

Article

Enhancing Joint Probability of Maxima Method Through ENSO Integration: A Case Study of Annapolis, Maryland

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Abstract: This study advances coastal flood risk assessment by incorporating El Niño–Southern Oscillation (ENSO) phase information into the Joint Probability of Maxima Method (ENSO-JPMM) for extreme water level prediction in Annapolis, MD. Using data from GLOSS/Extended Sea 135 Level Analysis Version 3 (GESLA-3) dataset and water level records from 1950–2021, we demonstrate that ENSO phases significantly affects flood risk probabilities through their influence on mean sea level, astronomical tides, and skew surge components. We introduce an enhanced JPMM framework that employs phase-specific scaling factors and vertical offsets derived from historical observations, with El Niño conditions associated with higher mean water levels (0.433 m) compared to La Niña (0.403 m) and Neutral phases (0.409 m). The ENSO-JPMM demonstrates improved predictive accuracy across all phases, with root mean square error reductions of up to 5.96% during Neutral conditions and 3.56% during El Niño phases. By implementing a detailed methodology for mean sea level estimation and skew surge analysis, our approach provides a more detailed framework for separating tidal and non-tidal components while accounting for climate variability. The results indicate that traditional extreme value analyses may underestimate flood risks by failing to account for ENSO-driven variability, which can modulate mean water levels by up to 3.0 cm in Annapolis. This research provides insight for coastal infrastructure planning and flood risk management, particularly as climate change potentially alters ENSO characteristics and their influence on extreme water levels. The methodology presented here, while specific to Annapolis MD, can be adapted for other coastal regions to improve flood risk assessments and enhance community resilience planning.



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1. Introduction

Coastal flooding poses an escalating threat to urban infrastructure and communities, particularly in regions like Annapolis, Maryland, where the convergence of rising sea levels, astronomical tides, and storm-induced skew surges has led to increasingly frequent and severe inundation events. Tide gauge records indicate a significant increase in high-tide flooding events in recent decades, with Annapolis experiencing a rise from an average of 3.8 flooding days per year in the 1950s to over 50 days annually by the 2010s [1–3]. Projections indicate this trend will continue, with 50–155 flooding days per year expected by 2050 [4]. The total observed water level at any given time comprises three primary components: Mean Sea Level (MSL), astronomical tide, and meteorological driven skew

surge [5,6]. Traditional methods for assessing extreme sea levels, such as extreme value analysis and joint probability methods, have provided critical insights, but often neglect the influence of large-scale climate variability, which significantly modulates these components [7]. This gap necessitates the development of methodologies that integrate climate variability into flood risk assessments to improve predictive accuracy.

While the El Niño–Southern Oscillation (ENSO) operates on interannual timescales [8] and is not a climate state in the traditional sense (i.e., weather statistics over 30+ years), its recurring patterns exert a significant influence on regional climate variability, including sea level anomalies and regional storm activity [9]. In this study, we will refer to ENSO as a modulator of climate phenomena to emphasize its role in shaping short- and long-term coastal flood risk.

Previous research has established that extreme skew surge events are significant drivers of coastal flooding in the Mid-Atlantic region, particularly within the Chesapeake Bay. Callahan and Leathers (2021) employed Generalized Extreme Value (GEV) and Generalized Pareto (GP) distributions to estimate return levels for these extreme events, revealing spatial variability in flood risk within the Delaware and Chesapeake Bays [10]. However, their analysis did not incorporate the influence of large-scale climate phenomena like the El Niño–Southern Oscillation (ENSO), known to affect extreme water levels through alterations in mean sea level, storm tracks, and precipitation patterns. This study advances the understanding of flood risk by incorporating ENSO phase information into the Joint Probability of Maxima Method (JPMM), thereby assessing how climate variability modifies extreme flood probabilities in Annapolis, Maryland.

The Chesapeake Bay, and specifically Annapolis, is highly sensitive to regional and global climatic influences such as ENSO. Recent studies have documented significant changes in the Bay's response to climate forcing [11,12], marked by increased warm events, fewer cold events, and changes in precipitation patterns. These trends are driven by prominent climate modes, including ENSO, the Atlantic Multidecadal Oscillation (AMO), and the Pacific Decadal Oscillation (PDO) [13]. The statistical correlation between ENSO and regional climate patterns in Annapolis suggests that extreme water levels are strongly influenced by these climate phenomena [1,14], offering potential predictability in flood risk assessments. This underscores the need for analyses that extend beyond traditional 30-year climate normals to capture both natural variability and long-term trends [9].

Extreme value analysis (EVA) has been widely used to estimate return levels for extreme water levels along the U.S. East Coast. Callahan and Leathers (2021) [10] applied both the Generalized Extreme Value (GEV) and Generalized Pareto (GP) distributions to analyze skew surge events in the Chesapeake Bay region, demonstrating the effectiveness of these methods in quantifying extreme coastal flooding risk. However, these approaches assume stationarity, meaning that climate variability—such as ENSO-driven changes in skew surge probabilities—is not explicitly incorporated. This study builds on the JPMM findings by implementing an ENSO-JPMM framework, allowing for the estimation of return levels and probability density functions across the different ENSO phase.

The JPMM extends the Skew Surge Joint Probability Method (SSJPM) developed by Batstone et al. (2013) [7], offering a robust statistical framework to estimate extreme water level probabilities by evaluating the concurrence of high tides and skew surges. However, traditional implementations of JPMM often fail to account for the influence of large-scale climate variability like the El Niño–Southern Oscillation (ENSO), despite its well-documented effects on mean sea level (MSL) fluctuations and storm activity along the U.S. Atlantic coast [15,16]. The Chesapeake Bay's unique bathymetry and orientation exacerbate ENSO-related impacts, thereby increasing the region's sensitivity to skew surge

events and highlighting the need for a thorough investigation into how ENSO modulates flood risk [17].

Historical tide gauge records from Annapolis reveal that the phases of the ENSO exert a significant influence on extreme water levels through multiple mechanisms. During El Niño events, regional mean sea level (MSL) can increase by approximately 5–15 cm, largely due to thermal expansion and shifts in ocean circulation patterns [16]. Additionally, El Niño conditions are associated with an enhanced frequency and intensity of winter storms that impact the Mid-Atlantic region, thereby amplifying coastal flooding risks [17].

Recent projections indicate that accelerating sea-level rise, with an average rate of approximately 3.3 mm/year along the U.S. Atlantic coast [3], will significantly increase flooding frequency in Annapolis within the next few decades. Sweet et al. [16] project that by 2050, Annapolis could experience 50–155 days of high-tide flooding annually under intermediate sea-level rise scenarios. When ENSO-driven variations are superimposed on these long-term trends, the resulting flood risk can vary substantially from year to year. This study extends the JPMM framework by explicitly incorporating ENSO phase information through three key contributions:

1. **Component Separation and ENSO Classification:** Water levels are decomposed following Palmer et al. [6], with additional ENSO phase classification based on the Oceanic Niño Index (ONI).
2. **Phase-Specific Distribution Analysis:** Probability distributions are computed separately for each ENSO phase, incorporating:
 - MSL distributions with phase-specific offsets and trends [16].
 - Tidal variations accounting for documented ENSO-related amplitude modulations [17].
 - Skew surge, defined as the difference between observed and predicted high water levels within a tidal cycle, and its distributions scaled according to observed phase-specific storm intensities [7].
3. **Climate-Aware Joint Probability Modeling:** The JPMM framework is enhanced to maintain seasonal dependencies while integrating ENSO conditioning, enabling more accurate representation of compound flooding events [6].

Long-term tide gauge records from Annapolis (1928–present) combined with ONI data (1950–present) provide a foundation for investigating ENSO-flood relationships [18]. Our analysis demonstrates that incorporating ENSO phase information improves flood prediction accuracy, particularly for total water distribution. This enhanced methodology offers valuable insights for adaptation planning in Annapolis and similar coastal communities facing increasing flood risks from climate change and sea-levels.

2. Methods

2.1. Overview

Our approach builds upon the JPMM, integrating distributions of mean sea level (MSL), tidal, and skew surge components while accounting for their interdependencies. Expanding on the frameworks of Batstone et al. (2013) [7] and Palmer et al. (2024) [6], we enhance JPMM by incorporating ENSO-phase conditioning. This refinement allows us to assess how ENSO variability influences coastal water levels, providing improved estimates of extreme water levels under differing climatic conditions. By explicitly considering El Niño, La Niña, and Neutral phases, this study captures the influence of climate variability on coastal flooding risks in Annapolis, Maryland.

Unlike previous approaches that rely on stationary extreme value analysis [10], such as Callahan & Leathers (2021) [10], our ENSO-JPMM explicitly accounts for climate variability in extreme water level predictions using non-stationary analysis. This advancement ad-

dresses a key limitation in traditional methods by incorporating the dynamic influences on sea level by investigating the ENSO phases and their potential impacts on coastal flooding risks. Additionally, while Callahan & Leathers (2021) [10] relied on historical skew surge records to estimate return levels for different flood recurrence intervals, our study refines these return levels by integrating ENSO-conditioned variability into the JPMM framework. This approach allows us to determine how climate oscillations affect flood probabilities and assess whether traditional methods overestimate or underestimate flood risks under different ENSO conditions.

2.2. Data and Preprocessing

This study utilizes high-frequency tide gauge data from the GLOSS/Extended Sea Level Analysis Version 3 (GESLA-3) dataset, covering the period from 1928 to 2020 [19]. The dataset consists of hourly water level measurements that have undergone quality control procedures to ensure reliability and consistency. Observations were interpolated to regular hourly intervals to address minor gaps, and records with more than 15% missing data were excluded. Standardizing all water levels to the Mean Lower Low Water (MLLW) datum ensured consistency across different time periods and locations by mitigating local datum shifts.

To account for long-term tidal variability, water levels were segmented into 19-year epochs, corresponding to the principal lunar nodal cycle [20]. This approach allows for the identification of decadal-scale shifts in tidal constituents, which are critical for understanding changes in extreme water levels [21,22]. By incorporating these cycles, the segmentation improves the reliability of statistical models predicting extreme events, mitigating biases from short-term climate variability or incomplete tidal cycles [23,24]. Additionally, this method allows for a clearer distinction between natural variability and man-made influenced sea level rise, providing a more structured framework for assessing coastal flood risks [25–28].

ENSO-phase data were obtained from the National Oceanic and Atmospheric Administration (NOAA) using the Oceanic Niño Index (ONI). The ONI, calculated as the three-month running mean of sea surface temperature anomalies in the Niño 3.4 region, was used to classify ENSO phases, with thresholds of ± 0.5 °C defining El Niño and La Niña events [18]. These classifications were incorporated into our analysis to evaluate their effects on skew surges and overall total extreme water levels.

2.3. Separation of Sea Level Components and Skew Surge Calculation

To accurately assess extreme water levels, observed sea level data were decomposed into three primary components:

- **Mean Sea Level (MSL):** The long-term average sea level, capturing local trends (e.g., sea-level rise) and interannual climate variability.
- **High Water Tide:** The predicted high tide relative to the annual MSL, representing the astronomical influence on water levels.
- **Skew Surge:** The residual difference between observed high water levels and predicted high tide, reflecting meteorological and other non-tidal influences.

Tidal predictions were generated using the UTide MATLAB/Python toolbox [29], available at <http://www.po.gso.uri.edu/~codiga/utide/utide.htm> (accessed on 5 February 2025), which provides a harmonic analysis framework for modeling astronomical influences on water levels. UTide is suitable for analyzing tide gauge records of varying lengths, from short-term time frames such as months to much longer time frames such as centuries. These time frames are dependent upon sufficient data resolution and continuity [29]. In this study,

UTide (v2.0) was applied to hourly water level records from 1928 to 2020, leveraging its capability to resolve long-term tidal variability across multiple 19-year nodal cycles.

Mean sea level (MSL) is calculated through a multi-step filtering process. First, hourly water level observations are processed using a Demerliac filter (71 symmetric elements) to reduce high-frequency tidal noise. Daily MSL values are then computed by averaging the filtered observations over 24-h periods, with a minimum requirement of 20 valid hourly measurements per day to ensure statistical robustness. Monthly MSL is calculated as the weighted mean of daily values, requiring at least 15 valid days per month. These criteria minimize bias from data gaps while maintaining temporal resolution adequate for capturing climate-driven sea level variations.

Tidal predictions are generated using UTide (v2.0) harmonic analysis with the following configuration:

- 146 astronomical constituents, including annual (Sa) and semi-annual (Ssa) terms.
- Least squares optimization with iteratively reweighted residuals.
- Rayleigh criterion of 1.0 for constituent selection.
- Nodal corrections applied using astronomical arguments.

For high water identification, the predicted tide is interpolated to 1-min resolution using cubic splines, with peaks detected using a 6-h window centered on predicted maximums. This approach ensures accurate timing of high water events while minimizing spurious peak detection.

Daily high water events were detected using a peak-finding algorithm, identifying the highest observed water level within each six-hour window (± 3 h from the predicted tidal peak). Skew surge was then computed as:

$$\text{Skew Surge} = \text{Observed High Water} - \text{Predicted High Water} \quad (1)$$

This metric isolates meteorological contributions such as wind-driven setup and pressure-induced surges, independent of tidal forcing [30,31]. By integrating epoch-based MSL estimation with tidal predictions, this method enhances the accuracy of skew surge calculations and ensures consistency in long-term extreme water level analysis.

To assess long-term sea level trends, we applied a multi-scale analysis of MSL rates over different time periods. The results are summarized in Table 1, showing that sea level rise in Annapolis has accelerated in recent decades.

Table 1. Mean Sea Level (MSL) trends for Annapolis, MD, derived from hourly tide gauge data in the GLOSS/Extended Sea Level Analysis Version 3 (GESLA-3) dataset [19] processed over the periods 1928–2021, 1960–2021, and 1990–2021. ENSO phase classification was based on the Oceanic Niño Index (ONI), obtained from NOAA’s Climate Prediction Center [18].

Period	Rate (mm/Year)	Uncertainty (mm/Year)	Time Span
Full Period	3.96	0.12	1928–2021
60-Year Trend	4.12	0.22	1960–Present
30-Year Trend	5.90	0.64	1990–Present

Additionally, we compared observed and predicted high water level variability to assess the contributions of non-tidal forces (Table 2). The skew surge standard deviation (0.208 m) is comparable in magnitude to tidal variability (0.234 m), underscoring the importance of meteorological forcing.

Table 2. Observed and predicted high water level variability, derived from hourly tide gauge data in the GESLA-3 dataset [19], 1928–2020.

Statistic	Standard Deviation (m)
Observed High Water (HW)	0.234
Predicted High Water (HW)	0.102
Skew Surge	0.208

2.4. Skew Surge Trends and Implications for Extreme Water Levels

Skew surge analysis provides insight into non-tidal contributions to extreme water levels. In Annapolis, skew surge values typically range from ± 0.3 m, with occasional extremes exceeding 1.5 m. Despite rising MSL, long-term skew surge magnitudes show no statistically significant trend, suggesting that meteorologically driven variability has remained stable over time.

Callahan and Leathers (2021) demonstrated that extreme skew surge events in the Chesapeake and Delaware Bays follow well-defined return level distributions [10], yet their analysis did not differentiate the influence of climate variability drivers such as ENSO. Our results indicate that while long-term trends in skew surge may appear stationary, ENSO phases and MSL introduce some variability, affecting both the frequency and intensity of events.

By segmenting skew surge data by ENSO phase and analyzing total water level distributions, we assess whether phase-specific deviations influence flood risk modeling and coastal adaptation planning. The results, discussed in Section 4, reveal that ENSO phases introduce a measurable influence on mean water levels, particularly through changes in skew surge characteristics and MSL offsets.

Figure 1 illustrates the high water level time series, highlighting observed and predicted water levels, skew surge variations, and seasonal distributions. These results emphasize the importance of accurate MSL estimation in total water level prediction and demonstrate how an epoch-based approach enhances the reliability of skew surge assessments.

2.5. Joint Probability of Maxima Method (JPMM)

The JPMM framework analyzes high water levels through a sequential convolution of probability distributions for mean sea level (MSL), high tide, and skew surge components. By focusing specifically on water level maxima rather than all water levels, this approach directly addresses conditions most relevant for coastal flooding assessment while preserving the statistical dependencies between components. The total water level at high tide, $\eta_{\text{total}}(t)$, at any given time t is expressed as:

$$\eta_{\text{total}}(t) = \eta_{\text{MSL}}(t) + \eta_{\text{tide}}(t) + \eta_{\text{surge}}(t), \quad (2)$$

where $\eta_{\text{MSL}}(t)$ represents long-term sea level trends, $\eta_{\text{tide}}(t)$ denotes the astronomical tidal height at high water, and $\eta_{\text{surge}}(t)$ corresponds to the skew surge effect at the time of high water. The probability distributions for each component are derived using optimized bin widths of 1 cm centered on the half-centimeter, with component-specific Gaussian smoothing parameters ($\sigma = 1.2$ for tide and $\sigma = 0.8$ for surge components). The framework assumes statistical independence between MSL and skew surge components while preserving tide-surge interaction through careful joint probability calculations. The total water level distribution is computed through a three-step sequential convolution process with normalization at each stage:

First, the joint tide-surge distribution is calculated through convolution:

$$P_{\text{tide+surge}}(z) = P_{\text{tide}}(z) * P_{\text{surge}}(z) = \int_{-\infty}^{\infty} P_{\text{tide}}(\zeta) P_{\text{surge}}(z - \zeta) d\zeta \quad (3)$$

where z represents the water level in meters (relative to MLLW), and the intermediate result is normalized using trapezoidal integration to ensure proper probability properties:

$$P_{\text{normalized}}(z) = \frac{P_{\text{tide+surge}}(z)}{\int P_{\text{tide+surge}}(z) dz} \quad (4)$$

where normalization is performed. Finally, the normalized distribution is combined with MSL through a second convolution:

$$P_{\text{total}}(z) = P_{\text{MSL}}(z) * P_{\text{normalized}}(z) = \int_{-\infty}^{\infty} P_{\text{MSL}}(\zeta) P_{\text{normalized}}(z - \zeta) d\zeta \quad (5)$$

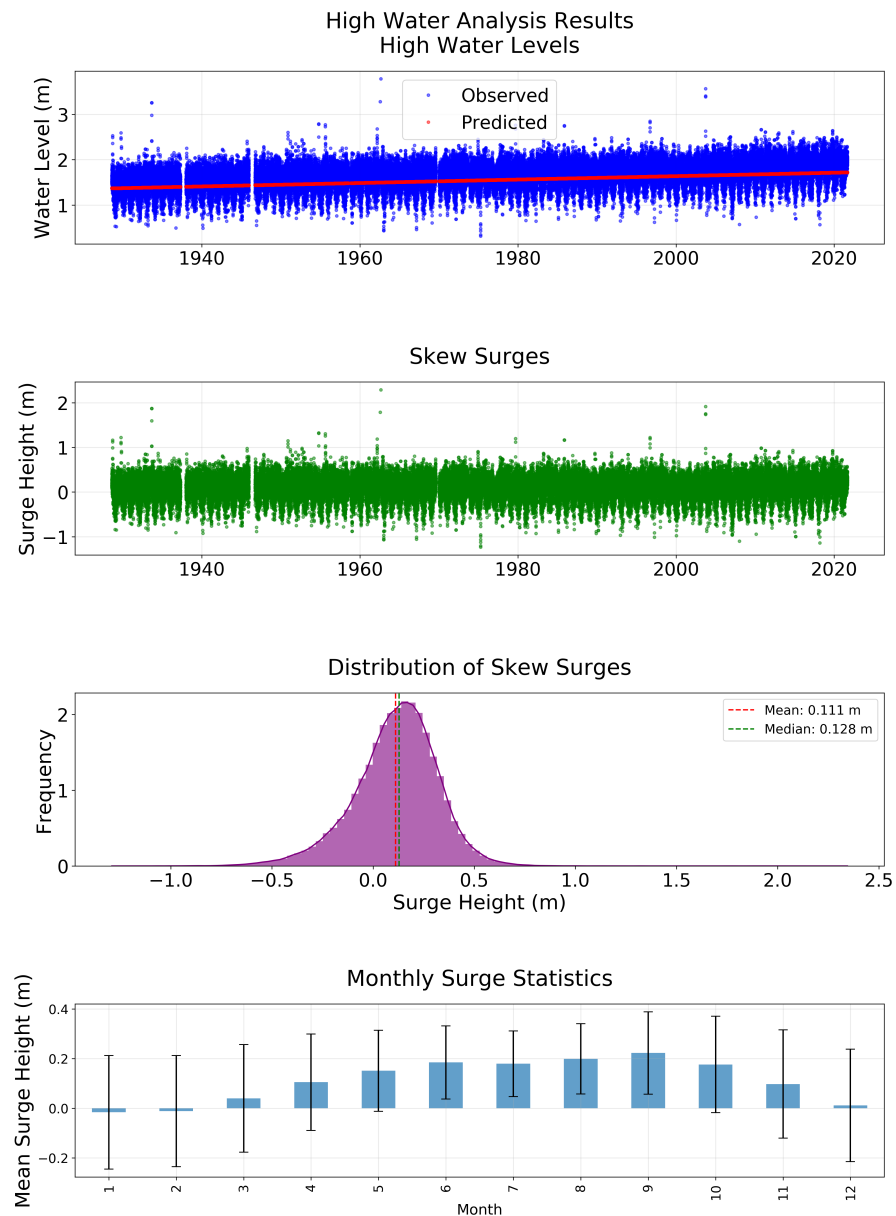


Figure 1. Plot descriptions from top to bottom: High water level analysis results, including observed and predicted mean water levels, skew surge time series, skew surge distribution, and monthly surge means and maxima showing seasonal dependency, based on hourly tide gauge data from Annapolis, MD, 1928–2020.

A key innovation of JPMM is its treatment of seasonal variations in tide-surge interactions. The framework analyzes joint probabilities on a month-by-month basis, recognizing

that the likelihood of large surges coinciding with high tides varies throughout the year. The monthly probability distributions are combined by summing probabilities along each 1 cm increment in bin height, with each month weighted as 1/12th of the total probability:

$$P_{\text{total}}(z) = \sum_{i=1}^{12} \frac{1}{12} (P_{\text{tide}}^i(z) * P_{\text{surge}}^i(z)) \quad (6)$$

This approach improves upon previous joint probability methods by working directly with observable water level maxima while maintaining natural interdependencies between components. The careful normalization at each step and explicit handling of seasonal variations ensures the resulting probability distributions accurately represent the complex interactions between different water level components. The maximum total water level for any site and epoch is constrained by the sum of the maximum computed MSL, the maximum predicted high tide above MSL, and the maximum computed skew surge above the predicted high water level. Similarly, the minimum total water level is bounded by the corresponding minimum values of each component. This framework accounts for both the interdependencies between different water level components and their seasonal variations (Figure 2).

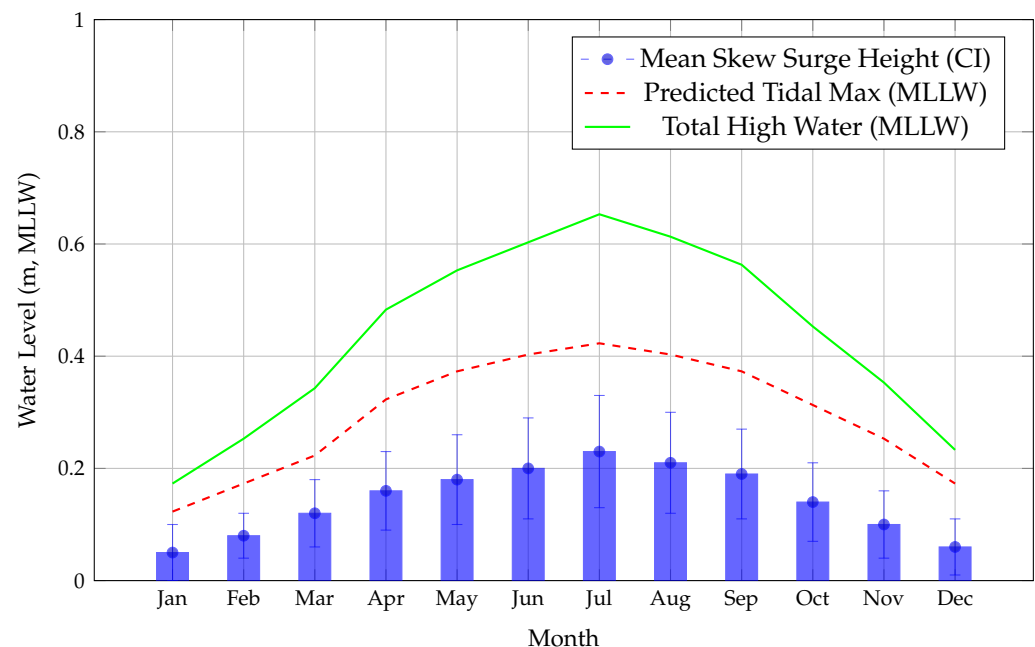


Figure 2. Monthly Mean Seasonal High Water, Mean Predicted Tidal Max Levels, and Mean Skew Surge for Annapolis, MD (referencing MLLW), derived from hourly tide gauge data, 1928–2020.

2.6. ENSO-Joint Probability Maxima Method (ENSO-JPMM)

We propose an enhancement to the standard Joint Probability Maxima Method (JPMM) by explicitly incorporating ENSO variability through a two-stage process: first deriving empirical scaling factors from historical data, then applying these factors within a probability density convolution framework. This method accounts for the influence of ENSO phases on extreme water levels by quantifying their modulation using a set of empirically derived scaling factors (SF_{phase}) and vertical offsets (δ_{phase}) applied to the surge component distribution. ENSO phases were classified using three-month running means of the Oceanic Niño Index (ONI), with transitions validated by requiring five consecutive overlapping seasons above or below threshold values, following NOAA's operational definitions. For our purposes, ENSO phases were defined as follows: El Niño ($|\text{ONI}| \geq 0.5^\circ\text{C}$), La Niña ($|\text{ONI}| \leq -0.5^\circ\text{C}$), and Neutral ($-0.5^\circ\text{C} < \text{ONI} < 0.5^\circ\text{C}$). The empirical scaling factors

are derived by analyzing three key statistical ratios that characterize each ENSO phase's influence on water levels:

$$SF_{\text{phase}} = 0.4 \times \text{Mean Ratio} + 0.3 \times \text{Std Ratio} + 0.3 \times \text{Extreme Ratio} \quad (7)$$

where:

- Mean Ratio = phase mean surge/baseline mean surge
- Std Ratio = phase surge standard deviation/baseline standard deviation
- Extreme Ratio = phase 95th percentile surge/baseline 95th percentile surge

The weights (0.4, 0.3, 0.3) reflect the relative importance of each metric in characterizing ENSO's influence on water levels. The mean ratio receives the highest weight (0.4) because it captures the predominant effect of ENSO phases on overall water level conditions, as evidenced by the systematic shifts observed in the Annapolis tide gauge record. The standard deviation ratio and extreme ratio are each weighted at 0.3, balancing the need to capture both general variability and extreme event behavior. The total water level distribution is computed through a sequential convolution process with a normalization at each step:

$$P_{\text{total}}(z) = P_{\text{MSL}}(z) * \left(P_{\text{tide}}(z) * P_{\text{scaled,surge}}(z) \right) \quad (8)$$

where the scaled surge PDF is computed as:

$$P_{\text{scaled,surge}}(z) = \frac{1}{SF_{\text{phase}}} P_{\text{surge}} \left(\frac{z - \delta_{\text{phase}}}{SF_{\text{phase}}} \right) \quad (9)$$

- SF_{phase} : A proposed scaling factor, unique to each ENSO phase and empirically fit to available data
- P_{surge} : Probability of a skew surge to a given threshold height
- z : Water level in meters
- δ_{phase} : A correction of vertical shift or bias in meters

The following steps are then taken to ensure numerical stability and statistical validity:

- Component-specific PDF estimation of water level height using optimized bin widths (1 cm) and Gaussian smoothing, with different smoothing parameters for tide ($\sigma = 1.2$) and surge ($\sigma = 0.8$) components
- Normalization at each convolution step using trapezoidal integration, ensuring proper probability distributions with tolerance of 1×10^{-2}
- Seasonal dependency preservation through separate monthly computations before weighted recombination

The convolution process then follows three main steps:

1. Calculate joint tide-surge distribution through convolution:

$$P_{\text{tide+surge}}(z) = P_{\text{tide}}(z) * P_{\text{scaled,surge}}(z) \quad (10)$$

2. Normalize the intermediate result using trapezoidal integration:

$$P_{\text{normalized}}(z) = \frac{P_{\text{tide+surge}}(z)}{\int P_{\text{tide+surge}}(z) dz} \quad (11)$$

3. Combine with MSL through final convolution:

$$P_{\text{total}}(z) = P_{\text{MSL}}(z) * P_{\text{normalized}}(z) \quad (12)$$

To validate the statistical robustness of our approach, Mann–Whitney U tests were applied to compare ENSO-phase skew surge distributions against the baseline, using a significance threshold of (p -value = 0.05).

This enhanced methodology provides several key advantages over the standard JPMM approach: explicit handling of ENSO-driven non-stationarity through empirically derived phase-specific adjustments, preservation of proper probability properties through careful normalization, component-specific treatment of smoothing and extremes, robust handling of seasonal dependencies, and efficient computation through vectorized operations. Results show significant improvements in capturing ENSO-related water level variations, particularly during El Niño phases where both the scaling factor and statistical significance are highest.

2.7. Model Validation and Performance Assessment

To properly evaluate the performance of the ENSO-JPMM, we employed a comprehensive set of validation metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), bias, and correlation coefficient. These metrics have been used in extreme water level modeling and coastal flood risk assessment due to their ability to quantify model accuracy and predictive skill [23,26,32,33].

RMSE serves as the primary validation metric due to its sensitivity to large errors, making it particularly suitable for assessing extreme water levels where accurate peak predictions are crucial for flood risk management [32,33]. The RMSE is computed for both the standard JPMM and ENSO-JPMM using:

$$RMSE_{\text{phase}} = \sqrt{\frac{1}{n_{\text{phase}}} \sum_{i=1}^{n_{\text{phase}}} (y_i - \hat{y}_i)^2}, \quad (13)$$

where:

- y_i represents the observed extreme water level at time i ,
- $\hat{y}_i$ represents the predicted extreme water level at time i ,
- n_{phase} is the number of observations within a given ENSO phase (El Niño, La Niña, Neutral).

RMSE penalizes larger errors more significantly than MAE, ensuring that the model's performance is evaluated with a focus on extreme events. In conjunction with RMSE, MAE is also calculated to provide a robust assessment of general model accuracy, as it measures the average absolute deviations between observed and predicted values without emphasizing extreme deviations [23,26].

To further assess the model's skill, we compute the bias, which quantifies systematic overestimation or underestimation in predictions, and the Pearson correlation coefficient, which measures the strength of the linear relationship between observed and predicted extreme water levels. The inclusion of these metrics ensures a well-rounded evaluation of model performance [23]:

- **Bias:** A measure of systematic deviation from observed values. A lower bias indicates that the model more accurately captures the mean trends in extreme water levels.
- **Correlation Coefficient:** Reflects the degree of agreement between observed and predicted values. A higher correlation value (closer to 1) indicates improved temporal consistency in model outputs.

Our validation framework incorporates these metrics across multiple dimensions:

- **Overall model performance:** RMSE, MAE, bias, and correlation coefficients are calculated for the full dataset, providing a baseline assessment of JPMM's predictive skill.

- **ENSO phase-specific validation:** Metrics are computed separately for El Niño, La Niña, and Neutral phases to evaluate the effectiveness of ENSO-JPMM in capturing variations in extreme water levels.
- **Monthly performance assessment:** Validation metrics are computed for each month, both across all ENSO phases and separately within each phase, allowing for the identification of seasonal biases and model strengths in different ENSO conditions.

The implementation of this validation framework ensures that the ENSO-JPMM not only reduces error magnitudes through RMSE but also improves agreement with observed extreme water levels via correlation and minimizes systematic deviations using bias. These enhancements reinforce the model's applicability in flood risk assessment, coastal infrastructure planning, and probabilistic extreme event prediction.

3. Results

3.1. Total Water Level Distribution Analysis

Results from steps shown in Section 2.6 are presented in Figure 3, which displays the total daily high water distributions across all three phases. The El Niño distribution peaks around 0.443 m MLLW, consistent with our derived El Niño scaling factor of 1.016 and vertical offset of +0.08 m. In contrast, the La Niña distribution (blue dashed line) shows a leftward shift with a peak probability around 0.407 m MLLW, aligning with its scaling factor of 0.985 and negative vertical offset (−0.002 m). The Neutral phase distribution (green line) lies between both El Niño and La Niña at 0.426 m but exhibits subtle departures in the upper tail, reflecting its intermediate scaling factor of 1.007.

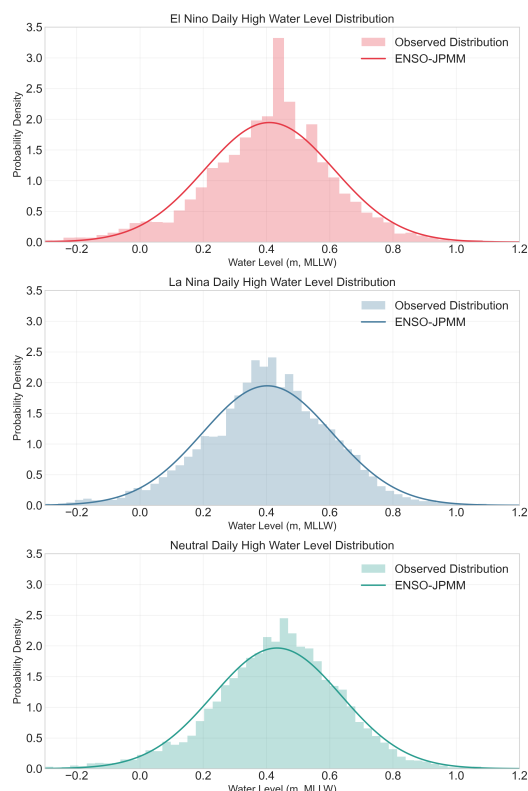


Figure 3. Comparison of normalized daily high water level distributions and the proposed ENSO-JPMM model for Annapolis, MD, by ENSO phase from El Niño (**top**), La Niña (**middle**), and Neutral (**bottom**), based on hourly tide gauge data, 1950–2020.

Bootstrap resampling (1000 iterations) constructed 95% confidence intervals for the seasonal scaling factors. The empirically derived scaling factors for Annapolis are: El Niño (1.016 ± 0.031), La Niña (0.985 ± 0.025), and Neutral (1.007 ± 0.023), as shown in Table 3.

Table 3. Determined Scaling Factors (SF) and Shift Values (δ) by ENSO Phase.

Phase	Scaling Factor (SF)	Vertical Shift (δ , m)
El Niño	1.016 (± 0.031)	0.08
La Niña	0.985 (± 0.025)	−0.002
Neutral	1.007 (± 0.023)	0.000
JPMM	0.992 (± 0.021)	0.001

The application of our ENSO-JPMM reveals significant phase-dependent variations in water level distributions at Annapolis. Figure 3 presents the probability density distributions with ENSO-conditioned distributions for El Niño (red solid line), La Niña (blue dashed line), and Neutral (green dotted line) phases. The most notable feature is the rightward shift and broader upper tail of the El Niño distribution, indicating both higher mean water levels and increased probability of extreme events during these phases.

3.2. ENSO Phase Impacts on Water Levels

Table 4 presents the statistical characteristics of total water levels across different ENSO phases. Analysis of all 27,272 observations reveals that while El Niño conditions exhibit the highest median water level (0.509 m), La Niña events are associated with the lowest mean (0.473 m), highlighting the typical suppression of higher water levels during La Niña phases. The Neutral phase falls in between, with a mean water level of 0.481 m, slightly above the standard JPMM estimate (0.498 m). In addition to mean values, skewness provides insight into the asymmetry of water level distributions. The El Niño phase has the least negative skewness (−0.139), indicating a more balanced distribution with fewer extreme low-water events compared to La Niña and Neutral phases. Conversely, the La Niña (−0.215) and Neutral (−0.278) distributions exhibit more negative skewness, suggesting a greater tendency for lower water levels relative to their central values. The standard JPMM model, with a skewness of −0.115, appears to underestimate the asymmetry observed under ENSO-specific conditions, reinforcing the importance of ENSO-conditioned modeling for capturing these deviations. To confirm the significance of mean water level differences between ENSO phases, a two-sample Student's t-test was conducted on El Niño (0.433 m, $n = 7706$) and La Niña (0.403 m, $n = 7663$) phases, incorporating additional observations (400 for El Niño and 50 for La Niña), yielding a statistically significant difference ($t = 9.07$, $df = 15,367$, $p < 0.0001$). This indicates that the 3.0 cm variation is unlikely to be due to random fluctuation. These results emphasize the role of ENSO phases in modulating water levels, where El Niño is associated with elevated mean levels and a more symmetric distribution, while La Niña conditions promote lower mean levels with a stronger left-skewed tendency. The differences between the phases, now statistically validated, suggest that ENSO-conditioned models provide a more refined representation of extreme water level risks, particularly for coastal flood planning and hazard assessments (Figure 4).

Table 4. Statistical summary of Total Water Levels by ENSO Phase. Data from Annapolis tide gauge records (1950–2020), analyzed using the ENSO-JPMM framework.

ENSO Phase	Mean (m)	Skewness
El Niño	0.433	−0.139
La Niña	0.403	−0.215
Neutral	0.409	−0.278

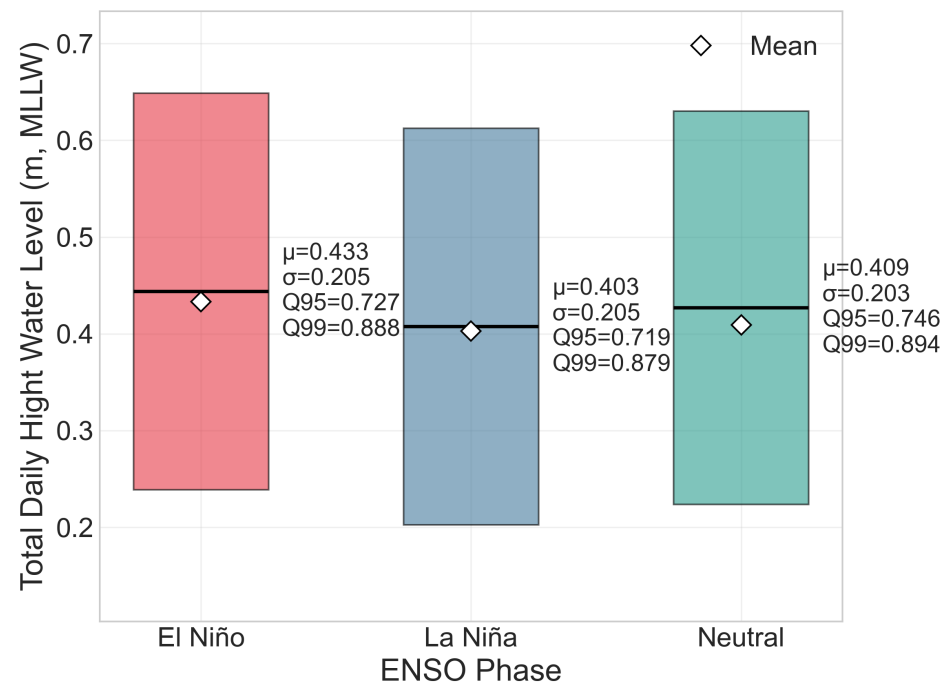


Figure 4. Comparison of total daily high water level distributions under different ENSO phases for Annapolis, MD. Data covers the period from 1950 to 2021. Bar represents the 25 to 75th quartile of occurrences, and line represents the median.

3.3. Performance of the JPMM and ENSO-JPMM Models

The results in Table 5 highlight the impact of incorporating ENSO-specific conditioning into the JPMM model for improved water level prediction. The ENSO-JPMM model demonstrates a consistent reduction in root mean square error (RMSE) across all ENSO phases, reinforcing the value of dynamically adjusting model parameters based on ENSO conditions. One of the key takeaways from these results is the ability of the ENSO-JPMM model to more accurately capture variations in water levels during different ENSO phases. The improvements observed, particularly under Neutral and El Niño conditions, suggest that incorporating ENSO conditioning refines the model's sensitivity to phase-dependent variability. This enhancement is particularly important for flood risk assessments, as standard JPMM models may overlook crucial phase-specific deviations that influence extreme water level events. While the improvements under La Niña conditions are relatively smaller, the results still indicate that ENSO-based adjustments contribute to overall model accuracy. This suggests that even during periods of lower water level variability, phase-aware modeling techniques help refine predictions by reducing systematic biases present in traditional models. These findings emphasize the need for advanced modeling approaches that incorporate climate variability factors such as ENSO, rather than relying solely on static probability methods. The improvements in RMSE illustrate the potential for enhanced flood risk assessments, better forecasting accuracy, and more informed coastal resilience planning. The ability to dynamically adjust predictions based on ENSO phase ensures that decision-makers and stakeholders receive more reliable information when preparing for extreme events, reinforcing the necessity of integrating climate-informed methodologies into hydrodynamic modeling frameworks.

Table 5. ENSO phase-specific model performance metrics.

ENSO Phase	RMSE (m)		Improvement (%)
	Standard	ENSO-JPMM	(%)
El Niño	0.5474	0.5279	3.56
La Niña	0.5417	0.5328	1.64
Neutral	0.5617	0.5282	5.96

Note: Improvement percentages based on RMSE reduction.

4. Discussion

Building on the results that demonstrate distinct water level modulations by ENSO phases, with El Niño leading to higher mean levels (0.433 m) compared to La Niña (0.403 m), and the notable reduction in RMSE (up to 5.96% during Neutral phases), this discussion explores the broader implications for coastal water level prediction and management in Annapolis, MD.

4.1. ENSO Influence on Water Level Variability

Our results reveal systematic differences in water level distributions across ENSO phases, with El Niño conditions associated with higher mean water levels (0.529 m) compared to La Niña (0.493 m) and Neutral (0.513 m) phases. These findings align with previous studies in the Chesapeake Bay region (Callahan et al., 2021) [10], but provide additional quantification of phase-specific impacts through our ENSO-JPMM. The observed phase-dependent modulation suggests that ENSO's influence extends beyond its traditionally recognized impacts on storm frequency and intensity to affect the underlying probability structure of extreme water levels.

The phase-specific scaling factors derived from our analysis (El Niño: 1.016, La Niña: 0.985, Neutral: 1.007) demonstrate quantifiable adjustments to surge probabilities that improve upon previous static approaches. This enhancement is particularly evident in the reduction in RMSE values across all ENSO phases, with the most substantial improvements observed during Neutral (5.96 percent reduction) and El Niño (3.56 percent reduction) conditions. These improvements align with findings from Sweet and Park (2014) [16], who identified ENSO as a significant driver of nuisance flooding along the U.S. East Coast, while providing a more robust statistical framework for quantifying these relationships.

4.2. Water Level Distributions Across Epochs

The analysis of daily high water level distributions across various epochs, as detailed in Table 6, provides several informative insights:

- **Epoch 1:** The ENSO-JPMM model shows a significant difference in daily high water levels, with El Niño at 0.6124 m compared to La Niña at 0.3724 m, suggesting a strong ENSO influence.
- **Epoch 2:** An anomaly is observed where La Niña results in the lowest daily high water level recorded at 0.2223 m, while Neutral conditions surpass those of El Niño, indicating possible non-ENSO factors at play.
- **Epoch 3:** There is a noted recovery trend in daily high water levels, with Neutral conditions slightly exceeding El Niño, prompting inquiry into additional influencing factors.
- **Epoch 4:** Daily high water levels across ENSO phases show convergence, which could imply a diminishing effect of ENSO or the influence of other climatic phenomena.

These findings from the ENSO-JPMM model epoch analysis, compared with the Standard JPMM, indicate the significance of considering ENSO phases for a more complete

understanding of daily high water level dynamics, crucial for coastal flood risk assessment. The epoch-specific variations suggest that further investigation and analysis could yield deeper insights into these patterns. Such research could enhance our predictive models and adaptation strategies in response to climatic variations.

While our epoch-based segmentation accounts for the 18.6-year nodal cycle by analyzing long-term variability, further research is needed to determine whether ENSO influences tidal amplitudes differently across lunar nodal cycles. While our epoch-based segmentation accounts for the 18.6-year nodal cycle by analyzing long-term variability, further research is needed to determine whether ENSO influences tidal amplitudes or skew surge differently across lunar nodal phases. A recent study found a statistically significant relationship between ENSO timing and the 18.6-year lunar tidal cycle, with El Niño and La Niña events occurring in distinct years relative to the cycle's maximum diurnal tide [34]. This suggests that phase alignment between ENSO and the nodal cycle could modulate sea level anomalies, potentially including skew surge variations. Future work should examine whether these ENSO-driven effects exhibit statistically significant dependencies on specific nodal cycle phases.

Table 6. Mean Water Levels by epoch, method, and ENSO phase.

Epoch	Method	Phase	Mean (m)
epoch1	ENSO-JPMM	El Niño	0.6124
epoch1	ENSO-JPMM	La Niña	0.3724
epoch1	ENSO-JPMM	Neutral	0.2917
epoch2	ENSO-JPMM	El Niño	0.4039
epoch2	ENSO-JPMM	La Niña	0.2223
epoch2	ENSO-JPMM	Neutral	0.4354
epoch3	ENSO-JPMM	El Niño	0.4218
epoch3	ENSO-JPMM	La Niña	0.3691
epoch3	ENSO-JPMM	Neutral	0.5069
epoch4	ENSO-JPMM	El Niño	0.5231
epoch4	ENSO-JPMM	La Niña	0.4692
epoch4	ENSO-JPMM	Neutral	0.5041

4.3. Methodological Advances

The ENSO-JPMM approach represents an accuracy improvement over standard joint probability methods by explicitly accounting for climate variability in extreme water level predictions. Our epoch-based analysis, spanning multiple nodal cycles, should yield higher fidelity predictions by capturing long-term trends and variability in water levels.

- **Skew Surge Calculation:** The use of Giloy's framework enhanced our JPMM by modeling extreme surge events through the Generalized Pareto Distribution (GPD) [35], better capturing the tail or more improbable behavior of surge events in Annapolis.
- **Tide-Surge Interaction:** By accounting for tide-surge interactions, Giloy's method improved the accuracy of surge component separation, directly contributing to the observed reduction in prediction errors, particularly during high variability periods.
- **Enhanced MSL Analysis:** The refined treatment of MSL variations allowed for a clearer distinction between long-term trends and short-term fluctuations, leading to more accurate skew surge estimates and thus more reliable predictions of extreme water levels across different ENSO phases.

4.4. Sea Level Rise Considerations

The non-stationarity implications of our findings suggest that traditional extreme value analysis methods may underestimate future flood risks by failing to account for

climate variability. Our results show that ENSO phases can modulate mean water levels by up to 3.01 cm, a significant factor when considering threshold exceedance frequencies for coastal infrastructure planning. The ability to quantify ENSO-driven variability in coastal water levels is crucial for improving flood risk assessments and ensuring that infrastructure resilience planning adequately considers the dynamic nature of climate influences.

4.5. Applications and Implementation

The ENSO-JPMM methodology offers practical improvements for coastal flood risk assessment and infrastructure planning. By capturing phase-specific water level variations, the model enables more precise estimation of threshold exceedance probabilities, which is critical for both short-term operational forecasting and long-term adaptation planning. The reduction in prediction errors, particularly during El Niño phases (3.56 percent RMSE improvement), enhances the reliability of flood risk assessments and provides decision-makers with improved information for resource allocation and mitigation strategies.

For infrastructure planning, the phase-specific water level distributions derived from this analysis offer a more comprehensive understanding of potential exposure to extreme events. This enhanced predictive capability allows coastal managers to better anticipate and prepare for periods of increased flood risk, particularly during strong El Niño conditions when mean water levels exhibit significant elevation (0.433 m compared to the overall mean of 0.415 m). These findings align with prior studies that have identified ENSO as a key driver of anomalous sea levels and nuisance flooding along the U.S. East Coast [4]. By incorporating ENSO-conditioning into probabilistic modeling frameworks, coastal engineers and planners can develop more adaptive infrastructure designs that account for climate variability.

4.6. Limitations

While the ENSO-JPMM demonstrates improvements, key limitations include:

- **Single Climate Mode Focus:** Although this study centers on ENSO, we recognize that other climate modes, such as the North Atlantic Oscillation (NAO) and Atlantic Multidecadal Oscillation (AMO), also drive sea level variability along the U.S. East Coast [36]. Future research should investigate potential non-linear interactions between NAO- or AMO-driven sea level anomalies and ENSO-phase effects, particularly their influence on the probability of extreme events.
- **Assumption of Stationarity:** The approach assumes static relationships between ENSO phases and water levels within epochs, which might not hold under climate change scenarios where ENSO characteristics could evolve.
- **Historical Data Reliance:** Current model parameters are based on historical observations, which might not predict future ENSO-water level dynamics accurately under changing climate conditions.
- **Lunar Nodal Cycle Interactions:** The 18.6-year lunar nodal cycle may modulate tidal amplitudes, potentially introducing dependencies with ENSO-driven skew surge. While our epoch-based approach (19-year segments) mitigates this effect, explicit modeling of tide-surge interactions across nodal cycles is not included, which could obscure their combined influence on extreme water levels.

Future studies should focus on integrating multiple climate indices and developing methods for dynamic adjustment of model parameters to maintain accuracy.

4.7. Future Work

Future research directions include:

- **Multiple Climate Indices:** Integrating NAO into the JPMM framework to refine predictions for regions like Annapolis, where both ENSO and NAO are influential, providing a multi-modal approach to capture complex climate interactions. Future research will also incorporate additional climate indices, such as the NAO and AMO, using multivariate regression or machine learning techniques to isolate their contributions from ENSO effects. This could involve deriving scaling factors for each mode based on their teleconnections to regional sea levels, enhancing the model's ability to disentangle overlapping influences.
- **Non-stationary Scaling Factors:** Developing dynamic parameters to adapt to evolving ENSO characteristics, enhancing model robustness against climate change scenarios and integrating projection uncertainties.
- **Expanded Methodology:** Incorporating additional regional climate indices for a more generalized framework, leveraging high-resolution data for better climate teleconnection understanding. This could extend to explicitly modeling tide-surge interactions across lunar nodal cycles to assess their combined influence on extreme water levels, building on the epoch-based approach.
- **Machine Learning Applications:** Using AI to explore nonlinear interactions between climate modes like ENSO and NAO, potentially improving real-time flood forecasting as suggested by studies like Ham et al. (2019) [37].
- **Operational Guidelines:** Establishing protocols for updating model parameters and integrating these predictions into existing frameworks, aiding coastal management and policy in practical applications.

These advancements would enhance the applicability of the ENSO-JPMM, fostering resilience in coastal communities by aligning research with actionable climate adaptation strategies.

5. Conclusions

This study sought to increase the fidelity of extreme water level prediction by incorporating ENSO conditioning into the JPMM. Through the analysis of 26,175 water level records from Annapolis from 1950 to 2021, we have highlighted the role of ENSO phases in modulating flood risk probabilities. These insights offers potential actionable strategies for coastal infrastructure design, flood risk management, and adaptive planning.

Our approach merges ENSO phase information with the JPMM framework, enhanced by Giloy's methodology [35] for skew surge analysis, to provide a more dynamic and precise prediction tool for extreme water level events in tidally-influenced regions. Water level records from Annapolis, MD show ENSO phases affect water levels, with El Niño conditions correlating with higher levels (0.433 m) compared to La Niña (0.403 m) and Neutral phases (0.409 m). A proposed application of phase-specific scaling factors has resulted in an improved model, with reductions in RMSE up to 5.96% during Neutral conditions, validating our methodological innovations over multiple tidal epochs.

This study may impact coastal management practices; incorporating ENSO phase data into risk assessments may offer higher precise operational responses and strategic planning, potentially mitigating economic impacts from flooding. The scaling factors developed can enhance existing flood prediction models, preparing communities better for nuisance flooding, particularly during El Niño phases. Moreover, recognizing ENSO variability in long-term infrastructure planning can lead to more resilient coastal defenses, ensuring that flood risks are not underestimated in varying climate conditions.

Future research directions are clear. Extending this methodology to other coastal regions will test its universality and uncover regional variations in ENSO's influence. It is crucial to investigate how climate change might modify ENSO characteristics, including changes in event frequency, intensity, and their relationship with sea-level rise. Additionally, examining the interaction between ENSO and other climate patterns, such as the North Atlantic Oscillation, could further refine our predictive models. Finally, translating these findings into operational tools and guidelines for coastal managers is essential for broad application.

In conclusion, this study underscores the importance of accounting for climate variability in coastal water level analysis, markedly enhancing our ability to predict extreme events. The methods introduced further indicate a correlation between climate patterns and coastal water levels. The successful application in Annapolis suggests broader potential across other coastal regions, advancing towards more resilient and adaptive management strategies.

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