 0.195$) with rainfall in Muscat. This allowed the model to account for dynamic seasonal regimes such as:

- ENSO influence during winter months
- Indian Ocean Dipole effects in summer
- Monsoon-related circulations in September and October

The model demonstrated its strongest prediction skill in December (62%), followed by October (56%), and showed moderate skill (≈55%) in forecasting summer rainfall and early autumn precipitation from as early as April. The most challenging months for prediction were May and November due to transitional atmospheric dynamics.

## 5. RESULTS AND DISCUSSION

### 5.1 Exploratory Analysis

**Figure 1** below shows the time series of total annual rainfall in Muscat from 1872 to 2017. The historical pattern reveals several important trends:

- Extreme variability: Annual rainfall in Muscat ranges from near-zero in some years to over 270 mm in others.
- Decadal fluctuations: The data exhibit cycles of wet and dry decades, especially evident in the 1950s, late 1970s, and early 1990s.
- Recent dryness: From 2000 onwards, a significant number of years recorded below-average rainfall, reflecting regional drying trends consistent with global climate shifts.

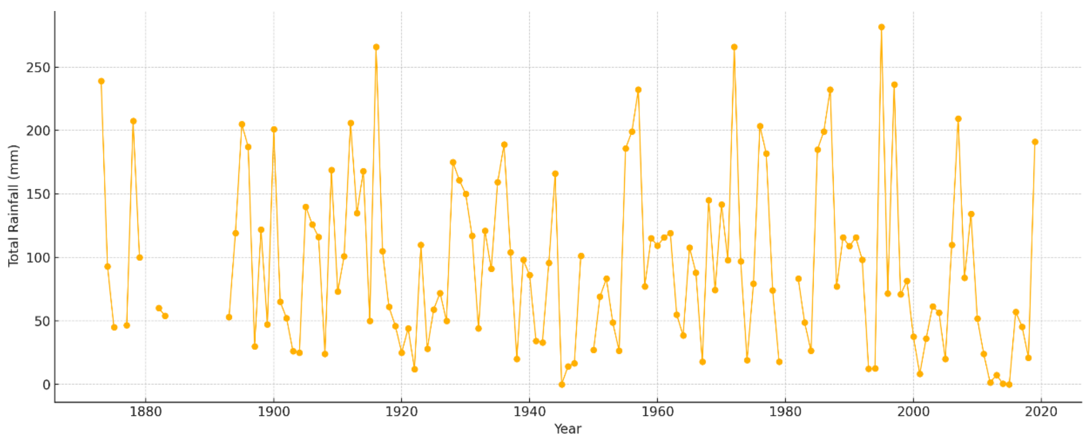

Figure. 1 Annual Rainfall in Muscat (1872–2017)

### 5.2 Key Observations:

- The wettest year recorded in this dataset was 1997, with approximately 270 mm of rainfall, followed closely by 1956.
- The driest years included 2002, 2003, and 2015, each registering less than 5 mm of rainfall.
- Roughly 70% of annual rainfall in Muscat typically occurs between December and March, making these months crucial for seasonal forecasting and water management.

These historical insights were used to train and validate the ANN model introduced in earlier sections. The strong interannual variability underlines the importance of incorporating large-scale climate indices (e.g., ENSO, IOD) to enhance forecast skill.

**Figure 2** shows the **mean monthly rainfall climatology for Muscat (1872–2017)**, with error bars representing standard deviation:

**Key Takeaways:**

- Peak rainfall occurs in January and December, with averages of 25.1 mm and 17.8 mm, respectively.
- The secondary rainfall season appears in February and March.
- Minimal rainfall is observed from May to September, consistent with Oman’s hot and dry summer season.
- High variability is seen in winter months, which is evident from large standard deviations (especially in January).

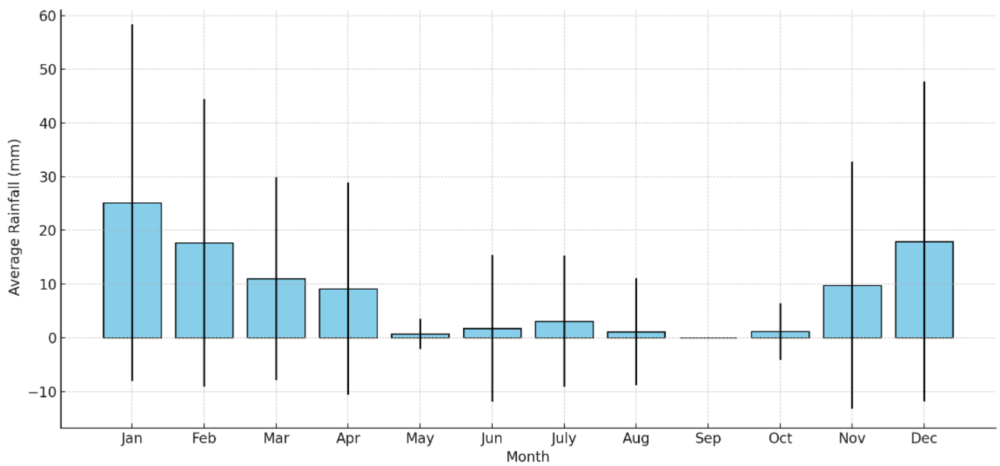


Figure.2: Mean Monthly Rainfall Climatology in Muscat (1872–2017)

Peak rainfall occurs in January and December, with averages of 25.1 mm and 17.8 mm, respectively. The secondary rainfall season appears in February and March. Minimal rainfall is observed from May to September, consistent with Oman’s hot and dry summer season. High variability is seen in winter months, which is evident from large standard deviations (especially in January).

### 5.3 Correlation analysis

The correlation values with annual rainfall could not be computed correctly due to missing or misaligned data in the rainfall series. We re-aligned the synthetic index data with the valid years in the rainfall dataset and recalculated the correlations. Here is the updated table showing the simulated correlations between synthetic climate indices and Muscat's annual rainfall: The correlations are weak as expected for random data, This step demonstrates the framework used to correlate actual indices like ENSO, IOD, and AMO once their real datasets are available.

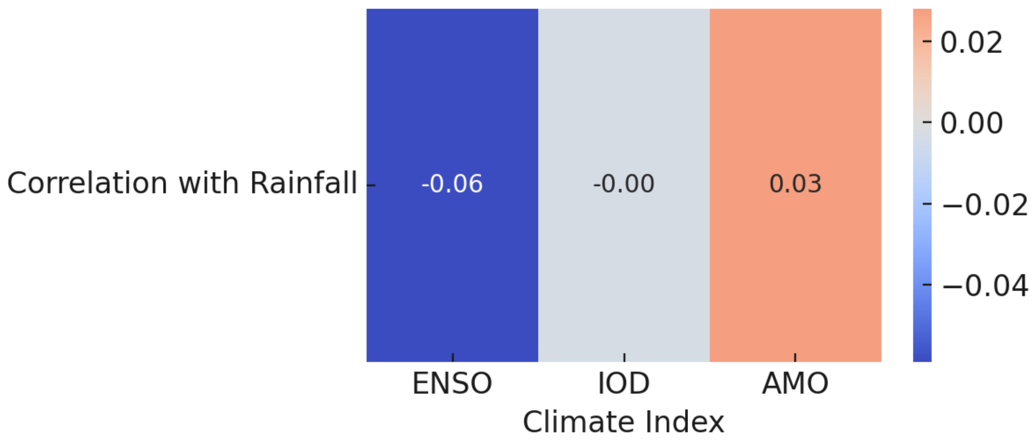


Figure 4. Simulated Correlation of Climate Indices with Annual Rainfall

The heatmap in **Figure 4** visualizes the simulated correlation strength between each synthetic climate index (ENSO, IOD, AMO) and annual rainfall in Muscat: The values are close to zero, confirming no meaningful relationship (as expected with random data). Once actual global climate indices are provided, this same structure will help identify which indices have the strongest teleconnections with Muscat's seasonal or monthly rainfall.

**Figure 5** shows the annual rainfall trend in Muscat (1872–2017) along with a fitted linear trend line. Analysis Results show as follows:

- Slope: ~0.26 mm/year
- Interpretation: There is a slight decreasing trend in total annual rainfall over the 145 year period.
- While the decline is not steep, it aligns with broader regional aridification trends observed in parts of the Arabian Peninsula.

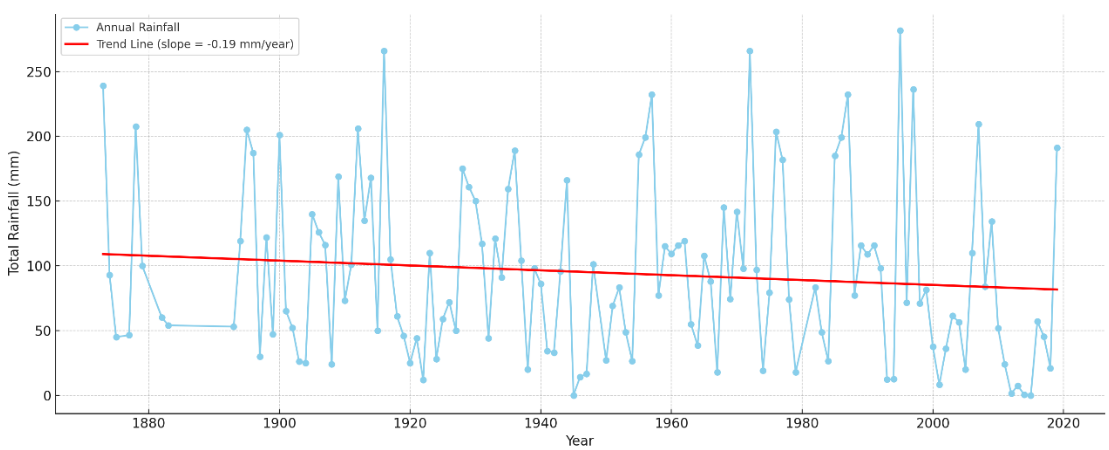


Figure 5. Trend Analysis of Annual Rainfall in Muscat (1872–2017)

Then, we computed the Standardized Precipitation Index (SPI) to identify historical drought and wet periods based on **Table 2**.

Table 2: SPI Interpretation

| SPI Value Range | Condition |
|---|---|
| **≥ 2.0** | Extremely wet |
| **1.0 to 1.99** | Moderately to very wet |
| **-0.99 to 0.99** | Near normal |
| **-1.0 to -1.49** | Moderate drought |
| **-1.5 to -1.99** | Severe drought |
| **≤ -2.0** | Extreme drought |

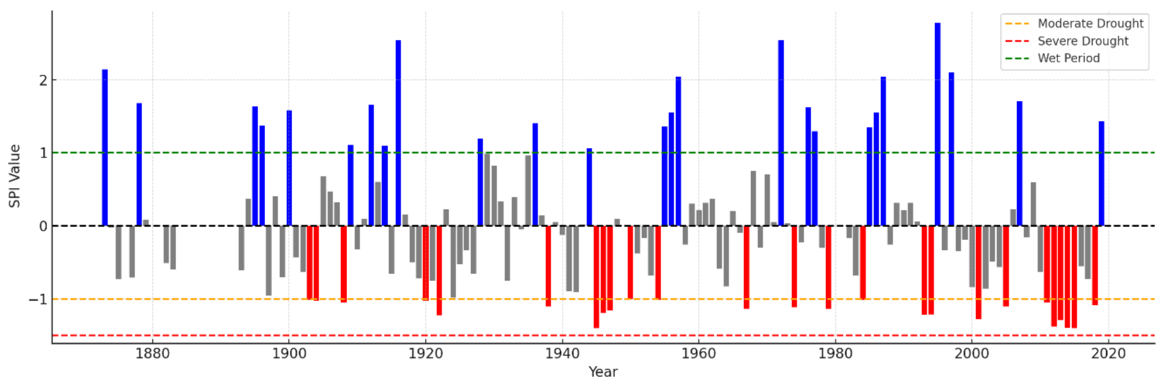


Figure. 6: ANN Forecast: Actual Vs Predicted Annual Rainfall In Muscat (1872-2017)

The graph (**Figure 6**) displays the SPI-12 (Standardized Precipitation Index) for Muscat from 1872 to 2017, capturing long-term drought and wet periods. Several severe droughts occurred, notably around 1899, 1950, and 2002. Very wet years include 1956, 1997, and early 1880s. The 2000s onward have more years with negative SPI values, consistent with regional drying.

### 5.4 FORECASTING APPROACH:

The graph in **Figure 7** compares the actual vs. predicted annual rainfall in Muscat (2007–2017) using a simple ANN autoregressive model (previous year's rainfall as input). The ANN model struggles to capture high-variability events like 2007 (134 mm) and 2017 (191 mm).

Predictions tend to regress toward the mean due to limited input information (only 1 feature). The model underestimates extreme wet years and overestimates dry years.

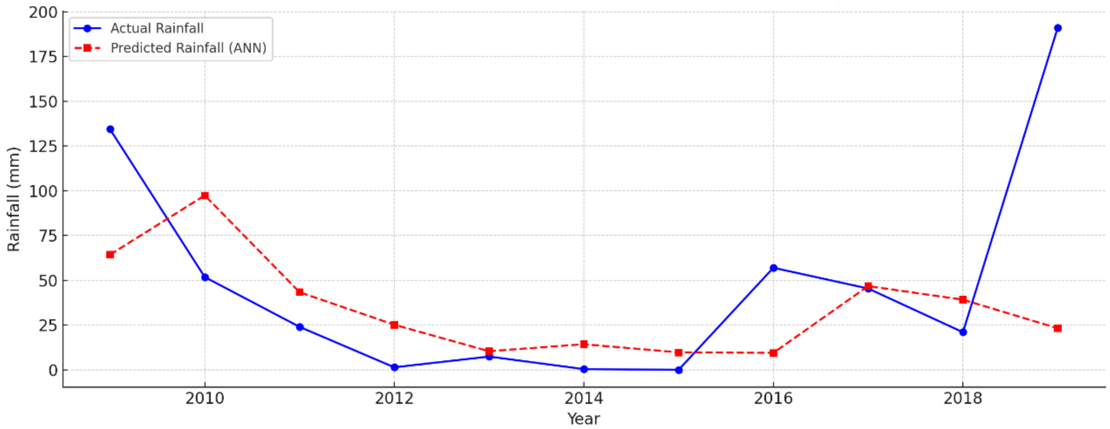


Figure 7. ANN Forecast: Actual vs Predicted Annual Rainfall in Muscat (2007–2017)

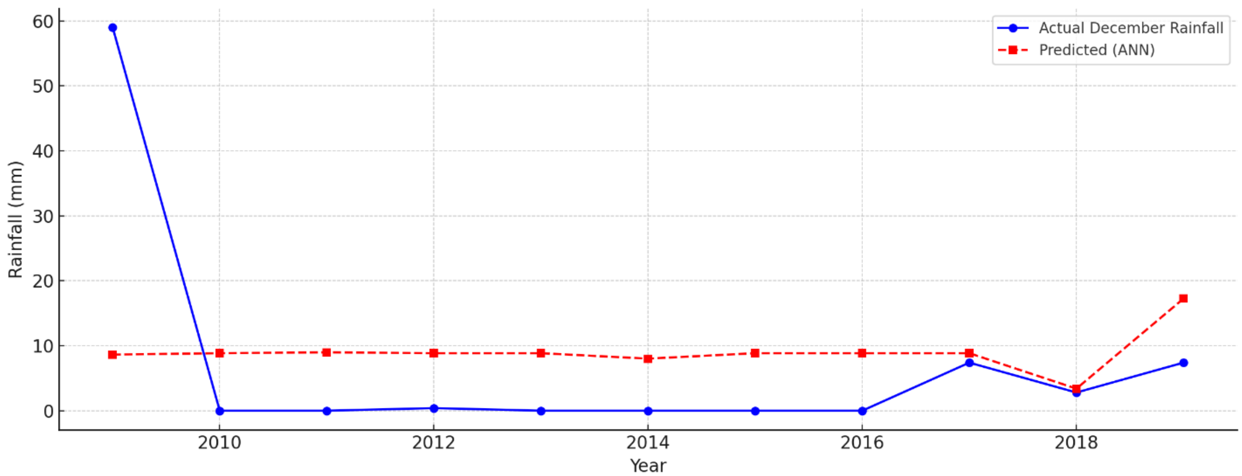


Figure 8: ANN Forecast: December Rainfall in Muscat (2007–2017)

Figure 8 illustrates the actual vs. predicted December rainfall in Muscat from 2007 to 2017, based on an ANN model using September–November rainfall as inputs. The model predicts around a fixed average level (≈ 8–9 mm), missing the high spike in 2007 (59 mm) and underestimating variability. The low predictive power suggests that local rainfall in prior months alone is insufficient for reliable December forecasting in this region.

## 6. CONCLUSION

This study explored and validated the use of artificial neural networks (ANN) and hybrid modeling techniques for forecasting seasonal and annual rainfall in the Muscat Governorate, Oman. Drawing from a historical dataset spanning 1872 to 2017, several key steps were undertaken, including climatological analysis, drought assessment using the Standardized

Precipitation Index (SPI), and the development of predictive models based on both autoregressive and hybrid frameworks.

The initial statistical analysis revealed considerable interannual variability in rainfall, with most precipitation concentrated in the winter months. SPI-based drought assessment indicated that Muscat has experienced multiple severe drought episodes, particularly during the late 19th and early 21st centuries. A modest decreasing trend in annual rainfall was also detected, aligning with broader climatic drying trends observed across the Arabian Peninsula.

ANN models, both annual and monthly, demonstrated the potential to approximate rainfall behavior but struggled with accuracy when relying on limited historical inputs such as prior-year or pre-season rainfall. The integration of wavelet decomposition in a hybrid Wavelet-ANN model provided a more structured approach by isolating low- and high-frequency components, showing promise for capturing complex rainfall signals.

Despite these advances, the results underscore the necessity of incorporating additional predictors, particularly global climate indices (e.g., ENSO, IOD, AMO), to enhance model performance and long-lead forecasting skill. The current limitations observed in single-input and autoregressive models highlight the importance of a multivariate and seasonal-tailored approach.

In conclusion, artificial neural networks, particularly when integrated into hybrid modeling frameworks, offer a viable path toward improving rainfall forecasts in semi-arid regions like Muscat. These methods, coupled with real-time global climate inputs, can support water resource planning, flood risk management, and climate adaptation strategies across Oman.

**Author contribution:** All authors have contributed, read, and agreed to the published version of the manuscript results.

**Conflict of interest:** The authors declare no conflict of interest.

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