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# Assessing Climate Change Impacts on Coastal Dynamics along the Pakistan Coastline Using Remote Sensing and Machine Learning

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## Abstract

Sea-level rise (SLR) driven by climate change is accelerating coastal erosion, which necessitates comprehensive assessments of shoreline dynamics to identify areas for targeted risk mitigation and adaptive planning. However, extracting coastlines from medium spatial resolution satellite data remains challenging due to limited large-scale annotated datasets, particularly for coastal risk assessment under future climate change. This study utilizes geospatial and machine learning based multispectral indices approach combining Random Forest (RF) classifier for shoreline extraction from Landsat data to quantify erosion and accretion along Pakistan 1,365 km coastline. Shoreline assessment was quantified using linear regression rates (LRR), incorporating SLR and sea surface temperature (SST) trends. Future erosion projections were derived from CMIP6 General Circulation Models (GCMs) under different Shared Socioeconomic Pathways (SSPs) and based on historical erosion for 2020-2050. Results reveal pronounced erosion along Indus Delta, with shoreline retreat reaching  $-50.4 \pm 1.02$  m associated with SLR of 0.015-0.15 m (2000-2020), with rises in SST (297-301 K). Sandspit coast showed accretion of 23.24 km<sup>2</sup>, with shoreline advancement rates of  $48.45 \pm 0.23$  m, Gwadar Port experienced accretion rates up to 40 m, together with annual SST of 0.02-0.05 °C. Under the high emission SSP5-8.5 scenario, persistent erosion of  $-23 \pm 1.35$  m is expected in the Indus Delta by 2050. Projections across different Global Warming Levels (GWL) ranging from 1.5 to 5.0 °C suggest SLR may reach 0.23 m at 5°C of warming. Our findings underscore the importance of Integrated Coastal Zone Management (ICZM) and reinforce the IPCC's call to limit global warming to safeguard coastal ecosystems and achieve SDGs 13 and 15 targets by 2030.

## Keywords

Sea-level rise (SLR), Coastal erosion and accretion, Random Forest (RF), Global Warming Level (GWL), Integrated Coastal Zone Management (ICZM)

## 1. Introduction

Sea-Level Rise (SLR) and Sea Surface Temperature (SST) are among the most significant impacts of climate change and are major contributors to coastal erosion. It is estimated that around 60% of the global population is dealing with coastal erosion (Komar 2012; Ciritci and Türk 2019), and approximately 70% of the world's sandy coasts are experiencing SWI (Komolafe et al. 2022). As SST increases because the ocean absorbs excess heat from greenhouse gas emissions, it contributes to SLR, which subsequently leads to the erosion of low-lying coastal regions. Coastal environments are crucial as they contain significant portions of the ecological services (Cenci et al. 2013) and are home to about 40% of the global population (Almeida et al. 2021), supporting industrial, and tourism activities (Lionello et al. 2021; ElKotby et al. 2023). SLR is particularly critical for low-lying areas and small islands that face risks of land loss due to inundation and coastal erosion. Like many other countries, Pakistan faces significant challenges from seawater coastal erosion, with its coastline severely impacted. However, the lack of ground truth data, station observations, and in-situ measurements have left variations under different climate scenarios largely unexplored. The Indus Delta in Pakistan is at particular risk, ranked as the third most vulnerable delta and significantly affected by rising sea levels and coastal erosion (Aeman et al. 2023). Serving as essential natural resources, coastal aquifers uphold various ecological roles and human endeavors, including agriculture, coastal infrastructure, and industry. According to the United Nations, more than 40% of the global population resides within 100 kilometers of the coast, and this figure is expected to rise in the future (Kanwal et al. 2020; Aeman et al. 2023). Coastal ecosystems and their dependent communities face threats from depletion, which is triggered by both natural processes and human actions. As a result, it is critical to effectively monitor and ensure the sustainability of coastal aquifers through proper management, securing the health and well-being of coastal populations.

Whereas, coastal subzones monitoring and change rates assessment at multiple temporal scale as it defined the interface with coastline positions (Almeida et al. 2021) and highly dynamic indicator towards coastal erosion and accretion. Moreover, the impact of the spatial temporal coastline variations and prediction under climate change using satellite data have also previously discussed extensively for example along the Kannyakumari coastline, India (Suresh and Sundar 2011) and Konya basin, Turkey (Durduran 2010; Duru 2017). Geographical information techniques have been combined with Machine learning (ML) with boosting algorithms such as XGBoost, Decision Tree, and Light Gradient Boosting Machine (LGBM) for the coastline recognition to investigate the coastline monitoring through remote sensing datasets for onshore and offshore coastline dynamics (Zhong and El-Diraby 2022; Andria et al. 2023). Along with these, deep learning architectures, especially CNNs, have transformed multiple fields, including remote sensing and have demonstrated promising performance in coastline segmentation, recognition, and object detection. These ML tools and spatiotemporal variations in coastlines serve as a proxy for monitoring coastal environmental changes, with assessing long-term trends essential for enhancing the understanding of coastal reactions to SLR and SST (Waqas et al. 2019). However, efforts to assess erosion impacts along the extensive coastlines remain insufficient.

The challenges persist using remote sensing to map lowland aquifers arise from the diverse land covers with varying spectral attributes, along with factors such as tidal variations, sharp contrasts in water density, wetlands variations, and high flow velocities. One of the critical challenges lies in accurately identifying land and water demarcation of the seawater interface within highly heterogeneous aquifers. To enhance accuracy and automation in coastline detection, the studies have increasingly turned integrating convolution layers of semantic segmentation methods from high resolution spatial data at small scales, which outperform traditional image processing techniques (Davranche et al. 2010; Behling et al. 2018). The existing studies utilizing machine learning, achieving notable success in accurately mapping coastal wetlands and delineating coastlines using highly spatial images detailed views of coastal features but also introduce challenges (Antonioli et al. 2017). Therefore, reliable coastal erosion assessments are essential for Integrated Coastal Zone Management (ICZM) planning and climate change adaptation (Cenci et al. 2013).

Traditionally, remote sensing information taken from satellites like Landsat (TM and ETM+), ASTER, SPOT, and MODIS has assisted in studying land cover, quantifying water turbidity, as consistent sources as well as for estimating suspended sediment concentrations, and other purposes in large coastal watersheds (Davranche et al. 2010; Santillan et al. 2011). Nevertheless, the 15 m, 20 m, 30 m, and 500 m spatial resolutions across visible, NIR, SWIR, and thermal bands are adapted for land cover studies and land-sea composites. Coastline extraction in multispectral satellite imagery is also accomplished using satellite spectral indices such as the NDWI (McFeeters 1996) or MNDWI (Xu

2006) as well as various other spectral indices techniques. These methods that involve the use of spectral band combinations have been investigated for mapping water fractions using normalized difference evaluations (Shukla et al. 2018). However, these methods are struggling with inland features with similar spectral characteristics, leading to potential confusion and identification errors where machine learning approaches offer a favorable solution to such challenges.

Despite these advancements, challenges also persist in achieving comprehensive coastal delineation and assessing its impact. These ongoing challenges underscore the importance of continued research and further technical development to enhance mapping and understanding of coastline dynamics, including the impact on mangrove ecosystems from coastal erosion. This segmentation process creates homogeneous areas or objects that represent distinctive features, such as land and water bodies along coastlines (Hossain and Chen 2019; Johnson and Ma 2020). However, limitations exist due to the extensive inventory of long-term coastline variations related to pixelated nature of coastline shapes often require refinement through vector generalization processes. This study aims to overcome the challenges posed by highly heterogeneous aquifers, where the pixelated nature of coastlines and the limited scope of large-scale coastal projections under diverse climate conditions hinder comprehensive risk assessments.

Our aim in this study is to employ spectral indices such as training predictors, integration into the Random Forest (RF) decision trees, for historical shorelines demarcation. Shoreline change rates are assessed by analyzing relationship of SLR and SST with the coastline accretion and erosion. This approach integrates SLR and SST projections to assess coastal erosion under climate change scenarios, reinforcing the IPCC's call to limit GWLs. Urgent mitigation and adaptation measures are critical to reducing the impacts of sea-level rise, safeguarding livelihoods, ecosystems, and infrastructure, and achieving the SDG 13 and 15 targets by 2030, all while addressing climate change, reducing land degradation, and promoting ecosystem sustainability.

This study, therefore, focuses on the following specific research objectives:

- First, to assess historic shorelines from 2000 to 2020 under climate change by integrating spectral indices-based predictors into the RF decision trees. Shoreline changes are quantified using End Point Rate (EPR), Linear Regression Rate (LRR) approaches along with the Brunn method.
- Second, to monitor long-term coastline dynamics under climate change scenarios, with projections derived from CMIP6 General Circulation Models (GCMs) following the IPCC AR6 framework under Shared Socioeconomic Pathways (SSPs) for the period 2020-2050 (in five-year intervals).
- Third, to evaluate long-term erosion at GWLs of 1.5, 2.0, 3.0, 4.0, and 5.0 °C to indicate projected impacts of climate change on SLR at different warming levels along the major coastal aquifers of Pakistan.

This study also discusses the assessments calculated in existing studies on coastline change rate through ground observations for the reliability of outputs across major coastal aquifers. It also offers recommendations, emphasizing the importance of advancing knowledge on coastal dynamics and promoting ICZM through sustainable conservation and management approaches.

## **2. Materials and Methods**

### **2.1 Study area and Datasets**

Pakistan's coastline, stretching approximately 1,365 km, is a crucial geographic and ecological asset. Within Sindh province, 320 km of the coastline encompass the Indus Delta aquifer, including world's fifth-largest delta system and home to the seventh-largest mangrove forest globally. The coastline includes major aquifers such as Indus Delta stretching 220 km in length, Gwadar port with a length of 198.8 km, Ormara extending 158.7 km from west to east, and the Sonmiani (Miani Hor) at a length of 102.3 km (Fig. 1). The mangroves are largely affected in these areas due to SWI and are under severe threat due to overexploitation and environmental degradation as well as erosion. The communities residing in lowland coastal areas primarily engage in fishing and agriculture. Notably, the area hosts the world's largest dry-climate mangrove forest. The shoreline features deltas topped with about 15 meters of sand,

underlain by clay and bedrock layers. The area near the Indus delta is also experiencing an SLR trend of approximately 1.1 mm/year from 1856 to 2000.

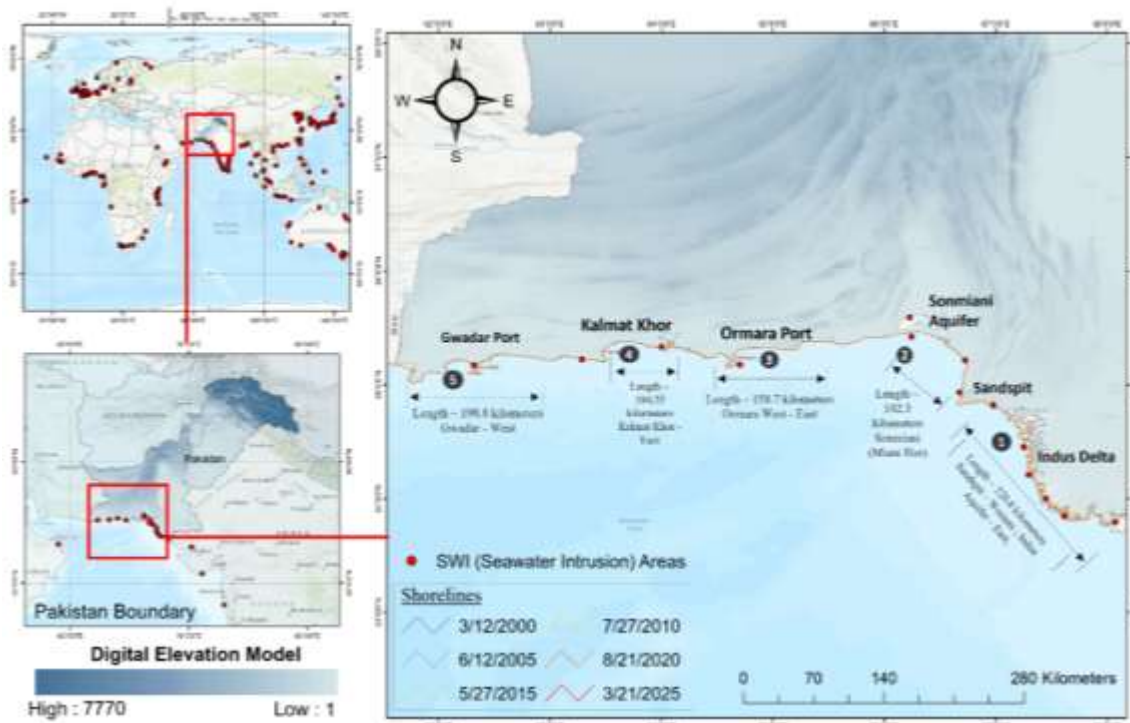


**Fig. 1.** Global SWI facing sites; along with study site Map (indicated by the red rectangle) covering 1,365 km coast (Basemap Credits: Esri, Garmin, OpenStreetMap contributors, National Geographic, USGS).

Therefore, at the time of satellite data acquisition, tidal height status was taken into consideration, and for tidal height predictions from <https://www.tide-forecast.com/>. The information related tidal gauge stations showed the approximation from 0.22 m to 1.21 m tidal height variation during the satellite (OLI/TIRS, ETM+) passes over the past decades. SLR measurements were obtained from the Copernicus Climate Change Service (C3S), while SST data were derived from the NOAA OI SST V2 High-Resolution (AVHRR) dataset, provided on a  $0.25^{\circ} \times 0.25^{\circ}$  global grid. In addition, in situ SST and SLR observations from tidal gauge stations from the Global Sea Level Observing System (GLOSS) located along the Pakistan coast, including the Indus Delta, Kalmat Khor, Ormara, and Sonmiani, were used for local analysis and validation. SLR and SST projections were evaluated relative to GWL thresholds of 1.5 °C, 2.0 °C, 3.0 °C, and 4.0 °C above pre-industrial levels (1850-1900), following the IPCC AR6 framework. These GWLs are associated with SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, representing low- to high-emission pathways. SST changes under each GWL were analyzed using climate model outputs tied to these thresholds, enabling comparison of climate impacts at defined warming levels rather than fixed calendar years.

**Table 1.** Description of datasets and the variables with spatial and temporal coverage used for the analysis

| Dataset                  | Variables           | Spatial Resolution | Temporal Coverage        | Source                                                                      |
|--------------------------|---------------------|--------------------|--------------------------|-----------------------------------------------------------------------------|
| Landsat (OLI/TIRS, ETM+) | Multispectral bands | 30 m               | 2000-2025 (16-day)       | USGS Landsat ARD Collection                                                 |
| Tidal Height Predictions | Tidal height (m)    | Point-based        | Satellite overpass dates | <a href="https://www.tide-forecast.com/">https://www.tide-forecast.com/</a> |

|                               |                           |                            |                                |                                         |
|-------------------------------|---------------------------|----------------------------|--------------------------------|-----------------------------------------|
| Tidal Gauge Observations      | SLR, SST                  | Point locations            | 2000-2014                      | GLOSS                                   |
| Sea Level Rise (SLR)          | Mean sea level change (m) | Global / regional coverage | 2000-2025                      | Copernicus Climate Change Service (C3S) |
| Ses Surface Temperature (SST) | Kelvin (K)                | 0.25°×0.25°                | 2000-2025 (Monthly aggregates) | NOAA OI SST-V2                          |
| SST and SLR Projections       | SSPs at GWLs              | 1°×1°                      | 2020-2100                      | IPCC AR6                                |

## 2.2. Remote sensing data acquisition and processing

### 2.2.1. Preprocessing of remote sensing datasets

All the Landsat satellite images were derived from Landsat Analysis Ready Data (ARD) Collections Level 1 terrain and atmospheric corrected images of OLI/TIRS and ETM+ sensors (USGS 2021). All images have its pre-defined projection, co-registration, top of atmosphere, and geometrical corrections for the long-term time series landscape analysis. All the Satellite images were radiometrically calibrated to prepare for the analysis and spectral information belonging to the different datasets bands were mosaicked using GDAL and satellite image processing platform of Google Earth Engine (GEE). Landsat data 'pixel\_Qa' band was also used to create a function to mask out clouds.

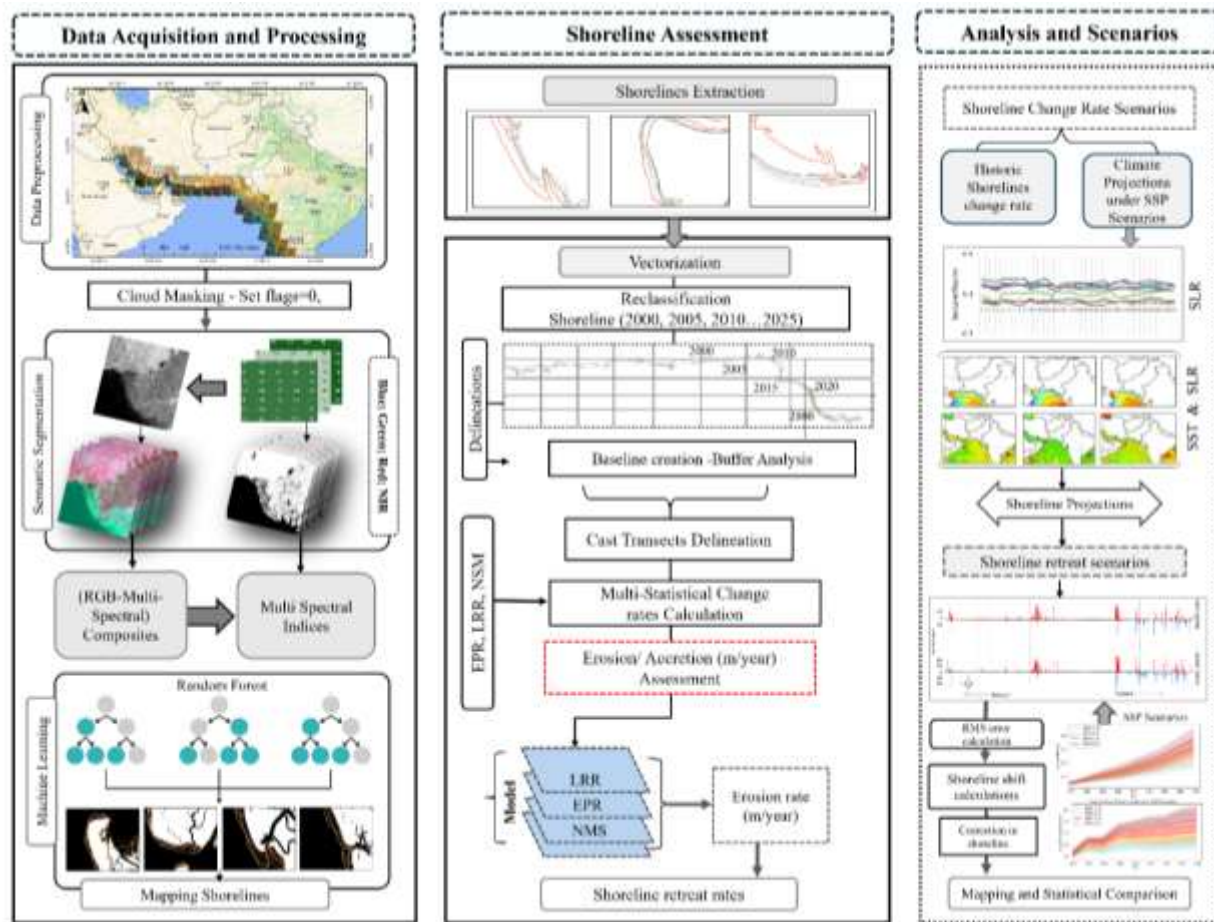


Fig. 2. Datasets Processing and Methodology Workflow.

The data processing and shoreline extraction used in this analysis for calculating the multi-statistical change rate, including erosion rates under various climate scenarios. SST and SLR datasets were subset to the study region and analysis period, and the data quality control was applied by removing missing values and excluding flagged observations where applicable. Moreover, daily fields were aggregated to monthly means to reduce noise and to ensure consistency in temporal resolution across variables, and gridded values were extracted along the entire coastline and at coastal station locations using the nearest grid cell approach. The detailed methodological workflow defined in the flow chart diagram (Fig. 2) for better understanding of the hierarchy of acquisition, processing and analysis.

### 2.2.2. Training Data Preparation and Methodological Workflow

All the datasets were pre-processed for training samples based on spectral indices derived from Landsat data. The shoreline extractions after vectorization and re-classification were used for shoreline retreats and assessment. A considerable number of annotated datasets were typically needed to train deep neural networks. Therefore, given the challenges in mapping diverse landscape features with varying spectral characteristics, multispectral indices selection and False Color Composite (FCC) were utilized for labeling the datasets, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Salinity Index (NDSI) (Khan et al. 2005), the Normalized Difference Mangrove Index (NDMI) (Shi et al. 2016), the Mangrove Index (MI) (Winarso et al. 2014), the Normalized Difference Water Index (NDWI), the Vegetation Soil Salinity Index (VSSI) (Dehni and Lounis 2012), and the Soil-Adjusted Vegetation Index (SAVI) (Alhammadi and Glenn 2008) depending on the heterogeneous land-cover and homogeneous feature spectral responses. For labeling and annotated datasets from spectral indices were thus used to create a binary mask, with background pixels ('0') characterize water and foreground pixels ('1') denote land or creeks. The datasets were then divided into three subsets through uniform sampling with an 8:1:1 ratio for training, testing, and validation to the selection of 2,553 training samples, 320 for validation and testing samples (Qayyum et al. 2020).

### 2.3. Spectral Indices Derived Random Forest

RF classifier was employed for coastline detection and segmentation using spectral indices derived from Landsat data. RF is an ensemble learning algorithm based on bootstrap aggregation, which improves classification robustness by reducing variance and mitigating the effects of noise and overfitting. The model constructs multiple decision trees using randomly sampled subsets of the training data and predictor variables, allowing it to capture nonlinear relationships between spectral features and coastline characteristics (Qamar et al. 2023) as shown in Fig. 3.

$$X_{(i,j)} = [NDVI, NDWI, MNDWI, GCVI, SAVI, VSSI]_{(i,j)} \quad (1)$$

In Eq. (1),  $X_{(i,j)}$  shows the input feature vector at pixel coordinates  $(i, j)$ . Each pixel is described in the feature space  $\mathbb{R}^C$ , where  $C = 6$  corresponds to the number of spectral indices used as predictor variables. These indices capture vegetation, water, moisture, and shoreline characteristics critical for coastline delineation. The RF model consists of an ensemble of  $k$  decision trees, each trained on a bootstrapped subset of the training data. At each node split, a random subset of predictor variables was selected, and the optimal split is determined by minimizing node impurity. The decision function for each tree is defined as:

$$h_k(X_{(i,j)}), \quad k = 1, 2, \dots, K \quad (2)$$

where  $h_k$  shows the classification function of the  $k$ -th decision tree. The final class prediction for each pixel is obtained through majority voting across all trees in the ensemble:

$$\hat{y}_{(i,j)} = \text{mode}\{h_1(X_{(i,j)}), h_2(X_{(i,j)}), \dots, h_K(X_{(i,j)})\} \quad (3)$$

where  $\hat{y}_{(i,j)} \in \{0,1\}$ , with class “0” representing non-coastline areas and class “1” representing coastline pixels. For model training, image patches of size  $320 \times 320$  were extracted, and pixel-wise feature vectors derived from the seven spectral indices were used as input samples. The corresponding annotated masks provided ground truth labels. The RF model was trained to learn the nonlinear relationships between spectral-index combinations and coastline presence, enabling accurate segmentation across varying coastal morphologies (Fig. 3).

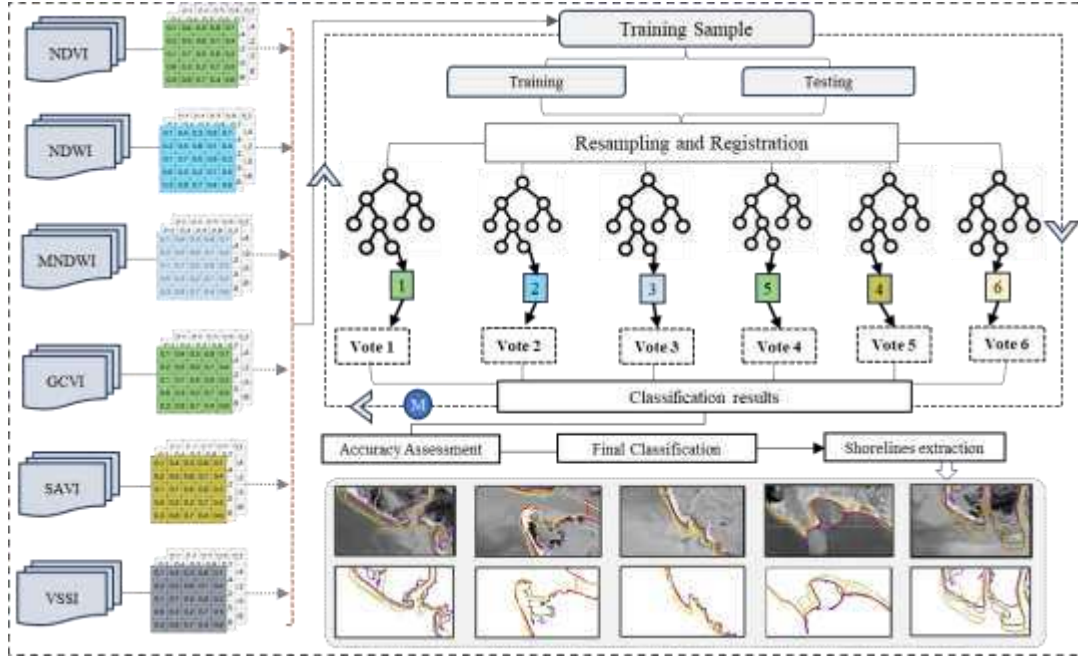


**Fig. 3.** Workflow of the spectral indices-based RF for coastline detection.

## 2.4. Coastline Change Rate Calculation

After coastline demarcation, the corresponding change rates were analyzed for coastal change rate assessment, based on EPR and LRR across different time steps. Baseline generation (i.e., buffered at 1 km) was conducted, and perpendicular transects were created along the baseline. Among all these methods, LRR and EPR were used most frequently for the coastal change assessment studies as this method was calculated by taking the difference between two coastline movements over the time elapsed period (Griffiths et al. 2019). Afterwards, computation distances are calculated at each perpendicular transect between the coastlines and baseline (Himmelstoss et al. 2018). The change rates assessment is calculated by coastline movement over the time elapsed period as from Eq. (4):

$$EPR = \frac{d_1 - d_2}{t_1 - t_2} \quad (4)$$

where  $d_1$  and  $d_2$  indicate the distance separating coastlines at two times  $t_1$  and  $t_2$  along various aquifers. Although EPR is sensitive to the selection of shoreline dates, it provides a straightforward estimate of net shoreline movement over a specified period. To reduce the influence of short-term shoreline variability and positional uncertainties, the LRR was employed. This method fits a least-squares regression line  $y = a + bx$  using all available shoreline positions along each transect and estimates the long-term rate of coastline change;  $Y$  shows the shoreline position (distance from baseline),  $X$  shows time (years),  $b$  is the shoreline change rate (m/year), and  $a$  is the intercept. The regression slope  $b$ , representing the LRR, is computed as:

$$b = \frac{n \sum_{i=1}^n (x_i y_i) - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n \sum_{i=1}^n (x_i^2) - (\sum_{i=1}^n x_i)^2} \quad (5)$$

From Eq. (5) where  $n$  is the number of shoreline observations,  $x_i$  is the time of observation, and  $y_i$  is the shoreline position along the transect. Compared to EPR, LRR provides a statistical estimate by incorporating all shoreline dates. The variability or uncertainty associated with EPR was also considered in terms of the ECI, which is specified as the confidence of EPR, calculated as:

$$ECI = \pm \frac{\sqrt{\text{Unc}(A)^2 - \text{Unc}(B)^2}}{t_1 - t_2} \quad (6)$$

From Eq. (6), Unc(A), Unc(B) refer to uncertainties associated with coastline A and B with respect to two different times  $t_1$  and  $t_2$  respectively. The annualized transect error specified at each transect for coastline change rate calculation is defined using the following Eq. (7):

$$E_{au} = \frac{\sqrt{E_{1990}^2 + E_{1995}^2 + E_{2000}^2 + E_{2005}^2 + E_{2010}^2 + E_{2015}^2 + E_{2020}^2}}{T_{total}} \quad (7)$$

where  $E_{au}$  shows the annualized uncertainty calculated over the cumulative coastline changes from the beginning to the end of the specified time, and  $T$  denotes the total duration of this time in years. The performance of the linear regression model along each transect was evaluated using the coefficient of determination.

$$R^2 = 1 - \frac{\sqrt{\sum_{i=1}^N (Y_{Cal} - Y_{pred})^2}}{\sqrt{\sum_{i=1}^N (Y_{Cal} - Y^*)^2}} \quad (8)$$

The  $R^2$  is calculated through linear regression at each transect,  $Y_{Cal}$  indicates the coastline distance from the baseline,  $Y_{pred}$  represents predicted values obtained through regression,  $Y^*$  denotes the average coastline position, with  $N$  referring to the number of observations.

## 2.5. Integration of SLR and Climate Projections for Coastline Change Estimation

The spatio-temporal distributions of historical SLR and SST were analyzed to quantify their contribution to observed shoreline change rates during the historical period (2000-2025). Historical shoreline positions extracted for the years 2000, 2005, 2010, 2015, 2020, and 2025 were used to establish baseline erosion and accretion trends through transect-based analysis. The future projections of SLR and SST were derived from GCMs following the IPCC AR6 SSP-GWL framework, in which climate impacts were evaluated at defined GWLs (1.5 °C, 2.0 °C, 3.0 °C, and 4.0 °C). A statistical scaling approach was adopted, whereby coarse-resolution ( $1^\circ \times 1^\circ$ ) climate projections were linked to localized coastline dynamics using an empirical coastal response model. The projected coastline retreat was quantified using the Bruun Rule relating SLR to horizontal shoreline displacement. The horizontal retreat  $R$  was calculated as:

$$R = \frac{SLR_t \times L}{\tan\beta} \quad (9)$$

From Eq. (9),  $R$  represents horizontal coastline retreat,  $SLR_t$  is the predicted SLR at time  $t$ , where  $L$  is the distance from the baseline to the depth of closure, and  $\tan\beta$  is computed as the ratio of the elevation difference between the baseline and the closure depth to the horizontal distance. Coastline retreat under scenarios of projected SLR and SST expressed as  $R_t = R \times (1 + f(SST_t))$ , where  $R_t$  show the coastline retreat due to SLR and SST, and  $f(SST_t)$  depends on SST with time, accounting for the impact of future SST on erosion dynamics.

## 2.6. Accuracy Assessment

The accuracy of the extracted coastlines was evaluated using land-water masks generated by the RF classifier. The RF-derived coastline outputs were validated against globally available land cover datasets, including ESA WorldCover, Copernicus Global Land Service (CGLS) Land Cover, and MODIS Global Land Cover. These reference datasets differ in spatial resolution, temporal coverage, and data acquisition methodologies, which can influence their ability to represent narrow and dynamic coastal features such as creek systems. The accuracy assessment was performed by calculating root mean square error (RMSE) between the RF-derived coastline positions and reference coastline masks. Coastline coordinates were extracted at each perpendicular transect, and positional differences between the classified coastline and reference datasets were used to compute RMSE, providing an estimate of spatial deviation in shoreline detection. For SLR and SST validation, in situ observations from tidal gauge stations along the Pakistan coast were used as independent reference data. These observations provided essential ground-based measurements to assess the reliability of the modeled and projected SLR and SST trends over time. In addition, the vertical sediment transport processes were considered qualitatively in the discussion to help interpret factors contributing to observed shoreline change.

### 3. Results and Discussion

#### 3.1. Model Evaluation

The results of the experimental spectral indices derived RF model on the validation datasets were evaluated using the following metrics of Precision (P), Recall (R), F1 Score, Kappa Coefficient, Intersection over Union (IoU), False Alarm rate (FA), and Overall Accuracy (OA). Spectral indices combined with RF, it achieves a precision of 95.01% and a recall of 96.06%, resulting in an F1 score of 96.91%. Its overall achieved accuracy was 91.01%, and the Kappa coefficient is 95.41%. The IoU score of 94.76% showed reliable model performance as this accurate segments features, despite significantly reducing the loss rate of pixel changes. The resultant detections from the historical datasets, after vectorization, highlighted coastline regions undergoing coastal variations as shown in Fig. 4.

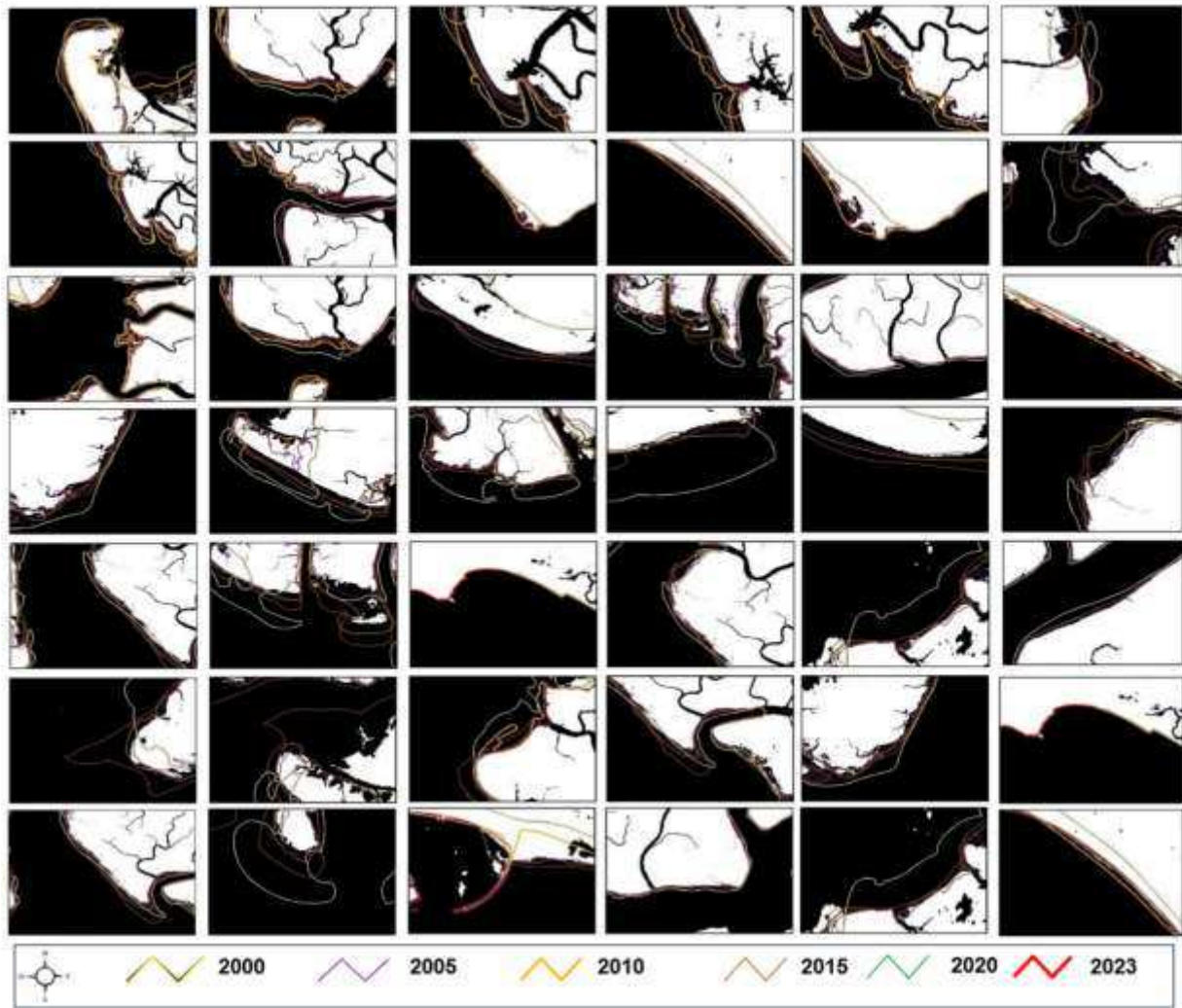


**Fig. 4.** Shoreline detection from spectral indices using RF model, overlaid with multi-temporal boundaries extracted through vectorization.

The validation of RF was also carried out against global land cover datasets of ESA WorldCover, CGLS Land Cover, and MODIS Global Land Cover shows differences in their ability to estimate creek areas based on spatial resolution, temporal scale, and data acquisition approaches. Among these, ESA WorldCover is the closest to the RF results, with area differences typically between 5-15%. For instance, in Sunhri Creek, RF estimated an area of 9.2 km<sup>2</sup>, while ESA WorldCover estimated 8.5 km<sup>2</sup>, a difference of only 8%. Similarly, in Khal Creek, ESA WorldCover's estimate of 5.8 km<sup>2</sup> is 11% lower than RF value of 6.5 km<sup>2</sup>. This closeness is attributed to ESA WorldCover's high spatial resolution

(10 m) and recent temporal coverage, which aligns closely with RF input data, allowing it to capture finer details and dynamic land-water transitions effectively (Table 2). However, ESA WorldCover represents annual averages, which may smooth out seasonal variations, particularly in environments like mangroves or tidal creeks. In contrast, CGLS Land Cover (100 m) demonstrates moderate closeness to RF, with area differences ranging from 20-30%. While spatial resolution of 100 m allows for the detection of larger features, it struggles with smaller and fragmented creeks along the coast. Moreover, CGLS Land Cover relies on annual data composites, which, like ESA WorldCover, may neglect seasonal exposures such as those observed during the dry season when mangroves and tidal creeks are more visibly exposed. MODIS Global Land Cover is the least close to RF detections, with a difference ranging from 30%-40%. For instance, in Sunhri Creek, MODIS estimated an area of 6.0 km<sup>2</sup> (Fig. 5), which is 35% lower than calculated from RF 9.2 km<sup>2</sup>, and in Khal Creek, it estimated 4.0 km<sup>2</sup>, showing a 38% reduction compared to RF of 6.5 km<sup>2</sup>.

**Table 2.** Comparison of test data at various creeks with area (km<sup>2</sup>) estimations by RF and Global land water masks

| Creek Names  | EfficientNet with U-Net | European Space Agency (ESA) WorldCover | MOD44W.006 Terra Land Water Mask | Copernicus Global Land Service (CGLS) Land Cover | MODIS Global Land Cover |
|--------------|-------------------------|----------------------------------------|----------------------------------|--------------------------------------------------|-------------------------|
| Wari         | 5.22                    | 1.53                                   | 1.51                             | 1.66                                             | 1.86                    |
| Khalri       | 5.91                    | 1.80                                   | 1.72                             | 1.78                                             | 1.94                    |
| Kajhar       | 6.22                    | 3.53                                   | 3.51                             | 3.66                                             | 3.86                    |
| Kahar        | 3.22                    | 0.53                                   | 0.51                             | 0.6                                              | 0.86                    |
| Chann        | 7.86                    | 4.56                                   | 4.01                             | 4.63                                             | 4.87                    |
| Tummi        | 8.87                    | 5.45                                   | 5.44                             | 5.65                                             | 5.78                    |
| Sunhri       | 6.65                    | 2.34                                   | 2.34                             | 2.36                                             | 2.45                    |
| Pitiani      | 5.67                    | 1.23                                   | 1.01                             | 1.24                                             | 1.33                    |
| Khalri       | 9.23                    | 4.53                                   | 4.53                             | 4.66                                             | 4.78                    |
| Khal         | 5.22                    | 1.53                                   | 1.51                             | 1.66                                             | 1.86                    |
| Daboo        | 5.22                    | 0.53                                   | 0.51                             | 0.66                                             | 0.86                    |
| Bhuri        | 5.42                    | 1.73                                   | 1.61                             | 1.86                                             | 1.99                    |
| West Pitiani | 6.22                    | 2.53                                   | 2.51                             | 2.66                                             | 2.86                    |
| West Bhuri   | 7.55                    | 4.53                                   | 4.51                             | 4.66                                             | 4.86                    |
| Middle Indus | 959                     | 1120                                   | 1553                             | 1193                                             | 1553                    |
| Kalmat Khor  | 887                     | 927                                    | 882                              | 837                                              | 847                     |

The coarse spatial resolution also leads to significant generalization, making it unsuitable for detecting smaller or fragmented water bodies. Additionally, MODIS also relies on annual composites, which smooth seasonal changes and neglect to capture the dry season exposure of features like mangroves. The temporal limitation further widens the discrepancy from season-specific inputs optimized for such environments.

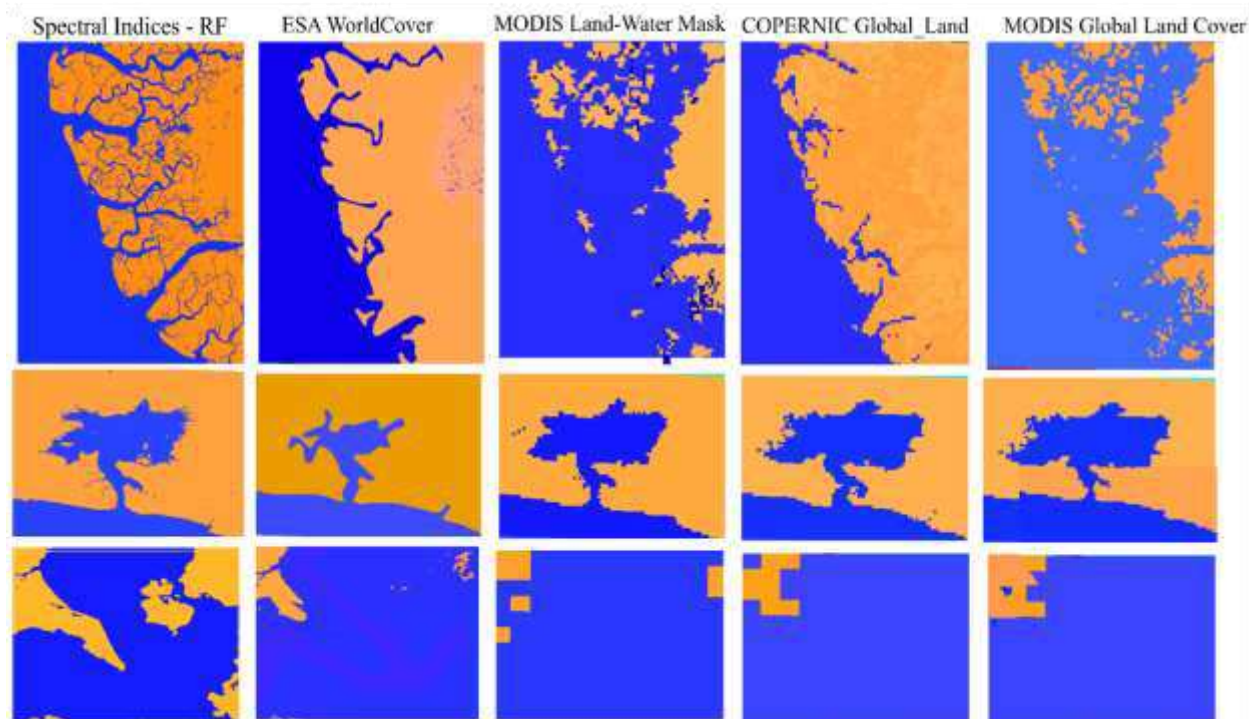


**Fig. 5.** Comparison of shoreline and land-water classification results derived from the spectral indices-based RF approach and existing global land cover products.

### 3.2. Temporal Variability and Relationship between SLR and SST

The multi-temporal analysis of SLR from 2000 to 2023 reveals a significant upward trend along the entire coastline, as illustrated in Fig. 6. SLR remained stable from 2000 to 2005, then increased sharply, particularly in the central and eastern regions, reaching record highs by 2023. SLR at the eastern side showed a drop in levels and the further years indicate a continued upward trend, with values reaching unprecedented highs. In the western direction towards Gwadar coast and Kalamat Khor similar patterns are observed with variability in SLR transitioning into a notable rise, reflecting an overall increase in SLR. Over 24 years, areas with low anomaly values (green) have decreased by approximately 10-15%, indicating a decline in stable climatic conditions. In contrast, regions experiencing extreme anomalies (red zones) have expanded significantly, with their spatial coverage increasing by nearly 25-30%, particularly in coastal and arid areas. Moderate anomalies have also increased by about 10-12%, with a shift towards more variability. The frequency and intensity of extreme anomalies have risen by 15-20% in the past decade. From 2012 to 2019, SLR along the coastal transects spanning the west-east direction revealed significant variability. From 2000 to 2005, SLR across the transects exhibited relative stability, ranging from 0.015 m/year to 0.053 m/year particularly across the central transects, including the Sonmiani to Ormara aquifers. From 2010, SLR is more noticeable across all transects reaching an annual range of 0.034 m/year to 0.087 m/year, indicating that the central and eastern regions began to experience more significant impacts from rising sea levels.

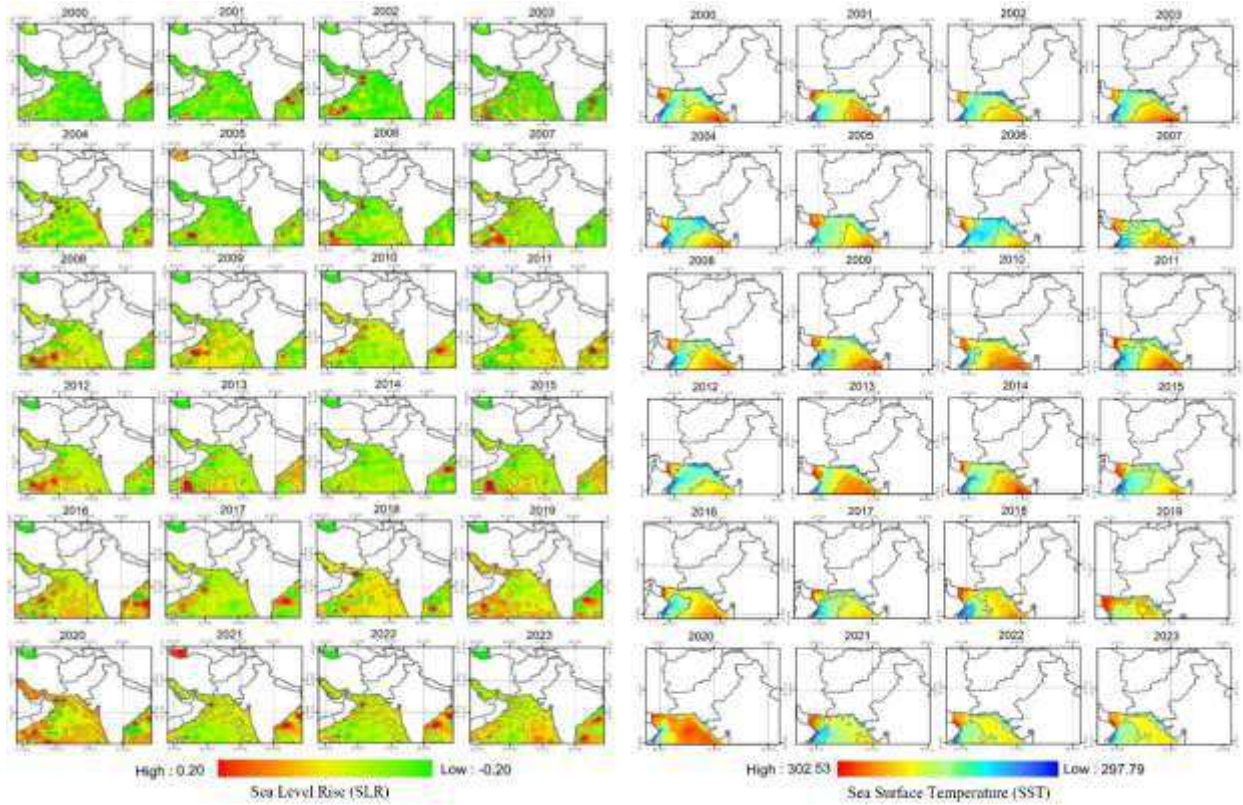


**Fig. 6.** Multi-temporal annual spatial variations in SLR (m) and SST (K) baseline period of (1993-2012) obtained from C3S for the period 2000-2023.

By 2015, transects along the eastern coastline, including the Indus Delta, experienced substantial increases, reaching 0.12 m/year. The central and western transects, including Sonmiani, Ormara, and Gwadar, also showed a marked increase, with 2021 and 2023 recording values consistently above 0.094 m/year. Whereas, SST showed relatively lower temperatures, especially along the eastern coastline of Pakistan near the Indus Delta and the Karachi coast, ranging from 297.79 K to 299.8 K, whereas the central region of the Arabian Sea appears to be warmer, at around 300.3 K from 2000 to 2003. By 2004, there is a warming trend in the central region, with temperatures in the 300 K to 301 K range spreading more extensively and continues in 2005 and 2006, as shown in Fig. 7, with the central parts of the Arabian Sea showing increased temperatures, particularly near Gwadar and Sonmiani (SST > 300.5 K). The year 2015 showed a particularly warm year, with areas starting from Indus Delta to Gwadar along the coastline showing SST values are consistently above 301 K. The central Arabian Sea reaches 302 K, indicating significant warming in the region.

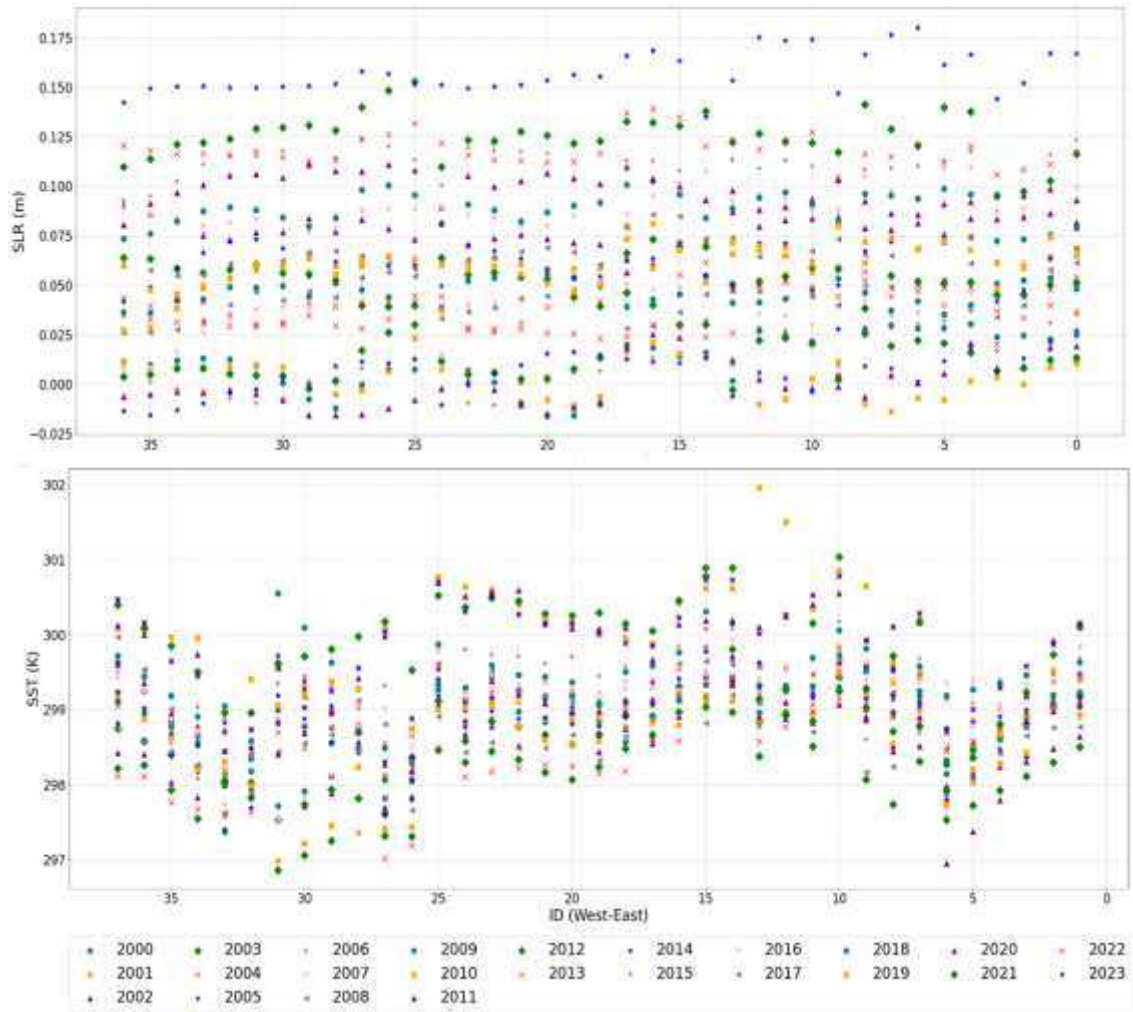


**Fig. 7.** Inter coastal zonal variations and trend of SLR and SST along major coastal sites of Pakistan from east to west, covering the transects ID of Indus Delta (0-10), Somniani Aquifer (15-20), Ormara Port (20-25), Kalamat Ghotr (25-30), and Gwadar Port (30-40) derived from C3S (baseline: 1993-2012).

SST values are mostly between 297 K and 299 K, particularly in the western transects near Gwadar and Ormara. In these years, the SST in the central Arabian Sea was slightly warmer, but still below 300 K as shown in Fig. 7. The eastern regions, particularly the Indus Delta, recorded the coolest values during this period. However, from 2006 to 2007, SST begins to rise across all transects, with values closer to 300.2 K, indicating the start of a regional warming trend. By 2010, warming becomes more evident, with SST exceeding 300 K, especially in the central and western coastal area. The continuous rise in 2015 showed a particularly warm year, with SSTs consistently reaching above 300 K across many transects. However, by 2022 and 2023, the warming trend intensifies across Sonmiani, Ormara, and Gwadar reaching similar SST levels, with uniform warming. Whereas the correlation between SST and SLR in these years remains relatively low in 2000 ( $R^2=0.10$ ), which gradually increased to ( $R^2=0.45$ ) by 2003 and ( $R^2=0.46$ ) in 2004. The central and western regions exhibit higher variations in SST, corresponding to slight increases in SLR. From 2005 to 2011 years show more variability in both SST and SLR values, as SST starts to increase with 299.5 K in some western and central transects, SLR fluctuate more drastically, with peaks in 2007 and 2011 reaching 0.04 m to 0.08 m (Fig. 8). The correlation between SST and SLR during this period varies significantly. In 2007, the correlation increase ( $R^2=0.48$ ), indicating a relationship between warming levels and SLR. The following years, particularly 2009 and 2011, showed lower correlations, suggesting the contribution of the other factors influencing SLR variation during this period, reducing the direct impact of rising SST. From 2012 to 2016, SST continues to increase, with values

surpassing 300 K, particularly in the central and western transects. SLR shows considerable variability, reaching a maximum value of 0.11 m in 2016.

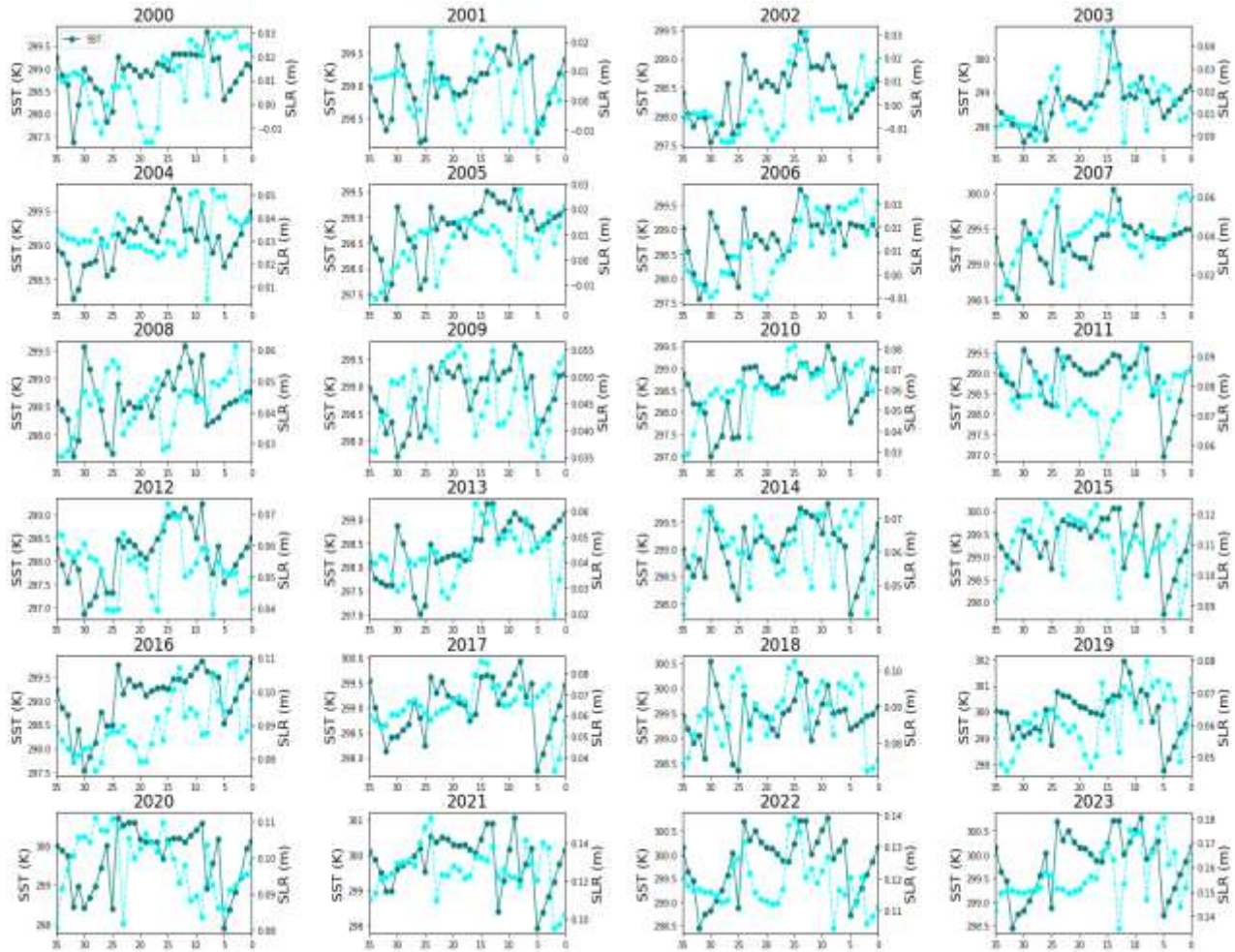


**Fig. 8.** Comparative Analysis of SLR and SST from 2000 to 2023 across west-east transects along Pakistan's coastline with transects ID of Indus Delta (0-10), Sominiani Aquifer (15-20), Ormara Port (20-25), Kalamat Ghotr (25-30), and Gwadar Port (30-40).

### 3.3. Erosion and Accretion Analysis: Coastline Retreat (2000-2020)

The erosion and accretion trend along the entire coastline of Pakistan shows that the westernmost section of the coastline, near Gwadar Port, experiences significant erosion, with LRR from 2000 to 2020 ranging along transects reaching -40 m/year to -56.2 m/year. The same pattern of erosion is observed in other parts of the western coastline, including Kalamat Khor, with LRR showing a coastline retreat at an average rate of -45.5 m/year for the last two decades. This level of erosion is indicative of intense coastal processes, likely driven by SST, SLR, and strong wave action, and possibly the geomorphological nature of the coastline. Whereas Indus Delta is a notable region experiencing severe erosion, positioned along the eastern side of the coast, erosion rates in this area are notably high, with LRR values reaching -35.4 m/year as shown in Fig. 9.

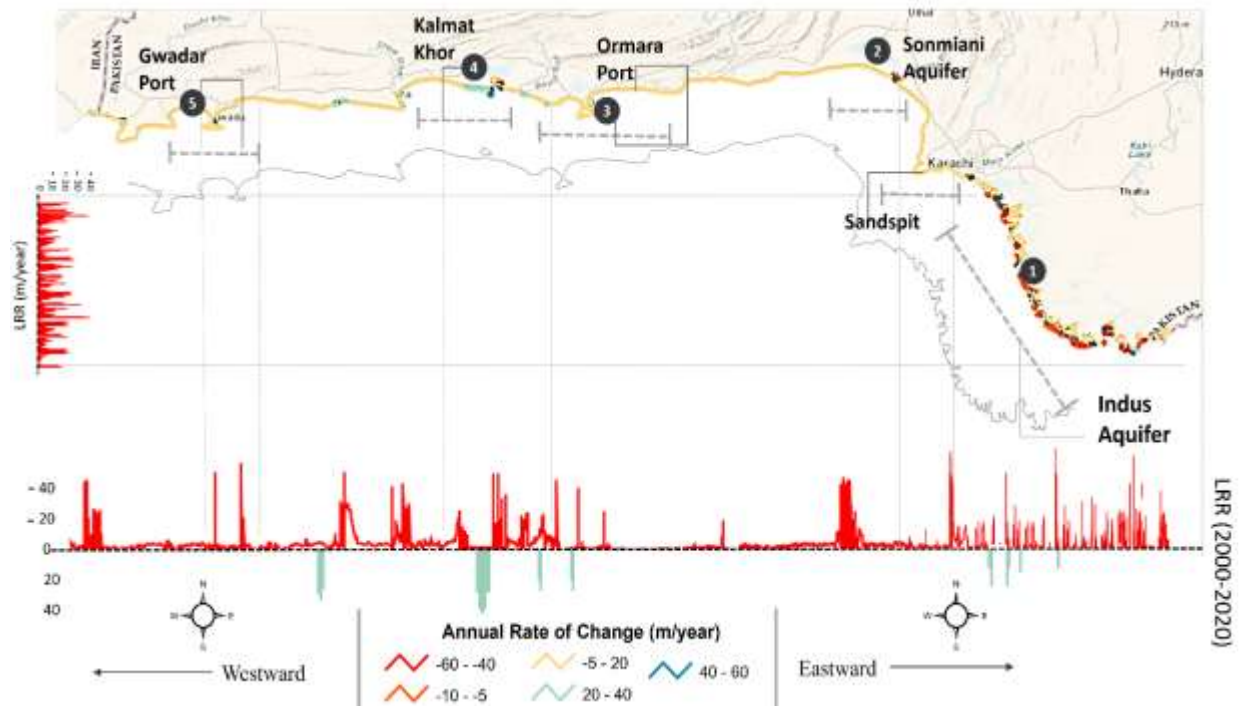


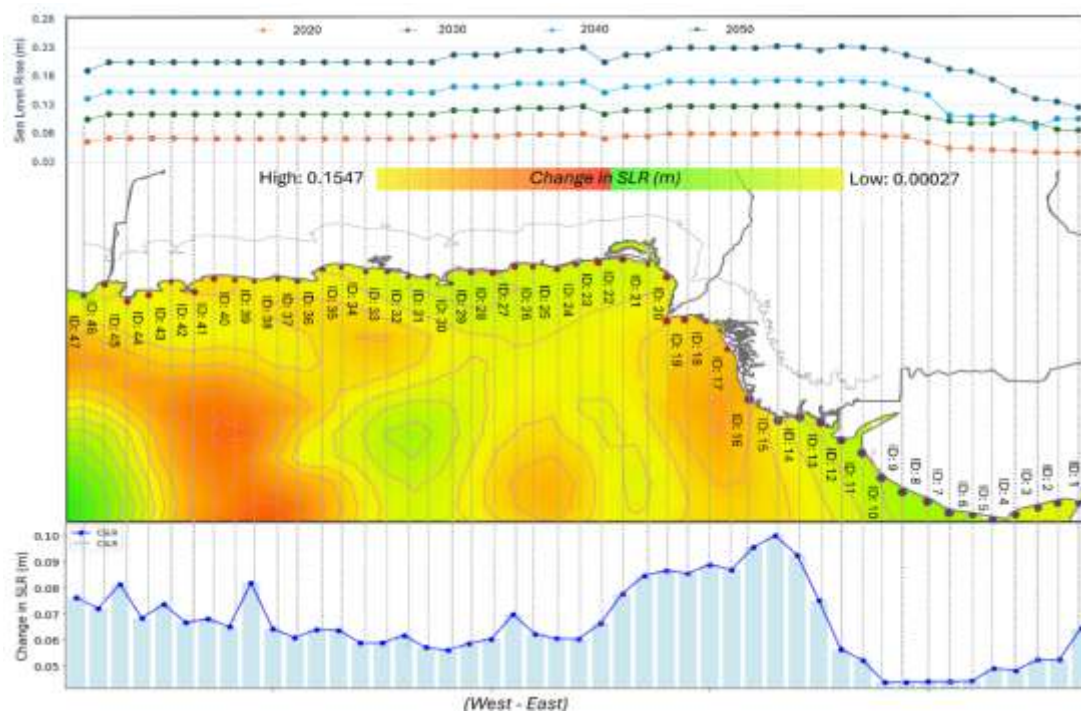
**Fig. 9.** Shoreline accretion and erosion assessment along the entire coastline of Pakistan historic (2000-2020), red areas indicate regions experiencing erosion, blue areas represent accretion.

This region (the Indus Delta) of the coast is particularly vulnerable due to its low elevation, continuous SLR and reduced sediment load from the Indus River, which is being diminished by upstream water diversions responsible for SWI. As a result, the reduced sediment supply and SLR are leading to substantial coastal retreat in the delta region, putting both the environment and local communities at risk. Furthermore, areas along the coastline are experiencing accretion with positive increments in LRR. The central part of the coastline, particularly towards Ormara Port, experienced highest rates of accretion, from 30.43 m/year to 57.32 m/year. This suggests that in this region, the coastline is advancing into the sea, likely due to the accumulation of sediments and some localized coastal infrastructures as mentioned in previous studies (Ullah et al. 2024). The Sonmiani Aquifer showed significant accretion, with LRR up to  $43.22 \pm 1.35$  m/year. The regions of Gwadar and Ormara Port highlighted several areas with pronounced accretion. Where the coastline experiences accretion rates peaking at over 40 m/year in some cases.

### 3.4. Analyzing the Projection Trends of SLR and SST

The linear transects along the Indus Delta showing the highest changes in SLR, with consistent increases over time. This region is expected to experience the greatest impacts from SLR due to its already vulnerable low-lying geography. From 2000 to 2020, the Indus aquifer experienced a cumulative SLR change of 0.12 m, followed by an SLR change of 0.09 m near the Sonmiani aquifer. The central part of the coastline with transects 20 to 40, including areas such as Sonmiani Aquifer and Kalamat Khor, indicates pronounced increases with a cumulative change of 0.09 m in SLR. Similarly, the western part of the coastline with transects 41 to 47, near Gwadar Port, shows significant changes, with SLR approaching 0.08 m in 2030 and 0.20 by 2050 as shown in Fig. 10. The easternmost transects showed more modest increases, with SLR remaining below 0.09 m over the same period. The Indus Delta is projected to experience one of the highest sea level rises, with levels increasing from 0.08 m in 2020 to around 0.21 m by 2050. This rise, combined with a gentle slope, makes the Indus Delta particularly vulnerable to coastal flooding, erosion, and SWI (Siddiqui and Maajid 2004; Ijaz et al. 2018). The westernmost transects, near Gwadar Port, also show significant increases, with SLR projected to reach a cumulative value of 0.174 m by 2050. Whereas the SST variations over time and across the coastline range from as low as 0.008 K to as high as 1.987 K between 2020 and 2050 as shown in Fig. 11. This substantial increase reflects a long-term warming trend, with some locations experiencing nearly a 2 K rise

399 in SST, which is substantial in the context of climate variability. The changes in SST ( $\Delta$ SST) show that the rate of  
 400 temperature increase is not uniform along the coastline.



401  
 402 **Fig. 10.**  $\Delta$ SLR (m) along west to east transects of Pakistan's coastline (2020-2050), along with predicted SLR for  
 403 2020, 2030, 2040, and 2050.

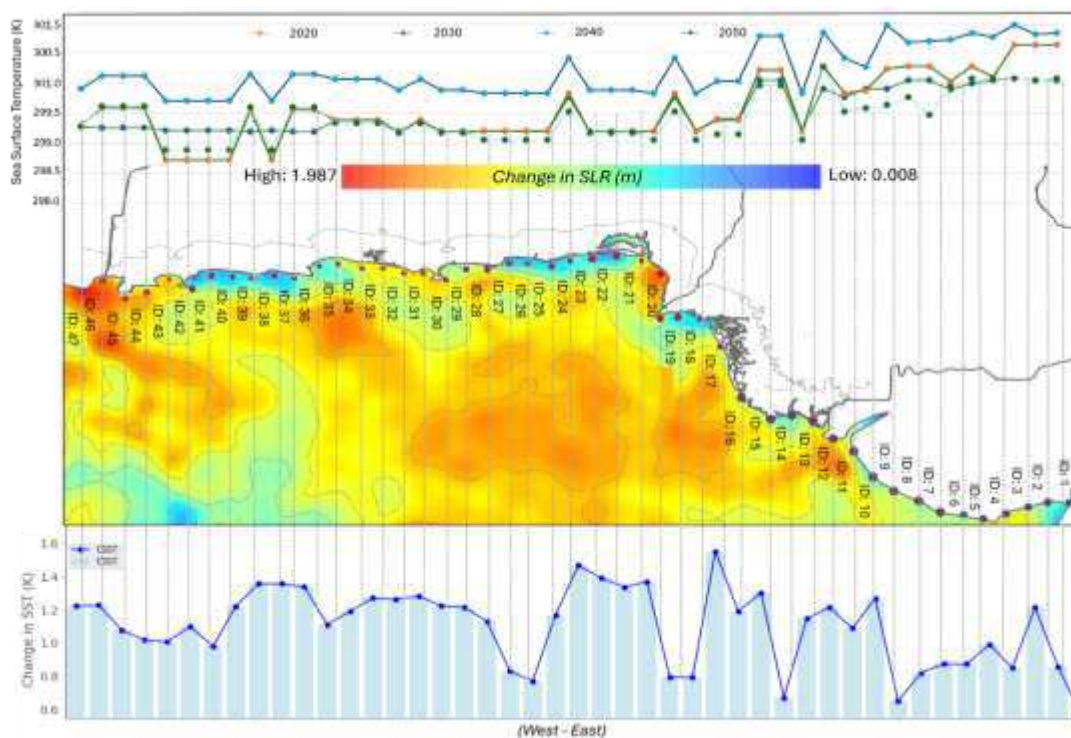


**Fig. 11.**  $\Delta$ SST (K) along west to east transects of Pakistan's coastline (2020-2050), including all major aquifers and predicted average SST for the years 2020, 2030, 2040, and 2050.

The transects 20-30 show higher temperature increases (1.5-1.8 K), while regions like IDs 1-10 and 40-47 have lower increases (0.8-1.0 K). These variations suggest differential thermal responses along the coast, potentially driven by local oceanographic processes, proximity to river mouths, or varying impacts of climate forcing. The projected SST along the coastline for 2020, 2030, 2040, and 2050, shows an increasing trend. The statistical breakdown reveals that the mean SST in 2020 is approximately 299.6 K, increasing to 300.4 K by 2050 (Fig. 12). This shows an average rise of 0.8 K over the 30-year period. The statistical evaluation of SLR and SST anomalies across various coastal transects of Pakistan from 2015 to 2050 indicates a clear upward trend in both parameters. The analysis revealed an average annual SLR increase ranging from 2.5 mm/year to 5 mm/year across different transects, reflecting a statistically significant linear growth over time ( $R^2 \approx 0.85$ ). SST anomalies exhibit pronounced interannual and seasonal fluctuations, with standard deviation values between 0.3 K and 0.8 K, and an average annual increase of 0.02 to 0.05 K as shown in Fig. 12. The coefficient of variation for SST anomalies ranges from 12% to 25%, highlighting substantial variability among the transects.

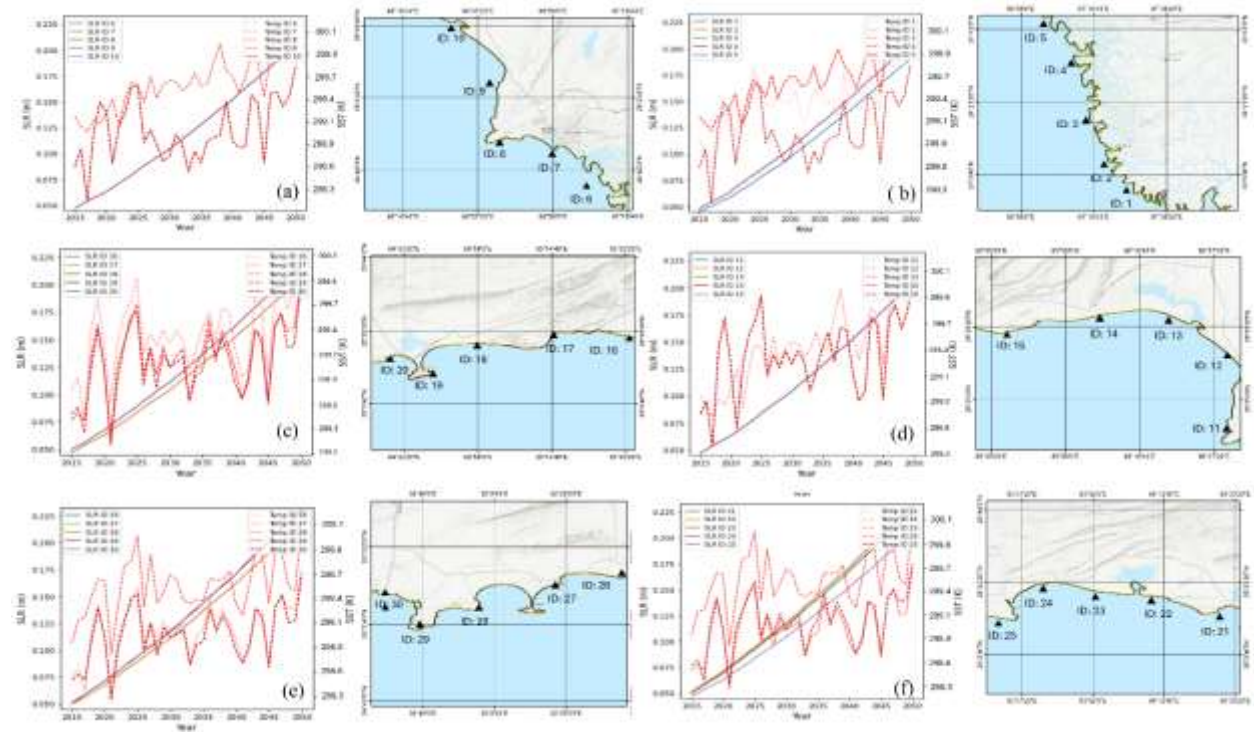


**Fig. 12.** Comparative Analysis of SLR and SST from 2000 to 2023 across west-east transects along Pakistan's coastline: (a) Sandspit, (b) Indus Delta, (c) Ormara, (d) Sonmiani, (e) Gawadar, and (f) Kalmat Khor. The transects are drawn parallel to the baseline along the coastline for distance calculations.

This region is particularly vulnerable due to its ecological and socioeconomic significance, as it hosts one of the world's largest mangrove ecosystems that support critical fishery resources and protect coastal communities from storm surges. According to (Alamgir et al. 2016), Gwadar has already witnessed significant erosion and the destruction of residential areas due to SLR encroachment and extreme weather events, threatening the viability of ongoing development. The report further notes that the cost of climate-related infrastructure damage in Pakistan could escalate to \$14 billion annually by 2050.

### 3.5. Erosion and Accretion Analysis: Coastline Retreat Trends (2020-2050)

For the 2025-2030 period, the trends remain consistent with the earlier period, though the LRR values indicate a more widespread occurrence of erosion across several regions. The Indus Delta continues to experience significant erosion

without effective adaptation measures. This ongoing trend suggests that the Indus Delta region will continue to face severe challenges related to land loss and coastline retreat. The Kalamat Khor exhibits more stable accretion rates, with LRR values around 15.3 m/year, indicating some coastal development and expansion (movement towards the sea). However, erosion hotspots remain along the coastline, particularly near Ormara Port, where variability in rates suggested some sections are eroding while others are accreting as shown in Fig. 13.

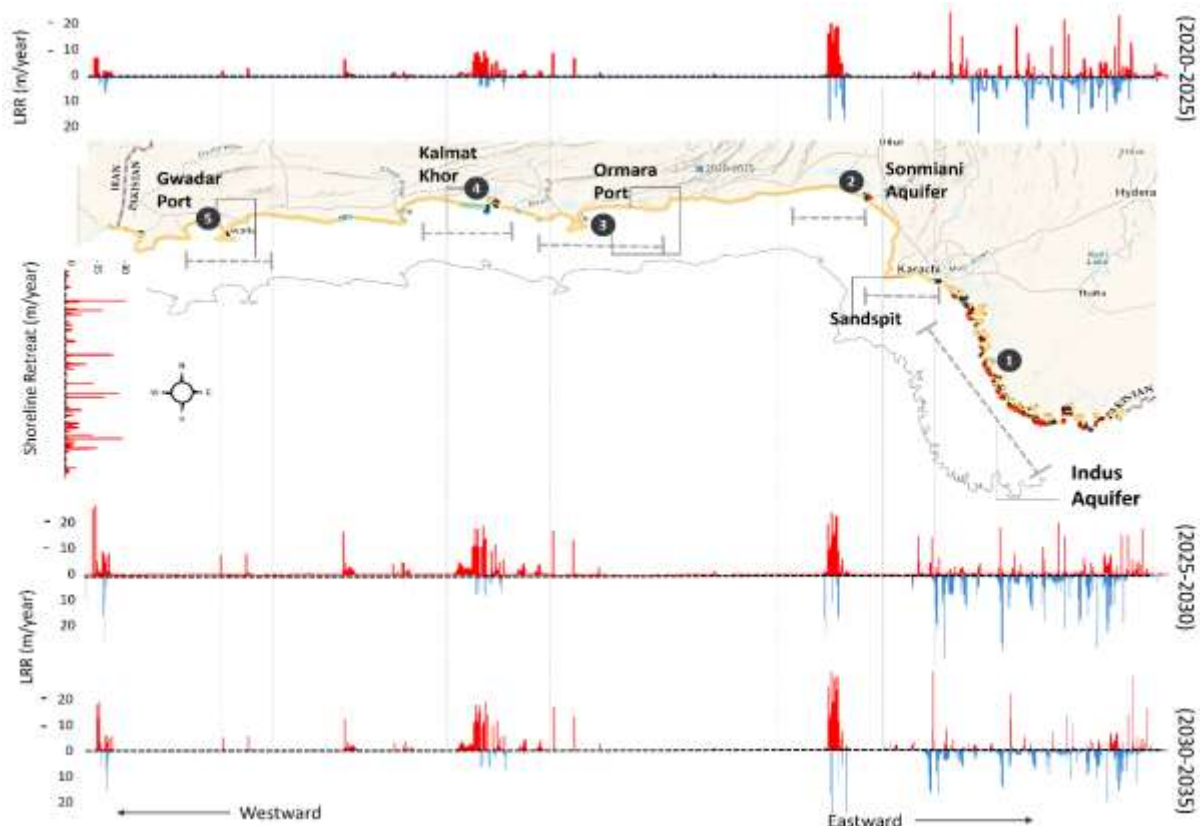


**Fig. 13.** Shoreline accretion and erosion assessment under SSP5-8.5 (2020-2025), (2025-2030), (2030-2035) red areas indicate regions experiencing erosion, blue areas represent accretion.

In the 2030-2035 period, the overall trends continue, but with more pronounced differences between the eastern and western portions of the coastline. The western section near Gwadar Port continues to show a positive LRR, suggesting that this region is benefiting from accretion processes, with coastline advancement rates remaining around 8.41 m/year. The impact of land erosion due to intrusion on coastal mangroves have also been indicated by the existing studies on the surrounding aquifer ecosystem (Kumar and Patnaik 2013; Giri et al. 2015; Yakubu et al. 2018). Conversely, the Gwadar Port region consistently demonstrates positive accretion rates, with LRR ranging from 5.45 to 9.45 m/year, indicating coastal advancement and stability. Similarly, Kalamat Khor and the Sonmiani Aquifer show erosion with LRR reaching around -18.3 m/year. In contrast, Ormara Port shows relatively stable conditions, reflecting dynamic and localized shifts in sediment transport (Fig. 13).

These trends suggest that while certain regions benefit from natural accretion processes, others, particularly the Indus Delta, remain critically vulnerable to erosion, necessitating targeted intervention and sustainable coastal management strategies (Siddiqui and Maajid 2004; Teodoro et al. 2007; Mukhtar and Hannan 2012; Pardo-Pascual et al. 2012). In contrast, the Indus Delta remains an area of concern, as erosion continues to dominate the region, with LRR indicating coastline retreat at a rate of  $-101 \pm 1.15$  m/year or more (Fig. 14).

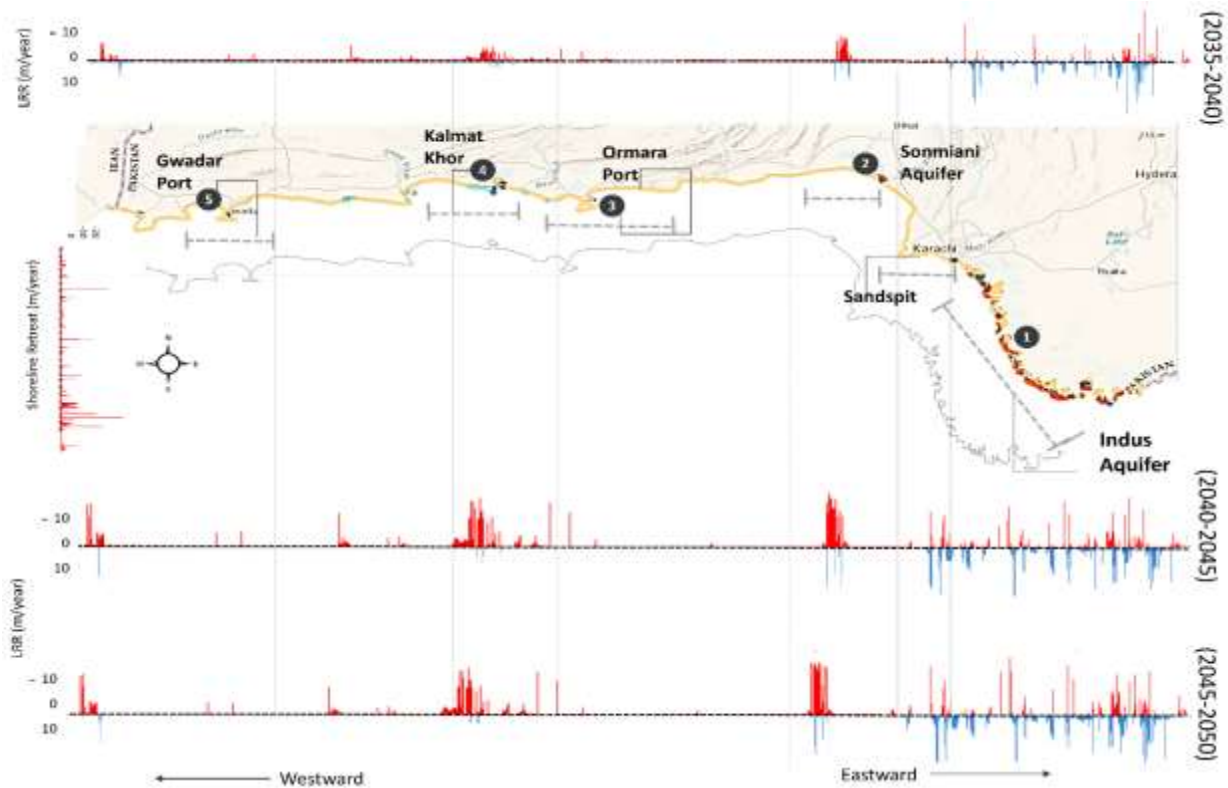


**Fig. 14.** Shoreline accretion and erosion assessment under SSP5-8.5 (2035-2040), (2040-2045), (2045-2050) red areas indicate regions experiencing erosion, blue areas represent accretion.

The existing studies also conducted the impacts of sediment flows into coastal aquifers sustainability and also aligned with the existing studies (Din Hashmi and Ahmad 2018; Waqas et al. 2019; Kanwal et al. 2020), confirming high erosion rates in Indus Aquifer Jhari/Rahu and Waddi/Pitiani creek areas as well as at certain banks of Kalamat Khor and Somiani Aquifer. For example, west Mal Creek region exhibited an erosion rate of -20.89 m/year from 1952 to 2006 (WWF-Pakistan, 2005), are also align with the findings of this research. Similarly, Khober Creek has shown an annual change rate of -34.9 m/year from 1990 to 2020, compared to -10 m/year from 1895 to 1952 (Giosan et al. 2006). Chann Creek's erosion rate of -15.61 m/year also aligns with studies indicating a landward-receding coastline (Waqas et al. 2019).

### 3.6. Climate Change Projections of Sea Level Rise and Sea Surface Temperature under SSPs and Global Warming Levels

The projected SLR for the coastal regions of the Indus Delta, Ormara Port, and Gwadar Port show a pronounced dependence on future emission scenarios and GWLs. For the Indus Delta, SLR projections under various SSP showed the highest change in SLR among all sites studied, exceeding 0.25 m by 2100 under SSP5-8.5 and uncertainty ranges extending beyond 0.30 m. Even under the lowest emission pathway SSP1-1.9, a median rise of around 0.08 m is projected. When examined across different GWLs, specifically 1.5°C, 2°C, 3°C, 4°C, and 5°C above pre-industrial baselines, the Indus Delta exhibits a clear, nearly linear increase in median SLR, with values surpassing 0.15 m at 3°C and exceeding 0.25 m at 5°C warming as shown in Fig. 15. This pattern aligns closely with the IPCC AR6 (Intergovernmental Panel on Climate Change (IPCC) 2023), which highlights that each additional degree of global warming results in approximately 0.1 to 0.2 m higher global mean sea level rise by 2100 (IPCC AR6 WGI Chapter 4) (Intergovernmental Panel on Climate Change (IPCC) 2023). The Indus Delta, which hosts one of the world's largest arid-climate mangrove ecosystems, is exceptionally sensitive to projected SLR. Recent assessments report that more than 70% of mangrove cover has already been lost, severely disrupting fish nurseries and diminishing coastal resilience (Zhang et al. 2023). Ormara Port, while exhibiting more moderate exposure, still shows significantly projected SLR.

Under SSP5-8.5, the median rise reaches about 0.20 m by 2100, whereas under SSP1-1.9 it remains around 0.05 m. Gwadar Port follows a similar trend, with projected median SLR approaching 0.18 m under SSP5-8.5 by 2100, and uncertainty ranges from 0.12 m to 0.24 m.

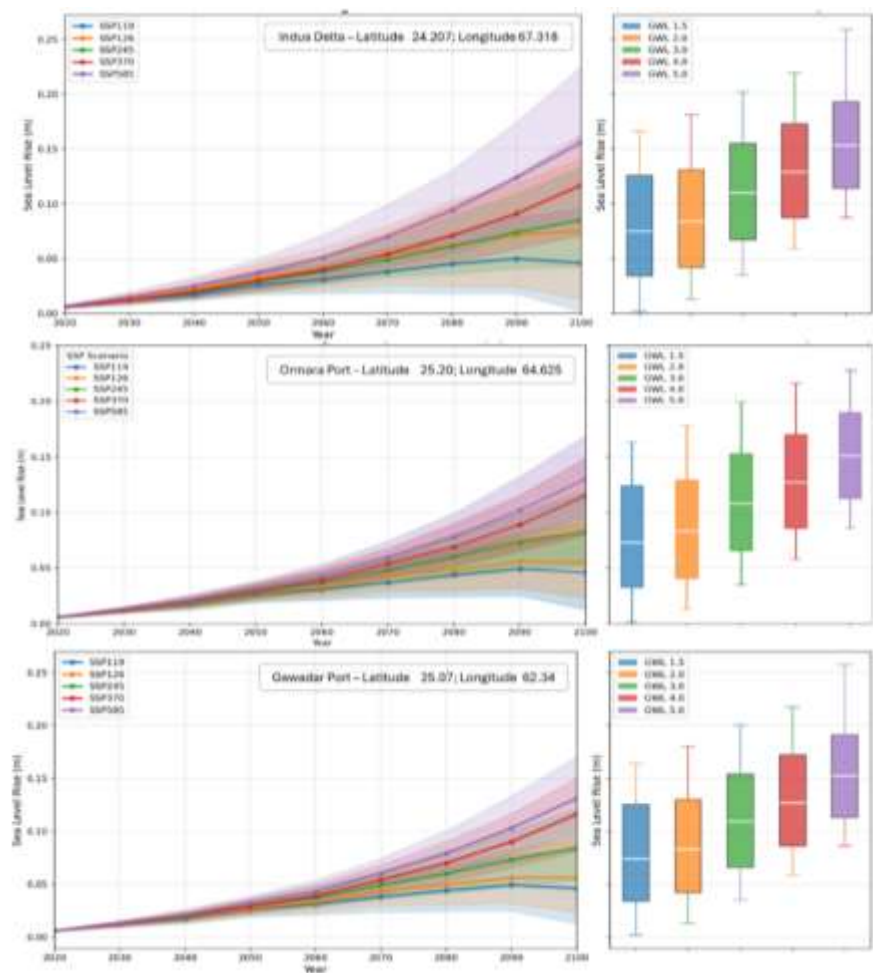


**Fig. 15.** Projected sea level rise in Indus Delta, Ormara and Gwadar Port under SSP scenarios (25<sup>th</sup> and 75<sup>th</sup> percentiles as shaded bands over time, boxplot of projected SLR for each GWL level (°C).

Under SSP1-1.9, the median SLR is limited to around 0.06 m. As a key node, Gwadar’s vulnerability to SLR directly threatens port operations, urban infrastructure, and local water security. All three sites are poised to experience measurable sea level rise by 2100, with severity scaling strongly with emissions and global temperature increases, in line with IPCC AR6 assessments.

### 3.7. Validation and Accuracy Assessment

For the validation of SLR and SST, it was conducted using tidal gauge measurements taken at various locations along the coastline. For Kalmat Khor, the calculated SST values generally follow the station trends but exhibit greater variability in some years. Ormara shows larger discrepancies between the calculated and observed SST values, especially in some years, such as around 2011. For Sonmiani, there are significant deviations between the station and calculated SST values, particularly in earlier years like 2003 and 2005, where the calculated SST is either overestimated or underestimated, contributing to an RMSE of 0.162 K (Fig. 16). The trend in SLR over time, as derived from tidal gauge measurements, along with a fitted trend line for analysis based on tidal gauge data from 1870 to 2020 as shown in Fig. 16.

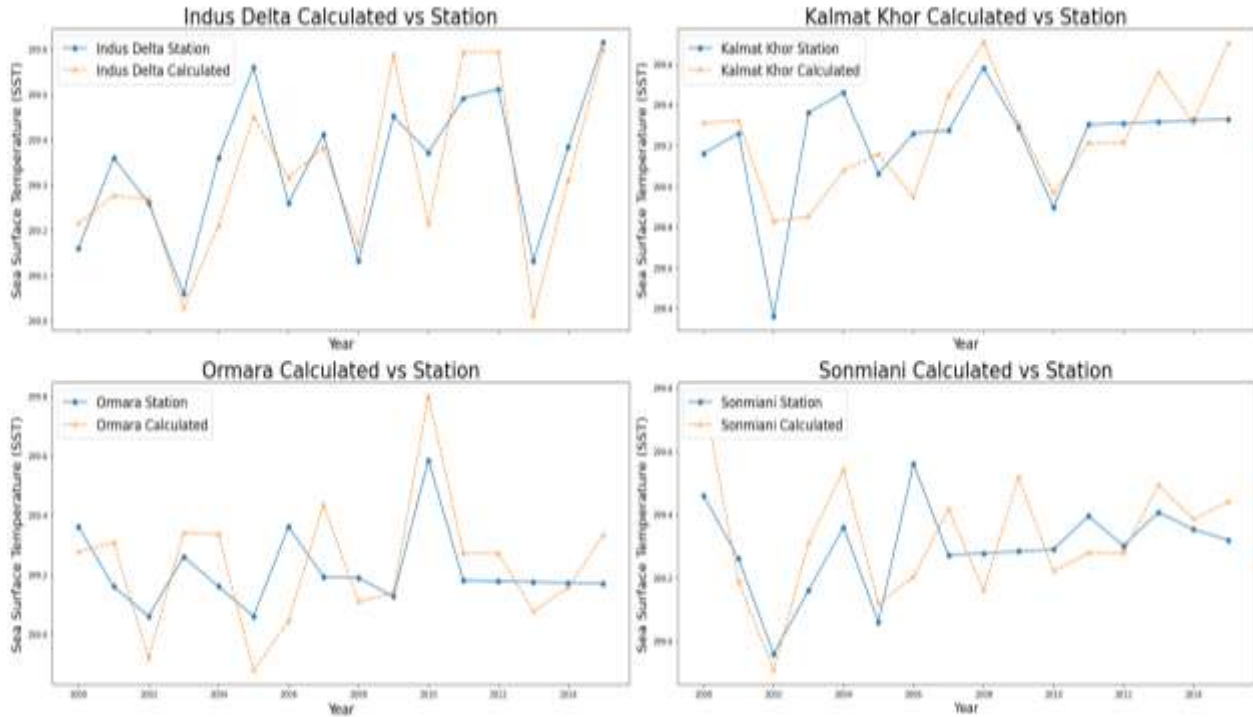


**Fig. 16.** Comparison of SST calculated from NOAA and with tidal gauge measurements e.g., Indus Delta, Sonmiani, Kalamat Khor, Ormara, and Gawadar.

Moreover, the information obtained from Fixed Point Photography (FPP) at various sites along the Indus Delta coast from May 2010, 2015, and 2020 shows inhabited areas which have transformed into sparsely vegetated mudflats, making them unsuitable for habitation due to coastal erosion, as shown in Fig. 17. The villages situated on the western mudflats of Indus Delta face a declining freshwater supply, further aggravated by SWI, emphasizing the need for immediate action to protect and restore the region's ecosystem (Aeman et al., 2023; Giosan et al., 2006). Moreover, existing studies highlight that reductions in sediment distribution and deposition significantly influence coastal processes, as sediment supply is critical for landscape-scale dynamics and provides essential information for effective policy planning and coastal management. Previous research indicates that seawater intrusion, together with erosion and accretion processes in Pakistan major coastal aquifers, is primarily driven by accelerated SLR and a substantial decline in upstream river discharge. Consequently, restoration efforts should prioritize the rehabilitation of eroded coastal zones and the adoption of sustainable land-use practices that promote mangrove regeneration and ensure long-term sustainability of associated coastal ecosystem services.



**Fig. 17.** Fixed Point Photography (FPP) along various creeks for the years 2010, 2015, and 2020, highlighting areas affected by coastal erosion.

The observations in 2020 showed a maximum salinity variation between 1.68 and 1.83 along the coastline, with higher salinity levels concentrated near the Indus Delta aquifer (Ijaz et al. 2018). The vertical distribution of sediment flow from the Kotri Barrage significantly decreased in 2010, reducing from 50 BCM to 0.05 BCM (Frihy and El-Sayed 2013; Aeman et al. 2023). This study highlights the significance of addressing climate change, reducing anthropogenic risks, implementing adaptation and mitigation plans, and integrating coastal zone management as essential strategies for dealing with the challenges faced by major coastal aquifers in Pakistan. These initiatives should be considered as case studies for demonstrating pilot projects that address coastal climate vulnerability. To address coastal erosion, the IPCC proposes three primary strategies protection, accommodation, and restoration. Accordingly, this study discusses the implementation of these strategies within the management framework of Integrated Coastal Zone Management Plans (ICZMPs).

### 3.8. Strategic Management Framework for Integrated Coastal Zone Management (ICZM)

The effective management of climate vulnerability, adaptation, and mitigation in coastal zones is crucial for addressing the challenges faced by the Indus Delta. These strategies should align with the country's commitments under the National and Provincial Climate Change policies and action plans. Since vulnerability levels differ across the Delta, Local Adaptation Plans of Action (LAPAs) at the district level play a critical role in detailed planning and managing coastal climate vulnerabilities and their associated ecosystems. Moreover, climate vulnerability risk management, adaptation and mitigation plans that incorporate coastal zone management are critical aspects for addressing the challenges to the Indus Delta. Those plans should be aligned with the country's commitment as part of the NDCs addressing climate change (Morzaria-Luna et al., 2014; Srinivasalu et al., 2009). Coastal management planning is progressively shifting towards a proactive and long-term approach to ensure the sustainability of deltaic systems. Nations like the Netherlands and the UK are implementing shoreline management strategies with a forward-looking perspective, extending over a 100-year timescale, for coastal communities globally by moving away from reactive management practices and advanced geospatial methods (Morzaria-Luna et al. 2014). These strategies align with ICZMP, as previously highlighted in other studies (Inam et al. 2008; Waldmüller et al. 2019). Moreover, to mitigate risks to the environment and human populations in eastern part of coastline, including the Indus Delta and Sonmiani aquifers. To stabilize the coastline, it is essential to restore the mangroves that have been lost and conserve the remaining ones (Mukhtar and Hannan 2012). Such coastal aquifers are home to 638 million people worldwide at the start of the 21<sup>st</sup> century as well as based on various other emission scenarios based global studies shows that population is expected to exceed 1 billion by mid-century of 2050 across all scenarios from SSP1 of sustainability, SSP2 of middle of the road, SSP3 with regional rivalry, SSP4 indicating inequality, and SSP5 indicating fossil-fuelled development ranging between 830 million and 1.2 billion by 2100, depending on the SSP scenario. Moreover, effective solutions are possible within ICZM, but there may be barriers to implementation. Technical support and stakeholder engagement can help overcome these challenges and choose the best management strategy. ICZM can serve as a platform for co-creation and education of stakeholders on available adaptation options.

### 4. Conclusion

This study demonstrates the implementation of spectral indices-based RF framework to demarcate shorelines at medium scale resolution for large-scale coastline mapping, addressing key challenges such as limited available training data. The long-term trends reveal alarming coastal erosion rates, particularly in the Indus Delta, where SLR has accelerated in recent decades, and significant shoreline retreat has occurred. Results reveal pronounced erosion along the Indus Delta, with cumulative shoreline retreat reaching  $50.4 \pm 1.02$  m between 2000 and 2020, corresponding to an increase in SLR (0.015-0.15 m) and SST (297-301 K). In contrast, the Sandspit coast exhibited notable accretion of up to 23.24 km<sup>2</sup> with shoreline advancement of  $48.45 \pm 0.23$  m, while Gwadar Port recorded accretion up to 40 m, coinciding with annual temperature rises of 0.02-0.05 K. Conversely, regions such as Sandspit and Gwadar Port show notable accretion, emphasizing the spatial heterogeneity of coastal dynamics. Under the high-emissions SSP5-8.5 scenario, the Indus Delta is projected to experience continued erosion of approximately  $-90 \pm 1.35$  m by 2050. Projections across GWLs of 1.5-5.0 °C suggest that sea level rise could reach up to 0.23 m at a 5 °C warming. Future work should focus on improving model generalization capabilities across diverse geographic locations by incorporating higher-resolution datasets, advanced feature selection techniques, and domain adaptation strategies. It is essential to adapt the selection of spectral indices and features to the unique characteristics of the new region, considering aspects such as vegetation indices, soil properties, and specific regional features as well as climate projection scenarios for the shoreline change rate assessment. Overall, the results reinforce the urgency of implementing Integrated Coastal Zone Management (ICZM) strategies that account for the complex interplay of SLR, shoreline dynamics, and ecosystem health. By identifying high-risk zones and quantifying the magnitude of ongoing and projected shoreline changes, this study contributes critical insights to risk management that support global efforts to meet SDG 13 (Climate Action) and SDG 15 (Life on Land) targets, ultimately guiding sustainable coastal development and ecosystem conservation.

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## Author Contributions

In this research article, all authors contributed significantly to this research article. Hafsa Aeman for data analysis, conceptualization, data collection, and writing. Hong Shu contributed to conceptualization, supervision, and review. Hafsa Aeman managed visualization, analysis, and writing. Imran Nadeem provided review and editing. Hamera Aisha collected ground data, designed and authored NbS recommendations, and validated content. Imran Nadeem edited and revised the manuscript.

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## Competing Interests

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

## Data Availability statement

The authors submitted all materials during article submission; additional data used for the analysis will be made available upon request.

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