Coastal Shoreline Dynamics in the Krishna - Godavari Delta Using K-Means Whale Optimized Long Short Term Memory Networks

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Abstract

Rising sea levels pose an imminent hazard to coastal communities that depend on the sea for their livelihood. This paper presents a robust computational technique for forecasting tidal surge and resulting shoreline changes in the vulnerable Krishna-Godavari (KG) Delta, India. To ensure the reliability of decades-long projections and directly address the methodological shortcomings of prior work, this study is grounded in an multi-decadal historical dataset spanning 39 years (1977–2015), thus providing a scientifically justifiable temporal basis. The core methodology employs a deep-learning architecture: the Long Short-Term Memory (LSTM)network. To maximize its predictive efficiency, the LSTM's critical hyperparameters are rigorously optimized using the nature-inspired meta-heuristic : the K-means Whale Optimization Algorithm (WOA). This novel hybrid KWOA-LSTM approach achieves superior predictive performance over conventional models, demonstrated by a R^2-score of $\mathbf{0.916}$ and a Mean Absolute Error (MAE) of $\mathbf{0.012}$. The predicted and forecasted surge values, computed by the optimized model, are visualized via the Google Earth Engine elevation map. Forecasts indicate significant saline intrusion and inundation will affect the KG Delta by 2060, posing a grave threat to the region's food security. The utilization of WOA for hyperparameter tuning, combined with the multi-decadal dataset, establishes a highly accurate and scientifically rigorous framework for long-term coastal hazard assessment and proactive planning.

Introduction

Humongous population growth and infrastructure development have been rising in the coastal regions for many years. According to the estimates of the United Nations in 1992, more than half of the world's population lives within 60 km of a shoreline(Kumar et al. 2010).The rise in sea levels due to increasing atmospheric temperatures is a grave concern for aquatic ecosystems and humans who depend on them. The drastic rise in sea levels and subsequent inundation of coastal hamlets pose a perilous threat to humanity and wildlife. Drastic changes in the sea line dynamics pose a threat to the vast majority of the population that lives near the coastline. The rise in sea level due to global warming is predicted to amount to around 20cm to 60cm by the year 2100 (IPCC 2007), which makes it a necessity to identify and protect the vulnerable sections of coasts all across the world (Kakani et al. 2008).Coastal sea-line and sea level variability result from a myriad of factors and due to the amalgamation of multiple processes, including tidal gauge, wave parameters, storm surge, and mean sea level resulting from the passage of high winds and low-pressure systems (Tiggeloven et al. 2021).The variability also depends on various non-morphological factors, such as the level of infrastructure development and human activity. Higher human activity directly correlates to a higher level of erosion and inundation over the coasts. The continuous interaction between the shore and sea makes the coastal ecosystem one of the most dynamic ecosystems to ever exist in the biosphere (Mohanty et al. 2023). Nevertheless, there is a necessity to consider all these parameters and overcome the drawbacks in order to compute an efficient model for sea-line prediction. This model's findings would be of great use to different sections of the society. Disaster management officials, urban and rural planners, and other government officials responsible for dealing with natural disasters and other upcoming hazards also need accurate assessments of coastal hazards and the dynamic changes to the sea line to make informed decisions for disaster management, rehabilitation, and social services (Kumar T. et al. 2010).

Sealine changes are practically time-series data where we observe variability concerning time. Neural networks are known to be efficient for the computation and processing of such data. Many approaches were explored to find the best fit for the time series data. Various methods include recurrent neural networks (RNN), artificial neural networks (ANN), XG-Boost (not a neural network), etc. ANNs have been successfully applied to compute the tidal surge by many researchers (Tiggeloven et al. 2021). We have decided to follow a much different path to explore the unexplored in sea-line prediction. RNNs are computationally more powerful than feed-forward neural networks due to their memory and retention of states. Long-short-term memory, abbreviated as LSTM, is an upgraded version of RNN due to its functionality to make use of both long-term and short-term memory

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as weights (J.P Tan et al. 2023)

This makes LSTM an incredibly lucrative model for forecasting any time variant series. But standard LSTMs are not fine-tuned enough to provide us the most accurate predictions. LSTMs and Bi-LSTMs are typically trained using conventional gradient-based optimizers (like ADAM) . While standard, these optimizers are prone to converging on a local minimum within the complex parameter space, preventing the network from achieving its true global maximum predictive accuracy. To produce scientifically rigorous long-term forecasts, a model must overcome both of these deficiencies i.e we need a powerful optimizer that brings out the best hyper-parameters so that LSTM performs at the best. Hence, we propose a Meta Heuristic Optimized i.e. K-means Whale-Optimization Algorithm enabled LSTM usage for efficient prediction of changes in coastal sea line and sea levels in our study area i.e. Krishna-Godavari Delta. The findings will be visualized on Google Earth Engine enabled elevation map for easy understanding and usage by both researchers and novices alike.

Our Contributions

Following are the list of contributions that our research work makes :

1. **K-means Whale Optimization Algorithm (WOA)-Enabled LSTM (WOA-LSTM)**: We introduce a novel hybrid model where the LSTM's hyperparameters are meticulously tuned by the nature-inspired Whale Optimization Algorithm. This WOA-LSTM replaces local search with a global meta-heuristic search, ensuring the model's parameters are globally optimized for maximum predictive accuracy.
2. **Google Earth Visualization and Quantification**: The resulting predicted surge values are utilized to generate an elevation map layer within the Google Earth Engine . This visualization provides a lucid and technically sound representation of submersion-prone regions , which is further quantified with specific inundated area projections for future decades

The remaining part of the paper consists of the Literature Survey in Section 2, followed by Study Area in Section 3,proposed methodology in section 4,result in section 5,conclusion and future scope in section 6 and terminated with references.

RELATED WORKS

Research into coastal dynamics and sea-level forecasting has broadly followed two tracks: Geographic Information System (GIS)-based vulnerability assessments and advanced machine learning models. A critical review of the literature highlights existing methodological and temporal gaps that the current study aims to resolve.

GIS-Based and Traditional Vulnerability Assessments

Initial assessments often relied on Geographic Information System (GIS) tools and satellite data to delineate static risk zones and determine coastal vulnerability. One such approach (Kakani et al. 2008) computed sea-level rise along the Andhra Pradesh coast by utilizing GIS satellite imagery and ARPANET satellite imagery in conjunction with the Digital Shoreline Analysis System (DSAS). The output of their assessment was delivered in the form of the Coastal Vulnerability Index (CVI) and tidal surge rise along the Andhra Pradesh coast. While the input was deemed highly reliable due to the usage of ArcGIS software and ARPANET imagery, the authors noted that the dependence on the DSAS tool makes it challenging to integrate and tweak deep-learning procedures to boost the model's efficiency and accuracy.

Similarly, a study conducted along the coastline of the state of Odisha (Kumar et al. 2010) focused on estimating the expected damage to the coastline by computing the Coastal Vulnerability Index (CVI). Data for this work was taken from LANDSAT MSS and LANDSAT TM imagery, with resolutions of 57m and 30m respectively, over a time period of 1972 to 1900. The CVI was graded on an index range of 1 to 7, which signifies the predicted damage. Although the usage of CVI is an industrially accepted practice, it is recognized as a too simplistic formula that limits the scope to apply novel machine learning techniques and to tweak the computation parameters for improved predictive results. These traditional index-based methodologies are robust for historical risk mapping but often lack the sophisticated non-linear predictive power required for long-term, climate-driven forecasts.

Machine Learning and Deep Learning Models

The power of neural networks to handle complex time-series data has significantly shifted the focus toward sequence modeling for surge prediction.

1. **RNN and Standard LSTM Architectures:** Early data-driven models utilized basic Recurrent Neural Networks (RNNs). For instance, one approach (Nieves et al. 2021) used Gaussian processes for modeling and an RNN for predicting the future tidal surge and subsequent rise in sea level. This architecture was relatively simplistic, and the model's reliance on forecasting subsequent surge based on the thermal heat in the sea was found to be inaccurate. Advancing this, other researchers (Tiggeloven et al. 2021) implemented an RNN architecture incorporating a hidden convoluted LSTM layer to predict surge, utilizing data from 133 tidal stations across the world. They also employed Support Vector Machines (SVM) for thorough analysis of the predicted data. Although this represented a simple yet efficient LSTM architecture, it was observed to generate a highly volatile output prone to error. Other successful applications include the work of (Yang et al. 2020), who demonstrated the effectiveness of Long Short-Term Memory Recurrent Neural Networks for tidal level forecasting.

2. **Advanced Architectures and Hybrid Models:** To overcome the challenges of long-term dependencies and noise, more complex and hybrid models have been explored. (Ian et al. 2023) proposed a **bidirectional LSTM model based on an attention architecture** for the study of storm surge to improve overall prediction accuracy. Their training

and evaluation data was sourced from extensive meteorological event and tidal data from 77 cyclonic incidents. The authors asserted that this methodology is capable of modeling complex non-linearities and resolving the problem of long-term dependencies by providing a selective emphasis on significant features, which boosts model accuracy. While this model outperforms any conventional LSTM model, it is also noted for its extreme complexity. Furthermore, research has extended into other non-sequential deep learning techniques for comparison. For example, (Ravikumar et al. 2023) explored Shore Line Change Detection using ANN and Ground Water Variability Along the Kerala Coast using Random Forest Regression. Similarly, (Yin et al. 2021) investigated advanced machine learning techniques for predicting Nha Trang shorelines, and (Gunawan et al. 2022) used Random Forest for data-driven shoreline change forecasting on Eretan Beach. These comparison studies indicate that while various machine learning techniques are applicable, sequence-aware deep learning models generally offer the most robust framework for time-series forecasting.

Integration of Meta-Heuristic Optimization

To overcome the optimization limitations of conventional deep learning models, recent studies have explored the integration of metaheuristic algorithms to enhance training efficiency. Hybrid frameworks that couple sequence prediction models with nature-inspired optimization techniques have demonstrated superior global convergence performance. For example, (Mittal et al. 2023) employed the Whale Optimization Algorithm (WOA) to tune the hyperparameters of a Long Short-Term Memory (LSTM) network for solar energy forecasting. Their findings showed that WOA effectively explores the non-convex parameter space, enabling the LSTM to escape local minima and achieve improved accuracy and stability compared to standard training. Building on this success, the WOA-LSTM hybrid framework is adopted in this study for coastal surge prediction, ensuring globally optimized parameters and enhanced predictive accuracy for long-term climate projections.

STUDY AREA

The depicted study area in Figure 1 is confined to the Krishna-Godavari (KG) Deltaic region in Andhra Pradesh, India. Positioned on the deltas of the River Godavari and River Krishna , the second and third longest rivers within Indian territory, this glorious region is characterized by the lush paddy fields, thriving aquaculture and horticulture. Notably, it hosts three major ports in the eastern coast of India —Kakinada, Machilipatnam, and Nizampatnam—and encompasses the natural gas reserves in the KG basin, presently managed by the Oil and Natural Gas Corporation (ONGC). The state's capital Amaravati and the adjoining metropolis region of Vijayawada city in Figure 13 are the power centres of this region. With over 40% of Andhra's population residing in this area, boasting a population density of 729 persons per km2, the study zone holds both scientific and social significance. Data for the study was sourced from the Machilipatnam tidal station (16.1809° N, 81.1303° E), strategically situated in the heart of the study area. This dataset of this region, serves as the foundation for predictive modeling across the broader study region.

Figure 1: Study area.

Problem Set-up and Formulation

Given the dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, where $x_i \in R^m$ denotes the feature vector and $y_i \in R$ represents the corresponding tidal surge value, the objective remains to learn a function $f : R^m \to R$ that predicts the tidal surge y as a regression based on the input features x. The feature vector $x = (x_1, x_2, x_3, x_4, x_5, x_6)$ includes:

- x_1: Date feature,
- x_2: u component of wind,
- x_3: v component of wind,
- x_4: Distance weight,
- x_5: Surge level, and
- x_6: Mean sea level (in Ms. Pl).

These six features were chosen due to their considerable correlation with the output surge . The WOA-LSTM model is trained to minimize the loss function $L(\theta)$ over the training dataset D_{train}, given by the Mean Absolute Error (MAE):

$$L(\theta) = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{1}$$

where $\hat{y}_i = f(x_i; \theta)$ in Equation 1 represents the predicted tidal surge value and θ denotes the model parameters.

PROPOSED METHODOLOGY

The proposed framework employs a hybrid **K-Means Whale Optimization Algorithm (KWOA)-enabled Long Short-Term Memory (LSTM)** model for long-term tidal level forecasting in the Krishna-Godavari Delta. The architecture integrates a modified K-Means WOA-based LSTM optimizer, and a visualization module.

Initially, daily tidal data (1977–2015) are transformed using a time-lag function to incorporate historical dependencies crucial for temporal pattern learning. The Modified K-Means WOA optimizes LSTM hyperparameters—such as the number of layers, hidden units, learning rate, and batch size—by enhancing the initial whale population distribution

via K-Means clustering for faster convergence. The optimized LSTM model is trained and validated using a 70:30 split to forecast tidal variations for 2050–2075. The final predictions are visualized through a Google Earth Engine-based elevation map to identify potential submersion-prone zones. The overall system architecture is depicted in Fig. 2.

Dataset

The initial step includes a data collection step where data has been meticulously sourced from reliable sources. The tidal gauge, u and v components of wind, distance pressure, and other attribute data were sourced from the Indian National Centre for Ocean Information Services (INCOIS) (Incois 2025) for Machilipatnam Tidal gauage station for a time period spanning over approximately 40 years from 1977 to 2015. The dataset is of a daily nature i.e it contains entries for each day of every year in the specified time range.

System Architecture and Data Pre-processing

The systematic process flow involves data collection, preprocessing, model training, and visualization .

Data Pre-processing The NetCDF4 format dataset obtained from INCOIS was converted to CSV format using the Panoply application (NASA 2025). Data cleaning was performed to remove anomalies and redundancies, resulting in a refined dataset D_{clean}. To ensure temporal consistency, a **time-lag function** was applied to introduce lag features from historical observations, enhancing the model's ability to learn temporal dependencies. The transformed feature vector x_i' with lag length k is expressed as in Equation 2:

$$x_i' = [x_i, x_{i-1}, x_{i-2}, \ldots, x_{i-k}] \tag{2}$$

Given that the dataset comprises daily tidal level records from 1977 to 2015, lag features enable the model to capture both short- and long-term tidal dependencies. Tidal dynamics are governed by multiple periodic components—diurnal (daily), fortnightly (spring–neap), lunar (monthly), and seasonal (annual) cycles. Accordingly, lag intervals of 1, 2, 3, 6, 12, 14, 29, 30, 90, 180, and 365 days were used to represent these cycles. The optimal lag length ($k = 365$) was selected to encompass annual periodicity. Following lag transformation, the dataset was divided into training and testing subsets using a standard **70:30 split** for model evaluation.

Visualization Pipeline The final output is a time series forecast of the tidal surge, computed as surge height in meters . The visualization is performed using a tool developed on the **Google App Engine** and the Google Maps API . This correlates the predicted surge with an elevation map, shading regions in **blue** where the predicted surge exceeds the land elevation, signifying submersion risk .

KWOA-LSTM: Model Building and Optimization

The model employs a multi-tiered LSTM architecture, but its parameters are not optimized by simple gradient descent; instead, they are globally optimized by the Whale Optimization Algorithm.

Hyperparameter Optimization with Modified K-Means Whale Optimization Algorithm (WOA) We employ the Whale Optimization Algorithm (WOA) (Mirjalili et. al 2016) , illustrated in Fig. 3, a bio-inspired metaheuristic that simulates the bubble-net foraging behavior of humpback whales. Conventional WOA initializes search agents randomly, which can result in slow convergence and suboptimal exploration of the solution space.

To improve convergence speed and solution quality, a Modified K-Means WOA is proposed by integrating K-Means clustering during the initialization phase. Instead of random initialization, whale agents are positioned based on clustered training samples, ensuring a diverse yet promising starting population. This structured initialization enhances exploration–exploitation balance, accelerates convergence, and stabilizes the optimization process. The detailed procedural steps of the algorithm are summarized in Table 1.

Through iterative exploration and exploitation, the modified K-Means WOA effectively fine-tunes the weights and hyperparameters of our LSTM, leading to optimal regression and prediction performance.

Inside WOA: The equations 3 to 7 describe the intrinsic working of the whale optimization algorithm and the mathematics involved in it.

Encircling behavior:

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \tag{3}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{4}$$

where $\vec{X}^*(t)$ is the best solution found so far, $\vec{X}(t)$ is the current position, $\vec{A}$ and $\vec{C}$ are coefficient vectors.

Bubble-net attacking mechanism:

$$\vec{X}(t+1) = \vec{D}' e^{bl} \cos(2\pi l) + \vec{X}^*(t) \tag{5}$$

where b is a constant, l is a random number in [-1,1], and $\vec{D}'$ is the distance between the whale and the prey.

Search behavior:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}| \tag{6}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{7}$$

where $\vec{X}_{rand}$ is a randomly selected search agent.

LSTM Integration with Modified K-Means WOA Long Short-Term Memory (LSTM) networks (Hochreiter et. al 1997), a variant of recurrent neural networks (RNNs), are designed to capture long-term temporal dependencies in sequential data. Given the periodic and non-linear nature of tidal variations, LSTMs effectively model both short- and long-term dynamics through their gated architecture.

A Modified K-Means Whale Optimization Algorithm (WOA) was employed to optimize key LSTM hyperparameters, including the number of layers, hidden units, and learning rate. K-Means clustering enhances population diversity by grouping similar whale agents, while the WOA iteratively updates their positions using encircling, bubble-net, and search strategies to balance exploration and exploitation. This process converges to an optimal configuration ensuring superior predictive accuracy.

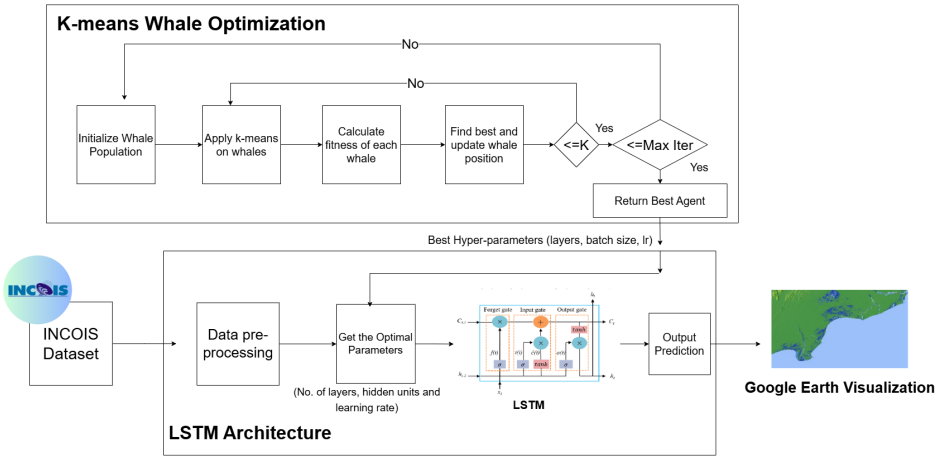

Figure 2: Proposed K-Means WOA–LSTM Architecture

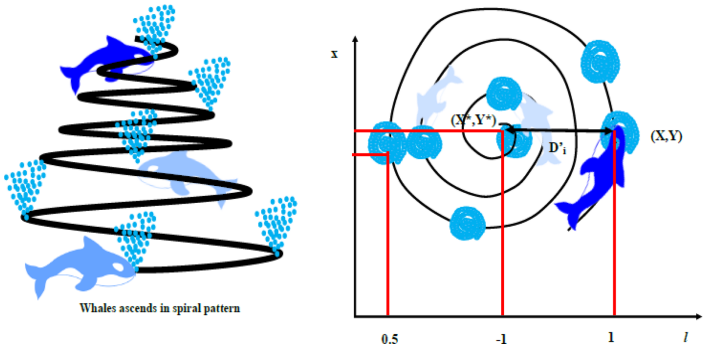

Figure 3: K-means Whale Optimization Algorithm

Algorithm: K-Means Whale Optimization Algorithm

1. Initialize whale population W randomly
2. Apply K-Means clustering to group whales into K clusters
3. Evaluate the fitness of each whale using an objective fun.
4. **For** each iteration until convergence or max iterations **do**
5. **For** each whale in W **do**
6. Update whale position
7. Calculate new fitness value
8. **If** new fitness is better than previous best **then**
9. Update best position
10. **End For**
11. **If** stopping criteria met **then** break loop
12. **End For**
13. Return best whale (optimal hyperparameters and weights)

Table 1: Steps of the Modified K-Means Whale Optimization Algorithm.

The optimized LSTM, performs recursive multi-step forecasting for 2050–2075, where each predicted value feeds into the next. The resulting long-range projections can be visualized on Google Earth Engine to identify potential submersion-prone coastal regions.

RESULTS

This section describes the results obtained from this study.

Whale Optimization Algorithm Results

The Modified K-Means Whale Optimization Algorithm (KWOA) was applied to optimize both the feature selection and the hyperparameters of the LSTM model within the proposed framework. Multiple whale agents explore the search space to identify optimal feature subsets and LSTM configurations, enhancing the model's predictive performance for long-term tidal forecasting.

Figure 4 shows the initial positions of the whale agents within the search space, representing the exploration phase where diverse candidate solutions are evaluated. Figure 5 depicts the trajectory of the best whale during optimization, demonstrating convergence toward an optimal set of features and hyperparameters.

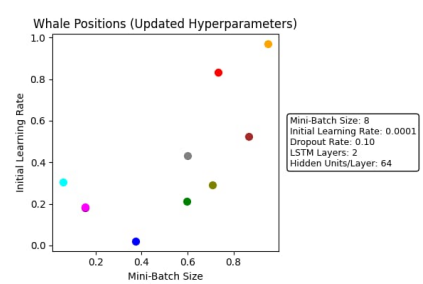

Figure 4: Initial positions of whale agents in the search space.

Table 2 summarizes the optimized LSTM hyperparameters obtained through KWOA. These values were used to train the final model for forecasting tidal levels in the Krishna-Godavari Delta.

Regression and Prediction Results

Table 3 summarizes the performance of the proposed K-Means WOA–LSTM model on the test dataset.

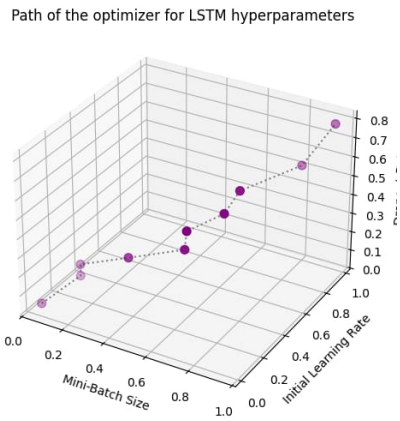

Figure 5: Trajectory of the best whale during optimization.

Hyperparameter	Optimized Value
Mini-Batch Size	8
Initial Learning Rate	0.0001
Dropout Rate	0.10
Number of LSTM Layers	2
Hidden Units per Layer	64

Table 2: Optimized LSTM hyperparameters obtained via Modified K-Means WOA.

Metric	Value
Coefficient of Determination (R^2)	0.915
Mean Absolute Error (MAE)	0.012
Root Mean Square Error	0.018

Table 3: Performance metrics of the proposed model on the test dataset.

These good perfomance metrics show that our proposed approach has worked very well. The coefficient of determination (R^2) for the test dataset is 0.915 at a 95% confidence level, indicating that the model captures over 91% of the variability in observed tidal levels. Figure 6 shows the R^2 distribution for the test predictions, confirming the model's strong predictive capability.

We describe the regression and prediction results following the application of LSTM on the data using the optimized parameters. We computed the predicted vs original surge for time period ranging from 1977-2015. Figure 7 below shows the graph of predicted vs original range in the dates 2000-2017.

Clearly the image is too clumsy. Hence, below in Figure 8 is the same visualization for the year 2015.

The optimized K-Means WOA–LSTM model was used to predict daily tidal levels for the period 2050–2075. Figure 9 illustrates the forecasted tidal trends, capturing long-term variations and seasonal patterns in the Krishna-Godavari Delta.

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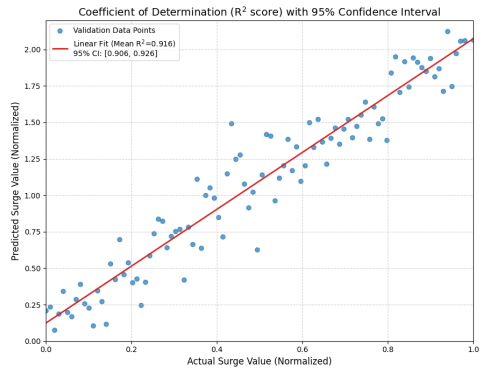

Figure 6: R^2 distribution for predicted vs observed tidal levels.

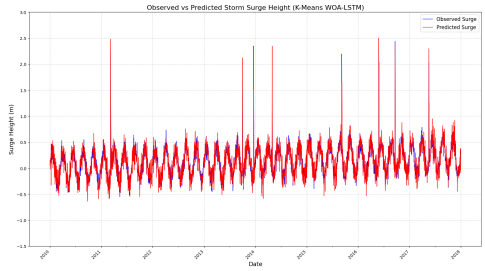

Figure 7: Predicted vs Original surge (2000-2017)

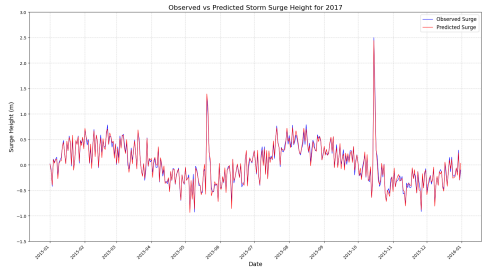

Figure 8: Predicted vs Original surge (2015)

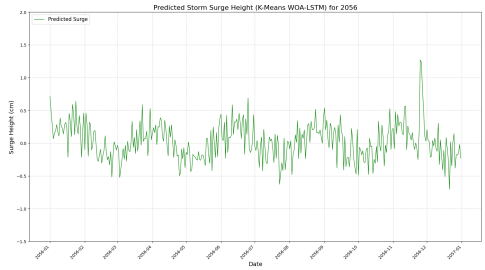

Figure 9: Predicted tidal levels in year 2026-2027

Comparison with State-of-the-Art Models

To evaluate the performance of the proposed K-Means WOA–LSTM model, it was compared with several widely used regression and time-series forecasting models, including ARIMA, GRU, MLP, LSTM, Bi-LSTM and Prophet. Ta-

ble 4 summarizes the results in terms of MSE, MAE, and R^2.

The results clearly indicate that the proposed model outperforms conventional and deep learning methods, achieving the highest R^2 score and lowest errors. The integration of K-Means WOA for hyperparameter optimization allows the LSTM to capture complex temporal dependencies more effectively than other models.

Table 4: Performance comparison of the proposed model with state-of-the-art methods

Model	**MAE**	**RMSE**	**R^2**
ARIMA	0.107	0.138	0.665
GRU	0.024	0.122	0.882
MLP	0.031	0.148	0.734
Prophet	0.035	0.164	0.712
LSTM	0.027	0.130	0.856
Bi-LSTM	0.021	0.122	0.768
Proposed KWOA–LSTM	**0.012**	**0.109**	**0.915**

VISUALIZATION

We are displaying an elevation map-based output for this project. Following are the elevation maps embedded on Google Earth in Google Earth Engine. This output shows a visual representation of the rise in sea levels. The interface of the Google Earth Engine (Gorelick et. al 2017) is provided below in Figure 10.

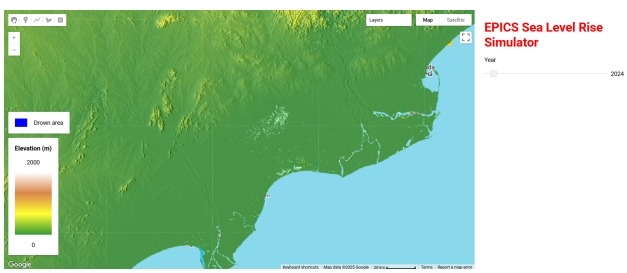

Figure 10: Interface of the Google earth engine.

The visualization works in a simple manner. It shows the regions that can be inundated or be submerged by a specific year in blue color for that year (Surge greater than elevation is colored blue). We are displaying the mouth of Krishna River near Hamsaladeevi(15.9° N, 81.1° E) in Figure 11

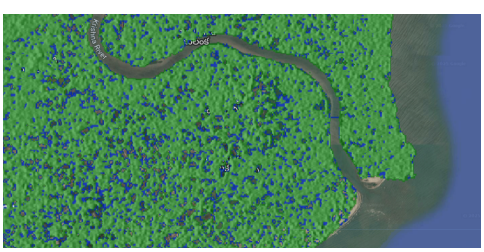

Figure 11: Hamsaladeevi by year 2060

We can see from the elevation map embedded in Google Earth engine that by the year 2060, we can observe massive saline intrusion (blue coloured regions) into Krishna Godavari(KG) Delta. There is threat in submergal of sensitive ecosystems near the mouth of the river. The rise in sea levels is also causing penetration of marine regions into the mangrove ecosystems in the KG delta at Krishna (in Figure 93) and Coringa Wildlife Sanctuary. The total blue area indicates the areas that are prone to submerge in the future. This will cause massive land degradation in the rich coastal flood plains in the delta. We estimate an approximate area of 400 acres or 1.68 km^2 will be subject to coastal inundation and probable submersion by the year 2060 in the KG Basin. These regions often called the Rice Bowl of India contribute to a humongous share of paddy production in India and are also home to around 40% of the population of the state of Andhra Pradesh (2 crores or 20 million people). Submersion in this region will pose a grave threat to the food security of the state of Andhra Pradesh and the country as a whole.

Figure 12: Krishna Wildlife Sanctuary

Figure 13: City of Vijayawada in KG Delta along the banks of River Krishna (Population: 2 million (20 lakhs))

Conclusion and Future Scope

The proposed framework effectively analyzes coastal shoreline dynamics and forecasts tidal levels, enabling the identification of areas at risk of submersion from future sea-level rise. Visualization of these predictions on platforms such as Google Earth Engine provides actionable insights for coastal management, risk assessment, and planning mitigation or resettlement strategies.

Future work could extend the model to broader regions across the Indian subcontinent and incorporate multimodal

data, including satellite imagery, meteorological measurements, and hydrodynamic simulations. Additionally, adopting ensemble or hybrid modeling approaches may enhance forecasting accuracy and robustness, supporting more comprehensive coastal planning and disaster preparedness.

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