Modeling Sea Surface Temperature Variability with Meteorological and Water Quality Indicators Using VAR and Prophet Forecasting Models.

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Abstract

Sea Surface Temperature (SST) is a crucial indicator of global climate change and oceanic conditions, significantly affecting marine and coastal ecosystems. This study investigates the dynamics of SST and its variations by utilizing ground observations and remote sensing data for the southeastern Arabian Gulf, particularly near Dubai's coastline. Correlation analysis uncovered relationships between SST and a selected set of water quality indicators and meteorological parameters. The Facebook Prophet model was applied to forecast SST and was proven capable of capturing seasonal variations and irregular spikes. Vector Autoregression (VAR) model was employed to analyze the influence of meteorological parameters on SST forecasting results and their interrelationships. The results demonstrate a significant impact of previous SST lags, particularly the third lag (p-value = 0.008), along with the notable influence of air temperature and wind speed on SST forecasting. The Prophet and VAR models yielded Root Mean Square Error (RMSE) values of 0.82 and 0.93, respectively. Furthermore, the study revealed an underlying relationship between SST, salinity, and nitrate concentrations, providing deeper insights into SST dynamics and water quality indices. The proposed analysis approach can be applied to study and understand other climatic applications with seasonal and limited time-series data, expanding its relevance to broader environmental studies.

1. Introduction

The global increase in greenhouse gas emissions has caused a rise in air and water temperatures worldwide, with ocean warming reflected in elevated Sea Surface Temperature (SST). The Arabian Gulf was reported as one of the warmest water bodies in the world, with its temperature being primarily driven by its high evaporation rates. Additionally, the increase in coastal populations and freshwater demands in countries in the Arabian Gulf basin increases the number and operations of desalination plants across the basin, which increases seawater salinity and decreases Dissolved Oxygen (DO) levels (Elneel et al., 2024b). All these factors significantly impact marine ecosystems and human coastal activities, as seen in jellyfish outbreaks and extinction of fish species by 10%, all linked to rising SST in the Arabian Gulf (Lincoln et al., 2021). Analyzing variations in SST and its influencing factors is essential for understanding its contributors and impacts, which enables accurate forecasting and provides effective environmental monitoring and climate change mitigation planning. Statistical and regression models were used in weather forecasting research to develop models that use the relationship between variable sets and forecast each variable under the influence of others (Abdallah et al., 2020, Song and Ma, 2023, Shahin et al., 2014).

Ground weather stations collect continuous data, including meteorological data such as air temperature, wind speed, and humidity. These observations are essential for analyzing environmental trends and understanding how various indicators influence each other. Generally, ground-sensed data can provide higher temporal resolution compared to remotely sensed data, which enables data verification against ground truth and increases the reliability of the data and analysis results (Cazenave and Cozannet, 2014). Furthermore, ground station data collection approaches offer more flexibility than remotely sensed data, as they can be often gathered on-demand over relatively short periods, making them suitable for real-time and near-real-time monitoring applications. Remotely sensed data from the Moderate Resolution Imaging Spectroradiometer (MODIS) have become an invaluable source of environmental factors to be used for monitoring and analysis. They provide spatial data across large geographic areas while offering high temporal resolution with a daily revisit time. MODIS sensors onboard the Aqua satellite collect data such as SST, chlorophyll concentration, and land surface temperature. Remotely sensed data are crucial for studying large-scale areas, as maintaining and calibrating ground weather stations over such vast regions is challenging. Meteorological factors, when integrated with remotely sensed SST, can enhance the predictive capabilities of forecasting models and time series analysis.

Statistical and regression models are widely used for analyzing and forecasting time series data, with approaches such as VAR and the Prophet model being common in recent studies, providing deeper insights into time series data and utilizing this information for forecasting. VAR models have proven effective in capturing linear interdependencies between multiple variables, while the Prophet model is capable of capturing seasonal variations. In the context of this paper, the VAR model was used to identify relationships between SST and related meteorological variables, allowing for a more comprehensive understanding of their interactions over time. Conversely, the Prophet model is a relatively new approach that offers robust handling of seasonal trends. It has recently been utilized in research where time series data exhibit irregular variations.

This study aims to analyze the relationships between SST, meteorological variables, and water quality indicators to predict SST using the VAR model and to forecast it based on historical SST data with the Prophet model. Through this approach this study seeks to: (1) evaluate the performance of the VAR model in predicting SST, (2) assess the effectiveness of the

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Prophet model in forecasting SST, and (3) analyze the relationship between SST and various meteorological and water quality indicators. Ultimately, the findings of this study will support future research aimed at enhancing SST forecasting to assist in mitigating the potential impacts of rising SST. Section 2 provides a literature review to support the methodologies adopted in this study. Section 3 discusses the methodology, including the data and models used. This is followed by the analysis, results, and discussion in Section 4, and finally, the study concludes with key findings.

2. Literature Review

SST forecasting has become a focus point in recent research due to its importance in understanding climate dynamics and marine biodiversity, as well as its role in extreme weather events that have been increasing in magnitude lately. As SST rises, the available heat energy increases, leading to higher intensity and longer durations of extreme events such as storms, hurricanes, and heavy rainfall. For example, recent SST warming patterns in the Indian, Pacific, and North Atlantic oceans have amplified tropical storms and heavy rainfall events (Zhao and Knutson, 2024). Furthermore, the increase in SST can drive seasonal patterns such as the El Niño–Southern Oscillation (ENSO), a climate phenomenon that describes fluctuations in ocean temperatures over the Pacific Ocean and significantly influences global weather. This climate event can lead to extreme drought in some regions and heavy flooding in others. Therefore, understanding SST variations is crucial in predicting extreme weather events. Another study by (Hereher, 2020) mapped SST changes in the Arabian Gulf over a 15 year period where the effects of increasing SST on coral bleaching were examined. Results obtained from this study found that average warming rates in the Arabian Gulf were high compared to global trends. Additionally, the study found that there is a significant negative influence of SST on coral bleaching. This work revealed the implications of the high rate of sea warming in the Arabian Gulf on marine biodiversity.

A number of studies have examined SST patterns and the influence of various environmental variables/drivers utilizing several models across multiple regions. (Alosairi et al., 2020) analyzed SST in the Arabian Gulf and several factors that may influence SST. They analyzed meteorological factors, such as air temperature, wind speed, and humidity, as well as power plants discharges affect on SST. This study concluded that wind speed and humidity inversely affect SST, while air temperature positively affects SST. This implies the three meteorological factors can be used to predict SST. Various statistical an regression models can be utilized in forecasting applications depending on the objectives and characteristics of the used data. The Prophet model has shown advantages in forecasting climate and environmental variables when compared to traditional models like Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA). A study by (Das et al., 2022) in the Ganga River near Varanasi in India used the Prophet model to forecast seasonal changes in river temperature and turbidity from climate-driven changes. The Prophet model resulted in higher accuracy in forecasting air temperature changes due to climate change, achieving a root mean square error (RMSE) of 3.2%, while the SARIMA had a lower accuracy with an RMSE of 7.54%. The results imply that the Prophet model has the capability to handle complex seasonality changes and long-term trends. These strengths highlight the model's potential in addressing challenges encountered in analyzing environmental parameters and climate forecasting (Das et al., 2022). (Elneel et al., 2024a) examined the capability of regression and statistical models, including ARIMA, VAR, and Facebook's Prophet model, in forecasting sea level rise and investigated the influence of oceanic and climatic indicators on forecasting mean sea levels. The results showed the effectiveness of regression models in long-term forecasting and the capability of the Prophet model to capture seasonal variations over extended periods. (Chapman et al., 2015) applied the VAR model to predict SST anomalies associated with ENSO. They used both the VAR model and the linear inverse method (LIM) to identify anomalies in 150 years of SST data from 1861 to 2010, with 120 years used for calibration and 30 years for verification. Their findings indicate that the VAR model improves forecast accuracy with a three-month lead time. (Lee et al., 2016) applied a multilevel VAR to forecast SST anomalies in the Atlantic's hurricane Main Development Region using monthly SST as predictors where the VAR model showed a notable difference in accuracy against the dynamic forecast model and deep learning model.

Other machine and deep learning models, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), were used in forecasting meteorological data. For example, (Comaniciu and Murakami, 2022) applied CNNs to predict the intensity of Atlantic hurricane seasons based on SST maps. Their model achieved high accuracy, demonstrating SST's importance as a predictive variable for atmospheric phenomena. Also, (Choi et al., 2023) used LSTM model to forecast weekly SST near the Korean Peninsula. Historical data from 5, 12, and 20 years were used, where each pixel for the past 14 days of the day of predictions was used for training to predict the next 7 days. This model yielded better results when trained on longer data sets like 12 and 20 years periods. Although deep learning models have yielded good forecasting results across multiple studies, they are constrained by high data requirements, long training times, and computational complexity.

3. Methodology

3.1 Materials and Data

Both ground observations and remote sensing data were utilized in this study. Water quality data were collected from a sea monitoring station located near Dubai's shoreline (Sea Water Qaulity, 2023). The water quality data spanned the years 2015 to 2023 and included yearly mean sea temperature (savg) (°C), DO (mg/L), mean annual pH, salinity, Phosphate (PO_4) (µg/L), and Nitrate (NO_3) (µg/L). Monthly mean meteorological data, including average air temperature (tavg) (°C), wind speed (wspd) (km/h), and humidity (%), were acquired from a ground monitoring station located at Dubai's International Airport spanning the years 2016 to 2023 (Climate Stastics, 2024). Figure 1 shows the location of the sea and ground monitoring stations.

SST data were acquired from MODIS Aqua Level 3 satellite from the Ocean Color website (MODIS Aqua Level 3 Sea Surface Temperature Data, 2024), providing monthly mean daytime SST values from January 2016 to September 2024, with a spatial resolution of 4.63 km. Figure 2 shows seasonal SST and the meteorological data used in this study where all variables show higher values during summer seasons.

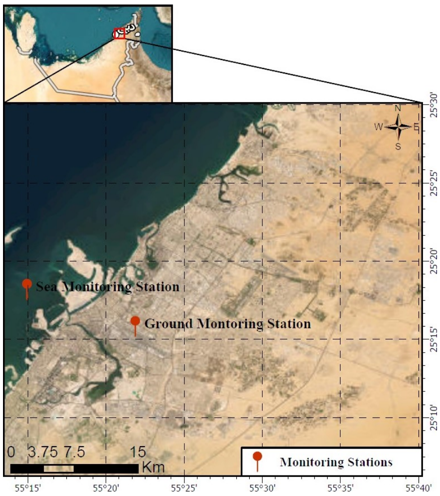

Figure 1. Sea and ground monitoring stations locations.

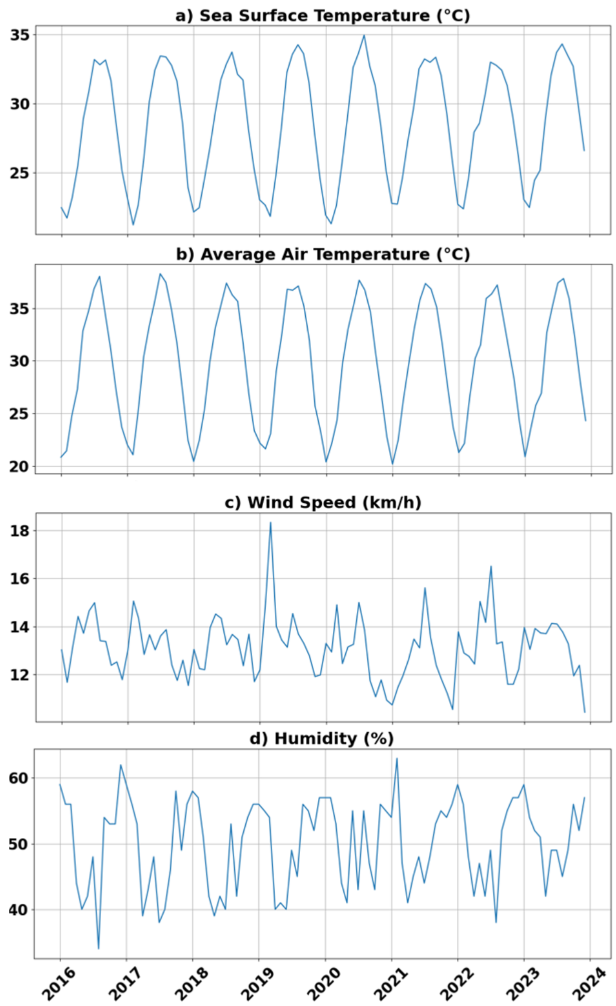

Figure 2. Illustration of meteorological data, where a) SST in Celsius b) average air temperature in Celsius c) wind speed in km/h, and d) the percentage of air humidity.

Monthly mean meteorological data were pre-processed, and yearly means were calculated to align with the data range required for correlation analysis with the water quality data. Additionally, MODIS images were pre-processed, and SST pixel values were collected at the pixel matching the location of the sea monitoring station. Figure 3 illustrates the methodology flowchart used in this study. Both ArcGIS pro tools and Python libraries were utilized for data pre-processing.

3.2 Prophet Model

The Prophet model is a forecasting model developed by Facebook to handle time series data with seasonal patterns, including both short- and long-term seasonal components, seasonal variations, and holiday effects. Its ability to manage missing data, capture complex seasonal patterns, and automatically select trend points and other parameters makes it highly suitable for various applications such as climate forecasting (Hyndman and Athanasopoulos, 2021). Equation 1 demonstrates the Prophet model formula, which can be described as a nonlinear regression model.

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

where $y(t)$ represents the observed value at time t
$g(t)$ non-periodic changes over time
$s(t)$ seasonal variations
$h(t)$ denotes the holiday effect
ϵ_t is the white error term

3.3 Vector Autoregression Model

The VAR model is used for multivariate time series analysis which, unlike unidirectional time series models, considers all variables as endogenous, analyzing the underlying relationships among variables and their influence on each other's predictions. Furthermore, VAR has proven to be useful in conducting pulse response analysis to examine how variables respond to a sudden and temporary change in another (Hyndman and Athanasopoulos, 2021). Equation 2 (Hyndman and Athanasopoulos, 2021) shows 2-dimensional VAR formulas with a lag of 1.

$$\begin{aligned}\hat{y}_{1,T+1|T} &= \hat{c}_1 + \hat{\phi}_{11,1} y_{1,T} + \hat{\phi}_{12,1} y_{2,T} \\ \hat{y}_{2,T+1|T} &= \hat{c}_2 + \hat{\phi}_{21,1} y_{1,T} + \hat{\phi}_{22,1} y_{2,T}.\end{aligned} \tag{2}$$

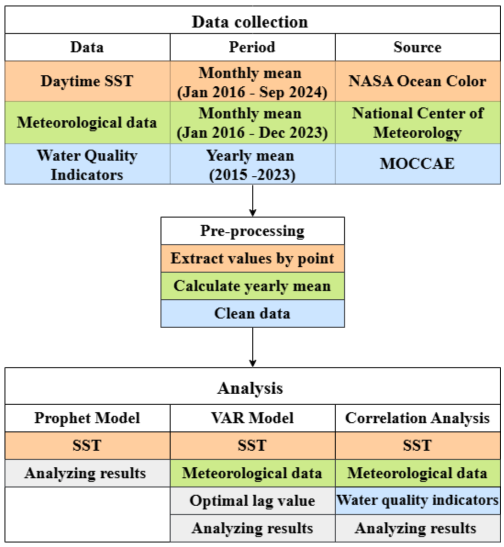

Figure 3. Methodology adopted in this study to forecast SST and analyze the co-influence of other parameters.

where $\phi_{ii,\ell}$ Variable's lag l influence on itself
$\phi_{ij,\ell}$ Variable's lag l influence on each other
$\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are correlated white noise

3.4 Forecasting SST and Correlation Analysis

To investigate SST dynamics, the Prophet model was used to forecast SST over two periods due to its capability in handling variations and trends that exists in the used SST time series, and provide insights into trend and seasonality patterns. Next, the influence of meteorological data (air temperature, wind speed, and humidity) on SST was examined using the VAR model, with the optimal lag value selected based on the used data. Outputs including coefficients, standard errors, t-statistics, and p-values were examined, and relational functions were formed. Finally, a correlation analysis of SST with meteorological and water quality indicators was performed to emphasize the relationships identified in the VAR analysis and to lay the foundation for future studies on the influence of SST on water quality indicators and vice versa.

4. Results and Discussion

4.1 SST Forecasting using the Prophet Model

Figure 4 shows the forecasting results for SST which yielded in RMSE of 0.82. The model captures seasonal variation, showing that predicted values are falling within the upper confidence interval, demonstrating the model's effectiveness in capturing seasonality patterns and generating accurate forecasts of SST data. Figure 5 reveals an increasing linear trend in the data with a gradual rise, especially after 2020. This trend may reflect global warming effects or region-specific climatic changes, which impact marine ecosystems and water quality indicators. Furthermore, the seasonal fluctuations observed in the SST data show higher temperatures from May to November and a noticeable drop from mid-November to March, aligning with expected seasonal ocean temperature patterns. The clear separation of trend and seasonality by the Prophet model demonstrates its suitability for environmental forecasting, providing insights into long-term changes and short-term variabilities. The results suggest that SST is influenced by both seasonal cycles and shows a significant upward trend, which can be associated with broader climatic changes. These findings highlight the importance of continuous monitoring and predictive modeling of SST, as these changes may have far-reaching effects on marine life, coastal activities, and water quality.

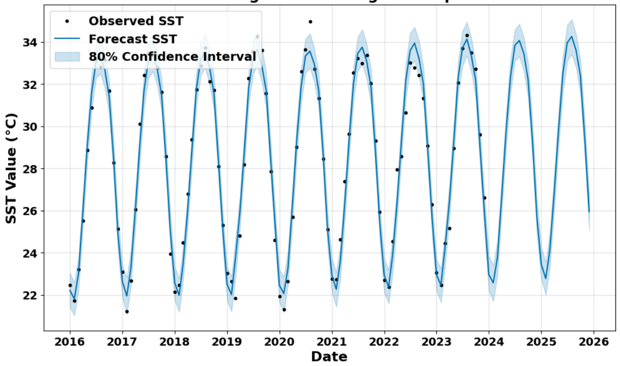

Figure 4. SST forecasting results using the Prophet model.

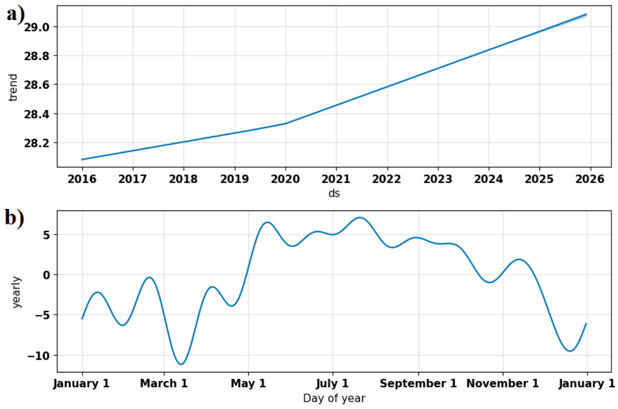

Figure 5. Prophet's model results where a) trends analysis of the time series and b) seasonality analysis.

4.2 Influence of Meteorological Parameters on SST Forecasting

Before using the VAR model, first-order differencing was applied to the time series to ensure the stationarity of the data, as shown in Figure 6. The figure presents the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which are essential tools for assessing the time series stationarity and identifying suitable lag parameters for the forecasting model. The ACF plot reveals how each data point in the SST time series is correlated with past values over different lags. In this case, there are significant correlations at various lags, which gradually decay. This gradual decay suggests a trend in the data, confirming that the SST time series is non-stationary. Non-stationary data often exhibit strong correlations across many lags, which is typical of environmental data with seasonality and long-term trends. Conversely, the PACF plot shows the correlation of each time point with its lagged values, controlling for intermediate lags. The PACF plot helps identify the most relevant lag terms. For the SST data, the PACF shows significant spikes at specific lag points, which could indicate periodic seasonal dependencies within the time series. These significant spikes support the selection of a lag order for the VAR model. The ACF and PACF analysis results confirm that the SST time series data has a seasonal trend. This finding justifies the use of first-order differencing to make the data stationary before applying the VAR model.

Considering that the used SST is monthly seasonal and the desired forecasting period is two years, the optimal lag value was selected to be 12. This value was also determined after analyzing parameters such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC). Those parameters tend to evaluate the fitness of a lag value to a model. The test results for up to 12 lags resulted in 12,2,5 for AIC, BIC, and HQIC respectively. The VAR model was applied to forecast each variable under the influence of the other variables in the set. Figure 7 shows the forecasting results of each variable over a two-year period. RMSE results for SST, average air temperature, wind speed, and humidity are 0.93, 0.99, 1.37, and 4.21, respectively. The summary of results of each variable equation produced by the VAR model shows that SST is significantly influenced by its past values, particularly at lag 3 where the p-value is 0.008. The influence of meteorological factors, such as average air temperature and wind speed, on SST was assessed via the equations that resulted from the VAR model summary for

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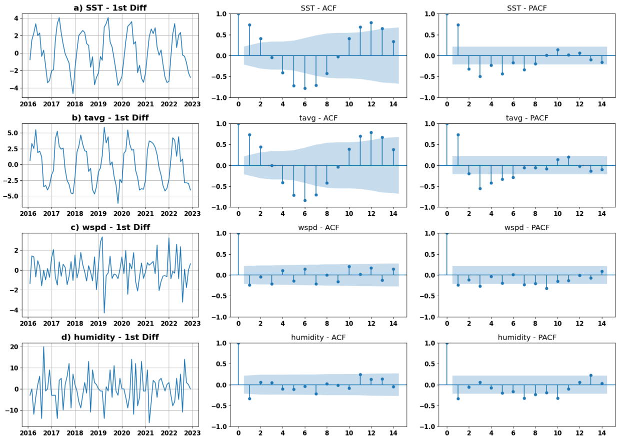

Figure 6. 1st order differenced data, ACF, and PCAF plots of the meteorological data used to forecast SST.

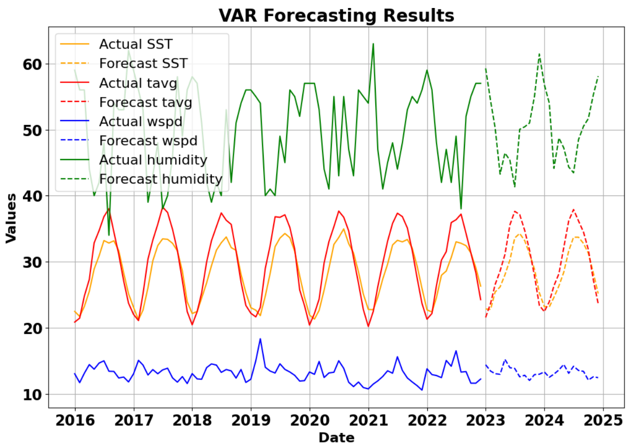

Figure 7. Forecasting results of VAR model.

SST, suggesting that while these factors do impact SST, their influence is secondary to SST’s own past values. Interestingly, humidity did not show a significant impact on SST, indicating that it may not be a key driver of seasonal SST variability within this dataset. The predicted SST values fall within an expected range, aligning closely with historical values, which suggests that the model captures both seasonality and underlying trends effectively. Overall, the results validate the effectiveness of the VAR model in multivariate time series forecasting, capturing SST’s dependency on both its lagged values and external factors. These insights help in understanding the dynamics of SST.

4.3 Correlation with Water Quality Indicators

Figure 8 shows the correlation analysis results to form a better understanding of the relation among these variables. SST demonstrated a strong positive correlation with air temperature, nitrate concentration, and salinity. This implies that higher SST may drive increases in nitrate concentration and salinity, potentially altering nutrient dynamics which affects the aquatic ecosystems and water quality. This finding reinforces the importance of integrated environmental monitoring. Conversely, SST showed a strong inverse relation with wind speed, indicating the cooling effect of wind-induced mixing. Additionally, wind speed exhibited a strong positive relationship with both salinity and pH, however more analysis are required to justify

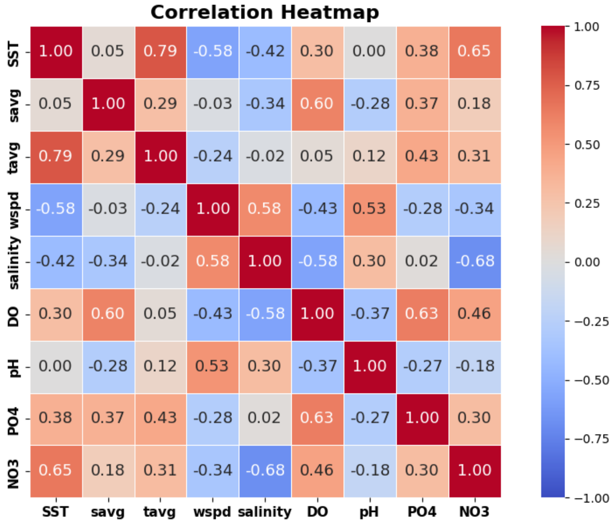

Figure 8. Correlation matrix among SST and other parameters.

the scientific reason behind this relation. DO levels also exhibited a strong positive relation with sea average, Phosphate, and nitrate and a strong negative relation with salinity. The results obtained from the correlation analysis highlight the complex interplay between SST, meteorological parameters, and water quality indicators. This understanding can help in developing more comprehensive models for SST forecasting and contribute to the effectiveness of environmental monitoring strategies. It also highlights the potential impact of changing SST on marine and coastal ecosystems.

4.4 Overall Discussion of Results

The study’s results demonstrate the effectiveness of correlation analysis and statistical and regression models —namely, the Prophet and VAR models— in forecasting SST and understanding its complex relationships with meteorological and water quality indicators. The Prophet model, highlighted in Figures 4 and 5, effectively captures the seasonality patterns and the increasing linear trend over recent years. The results suggest that SST is gradually increasing, which may be attributed to broader climatic changes. The VAR model, illustrated in Figures 6 and 7, complements this by capturing short-term dependencies and interrelationships between SST and related meteorological indicators. The analysis confirms that SST is significantly autocorrelated with its past values, exerting a strong influence on future SST levels. Both air temperature and wind speed showed notable but limited impact on SST, while humidity had no impacts within the context of the dataset used in this study. These findings underscore the multifaceted nature of SST, influenced by both its own historical values and specific meteorological factors. Correlation analysis reinforced findings from the VAR model regarding the influence of air temperature and also revealed additional relations within other water quality indicators.

Despite the limitations in acquiring monthly data for the selected indicators and other relevant factors, the models performed well and provided valuable insights into the subject. Since no other research has been conducted on the same dataset, a direct comparison of the results obtained using the proposed models could not be made. However, the RMSE values obtained were found to be lower than those reported in other studies that used different regression models, as discussed in Section 2. Having access to more data would enable testing additional models, including deep learning approaches, for comparison and for understanding the effect of other climatic and oceanic factors on SST.

5. Conclusion

In conclusion, this study successfully applied time-series forecasting techniques, specifically Facebook's Prophet and VAR models, to predict SST and analyze its relation with meteorological and water quality indicators and how they influence its future prediction. The Prophet model effectively captured both seasonal and long-term trends, while the VAR model offered insights into the interdependencies among SST and related environmental variables. The SST results using the Prophet and VAR models yielded RMSE values of 0.82 and 0.93, respectively. Key findings include seasonal and long-term trends where SST exhibited a clear seasonal pattern marked by high values for most months and a notable upward trend, potentially driven by climate change. The influence of meteorological variables like air temperature and wind speed significantly influence SST, with an inverse relationship between wind speed and SST. SST was also found to be positively correlated with some water quality indices such as nitrate concentration and salinity, suggesting that increases in SST could impact nutrient and salinity levels in coastal waters, with implications for marine life and water quality. These results highlight the need for integrated SST forecasting and environmental monitoring to form a better understanding and prediction of changes in the marine and coastal ecosystems, especially in the context of climate change. Generally, the techniques used in this study extend the proof of the effectiveness of similar approaches for climate-related applications, including forecasting and analysis. This aligns with previous research (Elneel et al., 2023, Elneel et al., 2024a), where annual and limited time series data were used to provide insights into each factor and to understand underlying effects from a numerical perspective. Additionally, this method overcomes the limitations of high data demand and computational requirements associated with deep learning models. Future research could focus on extending this analysis across broader temporal and spatial scales, examining the ecological implications of SST variability and incorporating additional environmental factors to improve forecasting accuracy and environmental decision-making.

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