Towards Efficient Assessment of Coastal Vulnerability to Sea Level Rise

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Abstract

Vulnerability is a compact term that represents an accumulative range of exposure, sensitivity and resilience of a system against both internal and external hazards. In light of this conceptual diagnosis, vulnerability assessment studies can measure the degree of a gap in which the system is vulnerable against various hazards by customizing a quantitative model while qualitative model studies indicate gap points. The results of quantitative models vary according to the adopted formula and the customized parameters. The study aims to improve the efficiency of the "coastal vulnerability index (CVI)" method which is used to assign degrees of coastal vulnerability to sea level rise (SLR).

The study is using a comparative analytical approach to empirically assess the vulnerability of the African coast to SLR based on a selected group of physical and socioeconomic parameters (seventeen parameters). Although the first model, based on a formula of the square root of product mean and the second model, based on a formula of average of the square root of product sum, have a positive correlation with semi-strong relation (+ 0.65), their results are varied. It is found that the first model is used when there is a dominant parameter in the study while the second model is used when there is an equality between parameter weights. Topography associated with proximity to the coast is a dominant factor when assessing the vulnerability of an area to SLR threat.

Keywords: Vulnerability assessment, coastal vulnerability index, formula, sea level rise, African coast.

Introduction

Vulnerability, as a conceptual term, represents the potential threat according to its pillars: exposure, sensitivity and resilience [4]. An assessment of the system's vulnerability to a certain hazard diagnoses weakness points and in other cases, the weakness degree could be estimated. The internal and external variables that impact the system are parameters of the assessment model which can be quantitatively and qualitatively classified into a set of categories in the GIS environment. To accurately determine the vulnerability degrees, parameters should be carefully selected from different aspects due to complicated relations with/within the system. Accordingly, the parameters used in the coastal vulnerability assessment models are intensively connected to climate change impacts and induced sea level rise (SLR). A relatively small increase in SLR could affect natural coastal systems [2]. Coastal sectors are highly dynamic areas in their internal and external variables which are sensitive to any threat from their content and their context.

Thus, the used parameters should be selected with an integrated and comprehensive view to include the variously connected aspects of the coastal system. Accurate assessment helps in minimizing the potential impact of accelerating threats by considering priorities for intervention with treatment and developmental allocation.

Vulnerability assessment methods and tools are varied. Coastal vulnerability index (CVI) is one such method which was created to statistically assess coastal vulnerability. It is widely used in such studies (e.g. Gornitz,[6] Gornitz et al[7], Gornitz et al[5], Thieler and Hammar-Klose[15], Hammar-Klose and Thieler[8], Dwarakish et al[3], McLaughlin and Cooper[12], Pendleton et al[14], Balica et al[1], Loinenak et al[11], Husnayaen et al[9], Kantamaneni et al[10], Mohd et al[13] and El-Shahat et al[4]. Also, it is a relatively functional method for estimating the vulnerability degree of the coast to SLR hazards (i.e. erosion, inundation). It is a functionally aggregated value for the selected parameters (indicators) to assign the coastal vulnerability.

Many CVI formulas identify the coastal vulnerability degree, such as product mean, modified product mean, the average sum of squares, square root of the product mean, sum of products and average of square root of product sum. Accordingly, the CVI formulas were passed with many numerical changes which led to a change in the assessment results. Moreover, any change in the selection and classification of the parameters could source different results. According to the circumstances of the study area, the index formula and its parameters (type, numbers, ranking range) can be set to have accurate results.

As being in table 1, CVI_1 formula was first used in Gornitz[6] and CVI_2 formula is also recently used to assess the coastal vulnerability to SLR. CVI_1 and CVI_2 are used in such cases.

Method and Study Area

The research provides a comparative analytical study. In particular, it will be focusing on two CVI formulas which are used in such studies. To precisely estimate the degrees of SLR vulnerability, an appropriate formula should be selected according to the area circumstances.

Table 1
The widely used formulas of the CVI method.

CVI's Formula	The Formula
The square root of the product mean	$CVI_1 = \sqrt{(x_1 \cdot x_2 \cdot x_3 \cdots\cdots x_n)/n}$
Average of square root of product sum	$CVI_2 = \sqrt{(x_1 + x_2 + x_3 \cdots\cdots x_n)}/n$

where x: parameters and n = number of the parameters.

The study model is based on a cell unit processed in the ArcMap (version: 10.3). African coast had been selected as a case study due to the lack of scientific research and spatial data there. The coast depth had been identified to be 100 km from the shoreline because it contains a high vital value in the natural and human content.

Gornitz[6] introduced CVI as in equation (1) which was later developed to be as in equation (2). Both equations are based on physical and/or socio-economic parameters ($(x_1, x_2, x_3 \cdots\cdots x_n)$):

$$CVI_1 = \sqrt{(x_1 \cdot x_2 \cdot x_3 \cdots\cdots x_n)/n} \quad (1)$$

$$CVI_2 = \sqrt{(x_1 + x_2 + x_3 \cdots\cdots x_n)}/n \quad (2)$$

The vulnerability by definition includes three pillars (E: exposure, S: sensitivity, R: resilience) that could function as in equation (3), or in the same sequence, it could be concluded as in equation (4):

$$V = (E \cdot S)/R \quad (3)$$

$$V = (E + S) - R \quad (4)$$

The selected parameters could be grouped into these three pillars, of which three indices are developed by integrating equations (1) and (3) to be an integral formula as being in equation (5), or the integration between 2 and 4 can be used as in equation (6):

$$CVI = (CEI \cdot CSI)/CRI \quad (5)$$

$$CVI = (CEI + CSI) - CRI \quad (6)$$

where CEI= coastal exposure index, CSI= coastal sensitivity index and CRI= coastal resilience index. The sequence of equation (1) is used to calculate each of these three indices in equation (5). Since equation (6) is based on the sum of parameters, a factor can be added to equation (6) due to the vitality of exposure parameters in accelerating SLR impacts compared to other factors (sensitivity, resilience) as in equation (7):

$$CVI = (0.5 * CEI) + (0.25 * CSI) - (0.25 * CRI) \quad (7)$$

Therefore, the study is based on equation (5) and equation (7) and their results will be analyzed. This methodology will be applied to the study area (Africa's coastal zone) to define the SLR vulnerability ranges based on the ranked parameters into five categories (very low, low, moderate, high, very high) as in table 2. The parameters used in the study are seventeen which were classified qualitatively and quantitatively as in table 9.

Exposure parameters are topography, slope, proximity to the coast, urban population percent, land cover, accessibility, soil type and elements at risk. Sensitivity parameters are vegetation percent, vegetation type, natural resources sensitivity indicator and growth rate. Resilience parameters are indicators of human capital, financial capital, institutional capital, infrastructure and household technology.

Results

Exposure, Sensitivity and Resilience of African Coast to SLR Threat: The mapping results of the first pillar (exposure) by the first model are shown in fig. 1 while the results of the second model are shown in fig. 2. The mapping results of the second pillar (sensitivity) by the first model are shown in fig. 3 while the results of the second model are shown in fig. 4. The mapping results of the third pillar (resilience) by the first model are shown in fig. 5 while the results of the second model are shown in fig. 6.

Vulnerability of African Coast by the First Model: Based on the cell unit (250 * 250 m), the resulted values of the vulnerability had been categorized into five classes in this model. The results had been classified by natural break method: very low (<64), low (65-230), moderate (231-420), high (421-740), very high (>741) as in fig. 7.

The results revealed that most of the eastern and western parts of African coast are ranging between very high to high vulnerability. The very high and high vulnerability had been noticed in West Africa in some coastal parts of Senegal, Guinea, Guinea Bissau, Siro Leon, Liberia, Togo, Benin, Nigeria and Zaire. The same had been also noticed in East Africa in some coastal parts of Somalia, Tanzania and Mozambique.

Vulnerability of African Coast by the Second Model: Based on the cell unit (250 * 250 m), the resulting values of the vulnerability had been categorized into five classes in this model. The results were classified by natural break method; very low (0.5-0.6), low (0.61-0.65), moderate (0.66-0.68), high (0.69-0.72) and very high (0.73-0.83) as in fig. 8.

Table 2
The ranked values and ranking bases of the selected parameters.

Rank / Parameter	Very Low	Low	Moderate	High	Very High
Topography	> 20 m: this area is safer from SLR hazard	15-20 m: high plateau associated with continental shelf are prone to erosion	10-15 m: most impacted by storm surge (exceed 7 m), saltwater intrusion, other extreme events	5-10 m: some parts of sand dunes and cliffs (sand belts) exist in this zone that prone to erosion	< 5m: DEM accuracy > 3.7 m
Slope *	> 3.0 %	1.0 - 3.0 %	0.5 - 1.0 %	0.1 - 0.5 %	0 - 0.1 %
Proximity to coast *	> 10000 m	7500 – 10000 m	5000 – 7500 m	2500 – 5000 m	0 – 2500 m
Urban Population	< 10 %: very unconcentrated	10 – 20 %: unconcentrated	20 – 50 %: semi-concentrated	50 – 75 %: concentrated	> 75 %: very concentrated
Land Cover	Snow and ice: non-existed in the coastal zone	Savannas, barren or sparsely vegetated: invaluable areas	Grasslands: semi-valuable areas.	Closed or open shrublands: valuable areas	Water, forest, wetland, croplands, urban, vegetation mosaic: very valuable areas
Accessibility to Major cities *	> 720 minutes	360 – 720 minutes	180 – 360 minutes	90 – 180 minutes	0 – 90 minutes
Soil Types	Lithosols & Humic Podzols & Yermosols (coarse land mainly), Dunes/Shifting sand, Rock debris	Rendzinas & Arenosols (mainly sand)	Fluvisols (clay and silt), Regosols & Nitosols (sand with clay), Histosols (organic materials sand and clay)	Cambisols, Luvisols, Planosols, Vertisols, Solonetz, Kastanozems, Xerosols andosols, Acrisols, Ferralsols: (mainly dry clay)	Solonchaks (semi salt flats), Salt flats (sabkhas), Phaeozems (saturated silt with clay), Gleysols (wet clay with sand)
Element at Risk Indicator *	2.50- - 0.70-	0.71- - 0.18-	0.19- - 0.40	0.41 - 1.10	1.11 - 3.1
Vegetation Percent *	< 10 %	10 – 20 %	20 – 40 %	40 – 65 %	> 65 %
Vegetation Type	Desert: unimportant areas.	grassland, sedge, swamp, shrubland, semi-desert: unvital areas.	Savanna: quite vital areas.	afro-alpine, dry forest and thicket: vital areas.	anthropic landscapes, fynbos, forest, swamp forest, mangrove, rainforest: very vital areas.
Natural Resources Sensitivity Indicator *	1.7- - 0.9-	0.91- - 0.33-	0.34- - 0.3	0.31 - 0.95	0.96 - 1.57
Growth Rate *	0.80 - 1.18 %	1.19 - 2.1 %	2.11 - 2.51 %	2.52 - 2.78 %	2.79 - 3.30 %
Human Capital Indicator *	0.91 - 1.7	0.2 - 0.9	0.13- - 0.26	0.49- - 0.14-	1.1- - 0.5-
Financial Capital Indicator *	0.8 - 2.3	0.33 - 0.79	0.054- - 0.32	0.44- - 0.055-	1.3- - 0.45-
Institutional Capital Indicator *	0.81 - 1.5	0.25 - 0.8	0.25 - - 0.24	0.83- - 0.26-	2.7- - 0.84-
Infrastructure Indicator *	0.59 - 2.7	0.17 - 0.58	0.35- - 0.16	1.5- - 0.36 -	2.6- - 1.6-
Household Technology Indicator *	1.04 - 1.7	0.36 - 1.03	0.24- - 0.35	0.75- - 0.25-	2.6- - 0.76-

*: The ranking system of those stared parameters is based on natural break (Jenks).

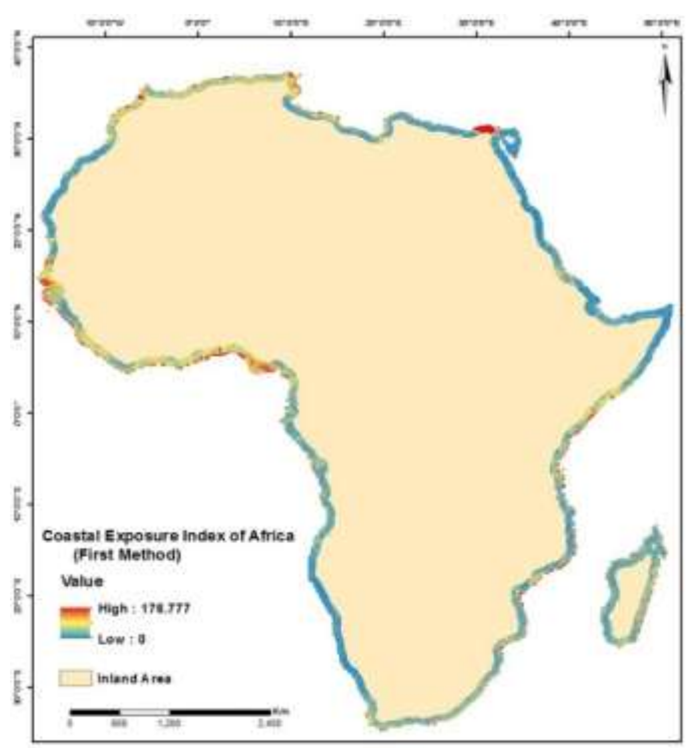

Fig. 1: CEI to SLR for Africa by the first model.

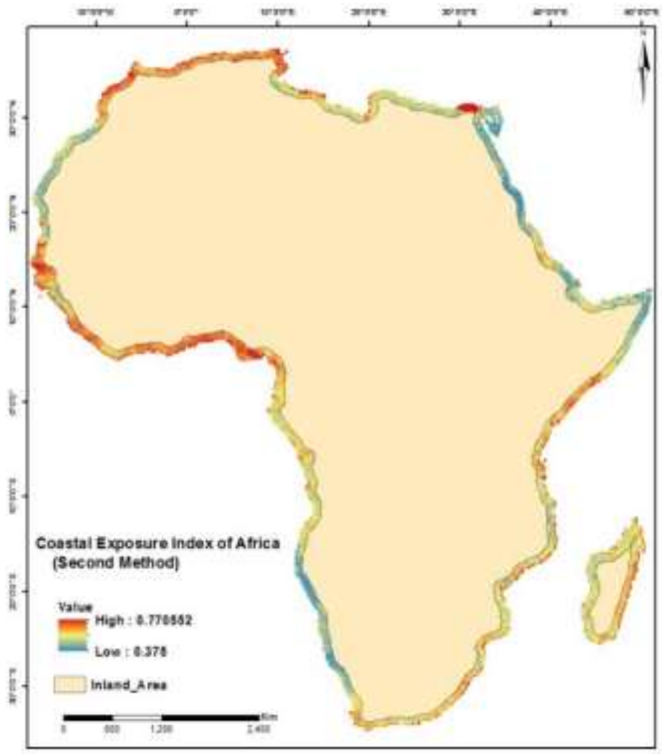

Fig. 2: CEI to SLR for Africa by the second model.

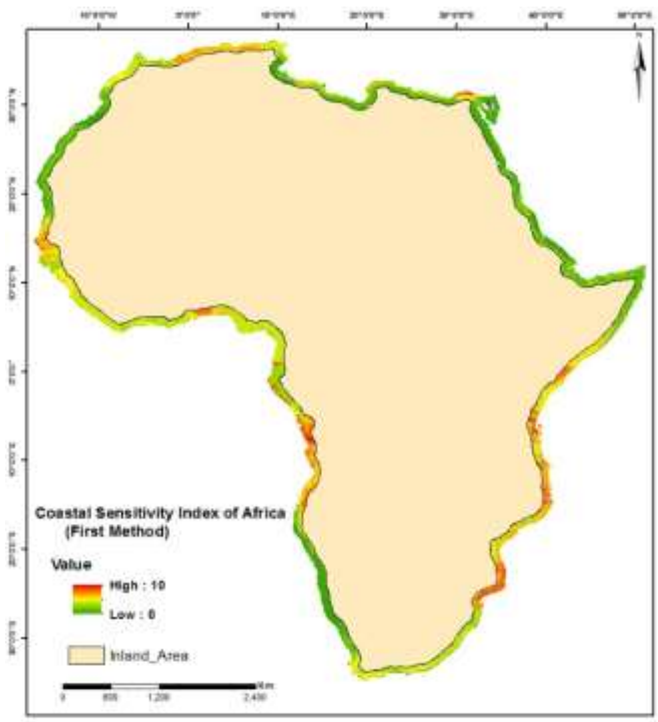

Fig. 3: CSI to SLR for Africa by the first model.

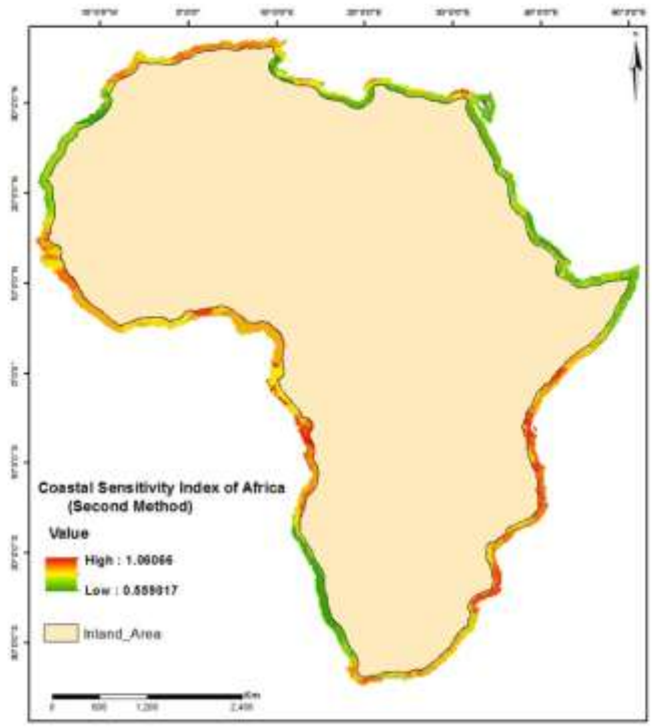

Fig. 4: CSI to SLR for Africa by the second model.

The results revealed that very highly vulnerable and highly vulnerable cells exist in few parts of North Africa and the majority of East and West Africa. In North Africa, it had been classified into a range of very high to high vulnerability in the middle of Egypt Coast (Nile Delta coast), high to moderate vulnerability at the north-west coast of Libya, the coast of Tunisia, Algerian Coast and north coast of Morocco.

In West Africa, it had been classified in a range of very high to high vulnerability at the coast of southern Somalia, Kenya, Tanzania and Mozambique. In West Africa, it had been classified in a range of very high to high vulnerability at coasts of Senegal, Guinea, Guinea Bissau, Siro Leone, Liberia, Benin, Togo, Nigeria, Cameron and Zaire as well as in a range of high to moderate vulnerability at coasts of Ghana, Congo and Angola.

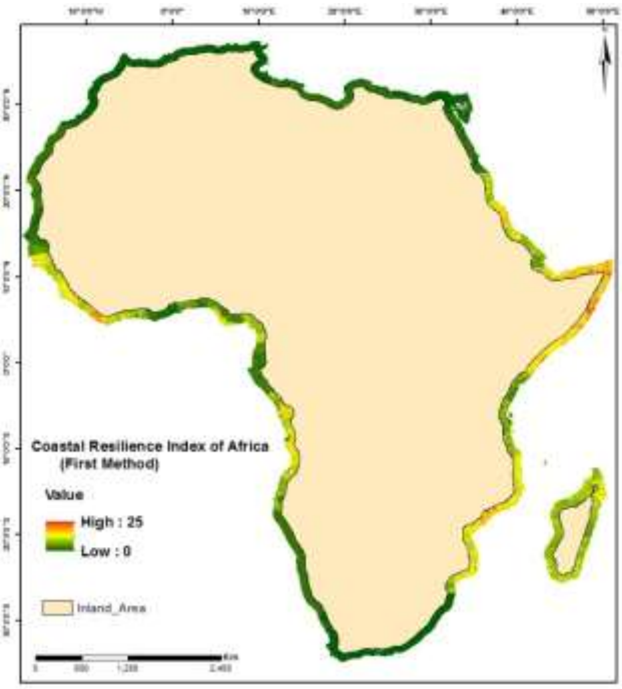

Fig. 5: CRI to SLR for Africa by the first model.

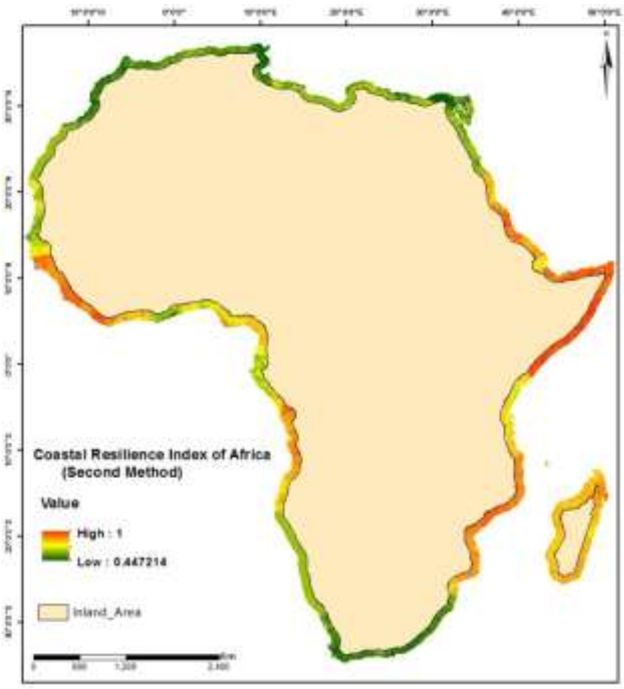

Fig. 6: CRI to SLR for Africa by the second model.

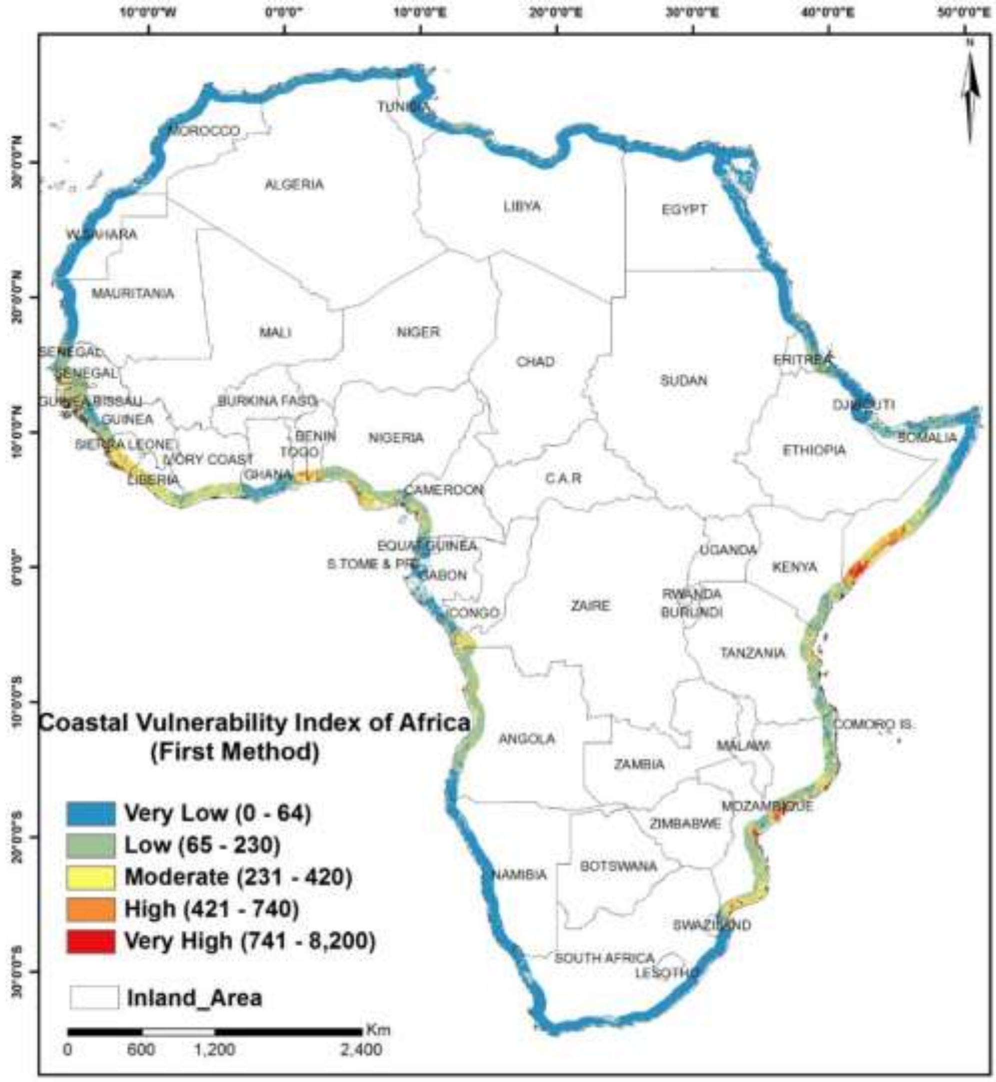

Fig. 7: CVI to SLR threat for the African Coast by the first model.

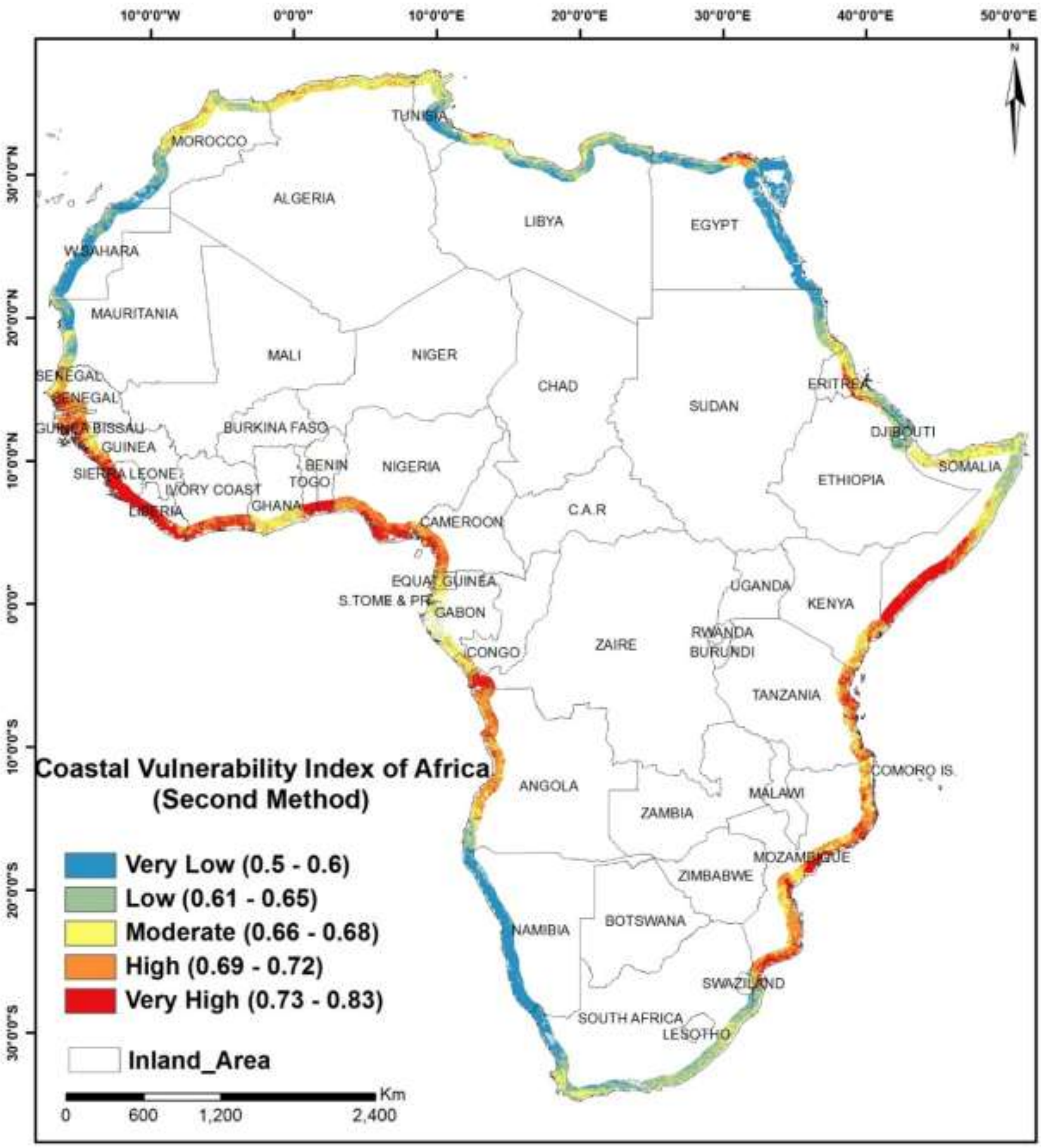

Fig. 8: CVI to SLR threat for the African Coast by the second model.

Discussion

Both the two models have vastly been used to estimate CVI degrees to SLR threat. Each model is based on a set of customized parameters which are selected from natural and anthropogenic aspects. To compare the results of the vulnerability of both models, these parameters are processed in each assessment model. Indeed, the results differed in both models; most cells have different values. Moreover, the second model resulted in more severely vulnerable areas than the first model. On the other hand, common hotspots in both models are found in some parts of East and West Africa.

To identify the type of relation between the results of these two models, it could be figuring the link between them in an excel sheet. First, some points will be created in the study area by using "create feature class" tool in ArcMap that will represent random samples from the whole area as in fig. 9. Secondly, by using "extract values to points" tool in ArcMap, it could be extracting values of the selected points from the two that resulted from vulnerability maps (two rasters).

In an excel sheet, the CORREL function is used to find the correlation coefficient between values of the two variables (extracted values). A correlation coefficient of +1 indicates a perfect positive correlation, which means that as variable X (extracted values of the selected points from the resulted vulnerability by the first model) increases, variable Y increases (extracted values of the selected points from the resulted vulnerability by the second model) and -1 indicates a strong negative relationship which means that as variable X decreases, variable Y increases.

But, if the correlation coefficient is zero, it means that there is no relation between the two variables. It was found that the relation between values of the two models results is a positive correlation with a result of 0.648676 (semi-strong) as shown in the linear relationship in fig. 10 which means that both models are validated.

Based on the mapped results, the first model is sensitive to the parameter type within the entire coastal system. It can be concluded that the first model is strongly suitable for study areas with a dominant parameter (i.e. proximity to the coast, topography, urban population percent, land cover type, soil type) and sensitive/valued areas (i.e. protected natural and heritage areas; an area with special features) while the second formula is significantly valid to an insensitive area or an area without a dominant parameter (having an equalization between the impact of all parameters and its area conditions).

Therefore, the results of the first model based on CVI_1 provide more realistic and accurate values compared to the CVI_2 model in such a case study, because the topography associated with proximity to the coast is a dominant parameter defining the potential extent of saltwater inundation. What confirmed these words were the results of CVI_2, where some highly vulnerable areas from the CVI_2 model exist in relatively high elevated areas that are unadjacent to the coast which give nonsense/unlogic results.

Even if the topography is low, other exposure parameters are also dominant factors. As shown in table 3, values of the second model are highly vulnerable despite the variance in parameter values. Also, there are other dominant factors in the vulnerability of the African case, for instance, the poor socio-economic aspects (e.g. poverty, conflict, low technology) that rolled in the resilience parameters. It can be concluded that the first formula (CVI_1) is more accurate and suitable to be applied in such cases.

Conclusion

Both the first model, based on a formula of the square root of product mean and the second model, based on a formula of average of the square root of product sum, are used widely to assess the coastal vulnerability to SLR. Although the two models have a positive correlation with semi-strong relation (+ 0.65), their results are not the same. There are common hotspots in their results in some parts of East and West Africa. While the first model is sensitive to any change in a parameter type (dominant or non-dominant variable) within the coastal area, the second model is relatively insensitive to this change.

Therefore, the first model should be used when there are dominant parameters while the second model should be used when there is an equality between parameter weights. For instance, topography associated with the proximity to coast is a dominant factor when assessing the area's vulnerability to SLR threat. Moreover, the first model should be used to assess the vulnerability when there are valued areas (i.e. protected natural areas, heritage areas). So, the first model is more suitable for such a case.

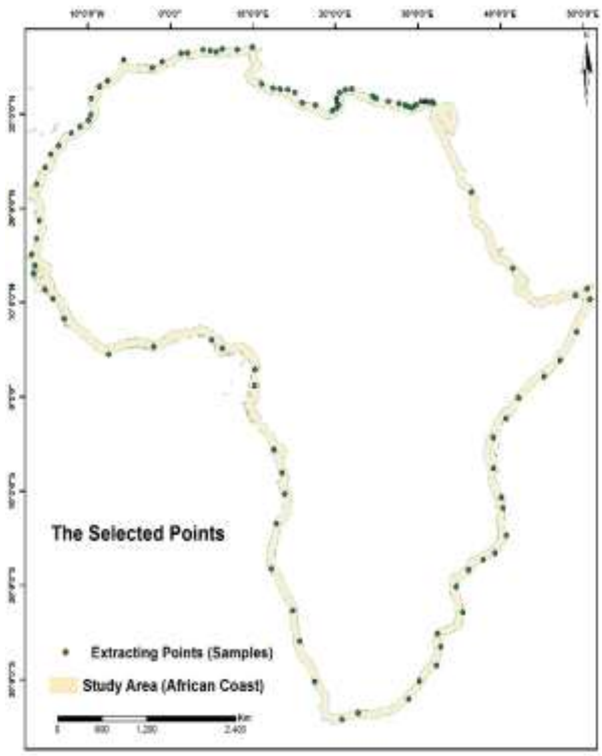

Fig. 9: The selected sample points.

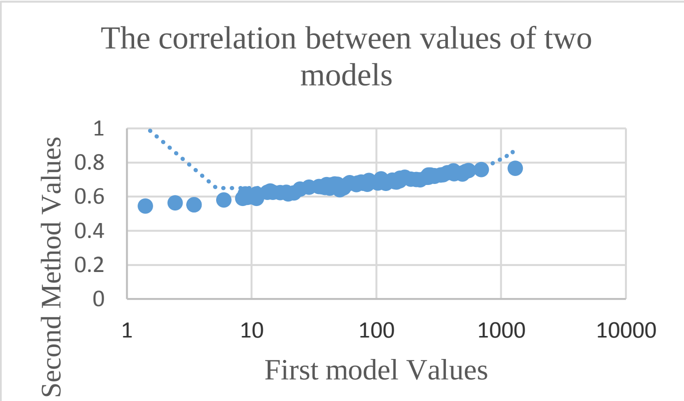

Fig. 10: Correlation relationship between values of two models.

Table 3
At six random points, values of each dominant parameter and their resulted vulnerability in the two models.

Point No.	Topography (m)	Slope (%)	Proximity To Coast (Km)	Land Cover	Soil Content	Vulnerability First Method	Vulnerability Second Method
1	118	2.69	25.43	Woody Savannas	Clay mostly	169.71 (Low)	0.71 (High)
2	126	0.22	53.76	Cropland/Natural Vegetation Mosaic	Wet salted sand with clay	61.24 (Very Low)	0.69 (High)
3	22	0.89	89.89	Evergreen Broadleaf Forest	Wet salted sand with clay	261.53 (Low)	0.73 (Very High)
4	405	6.57	61.97	Evergreen Broadleaf Forest	Clay mostly	70.99 (Low)	0.68 (High)
5	797	6.32	68.21	Deciduous Broadleaf Forest	Clay mostly	46.48 (Very Low)	0.69 (High)
6	301	46.86	34.67	Evergreen Broadleaf Forest	Clay mostly	154.92 (Low)	0.71 (High)

And for the results of the first model, it has been revealed that West and East Africa have highly and very highly vulnerable areas. Although other coasts are highly exposed areas to SLR, i.e. coast of the Nile Delta, they are low vulnerable due to their low sensitivity or/and high resilience in such areas. Therefore, some coasts could be low vulnerable areas associated with their high exposure to SLR hazards according to their relative circumstances.

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