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Original Article

Data-Driven Sea Level Forecasting for Cambridge, Maryland: Leveraging Time Series Models

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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 Cambridge, Maryland, spanning January 1971 to February 2025, a comparative analysis was conducted. The NNAR(27,1,14)[12] model emerged as the most accurate, performing exceptionally well across all metrics, especially 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.*

Keywords *- Mean Sea Level, Time Series Forecasting, Neural Network Autoregression, Ocean City, Maryland.*

1. Introduction

Predominantly by human activities such as fossil fuel combustion and deforestation, alongside natural phenomena like volcanic eruptions. According to the National Oceanic and Atmospheric Administration [1], global annual temperatures have risen at an average rate of 0.07°C per decade since 1880, with the rate doubling to 0.18°C per decade since 1981. One of the most critical consequences of ecological change is the rise of global sea levels, primarily caused by melting glaciers and ice sheets and the thermal expansion of warming oceans. However, the magnitude and pace of sea level rise vary regionally, influenced by factors such as land subsidence and ocean current shifts, including the deceleration of the Gulf Stream. The impacts are profound, including increased coastal flooding and erosion, loss of agricultural productivity, damage to infrastructure, and disruption of coastal ecosystems.

Empirical data highlights the scale of the problem. NOAA reports that the global sea level has risen by approximately 21–24 cm since 1880. The Intergovernmental Panel on Climate Change (IPCC) [2] projected a rise of 52–98 cm by 2100 under high-emission scenarios. Similarly, the U.S. Global Change Research Program (USGCRP) [3] noted a 16–21 cm rise since 1900, with nearly half occurring since 1993. Future projections suggest sea levels may increase by 9–18 cm by 2030 and 30–130 cm by 2100, relative to 2000. Long-term analyses, such as those by Church and White [4], estimate sea level rise at rates of 3.2 ± 0.4 mm/year from satellite data and 2.8 ± 0.8 mm/year from in situ measurements, with an accelerating trend since the late 19th century. The observed variability underscores the importance of continuous monitoring and accurate forecasting.

A growing body of literature confirms that sea level rise is accelerating [5]-[8]. As a result, understanding historical trends is essential for anticipating future changes. Recent advances in in situ and satellite observations have significantly improved the modeling of sea level dynamics [9], [10]. Despite this progress, there remains a notable gap in studies focused on localized forecasting techniques. Time series forecasting, particularly using neural networks, has emerged as a promising approach to modeling sea level trends. Neural networks excel in identifying complex patterns in temporal data and have shown growing success in sea level rise applications [11]-[13]. This study aims to demonstrate the effectiveness of time series models in forecasting sea level rise by analyzing long-term monthly mean sea level data from Ocean City, Maryland. By advancing predictive modeling techniques, this research seeks to contribute to more accurate, localized forecastsessential tools for coastal resilience planning and policy formulation in the face of rising seas.

2. Literature Review

Understanding and projecting sea level rise (SLR) has been a central focus of climate science, with numerous studies seeking to quantify its magnitude, identify its drivers, and evaluate its long-term implications. Early investigations, such as those by Church et al. [5], laid the foundation for recognizing the accelerating nature of SLR, citing global temperature rise and cryospheric melt as primary factors.

Subsequent research by Cazenave and Llovel [6] and Church and White [4] reinforced this acceleration and highlighted the increasing role of satellite altimetry in capturing global sea level trends with higher precision. Several studies have established robust historical records of sea level changes. Church and White [4] estimated that the global mean sea level rose at an average rate of 1.7 ± 0.2 mm/year from 1900 to 2009, with a notable increase to 3.2 ± 0.4 mm/year in the satellite era. Regional disparities have also been explored, attributing localized deviations to factors such as ocean circulation patterns, gravitational effects from melting ice sheets, and land subsidence [14], [15].

The modeling of future SLR has evolved from simplistic linear extrapolations to complex simulation frameworks integrating climatic, hydrologic, and geophysical variables. The Intergovernmental Panel on Climate Change (IPCC) [2] employs multi-model ensemble approaches, incorporating both greenhouse gas emission scenarios and socioeconomic variables to project a likely sea level rise of up to 98 cm by 2100 under high-emission pathways. Similarly, the U.S. Global Change Research Program (USGCRP) [3] emphasizes the importance of incorporating probabilistic risk assessments to better understand the range of plausible future outcomes, particularly for coastal planning. Despite progress in physical and statistical modeling of SLR, challenges remain in translating these models to localized, actionable forecasts. Traditional methods, including autoregressive integrated moving average (ARIMA) models, have been widely used in time series analysis for sea level prediction [16], [17].

However, such models often assume linearity and stationarity, which limit their applicability in dynamically changing climatic contexts. To overcome these limitations, machine learning (ML) techniques, particularly neural networks, have gained traction in environmental time series forecasting. Artificial neural networks (ANNs), with their capacity for nonlinear mapping and adaptability, have been successfully applied to sea level data forecasting in recent years. For instance, Bruneau et al. [11] used a multi-layer perceptron model to predict sea level variability with high accuracy, while Bruno and Afonso [12] demonstrated the effectiveness of recurrent neural networks (RNNs), including long short-term memory (LSTM) architectures, in capturing temporal dependencies in sea level datasets. Other studies have explored hybrid and ensemble methods to enhance forecasting accuracy. Alenezi et al. [13] integrated LSTM models with wavelet decomposition to improve predictions by denoising the input signal, showing that combining deep learning with signal processing techniques can offer superior performance. These approaches represent a shift from purely deterministic models toward data-driven, adaptive frameworks that can assimilate heterogeneous datasets and accommodate evolving patterns.

Moreover, the incorporation of satellite-derived datasets and in situ measurements has significantly enriched the training and validation of ML models. Foster and Brown [9] and Visser et al. [15] emphasized the utility of integrating diverse sources of sea level data, including tide gauges, altimetry, and gravimetric observations, to support high-resolution forecasting efforts. Despite these advancements, the application of neural networks to localized sea level prediction remains underdeveloped in the literature, especially in mid-Atlantic coastal zones such as Ocean City, Maryland. This study addresses this gap by employing neural network-based time series models to analyze long-term sea level trends and project future changes at the local scale. In doing so, it contributes to the growing body of research aimed at enhancing predictive accuracy and informing coastal resilience strategies in the face of ongoing climate change.

3. Materials and Methods

3.1. Study Site

Cambridge is a city located at 38°33′59″N 76°4′37″W in Dorchester County, Maryland, United States (Figure 1). It is the county seat of Dorchester County and the county's largest municipality. The population of Cambridge was 13,096 at the 2020 census, which is the fourth most populous city in Maryland's Eastern Shore region, after Salisbury, Elkton and Easton [18]. Cambridge is on the southern bank of the Choptank River. According to the United States Census Bureau, the city has a total area of 12.64 square miles (32.74 km^2), of which, 10.34 square miles (26.78 km^2) is land and 2.30 square miles (5.96 km^2) is water. The climate in this area is characterized by hot, humid summers and generally mild to cool winters [19].

3.2. Data Source

The long-term records of monthly mean sea level from January 1971 to February 2025 at Cambridge, Maryland, used for this study is available to the public from NOAA Tides and Currents (https://tidesandcurrents.noaa.gov/). Average monthly mean sea level was 0.032 mm/year with the standard deviation of 0.0911 mm/year (Minimum: -1940 mm/year, Maximum: 0.3690 mm/year, and Median: 0.0240 mm/year) at Cambridge, Maryland, from January 1971 to February 2025 (Figure 2). 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 is the basis of marine boundaries, can be used as a vertical reference plane in producing nautical charts, and can provide important baseline information for observing changes in sea level over time. Mean sea level as a tidal datum is computed as a mean of hourly water level heights observed over 19-years [20]. Monthly means generated in the datum calculation process, which is used to generate the relative local sea level trends observed at a tide station.

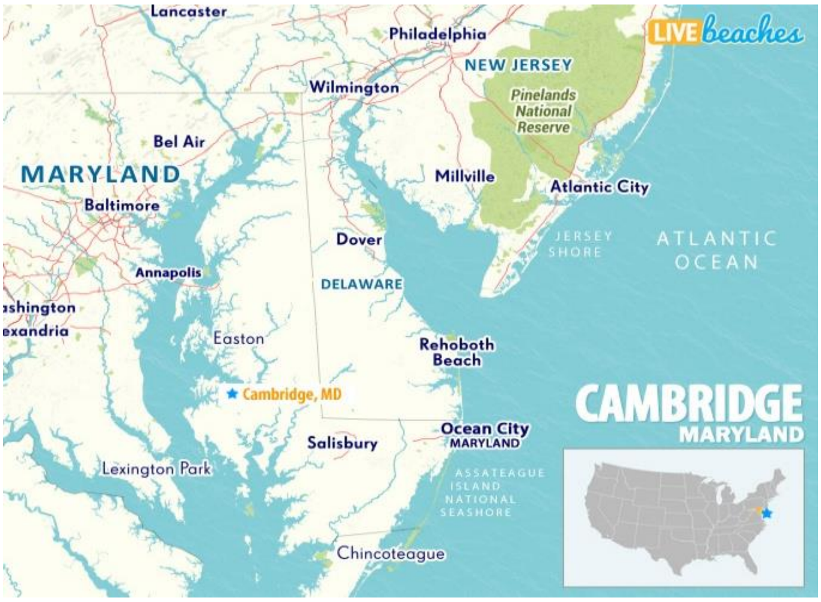

Fig 1: Cambridge, Maryland, USA
(Source: Map of Beaches in Maryland, adapted from: https://www.livebeaches.com /map-of-beaches-in-maryland/)

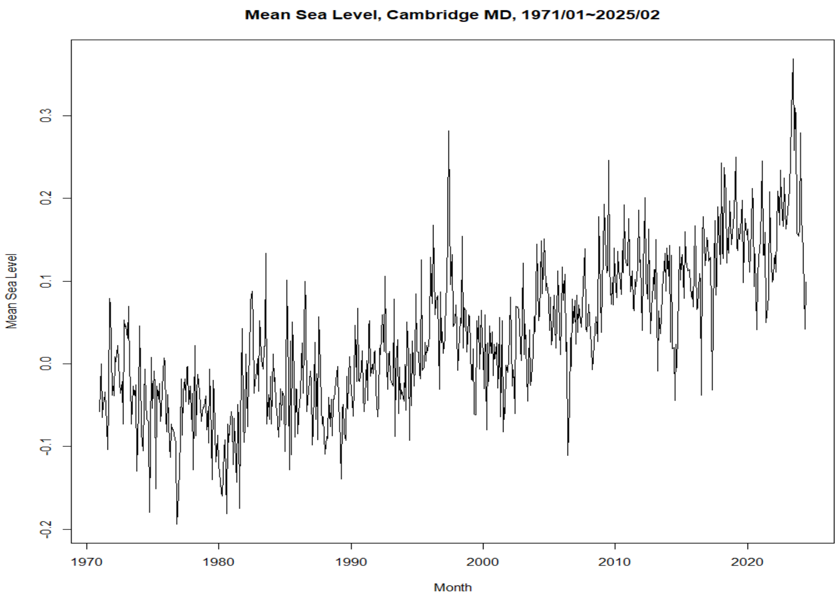

Fig 2: Time Series Plot of Monthly Mean Sea Level at Cambridge, Maryland, January 1971 ~ February 2025 (Source: R Output)

3.2. ForecastHybrid

The "forecastHybrid" (convenient functions for ensemble time series forecasts) package in R (https://cran.r-project.org/web/packages/forecastHybrid/index.html) provides functions 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 [21]. ARIMA (AutoRegressive Integrated Moving Average) is a model that 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) is a model that 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) is a model that 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) is a model that 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.

3.3. 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 [22]. These models treat lagged values of the time series as inputs, like autoregressive (AR) models, but use a non-linear function (the hidden layer) to predict the next value [23]. 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:

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

The notation β_{ij} ($i = 0, 1, 2, \ldots, n$; $j = 1, 2, \ldots, h$) and α_j ($j = 0, 1, 2, \ldots, h$) are weight in the model. The notation p is the number of neurons in the input layer and h is the number of neurons in the hidden layer.

This autoregressive neural network uses a single hidden layer, and then 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:

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

The notation z_j is the sum function of the bias unit to j on the hidden layer, β_{0j} is the weight of the bias unit to j , β_{ij} is the weight of i the layer of the bias to j , y_{t-i} is the input to i , network activation function is a non-linear function in the form of a binary sigmoid function and is 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 [24]-[26] (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 that are used as inputs. K denotes the number of hidden nodes that are present. 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 y_t, 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 then also the notation is pretty similar, i.e., 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 layer. 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-Pm}) 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 [27].

3.4. 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) 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 [21], [24]-[26].

4. Results

Decomposing a seasonal time series means separating the time series into a trend component, a seasonal component and an irregular component respectively [28]. The function "decompose()" in R can be applied to separate the seasonal component, trend component and irregular components of a seasonal time series. The plots in Figure 3 showed 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 showed a steady increase over time, and the estimated seasonal component displayed seasonality, with a pattern recurrence occurring once every 12 months (yearly).

One of the main objectives for a decomposition is to estimate seasonal effects that can be used to create and present seasonally adjusted values. Thus, seasonal adjustment is the removal of 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 the seasonal variation was removed, the seasonally adjusted time series only contained the trend component and an irregular component (Figure 4).

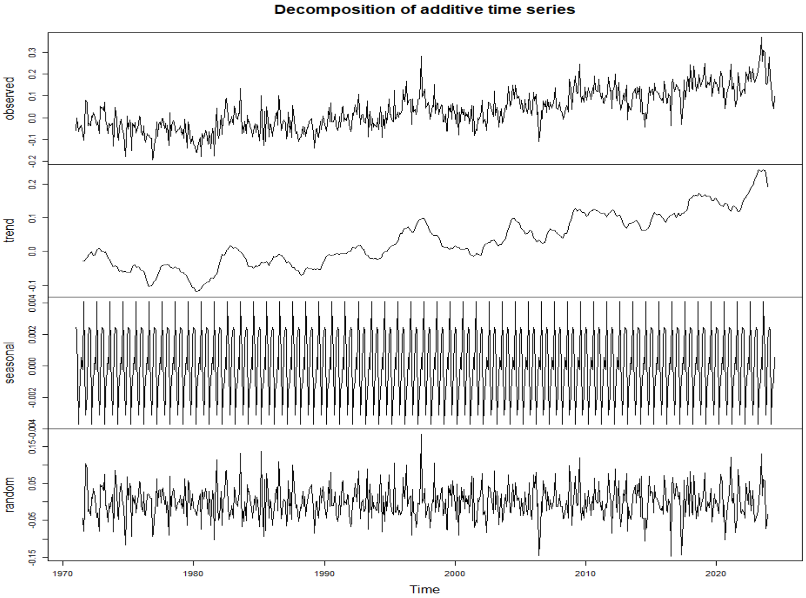

Fig 3: Decomposition of Monthly Mean Sea Level at Cambridge, Maryland, January 1971 ~ February 2025 (Source: R Output)

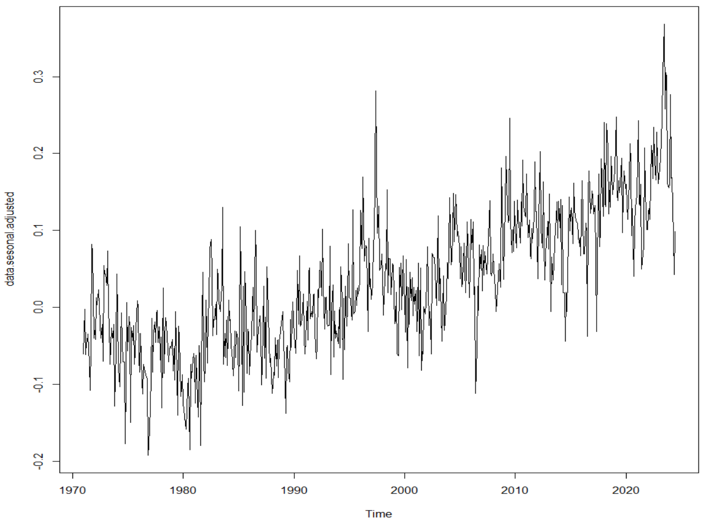

Fig 4: Time Series Plot of Seasonal Adjusted Monthly Mean Sea Level at Cambridge, Maryland, January 1971 ~ February 2025

(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 (Table 1). 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 2. Based on the comparison of various forecasting models, it is evident that the NNAR(27,1,14)[12] model stands out as the most accurate and reliable with the lowest RMSE (0.0077) and MAE (0.0053), indicating high accuracy (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 [29] combining NNAR with other methods, such as Hybrid (NNAR × STLM), also show strong performance with low RMSE (0.0264) and MAE (0.0202). On the other hand, the THETAM model exhibits the highest MPE (82.3481) and MAPE (114.2058), suggesting higher errors in percentage terms. Hybrid models generally perform better than individual models, with combinations like Hybrid (ARIMA × NNAR) and Hybrid (ETS × NNAR) showing improved accuracy and lower error rates. Overall, the NNAR model and its hybrids demonstrate superior forecasting capabilities, while the THETAM model appears less reliable in terms of percentage errors. 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. The comparison underscores the potential of hybrid models to improve forecasting accuracy by combining the strengths of different approaches.

Table 1: Model Comparison with Equal Weights Using Whole Data

Model	ME	RMSE	MAE	MPE	MAPE
ALL	0.0048	0.0426	0.0323	29.8305	117.7962
ARIMA(3,1,1) with Drift	-0.0004	0.0497	0.0376	28.7359	140.2303
ETS(A,N,N)	0.0009	0.0506	0.0390	28.2271	152.6493
NNAR(27,1,14)[12]	-0.0002	0.0077	0.0053	4.4976	21.6931
THETAM	0.0251	0.0787	0.0620	82.3481	114.2058
TBATS	0.0037	0.0499	0.0379	27.9573	147.9023
STLM	0.0008	0.0462	0.0356	7.0253	150.1634
Hybrid (ARIMA × ETS)	0.0003	0.0498	0.0380	28.4815	145.5239
Hybrid (ARIMA × NNAR)	-0.0005	0.0279	0.0211	17.7126	76.0891
Hybrid (ARIMA × TBATS)	0.0016	0.0497	0.0376	28.3466	143.7038
Hybrid (ARIMA × THETAM)	0.0124	0.0587	0.0455	55.5420	117.9888
Hybrid (ARIMA × STLM)	0.0002	0.0469	0.0357	17.8806	142.8553
Hybrid (ETS × NNAR)	0.0002	0.0286	0.0219	15.0240	83.1097
Hybrid (ETS × TBATS)	0.0023	0.0501	0.0382	28.0922	149.7379
Hybrid (ETS × THETAM)	0.0130	0.0578	0.0447	55.2876	121.2567
Hybrid (ETS × STLM)	0.0009	0.0477	0.0366	17.6262	149.6273
Hybrid (NNAR × TBATS)	0.0015	0.0281	0.0212	14.1207	78.5595
Hybrid (NNAR × THETAM)	0.0129	0.0419	0.0329	38.9262	66.7577
Hybrid (NNAR × STLM)	0.0001	0.0264	0.0202	3.6403	83.0867
Hybrid (TBATS × THETAM)	0.0144	0.0587	0.0453	55.1527	121.1954
Hybrid (TBATS × STLM)	0.0022	0.0472	0.0359	17.4913	146.7048
Hybrid (THETAM × STLM)	0.0132	0.0553	0.0427	44.6867	120.2923

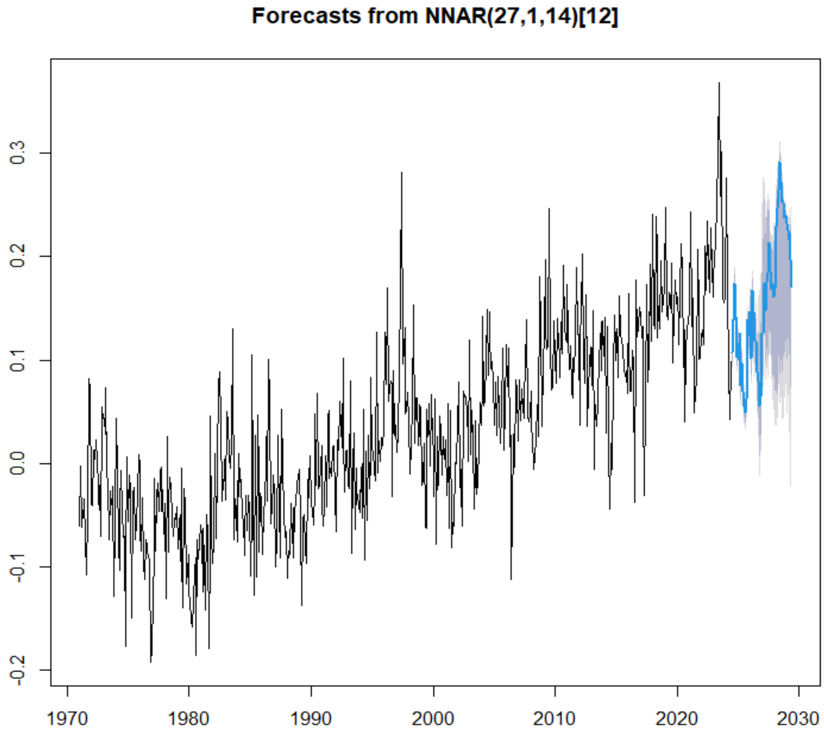

Fig 5: Time Series Forecasting Model of NAR (27,1,14)[12] (Source: R Output)

5. 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, NNAR(27,1,14)[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) model, 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.

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

5.2. Acknowledgements
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