LONG-TERM PREDICTION OF CLIMATE VARIABLES OF THE LAKE VAN BASIN: A COMPREHENSIVE ANALYSIS USING STATISTICAL AND DEEP LEARNING MODELS

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Abstract

The aim of the present study is to predict environmental conditions in the basin of Lake Van in the Eastern Anatolia, Türkiye. The datasets for the period between January 1950 and June 2023 that include critical parameters like sunshine hours, temperature, precipitation, and humidity were used for predicting. The research developed a two-way approach that combines statistical-based models which include Auto.Arima, SARIMA and TBATS models together with deep learning-based models like NNTAR, MLP and ELM.

The model's accuracy and reliability are being evaluated by using the test lengths of 60, 72, and 84 months periods during the forecasting process. Evaluation metrics, especially the root mean square error (RMSE) and mean absolute error (MAE) were used to numerically show the capability of every model. This trial is a major contribution to environmental forecasting literature by focusing on a particular geographical zone, ensuring environment parameters diversity, employing diverse prediction models, and offering a long-term view. The conclusions have been proved meaningful for researchers and environmentalists who dedicate their time to climate science, environmental management, and sustainable development in the Eastern Anatolia region of Türkiye.

Key words: R-based models, meteorological variables, time series prediction, statistical models, Lake Van Basin

1. INTRODUCTION

Global climate change poses profound impacts on our world, manifesting through altered weather patterns, rising sea levels, extreme events, and ecological disruptions (Campbell-Lendrum & Corvalán, 2007). Understanding and addressing these changes are critical, and time series forecasts play a pivotal role by providing insights into future trends based on historical data. Climatic future predictions are crucial for informed decision-making across various sectors, offering the opportunity to anticipate and mitigate the impacts of climate change, particularly in addressing issues like global warming and droughts. While these predictions alone may not directly slow down global warming or prevent droughts, they guide the development of strategies to mitigate these challenges. Long-term forecasting of meteorological variables in specific regions contributes scientifically by enhancing our understanding of climate trends, regional variations, and potential risks (Mohsenzadeh Karimi, Kisi, Porrajabali, Rouhani-Nia, & Shiri, 2020). Forecasting models, including statistical, machine learning, and deep learning approaches, play a crucial role in this process. The selection of forecasting models involves considerations such as data quality, forecast horizon, and the complexity of underlying processes (Shen, Zhang, Lu, Xu, & Xiao, 2020). The performance differences among these models on the same time series arise from their unique strengths and limitations, emphasizing the importance of choosing the most suitable model based on the specific characteristics of the data and forecasting goals. In essence, the integration of time series forecasts, climatic predictions, and long-term meteorological forecasting, guided by appropriate modeling techniques, equips us to comprehend and address the multifaceted challenges posed by global climate change, promoting a more sustainable and resilient future.

Prediction of future values on monthly average sunshine duration, monthly relative humidity, monthly precipitation, and monthly temperature for Lake Van Basin based on given historical data from 1950-2023 can be of great help for future region's development and resiliency. The seasonal and long-term climate outlooks and predictions provide invaluable insights which can then be utilized in making informed decisions for the sustainable means of agricultural practices, water resource management as well as proactive measures to deal with any possible environmental challenges. Furthermore, sectors such as energy, tourism and infrastructure can gain advantage by knowing the future weather, resulting in more efficient operations and better risk management. With the support of historical data and innovative forecasting methodologies, the area can progressively improve its resilience to variations in the climate, giving the area a secure and sustainable future.

Within the scope of this study, many studies on temperature, precipitation and relative humidity forecasts were examined. The studies examined in the literature are given in Table 1.

Table 1 Some literature on temperature, precipitation and relative humidity forecasts.

Authors	Contribution and results
(Shad, Sharma, & Singh, 2022)	In this research, the authors utilize SARIMA and artificial neural network (ANN) with multilayer perceptron (MLP) models to forecast monthly relative humidity in Delhi, India, spanning 2017–2025. Significantly, the MLP model demonstrates superior accuracy compared to SARIMA, suggesting its efficacy in minimizing forecasting errors.
(Aghelpour, Singh, & Varshavian, 2021)	This study compares the efficacy of various forecasting models, including SARIMA, MLP, ANFIS-SC, and ANFIS-FCM, in predicting seasonal precipitation across different climatic zones in Iran. Using data from 1951 to 2018 from eight stations, the SARIMA model emerges as the most accurate predictor, outperforming artificial intelligence methods in terms of RMSE.
(Papacharalampous, Tyralis, & Koutsoyiannis, 2018)	In this study, the authors explore the predictability of monthly temperature and precipitation using various automatic univariate time series forecasting methods on extensive datasets. They include traditional methods like random walk and exponential smoothing. Through testing on a 40-year dataset, the study reveals that most methods, except naive and random walk, offer accurate long-term forecasts.
(Ye, Yang, Van Ranst, & Tang, 2013)	The authors present a generalized, structural time series modeling framework for analyzing monthly absolute surface temperature records, using a deterministic-stochastic combined (DSC) approach. This framework, developed based on a global dataset, incorporates deterministic processes for characterizing global trends and

Authors	Contribution and results
	cyclic oscillations, employing polynomial functions and the Fourier method. Stochastic processes, specifically seasonal autoregressive integrated moving average (SARIMA) models, account for residual patterns.
(Chang, Zhao, & Zhang, 2012)	This study proposes an innovative approach to enhance precipitation prediction accuracy by integrating time series and environmental factors. The novel model employs a support vector machine (SVM) to nonlinearly screen environmental factors, followed by estimating the order through controlled autoregressive (CAR) modeling. Overall, the study contributes a refined forecasting model that addresses the dynamic nature of precipitation prediction, offering improved accuracy and applicability in the context of climate dynamics and environmental influences.
(Sarraf, Vahdat, & Behbahaninia, 2011)	This study addresses the critical impact of global climate changes on water resources by focusing on temperature and humidity forecasts, crucial for informed decision-making and optimal water resource utilization. Using statistical distribution and time series analysis, the authors employ the ARIMA model to forecast the average monthly temperature and relative humidity in Ahvaz synoptic station over a 20-year period.
(H. Li et al., 2020)	This paper focuses on the vital task of predicting relative humidity, crucial in the context of global climate change. Using the relative humidity data from Ya'an city, Holt-Winters, SARIMA, and XGBoost to establish time series models. This finding suggests that the XGBoost model holds promise for more accurate relative humidity predictions, serving as a valuable reference for practical applications.
(Kisi, Mohsenzadeh Karimi, Shiri, & Keshavarzi, 2019)	In the study the authors consider different ways to estimate the monthly precipitation rates applying the data from geographical locations, such as latitude, longitude, altitude, and periodicity components, for example. They show that the LSSVM and MT models are superior to polynomial regression not only at stations but also in pooled cases. Results showed that the LSSVM method was much ahead in benchmarking MT technique, especially in arid / semi-arid areas. In their conclusion they also score these heuristic methods against geostatistical kriging and found that kriging usually has best results in spatial rainfall forecasting. Finally, the study is of great importance for rainfall models being the considerable contribution to the modeling techniques, especially in the highly climatic contexts like those found in Iran.

The role of this study in literature is going to be well-distinguished and, to our opinion, it will remain the first study which forecast the future changes of climate parameters in the Lake Van Basin. For starters, the use diverse data sets and deep research on temporal features in their predictive models welcomes the chance to add more robustness, allowing for a better understanding of the factors influencing the lake level conditions. This is brought into the loop of the already existing literature through the provision of the deep insight into the interacting properties of climatic factors and Lake Van.

In addition, a number of use cases of different prediction models, - traditional statistical methods and machine learning algorithms, - demonstrate the methodical diversity that can be beneficial for the researcher and the practitioner in studies with similar aims. The models comparison process encompasses Auto.Arima, SARIMA, TBATS, NNTAR, MLP, and ELM deep dives to establish their fitness in the forecast of the parameters of the ecological conditions of interest.

Finally, the use of prediction results as benchmarks and measurement indices such as the RMSE and MAE, adds another quantitative dimension to the study, making a comprehensive evaluation of the models' accuracy possible. Not only does it change the scientific rigor of research but it also gives hints of how well computer modeling can give predictions about the future of Lake Van state.

2. MATERIALS AND METHODS

2.1 STUDY AREA: LAKE VAN BASIN

Lake Van is a very large lake located in the Eastern Anatolia region of Türkiye. The increase in temperature in the atmosphere affects the Van Lake basin in different ways, like many other places. For example, the increase in temperature can change the lake ecosystem and organisms such as some fish species can be sensitive to temperature changes. As a result of global warming affecting the rainfall pattern, changes in the amount of rainfall can be clearly observed in the Van Lake basin. Recently, Lake Van has received less rainfall, which has reduced the water level in the lake. This can have a negative impact on water resources and ecosystems. It can be seen that global warming increases the risk of drought in some regions. Due to all these negative situations, making future predictions using meteorological data measured from past to present, such as relative humidity, sunshine duration, precipitation and temperature in the Van Lake basin, can provide many advantages.

2.2 PREDICTION SYSTEM ARCHITECTURE AND MODELS

The steps that summarize the main theme of this study are given in Figure 1

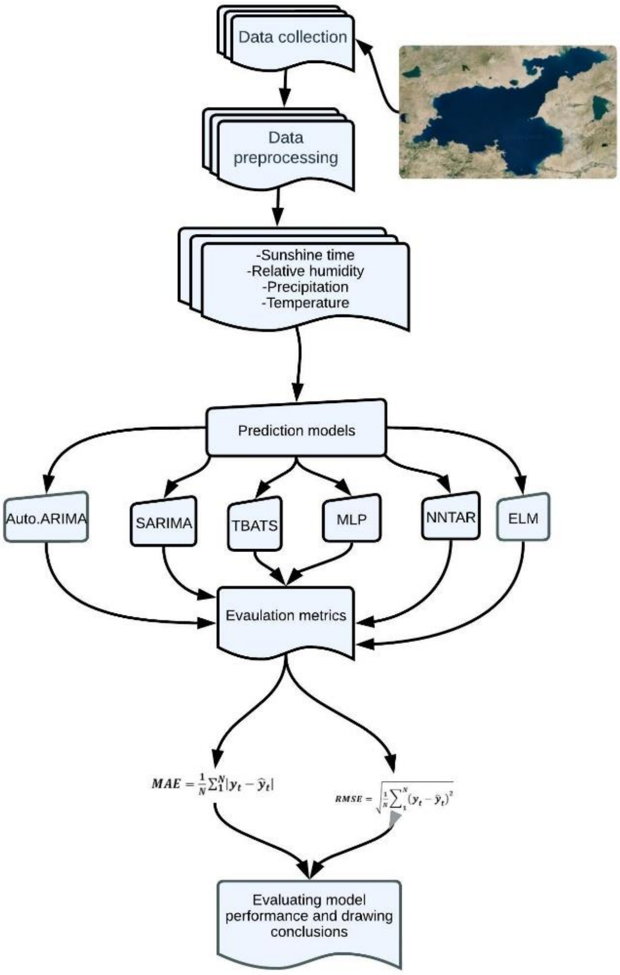

Figure 1 Architectural structure of the forecast system

First of all, the data, which is the main raw material of the study, was procured, and then all of the data was cleared of errors and converted into monthly time series format. As a result of the transformation, four different climatic variables were obtained. These data, which vary depending on time, are listed as sunshine duration, relative humidity, precipitation and temperature. Then, future predictions were made for each time series with seven different prediction models, and the results were evaluated with the help of RMSE and MAE metrics and the findings were discussed.

The description of the models used in the forecasting process and their working methods are briefly summarized below.

MLP: Multilayer Perceptron (MLP) is a type of model that belongs to the artificial neural network family. MLP is an artificial neural network that contains at least one hidden layer and is often included in the deep learning literature. This model is used in various applications due to its ability to model complex and non-linear relationships (Liao & Liang, 2021). MLP and similar neural network models have a wide range of applications, but they perform better with large data sets and complex problems. Factors such as training processes, appropriate hyperparameter tuning, and overfitting of the model are important elements that affect the success of MLP.

In the MLP model, the relationship between y_t output and $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ inputs can be expressed as follows:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j . g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t, \quad (1)$$

Where α and β are the weights; p is the number of inputs, q is the number of hideen nodes, and g is the transfer function (Luis, Maia, De Carvalho, & Ludermir, 2008).

ELM: Extreme Learning Machine (ELM) is a learning paradigm used in the field of machine learning and artificial neural networks (Salaken, Khosravi, Nguyen, & Nahavandi, 2017). ELM is known for its ability to learn quickly and effectively, especially on large data sets, and is a single-layer artificial neural network with only one hidden layer. With this feature, it differs from other artificial neural network models. This layer connects input data directly to the output. ELM initializes the connections in the input layer with randomly generated weights. These random weights increase the speed at which the model starts learning. ELM randomly selects the weights in the input layer and solves the weights in the output layer analytically. Therefore, the training process is fast, which can be an advantage especially when working with large datasets. However, ELM is generally effective in applications that require low-dimensional datasets and fast training. Suppose there is an ELM with k hidden layer neurons and an activation function g. In this case, modeling $\{X_i, y_i\}_{i=1}^{N}, x_i \in R^s$ data samples can be represented mathematically as follows:

$$\sum_{j=1}^{k} g_i\left(w_j, b_j, x_i\right)\beta_j = t_{i,}\, i = 1,2, \dots, N \qquad (2)$$

Here w_j is the vector of input weights connecting the jth hidden neuron and the inputs. β_j is the output weight connecting the jth hidden neuron and the output and represents the bias of the jth hidden node (X. Chen et al., 2012).

NNTAR: It is a function included in the forecast package in the R language and creates a time series forecast model using neural networks. This function is designed to address complexities in time series data and improve predictive performance (Zeydin Pala, 2023). NNTAR or NNETAR uses a multilayer artificial neural network in time series forecasting (Hyndman & Athanasopoulos, 2018). This ensures that the model can handle complex and non-linear relationships. The model makes predictions by automatically selecting important features in the data and learning their weights. The NNTAR function automatically determines the architecture of the neural network and other hyperparameters. This allows the model to learn complex structures and increase its generalization ability. The model can handle seasonal and trend components and thus model these features of the time series.

TBATS: Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS) model is an automatic forecasting model for complex time series (Munim, 2022; Zeydin Pala, 2021). The TBATS model includes a set of specifications for modeling the error term with both seasonal and trend components. The TBATS model can handle multiple seasonal frequencies and represent them with trigonometric functions. This ensures that the model can handle complex seasonal patterns in the data. If the data does not follow a normal distribution or has heteroscedasticity, the Box-Cox transformation can be used. The TBATS model can model the trend and seasonal components of time series data. It is specifically designed for data with complex seasonal patterns and heteroscedasticity.

AUTO.ARIMA: Auto.Arima is a package in the R programming language used for automatic time series modelling. The auto.arima function has the ability to automatically identify and adapt AutoRegressive Integrated Moving Average (ARIMA) models (Basha, Zhenning, Rajput, Caytiles, & Iyengar, 2017; Zeydin Pala & Pala, 2021; Petropoulos & Svetunkov, 2020). ARIMA models are widely used to model trends and seasonal patterns in time series.

For a dependent time series$\{X_t: 1 \leq t \leq N\}$, ARIMA can be modeled mathematically as follows:

$$\emptyset(B)\nabla^d X_t = \theta(B)\varepsilon_t \tag{3}$$

Where B is the backshift operator, $BX_t = X_{t-1}$ and $\emptyset(B)$ is the autoregressive operator represented as a polynomial in the backshift operator:

$$\emptyset(B) = 1 - \emptyset_1(B) - \cdots - \emptyset_p B^p \tag{4}$$

$\theta(B)$ is the autoregressive operator, represented as a polynomial in the backshift operator:

$$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \tag{5}$$

ε_t is the independent disturbance, also called the random t error (Yang, Gao, & Guo, 2018).

SARIMA: Seasonal autoregressive integrated moving average (SARIMA) model extends the ARIMA framework to incorporate seasonality into time series forecasting. It is utilized in fields such as retail sales, demand forecasting, economic indicators, supply chain management, and climate studies, where data exhibits distinct seasonal patterns. SARIMA effectively captures and models seasonal variations, providing more accurate forecasts for such data. Its advantages include robust handling of seasonality, versatility across various domains, and clear interpretability of parameters. However, SARIMA requires a sufficiently long time series dataset for accurate parameter estimation, and manual selection of model parameters can be challenging. Additionally, the model may be sensitive to outliers in the data, which could impact forecasting performance. We can represent an SARIMA model as (p,d,q)(P,D,Q)m. Where P, D, Q, the seasonal component of the model and (p, d, q) nonseasonal component of the model and m is the length of the season. With the help of the backshift operator B, the general form of the SARIMA model can be shown as Eq.6.

$$\varphi_p(B)\emptyset_P(B^m)\nabla^d\nabla_m^D Z_t = \theta_q(B)\Theta_Q(B^m)a_t \tag{6}$$

Where $\emptyset(B)$ and $\theta(B)$ are polynomials of order p and q, respectively. $\emptyset(B^m)$ and $\Theta(B^m)$ are polynomials of order P and Q in B^m, respectively. ∇^d is nonseasonal operator and ∇_m^D is seasonal operator (Ahmadpour, Mirhashemi, & Panahi, 2023).

2.3 EVALUATION METRICS

The Root Mean Square Error (RMSE) metric is widely used in diverse fields, particularly in assessing the accuracy of predictive models, such as those in climate studies, finance, and machine learning (Jierula, Wang, Oh, & Wang, 2021). It measures the average magnitude of prediction errors by calculating the square root of the mean of squared differences between predicted and observed values.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{1}^{N}(\boldsymbol{y_t} - \boldsymbol{\hat{y}_t})^2} \tag{7}$$

Where $\boldsymbol{y_t}$, is the time series value at time t and $\boldsymbol{\hat{y}_t}$ is the estimated prediction value. The advantages of RMSE lie in its ability to provide a comprehensive measure of prediction accuracy, reflecting both bias and variance in the model. Additionally, it is widely interpretable due to its unit consistency. However, RMSE can be sensitive to outliers, giving disproportionate weight to large errors, and it may not always offer clear insights into the direction of errors. Careful consideration of the context and potential implications of large errors is necessary when interpreting RMSE values.

The mean absolute error (MAE) metric finds broad applications in diverse fields, particularly in evaluating the performance of predictive models, such as those in economics, environmental science, and machine learning. MAE measures the average magnitude of absolute errors between predicted and observed values. Its advantages include simplicity, as it provides a straightforward and easily interpretable assessment of prediction accuracy (Willmott & Matsuura, 2005).

$$MAE = \frac{1}{N}\sum_{1}^{N}|y_t - \hat{y}_t| \tag{8}$$

MAE is less sensitive to outliers compared to metrics like RMSE, making it suitable for scenarios where extreme values might disproportionately impact other metrics. However, MAE does not differentiate between overestimations and underestimations, and it may not penalize large errors as effectively as metrics like RMSE, potentially overlooking the significance of certain prediction inaccuracies.

2.4 TIME SERIES ANALYSIS

Time series are data sets that show the change of an event or value over time. This type of data has a variety of applications in many different fields and industries. Some areas where time series are used: These can be listed as weather (Hossain, Rekabdar, Louis, & Dascalu, 2015), health (Yaldız & Pala, 2019), speech recognition (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014), energy consumption (Hwang & Yoo, 2014; Mohsin, Naseem, Sarfraz, & Azam, 2022), radiation predictions (Etem, Pala, & Bozkurt, 2017; Z. Pala, Ünlük, & Yaldız, 2019), sunspot prediction (C. Chen et al., 2010; Zeydin Pala & Atici, 2019), natural gas production prediction (N. Li, Wang, Wu, & Bentley, 2021; Zeydin Pala, 2023), sensor data analysis (Dhillon, Madhu, Kaur, & Singh, 2020).,energy production (Zeydin Pala, 2024).

Time series analysis provides a valuable tool for predicting future events by combining a number of functions. However, successful time series forecasting model selection and implementation includes factors such as correct parameter tuning and regular model updates. Forecasting future values of monthly sunshine duration, monthly average relative humidity, monthly average precipitation, and monthly average temperature in the Van Lake Basin through time series models offers multifaceted advantages. These forecasts facilitate informed decision-making across sectors such as agriculture, water resource management, energy, tourism, health, infrastructure, environmental conservation, transportation and research By providing reliable insights into upcoming weather conditions, these predictions enable efficient resource allocation, risk mitigation, infrastructure planning, and societal preparedness, ultimately fostering sustainable development and enhancing overall resilience in the region.

2.5 DATA DESCRIPTION

Four different datasets were used in this study. Data sets consist of monthly data between January 1950 and June 2023. All data sets were obtained from Van Meteorology Directorate, one of the eastern provinces of Türkiye. The data constituting the data sets used consist of relative humidity, sunshine time, precipitation and temperature respectively. Before using each supplied data set, any erroneous data they contained were corrected and then converted into time series format. Statistical properties of time series such as length, min, max, median and mean are given in Table 2.

Table 2 Statistical information of the experimental datasets

Datasets	Length	Min.	1st Qu.	Median	Mean	3rd Qu.	Max
1-Monthly sunshine time (hours)	882	0.8	162.0	226.4	239.1	319.8	407.4
2-Monthly average relative humidity (%)	882	28.20	47.80	59.35	57.76	68.30	83.10
3-Monthly precipitation kg/m²)	882	4.00	16.32	29.40	35.75	47.88	168.30
4-Monthly average temperature (°C)	882	-10.20	1.20	9.65	9.451	18.00	25.30

Time series of monthly humidity, number of sunny hours, monthly precipitation, and monthly temperature for the Van Lake basin measured between January 1950 and June 2023 are shown in Figure 2.

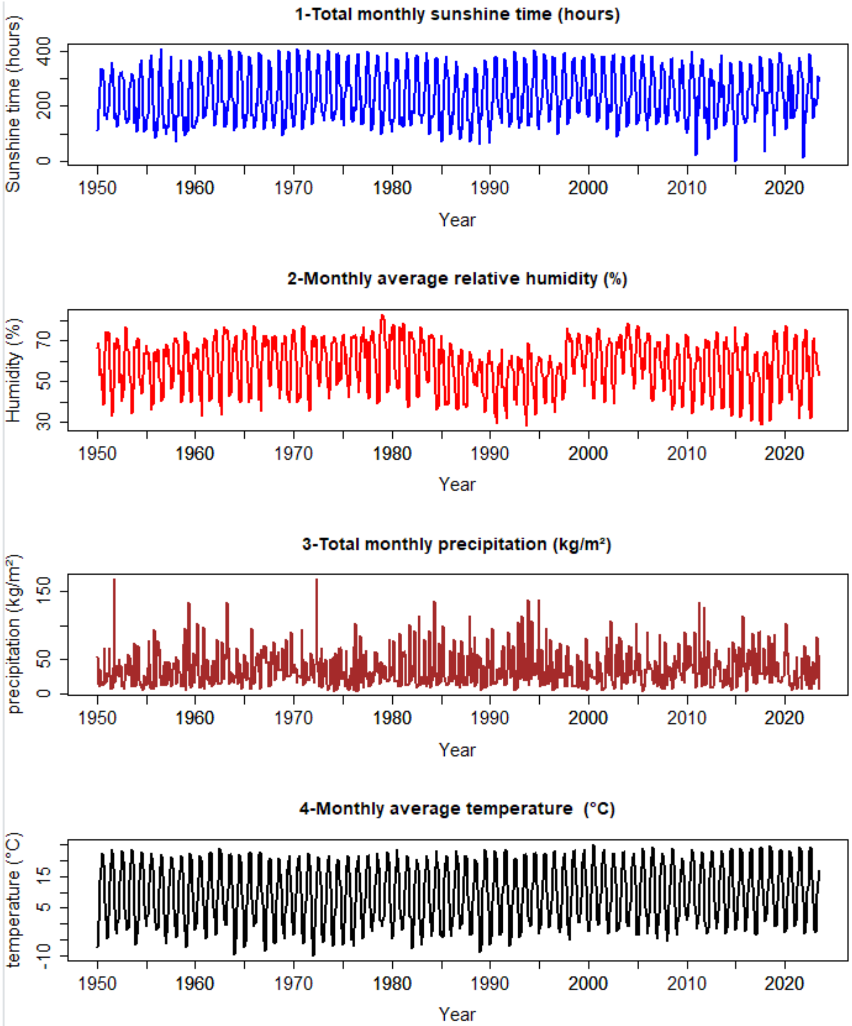

Figure 2 Graphs of measured monthly average relative humidity, number of sunny hours, monthly precipitation and monthly temperature time series of the Lake Van basin.

3. RESULTS AND DISCUSSION

The time series forecasts made here were carried out in the Rstudio environment. All analyzes were performed using a computer with an Intel i5 PC 3.2 GHz CPU, 8 GB RAM, SATA disk and Windows 10 Pro operating system configuration. In the prediction analyses, while AUTO.ARIMA, SARIMA and TBATS statistical-based models were used, on the other hand, deep learning models such as NNTAR, MLP and

ELM were also used. While statistical models generally work well with stable time series data, deep learning models can adapt to more complex and variable data structures. Considering the complexity of many factors affecting climate variables, using both statistical and deep learning models together can solve the problem of data heterogeneity and provide more accurate predictions.

In this study, the monthly average of four different phenomena such as relative humidity, sunshine duration, precipitation and temperature measured daily in the Van Lake basin between January 1950 and June 2023 was taken and the monthly time series obtained for each were used. Future predictions were made using six different time series forecast models.

In the first analysis performed during the forecasting process, six models were used for the Sunshine time series and the forecasts of the series in different horizons. Three different analyzes were performed for each model from the prediction processes. The data lengths allocated for the training processes of each analysis were set to 822, 810 and 798 months, respectively, while the test lengths were set to 60, 72, and 84 months, respectively. If we express test lengths by year, this corresponds to five-year, six-year and seven-year estimates, respectively. For each prediction, training data length, test data length, RMSE and MAE metric values were calculated and given in Table 3. In the same table, in addition to the average of the actual data at each test length, the average of the predicted data for the same length is also given. In addition, a benchmark column was added to the table to better interpret metric values. With this, a percentage ratio was created for each analysis by taking the ratio of the MAE metric value to the average of the actual values used for the testing process.

As seen in Table 3, in three different lengths of prediction for Auto.Arima, the best MAE/actual values ratio was obtained as 12.75% when the test data was 84 months long. In the literature, cases where the ratio of the MAE value to the average of real values is considered to be less than 10% are considered reasonable, and cases where it is between 10% and 20% are considered acceptable (Willmott & Matsuura, 2005)(Ludden, Beal, & Sheiner, 1994).

Table 3. Forecast information using the Sunshine time series

Dataset	Train Set			Test Set					
Sunshine	Length	RMSE	MAE	Length	RMSE	MAE	Avg. Pred.	Avg. Act.	MAE/Act.
Auto.Arima	822	32.25	24.17	60	47.19	33.19	237.71	248.16	13.37%
	810	32.05	27.07	72	45.04	32.17	235.79	247.6	12.99%
	798	**32.21**	**24.20**	**84**	**43.96**	**31.52**	**231.99**	**247.27**	**12.75%**
SARIMA	822	32.25	24.17	60	47.19	33.19	245.09	248.16	13.37%
	810	**35.60**	**26.18**	**72**	**46.13**	**32.13**	**240.69**	**247.6**	**12.98%**
	798	35.02	26.16	84	54.09	41.68	220.16	247.27	16.86%
TBATS	**822**	**30.74**	**23.41**	**60**	**45.31**	**29.96**	**241.07**	**248.16**	**12.07%**
	810	30.42	23.34	72	45.37	30.91	237.38	247.6	12.48%
	798	30.45	23.23	84	48.5	37.98	223.67	247.27	15.36%
NNTAR	**822**	**11.14**	**8.43**	**60**	**50.47**	**36.73**	**240.12**	**248.16**	**14.80%**
	810	10.78	8.08	72	50.14	36.84	245.2	247.6	14.88%
	798	11.33	8.46	84	57.68	46.96	216.2	247.27	18.99%
MLP	822	32.11	24.59	60	84.58	70.44	207.95	248.16	28.38%
	810	32.05	24.75	72	104.4	84.25	325.6	247.6	34.03%
	798	**22.36**	**17.12**	**84**	**57.88**	**47.9**	**210.79**	**247.27**	**19.37%**
ELM	**822**	**38.4**	**29.24**	**60**	**71.97**	**57.31**	**225.14**	**248.16**	**23.09%**
	810	38.2	29.33	72	132.2	110.9	346.38	247.6	44.79%
	798	36.16	24.11	84	74.87	66.38	193.89	247.27	26.85%

In the three analyzes conducted for the SARIMA model, the average MAE/true values ratio was found to be 12.98% when the test length was taken as 72 months. This ratio varies with different test lengths for the remaining models. When we evaluate the entire table with the same approach, it can be seen that the best ratio in Table 3 is the MAE value obtained for the TBATS model. In the analysis where the test length for this model was taken as 60 months, the ratio of MAE to the average of real values was calculated as 12.07%. In Table 3, with the help of the Sunshine time series, the estimated average was calculated as 237.71 when the test length of the Auto.Arima model was 60 months. The values to which this average belongs are given in Table 4, in the Jul 2018-June 2023 time period, under the "prediction" heading in the third column of the table, and the average is given in the bottom row.

In the Table 4, prediction interval 1 and prediction interval 2 are also given in addition to the actual values. Here, the prediction interval refers to the range within which $\boldsymbol{y_t}$ is expected to fall with a certain probability and $\hat{\boldsymbol{y}}_{\boldsymbol{T+h|T}}$ means the estimate of y_{T+h} that takes into account $y_1, y_2, y_3 \dots, y_T$ $\boldsymbol{y_T}$). In other words, it represents an h-step prediction that takes into account all observations up to time T.

$$\hat{\boldsymbol{y}}_{\boldsymbol{T+h|T}} \pm \boldsymbol{c}\hat{\boldsymbol{\sigma}}_{\boldsymbol{h}} \tag{9}$$

where $\hat{\boldsymbol{\sigma}}_{\boldsymbol{h}}$ indicates an approximation of the standard deviation of the h-step forecast distribution and multiplier c is dependent on the likelihood of coverage. The value of the constant c is 1.28 for the 80% prediction interval and 1.96 for the 95% prediction interval (Hyndman & Athanasopoulos, 2018).

Table 4. With the help of Sunshine time series, 60-month prediction results made with the Auto.arima model when the dataset test length is set to 60 months

Sunshine	Values		Prediction interval 1		Prediction interval 2	
Months	**Actual**	**Prediction**	**Low 80%**	**High 80%**	**Low 95%**	**High 95%**
Jul 2018	372.70	365.82	324.09	407.54	302.01	429.63
Aug 2018	357.00	327.11	284.42	369.80	261.82	392.40
Sep 2018	301.50	293.71	251.02	336.40	228.42	359.00
Oct 2018	211.30	215.07	172.38	257.76	149.78	280.35
Nov 2018	130.20	184.21	141.52	226.89	118.92	249.49
Dec 2018	92.70	107.13	64.44	149.82	41.85	172.42
…	…	…	…	…	…	…
Jan 2023	228.60	142.92	97.72	188.13	73.79	212.05
Feb 2023	201.00	159.85	114.65	205.06	90.72	228.98
Mar 2023	216.40	192.67	147.47	237.87	123.54	261.80
Apr 2023	225.20	242.91	197.71	288.12	173.79	312.04
May 2023	307.70	278.32	233.12	323.52	209.19	347.45
Jun 2023	291.10	344.11	298.91	389.31	274.98	413.24
Averages	**248.16**	**237.71**	**193.78**	**281.65**	**170.52**	**304.91**

The models used in this study gives us the forecast for a year, an 80% prediction interval (low and high) for the forecast, and a 95% prediction interval (low and high) for the forecast. For example, as shown in Table 4, the forecasted sunshine time for Jul 2018 is about 365.82, with a 95% prediction interval of (low 302.1, high 429.63). The prediction value given in the tables corresponds to the average of both 80% (low and high) and 95% (low and high) forecast interval values separately.

For the Sunshine time series, the future prediction graphs of the six models used for forecasting when the test length is set to 60 months are given in Figure 3. In the chart, it can be seen how the predictions made by the models capture the seasonal pattern seen in historical data and repeat it for the next 60-months. The blue lines in each chart show forecasts 60-months into the future (here Jul 2018-Jun 2023). The dark shaded region indicates the 80% prediction interval. That is, each future value is expected to be in the dark shaded region with an 80% probability. The lighter shaded region shows the 95% prediction interval. These forecast ranges are a useful way to illustrate the uncertainty in forecasts. In addition, each model prediction and test data used are given together in Figure 4 to make the predictions made with the help of test data of the sunshine time series appear more clearly in the graphics. Additionaly, as seen in the Figure 5, the predictions of Auto.Arima, SARIMA and TBATS, NNTAR, MLP and ELM models are given with the options (a), (b), (c), (d), (e), and (f), respectively. The most prominent part of the same color in the predictions shows the prediction average, the slightly lighter part shows the 80% prediction range, and the lightest parts show the 95% prediction range.

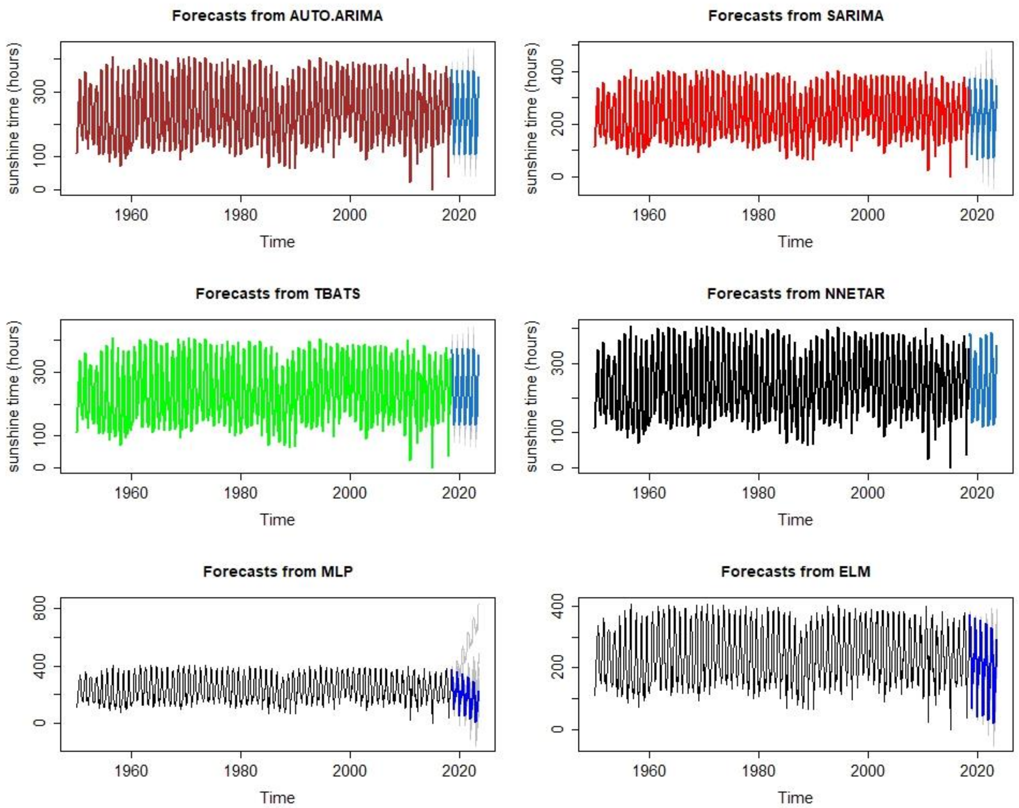

Figure 3 Model predictions of the Sunshine time series when the training data length is set to 822-months and the test data length is set to 60-months.

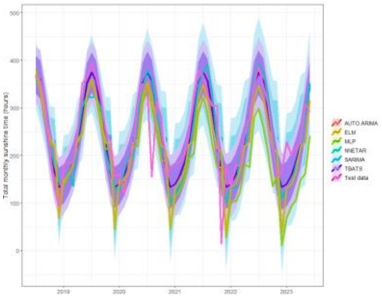

Figure 4 When the test length of the Sunshine time series is set to 60 months, all model predictions used are given together with the test data.

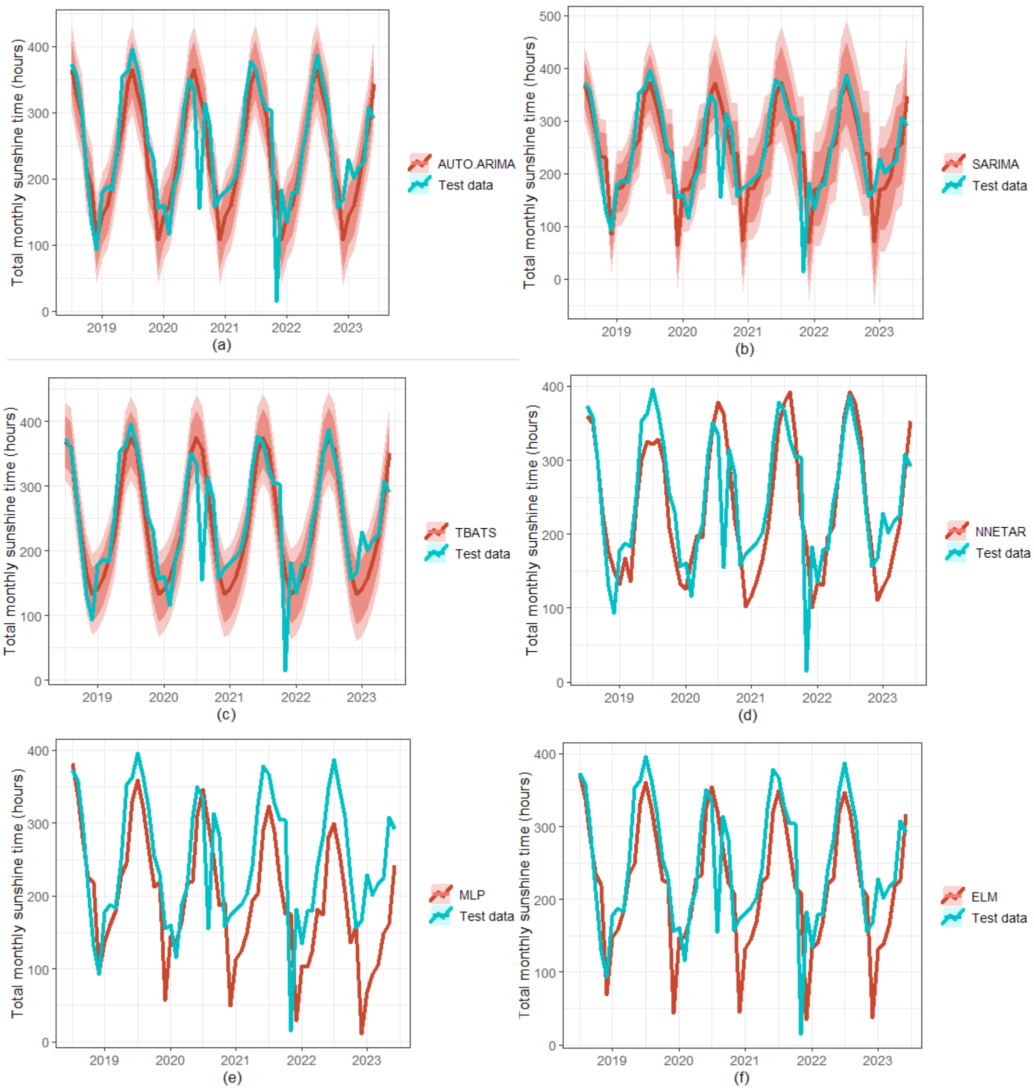

Figure 5 When the test length of the Sunshine time series is set to 60 months, the predictions of the models are given separately along with the test data.

In the second stage of time series forecasting analyses, Table 5 was created from the results obtained using the Tempereture dataset. Six different forecast models were used for the temperature time series. Three predictions were made for each prediction model based on the test data lengths. As seen in Table 5, the best results of each prediction are shown in bold. The performance of prediction models varies depending on test lengths. For example, for the Auto.arima and SARIMA models, the test length of 84-months showed the best performance, while the remaining models showed better performance when the test length was set to 60-months. The ratio of MAE metric test results to actual test results in the table is expressed as a percentage. Considering this rate, the best prediction was obtained with the MLP (9.10%) and TBATS (9.28%) models when the test data length was set to 60-months.

Table 5. Forecast information using the Temperature time series

Dataset	Train Set			Test Set					
Temperature	Length	RMSE	MAE	Length	RMSE	MAE	Avg. Pred.	Avg. Act.	MAE/Act.
Auto.Arima	822	1.87	1.40	60	1.70	1.34	11.33	11.105	12.07%
	810	1.87	1.4	72	1.99	1.56	10.15	11.25	13.87%
	798	**1.87**	**1.41**	**84**	**1.68**	**1.30**	**10.8**	**11.04**	**11.78%**
SARIMA	822	1.87	1.4	60	1.69	1.34	11.22	11.105	12.07%
	810	1.87	1.40	72	2.02	1.58	10.1	11.25	14.04%
	798	**1.87**	**1.41**	**84**	**1.70**	**1.32**	**10.69**	**11.04**	**11.96%**
TBATS	**822**	**1.54**	**1.16**	**60**	**1.29**	**1.03**	**10.76**	**11.105**	**9.28%**
	810	1.53	1.15	72	1.71	1.36	10.24	11.25	12.09%
	798	1.54	1.63	84	1.55	1.21	10.45	11.04	10.96%
NNTAR	**822**	**0.81**	**0.62**	**60**	**1.93**	**1.54**	**10.08**	**11.105**	**13.87%**
	810	0.79	0.6	72	2.42	2	9.42	11.25	17.78%
	798	0.76	0.59	84	2.25	1.84	9.87	11.04	16.67%
MLP	**822**	**1.24**	**0.93**	**60**	**1.3**	**1.01**	**11.51**	**11.105**	**9.10%**
	810	1.26	0.95	72	1.78	1.44	10.11	11.25	12.80%
	798	1.25	0.94	84	1.47	1.13	10.83	11.04	10.24%
ELM	**822**	**1.67**	**1.27**	**60**	**1.45**	**1.15**	**11.29**	**11.105**	**10.36%**
	810	1.64	1.24	72	2.08	1.72	9.73	11.25	15.29%
	798	1.65	1.25	84	1.57	1.27	10.44	11.04	11.50%

The results obtained using the Precipitation dataset in the third stage of the time series forecasting analyzes are given in Table 6.

Table 6. Forecast information using the Precipitation time series

Dataset	Train Set			Test Set					
Precipitation	Length	RMSE	MAE	Length	RMSE	MAE	Avg. Pred.	Avg. Act.	MAE/Act.
Auto.Arima	822	24.41	18.40	60	23.19	19.69	35.56	30.91	63.70%
	798	24.41	18.37	84	22.84	18.91	35.54	33.63	56.23%
	774	**24.15**	**17.97**	**108**	**24.13**	**19.07**	**34.85**	**36.65**	**52.03%**
	750	24.32	18.14	132	23.14	18.87	36.5	35.55	53.08%
SARIMA	822	26.68	18.5	60	27.02	20.77	39.6	30.91	67.20%
	798	26.62	18.40	84	29.19	21.67	41.38	33.63	64.44%
	774	**26.84**	**19.37**	**108**	**24.13**	**16.79**	**29.7**	**36.65**	**45.81%**
	750	26.79	19.28	132	29.31	22.17	43.03	35.55	62.36%
TBATS	822	22.77	15.22	60	20.09	14.52	32.19	30.91	46.98%
	798	22.68	15.09	84	21.88	15.58	30.59	33.63	46.33%
	774	22.88	15.77	108	23.22	17.24	30.21	36.65	47.04%
	750	**23.01**	**15.9**	**132**	**21.48**	**15.83**	**31.64**	**35.55**	**44.53%**
NNTAR	822	6.93	4.28	60	23.81	17.81	37.41	30.91	57.62%
	798	**6.93**	**4.06**	**84**	**23.59**	**17.15**	**34.32**	**33.63**	**51.00%**
	774	6.46	3.98	108	25.66	18.64	36.05	36.65	50.86%
	750	6.45	3.92	132	24.42	19.02	36.82	35.55	53.50%
MLP	822	17.01	12.23	60	27.84	22.35	46.63	30.91	72.31%
	798	16.63	11.82	84	34.14	29.19	55.34	33.63	86.80%
	774	**17.14**	**12.14**	**108**	**28.85**	**24.12**	**46.35**	**36.65**	**65.81%**
	750	17.01	12.01	132	35.11	28.55	57.19	35.55	80.31%
ELM	822	23.25	17.15	60	26.86	21.86	46.25	31.43	69.55%
	798	23.48	17.22	84	36.21	29.71	58.09	34.78	85.42%
	774	23.45	17.13	108	30.34	25.28	48.6	36.65	68.98%
	750	**23.64**	**17.29**	**132**	**29.94**	**24.61**	**51.73**	**35.55**	**69.23%**

As in previous time series analyses, six different forecast models were used here. Four predictions were made for each prediction model based on the test data lengths. As seen in Table 6, the best results of each prediction are shown in bold. The performance of prediction models varies depending on test lengths. The high variability of the data forming the precipitation time series also negatively affected the forecast performances. For this reason, the model performances used are lower than other time series model performances. Here, unlike other time series, four different analyzes were conducted for each model instead of three in order to better interpret the performance values. Among the 24 analyzes made for the Precipitation time series, the best result was obtained with the help of the TBATS model, with 44.53%. The results obtained using the Humidity dataset in the fourth and final stage of time series forecasting analyzes are given in Table 7. Three analyzes were conducted for each of the six prediction models used, based on test data lengths. As seen in Table 7, the best results of each prediction are shown in bold. The performance of prediction models varies depending on test lengths.

As seen in the table, the performances of the prediction models vary depending on the test lengths. While the best predictions for the Auto.Arima and SARIMA models are obtained when the test data length is set to 72-months, for the remaining four models this length is 84-months. Here, the best result was obtained as 8.89% when the test data length was set to 72-month length through the Auto.Arima model. The prediction range in the table varies between 8.89% and 13.99%. The graphs of the six forecast models used for the Humidity time series when the test data length is set to 84 months are given in Figure 6.

Table 7. Forecast information using the Humidity time series

Dataset	Train Set			Test Set					
Humidity	Length	RMSE	MAE	Length	RMSE	MAE	Avg. Pred.	Avg. Act.	MAE/Act.
Auto.Arima	822	5.08	3.98	60	6.38	5.32	52.92	56.41	9.43%
	810	**5.06**	**3.96**	**72**	**5.97**	**4.91**	**54.5**	**55.26**	**8.89%**
	798	5.06	3.96	84	6.06	4.87	56.7	54.71	8.90%
SARIMA	822	5.30	4.17	60	8.66	7.53	50.34	56.41	13.35%
	810	**5.28**	**4.15**	**72**	**6.79**	**5.52**	**52.87**	**55.26**	**9.99%**
	798	5.26	4.15	84	7.01	5.47	56.23	54.71	10.00%
TBATS	822	4.45	3.47	60	7.2	5.97	51.95	56.41	10.58%
	810	4.43	3.45	72	6.46	5.21	53.13	55.26	9.43%
	798	**4.43**	**3.46**	**84**	**6.1**	**5.01**	**55.85**	**54.71**	**9.16%**
NNTAR	822	1.31	1.01	60	6.73	5.71	53.83	56.41	10.12%
	810	1.26	0.96	72	6.4	5.17	54.38	55.26	9.36%
	798	**1.26**	**0.97**	**84**	**6.13**	**5.03**	**56.22**	**54.71**	**9.19%**
MLP	822	3.27	2.53	60	9.25	7.89	49.09	56.41	13.99%
	810	3.24	2.5	72	7.18	5.98	51.65	55.26	10.82%
	798	**3.19**	**2.47**	**84**	**6.73**	**5.52**	**57.97**	**54.71**	**10.09%**
ELM	822	4.52	3.52	60	7.63	6.32	51.55	56.41	11.20%
	810	4.52	3.53	72	7.98	6.75	50.25	55.26	12.21%
	798	**4.52**	**3.53**	**84**	**6.31**	**5.21**	**56.65**	**54.71**	**9.52%**

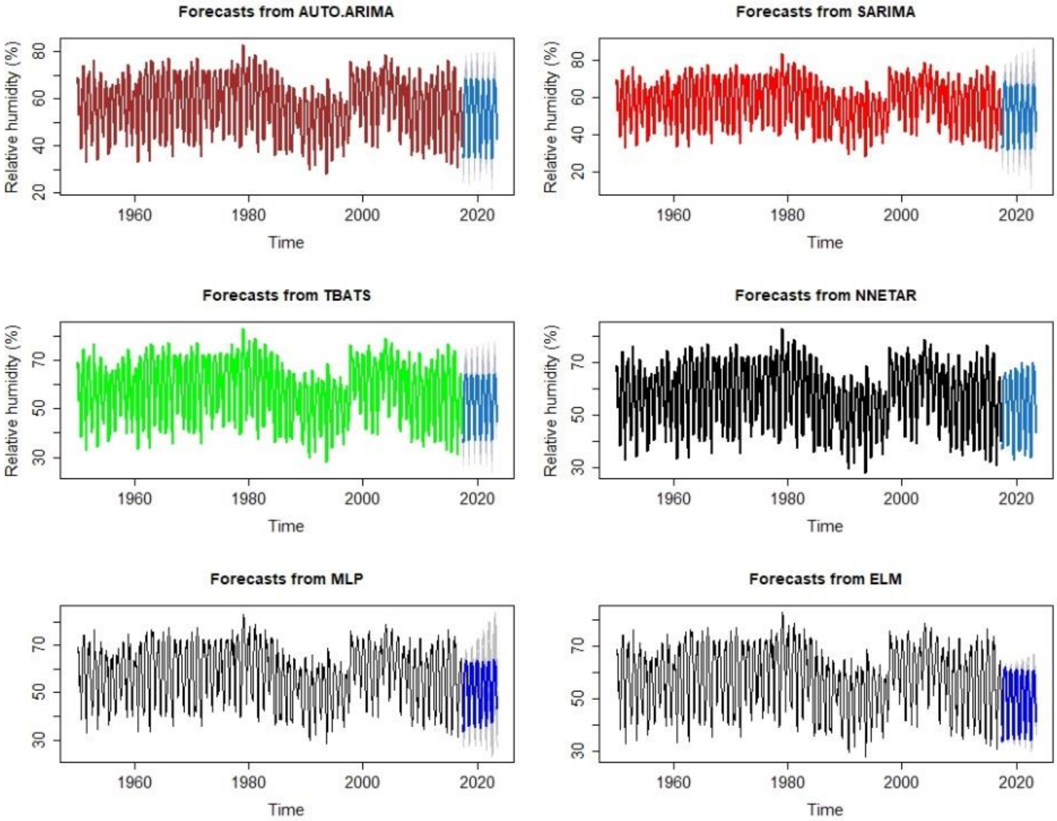

Figure 6 Model predictions of the Humidity time series when the training data length is set to 798-months and the test data length is set to 84-months.

3.1 DİSCUSSİON

Here, when we evaluate together the prediction analyzes of four different climatic data sets measured from the past to the present in the Van Lake basin, we reach the following conclusions:

1. When the ratio of MAE metric values to actual test values for the Sunshine time series is examined, we see that the best result is obtained by the TBATS model. This performance was achieved when the test dataset was set to 60-months. In this analysis, the ratio of MAE to the average of actual test values was calculated as 12.07%.
2. In the analyzes performed for the temperature dataset, the best performance was obtained with the help of the MLP model when the test data length was taken as 60

months. In this analysis, the ratio of MAE to the average of actual test values was calculated as 9.10%.

3. In the analyzes performed for the Precipitation dataset, the best performance was obtained with the help of the TBATS model when the test data length was taken as 132 months. In this analysis, the ratio of MAE to the average of actual test values was calculated as 44.53%. Too much variability in the dataset resulted in lower performance compared to other models.
4. In the analyzes performed for the Humidity dataset, the best performance was achieved with the help of the Auto.Arima model when the test data length was taken as 72 months. In this analysis, the ratio of MAE to the average of actual test values was calculated as 8.89%. The next best value was obtained with the help of the NNTAR model. Compared to other time series, model performances were obtained close to each other here. The fact that the dataset has seasonal characteristics had an impact on the results.
5. When we consider the percentage ratio of the MAE metric to the real test data for each dataset, it is possible to say that the statistical-based models used here perform better than deep learning models.
6. The superior performance of statistical-based models over deep learning models in predicting long-term climatic variables, including sunshine duration, temperature, relative humidity, and precipitation in the Van Lake basin, suggests that the inherent characteristics of the climatic data in this region may align more favorably with the assumptions and capabilities of traditional statistical approaches. Factors such as the nature of temporal patterns, the availability and quality of data, and the interpretability of models may contribute to this observed phenomenon. Additionally, the simplicity and efficiency of statistical models, along with their potential ability to capture specific patterns in the climatic data, could be more advantageous in this context. This outcome highlights the importance of tailoring modeling approaches to the unique characteristics of the dataset and underscores the

potential limitations of applying complex deep learning models in certain climatic prediction scenarios.

CONCLUSIONS

In summing up, our complete investigation of forecasting near future environmental conditions in Lake Van basin took a dual way in which a statistical and deep learning approaches were used. The inclusion of the time-series data from month to month providing 4 decades background of information has made the modelling process as robust as can be through comprehensive catchment of the key environmental indicators. Comparing different forecasting models that take the test period into account using numerical metrics like RMSE and MAE are the key aspects of performance evaluation with the models. When the comparisons of the four different time series which is for consideration here are examined, it is concluded that the models based on statistics usually fit better than the deep learning models. What makes this study viable and relevant is that it concentrates on a specific geographical area (the chosen region), uses varied environmental parameters, and employs diverse prediction models together. The visionary approach shown in this study adds valuable information to researchers in the field of climate science, environmental management, and on the sustainable development of the East Anatolia region in Türkiye. The use of high grade modelling techniques and continuous monitoring of environmental parameters will form basis for well-informed decision making in the light of the ongoing climate change threats.

Moving forward, the research would go ahead to lengthen the time frame of the study to cover the period after June 2023. The forecast models would be repeatedly refreshed and validated with the real time data to ensure consistently high level of accuracy.

Acknowledgment

We would like to thank Van Provincial Directorate of Meteorology for allowing us to use the four different datasets used in this study.

Availability of data and materials

The data sets used in the current research are available in the Van Provincial Meteorology database for Van Lake research. Data can be shared if desired.

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