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Time Series Forecasting Mean Sea Level in Ocean City, Maryland Using a Neural Network Autoregressive Model

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Abstract

The accelerating rise in sea levels poses a significant challenge for coastal communities, necessitating accurate forecasting methods. This study evaluates the efficacy of various time series models in predicting long-term sea level changes, including ARIMA, ETS, NNETAR, THETAM, TBATS, STLM, and their hybrid combinations. Using monthly mean sea level data from Ocean City, Maryland, spanning August 2002 to February 2025, a comparative analysis was conducted. The NNAR(24,1,12)[12] model emerged as the most accurate, performing exceptionally well across all metrics, particularly with very low RMSE and MAE values among all tested models. These findings underscore the potential of neural network-based approaches in sea level forecasting and highlight the importance of integrated modeling techniques as decision-support tools for local mean sea level predictions. Understanding historical sea level trends is crucial for improving future projections, and this study contributes to that knowledge base. Continued research efforts leveraging these data-driven insights can significantly enhance our ability to refine predictions and develop effective strategies to mitigate the impacts of sea level rise

Introduction

Ecological change refers to the long-term alteration in the average weather patterns of the Earth. It is primarily triggered by human activities such as the burning of fossil fuels and deforestation, as well as natural events like volcanic eruptions. The National Oceanic and Atmospheric Administration (NOAA) 2019 Global Climate Annual Report summarized that the global annual temperature has increased at an average rate of 0.07°C (0.13°F) per decade since 1880. This rate of increase (+0.18°C / +0.32°F) has doubled since 1981.

Two major factors related to ecological change cause global sea level rise: the addition of water from melting ice sheets and glaciers, and the thermal expansion of warming waters. Locally, the amount and speed of sea level rise vary by location, particularly due to the slowing Gulf Stream and sinking land, which affect some areas in the United States at varying rates. The potential impacts of sea level rise include, but are not limited to, increased coastal flooding and erosion, damage to agricultural land and crops, damage to coastal and urban settlements and infrastructure, and harm to coastal flora and fauna ecosystems.

According to NOAA Climate.gov, the global average sea level has risen about 8-9 inches (21-24 cm) since 1880. The Intergovernmental Panel on Climate Change (IPCC) estimated in 2014 that the sea level has risen by 26-55 cm (10-22 inches) with a 67% confidence interval. If emissions remain very high, the IPCC projects that sea level could rise by 52-98 cm (20-39 inches). The U.S. Global Change Research Program (USGCRP) estimated in its Fourth National Climate Assessment Report (2017) that sea level has risen by about 7-8 inches (16-21 cm) since 1900, with about 3 of those inches (7 cm) occurring since 1993. Relative to the year 2000, sea level is very likely to rise by 1.0-4.3 feet (30-130 cm) by 2100, and 0.3-0.6 feet (9-18 cm) by 2030.

Furthermore, Church and White (2011) revealed that the estimated rate of sea level rise was 3.2 ± 0.4 mm/year from satellite data and 2.8 ± 0.8 mm/year from in situ data. The average global sea level rise from 1880 to 2009 was about 210 mm. The linear trend from 1900 to 2009 was 1.7 ± 0.2 mm/year, and since 1961, it has been 1.9 ± 0.4 mm/year. They also documented considerable variability in the rate of sea level rise during the twentieth century, but there has been a statistically significant acceleration since 1880 and 1900 of 0.009 ± 0.003 mm/year^2 and 0.009 ± 0.004 mm/year^2, respectively.

Many studies have pointed out that sea level is rising at an increasing rate (Church et al., 2008; Cazenave &Llovel, 2010; Church & White, 2011; Cazenave &Cozannet, 2013; Horton et al., 2018; Kulp & Strauss, 2019; Haasnoot et al., 2020; Boumis et al., 2023). Thus, understanding past sea levels is important for analyzing current and future sea level changes. Modeling sea level changes and understanding their causes have considerably improved in recent years, primarily due to new in situ and remote sensing observations (Foster & Brown, 2014; Visser et al., 2015; Bolin et al., 2015; Srivastava et al., 2016). Despite the importance of sea level rise and its consequences, there is a lack of studies in the technical literature on forecasting schemes for local consideration.

Time series forecasting uses a model to predict future values based on previously observed values. Neural networks have become one of the most popular trends in machine learning for time series modeling and forecasting. Recently, there has been increasing interest in using neural networks to model and forecast time series, particularly in addressing sea level rise issues (Bruneau et al., 2020; Bruno & Afonso, 2021; Alenezi et al., 2023).

The primary purpose of this study was to demonstrate the role of time series models in the prediction process and to analyze long-term records

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of monthly mean sea level at Ocean City, Maryland. Future directions in data-driven sea level forecasting aim to enhance model accuracy, integrate diverse data sources, and provide more detailed and actionable predictions. These advancements will play a crucial role in helping coastal communities and policymakers prepare for and respond to the challenges posed by rising sea levels.

Materials

Study Site

Ocean City, officially the Town of Ocean City, is an Atlantic resort city in Worcester County, Maryland, along the East Coast of the United States (Figure 1). Known for its beautiful beaches, bustling boardwalks, and lively entertainment scene, Ocean City, Maryland, attracts millions of visitors annually, particularly during the summer months, making it a major vacation destination. Ocean City's history traces back to its origins as a fishing village, evolving into a thriving resort town with a strong emphasis on family fun and entertainment (Wikipedia: Ocean City, Maryland).

According to the U.S. Census Bureau, the town has a total area of 36.37 square miles (94.20 km²), of which 4.41 square miles (11.42 km²) is land and 31.96 square miles (82.78 km²) is water. Ocean City is located on Fenwick Island, a barrier spit that encompasses Ocean City, as well as South Bethany and Fenwick Island, Delaware. Ocean City's southern point is an inlet formed by the 1933 Chesapeake–Potomac hurricane. Rainfall and tides swelled the rivers and bays surrounding Ocean City until the overflowing water cut a 50-foot crevasse from the bay to the ocean (Wikipedia: Ocean City, Maryland).

Figure 1: Ocean City, Maryland, USA (Source: Map of Beaches in Maryland, adapted from: https://www.livebeaches.com/map-of-beaches-in-maryland/)

Data Source

The long-term records of monthly mean sea level from August 2002 to February 2025 at Ocean City, Maryland, used for this study are available to the public from NOAA Tides and Currents. The average monthly mean sea level was 0.1123 mm/year with a standard deviation of 0.0794 mm/year (Minimum: -0.0880 mm/year, Maximum: 0.3590 mm/year, and Median: 0.1123 mm/year) at Ocean City, Maryland, from August 2002 to February 2025.

According to NOAA Tides and Currents, the term "mean sea level" can refer to a tidal datum, which is locally derived based on observations at a tide station and is typically computed over a 19-year period, known as the National Tidal Datum Epoch (NTDE). Tidal datum forms the basis of marine boundaries, can be used as a vertical reference plane in producing nautical charts, and provides important baseline information for observing changes in sea level over time. Mean sea level as a tidal datum is computed as the mean of hourly water level heights observed over 19 years. Monthly means generated in the datum calculation process are used to generate the relative local sea level trends observed at a tide station.

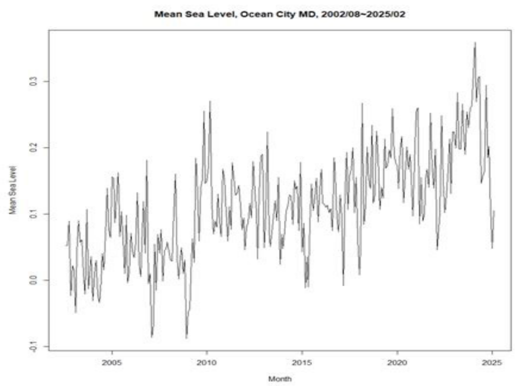

Figure 2: Time Series Plot of Monthly Mean Sea Level at Ocean City, Maryland, August 2002 ~ February 2025 (Source: R Output)

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Method

forecast Hybrid

The "forecastHybrid" package in R provides convenient functions for ensemble time series forecasts. It allows users to build composite models using multiple individual component models from the "forecast" package. Forecasts generated from auto.arima(), ets(), nnetar(), tbats(), thetam(), and stlm() can be combined with equal weights or cross-validated weights (Perone, 2022).

ARIMA (AutoRegressive Integrated Moving Average) combines autoregressive (AR), differencing (I), and moving average (MA) components. It is particularly suitable for univariate time series forecasting, especially when the data exhibits trends and seasonality. One of its strengths is its effectiveness for non-stationary data after differencing, making it widely used and well-understood in the field. However, ARIMA requires manual tuning of its parameters (p, d, q), which can make it complex to implement.

ETS (Error, Trend, Seasonal) incorporates error, trend, and seasonal components, offering options for additive or multiplicative models. It is particularly suitable for time series data with clear seasonal patterns. One of its strengths is its flexibility, as it can handle various types of seasonality and trends, and it features automatic model selection. However, ETS can be computationally intensive and may not perform well with very irregular data.

NNETAR (Neural Network Time Series) utilizes feed-forward neural networks with lagged inputs for forecasting. It is particularly suitable for capturing nonlinear relationships in univariate time series data. One of its strengths is its ability to model complex patterns and interactions, making it adaptable to various data types. However, NNETAR requires significant computational resources, and the results can vary due to randomness in the training process.

TBATS (Trigonometric, Box-Cox, ARMA, Trend, Seasonal) incorporates trigonometric seasonality, Box-Cox transformation, ARMA errors, trend, and seasonal components. It is ideal for time series data with complex seasonal patterns and long seasonal cycles. One of its strengths is its ability to handle multiple seasonal periods and complex seasonality, making it robust to outliers. However, TBATS is computationally demanding and slower to fit compared to simpler models.

TEHTAM (Technology Acceptance Model) focuses on perceived usefulness and ease of use to predict technology acceptance. Unlike time series models, TEHTAM is used to understand user acceptance of technology. Its strengths lie in providing valuable insights into user behavior and technology adoption. However, it is not applicable for forecasting time series data.

STLM (Seasonal-Trend decomposition using Loess) decomposes time series data into seasonal, trend, and remainder components using Loess smoothing. It is particularly suitable for time series with strong seasonal and trend components. One of its strengths is its flexibility and robustness to outliers, and it can be combined with other forecasting methods. However, STLM requires careful selection of smoothing parameters and can be sensitive to noise.

Neural Network Autoregression (NNAR) Models

Feed-forward neural networks with a single hidden layer and lagged inputs, also known as Neural Network Autoregression (NNAR) models, are commonly used for forecasting univariate time series (Zhang et al., 1998). These models treat lagged values of the time series as inputs, similar to autoregressive (AR) models, but use a non-linear function (the hidden layer) to predict the next value (Tealab, 2018). NNAR models can be adapted to seasonal time series by including lagged values from previous seasons as inputs.

NNAR is a type of autoregressive model where neural networks are used to learn the non-linear relationships between past and future values in a time series. The equation of NNAR can be expressed as follows:

$$y_t = \alpha_0 + \sum_{j=1}^{h} \alpha_j f\left(\sum_{i=1}^{p} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t$$

In this equation, (where βij = 0, 1, 2, …, n and j = 1, 2, …, h) and αj (where j = 0, 1, 2, …, h) are weight in the model. The notation p represents the number of neurons in the input layer, and h represents the number of neurons in the hidden layer.

This autoregressive neural network uses a single hidden layer, and the results of weighted linear combinations are modified into artificial neural network output using non-linear functions. The linear combination function can be written as follows:

$$z_j = \beta_{0j} + \sum_{i=1}^{p} \beta_{ij}\, y_{t-i}$$

Here, Z_j is the sum function of the bias unit to *j* in the hidden layer, β_{0j} is the weight of the bias unit to *j* , β_{ij} is the weight of *i.* in the layer to *j,* and β_{ij} is the input to *i.* The network activation function is a non-linear function in the form of a binary sigmoid function, written as follows:

$$f(z) = \frac{1}{1+e^{-z}}$$

The equation above is a function of z; this sigmoid function is a part of the activation function in the single-layer network model (Daniyal et al., 2022; Almarashi et al., 2024; Hightower et al., 2024).

Output is denoted by NNAR(p,k), where p denotes the number of lagged values used as inputs, and k denotes the number of hidden nodes. For example, a NNAR(13,7) model is a neural network with the last thirteen observations (y_{t-1}, y_{t-2}, …, y_{t-13}) used as inputs for forecasting the output yt, and with seven neurons in the hidden layer. A NNAR (p,0) model is equivalent to an ARIMA (p,0,0) model, but without the restrictions on the parameters to ensure stationarity.

If the dataset is seasonal, the notation is similar: NNAR(p,P,k) where P denotes the number of seasonal lags. P is chosen based on the information criterion, like AIC. For example, an NNAR(3,1,2)[12] model has inputs y_{t-1}, y_{t-2}, y_{t-3} and

y_{t-12}, and two neurons in the hidden layers. More generally, an NNAR (p,P,k) [m] model has inputs (y_{t-1}, y_{t-2}, …, y_{t-p}, y_{t-m}, y_{t-2m}, …, $y_t - P_m$) and k neurons in the hidden layer. A NNAR (p,P,0)[m] model is equivalent to an ARIMA (p,0,0) (P,0,0) [m] model but without the restrictions on the parameters that ensure stationarity.

Model Evaluation Metrics

Five model evaluation metrics were employed to assess model accuracy and determine the best-fit time series model. The Mean Error (ME) was used to measure bias, indicating whether the model systematically over- or under-predicts the actual values. The Root Mean Squared Error (RMSE)

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penalized large errors, making it particularly sensitive to significant deviations between predicted and actual values.

Additionally, the Mean Absolute Error (MAE) provided insight into the average magnitude of forecast errors, offering a straightforward measure of accuracy. The Mean Percentage Error (MPE) was applied to evaluate bias in percentage terms, helping to understand whether the model tends to overestimate or underestimate in relative terms.

Lastly, the Mean Absolute Percentage Error (MAPE) was used to assess overall forecast accuracy, ensuring a robust evaluation of the model's predictive performance. These model evaluation metrics provide insights into model accuracy, bias, and forecasting reliability. The lower the values, the better the model's predictive accuracy (Perone, 2022; Daniyal et al., 2022; Almarashi et al., 2024; Hightower et al., 2024).

Results

Decomposing a seasonal time series involves separating the time series into a trend component, a seasonal component, and an irregular component. The function decompose() in R can be applied to separate these components of a seasonal time series. The plots in Figure 3 show the original time series (top), the estimated trend component (second from top), the estimated seasonal component (third from top), and the estimated irregular component (bottom). The estimated trend component shows a steady increase over time, and the estimated seasonal component clearly displays seasonality, with a recurring pattern occurring once every 12 months (yearly).

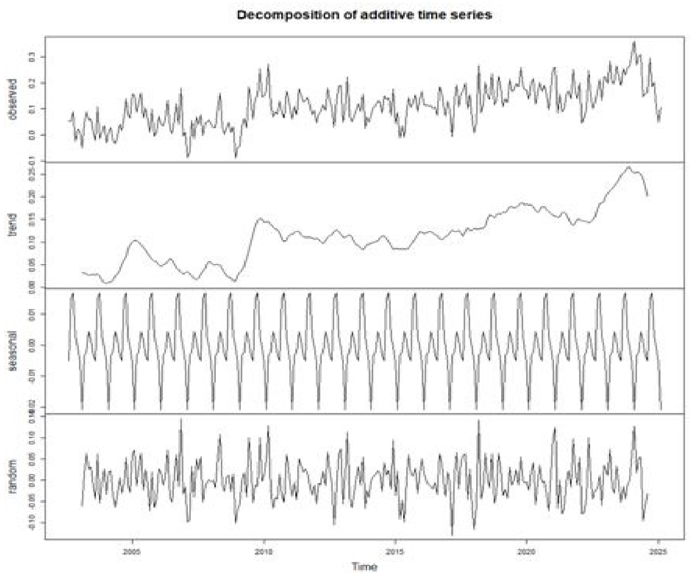

Figure 3: Decomposition of Monthly Mean Sea Level at Ocean City, Maryland, August 2002 ~ February 2025 (Source: R Output)

To ensure reproducibility of results, the set.seed() function was used before building time series forecasting models with auto.arima(), ets(), nnetar(), tbats(), thetam(), and stlm(). These models were then combined with equal weights to maintain a balanced influence. The accuracy of time series forecasting was measured using five evaluation metrics: ME (Mean Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MPE (Mean Percentage Error), and MAPE (Mean Absolute Percentage Error), as shown in Table 1.

Table 1. Model Comparison with Equal Weights Using Whole Data

Model	ME	RMSE	MAE	MPE	MAPE
ALL	0.0019	0.0464	0.0362	22.0105	80.1503
ARIMA(0,1,2)(0,0,1)[12]	0.0028	0.0549	0.0433	32.6959	99.5376
ETS(A,N,N)	0.0011	0.0563	0.0442	28.9727	102.0032
NNAR(24,1,12)[12]	2.35e-05	0.0011	0.0006	-0.0911	1.2191
THETAM	-0.0015	0.0577	0.0454	27.8751	104.4574
TBATS	0.0048	0.0554	0.0431	31.5363	97.9432
STLM	0.0008	0.0529	0.0417	27.2736	96.1549
Hybrid (ARIMA × ETS)	0.0019	0.0552	0.0434	30.8343	100.3814
Hybrid (ARIMA × NNAR)	0.0018	0.0284	0.0224	15.5025	49.0385
Hybrid (ARIMA × TBATS)	0.0038	0.0548	0.0429	32.1161	97.5751

Hybrid (ARIMA × THETAM)	0.0006	0.0555	0.0436	30.2855	101.2597
Hybrid (ARIMA × STLM)	0.0018	0.0527	0.0413	29.9847	96.3022
Hybrid (ETS × NNAR)	0.0008	0.0293	0.0229	12.9262	50.6615
Hybrid (ETS × TBATS)	0.0030	0.0556	0.0434	30.2545	98.9815
Hybrid (ETS × THETAM)	-0.0002	0.0566	0.0445	28.4239	102.9636
Hybrid (ETS × STLM)	0.0010	0.0541	0.0423	28.1231	98.1489
Hybrid (NNAR × TBATS)	0.0032	0.0286	0.0222	14.3976	47.9376
Hybrid (NNAR × THETAM)	-0.0007	0.0299	0.0235	12.0620	51.7234

Based on the comparison of various forecasting models, it is evident that the NNAR (24,1,12)[12] model stands out as the most accurate and reliable (Figure 5). This model consistently achieved the lowest error metrics across all categories, including ME, RMSE, MAE, MPE, and MAPE. Its performance is particularly noteworthy in terms of RMSE and MAE, where it significantly outperformed other models, indicating its high precision in forecasting.

Hybrid models (Zhang, 2003) that incorporate NNAR also demonstrated strong performance, especially Hybrid (NNAR × STLM) and Hybrid (NNAR × TBATS). These models leveraged the strengths of NNAR and other methods to achieve lower error rates, making them viable options for accurate forecasting. The combination of NNAR with STLM, in particular, showed promising results with low RMSE and MAE values, suggesting that hybrid approaches can enhance forecasting accuracy.

On the other hand, models like ETS(A,N,N) and THETAM exhibited higher error metrics, indicating less reliability in their forecasts. While these models may still be useful in certain contexts, their higher error rates suggest that they may not be the best choice for applications requiring high precision.

In conclusion, the NNAR model and its hybrid variations offer the best overall performance for forecasting, with significantly lower error metrics compared to other models. These findings highlight the importance of selecting models that balance accuracy and reliability, especially in fields where precise forecasting is crucial. Comparison underscores the potential of hybrid models to improve forecasting accuracy by combining the strengths of different approaches.

One of the main objectives of decomposition is to estimate seasonal effects that can be used to create and present seasonally adjusted values. Seasonal adjustment involves removing seasonal effects that are not explainable by the dynamics of trends or cycles from a time series to reveal certain non-seasonal features. This can be done by subtracting the estimated seasonal component from the original time series. After removing the seasonal variation, the seasonally adjusted time series contains only the trend component and an irregular component (Figure 4).

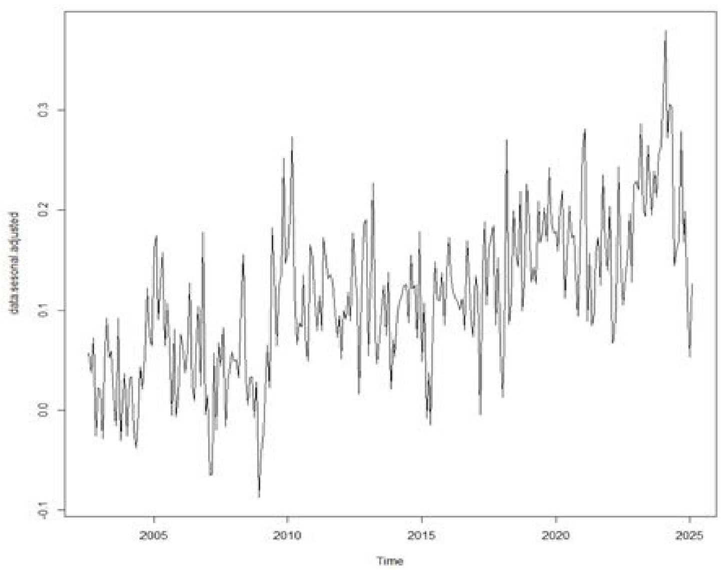

Figure 4: Time Series Plot of Seasonal Adjusted Monthly Mean Sea Level at Ocean City, Maryland, August 2002 ~ February 2025 (Source: R Output)

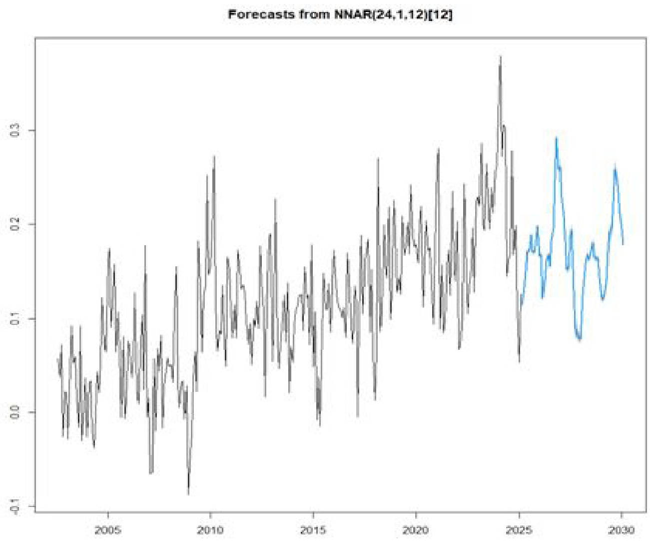

Figure 5: Time Series Forecasting Model of NNAR(24,1,12)[12] (Source: R Output)

Discussion and Conclusion

The importance of sea level forecasting cannot be overstated. It plays a vital role in protecting lives, preserving ecosystems, and ensuring sustainable development in coastal regions. By leveraging advanced time series models and integrating data from various sources, scientists and policymakers can better anticipate and respond to the challenges posed by rising sea levels.

Accurate forecasts enable early warning systems and disaster preparedness, allowing communities to respond effectively to impending floods. Additionally, forecasting aids in designing resilient structures and retrofitting existing infrastructure to withstand future sea level changes. It plays a vital role in environmental conservation by protecting critical habitats such as wetlands, mangroves, and coral reefs, and supporting restoration projects.

Policymakers rely on sea level forecasts to make informed decisions about land use, zoning, and coastal development, ensuring sustainable development. Furthermore, sea level forecasting drives scientific research and innovation, leading to improved predictive models and technological advancements. Overall, sea level forecasting is essential for protecting lives, preserving ecosystems, and ensuring sustainable development in coastal regions.

In this study, the NNAR (24,1,12)[12] model demonstrated the best overall performance with the lowest error metrics across all categories, making it the most accurate and reliable forecasting model. Hybrid models that combine NNAR with other methods, such as STLM and TBATS, also showed strong performance. These models leverage the strengths of multiple approaches to achieve lower error rates and enhance forecasting accuracy. ETS(A,N,N) and THETAM models exhibited higher error metrics, indicating less reliability in their forecasts compared to NNAR and hybrid models.

The superior performance of NNAR and hybrid models suggests that neural network-based and hybrid approaches can provide highly accurate forecasts, which can benefit various domains such as finance, supply chain management, and strategic planning. Overall, the NNAR model and its hybrid variations offer the best forecasting accuracy, highlighting the potential of advanced machine learning techniques and hybrid approaches in improving forecasting reliability.

The future of data-driven sea level forecasting is promising, with several innovative approaches and advancements on the horizon. One key area of focus is the integration of advanced machine learning techniques, such as Long Short-Term Memory (LSTM) models, which have shown superior performance in forecasting sea level rise. Researchers are working on refining these models further to enhance their accuracy and computational efficiency. Another promising approach is the use of synthetic data to augment real-world datasets, which helps in training models more effectively, especially when historical data is limited.

Addressing uncertainty in sea level forecasts is crucial, and future research focuses on developing methods to quantify and reduce uncertainty using probabilistic models and ensemble forecasting techniques. Real-time monitoring and forecasting advancements will enable more timely and accurate sea level forecasts by integrating real-time data from sensors and satellite observations with predictive models. Finally, developing decision support systems that utilize advanced forecasting models can aid policymakers in making informed decisions, providing actionable insights and recommendations based on the latest sea level predictions. These advancements will play a crucial role in helping coastal communities and policymakers prepare for and respond to the challenges posed by rising sea levels.

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Conflicts of interest

The author declares that there is no conflict of interest concerning the publishing of this paper.

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