

Article

A Developed VMD-DMD Algorithm with Machine Learning Models for Improving Sea Level Predictions: A Case Study of the Mediterranean Coastlines

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Abstract

Accurate prediction of sea level change in the Mediterranean Sea is essential for coastal risk management; however, the nonstationary behavior of sea level makes this difficult. This study presents a hybrid framework that integrates variational mode decomposition (VMD) and dynamic mode decomposition (DMD) with long short-term memory (LSTM) and extreme gradient boosting (XGBoost) to forecast monthly sea level anomaly (SLA). Thirty years of records from sixteen Mediterranean tide gauge stations (1993–2022) were used. The proposed VMD-DMD algorithm decomposed SLA signals into distinct multi-scale temporal components. It improved reconstructed signal accuracy compared to VMD-only decomposition, reducing average RMSE from 24.22 to 7.38 mm. For prediction, we compared our models against multiple baselines: the mean annual cycle with anomaly persistence (MAC_AP) and three-layer MLP. The proposed VMD-DMD-LSTM achieved the best overall performance (mean $R^2 = 0.92$, RMSE = 20.37 mm, and MAE = 15.31 mm) with an 18% error reduction compared to three-layer MLP. VMD-DMD-XGBoost achieved RMSE = 24.90 mm and $R^2 = 0.88$. Furthermore, in a direct comparison on identical data, our VMD-DMD-LSTM outperformed the benchmark VMD-EEMD-LSTM model, achieving about 12% lower errors. Thus, the proposed framework effectively isolates multi-scale dynamics and reduces residual noise, providing more reliable sea level forecasts for coastal operational planning.

Keywords: Variational Mode Decomposition (VMD); Dynamic Mode Decomposition (DMD); sea level prediction; VMD-DMD-LSTM model; the Mediterranean region

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1. Introduction

Sea level variation monitoring and prediction on a global and regional scale are still a complex task in current Earth sciences studies [1,2]. Observation and study of short- and long-term sea level changes are vital for coastal area management, applied oceanography, and marine meteorology [3]. The climatically most exposed region of the world is the Mediterranean Sea [4,5]. Its multiple low-lying densely populated coastlines are the

reasons for its exposed position [6]. SLR and risk futures simultaneously may have a devastating effect on coastal societies due to activities [6].

The power and effectiveness of machine learning (ML) and deep learning (DL) have recently been demonstrated in a variety of scientific and daily domains [7]. The use of these techniques for studying coastal and sea level phenomena has seen an impressive growth recently [8], following two related tracks: (i) evaluation of impacts and vulnerability to sea level rise (SLR) of coastal systems and infrastructure [9], and (ii) forecasting of sea level anomalies (SLAs) and sea surface height (SSH) using time series analysis [10]. Both approaches have several technical aspects in common but pursue different scientific aims.

Several timeseries forecasting models have been constructed by merging the decomposition algorithms with ML and DL models [11–16]. Recently, the LSTM model, a prominent neural network approach, showed significant advantages in long-term timeseries forecasting thanks to its powerful memory capabilities, which enhanced its predictive accuracy. However, the constraints of LSTM in feature extraction from intricate time series require the combination of supplementary methodologies to achieve high-precision predictions. Ban et al. (2023) proposed a VMD-LSTM combined model for long-term tidal height prediction and demonstrated its superior performance compared to classical harmonic analysis, SVM, standalone LSTM, and CEEMDAN-LSTM models [17]. Nonetheless, the experimental findings of Ban et al. (2023) indicate that the VMD-LSTM model achieves prediction accuracy for individual IMFs. However, its prediction of the residual term shows a greater error, leading to a significant source of inaccuracy for the model [18].

Zid et al. (2024) used four tide gauges on the Mediterranean coast for a multi-scale analysis, rather than prediction [19]. They used EMD to decompose nonseasonal SLA into IMFs, then Hilbert–Huang transform (HHT) to analyze time-varying frequency and amplitude. In addition, Chen et al. (2023) introduced the VMD-EEMD-LSTM model, which was applied along the Dutch coast and showed great results where the coefficient of determination (R^2) reached 0.9 [18]. Another model is EEMD-LSTM, which was applied to the Chinese coast by Jin et al. (2023) and Yang et al. (2023), achieving good results of about 0.89 and 0.88 in R^2 [1,20], respectively. Meanwhile, Sun et al. (2023) employed a decomposition method for sea level anomaly time series prediction (DMSLAP) and time-varying filtering based on empirical mode decomposition (TVF-EMD) with the LSTM model, achieving high accuracy levels [21].

Because of its higher decomposition ability, VMD outperformed most other decomposition algorithms. It has been deeply applied in hybrid DL and ML time series forecasting [22–25]. Like a separation of variables, the DMD is a modal decomposition of a high-dimensional spatiotemporal signal decomposed into a triplet of purely spatial modes, scalar amplitudes, and purely temporal signals [26,27]. The characterization of the decomposition permits us to define the flow process as a sequence of easier procedures such that, when linearly combined, they generate the whole succession of data. The flow is segregated into dynamic components (spatial-mode–temporal-signal pairings) that can be analyzed independently, which is enabled by such a decomposition. DMD may be considered another means of dimensionality reduction compared to proper orthogonal decomposition (POD) or singular value decomposition (SVD) [28,29]. Uchida et al. (2025) used the DMD to perform one-day-repeat SWOT observations of sea surface height (SSH) in the Gulf Stream extension and for a tidally forced numerical simulation [30]. Mankovich et al. (2025) used the DMD with control to analyze surface air temperature trends from climate simulations for understanding the impact of multiple climate-forcing agents [31].

This study has two main goals. First, we develop and validate a hybrid VMD-DMD approach that captures the multi-scale characteristics and temporal dynamics of SLA signals. Second, we use this decomposition as a preprocessing step to improve two standard

forecasting models: LSTM and XGBoost. We test the framework on 16 tide gauge stations distributed across the Mediterranean basin, using data from 1993 to 2016 for training and 2017 to 2022 for testing. In operational terms, historical SLA observations up to the current month can easily be accessed. Therefore, all predictions are one month ahead and use only historical SLA data (no atmospheric inputs). This setup ensures that the model's predictive skill is attributable solely to the information contained in the SLA signal itself.

2. Data and Methods

2.1 Dataset Selection

We used the Revised Local Reference (RLR), which has a known datum history, to evaluate the tide gauge (TG) time series of monthly mean sea level (MSL). The data were provided by the permanent service for mean sea level (PSMSL) [32,33]. The RLR datum for each site is approximately 7000 mm below mean sea level. The PSMSL adopted this convention, as advised for scientific applications, to avoid negative values in the resulting RLR monthly sea level time series [34].

We selected the tide gauge (TG) stations around the Mediterranean coast using the same standards that were established by Youssef et al. (2025), which applied the modified seasonal Mann–Kendall test [3]. However, we depended on choosing the same time series for each station spanning from 1993 to 2022. After handling the raw data and eliminating outliers, the resulting time series shows a completeness of over 80% for the available monthly values. This threshold allows for more reliable evaluation of tidal data throughout the Mediterranean basin.

Sixteen stations were selected after meeting the established criteria; their detailed information is presented in Table 1. Figure 1 shows the IDs and positions of the TGs along the Mediterranean coastline and within their principal subbasins.

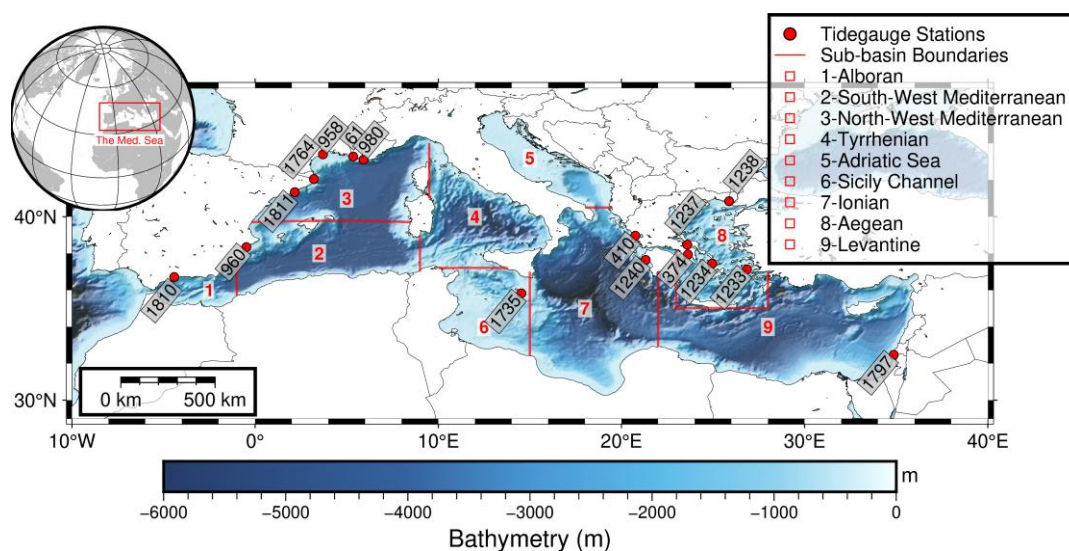


Figure 1. Locations and identification numbers of the 16 tide gauge stations used in this study, distributed along the Mediterranean coastline and its main subbasins.

Table 1. Geographic information, data availability, and mean sea level anomaly values for the selected tide gauge stations along the Mediterranean coast covering the period from 1993 to 2022.

Station ID	Station Name	Latitude (Degree)	Longitude (Degree)	Available Data (%)	Mean SLA (mm)
61	MARSEILLE	43.28	5.35	80	7006
374	PIRAIEVS	37.94	23.63	84	6988
410	PREVEZA	38.96	20.76	82	7099
958	SETE	43.40	3.70	80	6941
960	ALICANTE 2	38.34	−0.48	87	7102
980	TOULON	43.11	5.91	84	7031
1233	LEROS	37.13	26.85	90	7068
1234	SIROS	37.44	24.95	86	6976
1237	KHALKIS NORTH	38.47	23.59	87	7012
1238	ALEXANDROUPOLIS	40.84	25.88	80	7083
1240	KATAKOLON	37.64	21.32	87	7119
1735	MARSAXLOKK	35.82	14.53	83	7148
1764	L'ESTARTIT	42.05	3.21	93	7061
1797	HADERA	32.47	34.86	87	7158
1810	MALAGA II	36.71	−4.42	96	7066
1811	BARCELONA	41.34	2.17	90	7093

2.2. Signal Processing Methods

For signal processing and data analysis, there are three commonly applied adaptive decomposition methods for data, namely empirical mode decomposition (EMD), variational mode decomposition (VMD), and dynamic mode decomposition (DMD) [26,35,36]. Although all three are best with multi-scale data, each has some advantages and limitations.

The straightforward, fact-driven concept of EMD, first proposed by Huang et al. (1998), is that any complex signals can be decomposed into a set of small, oscillating chunks named intrinsic mode functions (IMFs) [37]. The method uses a repeated “sifting” process to accomplish this. To remove a single IMF, it first locates the local maxima and minima of the signal, then uses spline interpolation to create upper and lower envelopes, and finally repeatedly removes the mean of the envelopes [18]. The algorithm is recursive in the way that the residual signal is processed equally until a trend that is monotonic remains by itself [37]. The main drawback of this heuristic method is its extreme flexibility. The “end effect” for which errors within signal limits extend inward and taint the entire decomposition is caused by the hypersensitivity of the sifting process to noise and end-points. More importantly, EMD frequently suffers from “mode mixing,” which is a process where a coherent physical vibration is decomposed into numerous IMFs or vibrations of enormously different timescales are incorrectly confined in one IMF. This indeterminacy makes the algorithm output statistically unstable and the temporal characterization of the modes problematic [18].

Dragomiretskiy and Zosso (2013) formulated VMD as a more robust, mathematically based version [36]. Unlike recursive shifting of EMD, VMD formulates decomposition as an approximately solvable variational optimization problem. The objective is to find a fixed number (K) of mode functions, $u_k(t)$, each concentrated around a center frequency (ω_k), such that their sum perfectly reconstructs the input signal. This is formulated as a constrained minimization of total estimated bandwidth of all modes [36]. In other words, VMD identifies both a set of modes and their center frequencies best representing the spectral content of the signal without intermode overlapping [38]. This technique realizes tremendous benefits with components having evident spectral separation and showing

greater natural immunity to noise [36]. It also greatly reduces the mode mixing issue. VMD is not flawless, however. Where the number of true underlying processes is ambiguous, prespecified selection of the number of modes, K , can be a drawback. Also, the method's assumption of harmonic-like modes may struggle to deal with highly transient or impulse-type "bursty" signals that are resistant to narrowband description. In addition, while boundary effects are minimized, they are not completely eliminated [18].

Conversely, DMD, as mentioned in works such as Proctor (2016), brings emphasis back to the identification of underlying dynamics from mere decomposition [39]. DMD is a data-driven approach that originated from fluid dynamics and attempts to approximate a high-dimensional, perhaps nonlinear system by a linear model [26]. It operates with time sequences of system state snapshots. The key concept is to identify a linear operator, A , that optimally propagates the system state in time such that $X_{t+1} \approx AX_t$ [26]. Singular value decomposition (SVD) is used on the data matrix to find dynamic modes with corresponding frequencies and growth/decay rates by examining the eigenvectors and eigenvalues of this estimated operator. This provides a strong spatiotemporal perspective of coherent structures, e.g., oceanic traveling waves in data. The fact that it can give an exact dynamic description is DMD's major advantage [26,39]. Its fundamental assumption, however, dissolving the evolution of the system into a linear model, is also DMD's greatest disadvantage. This linearity can be a harsh constraint on very nonlinear processes, such as regional sea level regulation, because it is not able to reproduce all the richness of the subsisting interactions. In addition, if not appropriately regularized, DMD can be prone to overfitting and generate a large number of modes that are noise or redundant dynamics rather than physically significant structures [39].

2.3. Hybrid Methodology VMD-DMD

Processing complex, nonstationary, and multi-scale SLA time series presents significant challenges [20]. The benefit of using the EMD is that it can effectively separate the yearly cycle and long-term trend, but its output is a set of static mode sequences, and it does not dynamically filter or describe how each mode changes over time [38]. VMD is very suitable for describing the components of the signal, but it does not explain how they work together as a dynamic system. In addition, when DMD is directly applied to the signal, a single linear operator is working to capture the evolution of the entire system [26,39], which, of course, leads to a lack of accuracy in detecting the dynamic changes. To process these different components and simulate their underlying dynamics, we have developed a novel hybrid method combining VMD and DMD. The hybrid VMD-DMD was developed to improve the estimation of multiple harmonic oscillations in signals and nonstationary frequencies.

A separate conventional spectral analysis, such as Fourier or power spectral density analysis, was not adopted in this study because the principal objective was not only to identify dominant periodicities but also to obtain temporally evolving components suitable for subsequent forecasting. Conventional spectral analysis provides a global description of signal energy as a function of frequency and is less informative when the amplitude and frequency characteristics of a nonstationary signal vary with time [40]. In contrast, VMD adaptively decomposes the SLA series into narrow-band modes characterized by estimated center frequencies, thereby retaining explicit frequency-scale information while accommodating the multi-component structure of the signal. DMD subsequently characterizes the temporal evolution of each VMD component through modal frequencies and growth or decay rates, rather than modeling a complex and nonstationary signal. Therefore, the resulting reconstruction is not only statistically improved but also incorporates the temporal dynamics of the individual VMD-derived modes identified through DMD. This hybrid model significantly improves the scientific interpretability of the analyzed

data. In addition, the automatic classification of the predominant period of each processed mode can be obtained (e.g., interannual (1.5–5 yr)). Furthermore, the addition of geographic data then adds regional context to this classification (e.g., low-frequency/long-timescale component and interannual variability occurring on timescales associated with NAO/EA/WeMO), ensuring a direct connection between the mathematical model and oceanographic events.

VMD, the initial step in our processing model, adaptively breaks down input signal $f(t)$ into a discrete number of predefined K modes, u_k . Equation (1) is used to obtain a constrained variational result [36].

$$\left\{ \begin{array}{l} \min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ \text{subject to } \sum_k u_k = f \end{array} \right. \quad (1)$$

Here, $\{u_k\} := \{u_1, \dots, u_K\}$ and $\{\omega_k\} := \{\omega_1, \dots, \omega_K\}$ represent the sets of all modes and their center frequencies, respectively. The term $\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t)$ corresponds to the analytic signal of $u_k(t)$, obtained via the Hilbert transform. The exponential term, $e^{-j\omega_k t}$, downconverts the mode to baseband, while the squared L2-norm of its gradient estimates the mode's bandwidth. To make the problem tractable, we introduce a quadratic penalty term and Lagrangian multipliers (λ), leading to the augmented Lagrangian (L) [36]:

$$\begin{aligned} L(\{u_k\}, \{\omega_k\}, \lambda) = & \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ & + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \langle \lambda(t), f(t) - \sum_k u_k(t) \rangle \end{aligned} \quad (2)$$

The alternating direction method of multipliers (ADMM) is used to solve this equation in the frequency domain, successively updating $u_k^{n+1}, \omega_k^{n+1}$, and λ^{n+1} until convergence. For our SLA data, this process effectively separated the composite signal into individual narrowband components, u_k . These components can be physically interpreted, as illustrated by Sun et al. (2023), into the trend, periodic changes, annual cycle, semi-annual signal, and higher-frequency residuals [21]. The trend is an element that denotes gradual or continuous change over time [41]. Annual or semi-annual seasonal variations refer to recurring variations linked to seasons where the pattern does not change, but the magnitude does [42]. Periodic variations occur over a few years, while higher-frequency residuals are random occurrences [43].

In the second step of our methodology, each VMD-derived mode is processed using a DMD framework. Although VMD offers a clear scale separation, it remains a static decomposition [18]. DMD, on the other hand, is an effective technique for extracting system dynamics from time series data. DMD's fundamental assumption is that a linear operator, A , can approximate the system's evolution such that $X_{t+1} \approx AX_t$, where X_t is the state vector at time (t) [39].

We first use time-delay embedding before applying DMD to each 1D mode, $u_k(t)$, to construct a state-space representation. Therefore, we generate a Hankel matrix, X [39]:

$$\begin{bmatrix} u_k(t_1) & u_k(t_2) & \cdots & u_k(t_m) \\ u_k(t_2) & u_k(t_3) & \cdots & u_k(t_{m+1}) \\ \vdots & \vdots & \ddots & \vdots \\ u_k(t_d) & u_k(t_{d+1}) & \cdots & u_k(t_N) \end{bmatrix} \quad (3)$$

In Equation (3), $u_k(t_i)$ denotes the value of the $K - th$ VMD-derived mode at the $i - th$ time step. Because monthly SLA data are used in this study, two consecutive time indices are separated by one month. N represents the total number of samples within the analyzed window, while d is the time-delay embedding dimension, i.e., the number of

consecutive samples included in each embedded state vector. The number of columns in the Hankel matrix is therefore $m = N - d + 1$ (in the optimized configuration that will be illustrated, $N = 36$ and $d = 24$, giving $m = 13$). Thus, $X \in R^{24 \times 13}$. Each column of X represents a d -dimensional delay-coordinate state vector. Then, depending on this matrix, two time-shifted matrices are constructed: $X_1 = X_{:,1:m-1}$ and $X_2 = X_{:,2:m}$. The DMD algorithm seeks the best-fit linear operator, A , that satisfies $X_2 \approx AX_1$ [26,39]. This issue is solved using the singular value decomposition (SVD) of X_1 :

$$X_1 = U\Sigma V^* \quad (4)$$

The subspace of the first singular vector, τ , is used to compute a low-rank approximation of A , where $\tilde{A} = U_\tau^*AU_\tau = U_\tau^*X_2V_\tau\Sigma_\tau^{-1}$. Then, the DMD modes are obtained by computing the eigenvalues, μ_i , and eigenvectors, w_i , of $\tilde{A}$ [39]:

$$\Phi = X_2V_\tau\Sigma_\tau^{-1}W \quad (5)$$

W is the matrix of $\tilde{A}$'s eigenvectors. Equation 6 provides the reconstructed data for a single mode [39].

$$X_{DMD} \approx \Phi \text{diag}(e^{\omega t})b \quad (6)$$

Here, b is the mode amplitude and $\omega = \ln(\mu)/\Delta t$ is the continuous-time eigenvalue [26,39]. In our implementation, we applied this DMD procedure as a sliding window along each VMD mode such that the linear dynamics can be adapted with slow variations in the system dynamics. The final reconstruction for each mode is a weighted average of these local DMD reconstructions such that a temporally adaptive and smooth result is obtained. The final VMD-DMD reconstruction of the original SLA signal is an accumulation of the individually treated modes:

$$f_{recon}(t) = \sum_{k=1}^k u_k^{DMD}(t) \quad (7)$$

In this study, a grid search was performed on the training dataset of data from 1993 to 2016 at representative stations to optimize the parameters of VMD. Decomposition was carried out using $K = 8$ intrinsic modes, a selection based on having enough modes to best recover the significant scales of variability, anywhere from long-term trends and interannual variability through to seasonal cycles, without overfitting. In order to apply narrow-band, multi-scale temporal components, the bandwidth constraint parameter α was set at 500. The decomposition was then carried out with a high convergence tolerance of $1e-6$ and under no noise assumption ($\tau=0$) in order to obtain good separation of modes. The one-dimensional SLA signal was then reduced here to a multi-dimensional array of eight lower-order, quasi-orthogonal components.

DMD was applied in a sliding-window manner to each of the eight VMD modes. Because the SLA series has a monthly temporal resolution, a window length of 36 monthly observations (3 years) was used, and the window was advanced by 12 monthly observations (1 year). Consequently, adjacent windows overlapped by 2 years. Within each window, the one-dimensional VMD mode was transformed into a delay-coordinate state-space representation before DMD was applied. By converting the one-dimensional mode in every window into a state-space representation via time-delay embedding with 24 delays, DMD identified the leading linear operator driving the short-term evolution. DMD was configured to use full rank in the embedded space ($r = -1$) to capture the dominant dynamics. Finally, weighted averaging with a Hanning window was used to average the separate windowed reconstructions to yield a continuous, smooth, and dynamically filtered portrayal of each original VMD mode. The final hybrid reconstruction was created by combining dynamically processed modes.

The VMD-DMD hyperparameters were optimized using only the 1993–2016 training data at four representative tide gauge stations: station 61 (MARSEILLE), station 410 (PREVEZA), station 1234 (SIROS), and station 1810 (MALAGA II). These stations were selected to provide a geographically distributed subset of the Mediterranean tide gauge network, representing different coastal sectors from the western Mediterranean to the Ionian and Aegean regions, rather than optimizing the decomposition separately for each of the 16 stations. The grid search evaluated $K = 4, 6$, and 8 ; $\alpha = 500, 1000, 1500$ and 2000 ; time-delay embedding dimensions of $6, 12, 18$, and 24 ; and $r = -1$. The grid search conducted independently at each of the four representative stations identified the same optimal configuration: $K = 8$, $\alpha = 500$, a time-delay embedding dimension of 24 , and $r = -1$. This common configuration was subsequently fixed and applied unchanged to all 16 tide gauge stations; no station-specific retuning was performed. The DMD sliding-window length and step were fixed at 36 and 12 months, respectively. Section (S1) of the supplementary data file provides the grid-search procedure and results, with station 61 presented as a detailed example.

The workflow starts with the raw monthly SLA time series, which is first subjected to data preprocessing. The preprocessed signal is then decomposed using a hybrid VMD–DMD approach. This process generates a set of intrinsic modes. Each decomposed mode is used as an independent subsignal and forwarded to the prediction stage, where machine learning models are applied separately to each mode. Finally, the individual mode predictions are merged to reconstruct the final SLA prediction, which is then evaluated against several baselines using standard statistical metrics. Figure 2 illustrates the workflow of the methodology.

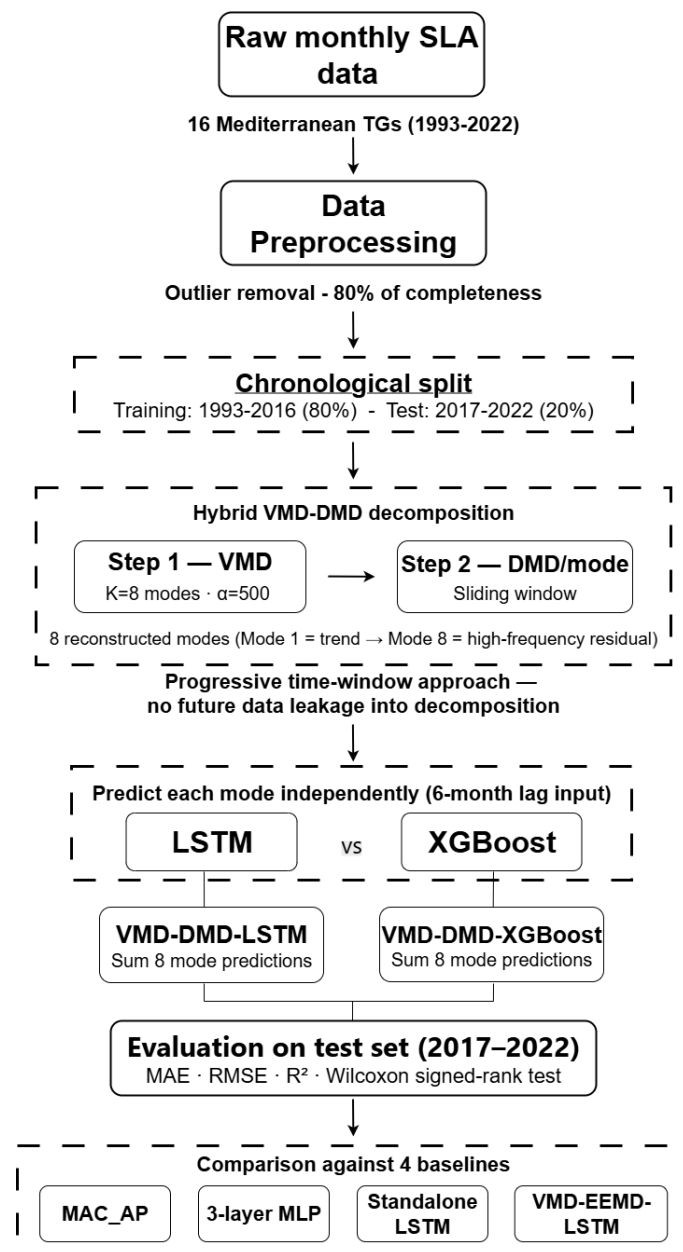


Figure 2. Workflow of the proposed hybrid framework combining variational mode decomposition, dynamic mode decomposition, and prediction models. The sea level anomaly signal is decomposed into multiple modes, predicted separately, and reconstructed for evaluation.

2.4. Deep Learning (DL) and Machine Learning (ML) Models

2.4.1. Input Formulation and Prediction Task

A wide range of DL and ML algorithms have been applied in the modeling and prediction of sea level change (SLC) [44]. Supervised learning is widely used in sea level modeling [44]. Many studies employ a range of algorithms, including support vector machines (SVMs) [45,46], regression models [47], ensemble methods [48], and sophisticated neural networks like convolutional neural networks (CNNs) [49], long short-term memory (LSTM) networks [50], and recurrent neural networks (RNNs) [51]. These studies encompass applications at local, regional, and global scales. Furthermore, they often use mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2) as performance measures [44,52–54].

Long short-term memory (LSTM) networks and extreme gradient boosting (XGBoost) are two of the most used for time series analysis. Many studies ensure the

efficiency of using the LSTM model in sea level prediction [18,44,52,55]. Moreover, many studies, such as Osman et al. (2021), Feng et al. (2022), Makky et al. (2024), Bhatta and Yang (2025), and Priyasiri et al. (2025), have proven the efficiency of the XGBoost model in analyzing time series data [56–60].

The two models that have been suggested were used for one-month-ahead prediction purposes. The use of SLA measurements for predicting SLA at a future time point (t) requires using SLA readings during the previous (L) months where L refers to the length of the lag in the inputs. The one-month-ahead forecast horizon was selected to provide a consistent medium- to short-term prediction task while retaining sufficient historical information for model training and evaluation. This includes coastal operational planning, monitoring, maintenance scheduling, and preparedness. It should be emphasized that the present monthly forecasting framework is not intended for operational prediction of short-duration coastal flooding events, which generally requires hourly or daily observations and explicit representation of tides, storm surge, atmospheric forcing, and waves. Likewise, the framework is not designed as a multi-decadal sea level projection. Such long-term applications require consideration of climate-driven sea level rise, vertical land motion, scenario uncertainty, and other slowly varying processes.

To determine the optimal number of past months to use as input features, we conducted a sensitivity analysis across all 16 TG stations using input lags ranging from 2 to 8 months. For each station and each lag, we trained the LSTM model on the training period (1993–2016) and evaluated the RMSE on the test period (2017–2022). Figure 3 presents a boxplot summary of the RMSE distribution across all 16 stations for each lag value. As can be observed, lag-6 proved to be consistently better than all others in terms of having the smallest median RMSE (around 58 mm) as well as having the smallest interquartile range among all stations. Shorter lags than four months were unable to supply adequate information, thus leading to higher median RMSE and interstation variance. Longer lags beyond seven months showed a minor loss in performance, possibly due to noisy data points from the distant past. Notably, lags of 5, 6, and 7 exhibit overlapping interquartile ranges, suggesting that the decision on which to choose is relatively insensitive as long as the lag falls in the five- to seven-month range. Lag-6 exhibited the optimal input window length due to its ideal trade-off between prediction accuracy and parsimony.

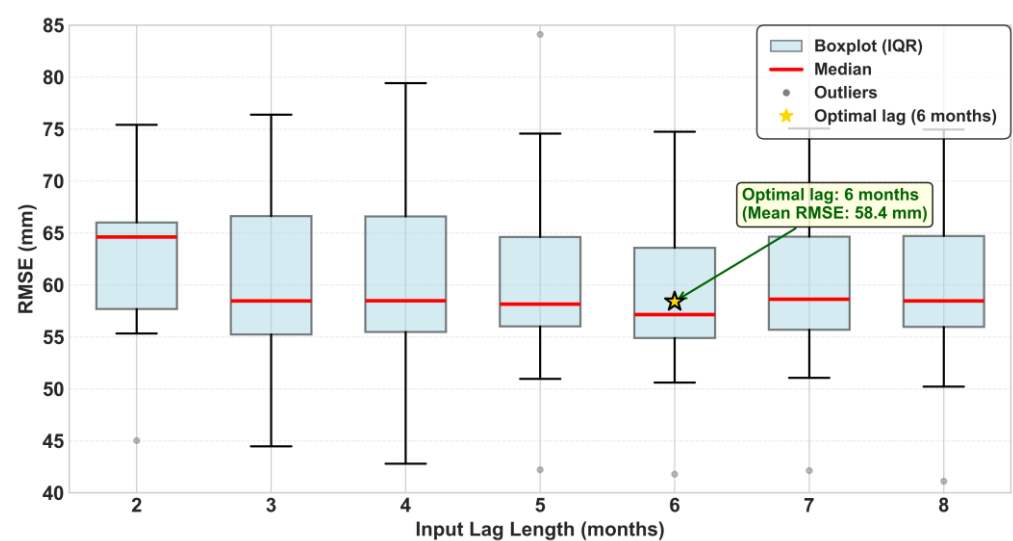


Figure 3. Sensitivity analysis of input lag length (2–8 months) for SLA prediction across all 16 tide gauge stations using the LSTM. Boxplot: Distribution of RMSE ($n = 16$ stations per lag) showing median (central line), interquartile range (box), and $1.5 \times$ IQR (whiskers). Highlighted: The optimal lag of 6 months, which exhibits the lowest median RMSE and smallest interquartile range across the Mediterranean basin.

After preprocessing, the signal was decomposed by applying the VMD-DMD method. In this procedure, we obtained several intrinsic modes (eight modes) of the signal. All decomposed modes were treated independently and applied to the models for prediction. The results were then combined to generate the final SLA time series. In order to conduct a realistic assessment of performance in prediction, the data from each station in terms of the tide gauge readings were divided based on chronology rather than random selection. In the time series data, the first 80% was selected for the training phase, consisting of years between 1993 and 2016, while the remaining 20%, including 2017 up to 2022, was used as the holdout test set. For purposes of validating the parameters and applying early stopping methods within the training phase, another 20% of the training data, the latter portion, was utilized as the validation set. To illustrate, consider station 61 (Marseille), for which we trained the models separately on each of the eight intrinsic modes of SLA data. The training set used data from January 1993 to 2016, which covered the first 80% of the full record. From that training period, we held out the last 20% for validation, which allowed us to use early stopping and avoid overfitting. For each mode, the model learned a simple mapping given the SLA values from the previous six months (months $t-6$ through $t-1$), predicting the SLA for the next month (month t). Once training was done, we tested the model on the remaining 20% of the data, which spanned 2017 to 2022. Finally, we combined the predictions from all eight modes to reconstruct the full SLA time series. We then compared those predictions against the actual observed SLA to calculate error metrics like RMSE, MAE, and R^2 .

To preserve causality and prevent information leakage, the complete 1993–2022 SLA record was not decomposed or reconstructed before the chronological separation of the training and test periods. VMD-DMD hyperparameters were determined using only the 1993–2016 training period and were then held fixed. During the independent 2017–2022 test period, forecasting was performed sequentially using a progressively expanding historical window. For each target month t , the VMD-DMD was recomputed using only observed SLA data available from January 1993 through month $t - 1$. The six most recent reconstructed component values available through $t - 1$ were then supplied to the trained models to generate the one-month-ahead component forecasts for month t . After the observation for month t became available, it was incorporated into the historical window for forecasting month $t + 1$. Importantly, predicted values were not fed back into subsequent decompositions. Therefore, neither the VMD-DMD components used as predictors nor the forecast for month t contained information from month t or any later observation. This procedure ensures that each forecast is generated only from information that would have been available in an operational forecasting setting.

2.4.2. Long Short-Term Memory (LSTM) Network Architecture

LSTM is a more developed variation of the RNN. Its memory mechanism has advantages in handling long-term dependencies and addressing the vanishing and exploding gradient problem [61]. In problems of long time series prediction, LSTM networks have some obvious advantages over conventional neural networks that made them extremely popular for tasks such as time series forecasting [18,62]. An LSTM network is structurally made up of an input layer, several hidden layers, and an output layer. As Figure 4 shows, all the hidden layers use input, forget, and output gates to regulate data storage and recall [18].

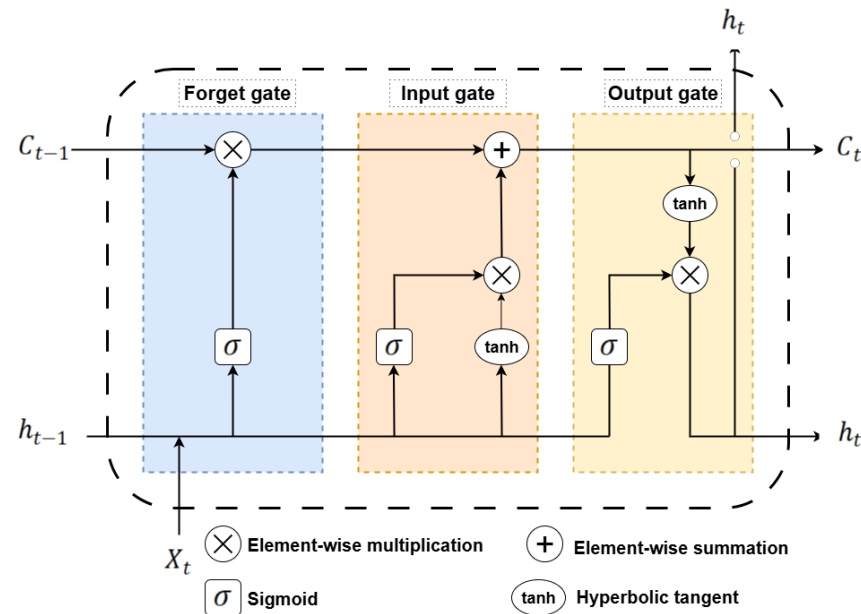


Figure 4. Schematic structure of the long short-term memory (LSTM) model used for sea level prediction, illustrating the input and memory gates, hidden layers, and output layer.

The LSTM model architecture began with an initial LSTM layer of 128 units, set up to return the full output sequence to the next layer. A dropout layer with a rate of 0.2 was then added to mitigate overfitting by randomly disabling neurons during training. This was followed by a second LSTM layer with 64 units, which processed the sequence and returned only the final output. Before the data reached a fully connected dense layer of 32 neurons with a ReLU activation function, an additional dropout layer was applied. The network culminated in a single-neuron output layer for the final SLA prediction.

The LSTM network, at each time step, was fed the real value of the previous SLA (instead of its predicted output) to make predictions about the following value. This is the usual procedure in case of one-step-ahead prediction, which avoids errors in the training process. When training the LSTM on the data from 6 consecutive months ($t-6$ to $t-1$), the network was unrolled into 6 time steps (n_{lags}), and BPTT calculated the gradients. The target of this training was the value of the SLA at month t .

For minimizing the mean squared error (MSE) loss function, the model was constructed with the Adam optimizer and 0.001 learning rate. The training procedure was configured with a maximum of 200 epochs and a batch size of 32. An early stopping callback was used to provide efficient training and avoid overfitting. It resumed the model weights from the top-performing epoch and halted training if the validation loss failed to improve for 20 epochs in a row.

2.4.3. eXtreme Gradient Boosting (XGBoost) Configuration

Chen and Guestrin (2016) introduced XGBoost, a powerful ensemble machine learning algorithm based on sequential decision trees [63]. It is a developed version of gradient boosting that depends on mechanisms such as regularization and tree pruning to improve performance [64]. Additionally, some research has proven that machine learning tree-based models, such as extreme gradient boosting (XGBoost), also have higher precision than traditional ML models in dealing with time series data [60]. As shown in Figure 5, all the trees in XGBoost are trained one by one to scale the previous trees' prediction residuals. Due to its efficiency, XGBoost has performed well in hydrological forecasting [60,65], including river water level [66] and flood events [67].

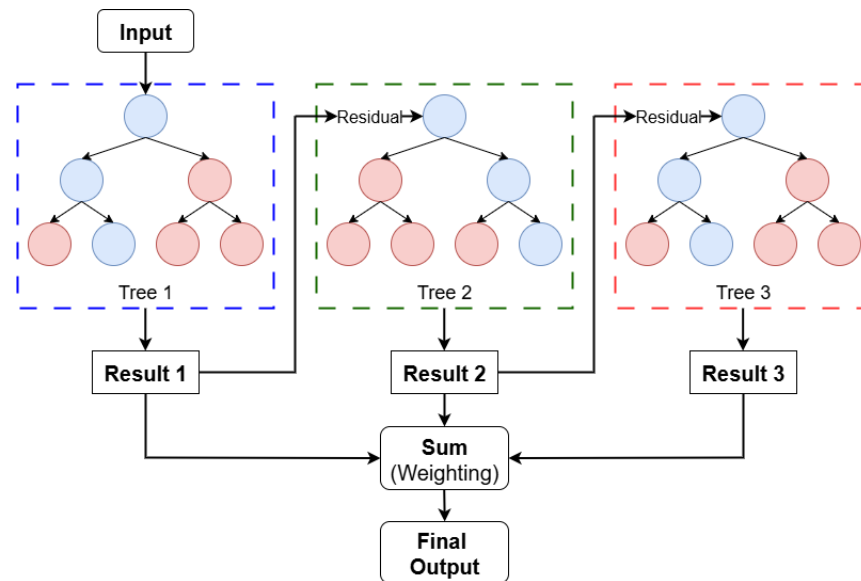


Figure 5. Conceptual structure of the extreme gradient boosting (XGBoost) model, showing the sequential training of decision trees to reduce prediction errors.

To compare fairly, the data preprocessing pipelines and input formulation for XGBoost and LSTM were the same. The XGBoost model was initialized with a well-chosen set of hyperparameters to trade off model complexity and generalization. The model was initiated with 1000 boosting iterations ($n_estimators$), a maximum depth of 6, and a learning rate of 0.01 to address the step size shrinkage. L1 ($reg_alpha = 0.1$) and L2 ($reg_lambda = 0.1$) regularization terms were employed to prevent overfitting. Also, by setting the column subsample ratio as 0.8 (using 80% of features for each tree) and subsample ratio as 0.8 (using 80% of data for each tree), stochasticity was introduced. One was used as the minimum weight for children. For preventing overfitting and for computational efficiency, an early stopping condition of 50 rounds was used, which would stop training if the validation score did not improve. The model was trained on the first 80% of chronological data.

2.4.4. Evaluation Metrics

Studies often use the mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2) as performance measures [44,52–54]. Therefore, the performance of all models, in our study, was evaluated using these three standard metrics. Equations (8)–(10) provide definitions for these three evaluation measures [68,69].

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

where y_i indicates the actual sea level values, $\hat{y}_i$ indicates the predicted value of the model. In addition, n represents the number of points of data, and $\bar{y}$ represents the mean actual sea level value. Related to MAE and RMSE, the smaller the values, the higher

the predictive accuracy. Conversely, the higher the R^2 value (closer to 1), the higher the predictive accuracy.

All reported metrics were computed on the held-out test set (2017–2022) after model training was complete. No metrics were computed on the training set to avoid overfitting assessment.

3. Results and Discussion

3.1. Decomposition Results of SLA by VMD-DMD Approach

We applied the VMD-DMD method to decompose the sea level anomaly (SLA) at every location into its intrinsic mode function (IMF) components and a nonlinear trend. The modes are arranged from low to high characteristic frequency, representing progressively shorter timescales from multi-decadal and interannual variability to seasonal and higher-frequency intra-annual variability. Decomposition yielded eight modes for the SLA of every site, the number that was ascertained to be ideal in retrieving the dominant scales of variability without overfitting. Figure 6 displays a multi-scale decomposition of the SLA time series for station “1238” as an example of using this hybrid VMD-DMD structure (applied on the training dataset only—from 1993 to 2016). The original SLA data is presented in black, while the resulting modes are presented in blue and the VMD-DMD reconstruction in red.

At the majority of the sites, VMD-DMD Mode 1 captures the low-frequency component associated with long-term sea level variability. The low-frequency modes exhibit decadal-scale variability, while the interannual components occur on timescales comparable to major climate oscillations such as the North Atlantic Oscillation (NAO), East Atlantic (EA), and Western Mediterranean Oscillation (WeMO). These similarities indicate potential links with large-scale climate variability, although further statistical attribution analysis would be required. This interpretation concurs with the one of Zid et al. (2024) [19]. Each mode’s temporal characterization was set by linking its most evident period and station location to known climate teleconnections. The clear distinction between intra-annual, interannual, and multi-decadal components reflects the multi-scale character of sea level variability and its local dependence on large-scale forcing of atmosphere and ocean.

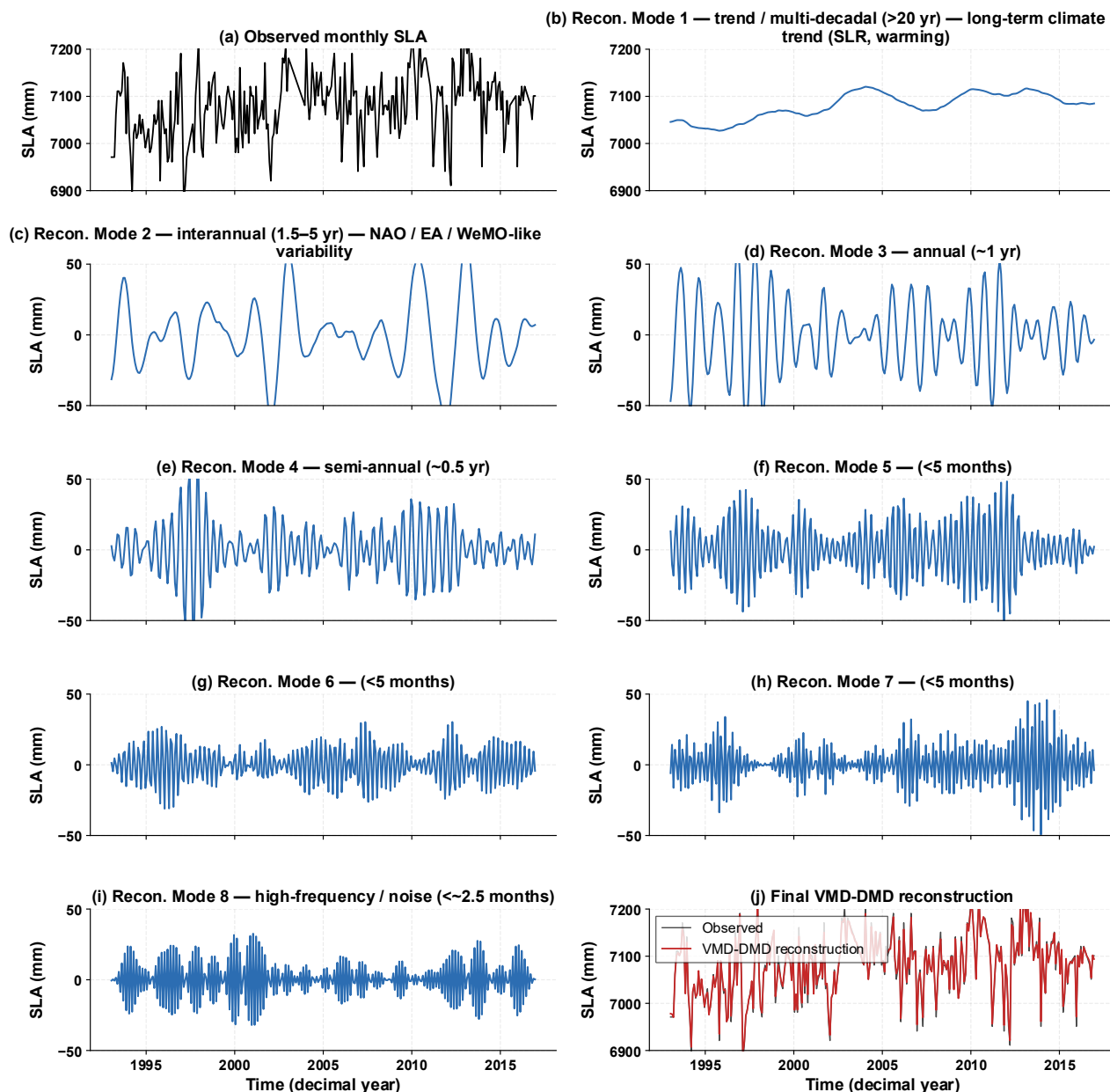


Figure 6. VMD–DMD analysis of sea level variability at station “1238.” Panel (a) shows the observed monthly SLA (black curve). Panels (b–i) display the decomposed intrinsic oscillatory modes, arranged from low to high frequency: (b) trend/multi-decadal, (c) interannual, (d) annual, (e) semi-annual, (f–h) components with periods shorter than 5 months, (i) high-frequency/noise components. Panel (j) illustrates the final VMD–DMD reconstruction (red) overlaid with the observed SLA (black).

How much of an intrinsic mode function (IMF) component’s frequency and amplitude of fluctuation enter into the overall nature of the original signal is measured by the variance contribution rate, or VCR. The biggest VCRs at each site were for Modes 1 and 2, then Mode 3, as indicated in Figure 7A. The other components’ VCRs were very small. In addition, Modes 1 and 2 also had the largest correlation coefficients with the original series, as shown in Figure 7B. Modes 5 to 8 may have relatively small correlation coefficients, while Modes 3 and 4 also have strong correlations.

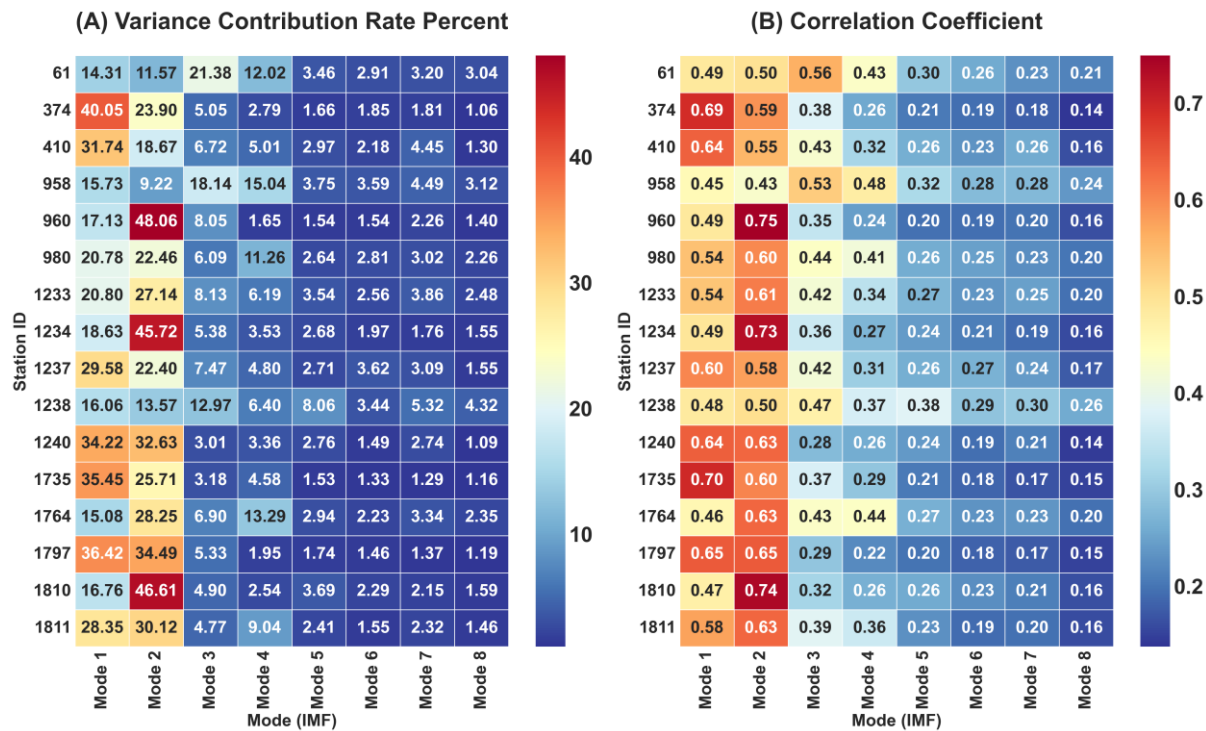


Figure 7. Variance contribution rate (A) and correlation coefficient (B) of each mode (IMF) component of SLA at 16 sites in coastal areas of the Mediterranean Sea.

To validate the proposed hybrid approach to signal processing, we applied VMD to the data and quantified the reconstruction accuracy of the hybrid VMD-DMD procedure with respect to the VMD-alone method. The results indicate that the hybrid VMD-DMD procedure improved signal reconstruction accuracy. Table 2 presents R^2 , RMSE in mm, and MAE in mm between true signal and reconstructions from both methods. The RMSE and MAE for all sites averaged considerably higher, decreasing from 24.22 mm and 18.62 mm with VMD-only to 7.38 mm and 5.69 mm with VMD-DMD. Furthermore, the mean R^2 value increased from 90% to 99%. These results prove the effectiveness and efficiency of the new VMD-DMD approach to decomposition analysis since it successfully captures the dynamic modes of the signal with a residue remaining only to a very small extent. A high residual would negatively impact prediction accuracy, but our method successfully avoids this. For clarification, Figure 8 shows the reconstructed signals from hybrid VMD-DMD and VMD-only for station “1238,” as an example, compared to the original processed data.

In addition, the proposed VMD-DMD approach makes an additional split of the signal into physically meaningful modes (interannual, annual, semi-annual, high frequency) and implements DMD analysis of their dynamics, which accounts for the improved result achieved by this approach. This makes it distinct from the classical physically based approach that splits the signal into the astronomical tide and the residual signal; the remaining part of the signal retains multi-scale variations due to forcing by the atmosphere, the ocean, and climatic phenomena [4,70].

Table 2. Reconstruction accuracy of sea level anomaly using VMD-DMD and VMD-only methods at each station, evaluated using root mean square error, mean absolute error, and coefficient of determination.

Station ID	Method	RMSE (mm)	MAE (mm)	R ²
61	VMD-only	24.06	19.61	0.89
	VMD-DMD	6.54	5.03	0.99
374	VMD-only	28.05	21.89	0.91
	VMD-DMD	9.17	7.25	0.99
410	VMD-only	23.98	18.14	0.89
	VMD-DMD	7.72	5.95	0.99
958	VMD-only	27.89	21.61	0.86
	VMD-DMD	7.50	5.91	0.99
960	VMD-only	19.02	14.45	0.93
	VMD-DMD	6.37	4.87	0.99
980	VMD-only	24.52	18.22	0.88
	VMD-DMD	7.25	5.45	0.99
1233	VMD-only	22.60	17.43	0.88
	VMD-DMD	6.55	5.10	0.99
1234	VMD-only	23.10	17.73	0.92
	VMD-DMD	7.08	5.48	0.99
1237	VMD-only	24.54	18.60	0.90
	VMD-DMD	7.67	5.99	0.99
1238	VMD-only	28.01	22.31	0.83
	VMD-DMD	7.21	5.66	0.99
1240	VMD-only	22.04	17.25	0.92
	VMD-DMD	7.16	5.71	0.99
1735	VMD-only	30.25	22.80	0.90
	VMD-DMD	10.09	7.64	0.99
1764	VMD-only	24.48	18.35	0.89
	VMD-DMD	6.94	5.21	0.99
1797	VMD-only	21.20	16.71	0.93
	VMD-DMD	7.20	5.52	0.99
1810	VMD-only	19.68	14.97	0.92
	VMD-DMD	6.57	5.06	0.99
1811	VMD-only	24.10	17.84	0.92
	VMD-DMD	7.08	5.28	0.99

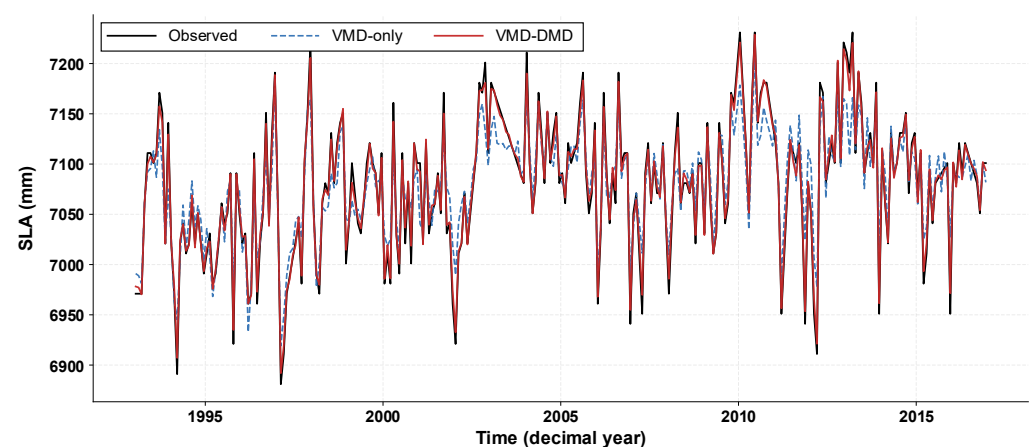


Figure 8. Comparison of reconstructed sea level anomaly at station “1238” using the hybrid VMD-DMD method (red) and the VMD-only method (blue), plotted against the observed signal (black).

3.2. Prediction of SLA Using the DL and ML Models (LSTM–XGBoost)

Following the decomposition of the original data into a sequence of modes (IMFs) using the hybrid VMD-DMD model, DL and ML models were used for prediction. The model then uses the LSTM and XGBoost models to forecast each mode sequence separately. Finally, the final model prediction is obtained by combining the expected results of each sequence. The names of these two models are VMD-DMD-XGBoost and VMD-DMD-LSTM.

Both the VMD-DMD-LSTM and VMD-DMD-XGBoost models captured the intrinsic pattern in the SLA time series well. To clarify that, Figure 9 presents the test results of each mode for station “61.” It can be observed from Figure 9 that, while all the modes have a high prediction accuracy, Mode 1 has a slightly lower performance. Standard metrics such as MAE, RMSE, and R^2 on the test dataset indicate that all the tide gauge stations consistently achieved excellent generalization. This should be considered one of the key points in this paper: the inclusion of the VMD-DMD preprocessing step plays an essential role in improving the models’ performance.

The average performance metrics across all 16 stations for each model were calculated and are summarized in Table 3. Among all tested approaches, the VMD-DMD-LSTM achieved the best overall performance, with a mean MAE of 15.31 mm, a mean RMSE of 20.37 mm, and a mean R^2 of 0.92. The VMD-DMD-XGBoost also demonstrated strong performance, yielding mean MAE, RMSE, and R^2 values of 18.85 mm, 24.90 mm, and 0.88, respectively. These results indicate that coupling VMD-DMD with advanced learning algorithms substantially enhances SLA forecasting accuracy across the Mediterranean basin.

First, to quantify the contribution of the decomposition stage, we ran the standalone models (LSTM and XGBoost) plus two main baselines. The standalone LSTM and XGBoost models performed poorly, with mean RMSE values of 58.26 mm and 63.32 mm, respectively, and mean R^2 of 0.36 and 0.25, respectively. Because the SLA records exhibit a pronounced seasonal cycle, a seasonally informed benchmark was considered [71]. This benchmark was the mean annual cycle (MAC) with anomaly persistence (AP) of the most recent anomaly (MAC_AP). For more details about the concept of the MAC_AP and the station-to-station comparison, check Section (S2) in the supplementary data file.

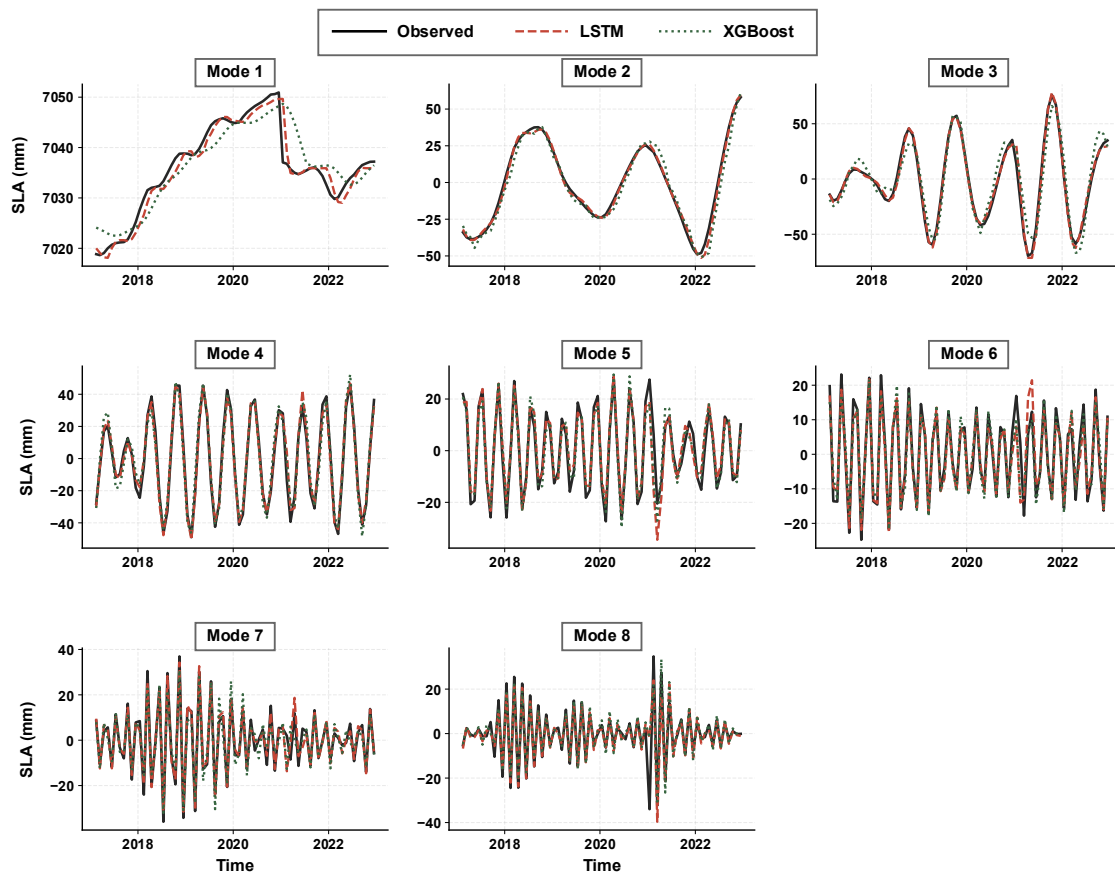


Figure 9. Observed and predicted values for each decomposed mode at station “61” during the test period using LSTM and XGBoost models.

Across all 16 stations, the MAC_AP baseline achieved a mean RMSE of 62.17 mm, MAE of 46.57 mm, and R^2 of 0.27 (Table 3). Despite their greater complexity, the standalone LSTM model only marginally improved upon the MAC_AP forecast, highlighting the difficulty of directly modeling raw SLA time series. The other baseline is the three-layer multi-layer perceptron (MLP), which refers to a feedforward artificial neural network with three layers of nodes (neurons). The three-layer MLP, configured with six input lags and the same input structure as the LSTM model, achieved a mean MAE of 44.60 mm, RMSE of 58.93 mm, and R^2 of 0.35. Collectively, these results demonstrate that conventional machine learning and deep learning models struggle to extract predictive information from the highly nonlinear and nonstationary SLA signals when no prior decomposition is applied.

Second, to validate the contribution of the LSTM/XGBoost, we applied the VMD-DMD with the two baselines (MAC_AP and three-layer MLP). Remarkably, once we added VMD-DMD, all results improved. Although the decomposed MAC_AP model remained relatively weak, its performance increased from an R^2 of 0.27 to 0.33, indicating that part of the forecasting difficulty originates from signal complexity rather than predictor limitations alone. More substantial gains were observed for the three-layer MLP model. After incorporating VMD-DMD, the mean RMSE of the three-layer MLP model decreased from 58.93 mm to 24.97 mm, corresponding to an improvement of approximately 57.6%, while the mean R^2 increased from 0.35 to 0.88. These results clearly demonstrate that decomposition contributes more to forecast skill than increasing model complexity alone.

Table 3. Performance comparison of all model variants across 16 Mediterranean tide gauge stations. Values represent the mean performance metrics. Models are grouped into those without decomposition (top) and those with VMD-DMD (bottom). Improvements show error reduction relative to MAC_AP and three-layer-MLP baselines. Lower MAE/RMSE and higher R² are better.

Model	Mean MAE (mm)	Mean RMSE (mm)	Mean R ²	Improvement in RMSE
Without Decomposition				
MAC_AP	46.57	62.17	0.27	-----
3-layer-MLP	44.60	58.93	0.35	-----
LSTM (standalone)	43.81	58.26	0.36	-----
XGBoost (standalone)	48.81	63.32	0.25	-----
With Decomposition				
MAC_AP	44.70	59.61	0.33	-----
3-layer MLP	18.95	24.97	0.88	-----
VMD-DMD-LSTM	15.31	20.37	0.92	↓ 65.8% (in errors) vs. MAC_AP ↓ 18.4% (in errors) vs. 3-layer MLP
VMD-DMD- XGBoost	18.85	24.90	0.88	↓ 58.2% (in errors) vs. MAC_AP ↓ 0.3% (in errors) vs. 3-layer MLP
Note: Percentage improvements for error (RMSE) are calculated as: $-((\text{MAC_AP} - \text{Proposed models}) / \text{MAC_AP}) \times 100$ $-((\text{3-layer MLP} - \text{Proposed models}) / \text{3-layer MLP}) \times 100$				

Nevertheless, the choice of predictor remains important once the signal has been decomposed. The VMD-DMD-LSTM model further reduced the RMSE by approximately 65.8% relative to the decomposed MAC_AP model and by about 18.4% relative to the decomposed three-layer MLP model, while increasing the mean R² to 0.92. Similarly, VMD-DMD-XGBoost achieved RMSE reductions of approximately 58.2% and 0.3% relative to the decomposed MAC_AP and decomposed three-layer MLP models, respectively, while maintaining a mean R² of 0.88. These findings indicate that, although VMD-DMD provides the primary improvement by isolating multi-scale variability and reducing noise, advanced predictors such as LSTM and XGBoost remain beneficial for capturing the temporal evolution of the decomposed modes. Overall, the results demonstrate a synergistic effect between signal decomposition and predictive modeling, where VMD-DMD supplies physically meaningful and dynamically coherent components and LSTM or XGBoost effectively learns its temporal behavior, leading to substantially improved SLA forecasts. Station-specific results for the two proposed models are provided in Section (S3) of the supplementary data file (Figures S1 and S2). Figure 10 shows a comparison of the observed SLA and the predicted values from different models for all sites. The subplots, each of which represents a TG site, demonstrate how effectively different prediction techniques capture the peaks and temporal variability of the observed SLA over the test period.

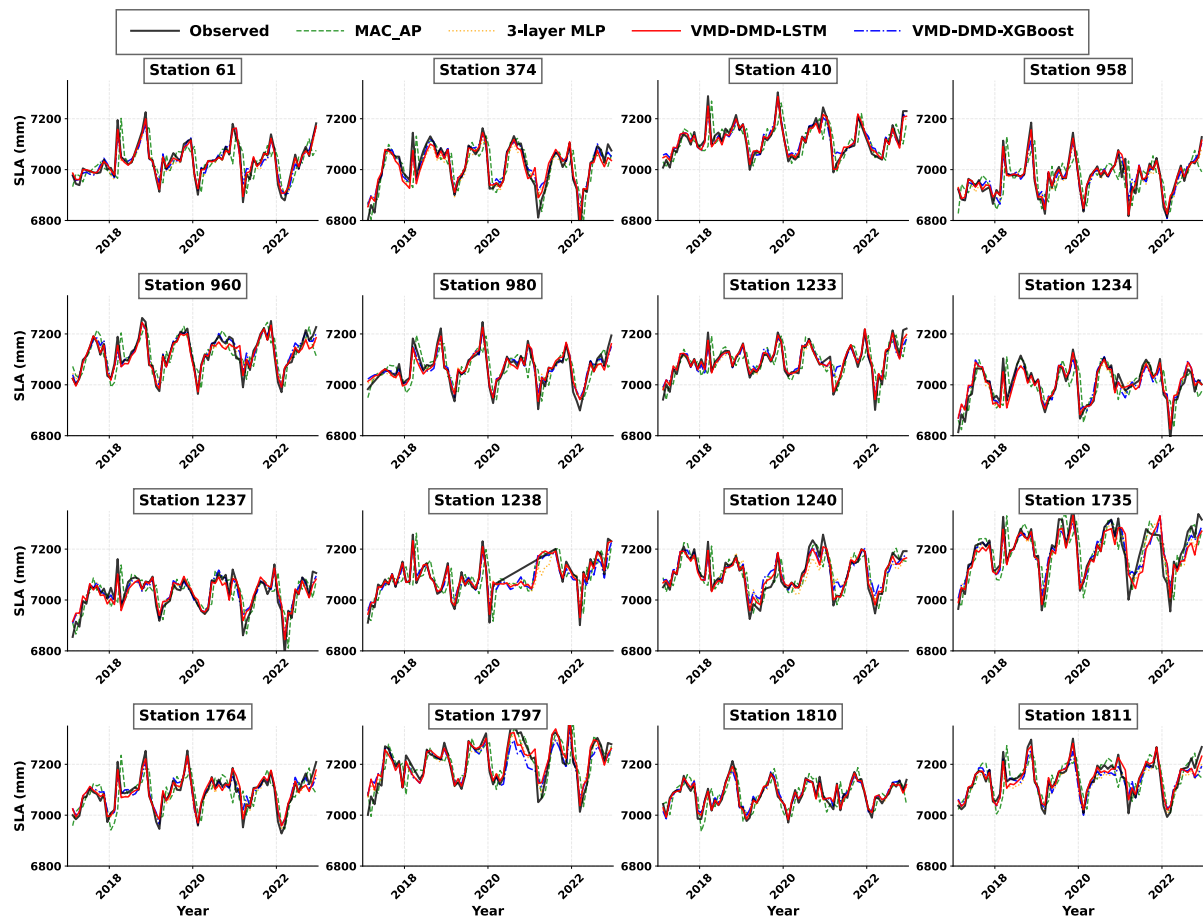


Figure 10. Comparison of observed and predicted monthly SLA during the test period for the 16 Mediterranean tide gauge stations. The solid black line denotes the observed SLA values. The dashed green and orange lines represent predictions from the MAC_AP and 3-layer MLP models (with decomposition), respectively. The red and blue lines correspond to predictions from the proposed VMD-DMD-LSTM and VMD-DMD-XGBoost models, respectively.

To quantify the performance difference between the two hybrid models, we calculated the average MAE, RMSE, and R^2 across all 16 stations (Table 4). In addition, to determine whether the observed performance differences between VMD-DMD-LSTM and VMD-DMD-XGBoost are statistically significant (not just due to random chance) [72,73], we applied the Wilcoxon signed-rank test (Table 4).

The VMD-DMD-LSTM achieved a 4.53 mm lower mean RMSE (18.19% improvement), a 3.54 mm lower mean MAE (18.78% improvement), and a 0.04 higher mean R^2 (4.55% improvement) compared to VMD-DMD-XGBoost. Therefore, the results confirm that VMD-DMD-LSTM outperforms VMD-DMD-XGBoost. The Wilcoxon signed-rank test confirms that these improvements are statistically significant ($W = 8.00$, $p = 0.000763$, Cohen's $d = -1.130$). VMD-DMD-LSTM outperformed VMD-DMD-XGBoost at 14 out of 16 stations (87.5%), with only two stations (station 1237 and 1735) showing marginally better performance by XGBoost. The large effect size ($d = -1.130$) indicates that the observed difference is not only statistically significant but also practically meaningful. Section (S4) of the supplementary data file illustrates in detail the Wilcoxon signed-rank test applied in this study.

Table 4. Performance comparison between VMD-DMD-LSTM and VMD-DMD-XGBoost across 16 Mediterranean tide gauge stations. Values represent the mean MAE (mm), RMSE (mm), and R^2 . Percentage improvements are calculated relative to VMD-DMD-XGBoost. In addition, the factors of the paired Wilcoxon signed-rank test are calculated and listed.

	Mean MAE (mm)	Mean RMSE (mm)	Mean R^2
VMD-DMD-LSTM	15.31	20.37	0.92
VMD-DMD-XGBoost	18.85	24.90	0.88
Difference (LSTM—XGBoost)	−3.54	−4.53	0.04
Percentage of Improvement	18.78%	18.19%	4.55%
Wilcoxon Test	W statistic = 8.00, p -value = 0.000763, Effect size (Cohen's d) = −1.130		

These results demonstrate that LSTM architecture, known to handle sequential dependencies, is likely to function more effectively as a core model for synthesizing decomposed multi-scale temporal features produced by VMD-DMD preprocessing. As a result, though both hybrid models show a jump forward, the VMD-DMD-LSTM combination becomes the most robust and accurate method for the complex task of sea level forecasting. Note that the slight difference in the accuracy at each location may be because the sea level changes are influenced by many factors. These factors include seabed topography, coastline, and ocean dynamics in each subbasin.

Chen et al. (2023) introduced a combined VMD–EEMD–LSTM method to predict sea surface height along the Dutch coast [18]. The model first applies variational mode decomposition (VMD) to the original sea surface height time series, decomposing it into a set of intrinsic mode functions (IMFs) with distinct frequencies plus a residual sequence (Residual 1). Because this residual often still contains nonwhite noise and fluctuating patterns that degrade prediction accuracy, the model then feeds that residual into ensemble empirical mode decomposition (EEMD) for a second-order decomposition, producing additional IMFs and a final residual (Residual 2). To balance accuracy and complexity, the model fuses the higher-order IMFs (beyond the original K) with Residual 2 into a single feature. All IMFs from both decomposition stages are then used as separate input features for a long short-term memory (LSTM) network, which predicts each component individually. Finally, the model aggregates all these individual predictions (totaling $2K+1$ forecasts) to produce the final sea level prediction, effectively combining VMD's strength in decomposing stationary signals with EEMD's strength in handling residual noise. Tests on six real-world datasets showed the model works very well (RMSE = 47.2 mm, MAE = 33.3 mm, R^2 = 0.9). In addition, it beat the VMD-LSTM model by cutting error by about 60% and raising accuracy by nearly 50%. It also outperforms the EEMD-LSTM model, with error reductions of roughly 27–28% and a 6.5% gain in fit.

Therefore, to validate the accuracy of our proposed VMD–DMD–LSTM model, we compared it with VMD-EEMD-LSTM. So, we constructed the VMD-EEMD-LSTM with its exact structure introduced by Chen et al. (2023), but with VMD and LSTM parameters that were used in our study for fair comparison [18]. Furthermore, the progressive time-window approach to ensure that no future information leaks, as in our model, was applied. Table 5 presents a comparative evaluation between the proposed VMD-DMD-LSTM model and the VMD-EEMD-LSTM benchmark across 16 tide gauge stations in the Mediterranean Sea. The proposed VMD-DMD-LSTM model achieved a mean RMSE of 20.37 mm, a mean MAE of 15.31 mm, and a mean R^2 of 0.92, whereas the VMD-EEMD-LSTM model yielded 22.98 mm, 17.42 mm, and 0.90, respectively. The VMD-DMD-LSTM model reduced RMSE by 2.61 mm (approximately 11.36%) and MAE by 2.11 mm (approximately 12.11%) while improving R^2 by 0.02 (approximately 2.22%) compared to the VMD-EEMD-LSTM benchmark. For more details of station-to-station comparison, check Section (S5) in

the supplementary data file. The Wilcoxon signed-rank test was used in a pairwise comparison of the VMD-DMD-LSTM and VMD-EEMD-LSTM models in 16 tide gauge stations in terms of RMSE values. The results revealed that VMD-DMD-LSTM performed better than VMD-EEMD-LSTM at 14 sites (87.5%) but only two tide gauge stations (12.5%) favored the EEMD model. The W-statistic value of 20.0 was found less than the critical value of 35 at a significance level of 0.05; hence, the null hypothesis was rejected. A two-tailed P-value of 0.011 and an effect size value of -0.670 were obtained indicating statistical significance and medium-to-large effect size, respectively.

Table 5. Performance comparison between the proposed VMD-DMD-LSTM model and the VMD-EEMD-LSTM benchmark across 16 Mediterranean tide gauge stations. Values represent the mean of root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) over the test period (2017–2022). Percentage improvements are calculated relative to VMD-EEMD-LSTM. The benchmark model follows the architecture of Chen et al. (2023) with identical VMD and LSTM parameters and the same progressive time-window approach to prevent data leakage.

	Mean MAE (mm)	Mean RMSE (mm)	Mean R^2
VMD-DMD-LSTM	15.31	20.37	0.92
VMD-EEMD-LSTM	17.42	22.98	0.90
Difference	-2.11	-2.61	0.02
Percentage of Improvement	↓ about 12% (in errors) vs. VMD-EEMD-LSTM		
Wilcoxon Test	W statistic = 20.00, p -value = 0.011, Effect size (Cohen's d) = -0.670		

These improvements are consistent across the majority of stations, indicating that the DMD-based dynamic filtering captures temporal evolution patterns more effectively than the EEMD-based residual decomposition, especially through the monthly sea level prediction. This systematic enhancement can be attributed to DMD's ability to model linear dynamics within each decomposed mode through a sliding-window approach, whereas EEMD, as a static decomposition method, does not explicitly account for temporal evolution. Consequently, the proposed VMD-DMD framework provides a more faithful representation of the underlying multi-scale sea level dynamics, leading to improved prediction accuracy even when compared against the VMD-EEMD benchmark.

Finally, the proposed VMD-DMD forecasting framework can be implemented at an individual tide gauge station. The practical implementation consists of the following steps. First, prepare a continuous and clean monthly sea level series in chronological order, maintaining consistent units and data throughout the record. Then, apply VMD to the historical SLA series using $K = 8$ modes and $\alpha = 500$. Then apply DMD independently to each VMD mode using a 36-month sliding window, a 12-month step, and a time-delay embedding dimension of $d=24$. For each of the eight reconstructed modes, form an input vector containing the previous six-monthly component values $[t - 6, \dots, t - 1]$. The target is the component value for month t . Next, train the optimal forecasting model (LSTM) for each component with the same configuration mentioned in this study. To predict a future month t , only observations available through month $t - 1$ are used. The VMD-DMD is updated using this progressively increasing historical window; the latest six values of each reconstructed component are supplied to the trained predictor, and the eight one-month-ahead component forecasts are generated. Predicted values are not fed back into subsequent decompositions; newly observed sea level values are used when they become available. This procedure prevents future observations from leaking into the forecast. Finally, the eight predicted components are summed to obtain the final one-month-ahead monthly SLA prediction, which provides useful information for coastal operational planning.

4. Conclusions

Sea level rise is considered one of the most significant environmental issues world-wide, driven by both climate change and human activity. Coastal changes in the Mediterranean pose serious threats to coastal communities. In this study, a new hybrid framework was proposed by incorporating the VMD and DMD with two advanced architectures of LSTM and XGBoost to enhance the monthly prediction of SLA along the Mediterranean coast. The approach relies on the multi-scale and nonstationary characteristics of sea level variations in one of the most climate-sensitive regions, supported by thirty years of records from sixteen tide gauge stations (1993–2022) along the Mediterranean coast.

The hybrid VMD-DMD significantly improved the reconstruction accuracy compared to the VMD-only, increasing the mean R^2 from 0.90 to 0.99 and reducing average RMSE from 24.22 to 7.38 mm. These results confirm the capability of hybrid decomposition to capture dynamic components effectively while minimizing residual noise.

For forecasting, we compared our models against multiple baselines: the mean annual cycle with anomaly persistence (MAC_AP), three-layer MLP, standalone LSTM, and standalone XGBoost. The MAC_AP baseline (without decomposition) achieved a mean RMSE of 62.17 mm and R^2 of 0.27, while the three-layer MLP performed a little better with a mean RMSE of 58.93 mm and R^2 of 0.35. In addition, the standalone LSTM performed only marginally better (mean RMSE = 58.26 mm, mean R^2 = 0.36). In comparison, the standalone XGBoost performed slightly worse (mean RMSE = 63.32 mm, mean R^2 = 0.25), highlighting the difficulty of predicting SLA directly from raw time series. After adding the VMD-DMD technique, all results improved substantially. The three-layer MLP with decomposition achieved RMSE = 24.97 mm (57.6% reduction) and R^2 = 0.88. The proposed VMD-DMD-LSTM achieved the best overall performance: mean R^2 = 0.92, RMSE = 20.37 mm, and MAE = 15.31 mm, with a 65.8% error reduction compared to MAC_AP and 18.4% better than the three-layer MLP with decomposition. Moreover, the VMD-DMD-XGBoost achieved RMSE = 24.90 mm and R^2 = 0.88, while the MAC_AP baseline succeeded in achieving a small improvement (mean RMSE = 59.61 mm, mean R^2 = 0.33).

A paired Wilcoxon signed-rank test confirmed that VMD-DMD-LSTM significantly outperformed VMD-DMD-XGBoost ($W = 8.00$, $p = 0.000763$, Cohen's $d = -1.130$), with LSTM performing better at 14 of 16 stations (87.5%). The large effect size indicates the difference is both statistically significant and practically meaningful.

To further validate our approach, we conducted a direct comparison with the benchmark VMD-EEMD-LSTM model, introduced by Chen et al. (2023), using identical data, train/test splits, and progressive time-window methodology. Our VMD-DMD-LSTM achieved about 12% lower errors (mean RMSE=20.37 mm vs. 22.98 mm and mean MAE = 15.31 mm vs. 17.42 mm) compared to VMD-EEMD-LSTM. A Wilcoxon test confirmed statistical significance ($p = 0.011$, Cohen's $d = -0.670$). These consistent improvements across most stations indicate that DMD-based dynamic filtering captures temporal evolution patterns more effectively than EEMD-based residual decomposition.

Besides quantitative performance, the hybrid decomposition can clearly provide a physical interpretation of the results. The resulting modes were able to isolate long-term SLR trends, interannual variability linked with large-scale oscillations such as the NAO, EA, and WeMO, and short-term seasonal signals. Such multi-scale decomposition provides information on the temporal structure of regional sea level variability and helps identify components occurring on timescales comparable to known climatic and oceanic variability. This insight is important knowledge for sustainable coastal planning and adaptation in the Mediterranean region.

Future work could extend this framework in several directions. First, integrating satellite altimetry data could provide broader spatial coverage and help validate the tide gauge results. Second, future work should explicitly evaluate forecast skill at additional

horizons. Short-term extensions should use hourly or daily sea level observations together with tide, wind, atmospheric-pressure, wave, and storm-surge information to quantify event-scale or weekly prediction errors. Long-term extensions should evaluate multi-year forecast or projection skill using climate-driven sea level rise information, vertical land motion, scenario uncertainty, and other slowly varying processes relevant to coastal infrastructure planning. Finally, integrating the atmospheric and oceanic data as feature inputs in the models may improve the prediction.

In conclusion, this paper concludes that the hybrid VMD-DMD algorithm, especially when integrated with the LSTM model, can provide significant enhancement in sea level prediction. It effectively isolates multi-scale dynamics and residual noise reduction, hence providing more reliable sea level forecasting and providing useful information for coastal operational planning, monitoring, maintenance scheduling, and preparedness.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse14191865/s1>, Figure S1: Results of MAE, RMSE, and R^2 of each component predicted by LSTM and VMD-DMD-LSTM models in the test set of 16 sites in the coastal areas of the Mediterranean Sea; Figure S2: Results of MAE, RMSE, and R^2 of each component predicted by XGBoost and VMD-DMD- XGBoost models in the test set of 16 sites in the coastal areas of the Mediterranean Sea; Table S1: The iteration configurations of the VMD-DMD hybrid approach on the training data set (1993–2016) at station ‘61’ and their corresponding performance based on the RMSE, MAE, and R^2 metrics. The bold line represents the hyperparameters that show the best performance; Table S2: the performance metrics (MAE, RMSE, and R^2) of the MAC+AP benchmark across 16 Mediterranean tide gauge stations; Table S3: the results of the Wilcoxon signed-rank test between VMD-DMD-LSTM and VMD-DMD-XGBoost; Table S4: Station-by-station comparison of RMSE performance (mm) between VMD-DMD-LSTM and VMD-EEMD-LSTM across 16 tide gauge stations. The difference column (DMD – EEMD) indicates the magnitude and direction of performance difference, where negative values denote superior performance of the proposed VMD-DMD-LSTM model. The final column indicates whether the proposed model achieves lower prediction error at each station [18,71–73].

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