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ORIGINAL PAPER

Statistical modeling for long-term meteorological forecasting: a case study in Van Lake Basin

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Abstract

Predicting environmental variables for a sustainable environment is vital for effective resource management and regional development, especially in sensitive regions such as the Lake Van basin in eastern Türkiye. This study focuses on long-term annual forecasts of important meteorological variables such as mean annual atmospheric pressure, wind speed and surface evaporation in the Van Lake basin. Long-term forecasts made using R-based statistical models such as AUTO.ARIMA, TBATS, EST, NAIVE, THETAF and HOLT-WINTERS are evaluated using mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). Here, it has been observed that the AUTO. ARIMA model consistently stands out with better performance than its counterparts in the field of time series analysis when predicting the variables mentioned above. Such scientific studies, which are of great importance especially for the regional structure, add valuable information to the literature by determining a superior prediction model for meteorological events in the specific geographical context of the Lake Van basin. The results of the study have far-reaching implications for further improving predictive modeling techniques, improving the reliability of long-term meteorological forecasts, and decision-making in climate-related research and applications.

Keywords Van lake basin · Meteorological forecasting · Statistical modeling · Long-term predictions · Environmental variables

1 Introduction

Global climate change is leading our world into a complex and multifaceted process with far-reaching consequences. At its core, global warming, driven primarily by the increase in greenhouse gas emissions, is altering climate variables such as temperature, precipitation

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patterns, sea level rise, and extreme weather events. The relationship between these climate variables and global warming is intricate and interconnected, as each variable influences and amplifies the effects of the others. Predicting climatic variables as time series data can significantly contribute to understanding future trends and impacts of climate change. By analyzing historical data and employing advanced modeling techniques, scientists can forecast how these variables will evolve over time, providing crucial insights for adaptation and mitigation strategies to mitigate the impacts of climate change on ecosystems, economies, and human societies.

In the realm of environmental stewardship and sustainable development, the Lake Van basin stands as a microcosm of interconnected challenges and opportunities. Long-term (Kisi and Shiri 2014) future predictions for key meteorological variables such as annual average real pressure, wind speed, and surface evaporation hold profound significance for various sectors within and beyond the basin's borders. These predictions not only offer insights into local environmental dynamics but also shed light on broader global concerns, particularly the specter of climate change.

Understanding the relationship between these meteorological variables (Aghelpour et al. 2021) and global warming is imperative. Real pressure, wind speed, and surface evaporation are intricately linked to climatic patterns and trends. As temperatures rise globally (Shad et al. 2022), changes in atmospheric pressure gradients can influence wind patterns, altering regional climates and precipitation regimes. Similarly, increased temperatures can intensify surface evaporation, impacting water availability and ecosystem health in the Lake Van basin and beyond (Ceribasi and Aytulun 2020).

Predictions stemming from these variables offer a crucial tool in the collective arsenal against global warming. By providing foresight into future climatic conditions, these forecasts empower stakeholders to enact proactive measures aimed at mitigating and adapting to climate change impacts (Chen et al. 2023). From water resource management and infrastructure planning to disaster preparedness and renewable energy strategies, the insights gleaned from long-term predictions play a pivotal role in fostering climate resilience.

The importance of such studies cannot be overstated. In a world grappling with the existential threat of climate change, informed decision-making grounded in scientific research is paramount. By harnessing the predictive power of meteorological variables, stakeholders can craft evidence-based policies and interventions that safeguard the ecological integrity of the Lake Van basin while bolstering the resilience of communities against the ravages of global warming.

As we delve deeper into the intricacies of climate science and environmental management, it becomes increasingly evident that the pursuit of sustainable solutions demands a comprehensive understanding of both local nuances and global trends. In this pursuit, long-term predictions for key meteorological variables emerge as indispensable tools, guiding our collective efforts towards a future where the Lake Van basin, and indeed the planet as a whole, thrives in harmony with nature. We can summarize the contributions of this study, which is a first study for the Van Lake Basin, to the literature as follows:

1. This study contributes to improving the accuracy of long-term future predictions for key meteorological variables in the Van Lake basin through the utilization of advanced statistical models.

2. By comparing the performance of various statistical models including AUTO.ARIMA, TBATS, EST, NAIVE, THETAF, and HOLT-WINTERS, the research offers insights into the relative effectiveness of different forecasting approaches.
3. Employing RMSE, MAE, and MAPE metrics allows for a comprehensive evaluation of prediction accuracy across different time horizons, providing valuable information for model selection and refinement.
4. The findings of this study have practical implications for environmental management, water resource planning, and climate change adaptation strategies in the region, aiding decision-makers and stakeholders in making informed decisions.
5. This study adds to the current body of research by showing how different statistical models can be used effectively to forecast meteorological variables. This enhances the range of methods that researchers and practitioners in the field can utilize.

1.1 Related works

The authors conducted literature reviews on various applications of machine learning and deep learning techniques in weather-related forecasting tasks, including wind speed prediction, space weather forecasting, precipitation forecasting, evapotranspiration estimation, and wind power generation prediction.

The authors (Wang et al. 2015) investigated wind speed forecasting techniques, particularly focusing on preprocessing outliers in wind speed data for improved accuracy. They combined Support Vector Regression (SVR) with seasonal index adjustment (SIA) and Elman recurrent neural network (ERNN) methods to create hybrid models named PMERNN and PAERNN. Their study analyzed medium-term wind speed forecasting performance at three sites in Xinjiang, China, over eight years. Experimental results demonstrated that the hybrid models outperformed other methods in accurately forecasting daily wind velocities across the prediction horizon.

In the study (Camporeale 2019), the authors examined the application of machine learning in space weather forecasting. They focused on various areas such as predicting geomagnetic indices, relativistic electrons at geosynchronous orbits, solar flares occurrence, coronal mass ejection propagation time, and solar wind speed. The authors emphasized the necessity of transitioning towards a probabilistic forecasting approach to better assess uncertainties, advocating for a combination of physics-based and machine learning methods, termed "gray-box." Their review serves as both an introduction to machine learning for the space weather community and highlights several challenges for future research in the field.

The authors investigated (Ak et al. 2016) methods for predicting time-series wind speeds, crucial for integrating wind energy into power grids. They compared two machine learning approaches: multilayer perceptron neural networks trained with a multiobjective genetic algorithm and extreme learning machines combined with the nearest neighbors approach. Utilizing real data from Regina, Saskatchewan, Canada, both methods showed high prediction precision and complementary strengths across various evaluation criteria, indicating their potential in facilitating efficient and reliable renewable energy integration into power grids.

The authors (Aghelpour et al. 2021) conducted a study comparing various predictive models, including SARIMA, MLP, ANFIS-SC, and ANFIS-FCM, to forecast seasonal precipitation in different climatic zones of Iran using data from 1951 to 2018. They found that SARIMA outperformed artificial intelligence methods in terms of accuracy and simplicity, exhibiting the least over- and under-estimations. Additionally, the models showed better performance in wet and normal years compared to drought years and were more accurate in per-humid and humid areas than in arid and extra-arid climates. The normalized root mean squared error (NRMSE) values indicated SARIMA's performance as medium to good.

In the study (Chen et al. 2020), the authors investigated the performance of various deep learning (DL) and classical machine learning models for estimating daily reference evapotranspiration using incomplete meteorological data in the Northeast plain, China. They compared DL models, including deep neural network (DNN), temporal convolution neural network (TCN), and long short-term memory neural network (LSTM) with CML models (support vector machine (SVM) and random forest (RF), as well as several empirical equations. Results showed that TCN and LSTM outperformed both classical and empirical models, particularly when temperature-based features were available, suggesting their applicability beyond the study areas. Additionally, all proposed models showed superior performance when compared to radiation-based or humidity-based empirical equations.

The authors (Chandran et al. 2021) investigated the application of deep learning algorithms, including LSTM, GRU, and RNN, to predict short-term wind power generation using wind speed data. Their study aimed to address challenges such as initial investment costs, stationary properties of wind power plants, and identifying suitable wind power zones. By applying machine learning models to six different wind farm outputs, they conducted error analysis to improve forecast accuracy. The results demonstrated the efficacy of machine learning algorithms in predicting wind power values, particularly beneficial for areas lacking established wind power models, suggesting their utility in pre-installation assessments for wind power plants in unfamiliar geographical locations.

The authors (Kisi et al. 2019) investigated rainfall modeling using geographical inputs through least squares support vector machine (LSSVM), model tree (MT), and geostatistical kriging methods. They utilized long-term rainfall data from 73 weather stations in Iran and compared the methods in at-station and pooled scenarios. LSSVM outperformed MT in at-station scenarios, especially in arid regions, while in pooled scenarios, LSSVM demonstrated superior performance over MT in modeling long-term monthly rainfall. However, geostatistical kriging generally yielded better results in spatial rainfall modeling compared to heuristic methods in both scenarios.

The authors (Du et al. 2019) researched wind energy prediction and proposed a hybrid model integrating improved complete ensemble empirical mode decomposition with adaptive noise technology and an optimized wavelet neural network. This model significantly reduced mean absolute percent errors compared to eighteen comparison models, with values of 5.0116% (one-step ahead), 7.7877% (two-step ahead), and 10.6968% (three-step ahead), demonstrating its effectiveness in enhancing prediction accuracy for wind power systems.

This study presented here delves into the domain of environmental forecasting, particularly focusing on the Van Lake basin in eastern Türkiye, a region of high environmental sensitivity. Unlike previous studies that explored various predictive models across different geographical contexts, this research uniquely concentrates on long-term annual predictions of critical meteorological variables specific to the Van Lake basin. Employing an array of statistical models, the study meticulously evaluates their performance in forecasting annual average actual pressure, wind speed, and surface evaporation, essential for sustainable resource management and development in the region. The standout contribution lies in the revelation that the AUTO.ARIMA model consistently outshines its counterparts in predicting these variables, marking a notable advancement in time series analysis within this geographical context. This insight not only adds to the scientific literature but also offers practical implications by enhancing the accuracy of long-term meteorological forecasts, thereby aiding informed decision-making processes crucial for climate-related research and applications in sensitive regions like the Van Lake basin.

2 Materials and methods

2.1 System model and prediction models

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, three different climatic variables were obtained. These data, which vary depending on time, are listed as pressure, wind speed and surface evaporation. Then, future predictions were made for each time series with six different prediction models, and the results were evaluated with the help of RMSE, MAE and MAPE metrics and the findings were discussed.

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

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 (Pala and Pala 2021; Basha et al. 2017; Petropoulos and Svetunkov 2020). ARIMA models are widely used to model trends and seasonal patterns in time series. For a dependent time series, ARIMA can be modeled mathematically as follows.

$$\varnothing(B)\nabla^{d}X_{t}=\theta(B)\epsilon_{t} \tag{1}$$

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

$$\varnothing(B)=1-\varnothing_{1}(B)-\cdots-\varnothing_{p}B^{p} \tag{2}$$

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

$$\theta(B)=1-\theta_{1}B-\cdots-\theta_{q}B^{q} \tag{3}$$

ϵ_t is the independent disturbance, also called the random t error (Yang et al. 2018).

ETS Error, Trend, Seasonality (ETS) model is a forecasting model used for time series analysis. ETS models try to explain time series by focusing on the error, trend and seasonal components contained in the data (Dong et al. 2021). These models are especially useful when modeling statistically irregular and variable time series. ETS models are especially useful for small data sets or when a simplified model is desired for statistical analysis. However, for more complex and larger data sets it is common to resort to other models such as Auto regressive integrated moving average (ARIMA) models.

TBATS Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS) model is an automatic forecasting model for complex time series (Pala 2021), (Munim 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 automatically predicts this transformation. The model includes autoregressive moving average (ARMA) errors. This can address correlations in the data and biases of the predicted values. 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.

THETAF THETAF model, like many forecast models, is included in the forecast package developed for the R environment. The THETAF model is an implementation of the Theta method, a powerful forecasting approach introduced by Assimakopoulos and Nikolopoulos in 2000 (Assimakopoulos and Nikolopoulos 2000). This model effectively isolates the long-term trend and short-term seasonal trend by decomposing a time series into two or more theta lines. The THETAF model used in the R environment stands out with its accuracy and simplicity and is preferred for practical applications (Makridakis et al. 2020).

NAİVE Naïve forecasts involve predicting future values by simply using the most recent observation as the forecasted value for all future time points (Ferbar Tratar and Strmčnik 2016). If we express the historical data in the form, we can express the Naive method mathematically as. Here, the notation is a short-hand for the prediction of (Hyndman and Athanasopoulos 2018).

HOLT-WINTERS: The Holt-Winters model, also known as the triple exponential smoothing method, is a widely used technique in time series forecasting (Ferbar Tratar and Strmčnik 2016). It extends the simple exponential smoothing method by incorporating components for trend and seasonality. The model comprises three smoothing equations: one for the level (average value), one for the trend (slope), and one for the seasonal component. By adjusting smoothing parameters, the Holt-Winters model adapts to different data patterns, effectively capturing trends and seasonal variations. It is particularly useful for data exhibiting both trend and seasonality, providing accurate forecasts for future time points. Additionally, the model allows for the incorporation of different levels of smoothing to balance between capturing recent changes and overall long-term patterns in the data, making it a versatile tool for forecasting in various domains.

2.2 Evaluation metrics

Root Mean Square Error (RMSE) is a commonly used metric in statistics and machine learning to quantify the accuracy of a predictive model by measuring the differences between predicted and observed values. It is calculated by taking the square root of the average of the squared differences between predicted and actual values. RMSE provides a single value that represents the typical magnitude of errors in a model's predictions, with lower values indicating better performance. It is particularly useful in regression analysis, where the goal is to minimize the discrepancies between predicted and observed outcomes. RMSE is sensitive to outliers and provides a measure of the overall goodness of fit for a predictive model.

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{\boldsymbol{N}}\sum\nolimits_{1}^{\boldsymbol{N}}\left(\boldsymbol{y_t} - \widehat{\boldsymbol{y}}_{\boldsymbol{t}}\right)^2} \tag{4}$$

Mean Absolute Error (MAE) is a metric commonly used in regression analysis to assess the accuracy of a predictive model. It quantifies the average absolute difference between the predicted and actual values of a set of observations. The MAE is calculated by taking the average of the absolute differences between the predicted and true values, without considering the direction of the errors. This makes MAE easy to interpret, as it represents the average magnitude of errors in the units of the dependent variable. A lower MAE indicates better predictive performance, with zero representing a perfect match between predicted and actual values. MAE is a straightforward and widely used metric that provides a simple measure of model accuracy and is particularly useful when the impact of outliers on performance needs to be minimized.

$$\boldsymbol{MAE} = \frac{1}{\boldsymbol{N}}\sum_{1}^{\boldsymbol{N}}\left|\boldsymbol{y_t} - \widehat{\boldsymbol{y}}_{\boldsymbol{t}}\right| \tag{5}$$

Mean absolute percentage error (MAPE) which is the most popular metrics, were preferred to evaluate the forecasting process (Pala and Ünlük 2022; Kim and Kim 2016; Pala et al. 2023). MAPE is a common error measures used specifically to evaluate the performance of time series forecasting models. MAPE represents the average of the percentage errors between actual and predicted values.

$$MAPE = \frac{\mathbf{1}}{n}\sum\nolimits_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \times 100 \tag{6}$$

Here, n represents the total number of observations, y_t represents the actual value, $\widehat{\boldsymbol{y}}_{\boldsymbol{t}}$ represents the predicted value. One of the advantages of MAPE is that it expresses the results in percentages, so it is straightforward in terms of measurability. However, dividing by actual values that are zero may cause errors and care must be taken.

2.3 Time series analysis

Time series analysis is crucial for forecasting because it allows for the exploration and prediction of data patterns over time. By analyzing sequential data points, time series methods capture trends, seasonal variations, and other underlying patterns that may inform future behavior. This enables businesses and researchers to make informed decisions, anticipate market trends, and allocate resources effectively. The advantages of time series analysis include its ability to identify patterns, detect anomalies, and provide insights into future trends, all of which are invaluable for strategic planning and decision-making in various fields such as finance (Siami-Namini et al. 2019), economics, weather (Hossain et al. 2015); Tugal and Sevgin 2023), health (Yaldız and Pala 2019), speech recognition (Srivastava et al. 2014), energy consumption (Hwang and Yoo 2014), (Mohsin et al. 2021), radiation predictions (Etem et al. 2017), (Pala et al. 2019), sunspot prediction (Chen et al. 2010), (Pala and Atici 2019), natural gas production prediction (Pala 2023), (Li et al. 2021), and sensor data analysis (Dhillon et al. 2020).

2.4 Data description

Three 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 pressure, wind speed and evaporation, respectively. Before each dataset was used, the erroneous data it contained was corrected and then converted into annual time series format. Statistical properties of time series such as length, min, max, median and mean are given in Table 1.

Time series of yearly actual pressure, yearly average wind speed and yearly average evaporation for the Van Lake basin measured between January 1950 and June 2023 are shown in Fig. 1. None of the three time series used here have a regular seasonality or trend. Since the data mostly consists of irregular variations, it is reflected in the graphs exactly.

3 Results and discussion

All analyzes in this study were carried out in the RStudio environment using the R programming language. Statistical-based time series models such as R-based AUTO.ARIMA, ETS, TBATS, NAIVE, THETAF and HOLT-WINTER were used in forecasting analyses.

There are some advantages of using statistical-based models in time series future forecast analyzes with limited data (Iaousse et al. 2023; Alzubaidi 2020; Dong et al. 2022). These models are often expressed with simple mathematical equations. This makes it easier to understand how the model works and makes the results simpler to interpret. These do not require large data sets. Even when the data length is limited, these models can produce

Table 1 Statistical information of the experimental datasets

Datasets	Length	Min.	1st Qu.	Median	Mean	3rd Qu.	Max
1-Annual average actual pressure (hPa)	74	822.4	827.8	831.6	830.6	833.2	838.3
2-Annual average wind speed (m/sec)	74	0.90	1.75	2.07	2.06	2.37	2.78
3-Annual Total Surface Evaporation (mm)	74	59.48	135.03	156.97	145.83	169.97	219.38

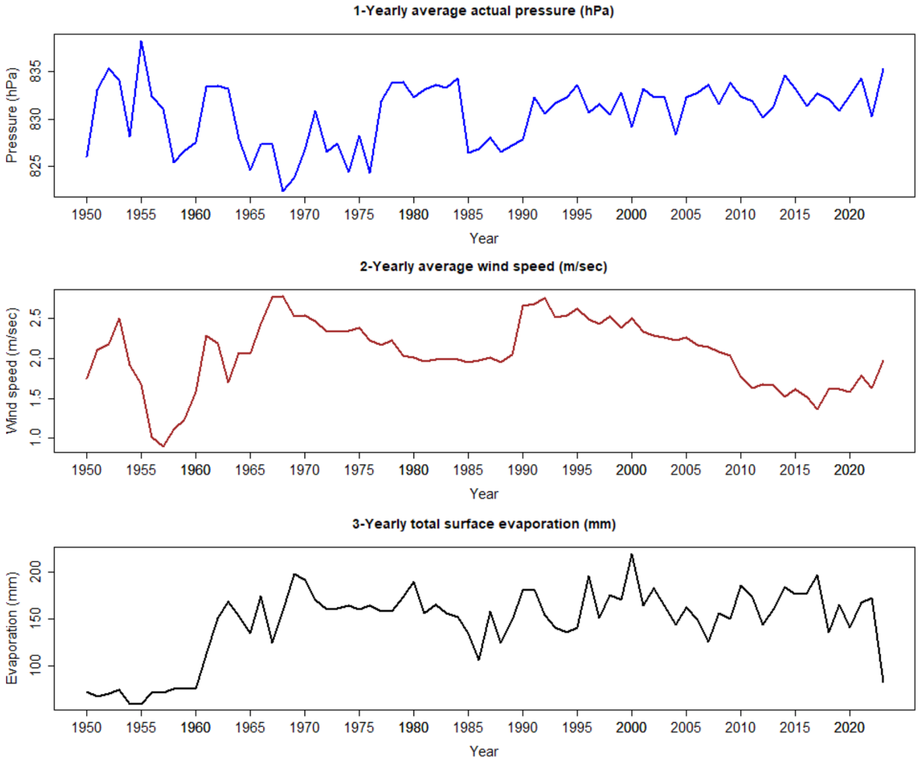

Fig. 1 Graphs of yearly actual pressure, yearly average wind speed and yearly average evaporation time series of the Van Lake basin

effective results. They are generally fast and use little memory. These are more resistant to overlearning and generally produce more balanced results (Du 2022). All analyzes were carried out using a computer with Intel i5 PC 3.2 GHz CPU, 8 GB RAM, SATA disk and Windows 10 Pro operating system configuration.

Here, annual time series were created by calculating the annual average of three different phenomena such as pressure, wind speed and evaporation, which were measured daily between January 1950 and June 2023 in the Van Lake basin. Here, firstly, analyzes were made at different horizon lengths for the pressure meteorological variable. Six different models were used for each future horizon forecast. Metric values of the test results of the prediction analyzes made using the 74-year atmospheric pressure data of the Van Lake basin between 1950 and 2023 are given in Table 2. In the time series used in forecasting here, the fact that periodic periods are not observed and the trends are random makes the forecasting process difficult. Keeping the data allocated for testing short also reduces the performance of the prediction models. Here, the best results were obtained by taking the training and test data very closely. In this case, the data lengths used for training processes were selected as 41, 40 and 39, while the test horizon lengths were selected as 33, 34 and 35.

Three predictions were made for each model, depending on three different data lengths. In the predictions made, the lengths of 41/33 (55% / 45%), 40/34 (54% / 46%) and 39/35 (53% / 47%) were preferred for the training/test pair, respectively, from the beginning of the

Table 2 Yearly average pressure predictions

Dataset: Pressure	Test results			
	Train/Test length	RMSE	MAE	MAPE %
Auto.Arima	41/33	3.13	2.84	0.34
	40/34	3.05	2.73	0.32
	39/35	**2.97**	**2.65**	**0.31**
ETS	**41/33**	**4.78**	**4.54**	**0.54**
	40/34	5.03	4.76	0.57
	39/35	4.97	4.63	0.55
TBATS	**41/33**	**4.78**	**4.54**	**0.54**
	40/34	5.00	4.72	0.56
	39/35	4.90	4.56	0.54
NAİVE	**41/33**	**4.53**	**4.27**	**0.51**
	40/34	5.02	4.75	0.57
	39/35	5.61	5.31	0.63
THETAF	**41/33**	**5.20**	**4.96**	**0.59**
	40/34	5.44	5.16	0.61
	39/35	5.33	4.99	0.59
HOLT-WINTERS	**41/33**	**5.68**	**5.42**	**0.65**
	40/34	6.14	5.83	0.70
	39/35	6.14	5.76	0.69

dataset. The smallest values of all RMSE, MAE and MAPE metrics in the table mean higher accuracy. In particular, the MAPE value expresses the error made as a percentage.

The best results for three different analyzes for each model are shown in bold. In general, the performances of the models were very close to each other. The performances of the models vary with different training/test data lengths.

However, in the analysis conducted for the atmospheric pressure dataset, the AUTO. ARIMA model stands out with better performance among the six models. The test length here also means the predicted future horizon length. In this case, estimates were made for lengths of 33, 34 and 35 years, respectively.

Graphical representations of the predictions of the six different models in Table 2 are given in Fig. 2.

The blue lines in each chart show the 35-year average forecast for the future (here, 1989–2023). 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. In addition, black lines show the training set, and red lines show the test set, that is, the real values.

In the analysis process of the second meteorological variable, six different models were used to analyze the wind speed time series. Three horizons of different lengths were estimated for each model. The majority of the models showed better performance in the first horizon, where the training and testing lengths were taken as 41 and 33, respectively. Table 3 shows that the AUTO.ARIMA model performs better than other models. Model predictions are presented graphically in Fig. 3.

Six different models were used in the analysis process of the surface evaporation time series, which is the third meteorological variable. For each model, three different prediction horizons were estimated. Notably, most models exhibited superior performance in the initial horizon, where training and testing lengths were 41 and 33, respectively. Table 4 highlights

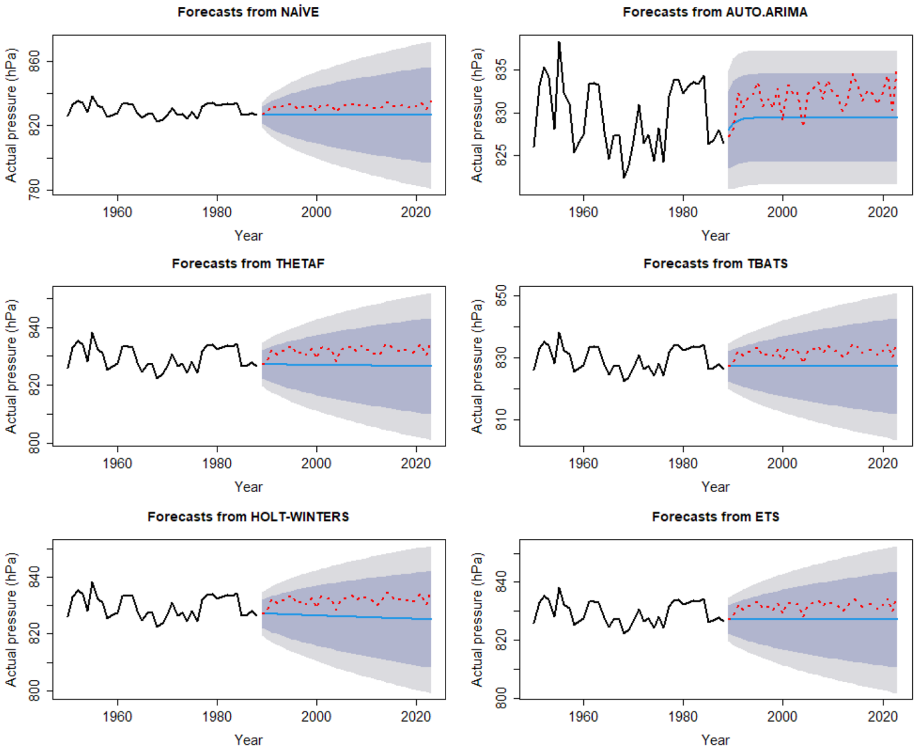

Fig. 2 Graphs of the predictions of six different models for the atmospheric pressure dataset

Table 3 Yearly average Wind speed predictions

Dataset: Wind speed	Test results			
	Train/Test length	RMSE	MAE	MAPE
Auto.Arima	**41/33**	**0.35**	**0.30**	**16.73**
	40/34	0.41	0.37	18.59
	39/35	0.41	0.37	18.48
ETS	41/33	0.72	0.60	34.44
	40/34	**0.41**	**0.37**	**18.29**
	39/35	0.42	0.38	18.36
TBATS	41/33	0.79	0.68	38.84
	40/34	**0.41**	**0.37**	**18.38**
	39/35	0.42	0.38	18.40
NAİVE	41/33	0.72	0.60	34.44
	40/34	**0.41**	**0.37**	**18.29**
	39/35	0.42	0.38	18.36
THETAF	41/33	0.82	0.69	39.44
	40/34	0.45	0.40	21.13
	39/35	**0.45**	**0.40**	**20.40**
HOLT-WINTERS	**41/33**	**0.39**	**0.30**	**17.91**
	40/34	0.48	0.42	22.74
	39/35	0.84	0.82	40.55

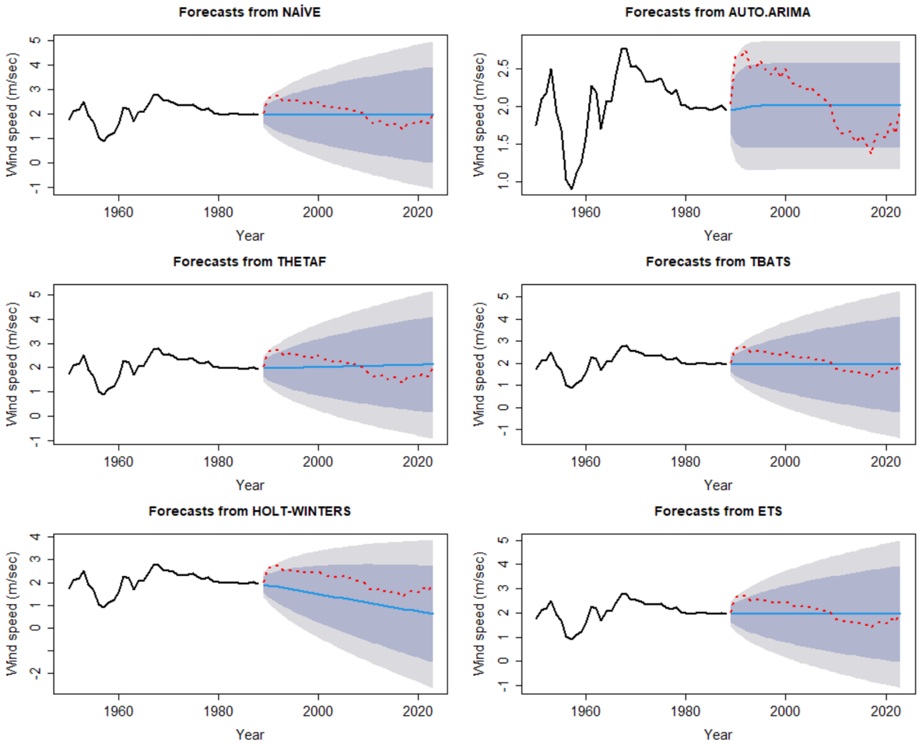

Fig. 3 Graphs of the predictions of six different models for the wind speed dataset

the AUTO.ARIMA model's superior performance compared to other models. The graphical representation of model predictions can be found in Fig. 4.

Due to the inherent qualities and complexities of the data, different models perform differently when estimating horizons of the same length on distinct time series. Trends, seasonality, cyclic patterns, volatility, and noise can all vary among time series. A model that works well for time series with prominent seasonal patterns might not work as well for a series that is characterized by erratic or random trends. Furthermore, the model's performance can be greatly impacted by the existence of outliers, structural flaws, and the duration of the historical data that is accessible. Since every model has different strengths and underlying assumptions, the accuracy of a model's predicting is determined by how well those assumptions match the particular characteristics of a time series.

4 Conclusions

The culmination of our study on long-term future predictions of key meteorological variables in the Van Lake basin underscores the critical role of statistical modeling in forecasting climatic parameters. Through the application of various models including AUTO. ARIMA, TBATS, EST, NAIVE, THETAF, and HOLT-WINTERS, we have endeavored to provide accurate predictions for annual average actual pressure, wind speed, and surface

Table 4 Yearly average evaporation predictions

Dataset: Evporation	Test results			
	Train/Test length	RMSE	MAE	MAPE
Auto.Arima	41/33	31.51	24.42	17.83
	40/34	**27.96**	**22.04**	**13.88**
	39/35	44.47	39.64	23.81
ETS	**41/33**	**27.44**	**24.42**	**14.98**
	40/34	30.97	24.75	15.19
	39/35	39.18	33.83	20.38
TBATS	**41/33**	**27.46**	**20.63**	**15.00**
	40/34	30.33	24.13	16.87
	39/35	40.69	35.52	21.37
NAİVE	41/33	31.51	24.42	17.83
	40/34	**27.96**	**22.04**	**13.88**
	39/35	44.47	39.64	23.81
THETAF	41/33	41.84	34.26	24.56
	40/34	**29.32**	**20.96**	**14.31**
	39/35	29.89	21.60	14.43
HOLT-WINTERS	41/33	62.99	53.96	37.65
	40/34	36.29	27.09	19.30
	39/35	**31.06**	**22.18**	**15.28**

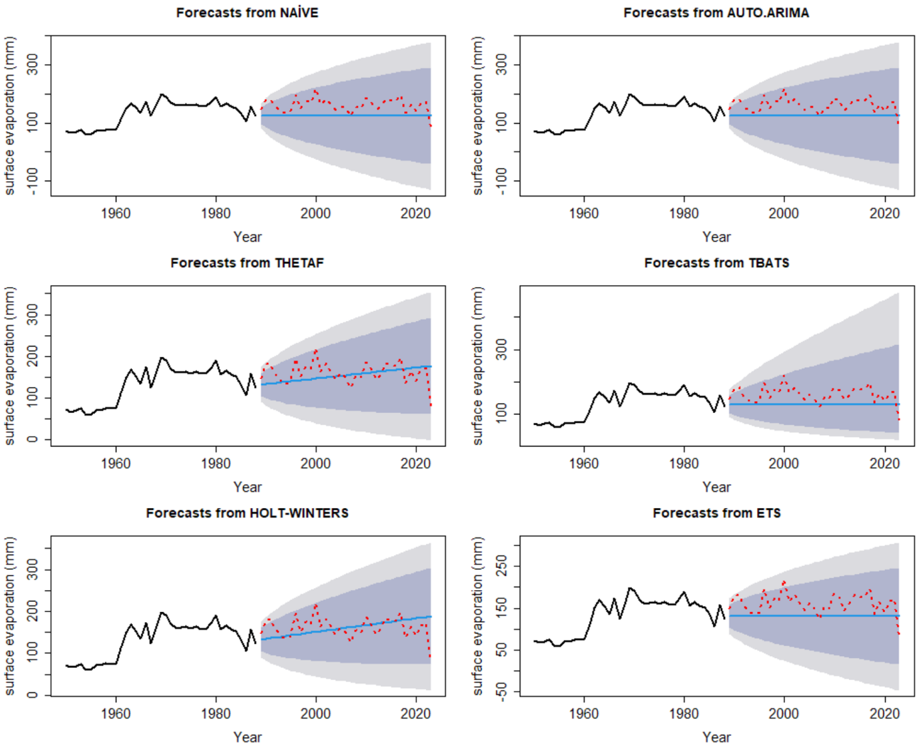

Fig. 4 Graphs of the predictions of six different models for the surface evaporation dataset

evaporation. Our findings reveal that among the models assessed, AUTO.ARIMA consistently outperforms others in terms of predictive accuracy across all analyzed time series. This observation highlights the robustness and efficacy of AUTO.ARIMA in capturing the complex temporal patterns inherent in meteorological data within the study area. The utilization of RMSE, MAE, and MAPE metrics for evaluating the predictive performance further strengthens the reliability of our conclusions. These metrics not only provide quantitative measures of model accuracy but also offer valuable insights into the strengths and weaknesses of each forecasting approach.

In conclusion, our study underscores the importance of employing advanced statistical techniques, particularly AUTO.ARIMA, for accurate long-term forecasting of meteorological variables in the Van Lake basin. The insights gained from this research hold significant implications for decision-makers, stakeholders, and researchers involved in environmental management, water resource planning, and climate change adaptation strategies in the region.

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Declarations

Conflict of interest The author has no competing interests to declare that are relevant to the content of this article.

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