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Harnessing Machine Learning to Decode the Mediterranean's Climate Canvas and Forecast Sea Level Changes

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Abstract: Climate change and rising sea levels pose significant threats to coastal regions, necessitating accurate and timely forecasts. Current methods face limitations due to their inability to fully capture nonlinear complexities, high computational costs, gaps in historical data, and bridging the gap between short-term and long-term forecasting intervals. Our study addresses these challenges by combining advanced machine learning techniques to provide region-specific sea level predictions in the Mediterranean Sea. By integrating high-resolution sea surface temperature data spanning 40 years, we employed a tailored k-means clustering technique to identify regions of high variance. Using these clusters, we developed RNN-GRU models that integrate historical tide gauge data and sea surface height data, offering regional sea level predictions on timescales ranging from one month to three years. Our approach achieved the highest predictive accuracy, with correlation values ranging from 0.65 to 0.84 in regions with comprehensive datasets, demonstrating the model's robustness. In areas with fewer tide gauge stations or shorter time series, our models still performed moderately well, with correlations between 0.51 and 0.70. However, prediction accuracy decreases in regions with complex geomorphology. Yet, all regional models effectively captured sea level variability and trends. This highlights the model's versatility and capacity to adapt to different regional characteristics, making it invaluable for regional planning and adaptation strategies. Our methodology offers a powerful tool for identifying regions with similar variability and providing sub-regional scale predictions up to three years in advance, ensuring more reliable and actionable sea level forecasts for Mediterranean coastal communities.

Keywords: regional-scale ocean variability; sea level forecasting; machine learning; clustering techniques; RNN-GRU models; Mediterranean Sea

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1. Introduction

Ocean warming and sea level changes have significant impacts on regions all over the world, influencing economies, societies, and human lives. These changes can lead to increased flooding, loss of habitat for marine and coastal species, and damage to infrastructure [1]. Understanding and predicting these changes is crucial for developing effective adaptation and mitigation strategies to protect vulnerable populations and sustain economic stability. However, the drivers of sea level variability differ between global and regional scales, resulting in distinct sea level trends. At the global scale, factors such as thermal expansion and melting ice sheets play a major role, while regional trends can be influenced by local ocean currents, land subsidence, and regional climate patterns [2]. In particular, in the Mediterranean Sea, more than 30% of coastal areas are facing moderate to high risks of erosion and coastal flooding [3]. Moreover, this basin is considered a hotspot in a warming climate, with projected annual and summer warming rates of 20% and 50% faster than the global ocean average, respectively [4]. Additionally, the historical sea level fluctuations in the Mediterranean Sea have exhibited significant spatial variability within the basin, making a sub-basin exploration necessary [5]. Thus, the unique characteristics of this semi-enclosed region demand more advanced tools to unveil and better understand the complexities of Mediterranean climatology. This understanding is crucial for accurately predicting near-future climate scenarios, including temperature fluctuations, and sea level changes, which are vital for effective regional planning and management.

Tide gauge records have been one of the main sources that contribute to the understanding of sea level fluctuations. Nevertheless, their utility is often constrained due to the lack of stations at some coastal locations and the presence of data gaps during certain periods [6]. In contrast, satellite altimetry and derived products provide a valuable alternative, offering more extensive spatial insights. However, this resource's data is only accessible from 1993 onwards, and it can encounter challenges in coastal regions due to shallower waters [7,8]. To overcome these problems, past studies combine both datasets on the Mediterranean Sea, in some cases to provide sea level reconstructions [9,10]. Even so, the temperature of the upper ocean layers, which reflect physical dynamical changes, can offer new insights into the study of sea level drivers, allowing for the reconstruction and prediction of future sea levels [11–14]. This approach is based on the premise that changes in ocean temperature are inherently linked to thermal expansion, a significant factor driving variations in sea levels [15,16]. Sea level in the Mediterranean Sea is, however, also highly influenced by evaporation processes (due to high temperatures) and a deficit of precipitation, which is reflected in an increase in water salinity [17]. This leads to high density and variations in sea level [18]. In addition, there is also the influence of other factors, such as vertical land motion and low elevation in some regions [3].

Over the past few years, machine learning (ML) techniques have emerged as a powerful tool to delve into the intricacies of climate scenarios and other underlying factors affecting sea level variability and change (see, e.g., [19]). These algorithms are capable of dealing with complex, highly-dimensional datasets and of establishing non-linear relationships between the variables involved at a low computational cost, in contrast to traditional models. Traditional methods like hydrodynamic models often require significant time and resources, whereas ML techniques can offer faster and robust solutions in complex scenarios. Moreover, ML techniques can also be evaluated for accuracy and reliability through various validation methods and metrics appropriate to the method used [20]. Additionally, ML models have the capability to continuously learn and adapt from large datasets, updating their predictions in real time and improving accuracy as they process more data. Among the ML techniques, methods like Random Forest (RF), Gaussian Process (GP), and Support Vector Machine (SVM), as well as neural networks such as Recurrent Neural Network (RNN) and Multi-Layer Perceptron (MLP), have successfully been applied to predict changes in ocean physical variables such as temperature, salinity, or sea level [21–23]. Coastal vulnerability has also been analyzed in the Mediterranean Sea, comparing the performance of various ML algorithms, including Artificial Neural Networks (ANNs), trained with several predictors such as sea level rise, geomorphology, or tidal range, as explored in [24]. More recently, unsupervised learning techniques, such as clustering algorithms, have proven effective in detecting underlying regional patterns related to local dynamics (such as the influence of gyres/eddies or currents) or climatic traits [17,25]. These techniques highlight areas with similar variability, also linked to coastal sea level changes and conventional climate modes in different parts of the world's oceans [11]. Although there have been advancements in this research field, accurately identifying sub-regions of climatic interest in the Mediterranean Sea and providing automated, precise local sea level forecasts continues to be a challenge, underscoring the need for advanced methodologies.

Our study presents a unique approach that has never been tested in the Mediterranean, or anywhere else, bridging significant gaps in the literature. The scope of the present work is to offer regional solutions to forecast near-future (from 1 month to 3 years) sea levels using an approach that combines a clustering technique with neural networks in the coastal regions of the Mediterranean Sea. First, we automatically identify regions of high variance using k-means applied to sea surface temperature data, following the methodology of [11]. Based on the spatial patterns revealed, we provide predictions of future coastal sea levels for each region using gated RNNs, which represent a significant improvement by incorporating mechanisms to better manage long-term dependencies, with historical tide gauge data and reanalysis of sea surface height, as discussed later. Our main contributions include the innovative integration of high-resolution sea surface temperature (SST) data with advanced ML techniques, offering unprecedented insights into regional sea level variability. This research is crucial as it addresses the urgent need for precise and actionable sea level forecasts, facilitating effective regional planning and adaptation strategies in the face of climate change.

2. Data and Methods

2.1. Data Sources and Preprocessing Steps

Several products (discussed below) were used to develop this study, incorporating information from sea surface temperature to water levels from tide gauge (TG) stations and sea surface height (SSH) data.

For the automated identification of the high-variance regions in the Mediterranean basin, we used The Operational Sea Surface Temperature and Ice Analysis (OSTIA) dataset that combines in situ and satellite data to provide daily, high-resolution SST measurements (https://data.marine.copernicus.eu/product/SST_GLO_SST_L4_REP_OBSERVATIONS_010_011/description, accessed on 12 February 2024). This dataset features a 0.05-degree spatial resolution, covers the period from 1981 to 2022, and is based on a mean climatological field from 1955 to 2017. It includes pixel-uncertainty estimates, which helped filter inaccurate SST data in coastal regions such as the Aegean and Adriatic Seas, where land features and shallow waters can distort satellite measurements (Figure 1) [26]. For the study's experimental purposes, the SSTs were detrended to help isolate the natural, internal SST patterns.

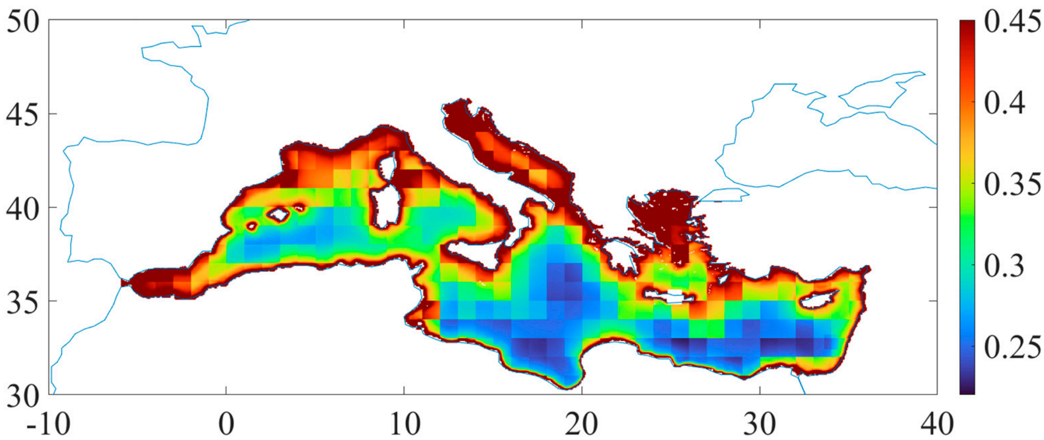

Figure 1. Map of the analysis uncertainty estimates for the OSTIA SST optimal interpolation product. Each SST value includes an uncertainty estimate, known as analysis error (https://catalogue.marine.copernicus.eu/documents/QUID/CMEMS-SST-QUID-010-011.pdf, accessed on 22 February 2024). We used a threshold of 0.45 K to discard values from our study.

To investigate the potential of forecasting water levels using the Recurrent Neural Network-Gated Recurrent Unit (RNN-GRU) in the identified regions, two different sea level datasets were employed. On the one hand, we accessed monthly TG records from the Permanent Service for Mean Sea Level (PSMSL, https://psmsl.org/data/, accessed on 30 January 2024) [27]. In particular, we used the Revised Local Reference (RLR) dataset, standardizing all station measurements to a common datum (https://psmsl.org/data/

obtaining/psmsl.hel, accessed on 30 January 2024) for accuracy. It is important to note that the Mediterranean TG network is unevenly distributed, with the majority of long-term records concentrated along European shorelines, which impacts the overall geographical distribution representation of the data [28]. Moreover, considering that long records are restricted to a few coastal locations, we strategically selected 82 stations from 1993 to the present for consistency among datasets. Instead of relying on individual TG stations, our approach involved creating a regional unified signal (Figure 2), leveraging the observed regional coherence among sea level patterns [13,29] within the regions identified in Section 2.2.1. Individual stations were first interpolated using the modified Akima cubic Hermite interpolation to address short gaps and then averaged to obtain the regional unified signal for each region [30]. This unified TG signal serves two purposes: it provides consistent data for the model to learn more robust and generalized patterns of variability during the training process, enhancing the robustness and continuity of the dataset, and it acts as a reference benchmark for further validation using a separate testing dataset. On the other hand, we also used GLORYS12V1 SSH data as an input into the model, specifically utilizing median regional values for each region, to enhance the accuracy and reliability of TG predictions by complementing the information from different sources, thus providing a more comprehensive understanding of sea level variations. Incorporating extensive historical regional data is crucial for improving the model's performance in detecting oscillations related to sea level changes on a regional scale. GLORYS12V1 is an eddy-resolving global ocean reanalysis product offering monthly SSH data from 1993 to 2020 with a 1/12-degree spatial resolution. (https://data.marine.copernicus.eu/product/GLOBAL_MULTIYEAR_PHY_001_030/description, accessed on 6 March 2024). Detrending was applied to all regional time series datasets (TG, SSH) prior to running the models to also emphasize natural internal variability associated with ocean/climate processes [22].

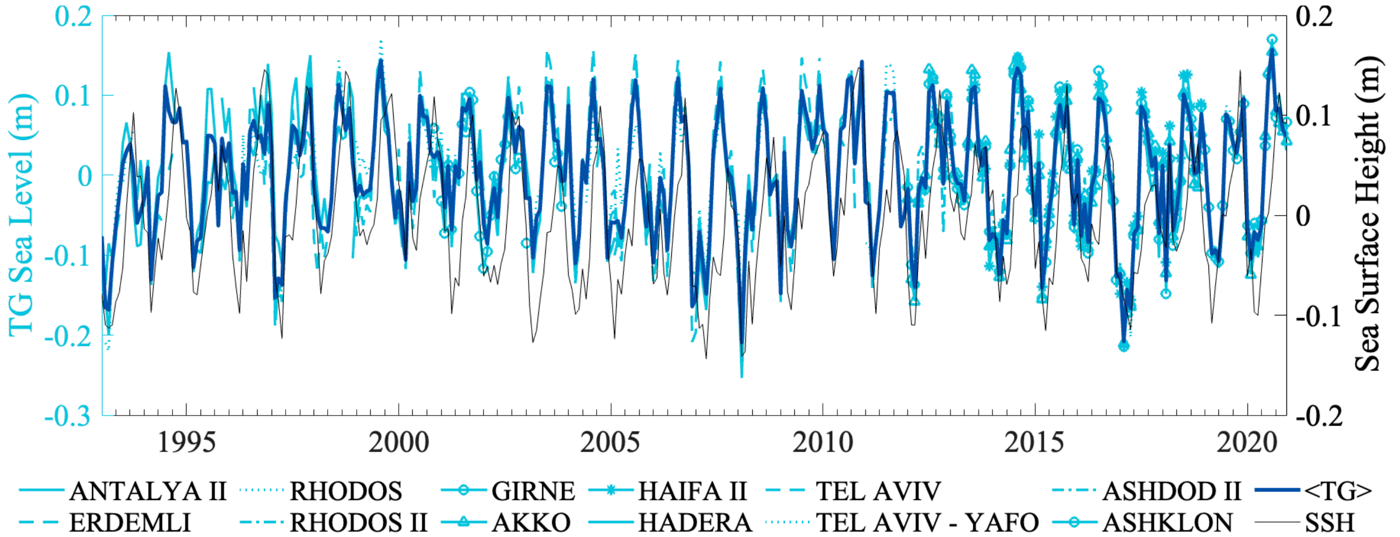

Figure 2. A comparison of the time series of the individual and unified TG signals with SSH data for the Cluster 18 region in the west Mediterranean Sea. Individual stations are represented in light blue, the unified signal as a blue solid line, and SSH as a black line. The regional consistency in the variability patterns is evident despite the differences between tide gauges and satellite altimetry in measuring sea levels (as well as their regional scope) and the presence of local factors, especially considering that satellite altimetry faces challenges in accurately measuring sea level data within approximately 10 km from the coast [31].

2.2. Proposed Hybrid Methodology

The hybrid approach presented in this study allowed us to pinpoint variability regions and generate sea level predictions by leveraging a combination of two ML techniques.

2.2.1. Climatic Region Identification in the Mediterranean through SST Clustering

In the Mediterranean basin context, we used the k-means technique, a widely employed unsupervised method for clustering and pattern recognition, to identify predominant regions of similarity within the extensive 40-year high-resolution SST dataset (described in the previous section).

The technique works by iteratively assigning data points to randomly initialized cluster centroids, maximizing inter-variance, and minimizing intra-variance among groups [32]. This approach unveils structures within complex datasets. In our study, we recalculated those centroids by taking the median of all centroid solutions, ensuring robust and reliable clustering results. Following [11], we used the correlation distance, 15 replicates, and 20 repetitions to build a robust model. The optimal number of clusters (i.e., k = 22 in this case) was found by exploring a wide range (between 5 and 25) and ensuring consistency with well-known dynamical regions [17,25]. In contrast to using the coarse subsurface temperature Levitus data [33] to explore the ocean depth layers (as in [11]), or the SSH data with a shorter temporal coverage of the entire water column, we opted for the long-term, high-resolution SST product. This choice provided a more refined regional definition of clusters and was sufficient to capture the more active regions.

This approach allowed for a more detailed representation of regional variability, as illustrated in the resulting clustering map (Figure 3), which highlights the distinct clusters identified across the Mediterranean.

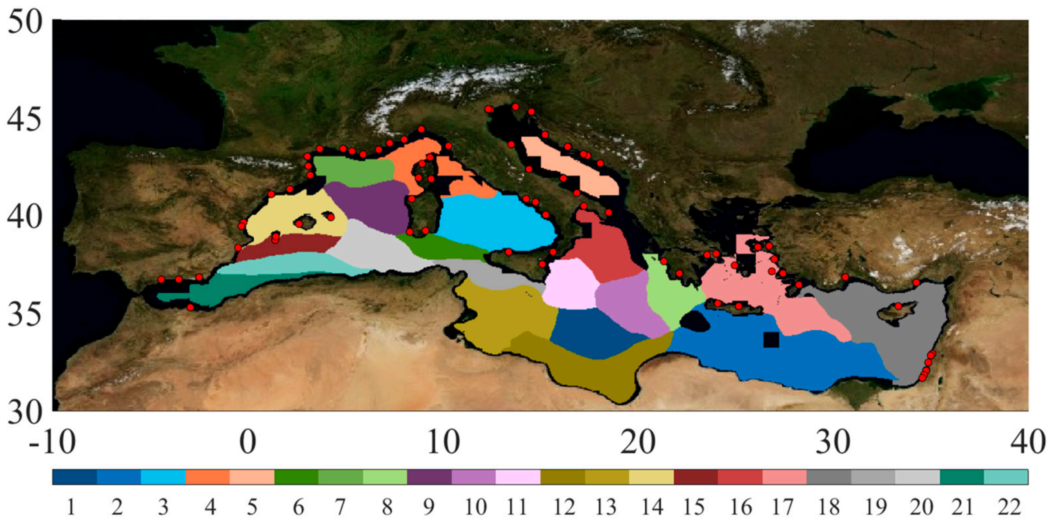

Figure 3. A representation of the 22 sub-regions identified through k-means clustering, following the methodology process indicated in [11]), using monthly SST data spanning 40 years (1981–2022). The selected TG stations are shown by red symbols.

2.2.2. Advanced Neural Network Models for Region-Specific Coastal Sea Level Change Prediction

With the identified regions, we delve here into the RNN-GRU methodology [13] adopted to predict sea level variability at the respective Mediterranean coasts for each region. Recognizing the non-linear nature of this problem, the use of RNNs was an appropriate choice, given their utility for similar purposes [22,34]. In our proposed configuration, RNN cells have two inputs: the state from the previous steps, implemented using sliding windows of different sizes, and the current observation, so the previous information is passed to the next cell at each step. We used backward sliding windows ranging from 1 month to 36 months, incremented every 3 months, to capture broader temporal dependencies for all clusters. The GRU is particularly effective in managing time dependencies, as it uses two gates: the reset, which controls the flow of new information, and the update gate, which determines what information should be retained. This architecture helps maintain consistent values for the hidden state, ensuring that relevant past information is preserved [34]. The RNN-GRU enabled the development of more complex models to predict regional coastal sea levels using past information.

More specifically, the architecture is built using five layers: the sequence input layer (the normalized time-series data fed into the RNN), a GRU layer, a dropout layer to prevent overfitting with a 20% dropout rate, a fully connected layer (that connects every neuron to each neuron in the next layer), and a regression output layer (that predicts continuous values). After testing a wide range of neurons (between 2 and 150), we found that 80 neurons are an optimal number for our experiments, based on the outcome metrics for all clusters, but there might be other suitable options. Additionally, we used the Adam optimizer with an initial learning rate of 0.0001. The network was trained with a batch size of 128 and an early stopping criterion, which involved validating the model at each run (i.e., with a validation frequency of 1) and halting the training process if the loss function did not show any improvement for 75 iterations (epochs). This approach helps to mitigate overfitting, by ensuring that the model does not continue to train on the data once it stops making meaningful progress in reducing the loss. These decisions were based on tests and similarities with previous studies [13], with the present study selecting a train/validation/test split of 85–5–10% to ensure the preservation of temporal dependencies. The test was conducted using the last part of the time series, which was not seen by the model during the training process, covering 16 to 33 months depending on the length of the record. For each cluster, forecasting time, and sliding window, the model underwent five repetitions to ensure robust results, with the median of these repetitions being evaluated. This process resulted in a total of 3640 experiments.

The metric used to evaluate the prediction was the correlation coefficient (R), indicating how strong the relation is between the predicted and expected output.

$$\boldsymbol{R} = \sqrt{\mathbf{1} - \frac{\sum_{i=1}^{N}\left(y_i - y_i^*\right)^2}{\sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2}} \tag{1}$$

Here, y_i and y_i^* represent the observed unified signal from TG data and the model prediction, respectively. This formula, directly related to the mean squared error (MSE) loss function inherent from the regression analysis, ensures that the closer the R value is to 1, the stronger the correlation between the predicted and observed data [22]. While we have also included the root mean squared error (RMSE) in the results, it is important to note that because we use inputs from various sources that may differ in magnitude, exact matches to sea levels are not anticipated. Our focus is on capturing variations and understanding the percentage of variability explained by the model, represented by the coefficient of determination (R^2).

This approach allows us to provide customized local solutions for each region, ensuring that our predictions are tailored to the unique characteristics and dynamics of individual coastal areas (see Figure 4 for details).

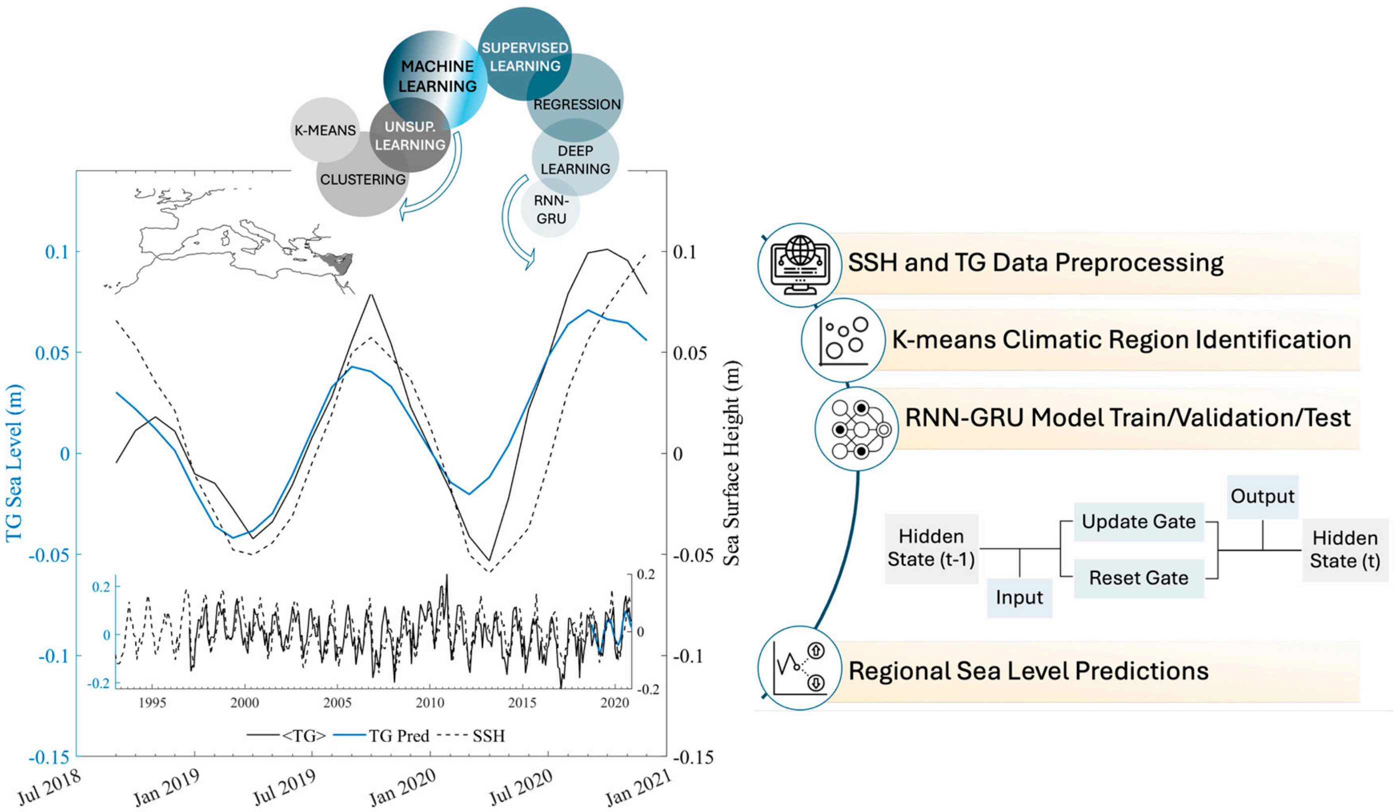

Figure 4. This figure presents the main overview of the proposed hybrid ML methodology to forecast regional sea level changes in the Mediterranean Sea. The process begins with high-resolution SST data collection, followed by k-means clustering to identify regions of high variance (as seen in Cluster 18 in the embedded map). Next, regional unified TG signals (in solid black line) and median SSH data (discontinuous black dash line) are integrated (post-detrending) into our RNN-GRU approach. The RNN-GRU model is then trained and validated using the identified clusters and historical data, concluding with the TG prediction of regional sea level changes (blue line) as depicted in the bottom plot. The time series in the left panel, highlighting the prediction against observations, is shown after smoothing was applied using a 6-month window for enhanced visualization. Although illustrative, this figure is based on the main results discussed later (in particular using a backward sliding window of 12 months and a forecasting time of 36 months). On the right, a flowchart details the steps of the methodology, accompanied by a diagram depicting the GRU process. Units are in meters.

3. Results and Discussion

In this section, we present the findings from our comprehensive analysis of regional sea level variability using advanced machine learning techniques (discussed in Section 2.2), with the goal of identifying areas with unique regional ocean/climate variability patterns and anticipating future changes.

The clustering obtained through k-means using SST (Figure 3) revealed regions consistent with known underlying ocean/climate physics. For example, in the central-northern Mediterranean where most TG stations are located, the dynamics of Atlantic water that flows into the basin through the Strait of Gibraltar, creating gyres, could be represented in Cluster 21. This inflow influences regional circulation patterns and water properties significantly [17]. Cluster 7 might represent the Gulf of Lion region, catheterized by well-defined physical characteristics influenced by the inflow of Atlantic water and the Levantine Intermediate water [35]. Similarly, Cluster 5 in the Adriatic Sea, which is defined by the Adriatic Gyre, the inflow of Levantine Intermediate water, and the discharge of the Po River, exhibits distinct characteristics [36]. Climatic features in the Gulf of Lion include strong wind-driven upwelling and significant seasonal temperature variability, while the

Adriatic Sea experiences pronounced seasonal changes and riverine input impacts. Clusters 3 and 18 are regions well separated, highlighted for their elevated temperature and salinity trends [17,37]. Cluster 3, in the Tyrrhenian sub-basin, has climatic characteristics of high evaporation rates and limited freshwater input, while Cluster 18, in the Levantine sub-basin, is influenced by high insolation and minimal precipitation, leading to higher temperatures and salinity. The Western Mediterranean Deep Water affects the ocean properties of the water column in the region of Cluster 14 [38]. This comprehensive analysis is somewhat comparable with other clustering studies, such as the one conducted by [17] or [25]. While their approach differs, and the number of extracted clusters is much lower, the resulting spatial clustering (for monthly SST or mean sea level anomalies (SLAs) data) reveals some similar spatial patterns, thereby reinforcing our results. The similarities suggest that our method is reliable and effectively captures the essential features of the region's ocean dynamics. This analysis helps in the local study of different sub-regions in this basin, considered a hotspot, to make predictions on regional scales.

For this purpose and knowing that spatial extension substantially influences the study of ocean/climate variability, we applied our RNN-GRU models (as in Section 2.2.2) to each clustered region with the unified regional TG signal based on information from neighboring stations and SSH as input variables. This strategy helps ensure that our model is well calibrated for diverse regional characteristics across the entire coastline rather than relying on just one individual station [13]. We present the results for three distinct regions in the east, center, and west of the Mediterranean Sea as examples, corresponding to Cluster 18, Cluster 3, and Cluster 14, respectively (Figures 5–7). It is worth noting that Clusters 14 and 18, with 7 and 12 TG stations, respectively, have 28 years of historical data for the average signal computation. In contrast, Cluster 3 has only four stations and 20 years of data, which affects the prediction results, as shown in Figure 5. The differences in data availability and station density likely contribute to the varying accuracy of predictions across these clusters. In particular, Cluster 3 shows consistent moderate agreement between observed and predicted values with correlation coefficients ranging from 0.51 to 0.57 across all forecasting intervals (from 1 to 36 months). Cluster 14 exhibits the highest correlation coefficients, ranging from 0.76 to 0.82, highlighting a strong predictive capability (Figure 6). Similarly, Cluster 18 shows strong correlation coefficients between 0.69 and 0.77 (Figure 7). The high correlation values in Clusters 14 and 18 suggest that our model performs exceptionally well in regions with more comprehensive datasets. The analysis of additional clusters in surrounding coastal areas is shown in the Supplementary Materials.

The average correlation value (for all studied coastal clusters totaling 12 clusters and all forecasting intervals) is 0.63. The regions where the model is capable of providing more accurate predictions are in the east and west Mediterranean Sea (Clusters 14, 15, 17, 18, and 21) with a correlation value ranging from 0.65 to 0.84. In other regions, such as Clusters 3, 6, 9, or 11, located around the south of Italy and the Balearic Islands, the performance ranges from moderate to moderately strong (0.51 to 0.70). This demonstrates the model's versatility and its capacity to adapt to different regional characteristics. In complex areas such as the Gulf of Lion, Adriatic, and Aegean sub-basins, the accuracy decreases due to unique bathymetry and challenging topography which pose a challenge to satellite altimetry in measuring SSH with high precision [39,40]. This discrepancy is particularly pronounced in the Gulf of Lion (see Cluster 7 in Supplementary Materials) with the steep and complex topography of the canyon systems along the coast. Therefore, in this particular case, we only used the TG stations to make predictions. Additionally, in regions where the number of TG stations is limited, there are regional discrepancies and occasional outliers, particularly in areas with extensive gaps (like for Cluster 8 and Cluster 16), the analysis was simply not possible. Except for these excluded cases, our models were always capable of mimicking sea level variability. This highlights the model's overall robustness, even in challenging regions. It is important to note that while the correlation values inform us about the strength of the relationship between predicted and observed data, our primary aim is to capture the variability to inform about changes in the tendency (increase or decrease in the following months/years) rather than the absolute magnitude.

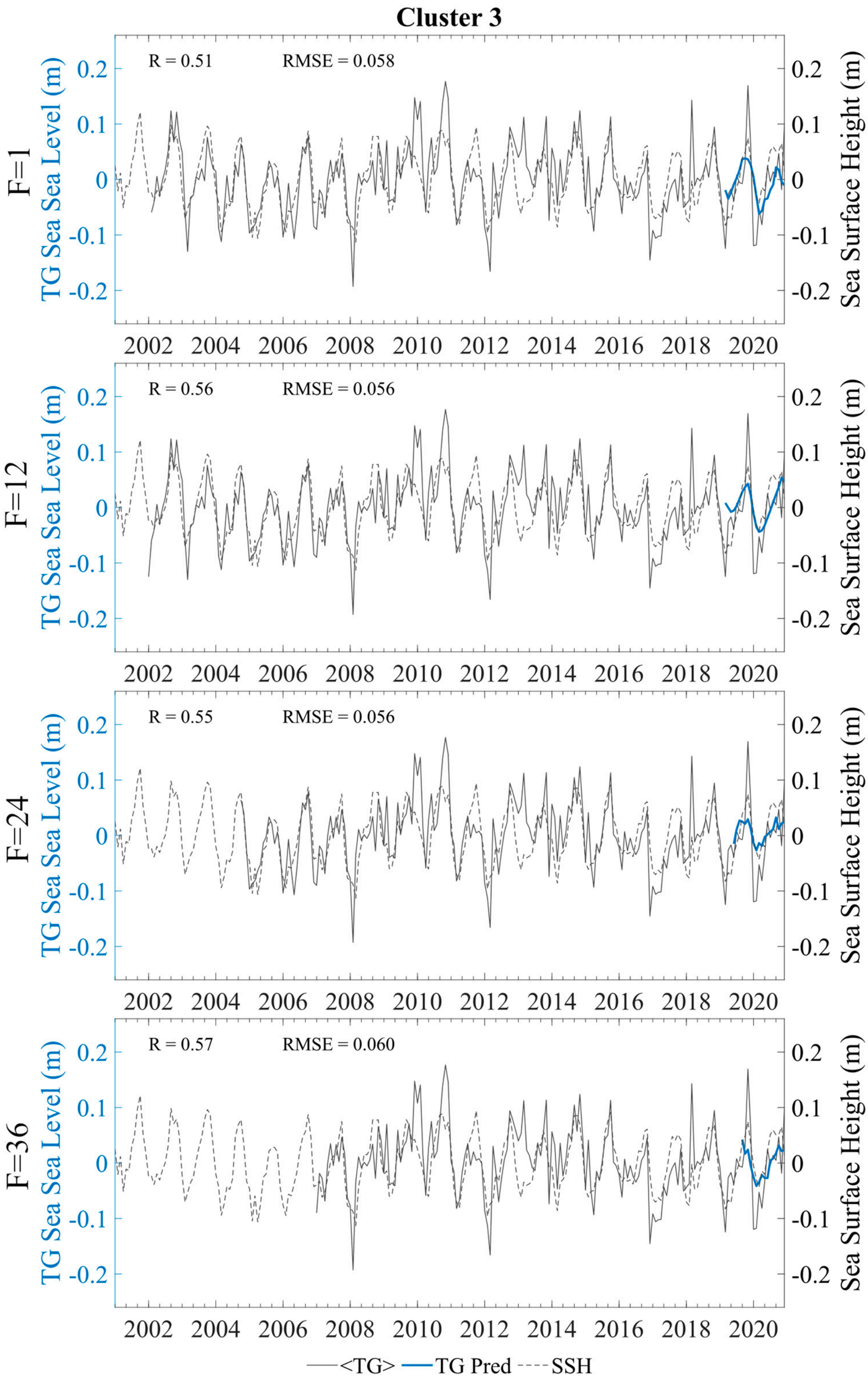

Figure 5. Time series of sea level historical data and predictions for Cluster 3 for each forecasting interval (F = 1, 12, 24, and 36 months), covering the final years of the record. Here, F = 1 indicates that the forecast for each given time in the plot was made 1 month prior to the actual observed value, while F = 12, 24, and 36 correspond to forecasts made 12, 24, and 36 months in advance, respectively.

The embedded correlation coefficient values (R, which correspond to the median of all repetitions) indicate the strength of the relationship between observed (TG, solid black line) and predicted values (TG Pred, blue line). SSH is also shown (black dash line). These results correspond to the following sliding windows for each forecasting time (in months): 12, 0, 21, and 36. These backward sliding windows were chosen to yield the best results, as determined by the model's performance near the median R value. The RMSE is also included. Units are in m.

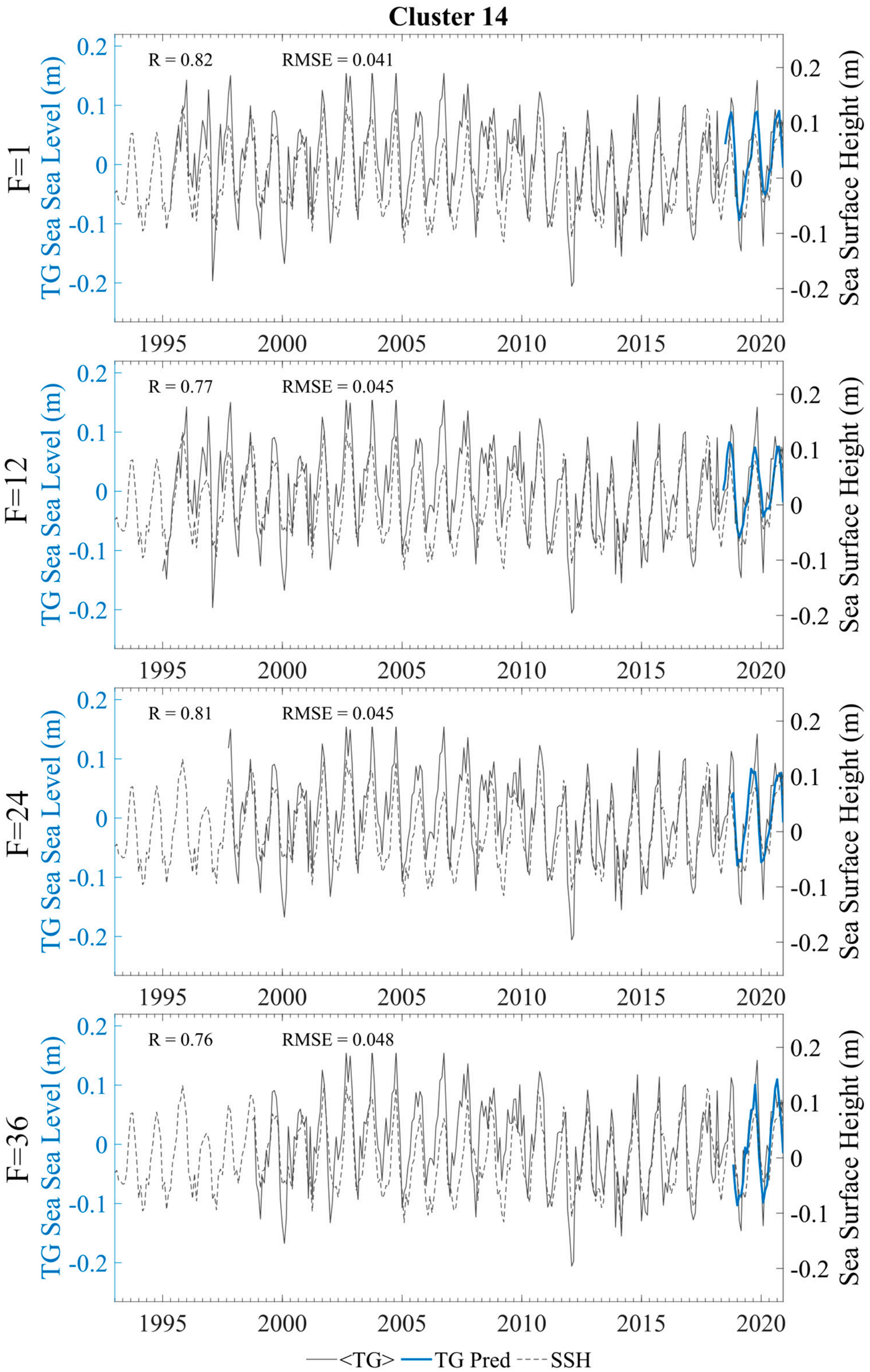

Figure 6. As in Figure 5, but for Cluster 14. These results correspond to the following sliding windows for each forecasting time (in months): 27, 12, 33, and 33.

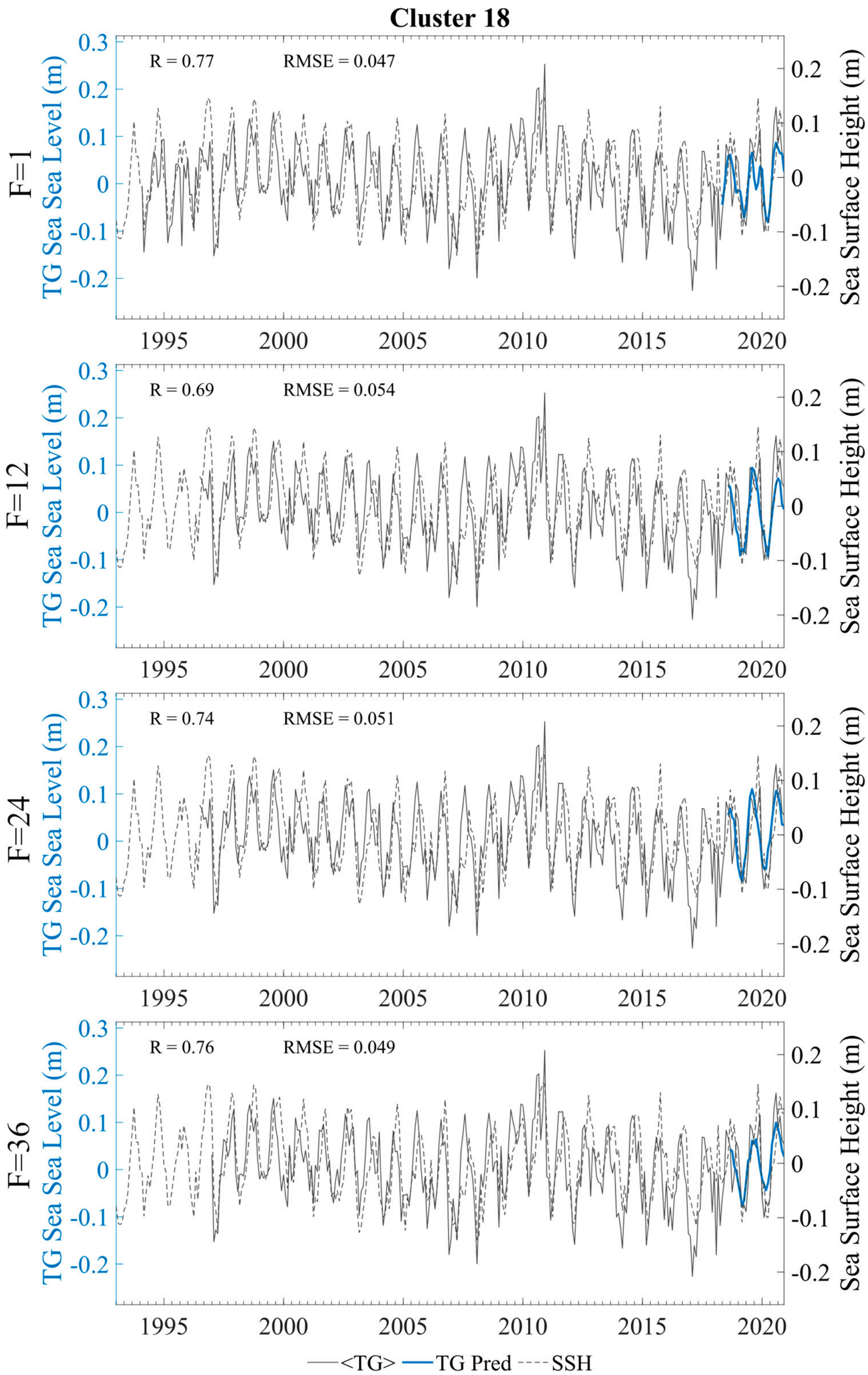

Figure 7. As in Figure 5, but for Cluster 18. These results correspond to the following sliding windows for each forecasting time (in months): 12, 30, 18, and 12.

Overall, this methodology is a powerful tool that can effectively identify regions with similar variability and provide sub-regional-scale predictions up to three years in advance. The ability to forecast sea level changes accurately at a sub-regional scale is crucial for local planning and adaptation strategies, making this approach highly valuable for policymakers and researchers alike. By leveraging this approach as more data becomes available, decision-makers can better prepare for and mitigate the impacts of ocean/climate variability on coastal communities.

4. Conclusions

This study presents a comprehensive approach to capturing sea level variability and providing near-future predictions by leveraging advanced machine learning techniques. The combination of clustering and RNN-GRU models has demonstrated significant promise in forecasting regional sea level changes in the Mediterranean Sea, addressing a critical need for short-term, localized predictions. This was achieved by first identifying regions of high variance through k-means clustering, revealing distinct sub-regions consistent with known oceanographic and climatic patterns. These clusters, derived from a 40-year high-resolution SST dataset, provided a robust foundation for further analysis and prediction.

The integration of historical TG data and SSH data into the RNN-GRU models enabled accurate predictions of sea level changes for different regions. Our results indicate strong correlation coefficients in areas with comprehensive datasets, while regions with fewer TG stations or shorter time series showed moderate agreement. The average correlation value for all studied coastal clusters and forecasting intervals was 0.63, with the most accurate predictions observed in the east and west Mediterranean Sea, reaching values between 0.65 and 0.84 (averaging 0.76). In regions with the confluence of complex local factors, such as unique shelf topography, the prediction accuracy declines. Despite these variations, the model's overall performance was robust, capturing sea level variability and trends effectively.

In summary, this methodology offers a powerful tool for identifying regions with similar variability and providing sub-regional scale predictions up to three years in advance. By capturing the variability and providing insights into future trends, our approach supports effective regional planning and adaptation strategies. The ability to forecast sea level changes accurately at a sub-regional scale is crucial for mitigating the impacts of ocean/climate variability on coastal communities. As more data become available, this approach can be refined and expanded, providing valuable insights for policymakers and researchers to better prepare for and address the challenges posed by sea level changes.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/cli12080127/s1, the time series analysis of RNN-GRU-based sea level predictions for additional clustered regions in the Mediterranean Sea.

Author Contributions: Conceptualization, V.N.; methodology, V.N. and C.R.; investigation, V.N. and C.R.; analysis, validation, and data curation, C.R., M.V.-M. and J.L.A.-M.; visualization, C.R. and V.N.; writing—original draft preparation, C.R. and V.N.; writing—review and editing, V.N. and M.V.-M.; supervision, V.N.; funding acquisition, resources, and project administration, V.N. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: All data used are available via the web links in the text and references. The datasets generated by this study are available at https://github.com/AI4OCEANS/ (accessed on 3 July 2024).

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