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Predicting Coastal Erosion Hotspots Using Machine Learning, Remote Sensing, and Multitemporal Satellite Imagery concerning Hurricanes

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Abstract

Shoreline environments are vulnerable to coastal erosion, as it affects the socio-economic stability and the ecological integrity of regions, particularly those prone to hurricanes. This research studies long-term shoreline changes and hurricane impacts on shoreline erosion in the coastal region of Oaxaca State in Mexico, specifically the impact of Hurricane Erick in June 2025. Shoreline dynamics and future projections were achieved for the years 2035 and 2045, using multi-temporal satellite imagery obtained in 1995, 2005, 2015, and 2025. For detecting and predicting changes, remote sensing (RS), geographic information systems (GIS), and machine learning (ML) techniques were incorporated to improve change detection and prediction. The approach used to assess shoreline changes included three established techniques: end point rate (EPR), linear regression rate (LRR), and net shoreline movement (NSM). Pre- and post-hurricane analyses highlighted the erosional and deposition trends induced by Hurricane Erick, with maximum observed changes captured by the NSM model. Results displayed severe erosion as much as -289 m in some of the hotspots, commonly near river mouths and naked beach portions, while accretion zones indicated development of, sometimes sheltered or sediment-rich areas by as much as 825 m. Spatial patterns showed that complex interplay exists between natural forcing mechanisms and anthropogenic influences

such as development in coastal infrastructures and changing sediment transport pathways. Prediction based on machine learning of shoreline positions for 2035 and 2045 indicates that the historically unstable segments will translate into further erosion, while some of them will move from being stable to having high erosion risk; gains will also be forecasted to be variable in the accretionary areas influenced by natural and probably coastal protection interventions. Combining historical trends with impact assessments of hurricanes and predictive modelling is highly essential for future proactive coastal zone management. Urgency in relation to including the event-induced hurricane variability in long-term erosion hazard mapping and policy planning is strongly advocated through the findings. Such will guide adaptive, data-driven strategies for coastal management to protect at-risk communities, infrastructure, and ecosystems from worsening climate threats.

Keywords: Machine Learning; Shoreline; Prediction; Dynamics; Erick; Hurricane; Climate

Introduction

Naturally, coastal zones are ranked as among the world's most dynamic and productive areas, yet they also remain extremely vulnerable to natural processes and influences of human activities (Rajaneesh et al., 2020). Shorelines are never the same for long durations of changing patterns, often with seasonal and long-term variations due to climatic and human influences (Ramachandran et al., 2024). In the recent past, fast-tracked coastal erosion owing to the joint forces of global climate change, increasing sea levels, and the more frequent and intensified extreme events have posed challenges to coastal communities, ecosystems, and economies (Angalaparameswari et al., 2024; Sheppard, 2005). Therefore, it requires accurate assessments and predictions for sustainable management (Rajasree et al., 2016).

Remote Sensing and Geographic Information Systems have thus become a fundamental application for understanding coastal change from its initiation to the present developed state (Ozturk & Sesli, 2015). RS provisions long-term, coordinated, and synoptic observations for shoreline monitoring from satellite/aerial imagery concerning subtle shoreline variability in time (Prasad & Kumar, 2014; Tucker et al., 2004). GIS, meanwhile, integrates diverse sets of spatially referenced records, provides support for performing various spatial analyses, and aids in visualizing complex coastal dynamics (Prosser et al., 2017; Vermote et al., 2016). In concert, all of these are essential for quantifying indicators regarding shoreline change, such as End Point Rate (EPR), Linear Regression Rate (LRR), and Net Shoreline Movement (NSM), and these indicators further serve as credits for carrying out historical and event monitoring programs (Salghuna & Bharathvaj, 2015; Zviely & Klein, 2004).

Machine learning in recent years has strengthened coastal studies with one more novel predictive dimension (Sivakumar et al., 2024; Thieler et al., 2001; Ramachandran et al., 2024). By revealing complex and non-linear relationships in multitemporal datasets, ML models can give improved predictions of future positions of the shoreline than many existing statistical approaches (Zhou et al., 2024a). Due to this predictive capability, areas prone to erosion can be identified much sooner, paving the way for targeted interventions, effective land-use planning, and improved disaster preparedness (Zhou et al., 2024b; Sivakumar et al., 2024). The coastal region of the State of Oaxaca, south of the Pacific coast of Mexico, constitutes a high-energy tropical environment of ecological diversity and socio-economic importance (Zviely & Klein, 2004).

Regular tropical cyclones and hurricanes frequently affect the region and lead to rapid, large-scale changes in the shoreline (Smith & Buddemeier, 1993; Ambika et al., 2024). In particular, due to their ability to increase erosion, create storm surges, and redistribute sediments in very short periods, hurricane events are indeed a major threat (Neelamani, 2018; Hapke et al., 2010; Nandi et al., 2016; Roy et al., 2023). Natural forces, in addition to human causes like unplanned development, alteration of natural drainage systems, and exploitation of resources, severely undermine the coastal area (Thieler et al., 2005; Nunn et al., 2019; Addo et al., 2011; Satta, 2014).

The present study thus provides an integrated view of the application of RS, GIS, and ML in monitoring, analyzing, and predicting shoreline dynamics of the Oaxaca State coastal region, emphasizing the impact of extreme weather events like hurricanes (Vieira et al., 2020; Chander et al., 2009). Based on satellite data obtained for several time domains, this application will bring spatial analysis and predictive modelling to an effective union to characterize the long-term trends of shoreline changes and predict potential future scenarios (Vermote et al., 2016; Boak & Turner, 2005). The results will aim to directly inform coastal zone management, enhance disaster risk reduction, and strengthen community resilience in hurricane-prone coastal regions (Chen et al., 2024).

Study Area

The study area comprises the whole coastal territory of the State of Oaxaca that extends along the southern Pacific coast of Mexico. The study area lies between the latitudes and longitudes 98° 15’ to 94° 30’W and 17° 15’ to 16° 25’ N, shown in Fig. 1. The coastline is around 590 km long, with different geomorphological settings such as sandy beaches, rocky

headlands, estuaries, and coastal lagoons. The coastal ecosystems of the region, including mangroves, coral reefs, and dune systems, harbour abundant biodiversity and are essential to local fisheries, tourism, and cultural heritage. There are various towns and fishing communities concentrated along the shoreline, making the region economically significant and extremely sensitive to environmental change.

The Oaxaca coastline is in a high-energy oceanic environment directly affected by the seasonal wave regime and tropical cyclone activities of the Eastern Pacific. Hotspots of erosion have emerged during the past decades due to the conjoint effects of natural processes and anthropogenic activities, namely, unplanned tourism development, infrastructure development near the shoreline, and sand mining. Such an imbalance has hindered the natural sediment transport processes and, in turn, diminished the resilience of coastal habitats while increasing the threat to the already vulnerable infrastructure and communities posed by storm damage. Erosion and accretion on account of spatially variable patterns in geomorphology, including open sandy stretches in places, while sediment-starved rocky coasts in others.

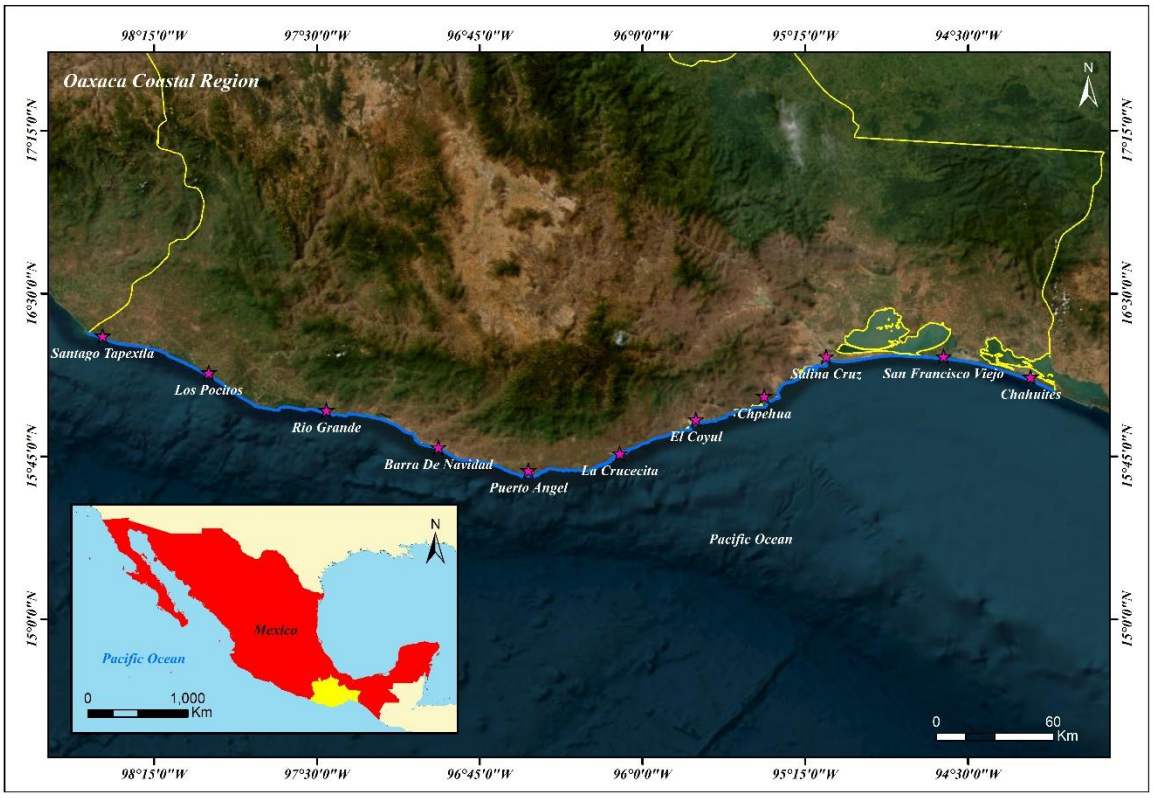


Fig. 1. Location map for this study

In June 2025, the site suffered a severe impact from Hurricane Erick, a powerful tropical cyclone characterized by vigorous winds, high-energy waves, and an extreme storm surge. The hurricane wreaked havoc along the coastline in terms of infrastructure damage, which also accelerated shoreline retreat in the more exposed zones and altered the morphology of the beaches and estuarine inlets. Some places experienced fierce erosion while others received short-duration sediment deposition due to storm-induced transport. The challenge laid bare the region's susceptibility to extreme climatic events and underscored the need to factor hurricane-induced impacts into long-term shoreline change assessment activities.

Due to ecological value, socio-economic importance, and high exposure to climate-related hazards presented by the coastal region of Oaxaca State, it is an important site for integrated coastal monitoring and predictive modelling. Understanding gradual shoreline shifts as well as abrupt hurricane-induced changes will be a key element in formulating workable coastal zone management strategies that reconcile the needs for environmental conservation with those of local communities.

Material and Methods

Data Collection

Multitemporal satellite data were acquired through the Landsat series in four vicinal year periods: 1995 (Landsat 5 TM), 2005 (Landsat 7 ETM+), 2015 (Landsat 8 OLI), and 2025 (Landsat 9 OLI-2) (Salghuna & Bharathvaj, 2015). The images were downloaded from the USGS Earth Explorer portal in spatial resolution of 30 m, geometrically corrected to the Universal Transverse Mercator (UTM) projection, Zone 5N, WGS84 datum (Smith & Buddemeier, 1993). The images were taken at a low-tide condition such that the effect of tide-induced distortion at the beach time position of the shoreline is minimized (Thieler et al., 2005).

Pre and post-hurricane shoreline states of Hurricane Erick (June 2025) were mapped using Landsat 9 OLI imagery supported by auxiliary data of meteorological and wave conditions by NOAA and the local tide gauges (Rajaneesh et al., 2020).

Shoreline Extraction

The Normalized Difference Water Index (NDWI) was applied to delineate the land–water boundary:

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (1)$$

where Green and NIR indicate spectral reflectance in the green and near-infrared bands, respectively (Prasad & Kumar, 2014). The shorelines were extracted using threshold-based classification. The result was then manually edited and smoothed using GIS tools to remove noise and ensure continuity (Vieira et al., 2020).

Analysis of Shoreline Changes with DSAS

The extension of the Digital Shoreline Analysis System (DSAS v5.1) integrated into ArcGIS was utilized for the computation of shoreline change statistics along the transects established at every 100 meters across the coastal stretch of Oaxaca. Three statistical models were performed:

(a) Net Shoreline Movement (NSM)

The NSM finds the distance between the earliest and latest shoreline positions:

$$NSM = St2 - St1 \quad (2)$$

where St1 are shoreline positions at the initial and final years. Positive values denote accretion and negative values indicate erosion (Zhou et al., 2024b).

(b) End Point Rate (EPR)

The EPR divides NSM by the elapsed time:

$$EPR = \frac{NSM}{t2-t1} \quad (3)$$

where (t2−t1) is the time interval (years).

(c) Linear Regression Rate (LRR)

LRR fits a least-squares regression line through all shoreline positions:

$$y = a + bx \quad (4)$$

where y is shoreline position, x is time, a is intercept, and b represents the regression slope (shoreline change rate in m/yr) (Roy et al., 2023).

Hurricane Impact Assessment

To assess the specific impacts of Hurricane Erick (2025), NSM was used to quantify pre- and post-event shoreline shifts:

$$\Delta SH = Spost - Spre \quad (5)$$

where Spost and Spre are shoreline positions after and before the hurricane event (Thieler et al., 2001).

The storm erosion index (SEI) was calculated to normalize hurricane impact across different transects:

$$SEI = \frac{\Delta SH}{Davg} \quad (6)$$

where Davg is the mean shoreline displacement across the study area (Tucker et al., 2004).

Machine Learning Forecasting of Shoreline Positions

To predict future shoreline positions for 2035 and 2045, ML models were trained using historical shoreline positions (1995–2025) and change rates (EPR, LRR, NSM) (Angalaparameswari et al., 2024). The following steps were implemented:

(a) Feature Construction

Input features included: Historical shoreline positions (St), Change rates (EPR, LRR, NSM), and Hurricane displacement factor (ΔSH).

(b) Model Framework

A Random Forest Regressor (RF) was applied due to its robustness in handling nonlinear relationships (Chen et al., 2024). The predicted shoreline position (Spred) is given as:

$$Spre = \frac{1}{N}\sum_{i=1}^{N} Fi(X) \quad (7)$$

where N is the number of decision trees and fi(X) is the prediction from the ith tree given input vector X.

(c) Model Validation

The Root Mean Square Error (RMSE) was used to evaluate accuracy:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Sobs, i - Spre, i)^2} \quad (8)$$

The Mean Absolute Error (MAE) provided an additional performance metric:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} Sobs, i - Spre, i \quad (9)$$

The Coefficient of Determination (R^2) was used to quantify variance explained:

$$R^2 = 1 - \frac{\sum(Sobs,i - Spre,i)^2}{\sum(Sobs,i - Sobs,i)^2} \quad (10)$$

Future Shoreline Forecasting

Using trained ML models, future shoreline positions were projected for 2035 and 2045 as:

$$Sfuture = St + (EPR + \Delta SH).\Delta t \quad (11)$$

where Δt is the time interval between the last observed year and the forecast year. ML predictions were compared with DSAS-based linear extrapolations to validate reliability. The methodology flow chart is shown in Fig. 2 (Sheppard, 2005).

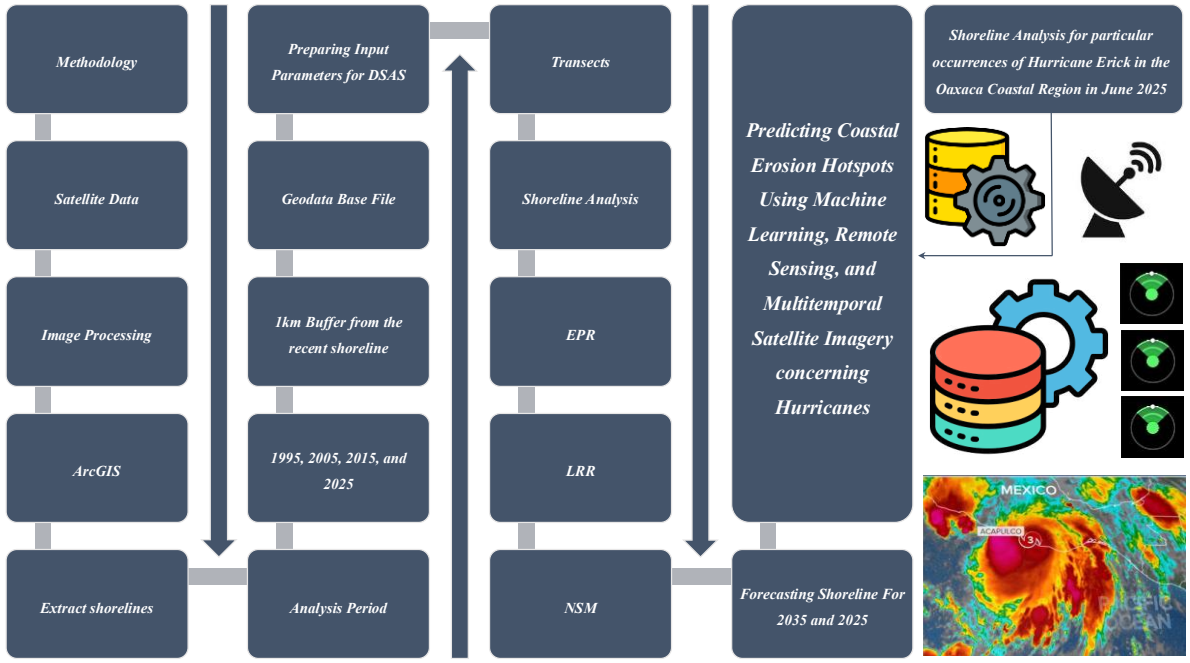


Fig. 2. Methodology flow chart for this study

Results and discussion

Shoreline Extraction (1995–2025)

Accurate shoreline position extraction for the Oaxaca coastal region was conducted with successful NDWI classification and GIS refinement using multitemporal Landsat imagery for 1995, 2005, 2015, and 2025 (Prasad & Kumar, 2014). The extracted shorelines are displayed in Fig. 3: the shoreline for 1995 is marked in blue, for 2005 in green, for 2015 in orange, and for 2025 in red (Salghuna & Bharathvaj, 2015). Several open sandy stretches have

shown gradual retreat landward, while certain estuarine mouths and protected lagoons indicated localized accretionary trends (Thieler et al., 2005). The spatial distribution of these shifts demonstrates that coastal dynamics in Oaxaca, both natural and anthropogenic, are thankfully heterogeneous.

Baseline, Transect, and Intersection Points

A baseline was established to establish change rates in the shoreline by creating it at 1 km inland from the most recent shoreline (2025) as shown in its figure below (Ozturk & Sesli, 2015). Fig. 4 below shows this. Computer-generated transects spaced equally apart were generated with the help of the DSAS tool to cross each historical shoreline layer (Roy et al., 2023). These transects form a framework for measuring positional displacements, as shown in Fig. 5, which represents intersect points as shoreline movement measurements along the length of the coast. This ensured consistent spatial change estimation for erosion and accretion rates (Nunn et al., 2019).

EPR, LRR, and NSM Analysis

The End Point Rate (EPR), Linear Regression Rate (LRR), and Net Shoreline Movement (NSM) models were used to estimate the extent of change in the shoreline (Ambika et al., 2024). EPR results are displayed in Fig. 6, divided into six classes: very high erosion, high erosion, moderate erosion, moderate accretion, high accretion, and very high accretion (Chen et al., 2024). Maximum EPR values were found as +48 m/year for a period of accretion and -30 m/year for erosion, with strong differentials across the coast (Hapke et al., 2010).

Similar to the indicated outputs in Fig. 7, such was also the case in the LRR-based analysis, wherein maximum values attained +42 m/year and -28 m/year. This regression-based methodology was able to capture long-term trends much more reliably than fluctuating coastline movements (Tucker et al., 2004). Fig. 8 shows the displacements gained through the NSM analysis, the greatest being as high as +1450 m of accretion and -890 m of erosion throughout the whole of the 30 years (Zviely & Klein, 2004). NSM was best at describing accumulative transformations as it highlighted both persistent erosion hotspots and deposition zones.

Coastal Forecasting (2035 and 2045)

Prediction through Machine Learning was undertaken to forecast shoreline locations for the years 2035 and 2045 (as shown in Fig. 9) (Angalaparameswari et al., 2024). The

predicted shorelines are indicated with yellow lines (2035) and white lines (2045). The predicted results suggest that many stretches of coastline, which are more prone to erosion due to exposure on beaches and river mouths, will likely continue their retreat shortly, while those sheltered coastal areas may experience further accumulation (Nandi et al., 2016). Importantly, some currently stable sections will then be subject to erosion, indicating increased vulnerability of the Oaxaca coast to future climatic and anthropogenic pressures (Boak & Turner, 2005).

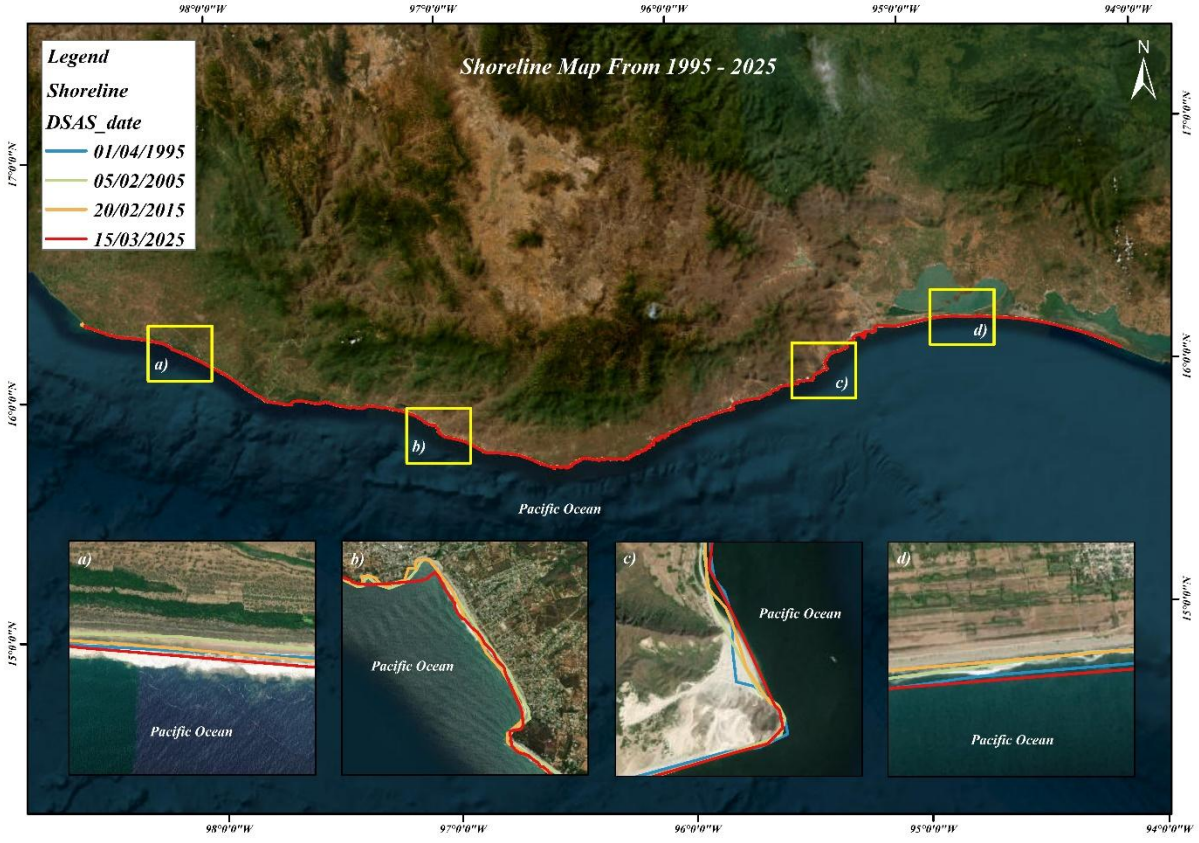


Fig. 3. Shoreline extraction map from 1995 – 2025 for the Oaxaca coastal region

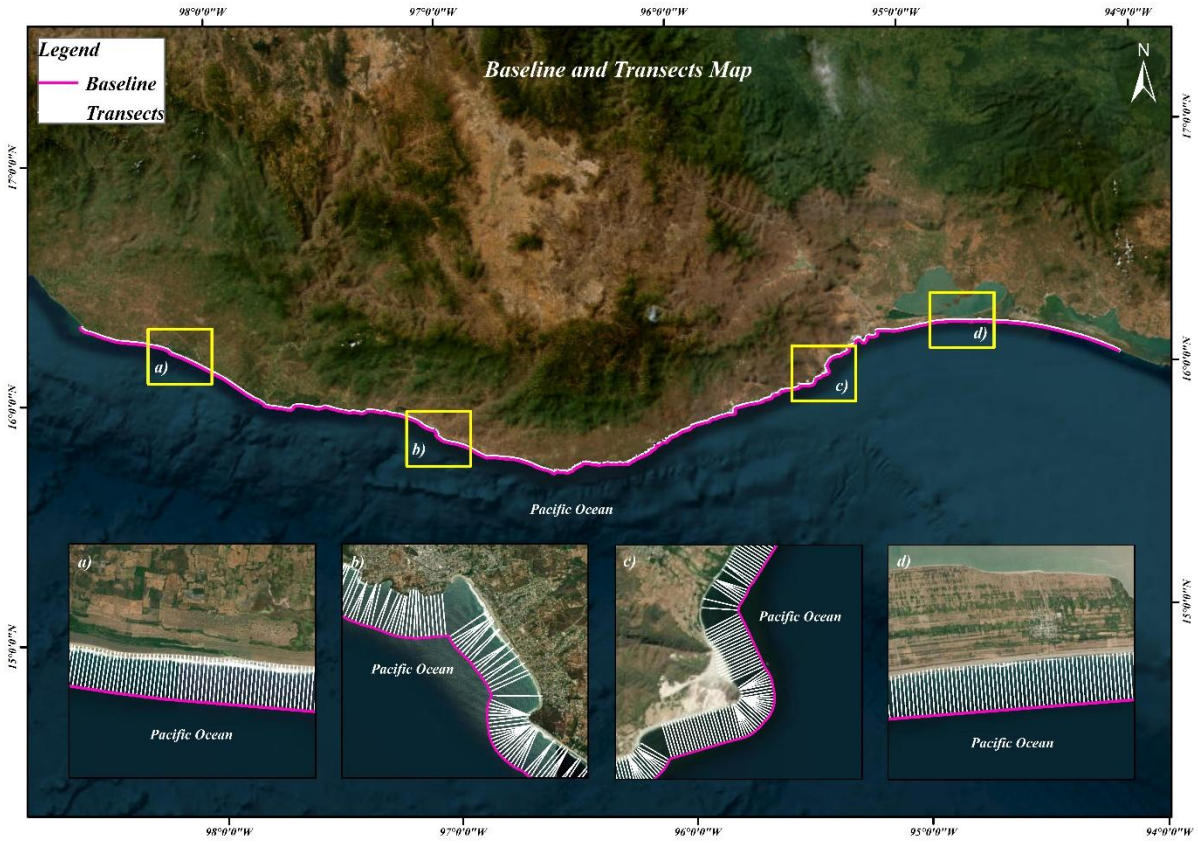


Fig. 4. Baseline and transect map for the Oaxaca coastal region

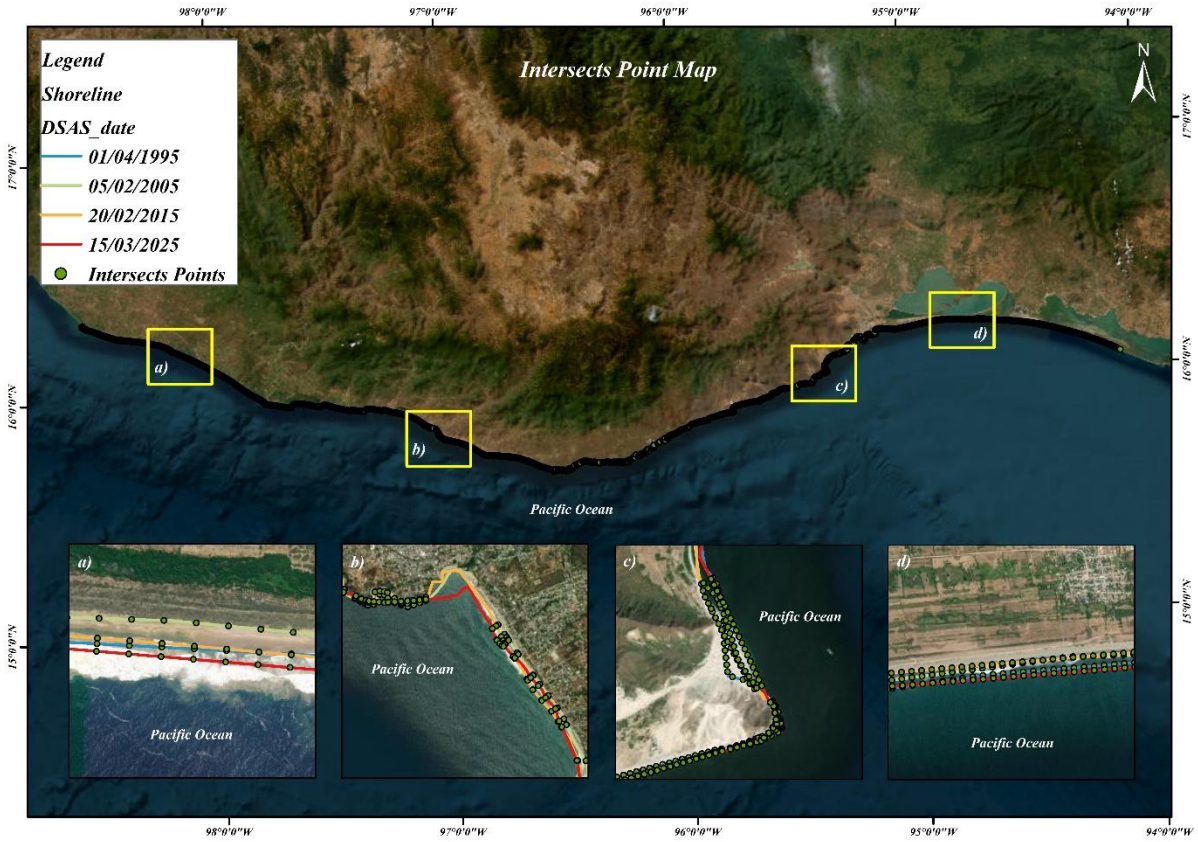


Fig. 5. Intersection Points map for the Oaxaca coastal region

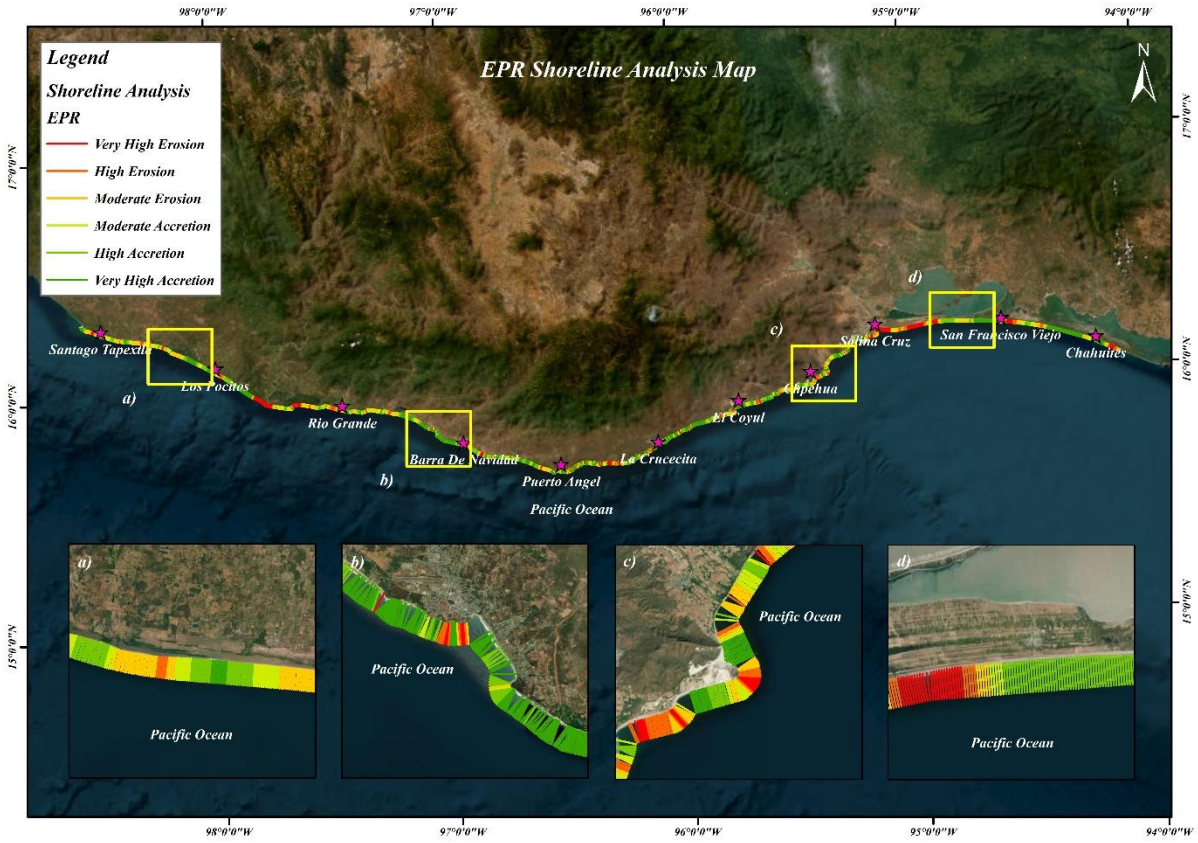


Fig. 6. EPR Shoreline Analysis map for the Oaxaca coastal region

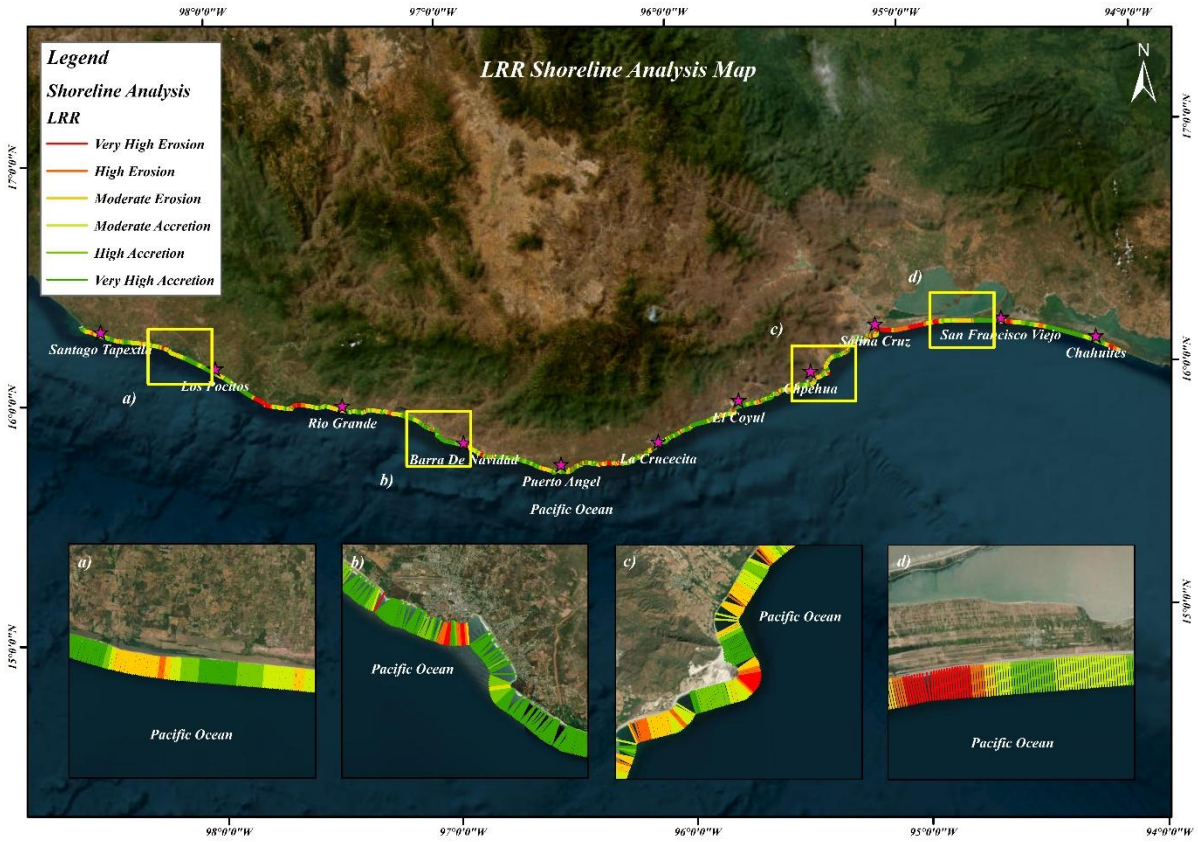


Fig. 7. LRR Shoreline Analysis map for the Oaxaca coastal region

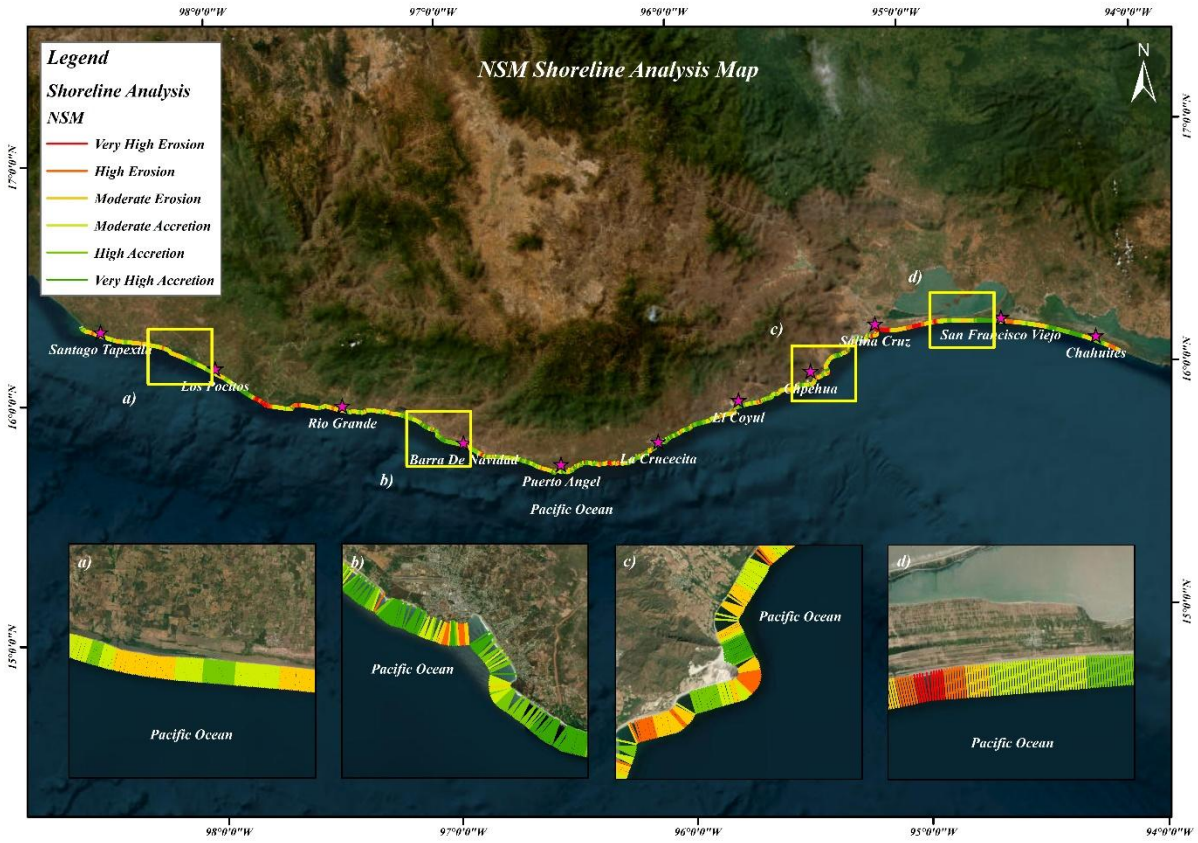


Fig. 8. NSM Shoreline Analysis map for the Oaxaca coastal region

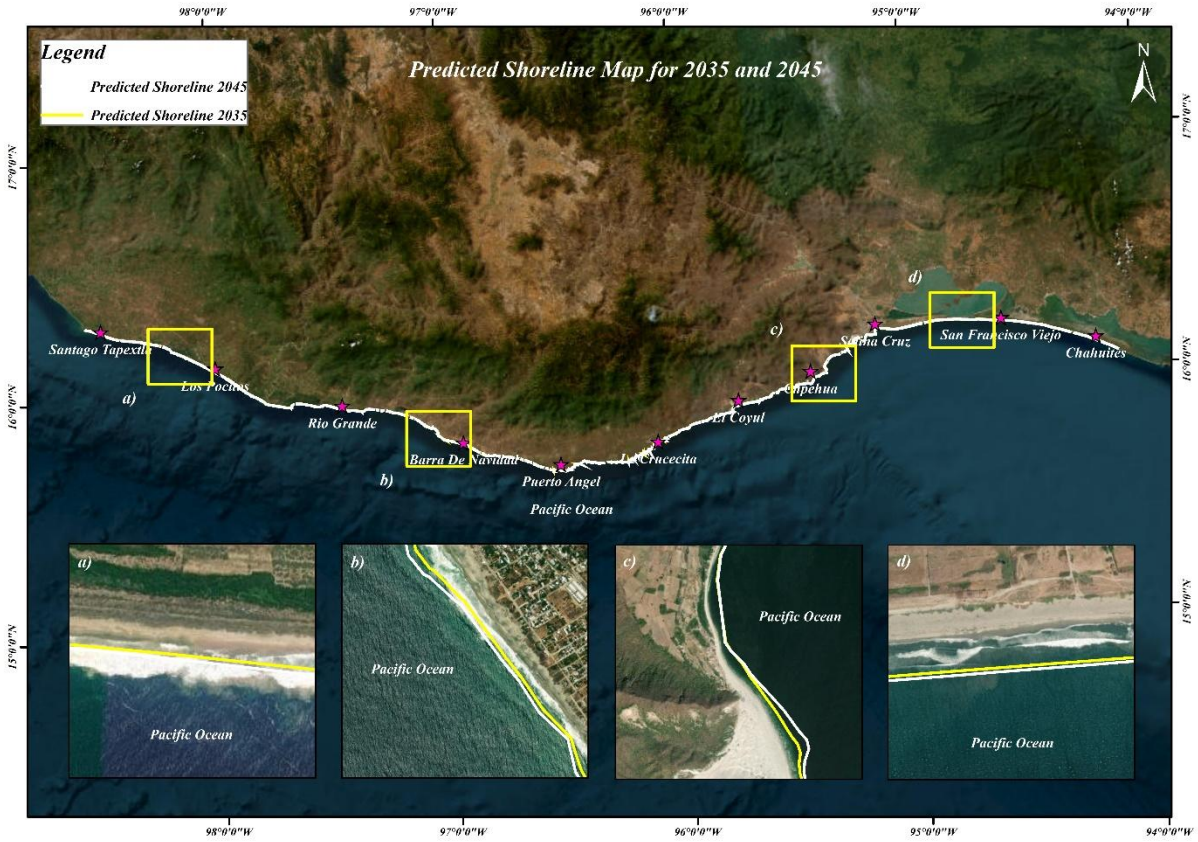
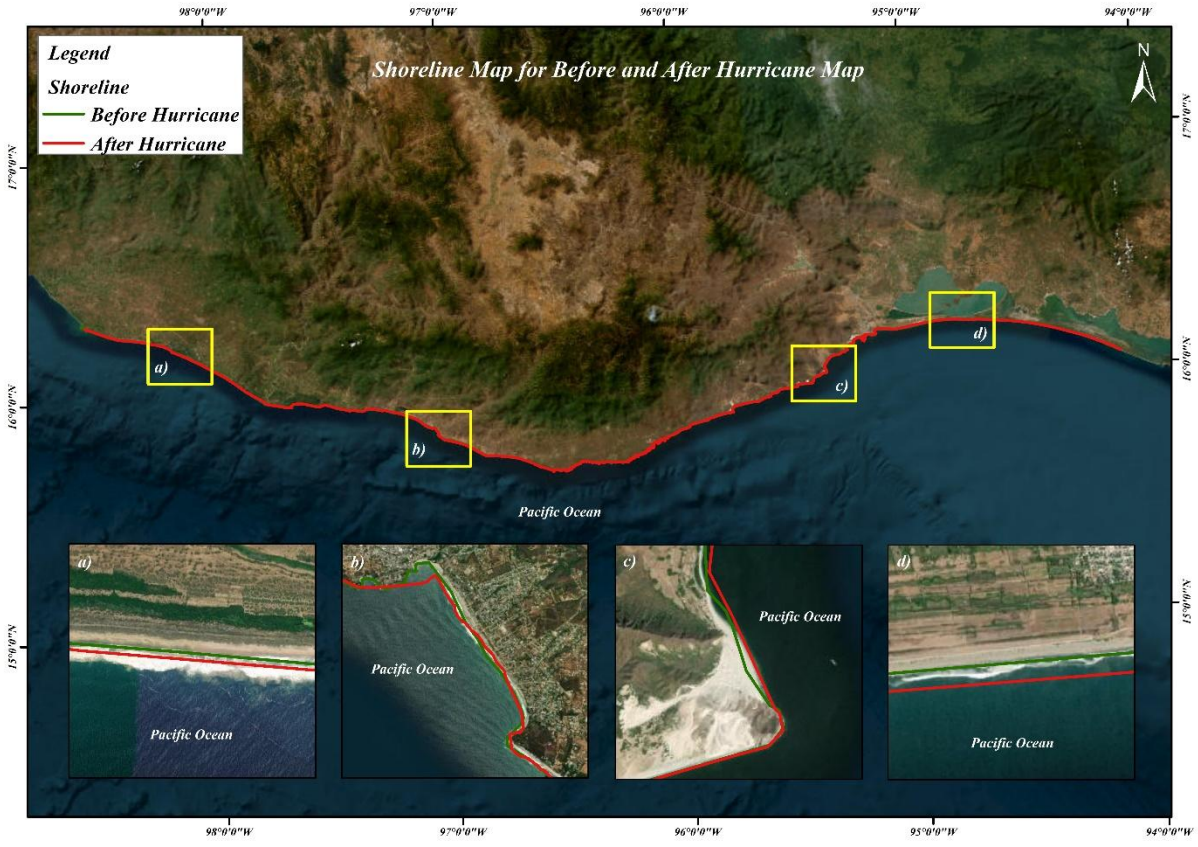
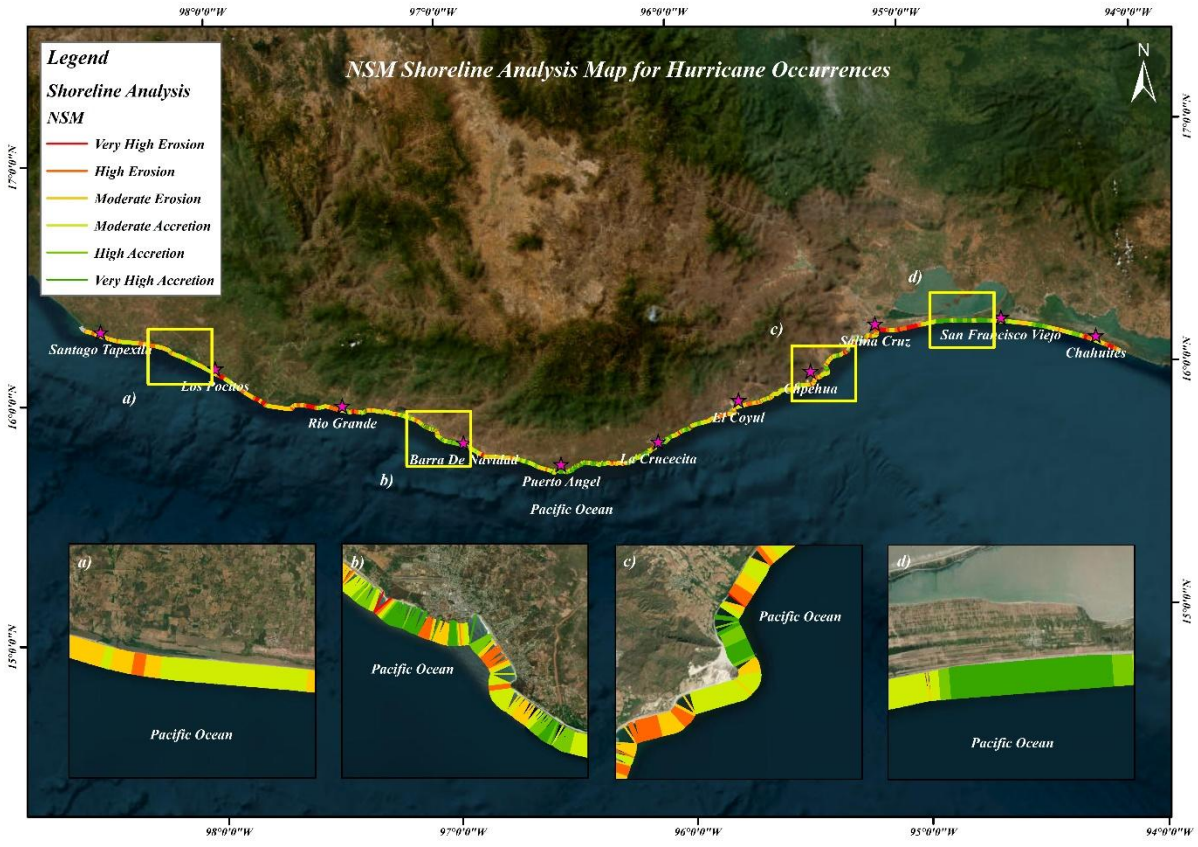


Fig. 9. Predicted Shoreline for 2035 and 2045 map for the Oaxaca coastal region



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275 Fig. 10. Hurricane Erick Shoreline extraction map for the Oaxaca coastal region



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Fig. 11. Hurricane Erick Impact analysis using NSM map for the Oaxaca coastal region

Post-impact Analysis of Hurricane Erick (2025)

Fig. 10 shows the shoreline before and after Hurricane Erick (within June 2025). The cyclone caused significant changes in the morphology of the shoreline, especially at the unsheltered sandy beaches and near the mouths of estuaries (Addo et al., 2011). NSM-specific criteria were utilized for this hurricane-based shoreline analysis, particularly the erosion and accretion classes shown in Fig. 11 (Hapke et al., 2010). The results found maximum eroded hotspots at -289 m, mostly at river mouths and open, sandy beaches, whereas accreted areas ended at +825 m in zones characterized by sheltering dominance or abundance of sediments (Ozturk & Sesli, 2015). This pattern reflects the counter influence of events such as storms (Prosser et al., 2017). While the eroded hot spots are in very exposed regions, deposition occurs within low-energy environments.

Comparing Models and Profile Trends

This indicates a comparative profile analysis based on EPR, LRR, and NSM (Fig. 12). While estimations of long-term rates were consistent between EPR and LRR, extreme movements of short duration during storm events were captured by NSM (Chander et al., 2009).

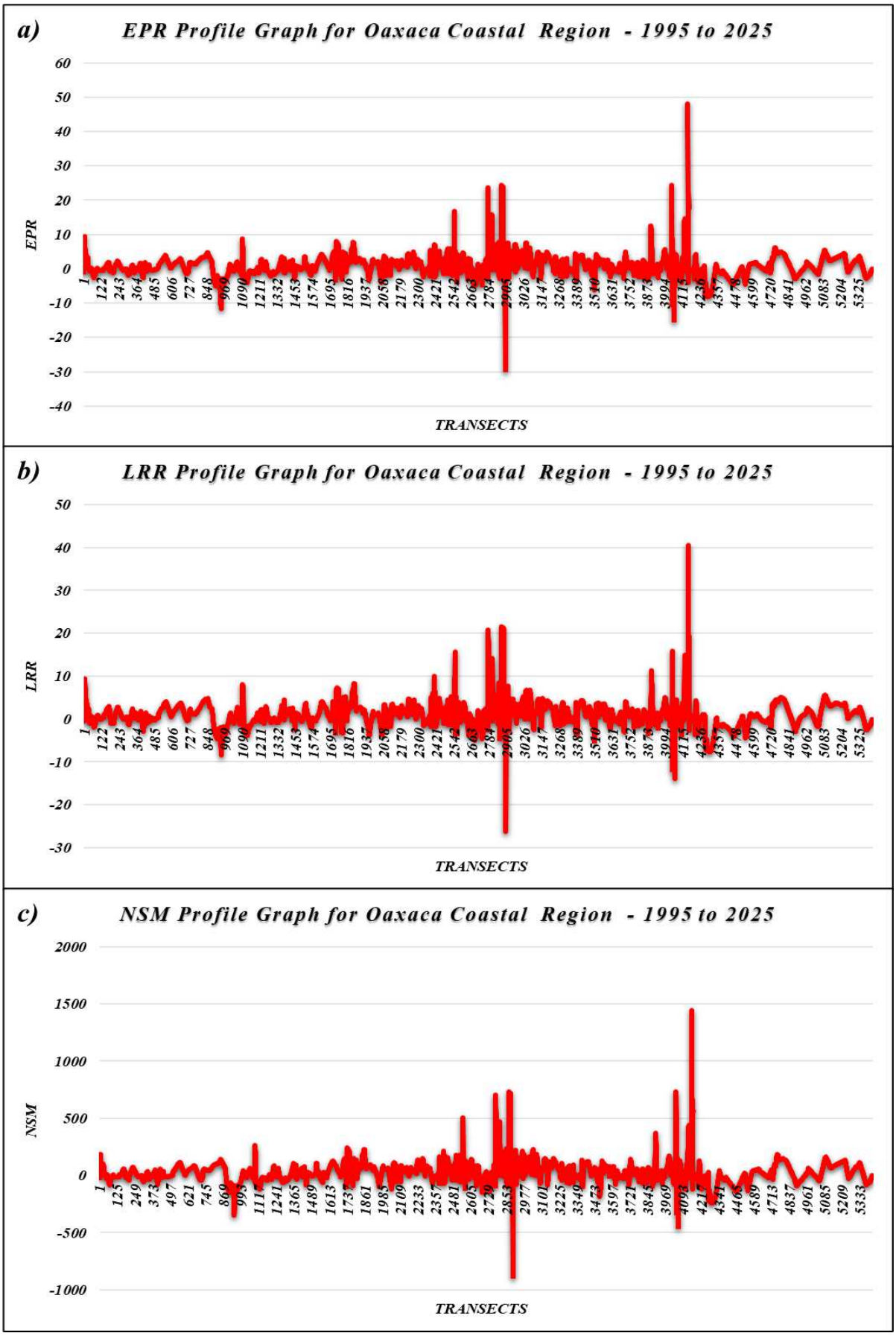


Fig. 12. EPR, LRR, and NSM Profile analysis for the Oaxaca coastal region

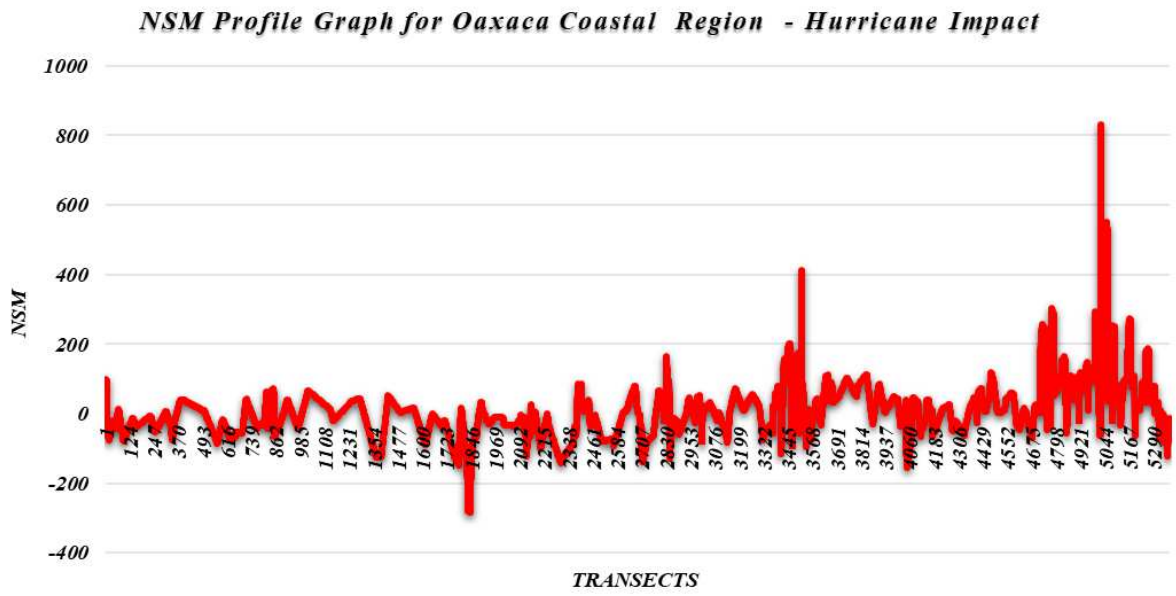


Fig. 13. Hurricane Erick Impact analysis using NSM Profile for the Oaxaca coastal region

Fig. 13 indicates the NSM hurricane effect assessment, which gives much higher erosion and accretion magnitudes (Rajasree et al., 2016). Hence, NSM is the most sensitive indicator of short-duration, high-energy events such as hurricanes, whereas regression-based approaches are better at recording the multi-decadal stability or slow trends (Zhou et al., 2024a). Such results highlighted the space variability in shoreline dynamics along Oaxaca coasts, with the severest erosion taking place on open beaches and river mouths, regions where sediment transport is heavily influenced by hydrodynamic forcing and by limited supplies of sediments because of anthropogenic activities (Boak & Turner, 2005). Accretion, on the other hand, points to coastal habitat formed or protected, such as sheltered lagoons and estuarine environments, since these deposits were made by both normal storm and surge conditions (Nandi et al., 2016).

The predictive modelling for 2035 and 2045 depicts the long-term vulnerability of Oaxaca´s coast (Ambika et al., 2024). Currently stable areas would transition to erosion zones, implying increasing coastal risks under future climatic drivers, together with unregulated human development. An example of how extreme events can accelerate erosion by decades within a single event is shown in the analysis of hurricanes (Nunn et al., 2019). This was necessary since the impact of variable storm patterns should also be accounted for in shoreline hazard mapping (Ambika et al., 2024). Generally, the combination of RS, GIS, DSAS models, and ML forecasting provides an effective approach for understanding both long-term and hurricane-driven changes in coastlines (Nandi et al., 2016). This multi-method approach not

only improves the reliability of predictions, but also assists coastal zone management well in terms of future hotspots of erosion and risk (Nunn et al., 2019). Findings underscore the urgent need for adaptive coastal policy, sustainable development practices, and ecosystem-based protective measures to enhance resilience in the Oaxaca coastal region against increasing natural hazards.

Analysis of shoreline change along the Oaxaca State coastal region shows highly dynamic patterns of erosion and accretion in natural-anthropogenic interplay. Similar to findings in other high-energy tropical coasts, erosion hotspots were more pronounced near river mouths and open sandy stretches, while sheltered lagoons and estuarine zones were the sites of maximum accretion. This observation concurs with previous studies that discuss fluvial sediment supply and wave energy gradients as controls influencing coastal morphodynamics (Prosser et al., 2017; Vieira et al., 2020).

Multitemporal satellite imagery (1995-2025) together with RS and GIS analysis was found to be indispensable for detecting long-term shoreline trajectories. Continuous availability and calibration of Landsat data constitute a strong basis for monitoring shoreline changes over decades as noted by Vermote et al. (2016). Accordingly, in case of Oaxaca, multi-decadal datasets allowed quantification of long-term gradual change and sporadic disruptions due to Hurricane Erick, clearly underlining the merit long-term remote sensing archives have for coastal science.

The models being applied based on DSAS techniques gave complementary stregths: Whereas EPR and LRR captured changes of constant long-term trend, NSM reacted particularly to extreme storm events revealing displacements beyond -289 m for erosion and +825 m for accretion after Hurricane Erick. This conforms with the work of Rajaneesh et al. (2020), which stressed including storm-displaced shorelines in below erosion assessments since singular events could trigger the decades of slow change. Likewise, regression methods typically underestimate short-term changes as evidenced by Rajasree et al. (2016), hence the need to integrate various metrics.

Machine Learning-based forecasting verified the projections regarding future shoreline dynamics, wherein the periods 2035 and 2045 saw considerable risk of erosion. ML's better capacity in managing nonlinearities and hurricane-induced anomalies strengthens the credibility of its prediction, especially for areas experiencing change in coastal settings. As pointed out by Sivakumar et al. (2024) and Zhou et al. (2024a), ML and AI-based techniques

are emerging as paradigm-shifting means for coastal prediction that are better suited than classical linear extrapolation methods in handling the complexities of rich datasets. Consequently, the Oaxaca investigation enhances the still-growing literature showing how ML has come to bear on hurricane-affected tropical codes.

The damage assessment highlights the urgency of incorporating the variability of extreme events into coastal management. Hurricane processes can be viewed as geomorphic resets that alter shorelines and sediment budgets rather fast. These findings support the conclusions of Ramachandran et al. (2024) that cyclone-related shoreline changes often surpass long-term erosion rates and should be integrated into hazard mapping and resilience planning. In Oaxaca, the devastating impacts of Hurricane Erick herald with the possibility that, without integrated monitoring and prediction, communities and infrastructures would still be grievously threatened.

This somehow puts forth the pressing need for shoreline dynamics assessment that would benefit tremendously from RS-GIS datasets, ML predictions, and hurricane-specific assessments. The results reiterate the need for adaptive and proactive coastal zone management measures in Oaxaca in line with global calls for these climate variability, storm hazards, and forecasting to be mainstreamed into coastal policy frameworks (Prosser et al., 2017; Vieira et al., 2020).

Conclusion

The study provided a comprehensive assessment of coastal change in the state of Oaxaca through the aggregation of multi-temporal remote sensed imagery (Landsat, 1995, 2005, 2015, and 2025) and other geospatial and machine learning methods. The use of statistical methods (EPR, LRR, NSM) from DSAS for eroding or accreting shorelines along with machine learning projections enhanced understanding of the spatiotemporal variability of retreat or accretion of the shoreline. The results suggested that over the past 25 years the coastline of Oaxaca has experienced longer periods of years of persistent erosion due to natural and anthropogenic disturbances. Specifically, both the landfall of hurricane Erick, as well as similar coastal cyclonic events highlighted the vulnerability of barrier beach, and deltaic systems, that experience rapid erosion in the short term, with long term shoreline retreat.

Better predictions by machine learning methods incorporated into traditional modelling of shoreline parameterize the nonlinear interactions that happen between oceanographic and geomorphic processes. This forecast also functions as a decision-support tool for future

sustainable coastal zone management. Furthermore, coupling pre- and post-hurricane shoreline analysis magnified the role of extreme events in promoting erosional dangers, necessitating a dynamic monitoring system.

From a management perspective, this finding presents an urgent need for adaptive strategies such as coastal setback regulations, ecosystem-based defences, including mangrove and dune restoration, and disaster preparedness frameworks. A novelty of this work involves its hybrid methodology that connects statistical shoreline change models to machine learning forecasts while explicitly accounting for disturbances associated with cyclones.

The Oaxaca coastline is experiencing measurable shoreline retreat, which is expected to accelerate with projected climate and storm impacts. This study offers a replicable framework for integrating RS, GIS, and ML techniques into coastal vulnerability assessments, representing important scientific input for policymakers and stakeholders working to protect socio-ecological resilience along Mexico's coast.

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Ethics declarations

Conflicts of interest

The authors declare that there are no conflicts of interest related to the publication of this manuscript.

Data Availability

Data will be available from the corresponding author upon reasonable request.

Author Contributions

M.O: Conceptualization, methodology, data curation, writing – original draft. **M.A**: Resources, validation, supervision, writing – review and editing. **T.A**: Software, formal analysis, visualization, writing – review and editing. **A.S.F.B**: Investigation, data acquisition, validation, writing – review and editing. **M.K**: Data analysis, methodology support, writing – review and editing. **A.S.B**: Investigation, writing – review and editing. **S.V**: Project administration, validation, writing – review and editing. **T.J**: Supervision, writing – review and editing.

References

1. Addo, K. A., Jayson-Quashigah, P. N., & Kufogbe, K. S. (2011). Quantitative analysis of shoreline change using medium resolution satellite imagery in Keta, Ghana. *Marine Science, 1*(1), 1–9.
2. Ambika, D., Sivakumar, V., Velusamy, S., & Panneerselvam, M. (2024). Geo-environmental monitoring of coastal and land resources for Coatzacoalcos coastal region, Mexico. *Journal of South American Earth Sciences*, 105119. https://doi.org/10.1016/j.jsames.2024.105119
3. Angalaparameswari, C., Ilavarasan, N., Sivakumar, V., & Priya, V. (2024). Analysis of volumetric and geomorphological changes mapping using remote sensing and GIS approaches for Joao Pessoa coastal region, Brazil. *Journal of South American Earth Sciences*, 104989. https://doi.org/10.1016/j.jsames.2024.104989
4. Boak, E. H., & Turner, I. L. (2005). Shoreline definition and detection: A review. *Journal of Coastal Research, 21*(4), 688–703.
5. Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment, 113*, 893–903. https://doi.org/10.1016/j.rse.2009.01.007
6. Chen, G., Kuang, R., Li, W., Cui, K., Fu, D., Yang, Z., & Shen, Y. (2024). Numerical study on efficiency and robustness of wave energy converter–power take-off system for compressed air energy storage. *Renewable Energy, 232*, 121080. https://doi.org/10.1016/j.renene.2024.121080
7. Hapke, C. J., Himmelstoss, E. A., Kratzmann, M. G., List, J. H., & Thieler, E. R. (2010). National assessment of shoreline change: Historical shoreline change along the New England and Mid-Atlantic coasts. *US Geological Survey Open-File Report 2010–1118*. https://pubs.usgs.gov/of/2010/1118
8. Nandi, S., Ghosh, M., Kundu, A., Dutta, D., & Baksi, M. (2016). Shoreline shifting and its prediction using remote sensing and GIS techniques: A case study of Sagar Island, West Bengal (India). *Journal of Coastal Conservation, 20*, 61–80. https://doi.org/10.1007/s11852-015-0418-4
9. Neelamani, S. (2018). Coastal erosion and accretion in Kuwait: Problems and management strategies. *Ocean & Coastal Management, 156*, 76–91. https://doi.org/10.1016/j.ocecoaman.2017.09.011
10. Nunn, P. D., McKeown, M., McCallum, A., Davies, P., John, E., Chandra, R., Thomas, F. R., & Raj, S. N. (2019). Origin, development and prospects of sand islands of the north coast of Viti Levu Island, Fiji, Southwest Pacific. *Journal of Coastal Conservation, 23*, 1005–1018. https://doi.org/10.1007/s11852-019-00692-1
11. Ozturk, D., & Sesli, F. A. (2015). Shoreline change analysis of the Kizilirmak Lagoon series. *Ocean & Coastal Management, 118*, 290–308. https://doi.org/10.1016/j.ocecoaman.2015.08.007
12. Prasad, D. H., & Kumar, N. D. (2014). Coastal erosion studies—A review. *International Journal of Geosciences, 5*(3), 341–345. https://doi.org/10.4236/ijg.2014.53033
13. Prosser, D. J., Jordan, T. E., Nagel, J. L., Seitz, R. D., Weller, D. E., & Whigham, D. F. (2017). Impacts of coastal land use and shoreline armoring on estuarine ecosystems: An introduction to a special issue. *Estuaries and Coasts, 40*(1), 1–17. https://doi.org/10.1007/s12237-016-0161-6
14. Rajaneesh, A., Logesh, N., Vishnu, C. L., Bouali, E. H., Oommen, T., Midhuna, V., & Sajinkumar, K. S. (2020). Monitoring and mapping of shallow landslides in a tropical environment using persistent scatterer interferometry: A case study from the Western Ghats, India. *Geomatics, 1*(1), 3–17. https://doi.org/10.3390/geomatics1010002

15. Rajasree, B. R., Deo, M. C., & Nair, L. S. (2016). Effect of climate change on shoreline shifts at a straight and continuous coast. *Estuarine, Coastal and Shelf Science, 183*, 221–234. https://doi.org/10.1016/j.ecss.2016.10.034
16. Ramachandran, A., Sujatha, M., Alruwais, N., & Alshahrani, H. M. (2024). Forecasting coastal stability: Digital shoreline analysis system and machine learning techniques in evaluating impacts of cyclones. *Regional Studies in Marine Science, 81*, Article 103961. https://doi.org/10.1016/j.rsma.2024.103961
17. Roy, P. D., Natarajan, L., García-Arriola, O. A., & Chokkalingam, L. (2023). Anthropogenic impact in and around Lake Coatetelco (south-central Mexico) from land use and land cover analysis between 1980 and 2020 CE. *Journal of South American Earth Sciences, 129*, 104495. https://doi.org/10.1016/j.jsames.2023.104495
18. Salghuna, N. N., & Bharathvaj, S. A. (2015). Shoreline change analysis for northern part of the Coromandel Coast. *International Journal of Geosciences*. https://doi.org/10.4236/ijg.2015.63022
19. Satta, A. (2014). An index-based method to assess vulnerabilities and risks of Mediterranean coastal zones to multiple hazards. *Mediterranean Coastal Risk Assessment Report*.
20. Sheppard, C. (2005). Coral mortality increases wave energy reaching shores protected by reef flats: Examples from the Seychelles. *Estuarine, Coastal and Shelf Science, 64*, 223–234. https://doi.org/10.1016/j.ecss.2005.02.016
21. Sivakumar, V., Kannan, V., Uppara, R. B., Sasivarman, B., Srinivasan, N. P., & Velusamy, P. (2024). Spatiotemporal variation of water quality in the context of suspended particulate matter in Laguna Mar Chiquita Lake, Argentina using ACOLITE. *Desalination and Water Treatment, 320*, 100684. https://doi.org/10.5004/dwt.2024.100684
22. Smith, S. V., & Buddemeier, R. W. (1993). Global change and coral reef ecosystems. *Annual Review of Ecology and Systematics, 23*, 89–118. https://doi.org/10.1146/annurev.es.23.110192.000513

Thenmozhi, M., Sujatha, M., Kavitha, M., Senthilraja, S., Babu, M., & Priya, V. (2024). Assessment of cyclone risk and case study of Gaja cyclone using GIS techniques and machine learning algorithms in coastal zone of Tamil Nadu, India. *Environmental Research, 246*, 118089. https://doi.org/10.1016/j.envres.2024.118089

23. Thieler, E. R., Himmelstoss, E. A., Zichichi, J. L., & Miller, T. L. (2005). Digital Shoreline Analysis System (DSAS) version 3.0: An ArcGIS extension for calculating shoreline change. *USGS Open-File Report 2005-1304*.
24. Thieler, E. R., O'Connell, J. F., & Schupp, C. A. (2001). The Massachusetts shoreline change project—1800s to 1994. *USGS Administrative Report* to the Massachusetts Office of Coastal Zone Management, Boston, MA.
25. Tucker, J. C., Grant, D. M., & Dykstra, J. D. (2004). NASA's global orthorectified Landsat data set. *Photogrammetric Engineering & Remote Sensing, 70*(3), 313–322.
26. Vermote, E., Justice, C., Claverie, M., & Franch, B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sensing of Environment, 185*, 46–56. https://doi.org/10.1016/j.rse.2016.04.008
27. Vieira, F., Cavalcante, G., & Campos, E. (2020). Analysis of wave climate and trends in a semi-enclosed basin (Persian Gulf) using a validated SWAN model. *Ocean Engineering, 196*, 106821. https://doi.org/10.1016/j.oceaneng.2019.106821
28. Zhou, B., Huang, X., Lin, C., Zhang, H., Peng, J., Nie, Z., & Jin, P. (2024). Experimental study of a WEC array–floating breakwater hybrid system in multiple-degree-of-freedom motion. *Applied Energy, 371*, 123694. https://doi.org/10.1016/j.apenergy.2024.123694
29. Zhou, B., Lin, C., Huang, X., Zhang, H., Zhao, W., Zhu, S., & Jin, P. (2024). Experimental study on the hydrodynamic performance of a multi-DOF WEC-type floating breakwater.

513 *Renewable and Sustainable Energy Reviews, 202*, 114694.
514 https://doi.org/10.1016/j.rser.2024.114694
515 30. Zviely, D., & Klein, M. (2004). Coastal cliff retreat rates at Beit-Yannay, Israel, in the 20th
516 century. *Earth Surface Processes and Landforms, 29*(2), 175–184.
517 https://doi.org/10.1002/esp.1019

518