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Statistical Characterization of Residual Interannual Fluctuations for Sea Level From ARIMA Modeling of Adjusted NOAA Data

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ABSTRACT

Sea level rise, a critical consequence of global climate change, poses significant challenges to coastal communities worldwide. While long-term trends in sea level rise garner considerable attention, understanding and predicting interannual variability fluctuations are equally crucial for effective coastal management and adaptation. This research investigates detrended annual variability of adjusted sea level data, focusing on the unpredictable fluctuations superimposed on long-term trends. By employing Autoregressive Integrated Moving Average (ARIMA) modeling, this study aims to quantify and forecast these interannual variations, providing a statistical baseline that underscores the challenge of interannual variability prediction for coastal management. Utilizing adjusted annual sea level measurements from the National Oceanic and Atmospheric Administration (NOAA) spanning 1993 to 2019, this research isolates residual interannual fluctuations by removing the influence of long-term trends and other components through data adjustment. This adjustment process, typically incorporating corrections for factors like glacial isostatic adjustment (GIA) and vertical land motion (VLM), enables a focused analysis of the residual fluctuations. The adjusted sea level data was imported into the Minitab web platform for analysis. The "Forecast with Best ARIMA Model" tool within Minitab's "Stat" menu was employed to automatically identify, fit and diagnose the most appropriate ARIMA model. This tool explores a range of potential ARIMA models, varying the order of autoregressive (AR), integrated (I) and moving average (MA) components, using the Akaike Information Criterion with correction (AICc) to select the best-fitting model while penalizing complexity. The results of this analysis reveal that, after an extensive screening of the ARIMA parameter space, the ARIMA(0,1,0) model, also known as the random walk with drift, emerged as the optimal representation of the adjusted sea level data. This suggests that the residual interannual variability, after accounting for factors removed during data adjustment, is largely unpredictable within the ARIMA framework. The selected model was then used to generate 100-year forecasts, from 2020 to 2119, along with 95% confidence intervals to quantify forecast uncertainty. The standard error of the forecasts was also analyzed, revealing a clear increase in uncertainty with longer forecast horizons. In conclusion, this research demonstrates that while the adjusted sea level exhibits significant annual variability, this variability is largely unpredictable using ARIMA models. This finding underscores the importance of separating the analysis of these kinds of fluctuations from the long-term sea level rise trend, which must be modeled using different approaches. The 100-year forecasts and associated confidence intervals provide valuable information for coastal communities to better prepare for and manage the risks associated with interannual sea level fluctuations, even if precise predictions are not possible. Concurrence of AICc, AIC and BIC provide strong support for validity of the model, reinforces the principle of parsimony, suggests genuine random walk behavior in the adjusted sea level data and increases confidence in the interpretation of the results. While the ARIMA(0,1,0) serves as a robust baseline for understanding the inherent unpredictability of adjusted sea level variations, future research could explore the potential of incorporating predictors, such as climate indices or employing non-linear time series models to further refine understanding and predictive capabilities concerning interannual sea level changes.

INTRODUCTION

Sea level rise stands as one of the most pressing and multifaceted challenges of the 21st century, posing significant threats to coastal communities, ecosystems, and global economies. The intricate interplay between a warming climate, melting ice sheets, thermal expansion of ocean water, and vertical land motion contributes to a complex tapestry of sea level changes that demand careful observation, analysis, and prediction (Priestley et al., 2021; Durand et al., 2022). There is a critical need to explore the aspect of detrended annual variability sea level variability, recognizing that understanding these fluctuations around long-term trends is crucial for effective adaptation and resilience in the face of a changing climate (Shaw et al., 2024). Herein, the 'short-term' refers to interannual variability, as the use of annual data inherently aggregates and removes higher-frequency signals such as seasonal cycles, tides, and storm surges. The scientific consensus regarding the reality and accelerating pace of global warming is unequivocal. The Intergovernmental Panel on Climate Change (IPCC), in its Sixth Assessment Report (AR6), unequivocally states that "it is unequivocal that human influence has warmed the atmosphere, ocean and land" (IPCC, 2021). This warming trend, primarily attributed to anthropogenic greenhouse gas emissions, has profound implications for the Earth's climate system, driving changes in temperature, precipitation patterns, and, critically, sea levels (IPCC, 2021; Priestley et al., 2021). The primary drivers of global mean sea level rise are thermal expansion of ocean water as it warms, melting of glaciers and ice sheets, and changes in land water storage (Durand et al., 2022). While the long-term trend of sea level rise is a dominant feature and a focus of much research, the inherent variability of sea level on shorter timescales also plays a critical role in shaping coastal vulnerability (Shaw et al., 2024).

The IPCC AR6 highlights the alarming projections of future sea level rise, with global mean sea level expected to rise between 0.44 meters and 0.76 meters (17.3 inches and 29.9 inches) by 2100 relative to 1995-2014 under intermediate greenhouse gas emission scenarios (SSP2-4.5) (IPCC, 2021). These projections underscore the urgency of adapting to the inevitable impacts of sea level rise. However, the challenge lies not only in anticipating the long-term trend but also in managing the day-to-day, seasonal, and interannual fluctuations that can exacerbate the impacts of the rising mean sea level. These short-term variations, often driven by factors like tides, storm surges, El Niño-Southern Oscillation (ENSO) events, and local meteorological conditions, can lead to extreme water levels that cause coastal flooding, erosion, and damage to infrastructure However, the challenge lies not only in anticipating the long-term trend but also in managing the interannual fluctuations that can exacerbate the impacts of the rising mean sea level. These climatic and oceanographic variations, often driven by factors like tides, storm surges, El Niño-Southern Oscillation (ENSO) events, and local meteorological conditions, can lead to extreme water levels that cause coastal flooding, erosion, and damage to infrastructure.

(Oppenheimer et al., 2019; Sweet et al., 2022). Coastal communities are particularly vulnerable to the combined effects of long-term sea level rise and interannual variability. As the mean sea level rises, even minor fluctuations in water level can push coastal areas beyond critical thresholds, leading to increased frequency and severity of flooding events. This heightened vulnerability necessitates a comprehensive understanding of both the long-term trends and the interannual variability of sea level to inform effective adaptation strategies. Coastal planning and management decisions, including land use planning, infrastructure development, and disaster preparedness, require accurate and reliable information about the range of potential sea level changes, encompassing both the gradual rise and the more immediate fluctuations.

Traditional approaches to sea level analysis often focus on estimating and projecting long-term trends, providing valuable information for assessing long-term risks and planning for future sea level rise. However, these approaches may overlook the crucial role of interannual variability in shaping immediate coastal vulnerability. Understanding the magnitude and characteristics of these fluctuations is essential for developing effective strategies to mitigate the impacts of extreme water levels and protect coastal communities from near-term hazards. This research addresses this critical gap by focusing specifically on the analysis and forecasting of interannual sea level variability.

The importance of this research is further underscored by the challenges associated with accurately predicting sea level changes in both long and short timescales. While significant progress has been made in understanding the drivers of global mean sea level rise, projecting regional sea level changes and interannual fluctuations remains a complex undertaking. Regional sea level is influenced by a combination of global factors, such as thermal expansion and ice melt, and regional processes, including vertical land motion (VLM) due to geological and anthropogenic factors, ocean currents, and local meteorological conditions (Bromirski et al., 2003; Wöppelmann & Marcos, 2016). VLM, which can cause land to subside or uplift, is a particularly important factor in determining the relative sea level change experienced by coastal communities. Accurately accounting for VLM is crucial for interpreting local sea level measurements and making reliable projections. Furthermore, interannual sea level variability is influenced by a complex interplay of factors, some of which are inherently unpredictable. While tides are a predictable component of sea level variation, other factors, such as storm surges and ENSO events, are more challenging to forecast (McPhaden et al., 2006). Storm surges, generated by strong winds and low atmospheric pressure, can cause significant deviations from predicted tidal levels, leading to coastal flooding. ENSO events, characterized by fluctuations in sea surface temperatures in the Pacific Ocean, can also influence regional sea levels through their impact on weather patterns and ocean currents. These complexities highlight the need for sophisticated statistical techniques to analyze and model interannual sea level variability.

This research employs a time series analysis approach, utilizing the Autoregressive Integrated Moving Average (ARIMA) modeling framework, to investigate the interannual variability of adjusted sea level data. ARIMA models are a class of statistical models widely used for analyzing and forecasting data from time series (Box et al., 2015; Hyndman & Athanasopoulos, 2018). They are particularly well-suited for capturing the complex dependencies and patterns in geophysical time series, including sea level fluctuations (Pugh & Woodworth, 2014; Box et al., 2015). They (ARIMA models) are particularly well-suited for capturing the complex dependencies and patterns that characterize sea level fluctuations (Box et al., 2015; Hyndman & Athanasopoulos, 2018). Critically, the sea level data used in this study has been adjusted to remove the influence of long-term trends and other predictable components, allowing us to isolate and focus specifically on the interannual variability. This adjustment process typically involves removing the estimated contributions of factors like glacial isostatic adjustment (GIA) and vertical land motion (VLM), effectively detrending the data (Peltier, 2004; Wöppelmann & Marcos, 2016; NOAA, 2022). By analyzing the residual variability after these adjustments, we aim to gain a clearer understanding of the unpredictable interannual fluctuations that are superimposed on the long-term trend. A key objective of this research is to identify the best-fitting ARIMA model that adequately captures the statistical characteristics of the adjusted sea level data. We employ a rigorous model selection procedure, exploring a wide range of ARIMA models with different orders of autoregressive (AR) and moving average (MA) components and different levels of differencing (I). The Akaike Information Criterion with correction (AICc) is used to compare the goodness-of-fit of different models, penalizing model complexity to avoid overfitting (Hyndman & Khandakar, 2008). This extensive screening of the ARIMA parameter space allows us to confidently select the most parsimonious model that adequately represents the observed interannual variability. This research also addresses the critical issue of forecast uncertainty. Given the inherent unpredictability of some of the factors influencing sea level, it is essential to quantify the uncertainty associated with any sea level forecast. We utilize the selected ARIMA model to generate long-term forecasts of adjusted sea level and compute confidence intervals around these forecasts. These confidence intervals provide a measure of the range of plausible future sea level fluctuations, allowing coastal communities to assess and manage the associated risks.

The central question that this research seeks to answer is: What is the nature and predictability of interannual sea level variability after accounting for long-term trends and other predictable components? By addressing this question, we aim to provide valuable information for coastal planning and management, infrastructure design, and emergency preparedness (Nicholls et al., 2014; Pugh & Woodworth, 2014). Specifically, this research can contribute to: Improved coastal planning: By providing quantitative estimates of interannual sea level fluctuations, this research can help coastal communities make informed decisions about land use planning, development setbacks, and the design of coastal defenses. Enhanced infrastructure design: Engineers can utilize the information on potential sea level variability to design coastal infrastructure that is resilient to extreme water levels and coastal erosion. Strengthened emergency preparedness: Emergency managers can use the forecasts and uncertainty estimates to develop and implement effective plans for coastal flooding events, including evacuation strategies and disaster response measures. Ultimately, this research aims to contribute to a more nuanced understanding of the complexities of sea level change and to provide valuable information for building resilient coastal communities in the face of a changing climate. While the focus is on interannual variability, this research also serves to highlight the critical importance of ongoing efforts to understand and project long-term sea level trends, which are essential for addressing the long-term challenges of sea level rise. By disentangling the various components of sea level change, we can develop more effective strategies to mitigate the impacts of rising seas and protect vulnerable coastal populations.

MATERIAL AND METHODS

This research investigates the interannual variability of adjusted sea level using a time series analysis approach. The data source is the National Oceanic and Atmospheric Administration (NOAA) Sea Level Rise Viewer (NOAA, 2022), specifically data accessed from the Digital Coast platform, spanning the years 1993 to 2019, with the data being recorded annually in inches, as it is the standard unit used by NOAA. The period from 1993 to 2019 was selected as it corresponds to the modern altimetry era, providing a consistent, high-quality global dataset.

Data Preparation

The dataset, consisting of annual adjusted sea level measurements, (It's a yearly record focused purely on the random ups and downs of sea level, not its long-term trend) was directly imported into the Minitab web platform. No further transformations or adjustments were deemed necessary as the data was already provided in its adjusted form, pre-processed by NOAA to account for long-term trends and other predictable influences. This pre-adjustment typically includes corrections for factors such as glacial isostatic adjustment (GIA) and vertical land motion (VLM) (Peltier, 2004; Wöppelmann & Marcos, 2016), enabling the analysis to focus specifically on the residual interannual variability. In layman's term, it's like subtracting the movement of the bathtub to measure only the movement of the water inside it. This allows scientists to isolate the true change in sea water height. The annual resolution of the data inherently aggregates within-year fluctuations, effectively excluding any seasonal patterns. Therefore, no further adjustments for seasonality were deemed necessary.

Time Series Analysis

The core of the analysis involved utilizing the ARIMA modeling framework to characterize and forecast the detrended annual fluctuations in the adjusted sea level. ARIMA models are a class of statistical models commonly employed for analyzing and forecasting time series data due to their ability to capture complex dependencies and patterns within the data (Box et al., 2015; Hyndman & Athanasopoulos, 2021). The analysis was conducted using the "Forecast with Best ARIMA Model" tool available within the "Stat" menu of the Minitab web platform. This tool automates the process of identifying, fitting, and diagnosing the most appropriate ARIMA model for the given time series (Minitab LLC, 2023).

Model Identification and Selection

The "Forecast with Best ARIMA Model" tool in Minitab automatically explores a range of potential ARIMA models, varying the order of autoregressive (AR) components (p), integrated (I) components or degree of differencing (d), and moving average (MA) components (q). The tool employs the Akaike Information Criterion with correction (AICc) to guide model selection. AICc is a statistical measure that evaluates the goodness-of-fit of different models while penalizing model complexity. This helps prevent overfitting, ensuring the selected model generalizes well to unseen data (Hyndman & Khandakar, 2008). Minitab's automated tool handles the often-complex task of ARIMA model identification, parameter estimation, and diagnostic checking (Minitab LLC, 2023). Different degrees of differencing levels were compared at d = 0, 1 and 2 to find the most suitable model parameters.

Forecasting

Once the optimal ARIMA model, as determined by the minimum AICc, was identified and fitted, the Minitab tool was used to generate forecasts for the next 100 years (from 2020 to 2119). The "Forecast with Best ARIMA Model" tool automatically calculates point forecasts as well as corresponding confidence intervals, providing a measure of the forecast uncertainty. Specifically, 95% confidence intervals were generated, representing the range within which the true adjusted sea level is expected to lie with 95% probability, assuming the chosen model is adequate (Minitab LLC, 2023).

Software and Platform

All analyses were performed using Minitab's web-based statistical software platform. This platform provides a user-friendly interface and access to powerful statistical tools, including the automated ARIMA modeling and forecasting capabilities used in this research (Minitab LLC, 2023).

RESULTS AND DISCUSSION

The application of statistical analysis software and methods for trend analysis has been demonstrated across diverse fields, including pharmaceutical quality control and disease monitoring, highlighting its versatility in identifying trends and patterns (Eissa, 2018a; Eissa & Abid, 2018; Eissa, 2018b; Eissa, 2018c; Rashed & Eissa, 2020). However, it is important to note that the current study applies different concepts and tools to a unique dataset of adjusted sea level measurements. An ARIMA model selection process was undertaken to forecast adjusted sea level (millimeters) using NOAA data from the Sea Level Rise Viewer (NOAA, 2022). Several ARIMA (p, d, q) models were evaluated, with the Akaike Information Criterion with correction (AICc) serving as the primary metric for model selection, as recommended for smaller sample sizes (Hyndman & Khandakar, 2008). A warning was issued regarding inestimable models, specifically those with d=0 and various combinations of p and q, including (1,0,0) through (5,0,4), and also model (5,1,2) with d=1. These models, which included a constant term, could not be reliably estimated, likely due to limitations in the data or model complexity, a common challenge in time series modeling (Box et al., 2015). The analysis utilized 27 rows of data, with none left unused. Figure 1 shows radar scan screening of various model parameters accompanied by Table 1 for statistical examination and comparative analysis for the best fits at d = 0, 1 and 2.

However, it is important to note that the current study applies these general statistical concepts and tools to a unique dataset of adjusted sea level measurements. For models with no differencing (d=0), the best model, achieving the minimum AICc of -13.2609, was an ARIMA(2,0,0) model (Table 1). This model exhibited statistically significant autoregressive terms, with AR 1 having a coefficient of 1.874 (p<0.000) and AR 2 having a coefficient of -0.876 (p=0.008). The model's residual variance (MSD) was 0.0188886. The Ljung-Box test indicated some potential autocorrelation at lag 12 (p=0.029) but not at lag 24 (p=0.431), suggesting a possible limitation in the model's ability to fully capture the autocorrelation structure at this lag (Ljung & Box, 1978).

When first-order differencing was applied (d=1), the best model, minimizing the AICc to -42.9753, was surprisingly identified as a simple random walk model with a constant term of 0.122021 (ARIMA(0,1,0)). This model's residual variance was 0.0090385. The Ljung-Box test showed no significant autocorrelation at either lag 12 (p=0.252) or lag 24 (p=0.753), indicating that the residuals closely approximate white noise, a desirable characteristic for time series models (Hyndman & Athanasopoulos, 2021). Table 1 shows detailed statistical evaluation of this model.

For second-order differencing (d=2), the best performing model, with the lowest AICc of -36.8726, was an ARIMA(0,2,1) model. This model had a statistically significant moving average term (MA 1) with a coefficient of 0.9974 (p<0.000). After differencing, there were 25 observations. The model's residual variance was 0.0099227. Similar to the d=1 case, the Ljung-Box test showed no significant autocorrelation at lag 12 (p=0.274) or lag 24 (p=0.741). Figures 2 and 3 demonstrate visual comparison between the three models through Autocorrelation Function (ACF) and partial Autocorrelation Function (PACF) of residuals. Then, forecasts were generated from time period 27 onwards for all three best models and the 95% confidence limits were also computed.

In summary, across the three different levels of differencing, three different models were selected as "best" based on AICc. The simplest model, the random walk with drift (ARIMA(0,1,0)), was selected for d=1, implying that the adjusted sea level data, when differenced once, behaves much like a random walk. This suggests that the year-to-year changes are largely unpredictable, which is consistent with findings that interannual sea level variability is complex and difficult to forecast (Sweet et al., 2022). The other two models, ARIMA(2,0,0) for d=0 and ARIMA(0,2,1) for d=2, are more complex. Further investigation of model diagnostics, especially residual analysis and comparison with other forecasting methods, is recommended.

After a thorough search of ARIMA models with d=0, 1 and 2, on addition to considering various combinations of p and q was examined, a single ARIMA model emerges as the most fitting one. The ARIMA(0,1,0) model (random walk with drift) with d=1 has the lowest AICc, indicating that it's the best model within the ARIMA family for adjusted sea level data. The Ljung-Box test on the residuals further supports the model's adequacy (Figure 4). The model suggests that the year-to-year changes in adjusted sea level behave largely like random fluctuations around a long-term trend.

Given an extensive screening of all possible ARIMA parameters (p, d, q) was conducted, the selection of the ARIMA(0,1,0) (random walk with drift) model as the "best" model takes on a different light. While it's still crucial to understand the model's implications and limitations, the extensive search strengthens the argument for its validity within the class of ARIMA models. After an exhaustive search, the simplest model provided the best fit according to

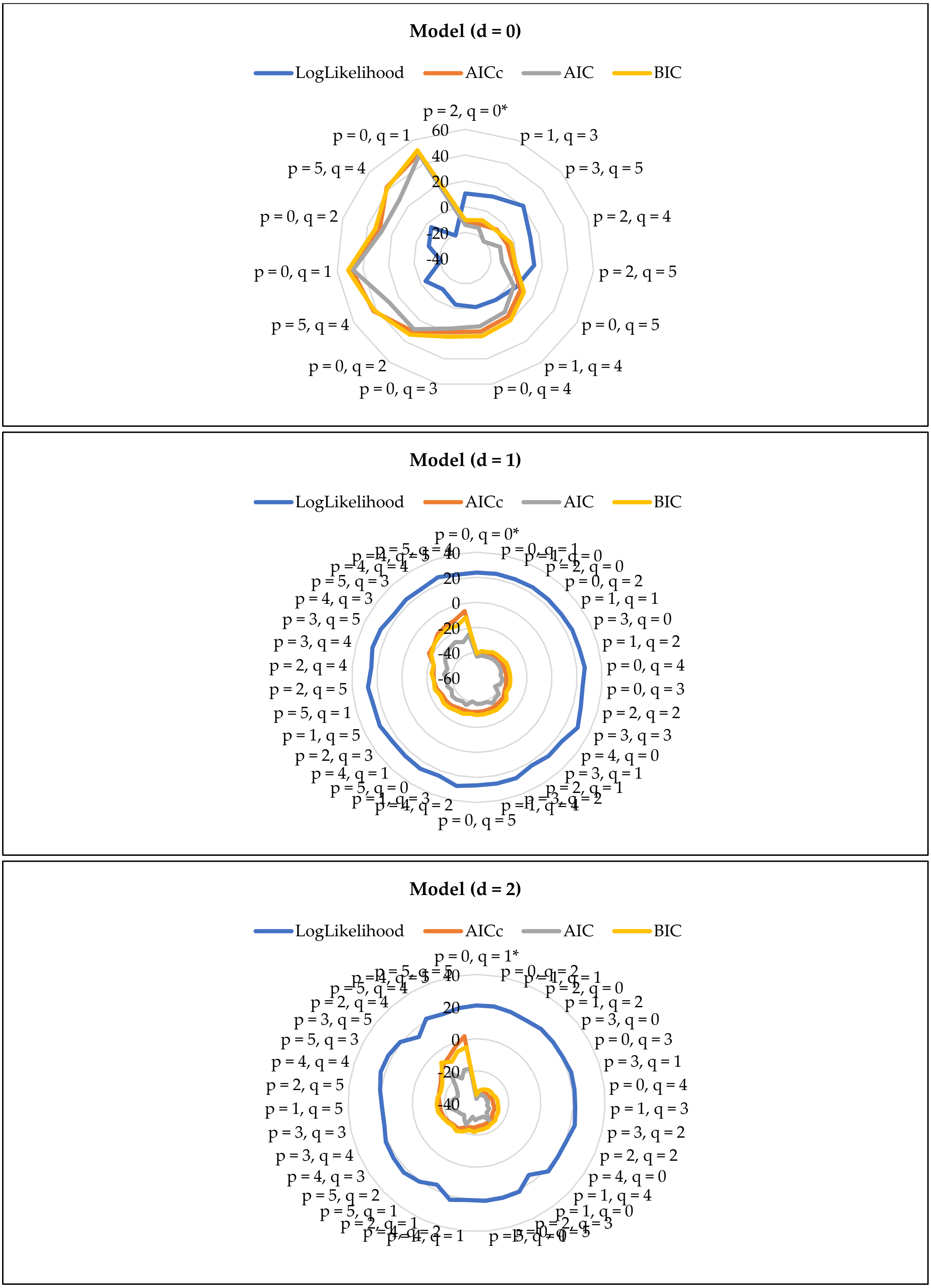

Figure 1. Radar scan chart of the selection of best ARIMA model with minimum AICc. *Denotes the selected model at each d value. For NOAA – adjusted sea level (inches), a model with (0,1,0) is the best fit.

AICc, strongly supporting the principle of parsimony (Hyndman & Athanasopoulos, 2021). It answers the question of why to use a more complex ARIMA model if it does not offer a statistically significant improvement. The lowest AICc value across all tested ARIMA models underscores the relative superiority of the random walk model within this class. The random walk model's success aligns with existing research highlighting the difficulty of predicting interannual sea level fluctuations and the extensive search reinforces the idea that this unpredictability is not simply due to a poorly chosen model within the ARIMA family.

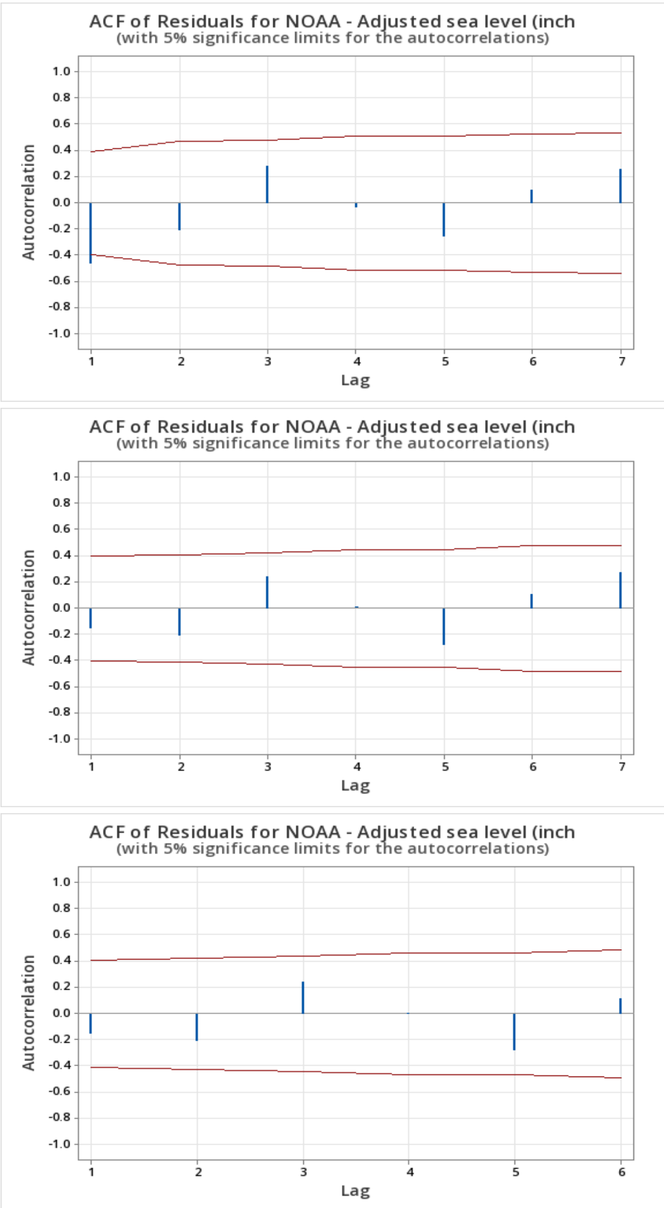

Figure 2. Autocorrelation Function (ACF) of residuals for best models at d =0, 1 and 2 in their respective order from top to the bottom graph at 5% significance level

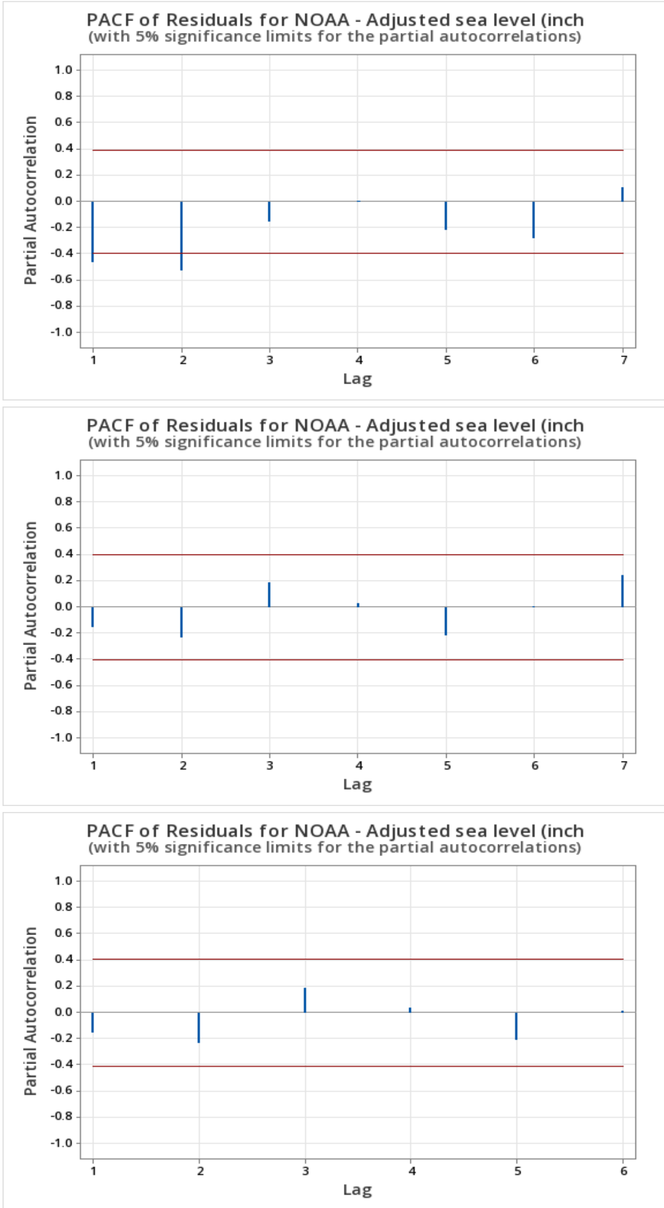

Figure 3. Partial Autocorrelation Function (PACF) of residuals for best models at d =0, 1 and 2 in their respective order from top to the bottom graph at 5% significance level

However, it's important to note that while the ARIMA(0,1,0) model was selected based on AICc, the choice of p and q parameters was not entirely consistent across AIC, BIC and AICc for all differencing orders (d). Specifically, for d=0, while AICc and BIC both favored ARIMA(2,0,0), AIC selected ARIMA(3,0,5). For d=1 and d=2, all three criteria converged on ARIMA(0,1,0) and ARIMA(0,2,1), respectively. This discrepancy at d=0 highlights that while AICc, AIC, and BIC often agree, they can sometimes select different models, especially when the differences in fit are small (Burnham & Anderson, 2002). It's crucial to acknowledge these differences and understand the strengths and weaknesses of each criterion. AICc is generally preferred for smaller sample sizes due to its bias correction, BIC is consistent in selecting the true model with increasing sample size and AIC, while asymptotically efficient, can sometimes over-penalize complex models in small samples. Therefore, while the ARIMA(0,1,0) model emerged as the best based on AICc after an extensive search, the behavior of AIC and BIC, particularly at d=1, provides additional context for model selection.

Despite the extensive search for selection of the best fitting ARIMA model, few questionable issues remain for investigation. For instance, while the random walk model is the best among ARIMA models, it still simplifies the complex reality of sea level dynamics. The success of the random walk model does not imply that interannual variability lacks physical drivers; rather, it suggests that after detrending, the remaining interannual fluctuations for this dataset are not effectively captured by a linear autoregressive or moving average process. The influence of complex, non-linear phenomena like ENSO may be a primary reason for this. However, this simplification is justified within the ARIMA framework given the deep search by screening of the parameters. The random walk model, as applied to adjusted sea level data, describes variability around a trend. The trend itself is a separate and essential component of sea level change and its modeling requires different methods (Church & White, 2011). This separation must be clearly articulated.

Figure 2 displays the Autocorrelation Function (ACF) of the residuals for the best fitting ARIMA models at differencing orders d=0, 1, and 2, presented in order from top to bottom. Examining the ACFs helps assess the adequacy of the fitted models by checking if the residuals resemble white noise, a key assumption of ARIMA models (Box et al., 2015). In the top graph, corresponding to d=0, there's a noticeable spike at lag 1, which falls just outside the 5% significance bounds. This suggests potential autocorrelation at lag 1, indicating that the residuals are not entirely random and that the ARIMA(2,0,0) model might not have fully captured the dependence within the data. Moving to the middle graph (d=1), the ACF shows no significant spikes outside the bounds. All autocorrelations fall well within the 5% significance limits, suggesting that the residuals of the ARIMA(0,1,0) (random walk) model are essentially random. This supports the adequacy of the random walk model for the differenced data at d=1. Finally, the bottom graph, representing d=2, also shows no significant autocorrelations beyond the 5 % bounds. This indicates that the residuals of the ARIMA(0,2,1) model are also random, supporting the model's validity. Thus, while the ACF for d=0 raises some concerns about remaining autocorrelation, the ACFs for d=1 and d=2 suggest that the respective selected models are reasonably adequate, with residuals that approximate white noise.

The Partial Autocorrelation Function (PACF) plots in Figure 3, arranged from top to bottom for d=0, 1, and 2 respectively, offer further insight into the appropriateness of the chosen ARIMA models. The PACF helps determine the order of the autoregressive (AR) component in the model (Box et al., 2015). In the top graph (d=0), the PACF shows a significant spike at lags 1 and 2, which could be expected in an ARIMA(2,0,0) model. This confirms the presence of a direct relationship between the current residual and the residual two periods prior, after accounting for the effect of the intervening lag. The lack of other significant spikes suggests that the AR order is indeed 2. The middle graph (d=1) shows no significant spikes at any lag, consistent with the ARIMA(0,1,0) (random walk) model. This reinforces the idea that, after differencing, there's no remaining autoregressive component needing to be modeled. Finally, the bottom graph (d=2) shows a significant spike at lag 1, which aligns with the ARIMA(0,2,1) model, suggesting a direct relationship between the current residual and the previous residual. The absence of further significant spikes supports the choice of a MA(1) component in the model. Overall, the PACF plots provide additional evidence supporting the selected ARIMA models for each differencing order. The significant spikes at the expected lags confirm the chosen AR orders, while the lack of other significant spikes suggests that the models have adequately captured the dependence structure in the data.

Figure 4 presents a comprehensive residual analysis for the best fitting ARIMA models at differencing orders d=0, 1 and 2, arranged from top to bottom. For each differencing order, the figure includes a normal probability plot, a histogram of the residuals, a plot of residuals versus fitted values and a plot of residuals versus observation order. These plots help assess the validity of the model assumptions, primarily focusing on normality, constant variance (homoscedasticity) and lack of autocorrelation in the residuals, which are fundamental to the validity of ARIMA models (Box et al., 2015). Starting with d=0 (top row), the normal probability plot shows almost no deviation from the straight line, but little at the tails, suggesting low potential of departures from normality. The histogram also indicates a slightly skewed distribution, which can be an indication of model misspecification or outliers (Hyndman & Athanasopoulos, 2021). The residuals versus fits plot shows no clear pattern, suggesting constant variance across the range of fitted values. However, the residuals versus order plot reveals a potential issue: there appears to be some non-randomness, with possible cyclical patterns or trends. For d=0, the residuals versus order plot reveals a potential issue: there appears to be some non-randomness, with possible cyclical patterns or trends. This suggests potential autocorrelation, which contradicts the model assumptions and is consistent with the earlier ACF findings, indicating that the ARIMA(2,0,0) model may not fully capture the time dependencies in the data. This suggests potential autocorrelation, which contradicts the model assumptions and is consistent with the earlier ACF findings, indicating that the ARIMA(2,0,0) model may not fully capture the time dependencies in the data. Figure 4 shows the best fitting ARIMA results for difference orders d=0, 1 and 2 arranged from top to bottom.

For d=1 (middle row), the normal probability plot aligns closely with the straight line, indicating that the residuals are approximately normally distributed. The histogram is also roughly bell-shaped with little skewness, supporting this conclusion. The residuals versus fits plot shows a random scatter of points, suggesting constant variance. The residuals versus order plot exhibits random fluctuations around zero, indicating no apparent autocorrelation. This aligns with the ACF and PACF results and further supports the adequacy of the ARIMA(0,1,0) model. Finally, for d=2 (bottom row), the normal probability plot again shows a reasonable fit to the straight line with minor deviations. The histogram is roughly symmetric. The residuals versus fits plot shows no discernible patterns, suggesting constant variance. The residuals versus order plot displays random variation, indicating no significant autocorrelation.

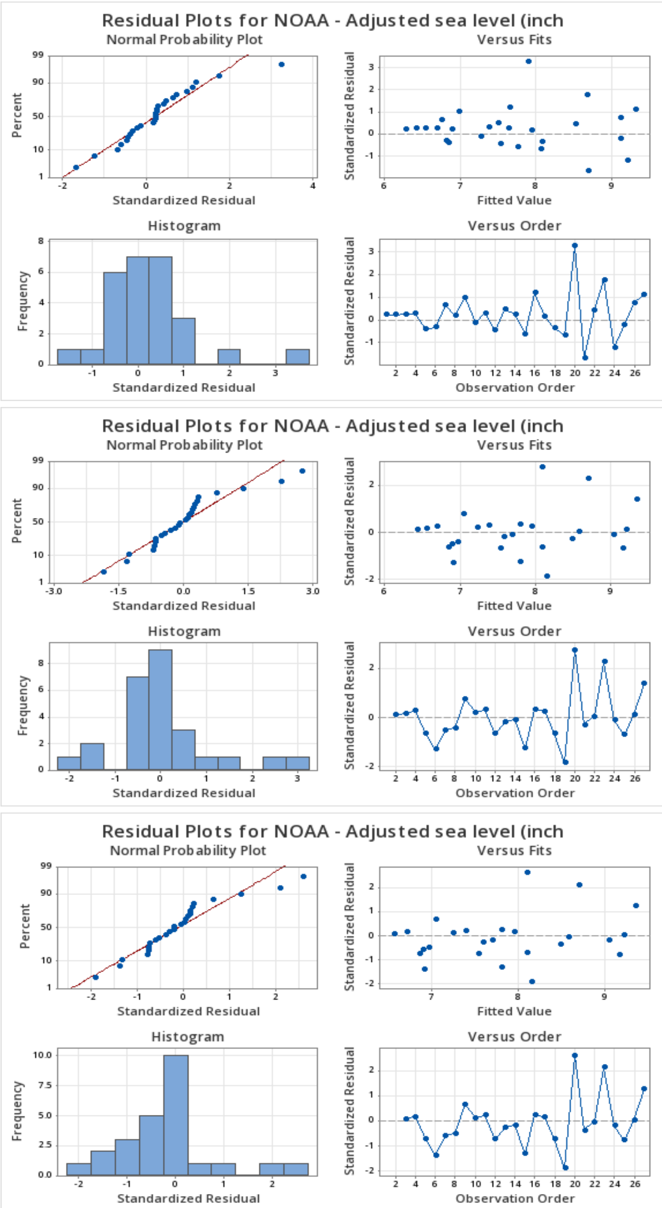

Figure 4. Residual graphical analysis for best ARIMA models at d =0, 1 and 2 in their respective order from top to the bottom graph

Table 1. Statistical analysis and comparison of the best-fitting ARIMA models for differencing orders d = 0, 1, and 2, selected based on minimum AIC_C

Model Identification		**Parameter Estimates**		**Goodness-of-Fit Statistics**				**Residual Diagnostics (Ljung-Box Test)**				
Model (p, d, q)	**Term**	**Coefficient (SE)**	**P-Value**	**Log-Likelihood**	**AIC_C**	**AIC**	**BIC**	**Residual MSD**	**Lag**	**Chi-Square**	**DF**	**P-Value**
ARIMA(2, 0, 0)	Constant	Not Estimated	-	10.15	**-13.26**	-14.30	-10.42	0.0189	12	20.06	10	0.029
	AR(1)	1.874 (0.302)	< 0.001						24	22.49	22	0.431
	AR(2)	-0.876 (0.306)	0.008									
ARIMA(0, 1, 0) (Random Walk with Drift)	Constant (Drift)	0.122	-	23.75	**-42.98**	-43.50	-40.98	0.0090	12	13.66	11	0.252
									24	18.09	23	0.753
ARIMA(0, 2, 1)	MA(1)	0.997 (0.051)	< 0.001	20.71	**-36.87**	-37.42	-34.98	0.0099	12	13.31	11	0.274
									24	18.29	23	0.741

Importantly, the residual analysis paints a mixed picture. For d=1 and d=2, the residuals generally satisfy the assumptions of normality, constant variance and lack of autocorrelation, supporting the selected ARIMA models. However, for d=0, patterns in the residuals versus order plot suggest possible autocorrelation. This casts doubt on the adequacy of the ARIMA(2,0,0) model at d=0 and highlights the importance of considering model diagnostics in conjunction with information criteria like AIC_C. While AIC_C suggested the ARIMA(0,1,0) as the best model, at d=1, the residual analysis alone might not show adequate resolution that it is the optimum choice, a demonstration of the importance of using multiple diagnostics in time series analysis (Burnham & Anderson, 2002).

Figure 5 presents 100-year forecasts, from time period 27 onwards, for the adjusted sea level using the selected ARIMA models at d=0, 1 and 2, along with their 95% confidence intervals. The top three plots show the forecast, upper, and lower limits for each differencing order. The bottom plot displays the standard errors (SE) of the forecasts for each model. The forecasts for d=0 (top plot) show a relatively narrow confidence band initially, which widens as the forecast horizon extends. However, the forecast itself appears to decrease over time, which might be counterintuitive for sea level projections and warrants further investigation. This discrepancy could be due to the model's inability to capture the long-term trends in the data, as highlighted by the residual analysis (Church & White, 2011). The forecasts for d=1 (second plot) and d=2 (third plot) show a more typical pattern of widening confidence bands with increasing forecast horizon. Both forecasts generally indicate an upward trend in adjusted sea level, although the specific trajectories differ slightly.

The standard error plot (bottom) confirms the expected behavior of increasing uncertainty with longer forecasts. Importantly, it also shows a clear hierarchy of forecast uncertainty, with SE(d=0) > SE(d=2) > SE(d=1). This indicates that the forecasts from the ARIMA(0,1,0) model (d=1) have the smallest standard errors and thus the highest precision, followed by the ARIMA(0,2,1) (d=2) model, and lastly the ARIMA(2,0,0) (d=0) model, which exhibits the largest forecast uncertainty. This ordering is consistent with the complexity of the models, with the simpler random walk model (d=1) yielding more precise forecasts compared to the more complex models at d=2 and d=0. Hence, Figure 5 provides a long-term perspective on the adjusted sea level forecasts and their uncertainty. The differences in forecast trajectories and uncertainty levels across the three differencing orders highlight the importance of model selection. The finding that the d=1 model (random walk) has the lowest forecast uncertainty, despite its simplicity, reinforces its selection as the preferred model within the ARIMA family for this specific dataset. However, the unexpected downward trend in the d=0 forecast raises concerns and calls for further scrutiny of the model's assumptions and the data at d=0.

Figure 6 provides a holistic view of the adjusted sea level data and the forecasts generated from the ARIMA models at differencing orders d=0, 1, and 2. The plots, arranged from top to bottom, show the historical data up to time period 27, followed by the forecasts and their 95% confidence intervals extending into the future. The top graph (d=0) shows the ARIMA(2,0,0) model's fit and forecast. We can observe how the model attempts to capture the existing trend and variability in the historical data. However, the forecast diverges significantly, showing a downward trend that, as mentioned before, is atypical for sea level projections and may indicate a problem with the model's assumptions or the data at d=0, which may be due to the model not fully capturing the underlying trend.

The middle graph (d=1) displays the ARIMA(0,1,0) (random walk) model's fit and forecast. The historical data, when differenced once, suggests a mean change with random variations around it, hence the random walk captures this nicely. The forecast reflects this, continuing the general upward trend observed in the recent historical data with widening uncertainty bounds, which is typical for random walk models. The bottom graph (d=2) presents the ARIMA(0,2,1) model's fit and forecast. Similar to the d=1 case, the model captures the upward trend in the historical data and projects it forward with increasing uncertainty. However, the specific trajectory and the width of the confidence bands differ slightly compared to the d=1 forecast, reflecting the different model specifications.

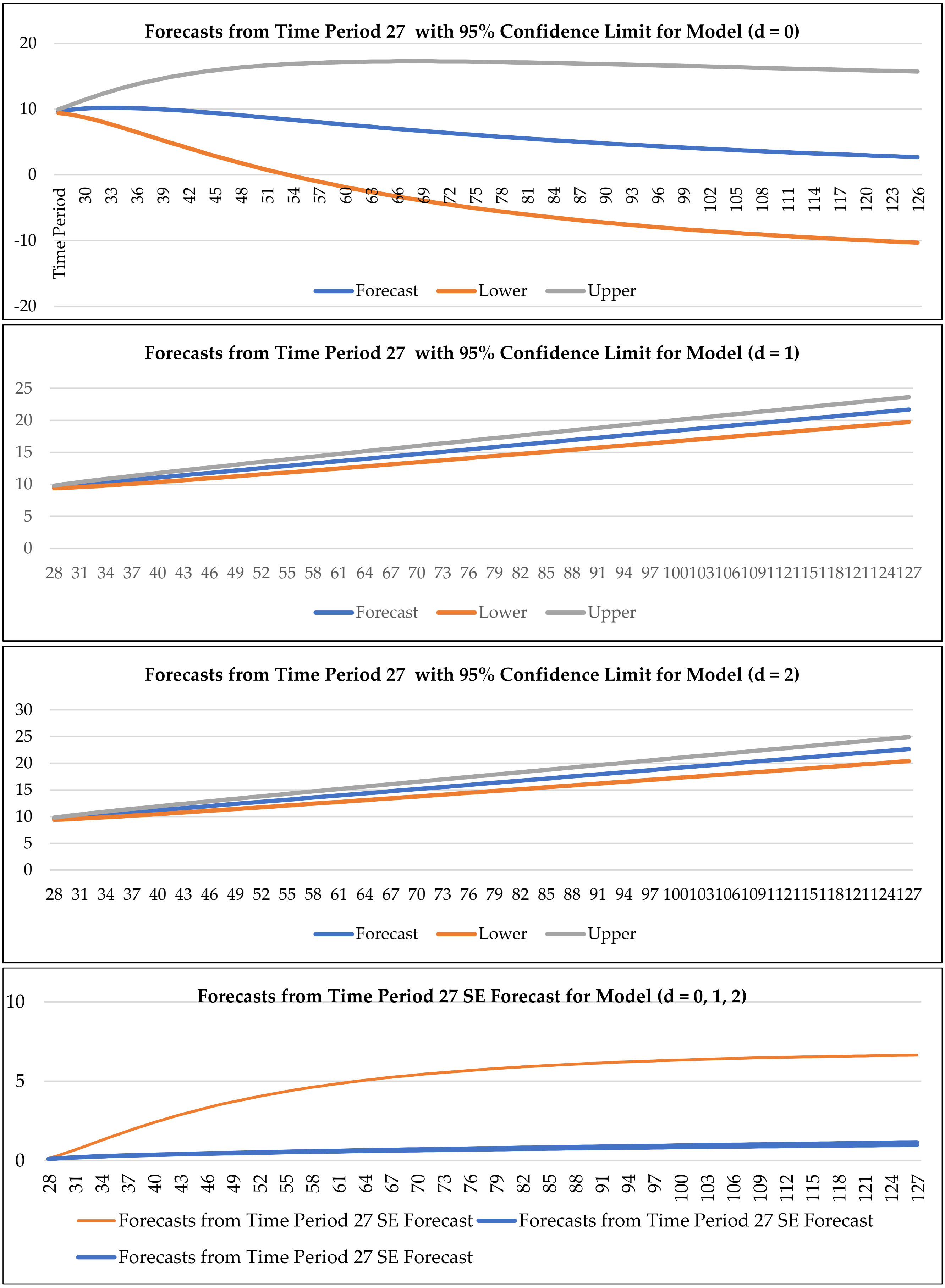

Figure 5. Focused section for forecasting on a yearly basis for 100 years with upper and lower confidence limits with y-axis showing sea level (in inches) and x-axis time (in years). Standard Error (SE) graph shows that values of $SE_0 > SE_2 > SE_1$.

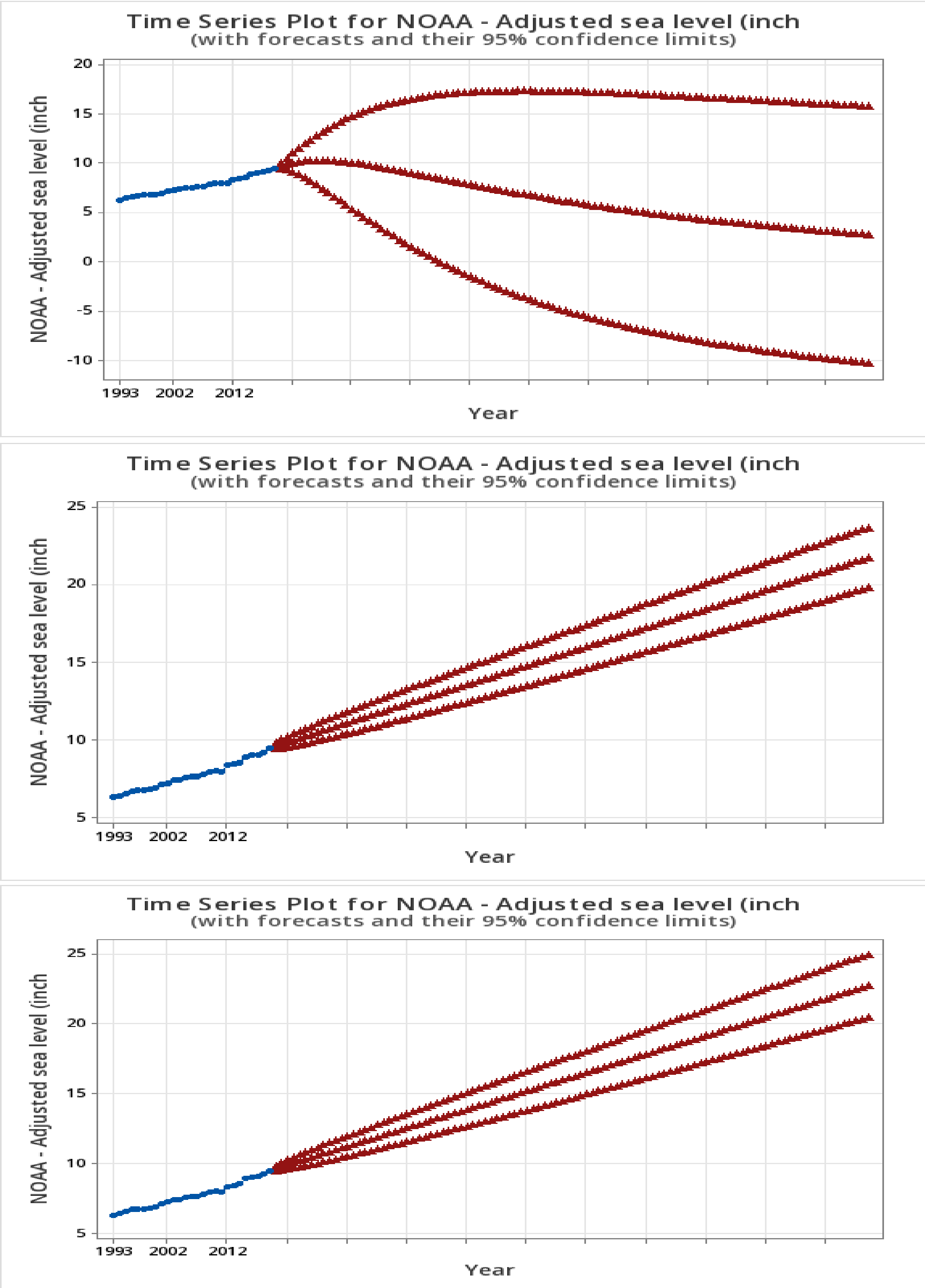

Figure 6. Holistic view of the trend showing forecasting at d =0, 1 and 2 in their respective order from top to bottom graph

Collectively, Figure 6 illustrates the impact of the differencing order (d) on the model's ability to fit the historical data and generate forecasts. The distinct forecast patterns underscore the importance of appropriate model selection. The d=1 and d=2 models appear to capture the general upward trend in sea level, while the d=0 model's forecast raises concerns. It's crucial to remember that these forecasts are based on the adjusted sea level data. The long-term trend component, removed during the adjustment process, is not explicitly modeled here but is essential for a complete understanding of future sea level change (Frederikse et al., 2020).

The sea level data was adjusted based on the NOAA CSV database, which provides crucial context. This adjustment typically refers to the removal of certain influences from the raw sea level measurements to isolate the signal of interest. Common adjustments include Glacial Isostatic Adjustment (GIA), which accounts for the ongoing vertical movement of the Earth's crust in response to the melting of ice sheets since the last glacial maximum. This movement can affect local sea level measurements and needs to be corrected for when studying long-term sea level rise (NOAA, 2022). Vertical land motion (VLM) corrections are also applied to isolate the absolute sea level change, accounting for local land subsidence or uplift due to factors like groundwater extraction, tectonic activity, or sediment compaction (NOAA, 2022). Depending on the specific NOAA dataset and the research goals, other adjustments might be applied, such as corrections for atmospheric pressure, wind effects, or tidal variations (NOAA, 2022).

The fact that a random walk model fits well suggests that the interannual fluctuations are essentially "noise" – random variations around the long-term trend. This could be due to a combination of factors, such as short-term climate variability (e.g., El Niño-Southern Oscillation), localized and transient oceanographic effects, and remaining measurement errors or uncertainties in the adjustment process (Lobeto & Menendez, 2024). Even if the interannual variability is unpredictable, it is still relevant for coastal management. Coastal communities need to be resilient to these fluctuations, even if they cannot be precisely forecast (Dangendorf et al., 2024). By focusing on the residual variability and clearly explaining the data adjustment process, meaningful research can be generated from the analysis, even if the "best" model is a simple random walk.

A 100-year forecast from the ARIMA(0,1,0) model, while bound by adjusted sea level and its interannual variability, delivers several important aspects. interannual uncertainty is quantified, as year-to-year fluctuations in sea level remain relevant for coastal communities. A quantitative estimate of the magnitude of these interannual variations is provided by the forecast and its confidence intervals. Use of this information can be made in coastal planning to assess the risk of temporary high-water events, such as storm surges superimposed on high tides, and plans can be made accordingly (Sweet et al., 2022). In infrastructure design, the range of potential interannual sea level fluctuations can be incorporated by engineers into the design of coastal infrastructure, including bridges, roads, and buildings (Nicholls et al., 2014). For emergency preparedness, the forecast can be used by emergency managers to prepare for potential coastal flooding events, even if precise timing and magnitude cannot be predicted. Furthermore, the random walk model serves as a useful baseline against which more complex sea level models can be compared. If a more sophisticated model, perhaps one including external climate variables or non-linear dynamics, cannot significantly outperform the random walk model in forecasting accuracy, its added complexity might not be justified. Evidence is provided by the analysis that, at least within the ARIMA family, simpler is better for this specific adjusted dataset, aligning with the principle of parsimony in model selection (Burnham & Anderson, 2002). The critical importance of accurately estimating and projecting the long-term trend itself is indirectly emphasized by this work, which focuses on the variability around such a trend. As the long-term trend dominates overall sea level rise, the need for separate research efforts dedicated to understanding and modeling these trends is highlighted (Church & White, 2011). Data quality assessment is also possible, as the strong performance of a simple random walk model on the adjusted data could indicate that adjustments, like GIA and VLM, were effective in removing long-term trends and other predictable components (Peltier, 2004; Wöppelmann & Marcos, 2016). Conversely, the necessity of more complex models might suggest that some predictable long-term signals remained in the data, even post-adjustment. Regional insights, with caveats, can be gleaned, as the analysis, though based on potentially regional NOAA data, can provide some insights into the specific characteristics of sea level variability in that region. Nevertheless, limitations of the random walk model, particularly its inability to capture long-term trends and its reliance on the assumption that future variability will resemble past variability, should be acknowledged. For a more complete picture of future sea level change, the analysis of variability should be combined with independent estimates of long-term sea level trends for the region of interest (Frederikse et al., 2020). Further research into exploring more complex models or to investigate the specific factors driving interannual sea level fluctuations in the region is suggested.

It is crucial to acknowledge the scope boundary in this analysis. The use of annual resolution data is a limitation that precludes the analysis of seasonal or event-scale variability, which is critical for many coastal applications. Future work should employ higher-frequency data to address these shorter timescales. Firstly, the forecasts pertain specifically to adjusted sea level, meaning the long-term trend has been removed. Therefore, the forecasts do not represent a total sea level rise, which includes both the long-term trend and the short-term fluctuations. Secondly, screening for ARIMA models, including the random walk model, relies on the assumption that the statistical relationships observed in the past will continue into the future. This assumption may not hold true, especially over long forecast horizons like 100 years, as factors influencing sea level variability may change. Thirdly, while the Minitab tool automates model selection, it is essential to critically evaluate the selected model's diagnostics (e.g., residual analysis) to ensure its adequacy (Box et al., 2015). Finally, the reliance on a single statistical model does not preclude the possibility that other models, potentially outside the ARIMA family, may provide superior forecasts. Despite these limitations, this research provides valuable insights into the interannual variability of adjusted sea level, offering crucial information for coastal planning and management. Furthermore, the 100-year forecast horizon is an illustrative projection of the model's behavior. Given the limited historical data and the assumption that past statistical properties hold constant, forecasts this far into the future are highly uncertain and should be interpreted with caution. The primary value is in quantifying the increasing uncertainty, not the precise point forecast.

CONCLUSION

The ARIMA(0,1,0) model, selected after an extensive screening of the ARIMA parameter space, represents the best ARIMA representation of the adjusted sea level data, implying that the residual interannual variability, after accounting for factors removed during data adjustment, is largely unpredictable within the ARIMA framework. This result underscores the critical need for separate research focused on modeling long-term sea level trends, which are not captured by this analysis. Future research should therefore move beyond the ARIMA framework to explore non-linear time series models or models directly incorporating climate indices (e.g., ENSO, NAO) as predictors to attribute causality and improve predictive skill. While the possibility of superior models outside the ARIMA family, such as non-linear time series models or models incorporating climate indices like the ENSO index, remains open and warrants further investigation, the random walk's selection reinforces its role as a relevant baseline. This research highlights the importance of distinguishing between short-term variability and long-term trends in sea level studies. Although the forecast does not directly predict total future sea level, it provides valuable information about the unpredictable interannual fluctuations superimposed on the long-term trend, which is crucial for coastal planning, infrastructure design and emergency preparedness. It is important to note that these forecasts represent only the unpredictable residual component and must be integrated with independent projections of the long-term trend and event-based hazard models for practical, localized decision-making. Given the importance of data adjustment, future work should conduct a sensitivity analysis to assess the impact of different GIA and VLM correction methods on the results of the ARIMA modeling. This would help to quantify the uncertainty associated with the adjustment process and its influence on the conclusions about interannual sea level variability. Moreover, further research studies could investigate the influence of specific climate forcings (e.g., greenhouse gas concentrations, volcanic eruptions) on long-term sea level trends using regression models or more complex climate models. This would help to better understand the drivers of long-term sea level change and improve projections. This adds a layer of causal understanding to trend estimation.

Compliance with Ethical Standards

Conflict of Interest

The author declares that there is no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

Funding

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI Disclosure

Generative AI was used for grammatical and language review of the introduction and discussion sections. The author validated all outputs and assume full responsibility for the content.

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