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Coastal Vulnerability Index sensitivity to shoreline position and coastal elevation parameters in the Niger Delta region, Nigeria

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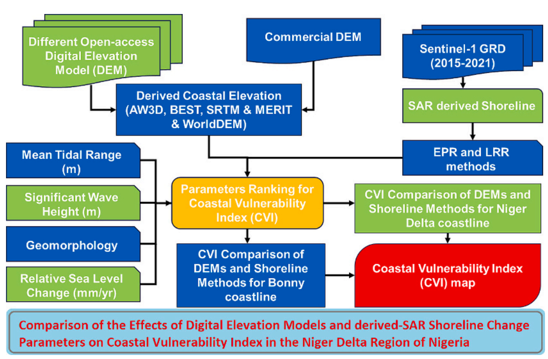
HIGHLIGHTS

- SAR-based shoreline derivation for shoreline change analysis and mapping shoreline positions
- Utilisation of DEM provides new insight on the degree of agreement for the coastal vulnerability index (CVI).
- Comparing shoreline change methods and DEMs to ascertain the degree of agreement for the CVI
- Monitoring the extent of coastal vulnerability along the Nigeria's Niger Delta region

GRAPHICAL ABSTRACT



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ABSTRACT

It is imperative to assess coastal vulnerability to safeguard coastal areas against extreme events and sea-level rise. In the Niger Delta region, coastal vulnerability index assessment in the past focused on open-access parameters without comparing the open-access parameters, especially coastal elevation and shoreline change. This sensitivity to the shoreline method and open-access coastal elevation limits the information for the planning of coastal adaptation. The area under investigation is the Niger Delta, which is distinguished by its low-lying coastal plains and substantial ecological and economic significance. In light of the selected parameters, Sentinel-1 GRD images from 2015 to 2022 during high tidal conditions were used to delineate the shoreline position and change rate. Also, different open-access DEMs were used to derive the coastal elevation using the Geographic Information

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Shoreline position change
Digital Elevation Model (DEM)

System (GIS) approach. The study employs 5 parameters, such as shorelines obtained from Sentinel-1 SAR images and several Digital Elevation Models (DEMs), geomorphology, mean sea level rise, significant wave height, and mean tide range, in conjunction with the initial Coastal Vulnerability Index (CVI) approach. The study reveals that the type of DEM used significantly influences the coastal elevation ranking and, subsequently, the CVI. Differences in shoreline change rate estimation methods (EPR and LRR) also impact the vulnerability rankings but to a lesser extent. The findings highlight that 40.1% to 58.9% of the Niger Delta coastline is highly or very highly vulnerable to sea-level rise, depending on the shoreline change rate or DEM used. The study underscores the potential of using CVI methods with open-access data in data-poor countries for identifying vulnerable coastal areas that may need protection or adaptation. Lastly, it points out the need for higher resolution DEMs.

Abbreviations

3D	Three-Dimensional
ALOS	Advanced Land Observing Satellite
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AW3D	ALOS World 3D
BEST	Bare-Earth SRTM Terrian
CVI	Coastal Vulnerability Index
DEM	Digital Elevation Model
DSAS	Digital Shoreline Analysis System
DTM	Digital Terrain Model
EPR	End-Point Rate
ETOPO2	Earth Topography and Bathymetry
FCN	Fully Convolutional Neural Network
GDEM	Global Digital Elevation Models
GIS	Geographic Information System
GRD	Ground Range Detected
GTOPO30	Global 30 Arc-Second Elevation
ICE-Sat	Ice, Cloud, and land Elevation Satellite
ICZM	Integrated Coastal Zone Management
IPCC	International Panel for Climate Change
LandSat	Earth-imaging satellite
LiNAR	Light Detection and Ranging
LRR	Linear Regression Rate
MERIT	Multi-Error-Removed Improved-Terrain
MSL	Mean Sea Level
MWH	Mean Wave Height
NASA	National Aeronautics and Space Administration
PSMSL	Permanent Service for Mean Sea Level
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
S.D	Standard Deviation
SLR	Sea Level Rise
SRTM	Shuttle Radar Topography Mission
TanDEM-X	TerraSAR-X add-on for Digital Elevation Measurements
USGS	United States Geological Survey
U.S.A.	United States of America

1. Introduction

The Niger Delta, an economically and ecologically significant region in Nigeria, is characterised by extensive environmental challenges and a unique juxtaposition of abundant biodiversity. The expansive system comprising rivers, estuaries, and wetlands serves as a sanctuary for a wide array of species while also providing sustenance for millions via fisheries, agriculture, and a huge oil and gas sector for the nation (Okeke and Ibe, 2021). The region is becoming more susceptible to the effects of both human activity and natural environmental changes, including pollution, erosion, and climate-induced fluctuations in sea levels (Ejikeme et al., 2017). Within this context, the monitoring of the coastal area arises as a crucial instrument for comprehending and alleviating these consequences. Efficient surveillance of the coastal areas of the Niger Delta is essential for monitoring the well-being of its ecosystems and ensuring the long-term viability of its resources. The process entails a systematic study and assessment of variations in the quality of water, dynamics of sediment, and diversity of living organisms, which offers crucial information for the purpose of environmental management (Lemenkova and Debeir, 2023). Furthermore, this monitoring process aids in predicting and tackling the negative effects of oil spills, which pose a substantial peril to the natural equilibrium of the region (Adebanjo and Oyebade, 2022). Additionally, coastal monitoring is crucial for providing information to make informed policy decisions, directing conservation initiatives, and facilitating the establishment of sustainable practises that achieve a balance between economic expansion and ecological preservation (Sam et al., 2023).

Coastal vulnerability has many definitions as these are derived from different disciplines and can be focused on either physical and natural systems or social and economic systems, or both (Bukvic et al., 2020). The report from the International Panel for Climate Change (IPCC) projected the severe impact of climate change on coastal natural and built environments. According to IPCC (IPCC, 2014) considers vulnerability as an internal property of the system comprising of its sensitivity and adaptive capacity (Sharma and Ravindranath, 2019). However, vulnerability is still mostly regarded as the susceptibility of the natural coastal environment to impacts of erosion or inundation caused by sea level rise and/or extreme weather conditions such as storm surges, which have severe effects on the infrastructure and livelihoods of coastal communities (Anfuso et al., 2021).

Coastal vulnerability is often assessed using four distinct ways, as described by Ramieri et al. (Ramieri et al., 2011). These methods include: (i) index-based approaches, (ii) indicator-based approaches, (iii) decision support systems based on GIS (Geographical Information System), and (iv) dynamic computer models. Index-based approaches have been devised to evaluate the susceptibility of coastal areas on a regional to national level. They are relatively easy to apply, and their results can be displayed in map form, clearly indicating areas of higher vulnerability. However, these methods do not contribute to understanding of processes contributing to vulnerability of the coastline (Kantamaneni, 2016). Despite this limitation, index-based methods are widely used, particularly in countries where there is a lack of data collection at local scales, as is the case in this study. The coastal vulnerability index is a one-dimensional unitless measure of coastline exposure based on a number of quantitative or semi-quantitative parameters (Ramieri et al., 2011). The original method for calculating the coastal vulnerability index (CVI) was developed by Gornitz et al. (Gornitz et al., 1991), who used six parameters, namely rate of relative sea level rise (mm/year), mean tidal range (m), mean wave height (m), geomorphology, shoreline erosion/accretion rates (m/year) and coastal slope (per cent). Over the years, other researchers have extended the CVI to include additional parameters based on increased data availability.

Since its introduction, the CVI has been used to assess coastal vulnerability in many countries including the USA (Thieler and Hammar-Klose, 2000), Bangladesh (Jana, 2020), India (Sheik Mujabar and Chandrasekar, 2013; Joevivek et al., 2013; Sankari et al., 2015), Malaysia (Mohd et al., 2019), Spain (Mohd et al., 2019), Ivory Coast (Tano et al., 2016), Australia (Abuodha and Woodroffe, 2010), and Canada (Cogswell et al., 2018).

Digital elevation models (DEMs) and rates of coastal erosion and accretion are crucial parameters when assessing coastal vulnerability, which informs planning for the potential impact of sea level rise and extreme storminess (e.g. McLaughlin and Cooper (Mclaughlin et al., 2010)) by coastal managers and policy makers. Not many countries, particularly those in developing world, have systematic means of collecting these data. Instead, they rely on freely available data, often derived from satellite images. The quality and resolution of DEMs and shoreline change data as well as methodologies used to extract these data from satellite images have improved exponentially in recent decades (Hamid et al., 2021). However, there are still limitations in accuracy and precision of these data and in particular those that are publicly available and used to assess coastal vulnerability at different spatial and temporal scales. Therefore, it is necessary to investigate the sensitivity of coastal vulnerability indices to different shoreline positional data and coastal elevation parameters derived from different DEM.

Many of the recent studies utilised freely available satellite images and information derived from these images to calculate CVI. The shoreline change rate, which is one of the major parameters when assessing the impact of sea level rise on the coastline, can be estimated from shorelines extracted from freely available optical satellite images such as Landsat and Sentinel-2 (Vos et al., 2019). Earlier, this thesis demonstrated that reliable shoreline data could also be extracted from Sentinel-1 SAR images, which is beneficial for regions with persistent cloud cover. Increased spatial resolution and repeat coverage by satellites allows shorelines in the same areas to be compared at various time intervals, from days, seasons to years. Over the years, a number of approaches have been developed for calculating shoreline change rates from remote sensing data. Two of the most common approaches are the end-point rate (EPR) and the linear regression rate (LRR) (Mani Murali et al., 2013; Paul and Sumam, 2013; Sankari et al., 2015; Akshaya and Hegde, 2017; Tahri et al., 2017). Each of these approaches has its advantages and disadvantages. The EPR is simple to compute and only requires two shorelines, however, the cyclical nature of erosion and accretion may be missed (Dolan et al., 1991; Crowell et al., 1997; Himmelstoss et al., 2018). The LRR approach uses all data, regardless of change or accuracy, is based on well-established statistical principles and is simple to implement (Dolan et al., 1991; Crowell et al., 1997; Himmelstoss et al., 2018). However, unlike EPR, this approach is prone to the effects of outliers and usually underestimates the rate of change (Dolan et al., 1991; Genz et al., 2007).

When determining the effect of rising sea levels coastal area, it is important to also include the coastal slope and/or elevation, along with the coastal morphology (Nageswara Rao et al., 2009). Both of these parameters can be derived from Digital Elevation Models (DEMs) and their availability and accuracy are important for assessment of coastal vulnerability. Since the release of the Global DEM from the Shuttle Radar Topography Mission (SRTM) by the National Aeronautics and Space Administration (NASA) (Hamid et al., 2019), the SRTM DEM has been widely used to generate coastal elevation parameters for CVI analysis. However, numerous studies have revealed that SRTM DEM contains considerable errors with a strong bias (Tighe and Chamberlain, 2009; Becek, 2014) owing to vegetation (Lalonde et al., 2010; Shortridge and Messina, 2011) and man-made features (Gamba et al., 2012). As a result of these errors, areas susceptible to coastal inundation can be underestimated by up to 60%, depending on assumptions about sea level rise (Kulp and Strauss, 2016). Many efforts have been made to reduce the vertical errors in this DEM using different techniques. For example, O'Loughlin et al. (O'Loughlin et al., 2016) developed the 'Bare-Earth' (BEST) SRTM DEM by combining multiple remote sensing datasets, (e.g., NASA's ICE-Sat laser altimeter, tree cover percentages from the MODIS satellite and global vegetation height map) to remove vegetation artefacts from within the original SRTM-DEM. The new DEM reduced the bias in vegetated areas by >10m in comparison to the original DEM. The Root Mean Square Error (RMSE) was also reduced globally from 14 m to 6 m. Yamazaki et al. (Yamazaki et al., 2017) developed the Multi-Error-Removed Improved-Terrain (MERIT) DEM by removing several error components (e.g., speckle noise, stripe noise, absolute bias, and tree height bias) from the DEMs obtained by SRTM, AW3D, and Viewfinder Panoramas. The resulting land areas were mapped to a vertical accuracy of 2 m or greater. Kulp and Strauss (Kulp and Strauss, 2018) introduced CoastalDEM which is derived using 23-dimensional vertical error regression analysis incorporating vegetation cover indices and other variables (such as local elevation points, population density, elevation slope, and local SRTM derivation from ICE-Sat), as well as LiDAR and ground truth data, using a multilayer perceptron artificial neural network. They reduced the vertical bias in the DEM from 3.67m to <0.01 m across the US coast and 2.49m to 0.11m along the Australian coast, reducing RSME from 5.36 to 2.39m and 4.15 to 2.45m, respectively. Aside from the SRTM, the Japan Aerospace Exploration Agency has created other GDEMs from SAR images, such as Advanced Land Observing Satellite (ALOS) World 3D (AW3D) (Tadono et al., 2015), ETOPO2, and GTOPO30. In addition to these open-access DEMs, there are a number of commercially available DEMs, with higher spatial resolution and with lower bias (e.g., ALOS World 3D at 5 m resolution, a TerraSAR-X add-on for Digital Elevation Measurements (TanDEM-X) at 12 m resolution). Recently, Meadows and Wilson (Meadows and Wilson, 2021) used machine learning to assess the vertical accuracy of open-access DEM in assessing flooding. The study applied a fully convolutional neural network (FCN) to predict the bias. A potential model was trained using high-resolution DEM (LiDAR) as reference data against open access (i.e., SRTM, ASTER, and AW3D30). The study found that the FCN outperforms the other models by reducing the root mean square error in the testing dataset by 71%. The study found to improve with increasing model complexity, with the simplest model which is the Random Forest (RF) reducing test RMSE by 55%, the more complex DCN outperforming that (60%), and the most complex model (FCN) going even further (71%). This may be because it can learn from spatial patterns at multiple scales, unlike other models, which learn pixel-by-pixel with only basic spatial context (such as slope values).

Until now, the absence of reliable open-access Global Digital Elevation Models (GDEM) has hindered assessment of coastal vulnerability in data poor regions (Kulp and Strauss, 2016; Kulp and Strauss, 2018). This is the case with Niger Delta where only few studies have focused on assessing coastal vulnerability. For example, Oyegun et al. (Oyegun et al., 2016) used the CVI to assess the vulnerability of coastal communities in the Niger Delta, while Musa et al. (Musa et al., 2014) combined the original CVI (Gornitz et al., (Gornitz et al., 1991)) and another CVI model (Dinh et al. (Dinh et al., 2012)) to assess the vulnerability of the region to river flooding whilst accounting for sea level rise. Recently, Oloyede et al. (Oloyede et al., 2022) quantified and classified the coastal vulnerability along the entire Nigerian coastline using an Analytical Hierarchical Approach. Based on the outcomes derived from both methodologies, it can be concluded that 59–65% of the complete Nigerian coastline is characterised by a moderate to high vulnerability to sea-level rise. With increasing availability of freely available higher-resolution data such as shorelines derived from Sentinel-1 SAR imagery and coastal elevation parameters derived from DEMs, it becomes possible to assess coastal vulnerability in data poor areas such as Niger Delta. It gives also opportunity to assess the sensitivity of the CVI to DEMs of different spatial resolution and vertical accuracies achieved by using different correction techniques.

Therefore, the aim of this study is to assess the effects of shoreline change rates and coastal elevation parameters on estimates of coastal vulnerability to sea level rise in Niger Delta region. The focus of this study is on geophysical coastal vulnerability. The original Coastal Vulnerability Index method (Gornitz et al., (Gornitz et al., 1991)) will be used with open-access data including shorelines derived from Sentinel-1 SAR based on Dike et al. (Dike et al., 2023) (Dike, 2022) and coastal elevation parameters derived from freely available DEMs including ALOS Global Digital Surface Model (AW3D), Multi-Error-Removed Improved-Terrain (MERIT)-DEM, Bare-Earth SRTM (BEST)-DEM, and the commercially available WorldDEM- Digital Terrain Model (DTM). The focus will be on comparison of the elevation and the shoreline change rate rankings, which are incorporated in calculations of coastal vulnerability. Specific objectives are to (a) compare the shoreline change rate ranking using EPR and LRR methods (b) compare the elevation rankings from different open-access DEMs (c) to compare CVI estimates obtained using different combinations of DEMs and shoreline change rates and to assess spatial variation in these estimates.

2. Materials and methods

2.1. Study area

The Niger Delta region has been described as a dynamic coastal one that is sensitive to changes brought about by humans as well as those brought about by nature (Daramola et al., 2022; Babatunde, 2008). In other words, it is susceptible to both anthropogenic and natural changes. Due to its location in the Atlantic Ocean, the climate there is influenced both by interactions between land and sea and by seasonal trends. The stretch of shoreline across the Gulf of Guinea that is the focus of this study is approximately 130 km long. The location does not have any seawalls or embankments protecting it and has an average elevation that is only two to five metres above sea level. As low-lying coastal plains, deltas are particularly susceptible to the effects of increasing sea levels because of their topography. They are also vulnerable to the climatic influences that are caused by rivers further upstream and those that originate directly from the inner deltas. They are also impacted by human activities such as alterations to land use, the construction of dams, mining, irrigation, the extraction of subterranean resources, as well as urbanisation (Nicholls et al., 2007). Recent studies that have also considered the Niger Delta region towards understanding the coastal behaviour reflect gaps in present knowledge, as this region is data-deficient (Porzycka-Strzelczyk et al., 2022; Ochege et al., 2017).

The study area is home to Nigeria's oil and gas extraction operations and supporting infrastructure. According to DPR (DPR, 2018) and NNLG (NNLG, 2020), the value of these assets is estimated to be approximately 17.5 billion dollars. The region is rich in natural resources and hosts several densely populated cities like Port Harcourt, Bonny, and Ibo, in addition to oil and gas exploitation and infrastructure, which are the primary economic drivers of Nigeria. As a result, an assessment of the nation's susceptibility to rising sea levels is of the utmost significance for the nation.

This study will be focused on the eastern portion of the Niger Delta, which stretches 130 km lengthwise from Bonny River to Cross river. This region is home to a number of important oil terminals and LNG facilities. The study area covers two states (Rivers and Akwa-Ibom) with a projected population of 12,483,101 people as of 2016, of which 885,600 people live in five Local Government Areas (Bonny, Andoni, Opobo/Nkoro, Eastern Obolo and Ibeno) along the coastline (Dike et al., 2023; Ochege et al., 2017). Taking into account the geomorphology, the region's geomorphologic attributes include mudflats, sandy beaches, and dunes (Sexton and Murday, 1994). These features make up the region's distinctive landscape, and the land use comprise of mangroves, forest, urban areas and beaches (Dike et al., 2023; Ochege et al., 2017). Precisely, the Niger Delta region lies within the southern portion of Nigeria, and one of the highest oil-producing regions of West Africa, as it is also near the Atlantic Ocean as well as the Gulf of Guinea. The present investigation bounds around the 12.2 km coastline that is located on Bonny Island in the Niger Delta region of Nigeria (see Fig. 1).

2.2. Methods

The present study employed the original model proposed by Gornitz et al. (Gornitz et al., 1991) to assess the coastal vulnerability index (CVI). The CVI was calculated along transects spaced at 50m distance along the shore. All parameters were kept constant except the rate of shoreline change and coastal elevation. Two different rates of shoreline change were used in conjunction with four different open-access DEMs. The estimated CVI used different combinations of these inputs in order to test the sensitivity of results to these inputs. In addition, comparison was made between results obtained using open-access DEMs and higher resolution commercially available DEM for a restricted area around Bonny Island (western part of the study area). The methodology that was employed for this study is represented in Fig. 2.

2.3. Coastal Vulnerability Index computation

The present study uses the original CVI proposed by Gorntiz et al. (Sheik Mujabar and Chandrasekar, 2013) which is based on six parameters. The first step is to determine the ranking for each of the parameters. The coastal vulnerability index is computed after each of the parameters for the coastline has been given a rank based on particular data for that characteristic or parameter. This coastal vulnerability index is determined by taking the square root of the product of the rated parameters and dividing that result by the total number of parameters. Alternatively, it can be determined by obtaining the geometric mean and then take its square root. As can be seen in the following formula, the expression for computing CVI is as follows:

$$CVI_1 = \sqrt{\frac{\alpha_1 * \alpha_2 * \alpha_3 * \ldots\ldots \alpha_n}{n}} \tag{1}$$

where α_1 denotes the Coastal elevation (m), α_2 denotes the Global Sea level rise rate (GSLR) (mm/yr), α_3 denotes geomorphology, α_4 denotes the shoreline changes rate (m/yr), α_5 denotes the mean significant wave height (m), and α_6 denotes the mean tidal range (m).

The CVI is computed for every location, in this instance, within an interval of 50m along the 130km shoreline length. After then, several fundamental parameters were computed for the entire length of the coastline. These statistics include the mean, the standard deviation, as well as the 25th percentile, 50th percentile (or the median), and 75th percentile. According to the classifications proposed by Thieler and Hammar Klose (Kulp and Strauss, 2018) as well as the quartile values, every location has been assigned into a category among these four, which are expressed using the percentile ranges: 75–100% (very high vulnerability), 50–75% (high vulnerability), 25–50% (moderate vulnerability), as well as 0–25% (low vulnerability).

2.4. Parameters for coastal vulnerability

The parameters that determine CVI's performance differ based on scale, data type, and data availability. However, there are six subcategories that are used to express the parameters of geologic and physical processes. These are as follows: mean tidal range, mean wave height, relative sea level rise, geomorphology, rate of shoreline change, and coastal elevation. Table 1 summarises all the parameters that were utilised, including the spatial resolutions for the data that were available, its format, the time frame, and the sources of the data.

The weights that are assigned to each variable are given a rank that is scaled from 5 to 1. This scale ranges from one extent to the other extent to reflect the severity of the vulnerability. As can be seen in Table 2, the value of 5.0 denotes a vulnerability class that is considered to be extremely severe, while the value of 1.0 denotes a vulnerability class that is considered to be low. The ranking that Gornitz et al. (Gornitz

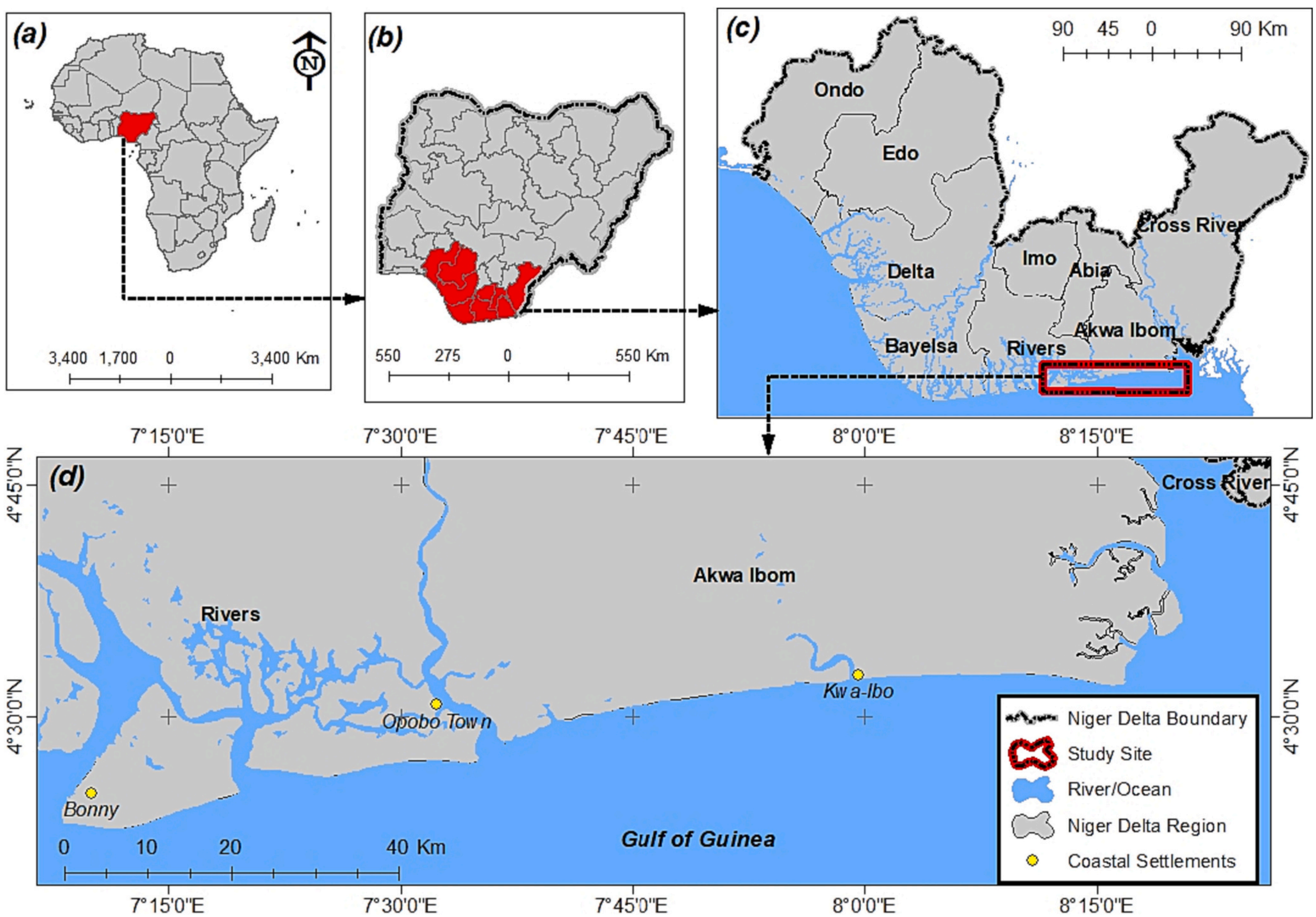

Fig. 1. Map showing (a) Africa (b) Nigeria and (c) Niger Delta Region (d) Study Site.

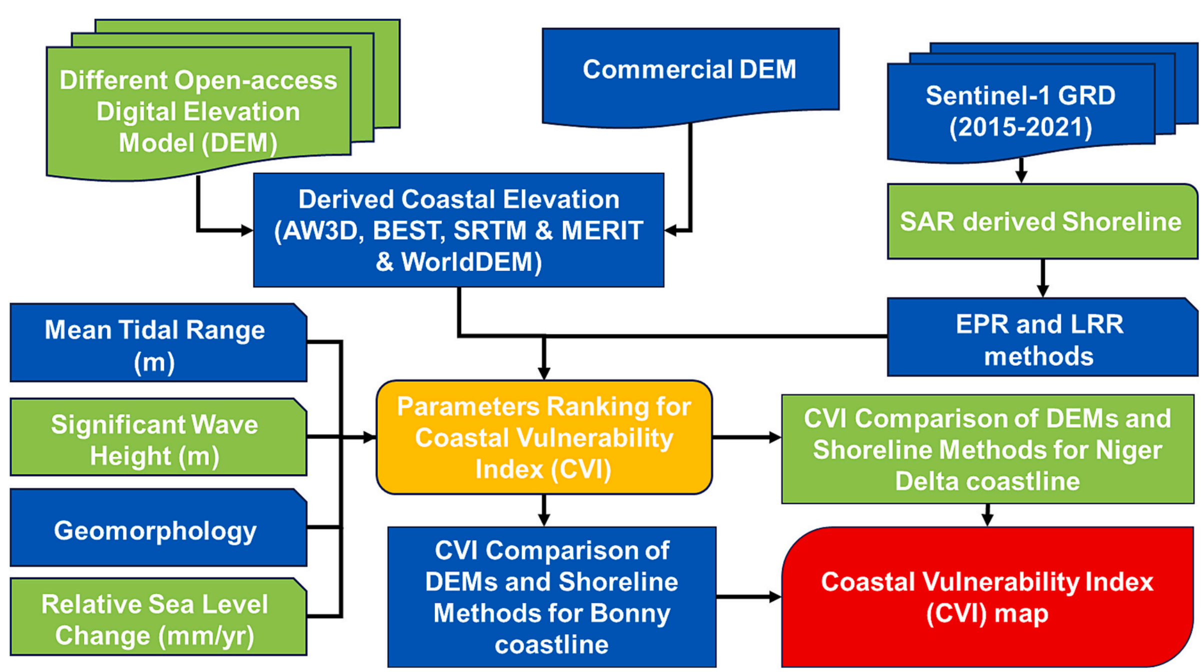

Fig. 2. Flow diagram for assessment of CVI.

et al., 1991) came up with was used in this investigation because it was able to give a common scale that enabled direct comparison on the ranking for each parameter that were produced from various datasets.

It is noteworthy to state that some considerations are made for each test. The coastline elevation parameters and the shoreline change rate are the two primary sets of parameters that are used in each test. For

Table 1
Parameters utilised on this research.

Parameter	Spatial resolutions (m)	Data format	Source of data	Date of data acquisition
Coastal elevation				
(i) SRTM	30.0	GeoTiff	SRTM (USGS, 2021); USGS (USGS, 2021); Earth Explorer	2000
(ii) AW3D	30.0	GeoTiff	Jaxa (Jaxa, 2003; Jaxa, 2021).	2015
(iii) MERIT	90.0	GeoTiff	Yamazaki et al. (Yamazaki et al., 2017); Yamazaki (Yamazaki, 2018); University of Tokyo's MERIT DEM;	2000, 2015
(iv) BEST	90.0	GeoTiff	Amatulli et al. (Amatulli et al., 2020); Jarvis et al. (Jarvis et al., 2008); University of Bristol's Bare-Earth SRTM (Bare-Earth SRTM, 2015; SRTM, 2018)	2000, 2003, 2009, 2011
(v) WorldDEM-DTM	12.0	GeoTiff	AirBus (AirBus, 2023)	2014
Shoreline change Rate (m/yr)		Vector	Sentinel-1 GRD SAR-Derived imagery (Dike et al., 2023; Sentinel-1 Data, n. d.)	2015, 2016, 2017, 2018, 2019, 2020
Mean tidal range (m)	Not applicable		Reports on Pilot Study (Usoro, 2010)	
Significant wave height (m)	Not applicable		Reports on Pilot Study (Nwaokocha et al., 2015)	
Relative sea-level rise	Not applicable		IPCC Reports (IPCC, 2019; IPCC, 2022)	
Geomorphology	Not applicable		Reports on Pilot Study (Sexton and Murday, 1994)	

each test, these parameters are used. They are generated through the use of various methodologies as well as datasets. The tests are performed with all other variables held constant.

2.5. Parameters and descriptions

2.5.1. Shoreline change rate

The shoreline rates were calculated from shorelines between 2015 and 2020, derived from Sentinel1 images using methods described in recent literature (Dike et al., 2023). When calculating shoreline change rates, two distinct approaches are utilised: the linear regression rate (LRR) and the end-point rate (EPR). The rates are computed based on the intersections of coastal transects and intercepts that are spaced every 50 m along the coast. The EPR technique determines the rate of shoreline change by dividing the distance that separates the most recent shoreline from the oldest shoreline by the amount of time that has passed since the most recent shoreline was formed (Mirdan et al., 2023). The LRR method determines the rate of shoreline change by taking into account all of the shorelines that are currently available. The shoreline change is computed by fitting a regression line with least-squares to all shoreline positions across an established transect (Gibbs et al., 2019). The regression line is calculated by squaring the distance of each shoreline data point from the regression line and adding the squared residuals (Himmelstoss et al., 2018.). Depending on the time period under investigation (seasonal, annual, decadal), estimates from these two methods can vary significantly (Dwarakish et al., 2009).

The calculations for the rates were achieved using statistical tools with the use of a software application called Digital Shoreline Analysis System (DSAS), which is an extension for the ArcGIS software and was produced by the United States Geological Survey (USGS). This is corroborated with a CVI study conducted in the USA (Thieler and Hammar-Klose, 2000). The DSAS is an advanced and reliable statistical system that measures the rates of change from historic coastline positions utilising a variety of statistical techniques. DSAS has both robust and automated features for computing statistical rates (Mani Murali et al., 2013; Himmelstoss et al., 2018). In addition to being available for free, the DSAS tool has undergone extensive validation in a variety of environments across the United States and globally. In the current investigation, vector-based coastline locations from 2015 to 2020 acquired from Sentinel-1 GRD SAR satellite data were analysed in two distinct ways to determine shoreline change rates. These methods were referred to as EPR and LRR. The erosion and accretion susceptibilities of these shoreline change parameters were ranked. Based on the CVI assessment ranking, when compared to another coastline, one that has negative shoreline change rates (also known as high erosion rates) is considered to be in a more precarious position than one that has positive shoreline change rates (also known as high accretion rates). In other words, the coastline that has a positive shoreline change rate is considered to be less vulnerable than a coastline that has a negative shoreline change rate. According to Yin et al. (Yin et al., 2012), a higher negative shoreline change rate indicates a region that is at high risk. Table 2 provides the ranking and classification information.

Table 2
Coastal vulnerability index showing rankings of the parameters.

Parameters	Ranking parameter for CVI				
	Very high	High	Moderate	Low	Very low
	5.0	4.0	3.0	2.0	1.0
Coastal elevations (m)	<5.00	5.10–10.0	10.10–20.0	20.10–30.00	>30.0
Shoreline changes (m/yr)	≤ -2.00	−1.10 to −2.00	1.00 to +1.00	1.00 to 2.00	>2.10
Sea level rise (SLR) rate (mm/yr)	>3.16	2.95–3.16	2.50–2.95	1.80–2.50	<1.80
Average tidal ranges (m)	<1.00	1.00–1.90	2.00–4.00	4.10–6.00	> 6.00
Average wave heights (m)	> 1.25	1.05–1.25	0.85–1.05	0.55–0.85	<0.55
Geomorphological features	Barrier beach, coral reefs, mangrove, deltas, sand beach, salt marsh, mudflats, coral reefs mangrove,	Cobble beaches, lagoons, estuaries,	Lower cliffs, alluvial plains, glacial drift,	Mid-level cliffs, indented coasts,	Fiords, rocky cliff coasts,

(Source: (Gornitz et al., 1991)).

2.5.2. Coastal elevations

Coastal elevation is a significant factor since the sensitivity towards sea level rise shows vulnerability to storm surge. Coastal elevation is one of the parameters for episodic coastal flooding. Studies have also found that regarding coastal elevations, episodic coastal flooding decrease at higher elevation (Gornitz et al., 1991). Coastal flooding can be caused by both rising sea levels and storm surges. In this study, the coastal elevation is derived from on-land elevation since the available open commercial-access DEM raster grid does not cover nearshore elevation. In order to match the coastal elevation, the study utilised a spatial interpolation approach based on the delineated shoreline position from SAR imageries using the GIS application. On the other hand, the transect line was used as the interpolation guide to aid in the extraction of the coastal elevation. According to the CVI evaluation ranking, coastal locations that have low-lying elevations are considered to be very vulnerable, whereas coastal areas that have higher elevations are considered to be less vulnerable (Gornitz et al., 1991). Additionally, vulnerability decreases with distance from the coast. Suitable vulnerability assessment would require high resolution elevation models (e.g., 1m–5m) with adequate vertical accuracy. For the purposes of this investigation, coastal elevation characteristics were obtained from open-access and commercial sources. For instance, SRTM, AW3D, Bare-Earth DEM (BEST), and Merit-DEM are open-access DEMs that will be utilised in the study, while WorldDEM is the commercial DEM.

2.5.3. Other parameters

2.5.3.1. Geomorphology. The geomorphology and geology are associated with coastal response to natural drivers of change. According to Gornitz and Kanciruk (Gornitz and Kanciruk, 1989), coastal resistance to erosion is dependent of bedrock lithology, coastal landforms, and shore material. In this study, only geomorphology is considered and is described as being deltaic, with sandy beaches and estuarine landforms (Sexton and Murday, 1994). These landforms are classed as “very high” in terms of their susceptibility considering they are extremely susceptible to spread out as wave erosion. More information on this can be seen on see Table 2.

2.5.3.2. Relative sea level changes. The understanding of the influence of relative sea level change in coastal management is also important in this study. Even though the Permanent Service for Mean Sea Level (PSMSL) compiles annual mean sea level (MSL) as well as monthly mean sea level (MSL) readings via a network of tidal gauges that is global, there is lack of data availability on PSMSL for the research region. Rather, the rate of sea level rise was determined by taking into account a report produced by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2021), which stated that the rate of change in sea level for the region was 3.2–4.2mm per year for data covering 2006 to 2018. This was used to make the decision. This rise in sea level is considered to be of a very high severity when compared to the degree to which the region is at risk or vulnerable.

2.5.3.3. Mean wave height. The wave energy is the most responsible for shoreline changes. The mean wave height (MWH) parameter is utilised so that exposure to wave energy can be taken into consideration. Primarily, wave height data are derived from wave-rider buoy observations (Mounet et al., 2023). Meanwhile, some studies have leveraged the development of several models for determining mean wave height on a global scale. However, it is difficult to acquire globally accurate and exhaustive validation data for wave energy models. This is due to the limited availability of observational data for different regions, which can hinder the validation process, making it difficult to assess the model's accuracy across diverse geographic locations (Laignel et al., 2023). Thus, this study will be based on previous literature on mean wave height in the Niger Delta region. Studies have found that the mean wave height within the Niger Delta region varies from 1.80 to 2.40 m between Bonny and Cross River (Nwaokocha et al., 2015). Also, this range belongs to the highly vulnerable category.

2.5.3.4. Mean tidal ranges. Tidal range is a vital variable which is linked to the two flood types, namely the episodic coastal flooding and the permanent coastal flooding. Shaw et al. (Shaw et al., 1998) as well as Gornitz et al. (Gornitz et al., 1991) considered a coastal region that has a high tidal range and one that is characterised to be extremely vulnerable. In contrast, Thieler and Hammar-Klose (Thieler and Hammar-Klose, 2000) considered macro-tide areas that are less vulnerable than micro-tidal areas due to the fact that storm surges occur at high tidal levels. This is because macrotidal areas are further away from the coast. In spite of this, the classification developed by Gornitz et al. (Gornitz et al., 1991) will be applied here. According to Usoro (Usoro, 2010), the mean spring tide range between Bonny River and Cross River ranges from 1.9 m to 3 m. This information was used to determine the tidal range for the region under investigation. The vulnerability associated with this tide range is rated as moderate. Further information can be seen on Table 2.

2.6. Comprehensive detail on tests

Table 3 provides a summary of various assessments for Shoreline Change Rate and DEM combinations utilised on the investigation.

3. Results

In this section, the results for the shoreline change rate and coastal elevations rankings are firstly compared. Following this, an examination of the sensitivity of CVIs to various coastal elevation (DEM) inputs and shoreline change methods is conducted.

3.1. Rankings for the shoreline change rates

Fig. 3 and Table 4 illustrate rankings for the shoreline change rates for a 130-kilometre stretch of the Niger Delta coast using LRR and EPR statistical approaches. In general, most of the rankings are within a similar range, and there is a general agreement along the coast (see Fig. 3). About half of the coastline is described to be highly vulnerable (for LRR) and slightly more than half (for EPR). Conversely, almost one third of this coastline can be described as having a very low vulnerability level. When the two methods are compared, the fraction of the total shoreline length that is ranked and classified to the groups of low, moderate, and high susceptibility has <1.5% as the percentage point difference between them. The difference between the percentage of total shoreline length that is listed as very high vulnerability and the percentage that is ranked as very low vulnerability has grown, but it remains as lesser than 5% (6.5 km). The findings indicate that although there are some changes in the rankings of shoreline change rate based on the various methods used, these variations have a small impact on the rankings despite the fact that there are some disparities in the rankings.

3.2. Ranking of coastal elevation

The spatial distributions regarding the coastal elevation rankings along a study region is depicted in Fig. 3, while the statistical distribution regarding the coastal elevation rankings along a study region is

Table 3
Comprehensive detail on the tests for this research.

DEMs/shoreline change rate	WorldDEM	AW3D	MERIT	BEST	SRTM
EPR	+	+ –	+ –	+ –	+ –
LRR	+	+ –	+ –	+ –	+ –

Note: + Bonny coastline, – Niger delta coastline.

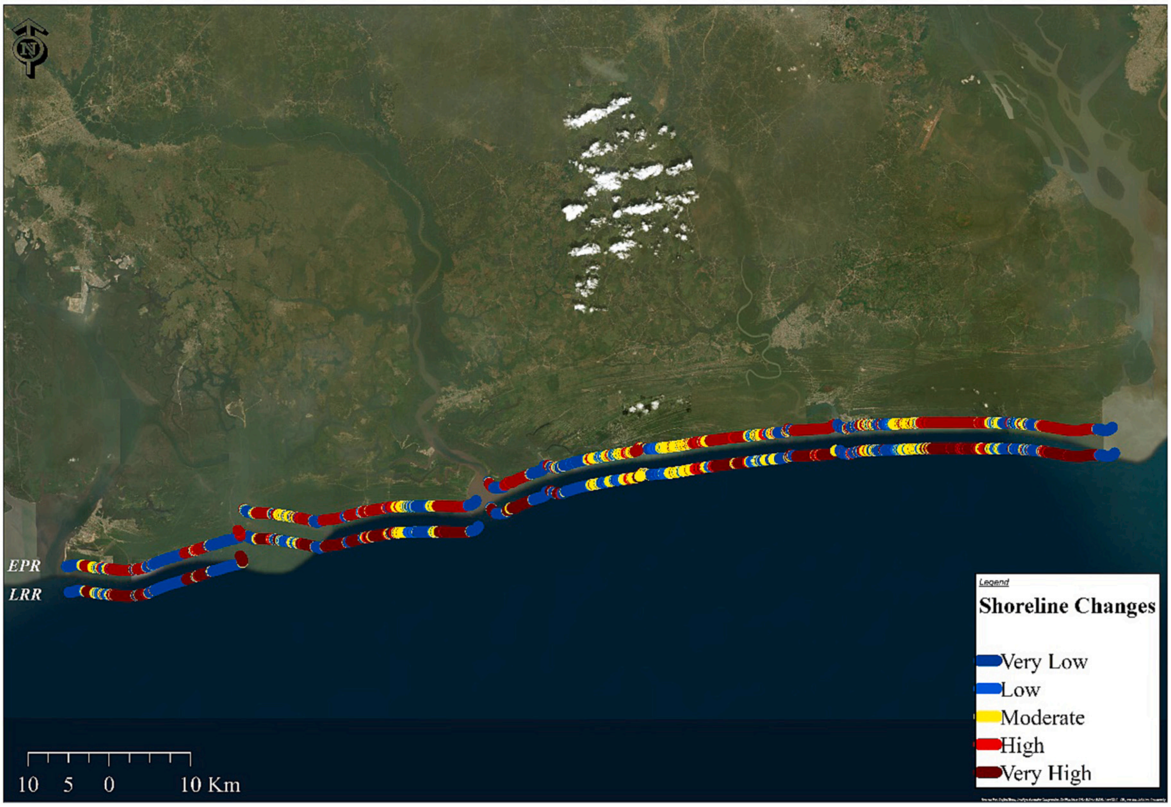

Fig. 3. Using EPR and LRR data for the ranking of the rates of shoreline change along the coast of the Niger Delta.

Table 4
The Shorelines change rankings utilised on the Niger Delta region.

Ranking	Very low	Low	Moderate	High	Very high	Total length (km)
LRR	39.7	10.4	22.7	7.7	50.0	*130.5*
%	*30.4*	*8.0*	*17.4*	*5.9*	*38.3*	*100.0*
EPR	33.5	8.6	24.6	7.9	55.9	*130.5*
%	*25.6*	*6.6*	*18.9*	*6.1*	*42.8*	*100.0*

depicted in Fig. 4. These rankings were produced from the various DEMs used in the analysis. As can be seen in these figures, the spatial distributions regarding the coastal elevation ranking changes across the coast but also depends on the DEM used.

The spatial distributions on the coastal elevation rankings obtained by using the MERIT DEM are depicted in Fig. 4, and the results suggest that the whole coastline of 130km is either considered to be extremely vulnerable or very highly vulnerable. When the BEST, AW3D, and SRTM datasets are taken into account, certain parts of Bonny, the Cross River mouth as well as the Ibo River, are all classified as having a high risk of vulnerability. The moderate-level coastal elevation rankings that were produced for MERIT share a certain resemblance with those that were derived from other products, notably throughout the central and eastern regions of the coastline. However, there are considerable variances between products, so these rankings should not be used interchangeably. When the BEST DEM is used, the differences become readily apparent, specifically in certain areas of Bonny as well as the direction of Cross River. When compared to the rankings that are obtained by using other DEMs, the usage of the AW3D DEM results in more parts of the coastline being classified as belonging to the low vulnerability class. This is the case in the middle section of the coastline.

When employing a variety of DEMs, the fraction of total shoreline that is given to each class is broken down and summarised in Fig. 5. When DEMs with a resolution of 30m are used (STRM and AW3D), the most extensive area of the coastline is categorised as having a high risk of erosion. Despite the fact that an agreement has been reached, there are still proportional variations between the rankings of each coastline. When DEMs with a resolution of 90m were used, the extremely high vulnerability category was allocated to the majority of the shoreline for MERIT, while the moderately susceptible class was assigned to the majority of the shoreline for BEST. In terms of the percentage of shoreline that fell within each category, BEST and SRTM were the most comparable to one another. In light of this, it appears that the vertical accuracy of the DEMs or the post-processing of bias of the DEMs plays an essential influence in the resulting rankings. This is in addition to the DEMs' high spatial resolution. In general, when comparing MERIT and BEST ranks, the bulk of ranking variances are equivalent to one category, although a small fraction of the coastline (3.9% of it) has a difference of two rankings. This is because the MERIT rankings are based on scientific evidence rather than subjective opinions. There is a high possibility that the CVI assessment result will be greatly impacted by the unpredictability in the coastline elevation ranking.

3.3. *The rankings for the coastal elevations along the Bonny coast*

Fig. 6 provides a concise overview of the percentage of a stretch of 12.2km of Bonny Island's coastline that correlates to various coastal elevation rankings. In this investigation, the elevation rankings that were gained from publicly available products such as SRTM, AW3D, BEST, as well as MERIT are contrasted with the rankings that were derived through data having high resolutions. It was collected from WorldDEM, which is a private company that commercialises data. It is interesting to note that 7.7% of the coastline was observed to be in this class when AW3D is used. When BEST is used, only 7.1% of the coastline was observed to be in this class, but when MERIT is used, it is higher at 26.4% of the coastline that was observed to be in this class, while 21.9% of the coastline was observed to be in this class when SRTM is used. When the WorldDEM was used, the entire coastline is categorised as

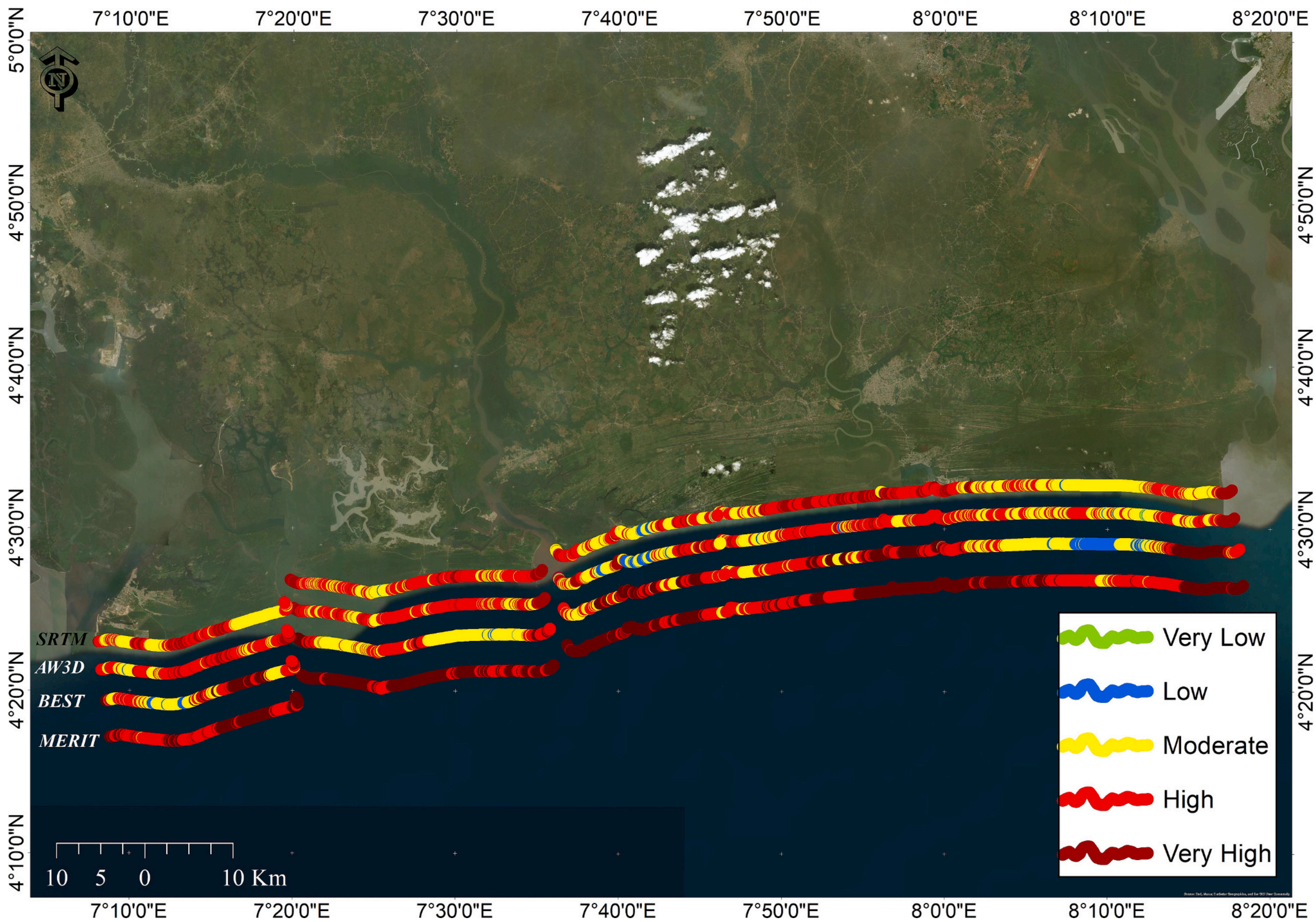

Fig. 4. Mapped rundown of the Niger Delta coast ranking regarding coastal elevation.

highly vulnerable coastline, or very high. The combination of BEST and AW3D is sufficient to assign a low-risk status to any given length of coastline. There is a discrepancy in the ranks for 73.2% of the coastline between MERIT and WorldDEM, with MERIT having a higher score for the very high vulnerability group. However, WorldDEM terrain models have distinct rankings, with differences of 27.5% (AW3D), 39% (SRTM), and 52.5% (BEST) respectively. In addition, among the observations are the differences found on these two rankings between BEST as well as AW3D (which is responsible for 7.78% of the coastline). The differences among DEMs are mostly found in one ranking compared to MERIT and BEST, although for a tiny portion of the coast, they can be observed in both rankings at the same time. This could be the effect of the spatial resolution and the way that these models deal with elevation error.

3.4. The CVI estimations

The CVI metrics that have been estimated are presented in Table 5, and they are based on a variety of shoreline change rates and coastal elevations. It is evident from the tabulated data that the criterion for each of the estimated CVIs differ, most noticeably in the 75th, the 50th (or median), as well as the 25th percentiles. In addition, the difference determined depends upon the DEMs as well as the shoreline change rates which are the variables that are used. When paired with LRR, the DEM products all yield results that are equivalent to one another, except for the AW3D in its 25th percentile. Table 5 presents CVI criterion estimated based on various shoreline change rates and coastal elevations. From the table, it is evident that the criterion for each of the calculated CVIs vary, particularly in the 25th, 50th, and 75th percentiles, and that the difference is dependent on the selected shoreline change rate and DEM. With the exception of AW3D at the 25th percentile, all DEM products produce comparable results when combined with LRR. Table 5 also displays the average value for the entire CVI percentile values to ensure uniformity in the exposure classification. In most contexts, percentile greater than 75th is one that is above-normal percentile or simply defined as the percentile that is more than 75th. It is considered normal to have a percentile that falls between 25th and 75th. Below normal is defined as having a percentile that is less than 25th. Also, the 50th percentile is also same thing as the median value, as seen in Table 5. Average CVI values are used to categorize vulnerability levels, with values below 16.3 representing low vulnerability, between 16.4 and 25.0 representing moderate vulnerability, between 25 and 32.1 representing high vulnerability, and above 32.1 representing very high vulnerability.

3.5. Vulnerability map for the Niger Delta coast

Fig. 7 shows the vulnerability map along the Niger Delta Coast using CVI classification. It indicates that, for various combinations of EPR and LRR shoreline change rates and DEM products, the percentage of shoreline length in various vulnerability classes. According to the findings, which depends upon the shoreline change rates and DEMs, between 40.1% and 58.9% of the coastline is classified as high or very high vulnerability, 15.5–30.0% as moderate vulnerability, whilst 20.5–30.7% as low vulnerability. The proportion of vulnerable coastline grew when the EPR method was used for calculating the shoreline change rate instead of the LRR method, while the proportion of least vulnerable coastline reduced. When using the shoreline change rates which are derived from EPR, about 5%–6% of the coastline was elevated to higher

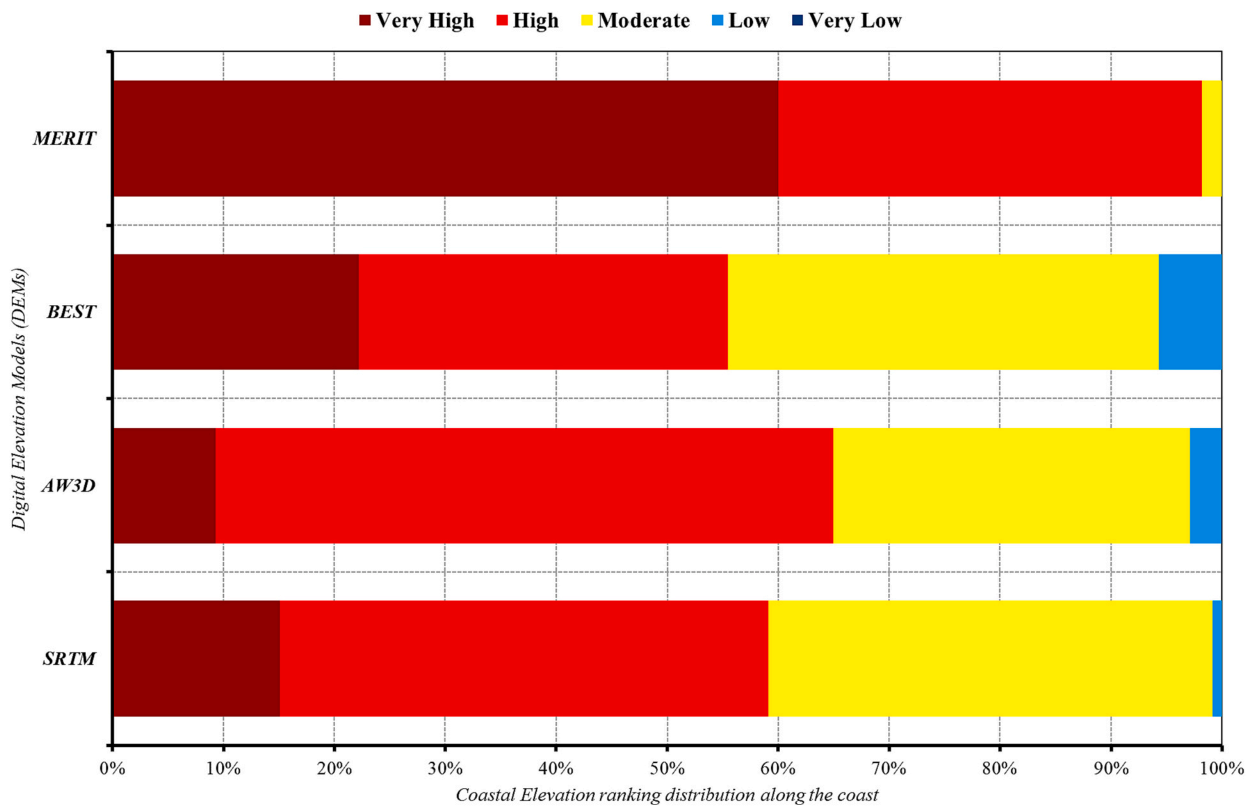

Fig. 5. Plotted rundown of the Niger Delta coast ranking in terms of the coastal elevation.

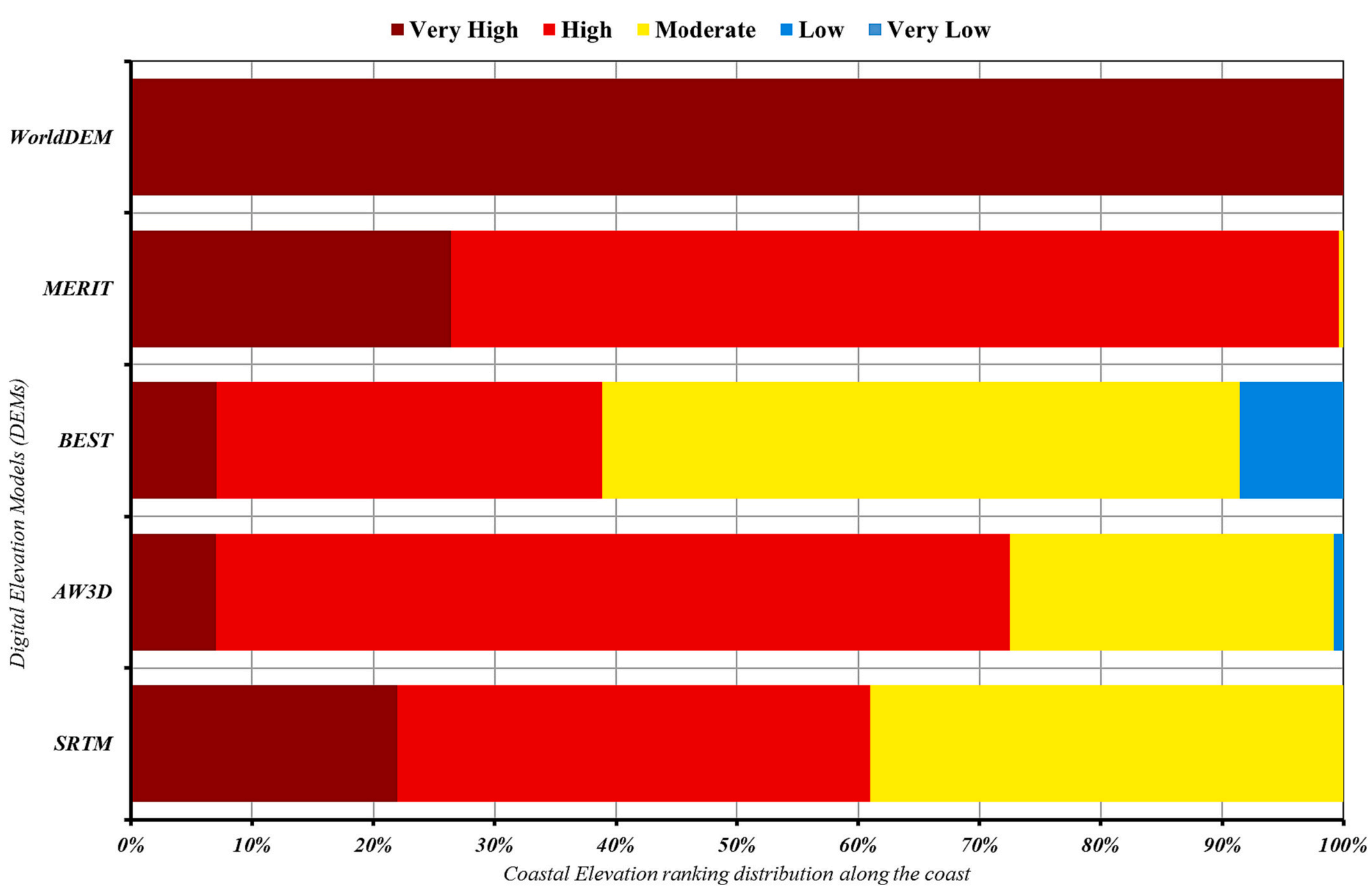

Fig. 6. Plotted rundown of the Bonny coast ranking in terms of the coastal elevation.

Table 5
The computed table for the CVI criterion used to categorize the risks.

Parameter	Metrics on DEMs	Minimum	Mode	Means	S.D.	Median or 50th percentile	75th percentile	25th percentile
	MERIT	12.2	35.4	25.7	8.1	27.4	35.4	15.8
	BEST	10.0	27.4	23.0	7.7	22.4	28.3	15.8
	AW3D	7.1	31.6	23.0	7.3	24.5	31.6	14.1
LRR	*SRTM*	10.0	27.4	23.1	7.3	24.5	31.6	15.8
	MERIT	12.2	35.4	26.6	7.8	27.4	35.4	20.0
	BEST	10.0	27.4	23.8	7.4	24.5	31.6	15.8
	AW3D	7.1	31.6	23.9	7.1	24.5	31.6	15.8
EPR	*SRTM*	10.0	31.6	24.0	7.2	24.5	31.6	17.3
	Total mean	9.8	31.0	24.1	7.5	25.0	32.1	16.3

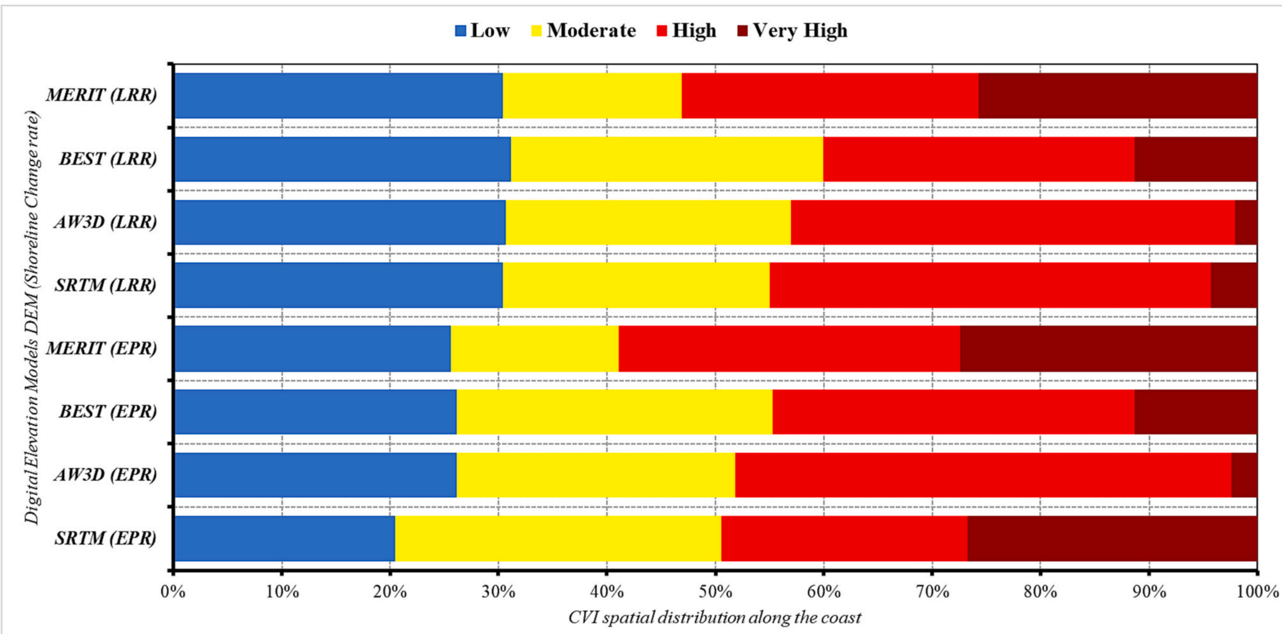

Fig. 7. A rundown on the CVI data obtained across the coast of the Niger Delta region.

vulnerability category. In contrast, when different DEMs are utilised, the percentage variations between vulnerability classes are higher. The results for BEST DEM as well as MERIT DEM found the largest difference (12%). In spite of this, differences remain within a single class, as they do for the ranking of the elevation parameter.

3.6. Categorizing vulnerabilities for the Bonny coastline

Fig. 7 illustrates the proportional length of the shoreline in various vulnerability categories. It was determined by utilising various DEMs as well as shoreline change rates (LRR and EPR). This information was derived from the analysis of the Bonny coastline. The results reveal that the shoreline change rates have a far lesser from the effect on the computed CVI compared to the coastal elevation which had a far greater effect on the computed CVI than the shoreline change rates, which was the situation whilst this entire shoreline was under study. The biggest percentages for this coastline were recorded when the coastal elevation was derived via WorldDEM. It was determined to be 60.2% for EPR while the LRR was found to be 56.4%. In addition to this, it was given the classification of being very highly vulnerable or highly vulnerable. Given that a vulnerability ranking based solely on elevation would classify this entire stretch of coastline as highly to very highly vulnerable, the combination of parameters decreased the proportion of the coastline in this category.

The distinctions between classes are not particularly significant. In a comparison of results obtained from WorldDEM and other freely available DEMs, the percentage of coastline assigned to different categories shows the most disparities at the very high vulnerability category. Also, in the lowest vulnerable category, the variations observed are at their smallest degrees (see Fig. 8). Thus, categorizing vulnerabilities for this Bonny coastline has been achieved using the CVI approach. Each classification has been observed to be a proportion of the effects resulting from the parameters like storm surges and elevation of the shorelines. However, further study on the flood mapping and use of cognitive approaches for the vulnerability maps are recommended in future study.

4. Discussions

This study highlighted the potential of employing CVI methods on open-access data in countries with limited data availability, including DEMs and shoreline change rates derived from Sentinel-1 GRD images. Along the Niger Delta coastline, the estimated vulnerability differs. Irrespective of the shoreline change rate or DEM employed, a total of 40.1% to 58.9% of the coastline was classified as extremely or extremely highly vulnerable to SLR. This contradicts the previous research by Oyegun et al. (Oyegun et al., 2016), which categorised the entire coastline as high and very high vulnerability. They assessed CVI across the entire Niger Delta using 1986–2010 data which is long-term position of the shoreline and parameters derived from SRTM such as the shoreline elevation as well as coastal slope, among others. According to the findings of this investigation, between 35% and 60% of Bonny Island's

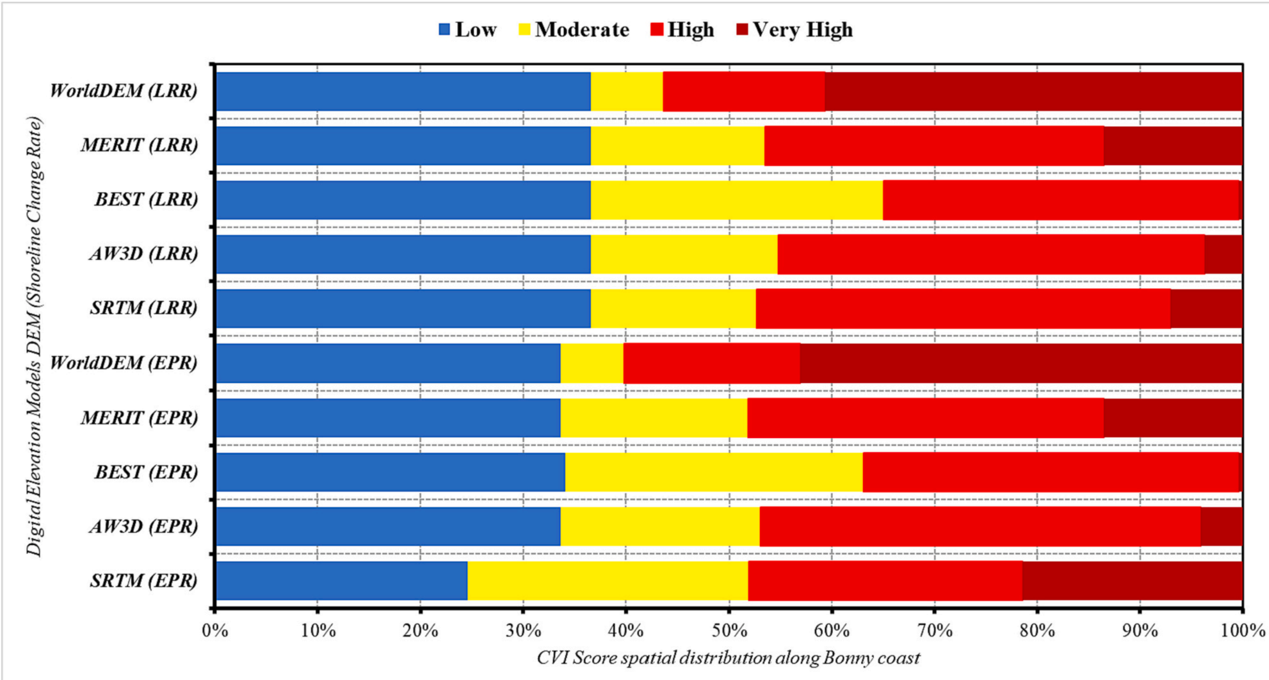

Fig. 8. A rundown on the CVI data in this region for the Bonny coast.

shoreline is either highly vulnerable or have very high vulnerability. Thus, it is consistent with an earlier investigation by Musa et al. (Musa et al., 2014), which reported that the easternmost portion of the coast, from Bonny to Opobo, has the highest proportion of high to very high SLR vulnerability. Their study employed a novel approach to evaluate CVI by incorporating physical factors such as predicted shoreline change, SRTM-derived coastal slope/elevation, and five additional criteria related to social and human effect. The results clearly demonstrate that classifications can vary significantly, as CVI estimations are contingent upon the assessment method, parameter ranks, and data utilised. The presence of errors in estimating vulnerability can impact coastal management. It is necessary to minimise or accurately measure the uncertainties related to the CVI approaches, as discussed by Koroglu et al. (Koroglu et al., 2019).

In regions devoid of ground truth data, the estimation of uncertainties presents an enormous challenge. Conversely, the sensitivity of CVI estimates to various parameters, methods, and rankings can be examined, as demonstrated in this study (e.g., Koroglu et al. (Koroglu et al., 2019)). This can subsequently aid in identifying the regions exhibiting disparities in rankings, necessitating subsequent monitoring in the future. This study examined the impact of shoreline change rates and digital elevation models (DEMs) on the accuracy of the coastal vulnerability index (CVI) calculations. Consistency was maintained in the study by using the same approach and ranking criteria. Different shorelines change and DEMs, along with other geomorphology and physical factors, were utilised, while ensuring that these parameters remained constant. Although the study utilised the same 5-year shoreline position data obtained from Sentinel 1 imagery, it revealed that the ranking of 1.5–5% of the coastline can vary depending on the approach employed to estimate the rate of shoreline change and therefore determine the ranking (Fig. 3 and Table 5). The disparity in ranking can impact the comprehensive evaluation of susceptibility. The findings of this study indicate that the EPR method yielded higher rates of change estimation, leading to a greater allocation of coastline to the high and very high-risk categories. For example, the headland at Bonny, the mouth of the Andoni River, the vicinity of the Imo and Ibo rivers, and the area near the mouth of the Cross rivers are regions where littoral erosion predominates in the CVI. In other investigations, disparities in shoreline change rate between the EPR and LRR methodologies have been documented. According to the study by Kankara et al. (Kankara et al., 2014), while EPR proves to be beneficial in assessing short-term shoreline change, it possesses intrinsic constraints when applied to long-term shoreline change due to its consideration of only two shorelines. In contrast, the LRR method accounts for all shoreline positions, rendering it compactable for linear change in both space and time (Chand and Acharya, 2010). This implies that utilising LRR estimations may offer greater reliability for future research, perhaps resulting in the classification of up to 10% of the coastline into a higher vulnerability category. This study established that the rate at which the shoreline changes is the main factor contributing to the small-scale variance in the Coastal Vulnerability Index (CVI), which aligns with prior research conducted by Thieler and Hammar-Klose (Thieler and Hammar-Klose, 2000), Abuodha and Woodroffe (Abuodha and Woodroffe, 2010), and Gaki-Papanastassiou et al. (Gaki-Papanastassiou et al., 2010). The findings differ from those reported by Thieler and Hammar-Klose (2000), who observed that coastline erosion has a greater influence on the CVI, even when other factors are held constant or vary. In addition, the uncertainties related to the rates of shoreline change are not solely caused by the methods used to calculate these rates. They also arise from the process of determining the shoreline positions using satellite images. For example, errors in the shoreline position can range from 10 to 430m (Dike et al., 2023), which in turn can impact the rate of shoreline change and the Coastal Vulnerability Index (CVI) estimates.

The assessment of coastal vulnerability relies heavily on local coastal elevation, as extreme weather events can cause sea levels to rise over the maximum elevation, resulting in flooding. Although open-access data has made some progress in enhancing spatial resolution and vertical accuracy, it still falls short of being optimal for estimating local coastline elevation, especially in vegetated regions. This study evaluated the impact of four open-access DEMs (SRTM, BEST, MERIT, and AW3D) and one commercially accessible DEM (WorldDEM) on the accuracy of CVI estimates. The DEMs had spatial resolutions ranging from 12 to 90m and varied in vertical accuracy. The spatial variability of the CVI was primarily influenced by the coastal elevation parameter, as anticipated. The method by which coastal elevation is derived from the DEM has a significant impact on the estimated vulnerability of the coastline. Figs. 4

and 5 illustrate a ranking discrepancy ranging from 0 to 1 in accordance with the DEM employed. Qualitative assessment on the location with different rankings showed that these were mainly areas with lots of tree cover, indicating that vegetation-related height differences (artefacts) in these models might have more influence on the resulting CVI than spatial resolution. The disparity in rankings, nevertheless, widened when comparing the rankings computed using open-access DEMs to those obtained from commercially available DEMs with authorised vertical accuracy and a 12 m resolution. Accordingly, local estimate coastal elevation and vulnerability rankings will be impacted by spatial resolution, particularly along coastlines with varied topography along the shore. The DEM that showed the highest degree of similarity in ranking across commercially available options was MERIT. If the commercially available Digital Elevation Model (DEM) has been verified using ground truth data, then the MERIT DEM would be the most optimal open-access alternative. Nevertheless, 66% of the coastline still exhibits a disparity in ranking for one category. This may be attributed to the existence of artefacts in the commercially available high-resolution model, as well as the presence of MERIT. It is still uncertain if all biases have been eliminated from DEMs and if excessive filtering was used. The identical pattern identified in the ranking of coastal elevation can also be discerned in the CVI estimates. The most significant disparities lie in the vulnerability categories classified as high to very high, and it has yet to be determined whether these discrepancies are a result of overestimating elevations using SRTM, BEST, and AW3D.

This study showed that CVI methods can be useful tool for identifying vulnerable coastal areas in data-poor countries but there is still scope for further improvement. There is scope for deriving higher resolution DEMs in data poor countries using satellite images and there is potential for these to be derived from Sentinel 1 images. The land-cover information derived from Sentinel-1&2 images can assist in identifying vegetated areas where elevation data might be of lower accuracy. In this study, coastal elevation, which is mostly used for assessing vulnerability to and risk of coastal flooding was used instead of the coastal slope. The coastal slope parameter has been widely used to calculate CVI around the world and might be more appropriate to use when the main hazard is coastal erosion. This parameter has its own limitations because the ability to generate an accurate near-beach slope is dependent on the proximity of the reference-DEM data to the current shoreline position. Furthermore, previous studies that have used beach slope to assess coastal vulnerability have tended to overestimate slope hence underestimate the extent of flooding (Diaz et al., 2019). It is noteworthy that both open-access and commercial DEMs have similar challenges in the study area in this respect. In future, the nearshore slope derived from higher resolution coastal DEMs will need to be merged with the slope of the beach face, which can be derived from shoreline positions derived from satellite images merged with near shore bathymetry.

Additionally, satellite photography can be utilised to extract other metrics such as wave height, tidal range, and geomorphology categorization (refer to Hamid et al. (Hamid et al., 2021)). In order to account for the spatial differences in Coastal Vulnerability Index (CVI), it is imperative to possess shoreline change data that has been thoroughly vetted. Enhanced resolution and spatial and temporal coverage of shorelines derived from satellite imagery will aid in the reduction of uncertainty in shoreline change rate data. Nevertheless, validation under local conditions will be necessary. Optimisation of littoral detection methods and classification of associated uncertainties can be achieved by considering factors such as the resolution of the image and the methodology employed in satellite image processing. When capturing shorelines, it is important to take into account uncertainties caused by variations in beach slope, wave heights, offset resulting from saltwater light absorption, tidal behaviour, and surge level. Additional attention should be directed towards the rankings (Koroglu et al., 2019) and the methodologies employed (Diaz et al., 2019; Fogarin et al., 2023; Tsai, 2022; Cabezas-Rabadán et al., 2019). Furthermore, this study, like others conducted by Koroglu et al. (Koroglu et al., 2019), demonstrated that conducting a sensitivity evaluation can be useful in pinpointing regions with significant uncertainties (Mishra et al., 2023a; Mishra et al., 2022a; Mishra et al., 2022b; Mishra et al., 2023b), hence indicating the necessity for additional assessment.

The study points out the need for higher resolution DEMs and improved methods for shoreline detection and emphasizes the importance of understanding and reducing uncertainties associated with these methods and data. In conclusion, the study demonstrates the applicability of the CVI method with open-access data for assessing coastal vulnerability in a data-poor country like Nigeria, providing valuable insights for stakeholders and decision-makers in coastal protection and adaptation strategies.

5. Recommendations

The research findings pertaining to the rate of shoreline change and the ranks of coastal elevation in the Niger Delta provide a basis for formulating practical suggestions for researchers and environmental managers. These recommendations are stated as follows:

i. Integrating Multiple Methods for Shoreline Change Analysis: It is recommended to employ a combination of the End-Point Rate (EPR) and Linear Regression Rate (LRR) methodologies in order to conduct a comprehensive analysis, as the rankings of shoreline change exhibit minimal discrepancies between the two approaches. This methodology has the potential to effectively document and analyse both immediate and prolonged alterations in coastal areas, hence enhancing the comprehensive evaluation of susceptibility to coastal hazards.
ii. Utilising Various DEMs for Coastal Elevation Analysis: The research emphasizes notable discrepancies in coastal elevation rankings depending on the digital elevation model (DEM) utilised. It is recommended that researchers and environmental managers use a multi-dimensional approach by utilising various Digital Elevation Models (DEMs) to enhance the accuracy of their assessments about coastal elevation and vulnerability. This approach should involve the utilisation of both open-access DEMs, such as SRTM, AW3D, BEST, MERIT, as well as commercial DEMs, such as WorldDEM. By employing different DEMs and doing cross-validation, a more precise comprehension of coastal elevation and vulnerability may be achieved.
iii. Critical Analysis of DEM Selection: The selection of a digital elevation model (DEM) can have a substantial impact on vulnerability assessments. Environmental managers are advised to conduct a thorough examination of the spatial resolution, vertical accuracy, and post-processing biases associated with digital elevation models (DEMs). In regions characterised by intricate topography or substantial vegetation, it is advisable to prioritise the utilisation of higher resolution Digital Elevation Models (DEMs) or those that have undergone more effective bias correction techniques.
iv. Regular Updating of Coastal Vulnerability Assessments: The study proposes that it is essential to conduct periodic updates of vulnerability assessments in coastal areas, incorporating the most up-to-date information on shoreline change and coastal heights.
v. Incorporating Local Data and Ground-Truthing: It is advisable to complement satellite data and digital elevation models (DEMs) with locally collected ground-truth data whenever feasible. This methodology has the potential to validate and enhance the outcomes derived from remote sensing and modelling methodologies.
vi. Comprehensive Risk Communication: When communicating risk to stakeholders, such as local communities and policymakers, it is of utmost importance to provide a comprehensive explanation of the potential variability and uncertainty inherent in the

assessments. This variability and uncertainty arise from the utilisation of many methods and data sources.

vii. Developing Adaptive Management Strategies: Considering the diverse range of vulnerability assessments, it is imperative for coastal management methods to possess a flexible and adaptive nature. The capacity to be modified in response to the availability of new data or changing environmental conditions should be ensured.

viii. Focusing on Highly Vulnerable Areas: The prioritisation should be focused on places that have consistently been identified as very vulnerable or exceptionally susceptible using a range of approaches and data sources. These locations should be prioritised for prompt implementation of management strategies, such as reinforcement, controlled retreat, or conservation initiatives.

ix. Research on Local Variability: It is recommended to encourage thorough examinations of localised variations in shoreline dynamics and coastal elevation to gain an in-depth knowledge of the specific elements that contribute to vulnerability in different coastal segments, particularly in areas experiencing notable transformations.

x. Cross-Disciplinary Collaboration: Participate in a collaborative effort across multiple disciplines, encompassing geospatial analysis, oceanography, coastal engineering, and community planning, in order to successfully tackle the complex aspects of coastal vulnerability.

6. Conclusion

This investigation has been carried out to present the applicability of satellite images in data-deficient regions of the Niger Delta region in Nigeria. Thus, data was obtained and analysed using DEMs derived from the satellite images. This study makes use of SAR-derived coastline data for a five-year period (2015–2020) and a number of DEMs acquired from satellite images to compile its findings. In this study, the LRR and the EPR techniques that were employed for ranking the shoreline change rates had their respective results compared. In addition to this, it does comparisons on CVI estimates that were derived utilising various arrangements of combined DEMs and combined shoreline change rates. Additionally, it evaluates the spatial heterogeneity that exists within these estimates. This was accomplished by analysing the elevation rankings provided by a number of different DEMs that were freely accessible online. The findings of this study reveal that there is a variance in CVI estimations along the coastline of the Niger Delta. The results of this study have shown that the CVI approach may be applied with open-access data to evaluate coastal vulnerability in a country like Nigeria that has a shortage of data. This was proved by the findings of this research. Because other parameters were given constant values along the entire coastline, the CVI exhibits a spatial variance that is dependent on the shoreline change method and the coastal elevation that was obtained from the multiple DEMs. This is because other parameters were given constant values along the entire coastline. This variation is due to the fact that some parameters were fixed at their levels throughout the analysis. According to the methodology that is currently being used for ranking, the criteria were given a ranking on a scale that ranged from 1 to 5, with 1 denoting “extremely low” susceptibility and 5 denoting “very high” risk. Other contributions to knowledge include some vulnerability maps that were generated from the sensitivity assessment for this region.

From this study, the examination of data using CVI with both the LRR and EPR approaches were achieved to obtain the shoreline change rate and the characteristics of the vulnerabilities. It demonstrates that there are only slight changes in the regional distribution of vulnerability. The very high vulnerability as well as the very low vulnerability categories are where the researchers found that these changes appeared and were most clearly seen as evident in those sections. Also, it has been demonstrated herein, that the coastal elevation figures in this study that were obtained from the various DEMs has greater impact on the spatial variation of the CVI. When comparison is made to other open-access DEMs, this MERIT product causes the highest and very highest vulnerability categories to be given to a greater proportion of the coastline than any of the other DEMs. In addition, when comparisons are made with other open-access DEMs, the MERIT product resulted within the smallest percentage of coastline falling into the intermediate vulnerability group. The study of CVI utilising LRR and EPR to determine shoreline change rate finds relatively small degree of vulnerability. In addition, it has been demonstrated that the coastal elevation produced from various DEMs has a greater impact on the spatial variance of the CVI. In other words, when compared to other open-access DEMs, the MERIT product places a greater amount of the coastline into groups on highly vulnerable as well as being very highly vulnerable.

The findings offer stakeholders and decision-makers with data as valuable resource for developing strategies on sustainable coastal protection, as well as adapting to threats around climate change in coastal habitat. When it comes to informing coastal preservation decisions, the findings give decision-makers as well as stakeholders with a vital resource to employ. In addition to this, it offers information regarding the region as well as coastal resilience to climate change-related challenges in the coastal environment of the Niger delta. In conjunction with this, it is useful in the formulation of policies and strategies for the implementation of integrated coastal zone management (ICZM). Since satellite image analysis has been highlighted as a potentially potent instrument used to monitor coastal shoreline positions, this research employed it to solve a coastal problem involving the delineation of shorelines using DEMs. Consequently, SAR imagery could be supplemented with optical imagery captured directly or derived from available domains, enabling ongoing reference and accuracy studies for shorelines. In the future, it may be possible to obtain environmental data as well as geographical data in the Niger Delta region of Nigeria utilising other sophisticated image processing techniques.

CRediT authorship contribution statement

Emmanuel Chigozie Dike: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chiemela Victor Amaechi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Salmia Binti Beddu:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Funding acquisition. **Innocent Ikezam Weje:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Funding acquisition. **Bright Godfrey Ameme:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Funding acquisition. **Olumese Efeovbokhan:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Funding acquisition. **Abiodun Kolawole Oyetunji:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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