



Evaluation of Ecological Vulnerability of Coasts of the Caspian Sea Based on Multi-criteria Decision Methods (Iran)

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Abstract

The Caspian Sea coast in northern Iran has faced a wave of pollution and a variety of critical conditions. In this regard, the study aimed to determine the spatial distribution of the ecological vulnerability in the Anzali coasts based on seven criteria and thirteen sub-criteria of soil texture, soil salinity, soil quality, coastal erosion, groundwater level, the electrical conductivity of groundwater, average annual temperature and precipitation, drought, elevation, geomorphological features, land use, and NDVI. In this study, the analytic network analysis method was used to determine the relative weight. Then, data layers were standardized with the fuzzy membership function, and the fuzzy gamma operator was used to overlay all standardized layers. Finally, an ecological vulnerability index was used to determine the ecological vulnerability of the Anzali coasts. The results indicated that 25% of Anzali coasts and also Anzali International Wetland are in the category of severe ecological vulnerability. Thus, 15 stressors of wetland were identified based on the driver, pressure, state, impact, and response and ranked according to VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. The results of the VIKOR method showed that the most risk in the Anzali wetland is in the physico-chemical environment of wastewater entering the wetland, the biological environment of uncontrolled extraction of plant resources, and the socio-economic environment of land use change. These results can be used as a guide to identify areas of high sensitivity and the need to focus on their conservation.

Keywords Fuzzy gamma · DPSIR · Vulnerability · VIKOR · Anzali

Introduction

The coastal environment is regarded as a natural and economic environment between the land and sea, which is affected by the ecological interactions of the two ecosystems and the functions of the two environments (Craig &

Ruhl, 2010). Coastal areas are considered as the ground for major economic and social activity in the world (Ricketts & Harrison, 2007). However, Coastal areas are extremely vital and vulnerable ecologically to various stresses (Mani Murali et al., 2013). These areas are always undergoing extensive changes due to natural hazards, such as heavy rainfall, waves, climate change, coastal erosion, sea-level change, etc. (Andalecio, 2010; Tahri et al., 2017). Furthermore, human activities such as increasing population density, industrialization, and tourism in coastal areas are important factors that increase the pressure and intensity of exploitation in coastal areas (Nouri et al., 2008; Tang et al., 2018). Therefore, coastal environmental protection is considered as a management requirement to realize the principles of sustainable development considering the nature of the permanent threat to coastal ecosystems (Mani Murali et al., 2013).

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Accordingly, ecological vulnerability (EV) identification is regarded as important to provide a sustainable management system with effective solutions for disaster management and prevention of further degradation (Doukakis, 2005; Sankari et al., 2015; Zhang et al., 2017). The main objective of EV research is to maintain the balance between conservation and exploitation, which is required for the sustainability of an ecosystem by identifying the factors affecting vulnerable areas. Thus, determining the boundaries of ecologically vulnerable areas is a necessary aspect of environmental protection management (He et al., 2018). EV is a function of pressure, sensitivity, and adaptive capacity, and its estimation is required for environmental protection modeling (Qiao et al., 2013). In general, a vulnerable area can be defined as an area that is both sensitive and exposed to human pressures, and the degree of vulnerability depends on the degree of sensitivity and the corresponding pressure (Bigot et al., 2000). Pressure and sensitivity factors in these areas are human activities and accelerated exploitation, especially destroying natural ecosystems and environmental pollution in recent years (Jafari, 2010; Jamshidi & Yousefi, 2013). Vulnerability mainly involves the three dimensions of exposure, sensitivity or susceptibility to loss, and the capacity of a system to adapt to changes and events (Adger, 2006; Füssel 2006; Field & Barros, 2014).

The ecological vulnerability index (EVI) has recently been developed for environmental assessment. This concept has been studied and used in different spatial scales and several regions (Fandohan et al., 2015; Jha & Gundimeda, 2019; Wang et al., 2019). Most of the studies conducted on coastal vulnerability have been based on the coastal vulnerability index (CVI) (Doukakis, 2005; Mani Murali et al., 2013; Sankari et al., 2015; Zhang et al., 2017). CVI is a relatively simple method of determining vulnerability including six variables related to physical processes about geological parameters, wave characteristic height, and changes in sea level, derived from the product of sequential variables divided by the total number of variables. This method only expresses the vulnerability of the coastline to physical and geological changes, where it is impossible to rank among the criteria based on expert opinions (Bagdavičiūtė et al., 2015; Koroglu et al., 2019). Thus, this study aims to investigate the ecological and economic criteria and their different importance in the vulnerability assessment of coastal areas based on multi-criteria decision-making methods (MCDM) in the geographic information system (GIS) environment (Mani Murali et al., 2013; Tahri et al., 2017).

GIS-based MCDM is among the universally accepted approaches to help decision-makers to assess and map coastline vulnerabilities and threats based on the system of evaluating criteria and options (Andalecio, 2010; Lima

et al., 2019; Tahri et al., 2017). So far, few studies have exploited GIS multi-criteria evaluation methods to assess the coastline vulnerability and risks. Cozannet et al. (2013) investigated the physical vulnerability of the Languedoc-Roussillon coastline in the northwest of the Mediterranean coast in France by the analytic hierarchy process (AHP) method. Tahri et al. (2017) used the FAHP method with seven ecological and economic factors to determine vulnerable areas on the coast of Morocco. They described the eastern coasts of the region as high-risk areas based on the vulnerability map in three levels as low, medium, and high. Further, Wu et al. (2018) prepared the EV map by FAHP and 21 indicators to determine such vulnerability in the Yellow River Delta in China.

Iran has approximately 5000 km of coastline along the Indian Ocean including the Oman Sea and the Persian Gulf, and more than 750 km of coastline adjacent to the Caspian Sea (Dibajnia et al., 2012; Pak & Farajzadeh, 2007). The Caspian Sea has an area of 371,000 km² and is considered as the largest enclosed one in the world with huge energy resources, unique ecosystem features, and special geopolitical and social conditions (Fazli & Taghavi Jelodar, 2013; Mirzajani et al., 2015). Unfortunately, human activities and natural factors have posed widespread threats to the Caspian coastal areas in recent years. The most important of these threats are sea-level changes, biodiversity reduction, land use changes, improper exploitation of natural resources, overfishing, coastal erosion, and reduction of coastal water quality (Mirzajani et al., 2015). Each of these factors has a different impact on coastal vulnerability. Therefore, zoning coastal vulnerabilities is necessary to mitigate the effects of threats.

On the other hand, these zonings should provide appropriate solutions in line with the goals of sustainable development. Thus, recognizing and evaluating changes in the environment and the threatening factors of ecosystems is a process that leads to an appropriate understanding of how humans and the environment interact in environmental management studies. This is even more critical in biologically sensitive areas (Lambin & Geist, 2006). As a result, using environmental risk assessment methods is one of the significant tools in studying environmental management, as well as identifying and reducing the potential causes of environmental harm in wetlands to achieve sustainable development (Makvandi et al., 2016). Environmental risk assessment evaluates the environmental risks associated with human activities and natural disasters and the appropriate level of risk management measures to reduce the risks and their adverse effects to an acceptable level of risk. Environmental risk assessment is an essential component and one of the appropriate technical methods in environmental assessment. Thus, it can be used to investigate,

prevent and reduce very adverse environmental effects (Wu & Zhang, 2014).

In this study, the conceptual framework of drivers, pressures, state, impact, and response (DPSIR) was used to organize cause-and-effect relationships and investigate the conditions of areas with severe vulnerability and express appropriate solutions. The DPSIR is an essential conceptual approach for organizing drivers, pressures, state changes, and impacts for an acceptable expression between human activities and environmental components, so that it can be useful in responding to policies (Gebremedhin et al., 2018). Therefore, this study attempted to use a hybrid approach based on MCDM methods and zone the EV in Anzali coasts based on the fuzzy gamma method and analytic network analysis (ANP) in the GIS environment. In addition, this study attempted to identify risk factors for an area with the severe vulnerability of this coast based on the DPSIR method, conduct risk assessment, and rank them based on vlse kriterijuska optimizacija I komoromisno resenje (VIKOR) method and express management strategies to achieve sustainable development. The results can pave the way for managers and planners to make significant environmental management decisions nationally and internationally for this ecosystem.

Material and Methods

Study Area

The coast of Bandar-e Anzali is located in an area of 891.475 km² between 37° 20′–35° 37′ north latitude and 49° 55′–50° 51′ longitude in northern Iran and the vicinity of the Caspian Sea (Fig. 1). Bandar-e Anzali has a humid subtropical climate (Cfa) under the Köppen climate classification and a humid subtropical climate (Cf) under the Trewartha climate classification. Bandar-e Anzali is the rainiest city in Iran with a record of 1892 mm of total annual rainfall. It has the largest port in Iran on the southern coast of the Caspian Sea with a population of 118,564 inhabitants. The port of Anzali is regarded as the economic, fisheries, and tourism industry pole in Iran due to its geographical location. Part of the natural environment in the area includes the sea (40 km coastal strip) with a large number of islands and peninsula, and the other important part forms the highly valued Anzali wetland ecosystem. It is worth noting that the Anzali wetland was registered in the Ramsar Convention in 1975 (Mousazadeh et al., 2015). The Caspian coast is severely affected by the oscillating behavior of the Caspian Sea. Over the last thousand years, the Caspian Sea level varied between 19 and 28 m below the mean sea level, based on Caspian Sea level reconstruction from combined historical documents

and geological records by Naderi Beni et al. (2013). Furthermore, the legal boundary of the Caspian Sea according to the definition provided in the Law of New and Coastal Lands of Iran is 60 m from the last point of seawater intrusion in 1963. Thus, the border of the studied coast was determined according to these issues.

Methodology

The Ecological Vulnerability Index (EVI)

EVI is an important tool to determine the ecological conditions in vulnerable areas (Hong et al., 2016). It is generally thought that EVI shows the degree of resistance of ecosystems in response to external interference, including natural and artificial factors, at a specific spatial scale (Beroya-Eitner, 2016; Hong et al., 2016). The EVI method in this study was performed with MCDM aggregation and GIS spatial analysis. In particular, the MCDM method can manage data from multiple sources and determine the weight of each criterion. GIS is used for spatial analysis and to generate an EV map (He et al., 2018). EVI is an indicator that integrates multiple multidimensional and multivariate criteria based on Eq. (1) (Wu et al., 2018):

$$EVI = \sum_{i=1}^N W_i A_i \quad (1)$$

where EVI represents the degree of ecological vulnerability on Anzali coasts, W_i is regarded as the weight of the i -th criterion, and A_i indicates the fuzzy value of the i -th criterion obtained from the gamma membership function. In general, there are five steps in assessing EVI:

- Selection of criteria based on the Delphi method;
- Data collection and processing;
- Normalization of ecological vulnerability criteria;
- Weight determination by analytic network process (ANP);
- Integrate criteria and produce an EV map in the GIS environment.

Selection of Criteria Based on the Delphi Method

In the current study, 19 primary sub-criteria were determined based on the comprehensive literature studies on coastal and marine issues, the report of the Department of Environmental Protection of Iran in coastal areas, experts' opinions, local conditions, and access to data (Table 1). Then, the Delphi method was used to prioritize the identified sub-criteria using the opinions of 15 experts. Delphi is an appropriate method to analyze the opinions of experts in decision-making processes, which normally recognizes

Fig. 1 Location of the study area

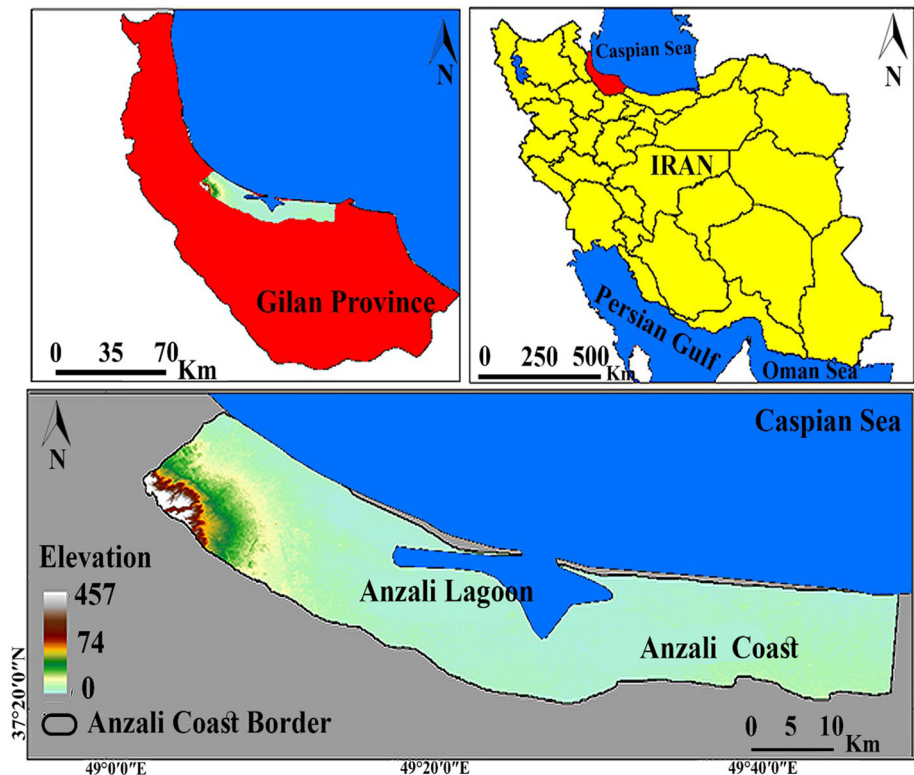


Table 1 Review of resources for effective sub-criteria in coastal ecological vulnerability

Sub-criteria	Status	Reference
Soil texture	Accepted	Qiao et al. (2013), Wu et al. (2018)
Soil salinity	Accepted	Qiao et al., (2013), Wu et al. (2018)
Soil quality	Accepted	Qiao et al. (2013), Wu et al. (2018)
Beach width	Rejected	Bagdanavičiūtė et al. (2015), Anfuso et al. (2021)
Mean tidal range	Rejected	Anfuso et al. (2021), Ghanavati et al. (2021)
Coastal erosion	Accepted	Wu et al. (2018), Sherein El-Shahat et al. (2020)
Storm surge height	Rejected	Brakenridge et al. (2013)
Mean wave height	Rejected	Ghanavati et al. (2021), Ružić et al. (2019)
Groundwater level	Accepted	Wu et al. (2018), Cozannet et al. (2013)
Electrical conductivity of groundwater	Accepted	Wu et al. (2018), Chang et al. (2012)
Average annual temperature	Accepted	Wu et al. (2018), Sudha Rani et al. (2015)
Land subsidence	Rejected	Rimba et al. (2018), Wibowo et al. (2015)
Average annual precipitation	Accepted	Wu et al. (2018), Sudha Rani et al. (2015)
Drought	Accepted	Wu et al. (2018), Dossou et al. (2021)
Elevation	Accepted	Tahri et al. (2017), Ružić et al. (2019)
Major geomorphological features	Accepted	Wu et al. (2018), Cozannet et al. (2013); Sankari et al. (2015)
Frequency of storms	Rejected	Anfuso et al. (2021), Gornitz et al. (1994)
Land use	Accepted	Wu et al. (2018), Sankari et al. (2015)
NDVI	Accepted	Wu et al. (2018), Sherein El-Shahat et al. (2020), Ružić et al. (2019)

the need to structure a group communication process to achieve a useful result for management purposes

(Foroozesh et al., 2002). The panel in this study included 15 experts including professional experts in government

organizations and academic experts from various geographical locations. Table 2 shows the demographic information of the survey experts. Experts were asked to rank the significance of the sub-criteria based on their opinions in the rank of 1–9 (insignificant = 1, low significance = 3, significant = 5, very significant = 7, too much significant = 9, and intermediate values = 8, 6, 4, and 2). In this study, the Delphi technique continued in two rounds and the criteria with an arithmetic mean of less than five were removed. After summarizing the total opinions of experts, the sub-criteria were placed in each criterion category based on their common characteristics.

Data Collection and Processing

The selected criteria along with the relevant sub-criteria and their information are shown in Table 3. In this study, satellite images, thematic layers, and statistical data were used to assess the EVI. Satellite images were accordingly selected so that (1) the cloud cover of the images was a maximum of 10% and (2) their dates were close enough to each other. In this study, geometric and atmospheric corrections have been carried out for all satellite images.

- **Groundwater status:** the quantity and quality of groundwater are the significant factors in the change of surface vegetation coverage, soil salinity, and soil degradation (Ma et al., 2013; Song et al., 2021) that lead to EV. In this study, groundwater data were acquired from the monitoring data of 55 borehole wells along the coast of Anzali (July 2017–June 2018) that were conducted by Mazandaran Province Water and Wastewater Company (2018). In this report, 55 wells were randomly sampled and the electrical conductivity (EC) and level of the

groundwater were measured. In this study, the mean of annual data was interpolated based on the kriging method and classified into 5 classes (Fig. 2a, b).

- **Land use:** Land use is carried out to identify the various classes on this coast that are vulnerable to environmental degradation. In this study, MODIS/Terra products were used to produce a land use map. MODIS products were downloaded from <https://ladsweb.modaps.eosdis.nasa.gov/> on 30 June 2018. Land use was classified into 6 categories based on the supervised classification method. The LULC features were categorized as built-up, farmlands, forest, grassland, water body, and wetland (Fig. 2c)
- **The normalized difference vegetation index (NDVI):** NDVI was used to measure the level of vegetation density in the research area. The reduction of vegetation density is one of the main factors in soil erosion, biodiversity reduction, and other major ecological vulnerability (Zaitunah et al., 2019). In this study, NDVI is derived from the Sentinel-2A image acquired on 30 June 2018 based on Eq. (2). Then, the NDVI map was classified into 3 classes: none, moderate, and dense vegetation (Fig. 2d).

$$NDVI = \left(\frac{NIR - RED}{NIR + RED} \right) \quad (2)$$

- **NIR and R** represented the near-infrared band and red band of the image, respectively.
- **Topography:** The topographical and morphological conditions of the coastal area are critical for assessing the vulnerability of groundwater resources to salinization (Michael et al., 2013) which can lead to EV. In this study, major geomorphological features were extracted from the Geological map of Anzali (Fig. 2e). Also, the

Table 2 Information related to the survey experts

Characteristic	N	Percentage	
Gender	Male	11	73
	Female	4	27
Age	30–40	6	40
	40–50	4	27
	More than 50	5	33
Education	Bachelor's degree	4	27
	Master's degree	7	46
	PhD	4	27
Job classification	Water Resources Management Company	3	20
	Management and Planning Organization	2	13
	University Professors	4	27
	Department of Environment	6	40
Work experience	5 to 10 years	6	40
	10 to 20 years	5	33
	More than 20 years	4	27

Table 3 Selected criteria and sub-criteria and their information resources

Criteria	Sub-criteria	Resolution	Period	Resource
Soil	Soil texture	150,000	2000	Studies for soil and water resources in Iran (Ministry of Agriculture Jihad)
	Soil salinity	30 m × 30 m	2018	https://earthexplorer.usgs.gov/ EC of region soil sampling
	Soil quality	150,000	2000	Studies for soil and water resources in Iran (Ministry of Agriculture Jihad)
Interaction with the sea	Coastal erosion index	30 m × 30 m	2000 2018	https://earthexplorer.usgs.gov/
Groundwater status	Groundwater level	Points data	2018	Mazandaran Province Water and Wastewater Company
	Electrical conductivity	Points data	2018	Mazandaran Province Water and Wastewater Company
Climate	Average annual temperature	Points data	2018	Meteorological Organization of Mazandaran Province
	Average annual precipitation	Points data	2018	Meteorological Organization of Mazandaran Province
	Drought	Points data	2018	Organization of Mazandaran Province Meteorological
Topography	Elevation	30 m × 30 m	2018	https://www.opendem.info/link_dem.html
	Major geomorphological features	1: 100,000	2001	Geological map of Iran
Land use	Land use	250 m × 250 m	2018	https://ladsweb.modaps.eosdis.nasa.gov/
Vegetation	NDVI	10 m × 10 m	2018	Sentinel -2 https://scihub.copernicus.eu/dhus/#/home

SRTM DEM was retrieved from https://www.opendem.info/link_dem.html on June 2018 (Fig. 2f)

- **Soil:** Soil is one of the important factors in biomass production, water storage capacity, and protection of flora and fauna (Meléndez-Pastor et al., 2017) and the reduction of its quality leads to ecological vulnerability. In this study, soil quality and texture data were derived from the report for soil and water resources in Iran's Ministry of Agriculture Jihad (2000). In the mentioned report, the soil quality map was prepared according to characteristics such as the percentage of soil mineral particles, pH, EC, and organic carbon, and the fuzzy membership function was used to standardize the sub-criteria in values ranging from 0 to 1. In this study, the soil quality map was classified into 4 classes based on the equal interval method: values less than 0.25 (bad), 0.25 to 0.5 (moderate), 0.5 to 0.75 (good), and more than 0.75 (best) (Fig. 3a). Soil texture was classified into 4 classes: silty loam, sand, sandy loam, and silty clay loam (Fig. 3b). Moreover, Landsat 5 TM and Landsat 8 OLI images (WRS_PATH = 166 and WRS_ROW = 34) were acquired on 5 May 2000, and 8 May 2018 to produce the soil salinity (Fig. 3c). These imageries are available on the <https://earthexplorer.usgs.gov/>. The salinity index is derived based on Eq. (3).

$$\text{Salinity Index} = \left(\frac{\text{Redband}}{\text{NIRband}} \right) * 100 \quad (3)$$

where, NIR and *R* represented the near-infrared band and red band of the image, respectively.

- **Climate:** In recent decades, coastal ecosystems and near-coast have been affected by climate change, which can lead to sea-level changes, loss of biodiversity, habitat destruction, and coastal erosion. The consequences of these changes potentially affect coastal livelihoods, the health of coastal and marine environments, ecosystem services, and coastal livelihoods (Halpern et al., 2012; Oloyede et al., 2021). In this study, precipitation and temperature data were obtained from 4 synoptic stations in Mazandaran province (July 2017–June 2018). Montazeri and Bayet (2012) stated that the change in climatic parameters in the northern regions of Iran which have led to the separation of climatic sub-regions is affected by factors such as distance from the sea and increasing elevation. Considering that the Anzali coast is a plain region (Fig. 2e), so the whole coastal area has a relatively homogeneous climate. Anzali city is the rainiest city in Iran with a total annual rainfall of 1892 mm and relative humidity fluctuates between 71 and 97% per year because there

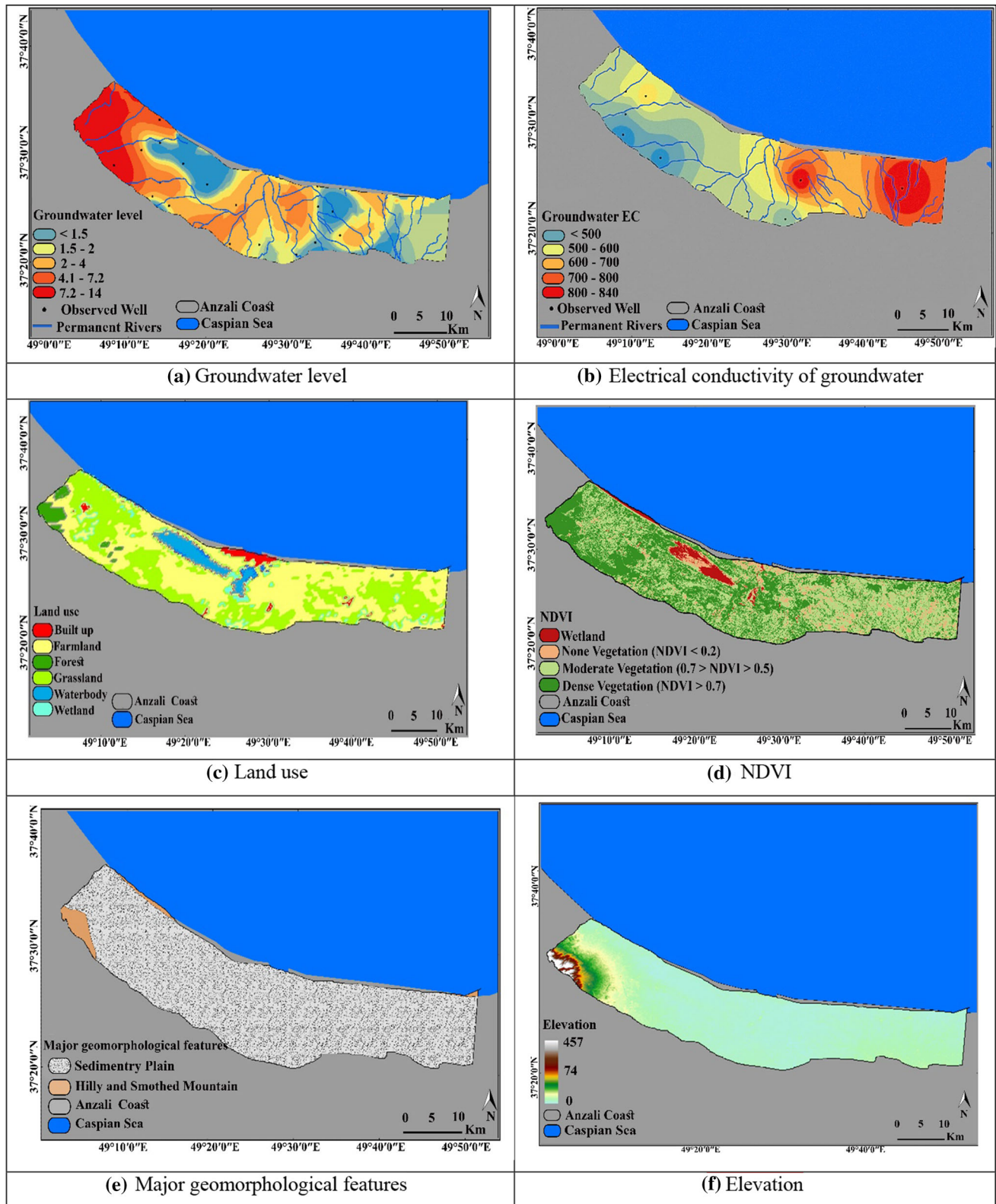


Fig. 2 Map of sub-criteria **a** Groundwater level, **b** Electrical conductivity of groundwater, **c** Land use, **d** NDVI **e** Major geomorphological features, **f** Elevation

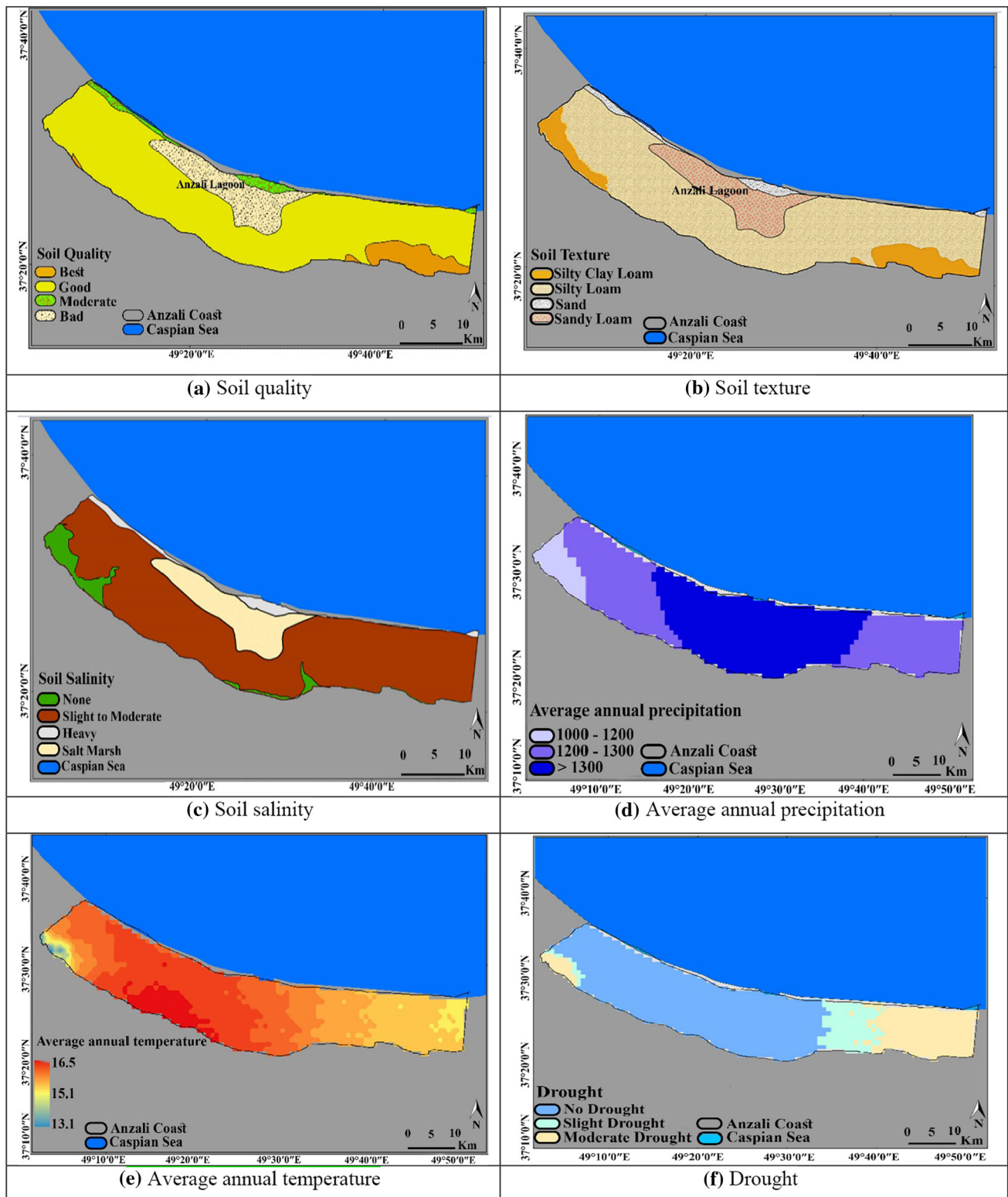


Fig. 3 Map of sub-criteria **a** Soil quality, **b** Soil texture, **c** Soil salinity, **d** Average annual precipitation, **e** Average annual temperature, **f** Drought

are no drastic changes in precipitation and temperature throughout the year. So the annual average has been used to study climatic parameters in this study. In this

study, the mean of annual data was interpolated based on the kriging method (Figs. 3d and 3e). Moreover, the standardized precipitation index (SPI) is widely used in

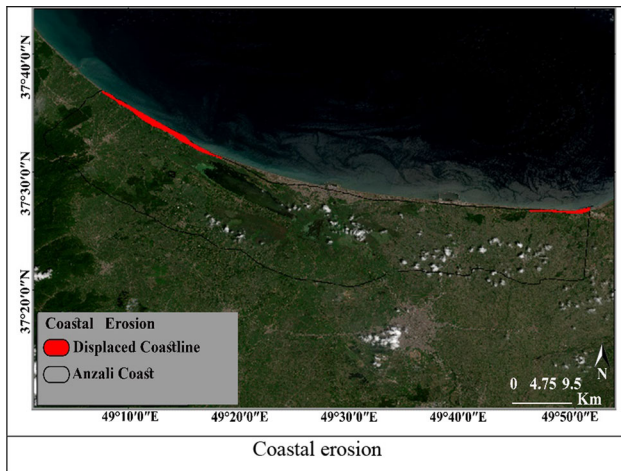


Fig. 4 Map of sub-criteria Coastal erosion

the research areas of drought analysis on a range of timescales (Wang et al., 2022). In this study, SPI was used to determine the drought for a year period and estimated based on Eq. (4). The SPI map is classified according to McKee et al. (1993) (Fig. 3f)

$$SPI = \left(\frac{P_i - \bar{P}}{SD} \right) \quad (4)$$

where, P_i is the amount of rainfall, \bar{P} is the average amount of rainfall and SD is the standard deviation.

- Interaction with the sea: The tides of the sea and the influence of storm waves change the coastline (Wu et al., 2018). In this study, the subtract of NIR bands of Landsat 5 TM and Landsat 8 OLI was used to extract the boundary between water and soil. NIR band has the largest difference in reflectance values between water and non-water bodies (Mondejar & Tongco, 2019). Also, a high-pass filter was used to highlight the boundary between features. In this map, pixels with negative values were considered as areas that have changed from sea pixels to land pixels. These areas can be eroded by sea waves and wind (Fig. 4).

The data related to each sub-criterion should initially be transformed into a layer in the GIS software for mapping the EV in Anzali coasts based on the aforementioned sub-criteria. All of the layers were projected based on the UTM system and WGS 1984 datum and converted to grid layers with $30 \text{ m} \times 30 \text{ m}$ cell size.

Normalization of Ecological Vulnerability Criteria

In the current study, the layers were standardized by the fuzzy logic technique. The theory of fuzzy logic as a knowledge-based approach is proposed by Zadeh (1965).

The basis of this method is to convert input data into normalized outputs by calculating weights for fuzzy members based on fuzzy set theory (Zhang et al., 2017). In the theory of fuzzy logic, fuzzy members are weighed based on significant distances of different features, for each pixel or spatial position, a weight is assigned between zero and one. In this study, linear and small membership function was used. The linear membership function transforms the input values linearly on the 0 to 1 scale, with 0 being assigned to the lowest input value and 1 to the largest input value (Tabrizi et al., 2012). The small function is a non-linear fuzzy membership. It is used when the low values in the membership map are close to one. This function is defined based on an intermediate point defined by the user. In this study, the minimum and maximum values for the sub-criteria were determined according to referring to the literature, the results of previous studies (Mani Murali et al., 2013; Rahmanipour et al., 2014; Wu et al., 2018) and professional books. The linear score allocation function was used for all sub-criteria, except the sub-criterion of coastal erosion. This function has two thresholds of minimum and maximum. In addition, other values were linearly fuzzy between these two values. In the case of coastal erosion sub-criteria, it is obvious that pixels with a negative value in the shoreline displacement map (indicating shoreline displacement and increased erodibility) have a higher fuzzy score. As a result, the small weighting method was used. Table 4 indicates the method of assigning fuzzy points to each sub-criterion.

In this study, the gamma fuzzy operator expressed according to Eq. (5), was used.

$$\mu_{\text{Combination}} = (\text{FuzzySum})^{\delta} * (\text{Fuzzyproduct})^{1-\delta} \quad (5)$$

where $\mu_{\text{Combination}}$, Fuzzyproduct, and Fuzzysum indicate the fuzzy gamma layer, product of the fuzzified layers, and algebraic summation of the fuzzified layers, respectively. In the above equation, the gamma fuzzy operator $\mu_{\text{Combination}}$ is a combination of the algebraic multiplicative fuzzy operator (PRODUCT) and the algebraic sum fuzzy operator (SUM) in which the gamma parameter (δ) is selected in the range of zero to one. Therefore, if (δ) is one, the composition will be the same product of algebraic sum (SUM) and if (δ) is zero, the composition will equal the product of algebraic multiplication (PRODUCT). The correct and conscious choice of gamma (δ) creates some values in the output which act as the increasing role of the fuzzy algebraic sum and the decreasing role of the fuzzy algebraic multiplication (Sadeghi & Khalajmasoumi, 2015). In this study, the fuzzy gamma operator was used to adjust the very high sensitivity of the algebraic multiplicative fuzzy operator and the very low sensitivity of the algebraic sum fuzzy operator. This operator works between two algebraic multiplication and sum operators. In this

Table 4 Fuzzy membership functions defined for the criteria and sub-criteria used in the study

Sub-criterion	Category	Membership function type	Membership function number
soil texture	Sand	Linear	0.7
	Sandy loam		0.6
	Silty clay loam		0.6
	Silty loam		0.4
Soil salinity	No salinity	Linear	0.0
	Slight to moderate		0.1
	Heavy		0.5
	Salt Marsh		0.8
Soil quality	Best	Linear	0.0
	Good		0.2
	Moderate		0.5
	Bad		0.7
Land use	Built-up	Linear	0.5
	Farmlands		0.4
	Forest		0.0
	Grassland		0.3
	Water body		0.2
	Wetland		0.4
	NDVI		No vegetation
Moderate vegetation	0.3		
Dense vegetation	0.0		
Major morphological forms	Plain area	Linear	0.1
	Mountainous areas and hills		0.2
Groundwater level	2 > m	Linear	0.4
	2–5 m		0.3
	More than 5 m		0.3
Electrical conductivity of groundwater	< 600 μ mho/cm	Linear	0.2
	600–800 μ mho/cm		0.5
	> 800 μ mho/cm		0.7
Elevation	> 100 m	Linear	0.3
	100–300 m		0.4
	< 300 m		0.5
Average annual precipitation	> 1000 mm/yr	Linear	0.1
Average annual temperature	13–15.1 °C	Linear	0.3
	> 15.1 °C		0.2
Drought	No drought	Linear	0.0
	Slight drought		0.1
	Moderate drought		0.4
Coastline erosion	Displaced coastline	Small	0.7
	Non-displaced coastline		0.2

study $\delta = 0.7$ was used to obtain the output map which has flexible compatibility between the increasing and decreasing tendencies of two fuzzy multiplication and sum operators.

Weight Determination by Analytic Network Process (ANP)

In the next step, the analytic network process (ANP) method was applied to weigh the criteria. ANP method is an extension of the analytic hierarchy process (AHP) method developed by Saaty (1996) to solve MCDM

problems. ANP can model complex decision problems more realistically by eliminating the hierarchical structure (Moradpour & Long, 2019) and constructing a network with inter-level relationships. In general, the steps required to prioritize options based on the ANP method can be described in six steps as follows (Afzali et al., 2014; Eldrandaly, 2013):

Step I Determine criteria, options, and decision structure.

Step II Form the matrix for pairwise comparisons of decision structure.

Step III Examine the decision consistency ratio and calculate the consistency ratio.

Step IV Determine the relative weight of decision elements based on the eigenvector method.

Step V Form a supermatrix of decision structure based on computational weights.

Step VI Calculate the range of the even powers in the supermatrix and determine the supermatrix related to ultimate preference.

In this study, a pairwise comparison of the criteria with their sub-criteria was performed using the analytic network process (ANP) after determining and screening the criteria and sub-criteria. To determine the significance of one criterion, a table of scoring preferences was used and the criteria were based on the degree of significance from 1 to 9 (insignificant = 1, low significance = 3, significant = 5, very significant = 7, too much significant = 9, and intermediate values = 8, 6, 4 and 2). Then, six types of pairwise matrices were designed for pairwise comparisons and provided to 15 relevant experts in the form of the main questionnaire. In one of these matrices, the pairwise criteria were compared while the pairwise (pairwise matrices) sub-criteria related to each criterion and their preference over each other were compared in the other matrices. At this stage, Super Decision software was used to analyze the criteria. This software is reliable for evaluating multiple criteria with many capabilities such as calculating the incompatibility coefficient and the relative weight and final weight of options. In this study, all of the questionnaires which had an incompatibility coefficient of less than 0.1 were selected. The average compatibility rate of the questionnaires approved in this study was 0.063. In this study, the weight of the criteria was obtained by their averaging.

The Vulnerability of the Area Based on the DPSIR Method and Risk Assessment

In this study, the area which was placed in a very high vulnerability category based on the zoning map was used as a goal to assess the conditions and assess the risk. This section focuses on the environmental conditions of the

region and all stressors causing the ecological balance, as well as endangering the survival of the ecosystem. The conceptual framework of this section is shown in Fig. 5. In general, this section includes three steps:

- Identification of risks and vulnerable factors in the wetland based on the DPSIR method;
- Risk assessment;
- Rank of risks based on the VIKOR method.

Identification of Risks and Vulnerable Factors in the Wetland Based on the DPSIR Method

The first step of this study includes system description and analysis using data and library study in the framework of the DPSIR model. The DPSIR approach was proposed for the first time by the European Environment Agency and is widely used in the assessment and management of different environmental issues (Song & Frostell, 2012). This approach is based on a causal relationship that begins with human activities (driving force) and pressure on the environment and leads to responses with quantitative and qualitative changes in natural resources. Indeed, this model can be used with a practical approach as a tool for decision-making and management plans. This issue is highly necessary for planning and formulating a strategy to cope with and adapt to the phenomena. The components of this model include driver, pressure, state, impact, and response.

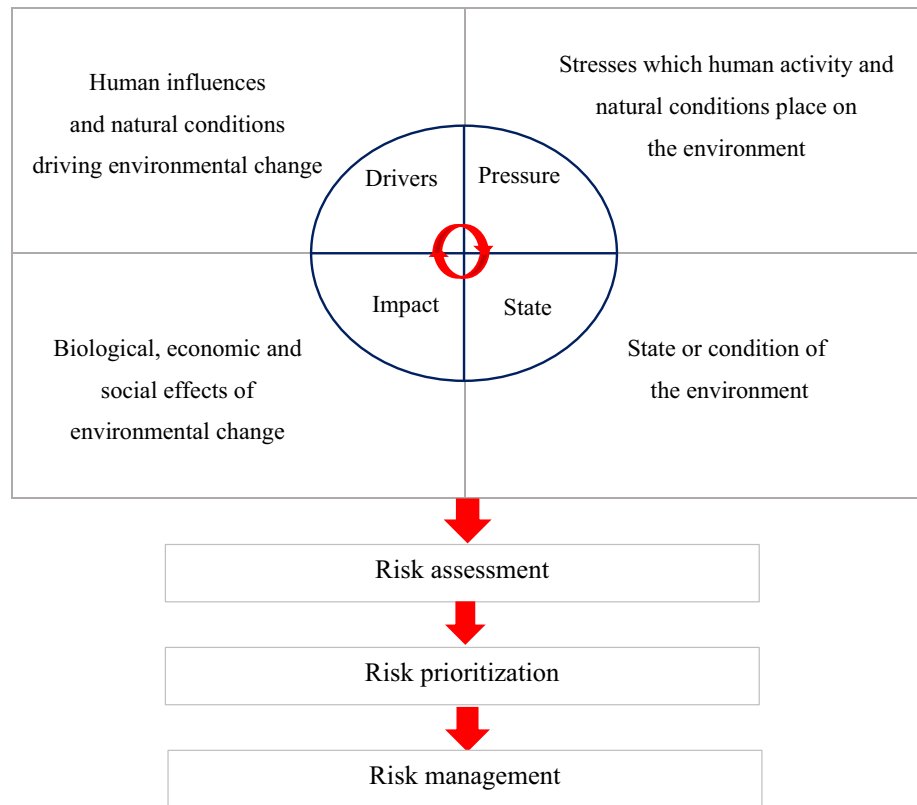
Drivers

Drivers (or driving forces) are various factors that lead to a change in the behavior of a system (Burkhard & Müller, 2008). These are any natural or human-induced factors that lead to major social, demographic, and economic changes (Schrevel & Kumar, 2010). In this study, the driving force refers to tourism, settlements and urban areas, population growth, and economic activities such as agriculture and aquaculture, which lead to environmental problems or changes in the lifestyle of coastal communities.

Pressure

This factor indicates the various consequences of human actions that are the result of driving forces. In most cases, all human activities affecting the environment can be classified as pressure (Zhou et al., 2013). In this study, various forms of human activities on the wetland that directly increase the risk of ecosystem degradation, such as land use patterns, water, and biological resources were been considered as factors of pressure.

Fig. 5 DPSIR conceptual model framework and risk assessment



State

The state index refers to the condition of the ecosystem resulting from drivers such as demographics, socio-economic natural factors, and pressures such as environmental factors (Kosamu et al., 2022). In this study, changes in the quantity and quality of various environmental elements in the wetland (soil, water, plants, animals, etc.) and subsequently their inability to provide ecosystem services were considered as factors of the wetland state.

Impact

The impact is defined as the socio-economic and environmental impacts that affect the local population's livelihood, social welfare, and the environment due to the changing state of the ecosystem (Kosamu et al., 2022). The impact component is very important for management and decision-making because they directly explain the environmental and social consequences of human activities (Pinto et al., 2013). In this study, the effect of each of the components described in the previous steps on physical, chemical, biological, economic, and social circumstances in the receiving environment was determined in this step.

Responses

Responses are also activities performed by human society to reduce environmental pressures and the improvability of the environment. Responses are the best way to reduce the stresses and effects of dependent systems (Saadati et al. 2013). In this study, the responses to the problems related to the driving force and pressure on the wetland ecosystem were expressed using legal procedures, government guidelines, and public participation.

Risk assessment

In the second step of the study, three indicators of risk intensity, risk probability, and sensitivity of the acceptor environment were used for risk assessment. Then, the method of determining the scores of each indicator was presented. In this study, Tables 5 and 6 were used to determine risk intensity and environmental sensitivity. Based on Table 5, the score will be high when the risk of the wetland and the losses to the wetland resources are high. As shown in Table 6, a more sensitive risk acceptor environment leads to a higher risk score (Jozi & Shafiee, 2009; Makvandi et al., 2016). Based on the probability index in Table 7, the higher the probability of occurrence of the outcome due to the risk factor, the higher the risk score.

Table 5 Values related to the intensity of occurrence of risk aspects

Intensity	Definition of intensity	Score
Catastrophic	Potentially very dangerous/severe loss to resources	5
Dangerous	Not harmful but potentially dangerous/severe loss to resources	4
Average	High risk/average loss to resources	3
Low	Low potential loss/low loss to resources	2
Insignificant	Loss is small and negligible/insignificant loss to resources	1

Table 6 Values related to the sensitivity of the recipient environment

Definition of recipient environment	Score
If the recipient environment has very low sensitivity to the risk factor	1
If the recipient environment has low sensitivity to the risk factor	2
If the recipient environment has average sensitivity to the risk factor	3
If the recipient environment has a high sensitivity to the risk factor	4
If the recipient environment has a very high sensitivity to the risk factor	5

Table 7 Values related to the probability of the occurrence of risk

Definition of probability of occurrence	Score
If the probability of the occurrence of risk factor is very low	1
If the probability of the occurrence of risk factor is low	2
If the probability of the occurrence of risk factor is average	3
If the probability of the occurrence of risk factor is high	4
If the probability of the occurrence of risk factor is very high	5

The Rank of Risks Based on the VIKOR Method

In the third step, the VIKOR method was used to rank the risks. The VIKOR method has been developed for the multi-criteria optimization of complex systems by Opricovic and Tzeng (2004). This method focuses on rating and selecting a set of alternatives and determining the agreed solutions to an issue with conflicting criteria (Chen & Wan 2009). The multi-criteria measure for compromise ranking is developed from the L_p -metric used as an aggregating function in a compromise programming method (Yu, 1973; Zeleny 1982). The various J alternatives are denoted as a_1, a_2, \dots, a_J . For alternative a_j , the rating of the i th aspect is denoted by f_{ij} , i.e. f_{ij} is the value of i th criterion function for the alternative a_j ; n is the number of criteria. Development of the VIKOR method started with the following form of L_p -metric in Eq. (6) (Opricovic & Tzeng, 2004):

$$L_{p,j} = \left\{ \sum_{i=1}^n [w_i (f_i^* - f_{ij}) / (f_i^* - f_i^-)]^p \right\}^{1/p} \quad (6)$$

$$1 \leq p \leq \infty; j = 1.2. \dots J.$$

In the VIKOR method $L_{1,j}$ (as S_j) and $L_{\infty,j}$ (as R_j) are used to formulate ranking measures. The solution (Q_j) obtained by $\min_j S_j$ is with a maximum group utility, and the solution obtained by $\min_j R_j$ is with a minimum

individual regret of the opponent. The VIKOR algorithm is as follows:

Step 1 It is the determination of the alternatives (A_m) and criteria (x_m) and the formation of the decision matrix according to Eq. (7).

$$D = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} x_1 & x_2 & \dots & x_n \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{13} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mm} \end{bmatrix} \quad (7)$$

Step 2 This step normalizes the decision matrix using Eq. (8).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (8)$$

Step 3 Determine the best and the worst values of all criterion functions, for $i = 1, 2, \dots, n$; based on Eqs. (9) and (10).

$$f^* = \text{Max}_j f_{ij}; \quad (9)$$

$$f^- = \text{Min}_j f_{ij} \quad (10)$$

Step 4 It determines the usefulness (S_j) namely the relative distance of alternative j th from the ideal point (Eq. 11), and regret (R_j), which shows the maximum discomfort of alternative j from the distance from the ideal

point (Eq. 12). The w_i is the weight of criteria that was calculated by the ANP method.

$$S_j = \sum_{i=1}^n w_j (f_i^* - f_{ij}) / (f_i^* - f_i^-) \tag{11}$$

$$R_j = \text{Max} [w_j (f_i^* - f_{ij}) / (f_i^* - f_i^-)] \tag{12}$$

Step 5 It calculates the VIKOR index (Q) according to Eqs. (13), (14), and (15). V in relation to weights for the maximum strategy represents the desirability of group decision-making, which is normally a constant value of 0.5.

$$Q_j = \frac{v(S_j - S^*)}{S^- - S^*} + (1 - v)(R_j - R^*) / (R^- - R^*) \tag{13}$$

where,

$$S^* = \text{Min}_j S_j; S^- = \text{Max}_j S_j; \tag{14}$$

$$R^* = \text{Min}_j R_j; R^- = \text{Max}_j R_j; \tag{15}$$

and v is the weight of the strategy of the majority of criteria. Normally, v was assumed as $v = 0.5$. However, v can take any value from zero to one.

Step 6 It ranks the options based on the values of R , Q , and S in three groups from small to large.

Step 7 Suggest a compromise solution of the alternative (a') that is on the top of the ranked list of Q if satisfy two conditions:

Condition 1 Acceptable advantage: if $Q(a'') - Q(a') \geq DQ$, where a'' is the second best alternative based on Q ranking, and $DQ = \frac{1}{J-1}$, while J is the number of alternatives.

Condition 2 Acceptable stability in decision-making. Alternative a' should be the best alternative based on S and R rankings. This compromise solution can be considered

stable in a decision-making process, which could be “voting by majority rule” (when $v > 0.5$ is needed), “by consensus” $v \approx 0.5$, or “with veto” ($v < 0.5$), where v is the weight obtained for the strategy of decision-making “the majority of criteria” (or “the maximum group utility”).

Results

Results of EVI on the Anzali Coast

As Table 8 represents, the weight of the criteria is obtained using the ANP method after entering the data layers related to the criteria into the GIS environment. Based on the results, the weight determined by the aforementioned method indicates that the soil criterion with a weight of 0.27 followed by the vegetation (0.24), groundwater (0.18), and land use (0.15) has the highest importance among the criteria involved in evaluating the vulnerability in the studied area, while the topography, interaction with the sea, and climate criteria account for the lowest weight (0.05).

In the next step, the standardized maps related to the decision-making criteria were created in the GIS environment. Finally, the maps related to the criteria and weights obtained from the ANP method were combined based on the EVI formula, and the final map of the EV on the Anzali coast was created. Finally, the vulnerability map is divided into five categories based on the natural break method. This method aims to minimize the standard deviation between the data in each category and maximize the standard deviation between the categories. In other words, this method aims to reduce the variance in the category and

Table 8 Weights obtained from the ANP method

Criteria	Inter-factor weight	Sub-criteria	Inter-factor relative weight	Final weight
Soil	0.27	Soil texture	0.15	0.041
		Soil salinity	0.45	0.122
		Soil quality	0.4	0.108
Interaction with the sea	0.042	Coastal erosion	1	0.042
Groundwater	0.185	Groundwater level	0.57	0.105
		Electrical conductivity of groundwater	0.43	0.080
Climate	0.07	Average annual temperature	0.35	0.025
		Average annual precipitation	0.48	0.034
		Drought	0.17	0.012
Topography	0.043	Elevation	0.92	0.040
		Major geomorphological features	0.08	0.003
Land use	0.15	Land use	1	0.150
Vegetation	0.24	NDVI	1	0.240

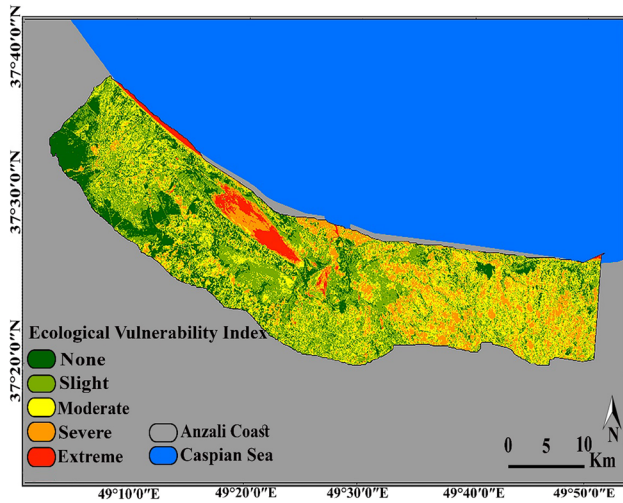


Fig. 6 Final map related to the EVI of the Anzali beaches

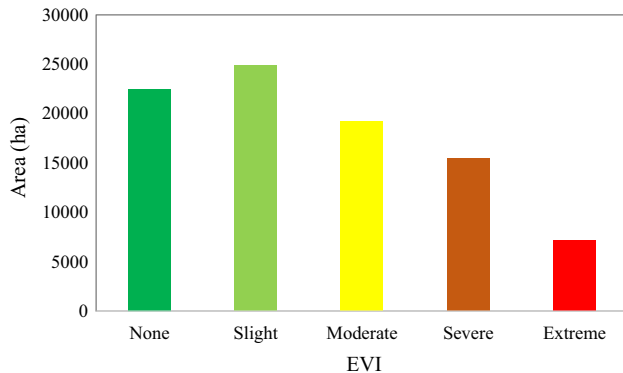


Fig. 7 Area and percentage of each EVI class on the Anzali coast

maximize the variance between categories and groups. Accordingly, this method presents its classification (George, 1967) which is an appropriate method for classifying zones based on the desired goals. Figure 6 illustrates the ecological vulnerability zoning of Anzali coasts in the studied area, classified into five categories none, slight, moderate, severe, and extreme vulnerability. Based on Figs. 6 and 7, 19,179.9 (21.51%), 15,464.1 (17.35%), and 7153.04 (8.02%) hectares of the entire area have

Table 9 Field validation matrix of ecological vulnerability classes based on soil salinity and NDVI

Vulnerability Classes	NDVI	SOIL-EC
None	> 0.7	< 0.7 ds/m
Slight	0.5	1.7 ds/m
Moderate	0.3	2.3 ds/m
Severe	0.2	3.1 ds/m
Extreme	0	> 3.5 ds/m

moderate, severe, and extreme degrees of vulnerability, respectively. However, 24,848.5 (27.87%) and 22,502 (25.24%) hectares of Anzali coasts have slight and none vulnerability potential, respectively.

Soil salinity is an important factor in reducing groundwater quality as well as the establishment of vegetation in natural habitats, which can reduce biodiversity, degrade natural habitats, increase soil erosion and accelerate the desertification process. In the present study, to evaluate and verify EV classes, field sampling was performed from soil salinity and vegetation in each of the EV classes (Table 9). As observed, two important indicators affecting the determination of ecological vulnerability, namely NDVI and soil salinity are measured in ds/m in the field samples. The results of the field validation revealed the accuracy of the designated classes so that the samples taken from the soil at the no risk ecological class had EC lower than 0.7 ds/m and vegetation was higher than 0.7, while the EC of soil salinity in soil with extreme vulnerability was more than 3.5 ds/m and lacked vegetation.

Sensitivity Analysis Results

Sensitivity analysis determines the extent and effect of input data on output data (Malczweski, 2006). Based on the change in each of the studied criteria, the change in the ecological threshold of the constructed model was examined (Fig. 8). Based on the result, the ecological threshold changes by -0.296 , 0.3002 , 0.5061 , -0.3187 , -0.2758 , and -0.2574 with a unit change in climate, soil, land use, groundwater, vegetation cover, topography, and interaction with coastline, respectively. The results of sensitivity analysis showed that the highest and lowest changes are related to land use and climate criteria, respectively.

Results of Conditions in the Region and Risk Assessment

As indicated in Fig. 6, Anzali Wetland has been considered a significant and international ecosystem that is located in the high EV class. In the first part of the findings, the DPSIR analytical model for Anzali International Wetland was used to find the driving force and pressure factors on the conditions of the wetland and to express a solution to improve the current situation. A cause and effect relationship was determined using its conceptual framework as shown in Fig. 9.

The VIKOR method was used to rank the risk factors after determining 16 risk factors based on DPSIR results in this section. To conduct the VIKOR model, three criteria of effect intensity, probability of occurrence, and sensitivity of the recipient environment were estimated for each risk factor (Table 10). Tables 11, 12, and 13 show the results of

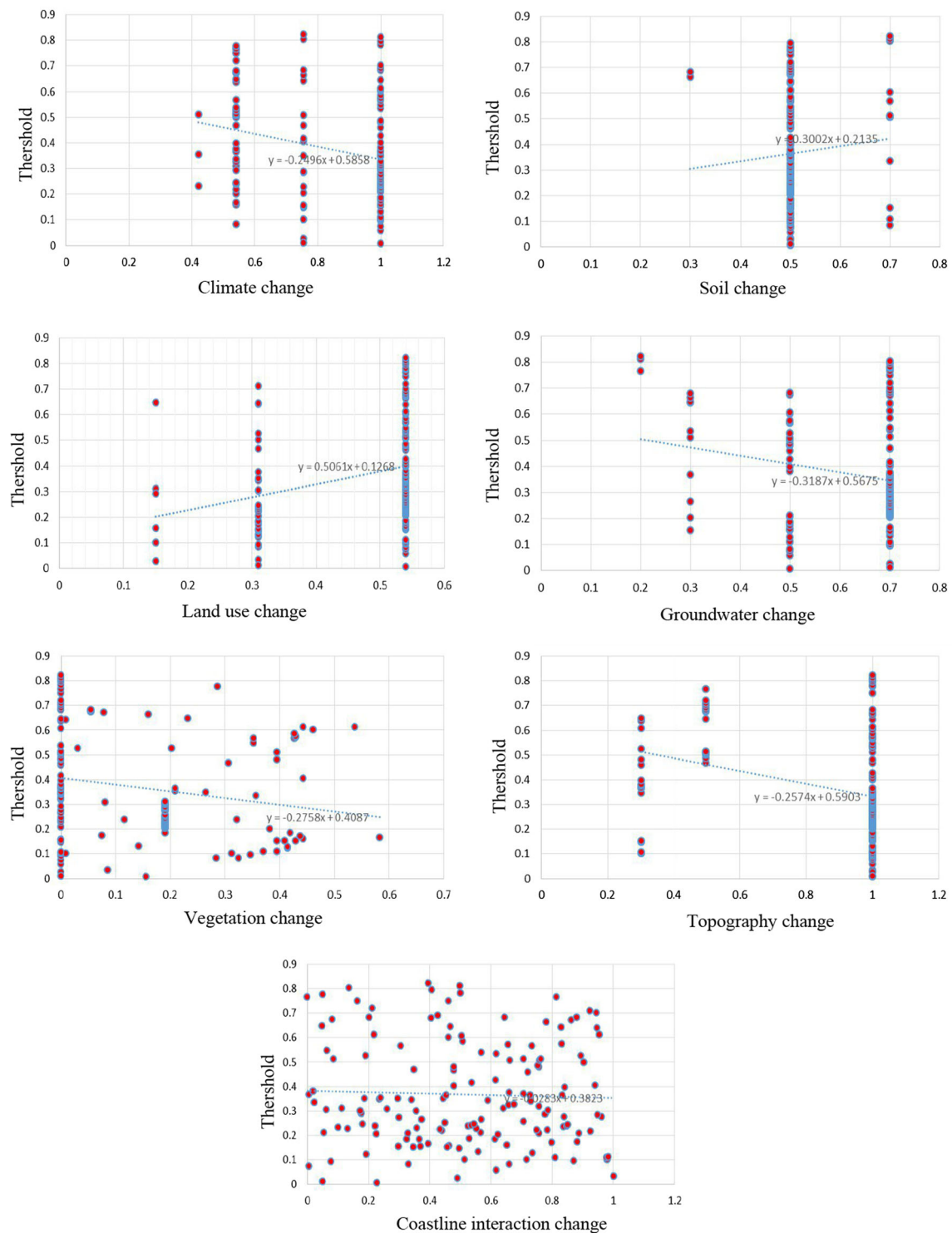


Fig. 8 Sensitivity analysis of the constructed model for changes in ecological threshold to coastline interaction change

ranking the hazards threatening the wetland in the three environments.

Based on Table 13, the results obtained from ranking the threatening risks of Anzali International Wetland using the VIKOR method indicated that the entry of wastewater from

the city and surrounding villages into the wetland in the physical–chemical environment, irregular harvesting of plant wetland resources in the biological environment, and occupying and changing the land use in the socio-economic environment were the priorities of each environment.

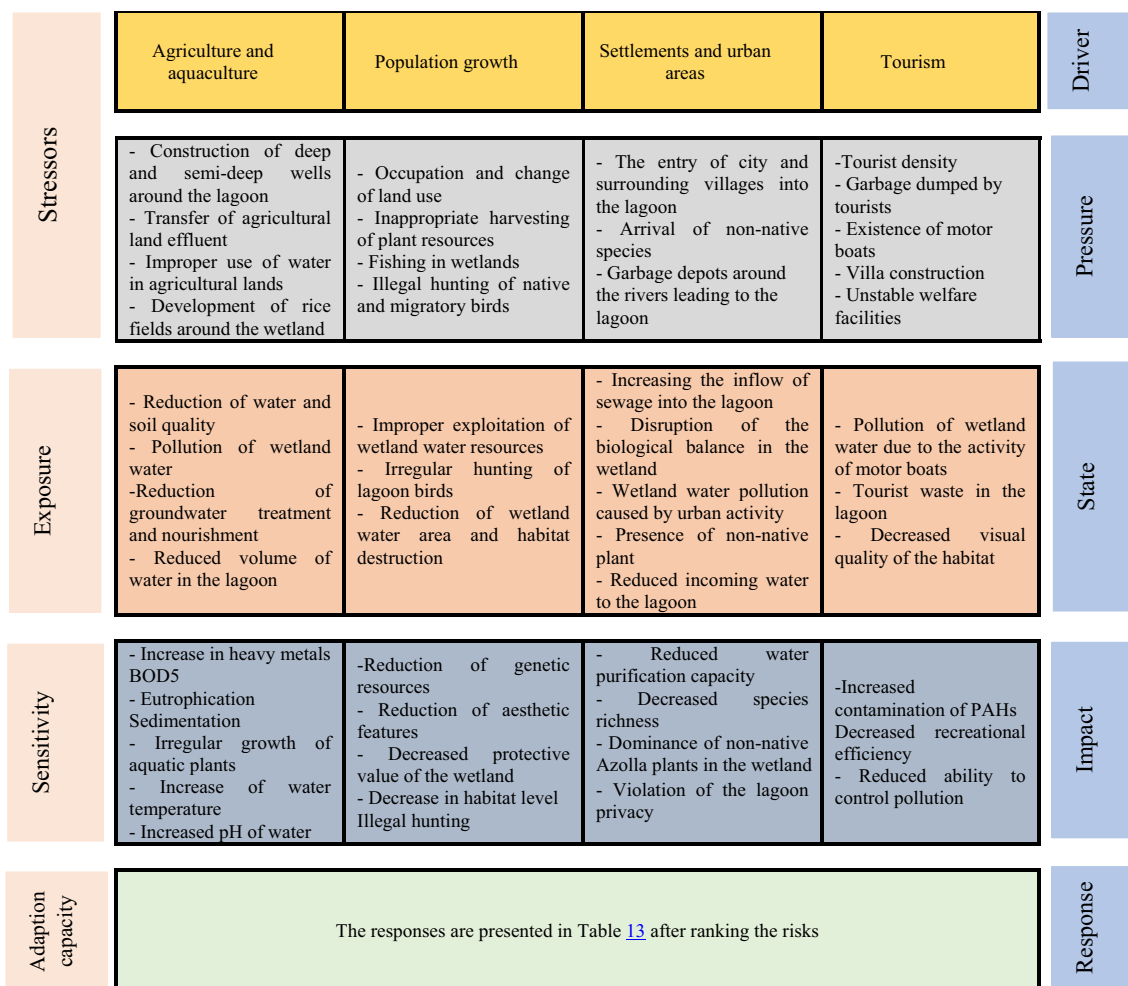


Fig. 9 Integrated DPSIR framework with vulnerability assessment

According to the risk ranking, control measures should be taken to reduce the environmental risks of Anzali International Wetland and some solutions in this regard are presented in Table 14.

Discussion

The length of the coastline in the Caspian Sea is considered the focus of valuable ecosystems such as estuaries, wetlands, important wildlife habitats, and the like, requiring special management. Furthermore, preparing EV maps for such coasts can be a valuable strategy in managing biological resources to ensure sustainable productivity and management. There is a need to assess the sensitivity of the Anzali coast as it faces a variety of pollutants, erosion, and various physical obstacles along with the gradual growth of the population and increasing development (Doukakis, 2005; Sankari et al., 2015). The present study aims to zone the vulnerable spots on the Anzali coast based on the GIS-

based MCDM. In this study, EVI mapping has been done based on the ANP method, which is one of the most efficient and widely used methods in vulnerability assessment (Andalecio, 2010; Mani Murali et al., 2013). ANP compares sub-criteria with the cluster of criteria as well as all criteria and their interrelationships with sub-criteria of other criteria. This analysis demonstrates the significance of each element on other elements as well as in the complete vulnerability assessment. Thus, the ANP was used to make optimized weights by considering the relative weights based on criteria and sub-criteria. Khodadoust et al. (2016) conducted a study on the prioritization and mapping of coastal areas to oil loss by comparing AHP and ANP methods in Nayband Marine National Park in Assaluyeh. They stated that the ANP method has more consistent than the AHP method to consider the interrelationship of different levels of decision with each other and also the internal relationship of decision criteria at one level. Mani Murali et al. (2013) and Tahri et al. (2017) introduced GIS-FAHP as an effective method in coastal vulnerability

Table 10 Scoring the indicators of intensity and sensitivity of the recipient environment

First level	Second level	Name	Third level Risk factor	effect intensity (C1)	Risk probability (C2)	Sensitivity of the recipient environment (C3)
Determining the probability of environmental risks in Anzali International Wetland	Physical and chemical	A ₁	Waste depot around the rivers leading to the lagoon	3	3	4
		A ₂	The entry of wastewater from city and surrounding villages to the lagoon	4	5	5
		A ₃	Construction of deep and semi-deep wells around the lagoon	3	4	4
	Biological	B ₁	Wetland fishing	4	3	2
		B ₂	Irregular harvesting of wetland plant resources	3	2	2
		B ₃	Illegal hunting of birds	2	2	1
	Socio-economic	C ₁	Improper use of water in agricultural lands	4	4	5
		C ₂	Development of rice fields around the wetland	4	5	4
		C ₃	Entry of non-native species	4	3	5
		C ₄	Occupying and changing the land use	5	5	5
		C ₅	Villa construction	2	3	3
		C ₆	Tourist density	2	3	3
	C ₇	Unstable welfare facilities	2	2	2	
	C ₈	Tourist waste	2	1	2	
C ₉	Presence of motor boats	3	3	3		

Table 11 Results of ranking the threatening risks in the physical–chemical environment of Anzali International Wetland based on VIKOR method

Risk	S	R	Q	Rank
A1	1.01	0.41	1.00	3
A2	0.00	0.00	0.00	1
A3	0.80	0.41	0.89	2

Table 12 Results of ranking the threatening risks in the biological environment of the Anzali International Wetland based on VIKOR method

Risk	S	R	Q	Rank
B ₁	0.51	0.51	0.63	2
B ₂	0.33	0.17	0.00	1
B ₃	1.00	0.51	1.00	3

Table 13 Results of ranking the threatening risks in the socio-economic environment of Anzali International Wetland based on the VIKOR method

Risk	S	R	Q	Rank
C ₁	0.207	0.107	0.237	3
C ₂	0.200	0.107	0.233	2
C ₃	0.307	0.200	0.403	4
C ₄	0.000	0.000	0.000	1
C ₅	0.707	0.320	0.753	6
C ₆	0.707	0.320	0.753	6
C ₇	0.900	0.320	0.850	8
C ₈	1.000	0.400	1.000	9
C ₉	0.600	0.213	0.567	5

analysis by investigating the east coast of India and the Mohammedia coast in Morocco, respectively. In

addition, Wu et al. (2018) conducted a study on the EV assessment of YRD based on the FAHP and fuzzy logic models. They demonstrated that the combination of the two models was useful for the assessment and the spatial distribution of all vulnerability grades was regular.

Table 14 Control measures to reduce the environmental risks of Anzali International Wetland

Risk factors	Measures
The entry of wastewater from the city and surrounding villages into the lagoon	Organizing urban wastewater
Waste depot around the rivers leading to the lagoon	Filtrating urban–rural wastewater before discharge into the wetland and continuous monitoring of water quality
Construction of deep and semi-deep wells around the lagoon	Preserving pollution control plants such as reeds along rivers and wetlands
Wetland fishing	Identifying and controlling illegal harvest and legal fines for drilling wells without a license
Irregular harvesting of wetland plant resources	Legal penalties for offenders
Illegal hunting of birds	Organizing and determining the license for hunting native birds of the region
	Establishing communication and interaction between local people and related organizations in discussing livelihood issues
	Determining the capacity to harvest biological resources from the wetland
Improper use of water in agricultural lands	Allocating wetland environmental water to maintain the stability of the wetland
Development of rice fields around the wetland	Monitoring the lands adjacent to the wetland and determining the boundaries and privacy of the wetland
Entry of non-native species	Using rowing boats instead of motor boats
Occupying and changing the land use	Developing binding regional guidelines to prevent land use change
Villa construction	Evaluating the potential of sustainable tourism and determining the capacity of the tourism range in the region
Tourist density	Providing environmental training to stakeholders and citizens to preserve the environment of the wetland
Unstable welfare facilities	Using physical and biological methods to deal with non-native species in the wetland
Tourist waste	
Vehicle traffic in the region	
Presence of motor boats	

In the current study, the ANP results showed that the NDVI (0.24), landuse (0.15), and soil salinity (0.122) sub-criteria had the highest relative weights, respectively. It is shown that the mentioned criteria play the most significant role in assessing the EV of the coasts. In addition, the sub-criteria of major geomorphological features and climate such as drought, annual average temperature and precipitation due to the small size of the study area, low height difference, and presence of coastal plains were the least important in vulnerability assessment. Mani Murali et al. (2013) stated that the slope, geomorphology, elevation, and erosion rate are important criteria for physical vulnerability, and the remaining criteria, including sea-level change, wave height, and mean tidal range does not vary with respect to vulnerability. They stated that this is because the extent of the shoreline under consideration is small and so only one relevant value is obtained for the data. Tahri et al. (2017) declared that the shoreline evolution, elevation, geomorphology, wave height, sea-level rise, tidal range, and distance to an urban area are important criteria to analyze coastal vulnerability. Moreover, Wu et al. (2018) stated that soil salinity, soil quality, groundwater quality, and land use had the highest weight in EV assessment, respectively. Considering the different weights of the criteria in various studies, it can be concluded that the

importance of the criteria will be a function of the environmental conditions and the location of the studied area.

Areas with slight or none vulnerability (53.11%) are mostly in the forest and grassland in the west and southwest, while the areas with severe and extreme vulnerability (25.37%) are more concentrated in the areas with the water bodies, Anzali Wetland, Siahkesham Protected Area, Sor-khangol Wildlife Refuge, and the Anzali City. The rest of the area is scattered in the northern part of the coastline, as well as east and southeast with the largest presence of agricultural land and scattered villages. In addition, the aforementioned areas correspond to those with medium to poor soil quality, high salinity of the soil, sandy to loamy sand, and the highest EC groundwater values at a glance. Further, GIS-based multi-criteria evaluation methods are considered an appropriate approach to decision-making given the nature of coastal vulnerability assessment, which involves various ecological, technical, and economic criteria (Cozannet et al., 2013; Ozyurt et al., 2011; Tahri et al., 2017; Wu et al., 2018). Furthermore, coastal vulnerability zoning based on fuzzy gamma is among the most efficient, widely used, and accepted methods (Andalecio, 2010; Mani Murali et al., 2013).

The evaluation of the zoning map in Fig. 6 indicated that Anzali International Wetland is located in a zone with severe vulnerability. The drivers, pressures, state, impacts,

and responses were identified in the area of Anzali Wetland with the help of the conceptual model, as shown in Fig. 9. The pressures resulting from the drivers cause a change in the state of the ecosystem and affect the natural and man-made conditions of the environment. This impact forces society to offer some solutions in the form of responses to reduce the impact. Based on the DPSIR framework, the drivers identified for the changes are agriculture, aquaculture, settlements and urban areas, population growth, and tourism. The requirements of the growing population are considered a driver which puts pressure on the land's basic resources. Increasing human population density increases the demand for access to production and service services from the wetland. This increase in population increases the entry of urban and rural effluents into the lagoon and the Caspian Sea, the entry of pesticides and chemical fertilizers into the lagoon, the entry of nutrients into water such as nitrogen, and phosphate, and the growth of wetland plants and eutrophication.

On the other hand, population increase has caused land use changes in the margins of Anzali Wetland. Based on the study of Mousazadeh et al. (2015) about 6500 hectares (about 69%) of pastures in the watershed of Anzali Wetland were destroyed and urban and agricultural areas expanded to 2982 hectares (~ 74%) and 2228 hectares (~ 6%) during 1975–2013. This change of use can increase the inflow of effluents, flood potential, and water utilization but reduce groundwater quality in the Anzali wetland, leaving numerous negative effects on the appearance and aesthetics of the wetland and reducing the habitat of aquatic species, birds, and the continuation of regeneration. In addition, another driver of this wetland is unstable tourism activities. Pristine nature, diversity of plant and animal communities, and temperate climate annually attract many tourists who use the welfare facilities along the lagoon created regardless of the ecological status of the lagoon in the region. This activity can have adverse effects on the environment such as soil erosion, destruction of wetland habitats, noise pollution caused by motor boat traffic, groundwater pollution, and endangering the health of inadequate waste and sewage networks in the wetland environment. Jahanishakib and Malekmohammadi (2017), Pirrone et al. (2005), and Zacharias et al. (2008) considered agriculture, population growth, tourism, and industry as drivers. In addition, the results of ranking the threatening risks of Anzali International Wetland using the VIKOR method indicated that the entry of wastewater from the city and surrounding villages into the wetland, uncontrolled harvesting of plant wetland resources, as well as occupying, and changing the land use cover significant factors in the vulnerability of Anzali wetland can be studied in all three dimensions.

Conclusion

Coastal ecosystems play a significant role in human welfare by providing essential services to human communities. However, the health of such valuable ecosystems is highly threatened by environmental pressures from natural and man-made activities throughout the world. Therefore, EV mapping on the Anzali coast is essential to implement integrated protection management. In this study, a quantitative analysis of the ecological vulnerability of the Anzali coast was conducted using ecological criteria and based on the MCDM approach in the GIS environment. Quantitative assessment of vulnerability can help decision-makers make accurate decisions regarding the management of vulnerable areas and investigate the factors affecting the vulnerability of the area. The vulnerability zoning map shows that the spatial distribution of vulnerability classes in the Anzali coasts has been irregular and scattered. In this study, areas with none and slight vulnerability are mostly located in the forest and grassland in the west and southwest, while most areas with severe to extreme vulnerability are mostly located near Anzali wetland, adjacent protected areas, and Anzali city. However, the comparison of the vulnerable areas with criteria maps showed that the vulnerable areas are located in areas with medium to poor soil quality, high soil salinity, sandy to loamy sand, and the highest amounts of EC groundwater. These results showed that GIS-MCDM is an appropriate approach for vulnerability zoning of coastal areas, and its results can provide better decision support for planning in the sustainable management of coastal areas.

In this study, a systematic analysis and identification of risks and vulnerable factors were conducted based on the DPSIR method and risk assessment of Anzali wetland as one of the high vulnerability areas. Based on the results, the entry of wastewater from the city and surrounding villages into the wetland, uncontrolled harvesting of wetland plant resources, and land use changes are the most significant factors threatening the environment of the Anzali wetland. Such factors are the main causes of adverse effects on the unique features of the wetland. Since Anzali International Wetland is a valuable wetland in the Ramsar Convention and Black Wetlands of Montreux, preserving and preventing its ecological changes as functional ecosystems are necessary for sustainable development. The results of this process can be highly essential for decision-makers to obtain a framework of the situation and the effects of their actions on wetlands based on factors such as driver and pressure for taking management measures to reduce the pressures on this international wetland. Of course, this study has its limitations. As this study only investigated the spatial distribution of EV in 2018, the analyses were

homogenous and limited. As a result, it is suggested that EV be conducted in different seasons and time series for a more in-depth analysis of environmental features due to the spatial dynamic changes of the studied data. In this study, the ANP method was used to nonlinear structure and considered the interrelationship of different decision levels with each other as well as the internal relationship of decision criteria at the same level. So, the authors suggest the use of other weighting methods such as BWM, DEMATEL-ANP, SWARA, or fuzzy methods such as fuzzy ANP to eliminate the uncertainty and ambiguity of verbal variables. In this study, ecological vulnerability assessment has been done with an emphasis on ecological criteria. Therefore, it is suggested that socio-economic criteria be used in future studies to increase the accuracy of analyses to consider all the principles of sustainable development to provide a comprehensive and complete view of the region's condition for decision-makers.

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References

- Adger, W. N. (2006). Vulnerability. *Global Environmental Change*, 16(3), 268–281. <https://doi.org/10.1016/j.gloenvcha.2006.02.006>
- Afzali, A., Sabri, S., Rashid, M., Samani, J. M. V., & Ludin, A. N. M. (2014). Inter-municipal landfill site selection using analytic network process. *Water Resources Management*, 28(8), 179–2194. <https://doi.org/10.1007/s11269-014-0605-3>
- Andalecio, M. N. (2010). Multi-criteria decision models for the management of tropical coastal fisheries. A review. *Agronomy for Sustainable Development*, 30, 557–580. <https://doi.org/10.1051/agro/2009051>
- Anfuso, G., Postacchini, M., Di Luccio D., & Guido Benassai. (2021). Coastal sensitivity/vulnerability characterization and adaptation strategies: a review. *Journal of Marine Science and Engineering*, 9(1), 72. <https://doi.org/10.3390/jmse9010072>
- Bagdavičiūtė, I., Kelpšaitė, L., & Soomere, T. (2015). Multi-criteria evaluation approach to coastal vulnerability index development in micro-tidal low-lying areas. *Ocean & Coastal Management*, 104, 124–135. <https://doi.org/10.1016/j.ocecoaman.2014.12.011>
- Beroya-Eitner, M. A. (2016). Ecological vulnerability indicators. *Ecological Indicators*, 60, 329–334. <https://doi.org/10.1016/j.ecolind.2015.07.001>
- Bigot, L., Canovas, S., Denis, J., Dutrieux, E., Hénocque, Y., & Quod, J. P. (2000). Guidelines for vulnerability mapping of coastal zones in the Indian Ocean. <https://doi.org/10.25607/OBP-1431>.
- Brakenridge, G. R., Syvitski, J. P. M., Overeem, I., Higgin, S. A., Kettner, A. J., Stewart-Moore, J. A., Westerhoff, R., (2013). Global mapping of storm surges and the assessment of coastal vulnerability. *Natural Hazards*, 66(3), 1295–1312 (2013). <https://doi.org/10.1007/s11069-012-0317-z>
- Burkhard, B., & Müller, F. (2008). Driver-pressure-state-impact-response. In the book: Ecological Indicators. Encyclopedia of Ecology, (Vols. 5, pp. 967–970). <https://doi.org/10.1016/B978-008045405-4.00129-4>.
- Chang, C., Chi C., Yao, M., Huang, N., Chen C., Theiss, J., Bushmaker, A. W., LaLumondiere S., Yeh, T., Povinelli, M.L., Zhou, C., Dapkus, P. D., & Cronin, S. B. (2012). Electrical and optical characterization of surface passivation in GaAs nanowires. *Nano Letters*. 12, 9, 4484–4489. <https://doi.org/10.1021/nl301391h>
- Chen, L. Y., & Wang, T. C. (2009). Optimizing partners' choice in IS/IT outsourcing projects: The strategic decision of fuzzy VIKOR. *Production Economics*, 120(1), 233–242. <https://doi.org/10.1016/j.ijpe.2008.07.022>
- Cozannet, G. L., Garcin, M., Bulteau, T., Mirgon, C., Yates, M. L., Méndez, M., Baills, A., Idier, D., & Oliveros, C. (2013). An AHP-derived method for mapping the physical vulnerability of coastal areas at regional scales. *NHESS*, 13(5), 1209–1227. <https://doi.org/10.5194/nhess-13-1209-2013>
- Craig, R. K., & Ruhl, J. B. (2010). Governing for sustainable coasts: Complexity, climate change, and coastal ecosystem protection. *Sustainability*, 2(5), 1361–1388. <https://doi.org/10.3390/su2051361>
- Dibajnia, M., Soltanpour, M., Vafai, F., Shoushtari, S. M. H. J., & Kebriaee, A. (2012). A shoreline management plan for Iranian coastlines. *Ocean & Coastal Management*, 63, 1–15. <https://doi.org/10.1016/j.ocecoaman.2012.02.012>
- Dossou, J. F., Li, X. X., Kouhondji, N. K. et al. (2021). Impact of Agriculture on the Oueme Basin in Benin. *Water Air Soil Pollut*, 232, 479. <https://doi.org/10.1007/s11270-021-05397-5>
- Doukakis, E. (2005). Coastal vulnerability and risk parameters. *European Journal & Water Quality*, 11(12), 3–7.
- Eldrandaly, K. A. (2013). Exploring multi-criteria decision strategies in GIS with linguistic quantifiers: An extension of the analytical network process using ordered weighted averaging operators. *Geographical Information Science*, 27(12), 2455–2482. <https://doi.org/10.1080/13658816.2013.815356>
- Fandohan, A. B., Oduor, A. M., Sodé, A. I., Wu, L., Cuni-Sanchez, A., Assédé, E., & Gouwakinnou, G. N. (2015). Modeling vulnerability of protected areas to invasion by *Chromolaena odorata* under current and future climates. *Ecosystem Health and Sustainability*, 1(6), 1–12. <https://doi.org/10.1890/EHS15-0003.1>
- Fazli, H., & Taghavi Jelodar, H. (2013). Stocks Status of Kilka in Iranian waters of the Caspian Sea. *Environment Research*, 1(2), 167–180. <https://doi.org/10.22069/ijerr.2014.1692>
- Field, C. B., & Barros, V. R. (2014). *Climate change 2014—Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press. Retrieved Jan 26, 2022, from https://www.researchgate.net/publication/272150376_Climate_change_2014_impacts_adaptation_and_vulnerability_IPCC_WGII_AR5_summary_for_policymakers.
- Foroozesh, F., Monavari, S. M., Salmanmahiny, A., Robati, M., & Rahimi, R. (2022). Assessment of sustainable urban

- development based on a hybrid decision-making approach: Group fuzzy BWM, AHP, and TOPSIS–GIS. *Sustainable Cities and Society*, 76, 103402.
- Füssel, H. M., & Klein, R. J. T. (2006). Climate change vulnerability assessments: An evolution of conceptual thinking. *Climatic Change*, 75, 301–329. <https://doi.org/10.1007/s10584-006-0329-3>
- Gebremedhin, S., Getahun, A., Anteneh, W., Bruneel, S., & Goethals, P. A. (2018). Drivers-pressure-state-impact-responses framework to support the sustainability of fish and fisheries in Lake Tana, Ethiopia. *Sustainability*, 10, 2957. <https://doi.org/10.3390/su10082957>
- George, F. (1967). The data model concept in statistical mapping. *International Yearbook of Cartography*, 7, 186–190.
- Ghanavati, E., Shah-Hosseini, M., & Marriner, N. (2021). Analysis of the makran coastline of Iran's vulnerability to global sea-level rise. *Journal of Marine Science and Engineering*, 9(8), 891. <https://doi.org/10.3390/jmse9080891>
- Gornitz, V. M., Daniels, R. C., White, T. W., & Birdwell, K. R. (1994). The development of a coastal risk assessment database: vulnerability to sea-level rise in the US Southeast. *Journal of coastal research*, 327–338.
- Halpern, B. S., Longo, C., Hardy, D., McLeod, K. L., Samhuri, J. F., & Katona, S. K. (2012). An index to assess the health and benefits of the global ocean. *Nature*, 488, 615–620. <https://doi.org/10.1038/nature11397>
- He, L., Shen, J., & Zhang, Y. (2018). Ecological vulnerability assessment for ecological conservation and environmental management. *Environmental Management*, 206, 1115–1125. <https://doi.org/10.1016/j.jenvman.2017.11.059>
- Hong, W., Jiang, R., Yang, C., Zhang, F., Su, M., & Liao, Q. (2016). Establishing an ecological vulnerability assessment indicator system for spatial recognition and management of ecologically vulnerable areas in highly urbanized regions: A case study of Shenzhen, China. *Ecological Indicators*, 69, 540–547. <https://doi.org/10.1016/j.ecolind.2016.05.028>
- Jafari, N. (2010). Review of pollution sources and controls in Caspian Sea region. *Journal of Ecology and the Natural Environment*, 2(2), 025–029. <https://doi.org/10.5897/JENE.9000095>
- Jamshidi, S., & Yousefi, M. (2013). Seasonal variations of seawater properties in the southwestern coastal waters of the Caspian Sea. *Marine Science and Engineering*, 3(3), 113–124.
- Jha, R. K., & Gundimeda, H. (2019). An integrated assessment of vulnerability to floods using composite index—A district level analysis for Bihar, India. *Disaster Risk Reduction*, 35, 101074. <https://doi.org/10.1016/j.ijdr.2019.101074>
- Joz, A., & Shafiee, M. (2009). Environmental risks analysis of helleh protected area of boushehr by using AHP method. *Marine Science and Technology Research*, 6(11), 14–97.
- Khodadoust, H., Vafai, F., & Hadipour, V. (2016). Determining priorities and mapping oil spill hazards index in shorelines by comparison AHP method and ANP method (case study: shoreline of Bushehr Province). *Journal of Marine Engineering*, 12(23), 57–68.
- Koroglu, A., Ranasinghe, R., Jiménez, J. A., & Dastgheib, A. (2019). Comparison of coastal vulnerability index applications for Barcelona Province. *Ocean & Coastal Management*, 178, 104799. <https://doi.org/10.1016/j.ocecoaman.2019.05.001>
- Kosamu, I. B. M., Makwinja, R., Kaonga, C. C., Mengistou, S., Kaunda, E., Alamirew, T., & Njaya, F. (2022). Application of DPSIR and Tobit models in assessing freshwater ecosystems: The case of lake Malombe, Malawi. *Water*, 14(4), 619. <https://doi.org/10.3390/w14040619>
- Lambin, E. F., & Geist, H. (2006). *Land-use and land-cover change. Local processes and global impacts*. Springer.
- Lima, M. L., Romanelli, A., & Calderon, G., et al. (2019). Multi-criteria decision model for assessing groundwater pollution risk in the urban-rural interface of Mar del Plata City (Argentina). *Environmental Monitoring and Assessment*, 191, 347. <https://doi.org/10.1007/s10661-019-7485-1>
- Ma, Y., Wang, D., & Liu, J.-M. (2013). Relationships between typical vegetations, soil salinity, and groundwater depth in the Yellow River Delta of China. *Chinese Journal of Applied Ecology*, 24(9), 2423–2430.
- Makvandi, R., Astani, S., & Lorestani, B. (2016). Environmental risk assessment of wetlands using TOPSIS and EFMEA (case study: International wetland Gavkhoni). *Environmental Researches*, 6(11), 35–58.
- Malczweski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. *Geographical Information Science*, 20(7), 703–726. <https://doi.org/10.1080/13658810600661508>
- Malekmohammadi, B., & Jahanishakib, F. (2017). Vulnerability assessment of wetland landscape ecosystem services using driver-pressure-state-impact-response (DPSIR) model. *Ecological Indicators*, 82, 293–303. <https://doi.org/10.1016/j.ecolind.2017.06.060>
- Mani Murali, R., Ankita, M., Amrita, S., & Vethamony, P. (2013). Coastal vulnerability assessment of Puducherry coast, India, using the analytical hierarchical process. *NHESS*, 13(12), 3291–3311. <https://doi.org/10.5194/nhess-13-3291-2013>
- McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, (Vol. 17, No. 22, pp. 179–183).
- Meléndez-Pastor, I., Pedreño, J. N., Lucas, I. G., & Zorpas, A. A. (2017). A model for evaluating soil vulnerability to erosion using remote sensing data and a fuzzy logic system. *Modern Fuzzy Control Systems and Its Applications*, 437–453.
- Michael, H. A., Russoniello, C. J., & Byron, L. A. (2013). Global assessment of vulnerability to sea-level rise in topography-limited and recharge-limited coastal groundwater systems. *Water Resources Research*, 49(4), 2228–2240. <https://doi.org/10.1002/wrcr.20213>
- Mirzajani, A., Hamidian, A. H., Bagheri, S., & Karami, M. (2015). The possible effect of Balanus improvisus on *Cerastoderma glaucum* distribution in the south-western Caspian Sea. *Marine Biological Association of the United Kingdom*, 96(05), 1031–1040. <https://doi.org/10.1017/S0025315415000788>
- Mondejar, J. P., & Tongco, A. F. (2019). Near infrared band of Landsat 8 as water index: A case study around Cordova and Lapu-Lapu City Cebu Philippines. *Sustainable Environment Research*, 29(1), 1–15. <https://doi.org/10.1186/s42834-019-0016-5>
- Montazeri, M., & Bay, N. (2012). Climatic regionalization of Caspian region using multivariate statistical methods. *Geographical Researches*, 27(2), 77–90.
- Moradpour, S., & Long, S. (2019). Using combined multi-criteria decision-making and data mining methods for work zone safety: A case analysis. *Case Studies on Transport Policy*, 7(2), 178–184. <https://doi.org/10.1016/j.cstp.2019.04.008>
- Mousazadeh, R., Ghaffarzadeh, H., Nouri, J., Gharagozlou, A., & Farahpour, M. (2015). Land-use change detection and impact assessment in Anzali international coastal wetland using multi-temporal satellite images. *Environmental Monitoring and Assessment*, 187(12), 776–816. <https://doi.org/10.1007/s10661-015-4900-0>
- Naderi Beni, A., Lahijani, H., Mousavi Harami, R., Arpe, K., Leroy, S. A. G., Marriner, N., & Reimer, P. J. (2013). Caspian sea-level changes during the last millennium: Historical and geological evidence from the south Caspian Sea. *Climate of the past*, 9(4), 1645–1665. <https://doi.org/10.5194/cp-9-1645-2013>

- Nouri, J., Karbassi, A. R., & Mirkia, S. (2008). Environmental management of coastal regions in the Caspian Sea. *Environment Science and Technology*, 5, 43–52. <https://doi.org/10.1007/BF03325996>
- Oloyede, M. O., Benson, N. U., & Williams, A. B. (2021). Climate change and coastal vulnerability assessment methods: A review. *In IOP Conference Series: Earth and Environmental Science*, 665(1), 012069. <https://doi.org/10.1088/1755-1315/665/1/012069>
- Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, 156(2), 445–455. [https://doi.org/10.1016/S0377-2217\(03\)00020-1](https://doi.org/10.1016/S0377-2217(03)00020-1)
- Ozyurt, G., Ergin, A., & Baykal, C. (2011). Coastal vulnerability assessment to sea level rise integrated with analytical hierarchy process. *Coastal, Management and Risk*, 1(32), 122–135. <https://doi.org/10.9753/icce.v32.management.6>
- Pak, A., & Farajzadeh, M. (2007). Iran's integrated coastal management plan: Persian Gulf, Oman Sea, and southern Caspian Sea coastlines. *Ocean & Coastal Management*, 50, 754–773. <https://doi.org/10.1016/j.ocecoaman.2007.03.006>
- Pinto, R., De Jonge, V. N., Neto, J. M., Domingos, T., Marques, J. C., & Patrício, J. (2013). Towards a DPSIR driven integration of ecological value, water uses and ecosystem services for estuarine systems. *Ocean & Coastal Management*, 72, 64–79. <https://doi.org/10.1016/j.ocecoaman.2011.06.016>
- Pirrone, N., Trombino, G., Cinnirella, S., Algeri, A., Bendoricchio, G., & Palmeri, L. (2005). The Driver pressure-state-impact-response (DPSIR) approach for integrated catchment-coastal zone management: Preliminary application to the Po Catchment-Adriatic Sea coastal zone system. *Regional Environmental Change*, 5, 111–137. <https://doi.org/10.1007/s10113-004-0092-9>
- Qiao, Z., Yang, X., Liu, J., & Xu, X. (2013). Ecological vulnerability assessment integrating the spatial analysis technology with algorithms: A case of the wood-grass Ecotone of Northeast China. *Abstract and Applied Analysis, Online Publication*. <https://doi.org/10.1155/2013/207987>
- Rahmanipour, F., Marzaioli, R., Bahrami, H. A., Fereidouni, Z., & Bandarabadi, S. R. (2014). Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. *Ecological Indicator*, 40, 19–26. <https://doi.org/10.1016/j.ecolind.2013.12.003>
- Ricketts, P., & Harrison, P. (2007). Coastal and ocean management in Canada: Moving into the 21st Century. *Coastal Management*, 35(1), 5–22. <https://doi.org/10.1080/10.1080/08920750600970545>
- Rimba, A. B., Osawa, T., Parwata, I. N. S., As-syakur, A. R., Kasim, F., & Astarini, I. A. (2018). Physical assessment of coastal vulnerability under enhanced land subsidence in Semarang, Indonesia, using multi-sensor satellite data. *Advances in Space Research*, 61(8), 2159–2179.
- Ružić, I., Dugonjić Jovančević, S Benac., Č. & Kravica N. (2019). Assessment of the coastal vulnerability index in an area of complex geological conditions on the Krk Island, Northeast Adriatic Sea. *Geosciences*, 9(5), 219. <https://doi.org/10.3390/geosciences9050219>
- Saadati, S., Motevallian, S. S., Rheinheimer, D. E., & Najafi, H. (2013). Indicators for sustainable management of wetland ecosystems using a DPSIR approach: A case study in Iran. *In 6th international perspective on water resources & the environment conference (IPWE 2013)*, At Izmir, Turkey. <https://doi.org/10.13140/2.1.2350.5921>
- Sadeghi, B., & Khalajmasoumi, M. (2015). A futuristic review for evaluation of geothermal potentials using fuzzy logic and binary index overlay in a GIS environment. *Renewable and Sustainable Energy Reviews*, 43, 818–831. <https://doi.org/10.1016/j.rser.2014.11.079>
- Sankari, T. S., Chandramouli, A. R., Gokul, K., Surya, S. M., & Saravanavel, J. (2015). Coastal vulnerability mapping using geospatial technologies in Cuddalore-Pichavaram coastal tract, Tamil Nadu, India. *Aquatic Procedia*, 4, 412–418. <https://doi.org/10.1016/j.aqpro.2015.02.055>
- Saaty, T. L. (1996). Decision making with dependence and feedback: The analytic network process (Vol. 4922): RWS publications Pittsburgh.
- Schrevel, A., & Kumar, R. (2010). The Livelihoods concept integrated into the DPSIR analytical tool. The Netherlands Ritesh Kumar, Wetlands International, India. Retrieved Jan 26, 2022, from <https://library.wur.nl/WebQuery/wurpubs/387602>
- Sherein El-Shahat, S., El-Zafarani, A. E., & Abou El Seoud, T., Ghoniem, S. A. (2021). Vulnerability assessment of African coasts to sea level rise using GIS and remote sensing. *Environment, Development and Sustainability*. <https://doi.org/10.1007/s10668-020-00639-8>
- Song, G., Huang, J. T., Ning, B. H., Wang, J. W., & Zeng, L. (2021). Effects of groundwater level on vegetation in the arid area of western China. *China Geology*, 4(3), 527–535. <https://doi.org/10.31035/cg2021062>
- Song, X., & Frostell, B. (2012). The DPSIR framework and a pressure-oriented water quality monitoring approach to ecological river restoration. *Water*, 4(3), 670–682. <https://doi.org/10.3390/w4030670>
- Sudha Rani, N. N. V., Satyanarayana A. N. V., & Bhaskaran, P. K. (2015). Coastal vulnerability assessment studies over India: a review. *Natural Hazards*, 77, 405–428. <https://doi.org/10.1007/s11069-015-1597-x>
- Tabrizi, N., Taghvaei, M., & Varesi, H. (2012). A fuzzy application on MICE hosting: An Iranian case study for locating suitable areas based on PL Indexes. *Management Science Letters*, 2(2), 503–510. <https://doi.org/10.5267/j.msl.2011.12.024>
- Tahri, M., Maanan, M., Maanan, M., Bouksim, H., & Hakdaoui, M. (2017). Using fuzzy analytic hierarchy process multi-criteria and automatic computation to analyze coastal vulnerability. *Progress in Physical Geography Standard*, 41(3), 268–285. <https://doi.org/10.1016/j.pseep.2013.11.005>
- Tang, D., Liu, X., & Zou, X. (2018). An improved method for integrated ecosystem health assessments based on the structure and function of coastal ecosystems: A case study of the Jiangsu coastal area, China. *Ecological Indicators*, 84, 82–95. <https://doi.org/10.1016/j.ecolind.2017.08.031>
- Wang, C., Jiang, Q. O., Shao, Y., Sun, S., Xiao, L., & Guo, J. (2019). Ecological environment assessment based on land use simulation: A case study in the Heihe River Basin. *Science of the Total Environment*, 697, 133928. <https://doi.org/10.1016/j.scitotenv.2019.133928>
- Wang, Q., Zhang, R., Qi, J., Zeng, J., Wu, J., Shui, W., & Li, J. (2022). An improved daily standardized precipitation index dataset for mainland China from 1961 to 2018. *Scientific Data*, 9(1), 1–12. <https://doi.org/10.1038/s41597-022-01201-z>
- Wibowo, S. N. E., Mamuaya, G. E., & Djamaluddin, R. (2018). Land subsidence analysis of reclaimed land using time-lapse micro-gravity anomaly in Manado, Indonesia. *In Forum Geografi* (Vol. 32, No. 1, pp. 53–63). <https://doi.org/10.23917/forgeo.v31i2.5882>
- Wu, C., Liu, G., Huang, C., Liu, Q., & Guan, X. (2018). Ecological vulnerability assessment based on fuzzy analytical method and analytic hierarchy process in yellow river delta. *International Journal of Environmental Research and Public Health*, 15(5), 855. <https://doi.org/10.3390/ijerph15050855>
- Wu, K., & Zhang, L. (2014). Progress in the development of environmental risk assessment as a tool for the decision-making process. *Service Science and Management*, 7, 131–143. <https://doi.org/10.4236/jssm.2014.72011>

- Yu, P. L. (1973). A class of solutions for group decision problems. *Management Science*, 19(8), 936–946. <https://doi.org/10.1287/mnsc.19.8.936>
- Zacharias, I., Parasidou, A., Bergmeier, E., Kehayias, G., Dimitriou, E., & Dimopoulos, P. (2008). A “DPSIR” model for Mediterranean temporary ponds: European, national, and local scale comparisons. In *Annales de Limnologie-International Journal of Limnology*, (Vol. 44, No. 4, pp. 253–266). <https://doi.org/10.1051/limn:2008009>
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353. https://doi.org/10.1142/9789814261302_0021
- Zaitunah, A., Thoha, A. S., & Siregar, K. S. (2019). Analysis of coastal vegetation density changes of Langkat Regency, North Sumatera, Indonesia. In *IOP conference series: earth and environmental science* (Vol. 34, No. 1, p. 012042). <https://doi.org/10.1088/1755-1315/374/1/012042>.
- Zeleny, M., & Cochrane, J. L. (1982). Multiple criteria decision making McGraw-Hill New York, 34.
- Zhang, J., Sun, J., Ma, B., & Du, W. (2017). Assessing the ecological vulnerability of the upper reaches of the Minjiang River. *PLoS ONE*, 12(7), 0181825. <https://doi.org/10.1371/journal.pone.0181825>
- Zhou, S. D., Mueller, F., Burkhard, B., CAO, X. J., & Ying, H. O. U. (2013). Assessing agricultural sustainable development based on the DPSIR approach: a case study in Jiangsu, China. *Integrative Agriculture*, 12(7), 1292–1299. [https://doi.org/10.1016/S2095-3119\(13\)60434-7](https://doi.org/10.1016/S2095-3119(13)60434-7)

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