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Artificial neural networks for monthly precipitation prediction in north-west Algeria: a case study in the Oranie-Chott-Chergui basin

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ABSTRACT

The north-west region of Algeria, pivotal for the nation's water resources and agriculture, faces challenges from changing precipitation patterns due to climate change. In response, our study introduces a robust forecasting tool utilizing artificial neural networks (ANNs) to predict monthly precipitation over a 12-month horizon. We meticulously evaluated two normalization methods, ANN-SS and ANN-MM, and assessed four distinct approaches for selecting input variables (no selection, ANN-WO, ANN-CO, and ANN-VE) to optimize model performance. Our research contributes significantly to the field by addressing a critical gap in understanding the impact of evolving precipitation patterns on water resources. Among the innovations, this study uniquely focuses on medium-term precipitation forecasting, an aspect often marginalized in previous research. Noteworthy outcomes include correlation coefficients of 0.48 and 0.49 during the validation phase, particularly with the Endogen variables and correlation-optimized models using Min-Max normalization. Additionally, the Min-Max normalized technique achieves an impressive 67.71% accuracy in predicting the hydrological situation based on the Standard Precipitation Index.

Key words: Algeria, artificial neural network (ANN), hydrology, precipitation prediction, water management

HIGHLIGHTS

- Regional First: Pioneering study in our region.
- 12-month forecast: Unique 1-year ahead prediction.
- Optimized inputs: fine-tuned data for accuracy.
- Normalization methods: effective data normalization.
- SPI evaluation: rigorous model performance assessment.

INTRODUCTION

The disruption of rainfall patterns has emerged as a significant concern, especially in the north-west region of Algeria, a pivotal area for the country's water resources and agricultural activities. This region, characterized by essential agricultural zones and numerous dams, is facing escalating challenges due to the impacts of climate change on precipitation. Climate change has notably affected the precipitation cycle, resulting in unexpected floods and droughts. Consequently, there is a pressing need for a reliable tool that can accurately forecast precipitation (Kueh & Kuok 2018).

The irregularity and unpredictability of rainfall pose serious threats to water management, agriculture, and overall socio-economic development in the region. To address these pressing issues and enhance the region's resilience, the development of a robust forecasting tool for monthly precipitation becomes imperative.

The task of modeling rainfall is inherently complex, primarily due to the intricacies of atmospheric processes that trigger rainfall and the substantial variation in scales both in space and time (Pérez-Alarcón *et al.* 2022). The intricate nature of precipitation patterns demands sophisticated techniques capable of handling diverse and non-linear variables.

Numerous studies have addressed this challenge with the goal of enhancing precipitation forecasting accuracy and reliability. For instance, Jeong *et al.* (2012) introduced a neuro-fuzzy model (ANFIS) for both quantitative and qualitative monthly precipitation forecasting. Their study utilized a forward selection method to identify suitable sets of input variables,

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resulting in reliable forecasts. The qualitative forecasts of the model were compared with data from the weather agency of Korea. In a similar vein, Hossain *et al.* (2018) conducted a study in 2018 to evaluate the efficiency of non-linear regression in predicting long-term seasonal rainfall in a region located in Australia. The model integrated lagged values of climate drivers, such as the South-Eastern Indian Ocean (SEIO) and El Niño Southern Oscillation (ENSO), which demonstrated notable correlations with precipitation. Notably, our study emphasizes that the highest correlation with predictands does not necessarily translate to the lowest error rates. In a similar vein, Chhetri *et al.* (2020) conducted monthly rainfall predictions in Simtokha, Bhutan, employing diverse models, including Linear Regression, Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), LSTM, Gated Recurrent Unit (GRU), and Bidirectional Long Short-Term Memory (BLSTM), based on data from the National Center of Hydrology and Meteorology Department. The proposed BLSTM-GRU model outperformed existing models by 41.1%, achieving a lower Mean Squared Error (MSE) score of 0.0075, signifying its potential for more accurate rainfall prediction. Additionally, Gong *et al.* (2022) utilized Autoregressive Integrated Moving Average models (ARIMA and ARIMAX) to forecast monthly and annual Tropical Rainfall Measuring Mission (TRMM) precipitation, respectively. The calibration procedure was employed to obtain long-term precipitation data (1982–2018) over the Yangtze River Basin, with ARIMAX yielding significantly higher precipitation estimates than ARIMA.

The study by Vonnisa *et al.* (2022) introduced a dual-frequency algorithm, merging observations from the 47 MHz Equatorial Atmosphere Radar (EAR) and the 1.3 GHz Boundary Layer Radar (BLR) for raindrop size distribution (DSD) retrieval in West Sumatra, Indonesia. The results emphasized the method's potential for observing microphysical processes and its applicability to remote sensing in Indonesian climates. By employing the DSD ΔZMP parameter to characterize profiles, the study identified diverse microphysical processes during rain events, highlighting the importance of adaptable ZR relations within an event. In Mann & Gupta (2022) study on the Western Ghats region from 1977 to 2016, they utilized parametric linear regression analysis and a student t-test to identify trends in rainfall. Their findings unveiled significant spatial distribution changes in rainfall and indicated a positive temperature trend. Trend studies play a crucial role in predicting precipitation, as demonstrated in the research by Faye (2022). He analyzed trends in the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) in two regions of Senegal from 1981 to 2017. The findings revealed a statistically significant increasing trend in both SPI and SPEI, providing insights into long-term precipitation patterns in the studied areas.

Among the diverse models employed for precipitation prediction, artificial neural networks (ANNs) distinguish themselves for their exceptional performance and efficiency. This approach excels without necessitating an extensive dataset, showcasing adaptability to heterogeneous data, and, notably, effectively handling intricate non-linear variables such as precipitation. A plethora of studies substantiate this claim: Aksoy & Dahamsheh (2008) conducted research on forecasting precipitation in arid and semi-arid regions using an ANN with a 1-month ahead horizon, yielding commendable forecasting performance. Confirming the efficacy of various forecasting models across different time scales, Darji *et al.* (2015) highlighted the challenge statistical techniques face in long-term precipitation forecasting due to the dynamic nature of climate phenomena. They underscored the advantage of employing neural networks in such scenarios. Afshin *et al.* (2011) demonstrated that precipitation forecasting by neural networks surpasses classical models in capturing highly non-linear dynamic atmospheric phenomena. Similarly, Khodashenas *et al.* (2006) applied multiple ANNs at the Mashhad station in Iran, and were evaluated using statistical parameters and achieved highly favorable results.

Moustris *et al.* (2011) applied ANNs to predict monthly precipitation totals in specific regions of Greece. Their study analyzed extensive time series data from four meteorological stations, revealing that the ANN methodology delivered satisfactory precipitation forecasts, surpassing classical statistical methods. Statistical evaluation demonstrated notable consistency between observed and predicted precipitation totals, particularly for mean monthly and cumulative precipitation. In the investigation conducted by Mekanik *et al.* (2013), the focus was on long-term spring rainfall forecasting in Victoria, Australia, utilizing ANNs and MR analysis, with lagged ENSO and Indian Ocean Dipole (IOD) as predictors. The results favored ANN over MR, showcasing better generalization ability. ANN models exhibited correlation coefficients ranging from 0.68 to 0.97 for central and west Victoria, while MR models ranged from 0.99 to 0.90. This underscores the effectiveness of ANN for rainfall forecasting, particularly when incorporating large-scale climate modes. In a distinct approach, Kueh & Kuok (2018) employed a novel meta-heuristic optimization algorithm named 'Cuckoo Search Optimization' to train a neural network-based long-term rainfall forecasting model. The results underscored the model's capability to forecast precipitation with high confidence levels, reaching up to 90–100%. In the study conducted by Sharadqah *et al.* (2021), neural networks were employed for rainfall prediction in Jordan, utilizing the Levenberg-Marquardt algorithm. The neural network architecture

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comprised three layers, with 25 neurons in the input layer and 12 in the hidden layer. The obtained results were highly satisfactory, exhibiting a negligible mean square error. Ghamariadyan & Imteaz (2021) introduced a forecasting model based on a wavelet-aided ANN (WANN) for predicting seasonal rainfall in Queensland, Australia. This model incorporated the Interdecadal Pacific Oscillation (IPO), Southern Oscillation Index (SOI), and Nino3.4 climate indices as predictors. Comparative analysis involving classical ANN, ARIMA, MLR, and the Australian Community Climate Earth-System Simulator–Seasonal (ACCESS-S) revealed that the WANN and ANN surpassed other models in terms of accuracy. Pérez-Alarcón *et al.* (2022) developed a hybrid model (combining ANN and ARIMA) for rainfall prediction, utilizing MLP, CNN, LSTM neural networks, and ARIMA models. The input data encompassed one-year lagged rainfall records from gauge stations within the basin, sunspots, sea surface temperature, and time series of nine climate indices. The predictions were compared against rainfall records from a gauge station network spanning 2015 to 2019, showcasing the model's efficiency in forecasting rainfall. In a different approach, Tang *et al.* (2022) proposed a data augmentation technique based on the K-means cluster algorithm and synthetic minority oversampling technique (SMOTE) to enrich sample information for medium- and long-term precipitation forecasting. While the impact on deep learning methods was less pronounced, the research significantly contributed to enhancing precipitation forecasting accuracy, offering novel insights for improving medium- and long-term hydrological forecasting precision. Conducting a spatio-temporal analysis of extreme precipitation in the Dongjiang River Basin, Li *et al.* (2023) observed variations between upper and lower reaches. The study employed a Back-Propagation Artificial Neural Network (BP-ANN) to predict and simulate extreme precipitation. The predictions indicated a decrease in total precipitation and an increase in extreme precipitation for 2023, with a qualification rate ranging from 27 to 72%. These findings carry substantial implications for climate change and water resource management strategies in the basin.

In the Algerian context, numerous studies have delved into precipitation forecasting employing a combination of statistical methods and Neural Networks. For instance, Benmahdjoub *et al.* (2013) conducted a study on precipitation forecasting in the Tizi-Ouzou region of Algeria. They employed a Time Delay Neural Network model (TDNN) and found that coupling the model with the Levenberg-Marquardt Algorithm yielded optimal results. In a comparative analysis within the Algerois basin, Djerbouai & Souag-Gamane (2016) assessed various models, including an ANN model, ARIMA, and SARIMA. Utilizing the SPI, the study demonstrated the superiority of the neural technique over other methods. Achour *et al.* (2020) presented a study focused on forecasting drought in the north-west Algeria, utilizing the SPI. The study leveraged monthly rainfall data collected from seven plains in western North Algeria from 1990 to 2010. An ANN model was employed to forecast drought with a lead-time of 2 months. Exploring the sensitivity of hydrological parameters to future climate change, Hadour *et al.* (2020) utilized the CNRM-CM5 model for climate scenarios coupled with the hydrological model GR2M. The study confirmed a decreasing trend in precipitation from 1979 to 1999, correlated with an increase in potential evapotranspiration (PET) due to rising temperatures. In the Highlands of Algeria, Bouznad *et al.* (2020) investigated climatic parameters using data spanning from 1985 to 2014. They calculated the aridity index, Standard Precipitation Index, and normalized difference vegetation index (NDVI). Forecasting was conducted through stochastic time series modeling with ARIMA models, yielding promising results.

In this study, a robust forecasting tool based on ANNs designed for predicting monthly precipitation over a medium-term horizon was introduced, spanning 12 months. This forecasting horizon holds paramount importance in the management of water resources and agricultural activities in the north-west region of Algeria. Despite its significance, the medium-term forecasting domain remains relatively underexplored, making this study particularly innovative in filling this research gap.

A crucial aspect of our investigation revolves around the careful selection and normalization of input variables in the context of ANN forecasting models. We conduct a comprehensive comparison to determine the optimal variables and the most effective normalization methods. This meticulous process is vital for enhancing the accuracy and applicability of precipitation forecasts, addressing a critical aspect often overlooked in similar studies.

Subsequently, we delve into the specifics of the study area, emphasizing the pivotal role of accurate precipitation forecasting in facilitating efficient water management and agricultural planning within the region. The core of the article focuses on presenting and analyzing results obtained from various ANN models. Noteworthy attention is given to the comparison of two normalization methods (standard score and Min-Max feature scaling) and three distinct input variable selection approaches (weighting optimized, correlation optimized, and endogen variables).

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The article concludes with a comprehensive discussion of the findings, their implications, and suggestions for further enhancements to bolster the tool's accuracy. These improvements aim to advance its practical applicability in supporting effective water management and agricultural planning strategies in the dynamic context of the north-west region of Algeria.

By incorporating insights gained from previous studies and utilizing advanced ANN techniques, this research aims to make a significant contribution to the field of precipitation forecasting, ultimately aiding in the sustainable management of water resources and agricultural activities in the region.

METHODS

Forecasting model

In this study, we employed a robust forecasting model based on the ANN approach. Specifically designed to deliver accurate monthly precipitation forecasts over a 12-month horizon, the model's structure underwent meticulous development through iterative performance studies. Its initial application in 2019 focused on hourly water demand forecasting (Bouach & Benmamar 2019). Subsequently, the model was adapted to forecast monthly precipitation in the Algerois basin, situated in the northern region of Algeria (Bouach & Benmamar 2022). The adaptation primarily involved leveraging endogenous variables, with a particular emphasis on precipitation.

In this study, our model surpasses prior investigations by incorporating several exogenous variables, including temperatures, sunshine, and other climatic factors. The integration of these additional variables enhances the versatility and scope of the current model, rendering it more adept at capturing the intricate relationships influencing precipitation patterns.

The employed ANN model in this study follows the Feed-forward BP type, structured with three layers (see Figure 1). The exit layer features a single neural unit, identified as the identic type. In contrast, the second layer comprises two neural units based on the logistic function. The number of neural units in the input layer varies, contingent on the specific model structure under evaluation.

Five distinct models are meticulously studied in this research, each with its unique characteristics. Let's briefly explore each model:

Artificial Neural Network with Standard Score normalization (ANN-SS): This model incorporates various climatic variables as input, such as precipitation, wind speed, pressure, vapor, radiation, actual evaporation, minimum temperature, maximum temperature, North Atlantic Oscillation index (NAO), Mediterranean Oscillation Index Algiers-Cairo (MOI), Western Mediterranean oscillation index (WeMOI), Nino 3.4, temperature anomaly, and sunshine index. The input variables are normalized using the 'Standard Score' method.

Artificial Neural Network with Min-Max normalization (ANN-MM): Similar to the ANN-SS model, this model utilizes the same input variables, but it employs the 'Min-Max feature scaling' method for normalization.

Artificial Neural Network with Weights Optimization (ANN-WO): This model optimizes the number of input variables based on synaptic weights and retains precipitation, wind speed, actual evapotranspiration, minimum temperature, NAO, NINO 3.4, and temperature anomaly as the key input variables.

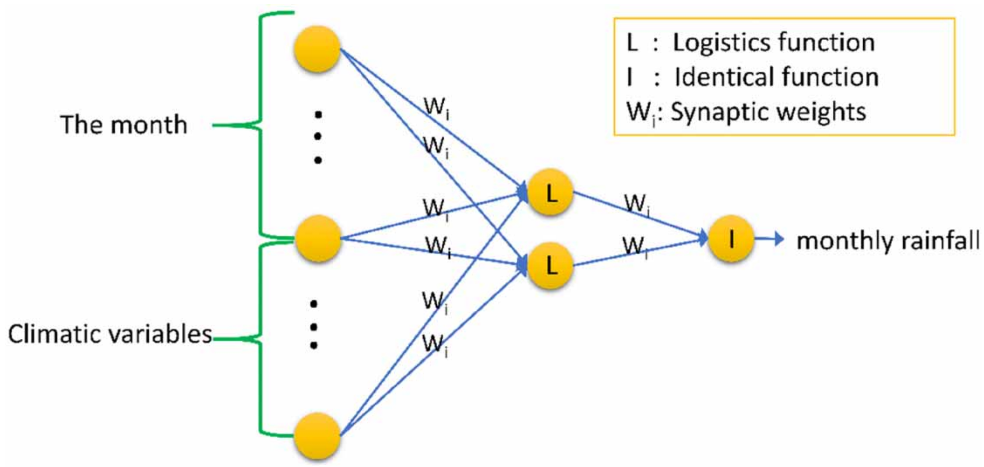

Figure 1 | Artificial neural network model.

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Artificial Neural Network with Correlation Optimization (ANN-CO): In this model, input variables are optimized based on their correlation coefficient with precipitation. The selected variables include actual precipitation, radiation, and evaporation.

Artificial Neural Network with Endogenous Variables (ANN-EV): This model exclusively employs precipitation as the sole input variable.

It's worth noting that the last three models (ANN-WO, ANN-CO, and ANN-EV) utilize the Min-Max normalization method, as it has demonstrated its effectiveness in the subsequent results.

For training the model, the highly effective gradient BP method is employed, which involves propagating the error from the output layer to the input layer during the learning process. The training data spans from 1959 to 2001, encompassing a total of 492 values for each variable. To validate the model's performance and assess its accuracy, independent data from the period 2002 to 2018 is utilized, comprising 204 values for each variable.

To ensure the reliability and comprehensiveness of our analysis, climate data from trusted sources is utilized. The Climate Engine site (https://app.climateengine.org) provides invaluable terraClimate satellite data with a spatial precision of 4 km and a temporal resolution of one month. Additionally, data from the Physical Sciences Laboratory (https://psl.noaa.gov) is incorporated to further enhance the quality of our analysis.

By employing this sophisticated methodology and leveraging comprehensive climate data, our study aims to present a valuable forecasting tool for monthly precipitation in the north-west region of Algeria. The incorporation of exogenous variables and meticulous model optimization ensures the robustness and versatility of our ANN-based forecasting model, offering valuable insights for enhanced water management and strategic agricultural planning in the region.

Study area: Oranie-Chott-Chergui Basin

The focal point of this research is the hydrographic basin known as Oranie-Chott-Chergui, situated in the western region of Algeria (see Figure 2). This basin is an integral component of the northern area of Algeria, which is subdivided into four distinct hydrographic basins. Oranie-Chott-Chergui is geographically bordered to the north by the expansive Mediterranean Sea,

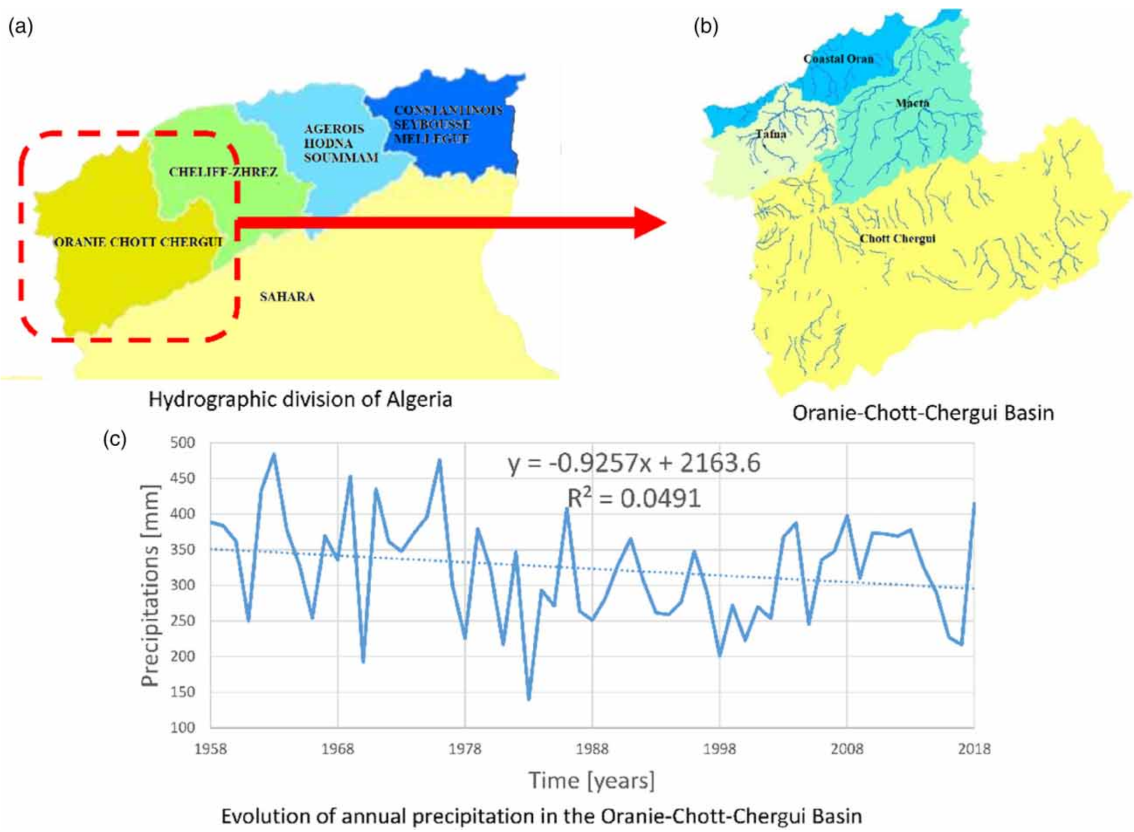

Figure 2 | Characteristics of the study region.

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to the east by the Chélif Zahrez region, to the west by the neighboring country of Morocco, and to the south by the vast Sahara basin. The basin encompasses four watersheds – Macta watershed, Tafna watershed, Chott-Chergui, and Coastal Oran – each ultimately draining into the sea, alongside one large endorheic watershed.

Covering an extensive area of approximately 77,169 km^2, the Oranie-Chott-Chergui basin constitutes nearly one-third of the entire northern region of Algeria. The region is inhabited by a burgeoning population exceeding 7 million, with 4.9 million residents dwelling in agglomerated urban environments and 2.1 million in scattered rural settings.

In terms of water resources, the Oranie-Chott-Chergui basin boasts a substantial surface potential estimated at 1,010 Hm3, underscoring its critical role in sustaining water availability for the region. The basin features a network of 14 dams, boasting an impressive total capacity of 673 Hm3. Additionally, the region is endowed with 29 groundwater units, contributing to a considerable potentiality of approximately 400 Hm3, further reinforcing water supply reliability.

The economic fabric of the Oranie-Chott-Chergui basin is characterized by a diverse range of activities, including robust industrial sectors, agriculture, and a vibrant tourism industry. Despite its substantial dam infrastructure and expansive agricultural lands, the region faces the persistent challenge of a continuous decline in annual rainfall. The average annual rainfall in the Oranie-Chott-Chergui basin is estimated at 323.29 mm, a trend supported by a noticeable downward trajectory in the regression line (refer to Figure 2). Additionally, the region experiences significant seasonal variation in precipitation, with an estimated coefficient of variation of 0.23, underscoring the necessity for precise and reliable precipitation forecasting.

Undoubtedly, the hydrographic basin of Oranie-Chott-Chergui plays a pivotal role in the socio-economic development of the entire north-west region of Algeria. However, the challenges posed by diminishing rainfall patterns and variable climatic conditions demand proactive measures. In response to these circumstances, the implementation of a robust precipitation forecasting tool, as proposed in this study, holds immense value in fortifying water management strategies, supporting sustainable agricultural practices, and fostering overall resilience in the region.

The accurate forecasting of monthly precipitation in this critical basin can significantly contribute to informed decision-making, assisting authorities in planning and allocating water resources effectively. Moreover, such forecasting provides valuable insights to farmers, enabling them to optimize irrigation practices and adapt agricultural activities to prevailing weather conditions. By harnessing the power of artificial neural networks and incorporating diverse climatic variables, our study endeavors to provide a reliable forecasting tool that will be an indispensable asset in enhancing the region's water resource management and promoting sustainable socio-economic development.

RESULTS AND DISCUSSION

Graphical analysis of forecasted rainfall

The graphical representation depicting the evolution of precipitation for the five forecasting models, in conjunction with the actual precipitation data, provides valuable visual insights into their performance. Upon careful observation, a noteworthy resemblance and correlation between the predicted curves and the actual curve become evident, particularly for the ANN-MM and ANN-WO models (Figure 3). These models demonstrate a close match to the observed precipitation pattern, signifying their relatively robust predictive capabilities.

Subsequently, the ANN-CO and ANN-EV models also exhibit a reasonable alignment with the actual precipitation curve, albeit with minor deviations. These models showcase potential in capturing precipitation trends but may necessitate further refinement for improved accuracy.

Conversely, the ANN-SS model presents certain points that diverge from reality, implying limitations in its predictive performance.

While the visualization provides valuable insights, a thorough analysis and investigation are imperative for a comprehensive interpretation of the results. A detailed examination of model parameters will enable us to gain a comprehensive understanding of the forecasting outcomes. Addressing these aspects will refine the models and enhance their reliability for more accurate precipitation predictions.

Analysis with evaluation indicators

To systematically assess the efficacy of our monthly precipitation forecasting models, we employed three pivotal evaluation indices: the correlation coefficient (R), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The results

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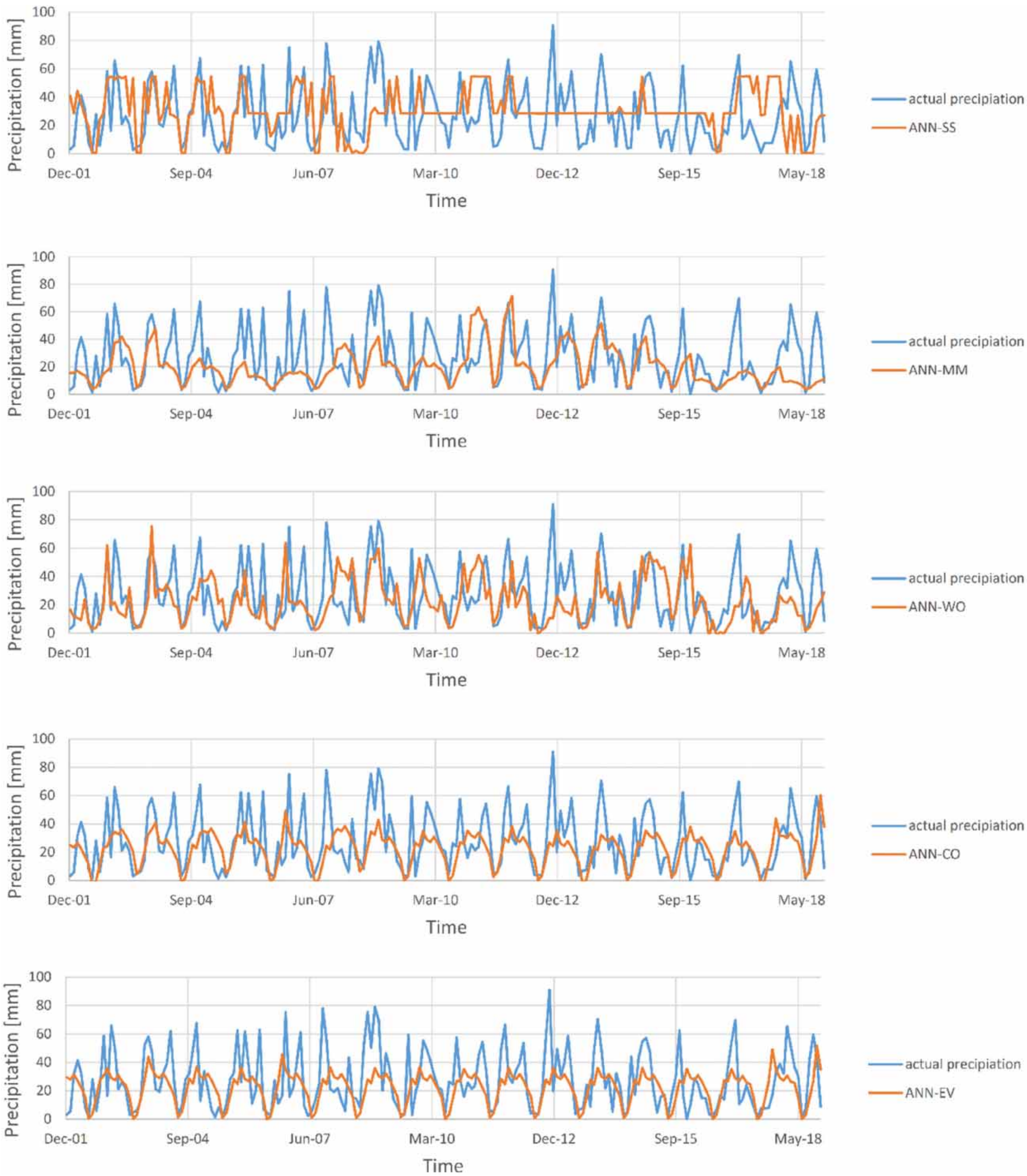

Figure 3 | Monthly precipitation forecasts from different models.

obtained for each model are succinctly summarized in Table 1, offering valuable insights into their respective forecasting capabilities.

The outcomes of this phase unveiled intriguing findings, particularly in the case of the ANN-SS and ANN-WO models, affirming their significant correlation and lower prediction errors, as supported by the RMSE and MAE indicators (refer to Table 1). Notably, the three remaining models, predicated on optimization selection and endogenous variables, produced nearly identical results, as elucidated in Table 1. This presents a nuanced and somewhat paradoxical scenario, posing a challenge in determining the optimal approach.

Surprisingly, the normalization methods yielded identical results for both models, with ANN-SS performing well with the standard score method, and ANN-WO excelling with the Min-Max method. Similarly, the input variable selection process did

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Table 1 | Evaluation indicators of the different models

	Learning				
	ANN-SS	ANN-MM	ANN-WO	ANN-CO	ANN-EV
R	0.66	0.59	0.67	0.56	0.54
RMSE	16.55	17.81	16.41	18.18	0.00
MAE	11.47	13.48	12.28	13.79	0.00
	Validation				
	ANN-SS	**ANN-MM**	**ANN-WO**	**ANN-CO**	**ANN-EV**
R	0.21	0.39	0.35	0.48	0.49
RMSE	23.35	21.22	21.78	18.96	18.84
MAE	18.93	15.09	16.35	14.60	14.44

not substantially impact the results, as both ANN-SS (with non-selective input variables) and ANN-WO (with optimized input variables) demonstrated comparable performance.

Evaluation of the validation phase

The evaluation indices applied during the validation phase unveil the performance of various models in forecasting precipitation. Topping the results are the ANN-EV and ANN-CO models, boasting relatively high correlation coefficients of 0.49 and 0.48, respectively. Additionally, both models demonstrated commendably low forecast errors, as evidenced by the RMSE and MAE coefficients. These findings suggest that optimizing the number of variables can indeed enhance the forecasting process for both models.

In the second position, the ANN-MM and ANN-WO models exhibited correlations between predicted and actual precipitation that fell below the average, registering coefficients of 0.39 and 0.35, respectively.

Conversely, the ANN-SS model yielded the least favorable results, displaying a weak correlation ($R = 0.21$) and significant errors (RMSE = 23.35, MAE = 18.93). This implies that utilizing the Min-Max feature scaling method may be more effective than the standard score normalization approach.

These results highlight two critical findings: Firstly, the Min-Max normalization method outperforms the Standard score normalization method; secondly, the optimization of input variables enhances the efficiency of the forecasting process. Among these optimization approaches, correlation emerges as the most reliable.

Evaluation with standard precipitation index

The forecast of the hydrological situation was evaluated solely using the SPI-based approach (Table 2). The success rates for predicting the hydrological situation using the SPI approach for each model are as follows:

- ANN-SS model: Success rate of 35.29%
- ANN-MM model: Success rate of 64.71%
- ANN-WO model: Success rate of 35.29%
- ANN-CO model: Success rate of 35.29%
- ANN-EV model: Success rate of 35.29%

The ANN-MM model stands out with the highest success rate among the models, reaching 64.71%. This underscores its relatively robust capacity to predict the hydrological situation at the forecast horizon using the SPI. Nevertheless, it is imperative to interpret these results with due caution and account for potential uncertainties and limitations associated with hydrological forecasting.

The SPI-based approach offers valuable insights into water resource management and climate-related decision-making processes. While the ANN-MM model exhibits promising results, a thorough analysis and investigation are imperative to enhance the accuracy and reliability of hydrological predictions. These endeavors will contribute significantly to the overall improvement and effectiveness of our forecasting tool, supporting water management and agricultural planning strategies for the north-west region of Algeria.

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Table 2 | Values of the Standard Precipitation Index at 12 months

Year	Actual precipitation	ANN-SS	ANN-MM	ANN-WO	ANN-CO	ANN-EV
2002	−0.94	0.47	−2.24	−1.73	−1.50	−0.77
2003	0.60	2.19	0.67	−1.03	−0.01	−0.62
2004	0.87	0.26	−1.58	−0.67	−1.20	−0.71
2005	−1.05	0.94	−1.81	0.06	0.00	−0.77
2006	0.17	−0.13	−2.59	−1.50	−0.75	−0.73
2007	0.33	1.94	−2.28	−1.73	−1.32	−0.77
2008	1.00	−2.51	0.05	2.09	0.25	−0.80
2009	−0.18	1.28	−1.46	−0.35	−0.97	−0.74
2010	0.68	0.56	−1.63	−1.17	−0.92	−0.91
2011	0.66	3.21	3.23	1.02	−0.49	−0.76
2012	0.62	0.25	−1.53	−2.05	−0.95	−0.81
2013	0.74	0.25	1.07	−1.35	−1.39	−0.82
2014	0.04	0.67	0.05	−0.32	−0.91	−0.80
2015	−0.45	0.25	−1.25	2.35	−0.51	−0.90
2016	−1.30	−0.60	−2.93	−2.85	−0.96	−0.89
2017	−1.44	3.60	−2.19	−1.87	−1.13	−0.61
2018	1.24	−2.29	−3.08	−1.68	−0.03	−0.53

CONCLUSION

In summary, this study conducted a comprehensive investigation into monthly precipitation forecasting in the north-west region of Algeria, employing ANNs. The proposed forecasting models incorporated various normalization techniques and input variable selection approaches, facilitating a thorough evaluation of their performance.

During the learning phase, consistent outcomes were observed for both normalization approaches. Specifically, the SS normalization and MM normalization produced similar results, with correlation coefficients (R) of 0.66 and 0.67, respectively. Likewise, the optimization of input variables yielded mixed results. The ANN-SS model, without any optimization, performed comparably to the model utilizing the optimization method based on synaptic weights.

Drawing on the results from the learning phase, we assert that the MM technique for normalization surpasses the SS approach. The ANN-SS model, employing the SS approach, demonstrated subpar performance across all evaluation indices (R, RMSE, and MAE).

Regarding the variable selection method, the assessment of results based on the correlation coefficient underscored the efficacy of the ANN-EV and ANN-CO models, achieving correlation coefficients of 0.49 and 0.48, respectively. However, when evaluated based on the Standard Precipitation Index, a different perspective emerged. It revealed that the model without optimization (incorporating all climatic variables) proved to be the most efficient, attaining a success rate of 64.71% in forecasting the hydrological situation, compared to 35.29% for the optimized models.

For a comprehensive interpretation of the forecasting results, a more thorough analysis and investigation are imperative, considering various factors that may influence model performance. Future research endeavors should prioritize the optimization of model parameters, exploration of additional input variables, and incorporation of more sophisticated methodologies to enhance the precision and reliability of monthly precipitation predictions.

This study confirmed the complexity of climatic phenomena, and precipitation in particular. They depend on several nonlinear variables that are difficult to model in a mathematical model. Regarding the forecast model, the Min-Max normalization method has shown its performance, while the best selection approach is the one based on correlation. However, if we use the SPI to evaluate performance, it is the approach based on all climatic variables which gives the best result. This shows that the parameterization of the model is not easy requiring several adjustments and tests, and what is best for one case may not be for another.

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Overall, this research provides valuable insights into precipitation forecasting in the north-west region of Algeria. The proposed ANN-based tool offers promising forecasts and can play a significant role in supporting effective water management strategies and agricultural planning, particularly in response to evolving climatic conditions. The proposed model can help water service managers to anticipate events well; with 12 months in advance it seems sufficient time to prepare for a possible drought, for example.

We hope that this study serves as a stepping-stone for further advancements in precipitation forecasting, ultimately contributing to the sustainable utilization of water resources and enhancing resilience to climate variability in the region. Continued efforts in this direction will aid in the development of effective climate adaptation and mitigation measures, ensuring a more sustainable and secure future for the region's water resources and agriculture.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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