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Research Article

Spatio-temporal variations of habitat quality in the Pars Special Economic Energy Zone (Iran South Coast)

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Abstract

Spatio-temporal monitoring of biodiversity, as the foundation of ecosystem service provision, is essential in areas undergoing rapid and extensive changes. The spatial information provided is valuable for evaluating the impacts of projects or policies on biodiversity. It aids policymakers and planners in making informed decisions for future initiatives. The Pars Special Economic Energy Zone (PSEEZ), located on the northern coast of the Persian Gulf, is currently the world's largest special economic zone dedicated to the oil, gas, and petrochemical industries. The *Nayband* National Marine Park, with rich biodiversity, is located in this zone. Since its establishment in 1998, the PSEEZ has experienced significant industrial investment in under a decade. This investment in the oil and gas industries caused many changes in land use and land cover. In this study, the biodiversity status of the PSEEZ was assessed before the establishment of this zone (1986-1998) and during its rapid development (1998-2018), over a total period of 32 years. The InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) Habitat Quality model, integrated with multi-temporal Landsat and Sentinel-2 imagery, was used to assess long-term changes in habitat quality. The results indicate that the habitat degradation trend after the establishment of the PSEEZ was 18 times higher. This means that 1.16, 3.15, and 27.40% of habitats in the studied area were affected by the threats in 1986, 1998, and 2018, respectively. Habitat degradation is evident in the Nayband Marine National Park and requires greater attention to protect it.

Keywords: Biodiversity, Habitat quality, Remote sensing, InVEST, PSEEZ, Iran.

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Introduction

Ecosystem services, including provisioning, regulating, cultural, and supporting services, are essential benefits people derive from ecosystems (MEA, 2005). Biodiversity is closely linked to ecosystem services, and changes in biodiversity affect the provision of these services (Takacs and O'Brien, 2023). In recent years, human activities have led to a widespread loss of biological diversity (Jaureguiberry et al, 2022). An example of human activity is the creation of Special Economic Zones (SEZs) within a country's national borders, in accordance with the laws governing the national territory (Rubini et al, 2015; Sosnovskikh, 2017; Ahmadi et al, 2026). The primary objectives of Special Economic Zones (SEZs) are to promote international trade, attract domestic and foreign investment, increase exports, generate employment opportunities, and stimulate economic development (Chaudhuri and Yabuuchi, 2010; Wang, 2013; Bräutigam and Tang, 2014; Ortega et al, 2015; Ambroziak and Hartwell, 2018; Frick and Rodríguez-Pose, 2023). Developing facilities and infrastructure associated with the activities, enhancing transportation infrastructure, and attracting population are the principal features of the SEZ that result in significant alterations in land use and land cover (Yang et al, 2023). Recent studies have shown that rapid industrial expansion in coastal Special Economic Zones can substantially alter landscape patterns, accelerate habitat degradation, and threaten biodiversity (Aung et al, 2022; Sultana and Al Mahmud, 2025). Spatio-temporal monitoring of environmental change enables researchers to assess the impacts of projects and policies on biodiversity while providing spatially explicit information that supports evidence-based decision-making and environmental policy development (Maes et al, 2012; Salata et al, 2017; Skidmore et al, 2021). In addition, the results of this monitoring contribute to sustainable social and economic development, biodiversity conservation, and the ecological security of the region by supporting effective, science-based environmental management (Scheller et al, 2007; Kamran and Yamamoto, 2023). Such monitoring is particularly important in regions with high biodiversity (IPBES, 2024). Since conventional biodiversity measurement over large areas is far more costly and time-consuming (Harper and Hawksworth, 1994), habitat quality is typically used as a proxy for such measurement (Sharp et al, 2018; Mott et al, 2023). The InVEST model for habitat quality, boasting low application costs, high-accuracy evaluations, and robust spatial analysis capabilities, has been effectively utilised to map habitat quality across various regions (Baral et al, 2014; Terrado et al, 2016b; Sallustio et al, 2017; Liu et al, 2017; Zarandian et al, 2017; He et al, 2017; Moreira et al, 2018). This model assumes that areas with higher habitat quality generally support greater biodiversity, whereas habitat degradation negatively affects biodiversity. Thus, changes in habitat quality can serve as an indicator of changes in regional biodiversity (Chu et al, 2018). Recent studies have further demonstrated that habitat quality assessment has become an effective tool for evaluating the ecological consequences of rapid urbanisation, industrialisation, and land-use change (Zhang et al, 2024; Parvar and Salmanmahiny, 2025). Although numerous studies have applied the InVEST Habitat Quality model to assess biodiversity changes resulting from urbanisation, agricultural expansion, mining, and land-use change in different regions, limited attention has been paid to rapidly developing oil, gas, and petrochemical industrial zones, particularly in ecologically sensitive coastal environments. Recent studies have highlighted the substantial environmental impacts of industrial expansion in the Pars Special Economic Energy Zone (PSEEZ), including shoreline changes, land-use transformations, and coastal habitat degradation (Ahmadi et al, 2026). However, these studies have primarily focused on individual environmental components rather than providing an integrated assessment of habitat quality and biodiversity. Furthermore, previous studies have rarely integrated long-term remote sensing observations with the InVEST Habitat Quality model to evaluate biodiversity changes before and after the establishment of large Special Economic Zones (SEZs). Consequently, a comprehensive long-term assessment of habitat quality and biodiversity using the InVEST Habitat Quality model remains lacking for this globally significant energy hub. To address these research gaps, this study integrates multi-temporal remote sensing data with the InVEST

Habitat Quality model to quantify long-term changes in habitat quality before and after the establishment of the Pars Special Economic Energy Zone. The study further identifies major biodiversity threats and evaluates their spatial impacts over 32 years (1986–2018). Unlike previous studies, this research integrates long-term remote sensing observations with the InVEST Habitat Quality model to evaluate habitat quality both before and after the establishment of one of the world's largest oil, gas, and petrochemical Special Economic Zones. It also provides the first comprehensive spatial assessment of biodiversity threats over 32 years within this rapidly industrialising coastal ecosystem. To achieve these objectives, all major biodiversity threats in the PSEEZ were identified, and the spatial and temporal capabilities of Landsat and Sentinel-2 imagery were utilised. Landsat imagery has been continuously acquired since 1972, while Sentinel-2 observations have been available since 2015, providing valuable data for long-term biodiversity monitoring (Roy et al, 2014; Vihervaara et al, 2017; Wulder, 2022; Radeloff, 2024). Key advantages of these satellite datasets include global coverage, free accessibility, and high spatial and temporal resolution (Wang et al, 2017; Flood, 2017; Zhu, 2019).

Materials and Methods

Study Area

This study focuses on the Pars Special Economic Energy Zone (PSEEZ), located along the northern coast of the Persian Gulf in Bushehr Province, southern Iran (Fig. 1). The study area extends approximately from 27°02′ to 27°43′ N latitude and from 52°06′ to 52°57′ E longitude, covering an area of approximately 300,000 ha (3,000 km²). The boundary of the study area used throughout the analyses and in the InVEST Habitat Quality model is shown in Fig. 1. In particular, it investigates Nayband National Marine Park, sited in this Zone (Davoodi et al, 2017). This zone was established in 1998 to extract oil and gas from the South Pars Gas Field and to conduct economic activities in the city of Asaloyeh in Bushehr province. South Pars Gas Field (the North dome on the Qatari side) is the biggest gas field in the world. It is situated on the joint boundary of Iran and Qatar in the Persian Gulf. This natural gas reserve spans 9,700 square kilometres, with 3,700 square kilometres (South Pars) situated in Iran's territorial waters and 6,000 square kilometres (North Dome) located in Qatar's territorial waters (PSEEZ, 2018). The establishment of the PSEEZ has transformed this formerly rural region into a national and transnational city by extracting, developing, refining and exporting natural gas. The PSEEZ has experienced significant industrial investment in less than a decade. The Nayband Bay is situated within the PSEEZ. In 1978, an area of 19,500 hectares comprising this Bay and a portion of Nayband's headland was established as the Nayband guarded region. This area, which encompasses a section of the Persian Gulf waters and has a proximate area of 49,815 hectares, was registered as Iran's first national marine park in 2003 (Owfi and Owfi, 2018). Coastal dunes, rocky and sandy shores, coral reefs, mangrove forests, seagrass meadows and estuaries are among the diverse terrestrial and marine ecosystems found in this area (Ashournejad and Garshasbi, 2026). Also, various aquatic species, including dolphins, whales, endangered green and Kemp's ridley turtles, and numerous types of aquatic birds, inhabit the region (Zahed et al, 2010; Owfi and Owfi, 2018; Ashournejad et al, 2019a). The PSEEZ climate is warm and wet, characterised by scorching summers and gentle winters. Specifically, July and August are the warmest months with an average temperature of 35°C (95°F). There is no rain from June to September. The majority of rain, averaging 39.8 and 38.1 mm, falls in November and January, with a mean temperature of 24.1 and 18 °C (75.3 and 64.4 Fahrenheit). The lowest temperature of the year occurs in January (IRIMO 2018). The vegetation in this region comprises palm trees and mangrove forests, which are distributed across the inlet of Nayband Bay.

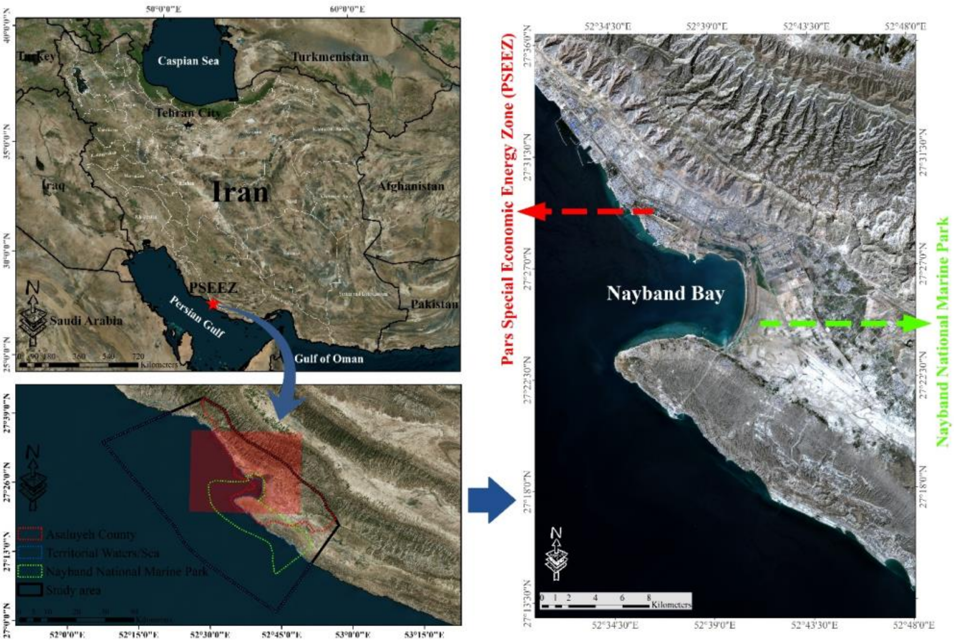

Fig. 1: Location of the PSEEZ in Iran and parts of the infrastructure of this zone and Nayband National Marine Park

Data Sources

Land Use and Land Cover (LULC) maps are generated from atmospherically corrected Landsat imagery provided by the USGS as spectral reflectances (USGS, 2018a; USGS, 2018b; Favretto, 2018) (Table 1). Three benchmark years (1986, 1998, and 2018) were selected for LULC mapping. The year 1998 marks the establishment of the Pars Special Economic Energy Zone (PSEEZ), while 1986 was selected as the baseline year to characterise pre-development conditions and enable comparison of biodiversity changes before and after its establishment. The selection of these images is a function of both the climatic conditions and the characteristics of the tides in the Persian Gulf and their impact on the mangrove forests (Ashournejad et al, 2019b; Miandej et al, 2024; Miandej et al, 2026). The region's weather conditions in the winter are favourable for farming, resulting in higher-resolution crop fields during January to March, as observed in remote sensing images, compared to other months of the year.

Table 1: Landsat images used to prepare Land use and land cover (LULC) maps in the PSEEZ

Images	Sat/sensor	Path/Row	Acquired	Datum/proj/zone
1	Landsat-5/TM	162/041	28/02/1986	WGS84/UTM/39 N
2	Landsat-5/TM	162/041	18/04/1998	WGS84/UTM/39 N
3	Landsat-8/OLI	162/041	24/03/2018	WGS84/UTM/39 N

Ship traffic has been identified as one of the threats to biodiversity. In this study, the ship traffic threat represents large industrial and commercial vessels associated with the development and operation of the Pars Special Economic Energy Zone (PSEEZ), including oil, gas, petrochemical, and port activities. Large industrial ship traffic associated with the PSEEZ was not observed in the available historical imagery before 1998. Although small traditional fishing boats may have been present, they could not be reliably detected due to their limited size and the spatial resolution of Landsat imagery. Since this study focuses on industrial maritime activities associated with the development of the PSEEZ, small-scale fishing boats were not included as a biodiversity threat. Therefore, 127 Landsat 8 and Sentinel-2 images acquired between 2013 and 2018 were used to identify and map the areas affected by industrial ship traffic in the PSEEZ (Ashournejad et al, 2019c). National 1:50,000 topographic map with the name of BANDAR-E ASALUYEH (No. 6544 IV), National 1:250,000 topographic map with the name of KANGAN (No. NG 39-3) and high-resolution Pleiades-1B (2018/06/29) image with a resolution of 50 cm available on

Google Earth, along with field survey data were used to map other biodiversity threats.

Methods

Landsat images from 1986, 1998, and 2018 were classified using the Random Forest classifier to obtain LULC maps. This method was chosen due to its superior accuracy and processing speed compared to other classification methods (Pal, 2005; Inglada et al, 2016; Belgiu and Drăguţ, 2016). Additionally, its lower sensitivity to the quality of training samples, reduced susceptibility to overfitting, and ability to internally optimise variable selection make it well suited for remote sensing applications (Belgiu and Drăguţ, 2016). With this classifier, the study area in 1986, 1998, and 2018 was classified into eight classes: barren lands, wetlands, water, agricultural lands, other vegetation, palm groves, built-up areas, and mangroves. Ground reference samples were collected using historical topographic maps, high-resolution satellite imagery, Google Earth images, field surveys, and ground observations. The reference samples were divided into two subsets, with 70% used to train the Random Forest classifier and the remaining 30% reserved for post-classification accuracy assessment. The training samples were selected to represent all land-use/land-cover classes and their spectral variability across the study area. The classification results were evaluated through visual verification, followed by the application of the Error Matrix to compute the overall accuracy, Kappa coefficient, user accuracy, and producer accuracy (Congalton, 1991). Samples for this assessment were selected using the stratified random sampling technique (Lyons et al, 2018). To provide a map of ship traffic as one of the habitat threats in the PSEEZ, hot spots analysis was run on detected ships from Landsat-4, Landsat-5, Landsat-8 and Sentinel-2 images. For identifying ships based on satellite imagery, a threshold method was used. As a classic and standard technique for ship identification, this method segments the image using a histogram-selected threshold value (Kanjir et al, 2018). In this study, the near-infrared bands (Landsat 4 & 5 band 4, Landsat 8 band 5, and Sentinel-2 band 8) were selected for ship detection and thresholding following a comparison of Landsat 8 and Sentinel-2 bands. To perform hotspot analysis on ships detected from satellite imagery, the study area was divided into a fishnet with a cell size of 400 × 400 m. The selected grid size follows the methodology of Ashournejad et al. (2019c), where the same spatial resolution was successfully used for hotspot analysis. The quantity of ships in each network was determined and linked to their corresponding descriptive data. This analysis examines each cell feature in relation to the nearby cell features. Features with high values are considered important, while those with lower values may not be statistically significant enough to be classified as hot spots. To qualify as a hot spot and achieve statistical significance, both the cell feature and its neighbouring features must exhibit high values. (Huang et al, 2013; Zhang et al, 2019). The maps of other biodiversity threat maps in the PSEEZ are created through digitisation processes and visual interpretation methods, utilising National topographic maps and Pleiades-1B imagery. (Sharma et al, 2018; Li et al, 2018). The LULC maps and biodiversity threat layers generated in the previous steps were used as inputs to the InVEST Habitat Quality model (version 3.5). Habitat quality and habitat degradation were then calculated using the following equations (Liang and Liu, 2017; Sharp et al, 2018):

Eq. 1)

$$Q_{xj} = H_j\left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^z}\right)$$

Eq. 2)

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{Y_r}\left(\frac{w_r}{\sum_{r=1}^{R} w_r}\right) r_y i_{rxy} \beta_x S_{jr}$$

Where Q_{xj} represents the habitat quality value of LULC type j; H_j indicates the habitat suitability score, ranging from 0 to 1, where non-habitat LULC types are assigned a value of 0 and optimal habitat types are assigned a value of 1. Following the recommendations of the InVEST User Guide, the scaling parameter was set to the default value of $z = 2.5$ and the half-saturation constant to $k = 0.5$ (Sharp et al, 2018). These default parameter values have also been widely adopted in recent InVEST-based habitat quality studies (Wang et al, 2022; Peng et al, 2023; Li et al, 2025; Ma et al, 2025; Xie et al, 2026). The total threat level in grid cell x having LULC type j is represented by D_{xj}. In this context, y represents all grid cells in raster map r, and Y_r denotes the total number of grid cells in raster map r. The threat weight, w_r, represents the relative impact of each threat source on habitat quality. r_y denotes threat r located in grid cell y. The accessibility coefficient, β_x, represents the level of legal or physical protection in grid cell x, where a value of 1 indicates full accessibility. The habitat sensitivity score ranges from 0 to 1, with higher values indicating greater sensitivity of a habitat type to a given threat. Finally, the impact of threat r originating from grid cell y on the habitat located in grid cell x, i_{rxy}, is calculated using the following equations:

Eq. 3)

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\,max}}\right) \quad if\ linear$$

Eq. 4)

$$i_{rxy} = exp\left(-\left(\frac{2.99}{d_{r\,max}}\right) d_{xy}\right) \quad if\ exponential$$

Where d_{xy} represents the Euclidean distance between grid cells x and y, and $d_{r\max}$ denotes the maximum effective distance over which threat r influences habitat quality. In this study, all natural land-cover classes, including barren lands, wetlands, water bodies, mangrove forests, and other vegetation types, were considered as habitats, whereas all human-dominated land-cover classes, including agricultural lands, palm groves, and built-up areas, were treated as non-habitats. The model parameters, including threat characteristics (Table 2) and habitat sensitivity scores for each land-use/land-cover class (Table 3), were determined based on the InVEST User Guide, previous studies, and expert knowledge. To quantify the spatial extent of habitat degradation, habitat pixels with a habitat degradation value greater than zero (D > 0) were considered as degraded habitats. Accordingly, the percentage of degraded habitats was calculated as the proportion of degraded habitat pixels (D > 0) relative to the total habitat area.

Table 2: Threat data used to run InVEST

Threats	Maximum impact distance (km)	Weight	Decay	Source
Agricultural lands	1	0.4	Linear	Chiang et al. (2014); Liang and Liu (2017)
Roads	2	0.6	Linear	Terrado et al. (2016); Chu et al. (2018)
Rural residential lands	3	0.8	Linear	Liang and Liu (2017)
Urban lands	5	0.9	Linear	Chu et al. (2018)
Other Built-up areas (Industrial land, airport and harbour)	8	1	Linear	Terrado et al. 2016; Expert knowledge
Ship traffic	10	0.9	Linear	Expert knowledge; Ashournejad et al. (2019c)

Table 3: Habitats and their sensitivity to each threat

Land covers/threats	Agricultural lands	Roads	Rural residential lands	Urban lands	Other Built-up areas	Ship traffic
Barren lands	0.4	0.5	0.6	0.6	0.8	0.3
Wetland	0.5	0.7	0.8	0.9	1	0.9
Sea Water	0.5	0.6	0.8	0.9	1	1
Mangrove	0.5	0.6	0.8	0.9	1	1
other vegetation	0.5	0.6	0.7	0.8	0.9	0.9

Source: Habitat sensitivity values were adapted from Chiang et al. (2014), Terrado et al. (2016a), Ntshane and Gambiza (2016), Gao et al. (2017), Liang and Liu (2017), and Chu et al. (2018), and refined using expert knowledge according to the ecological characteristics of the PSEEZ. Fig. 2 summarises the overall workflow adopted in this study. The methodology consists of data collection and pre-processing, land use/land cover classification using the Random Forest algorithm, biodiversity threat mapping, preparation of habitat sensitivity and threat layers, implementation of the InVEST Habitat Quality model, and analysis of habitat quality and habitat degradation over the study period.

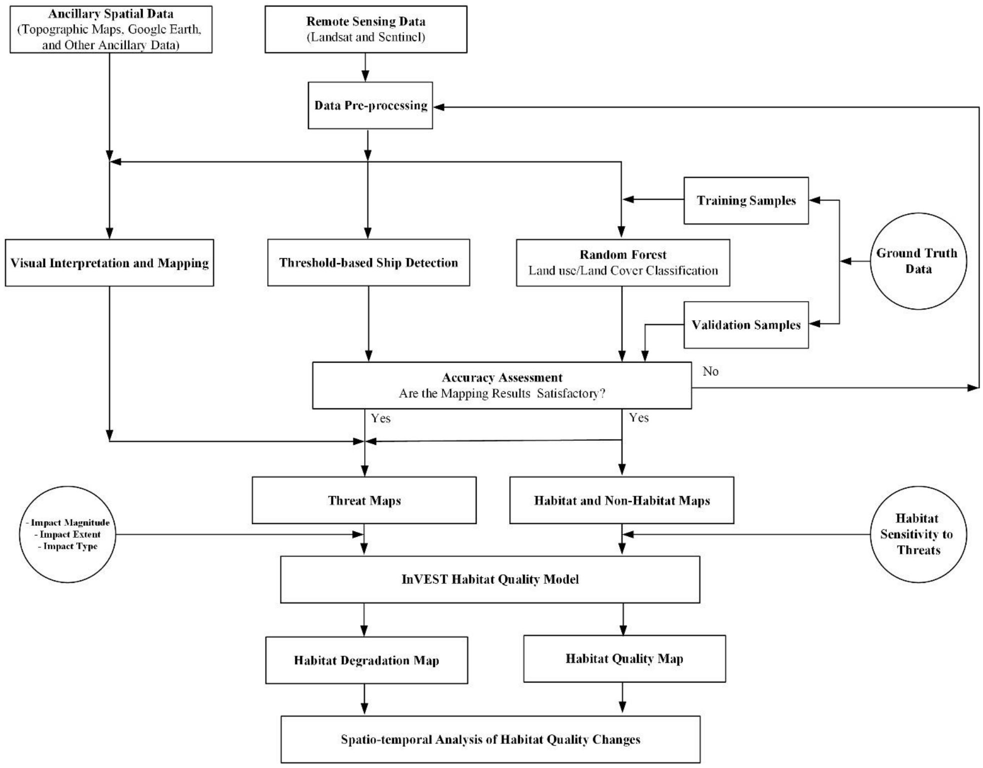

Fig. 2: Overall workflow of the proposed methodology for habitat quality assessment using remote sensing and the InVEST Habitat Quality model.

Results and Discussion

LULC maps

LULC maps derived from the Random Forests classifier had overall accuracy and kappa coefficients greater than 90% in 1986, 1998, and 2018. (Table 4). The results indicate that increasing human-built-up areas and decreasing the Nayband wetland are the most important changes in LULC in the PSEEZ (Table 3 and Figs. 3 and 4).

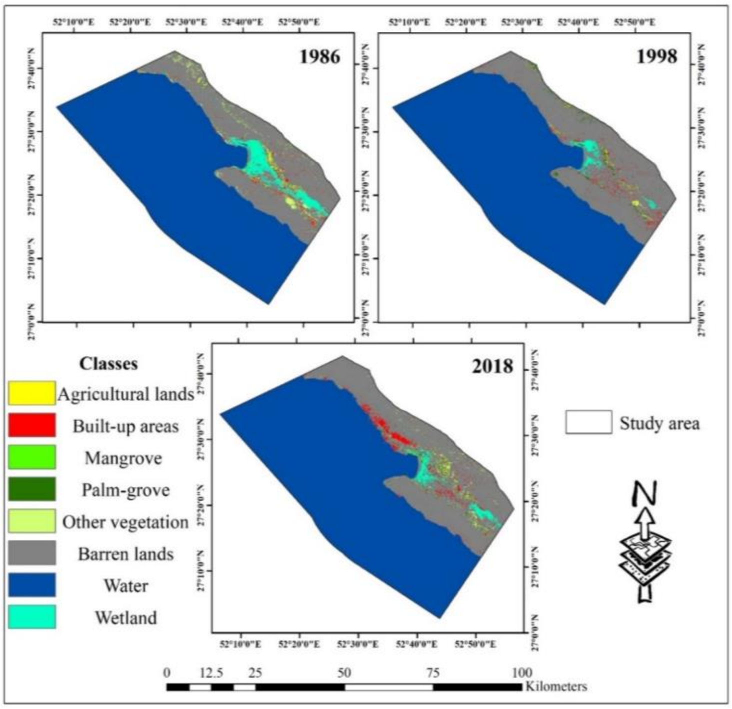

Fig. 3: Spatial distribution of LULC in 1986, 1998 and 2018

Table 4: LULC area and its changes in 1986, 1998 and 2018

Class/Year	1986 (ha)	1998 (ha)	2018 (ha)	Trend of changes 1986-1998 (ha-%)		1998-2108 (ha-%)		1986-2018 (ha-%)	
Barren lands	75974.58	84922.02	80270.19	8947.35	11.78%	-4651.92	-5.48%	4295.43	5.65%
Wetland	8678.34	2812.41	4617.63	-5865.93	-67.59%	1805.22	64.19%	-4060.71	-46.79%
Water	207461.7	207731.3	206759.3	269.37	0.13%	-972	-0.47%	-702.63	-0.34%
Agricultural lands	408.69	717.48	319.95	308.79	75.56%	-397.53	-55.41%	-88.74	-21.71%
other vegetation	4896.81	295.02	2220.57	-4601.79	-93.98%	1925.55	100%	-2676.24	-54.65%
Palm grove	840.87	1693.35	1114.02	852.48	100%	-579.33	-34.21%	273.15	32.48%
Built-up areas	1900.53	2057.94	4814.55	157.41	8.28%	2756.61	100%	2914.02	100%
Mangrove	185.67	117.99	231.39	-67.68	-36.45%	113.40	96.11%	45.72	24.62%
Overall Accuracy	93.97%	96.06%	95.61%	-	-	-	-	-	-
Kappa Coefficient	91.92%	94.00%	93.94%	-	-	-	-	-	-

The human built-up areas increased only 157.41 ha (8.28%) from 1986 to 1998 but increased to 2756.16 ha (100%) from 1998 to 2018. This significant increase in human-built-up areas includes refineries and infrastructure related to the development of PSEEZ. The development of human settlements for the working population in the PSEEZ is another reason for this increase. A proportion of these construction activities have taken place in the Nayband wetland, including the construction of a new airport (Persian Gulf Airport) and the construction of several roads. To access more space and attract investors, these roads have dried up 4,000 hectares of the Nayband wetland. The water class increased by 269.37 ha (0.13%) from 1986 to 1998 due to the coast's seaward advancement. Later, it was reduced by 972 ha (-0.47%) due to the construction of ports to develop maritime transport Additionally, the findings suggest that before the establishment of the PSEEZ, there was a significant increase of 308.79 hectares (75.56%) and 852.48 hectares (100%) in agricultural lands and palm groves, respectively, while there was a decrease of 67.68 hectares (-36.45%) in mangrove forests. However, after the establishment of the PSEEZ, mangrove forests increased by 113.4 hectares (96.11%), while agricultural lands and palm groves decreased by 397.53 hectares (-55.41%) and 579.33 hectares (-34.21%). Other vegetation classes, most of which are found on the margin of the Nayband wetland, have decreased dramatically over the last 32 years by 2676.27 ha (-54.65%). Barren lands increased by 8947.35 ha (11.78%) from 1986 to 1998 and then decreased by 4651.91 ha (-5.48%) to 2018. The increase in the first period is characteristic of the Nayband wetland, which is not always humid and is affected by climatic conditions in different seasons. These conditions make the Nayband wetland class be grouped in the barren land class.

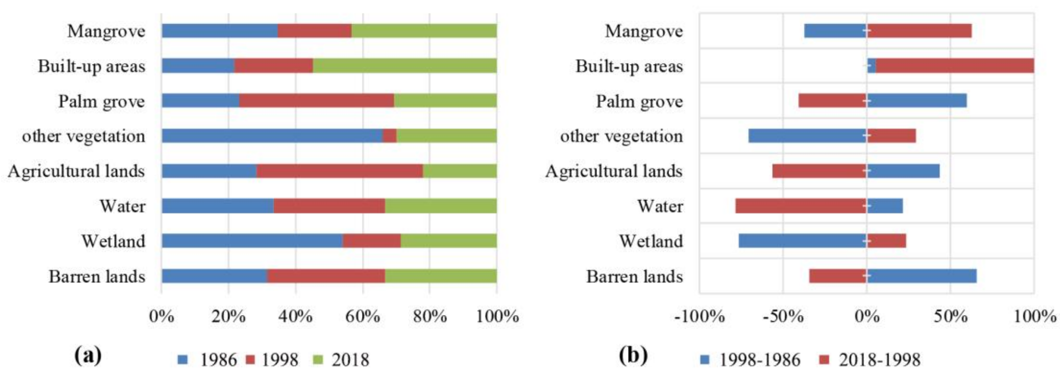

Fig. 4: a: The percentage of LULC in 1986, 1998 and 2018, b: Trend of LULC changes during 1986-1998 and 1998-2018

Threat Maps

The results of the Hot Spot Analysis on 3361 identified ships after the establishment of the PSEEZ show that more than 8000 ha of sea surface are affected by the traffic of ships (Fig. 5). 127 images from Landsat 8 and Sentinel 2 captured between 2013 and 2018 were utilised to recognise these vessels. For the period preceding the establishment of the PSEEZ, no ship was observed in 27 images captured by Landsat 4 and Landsat 5 between 1987 and 1998. The spatial data for habitat threats of the InVEST habitat quality model for PSEEZ were completed by using the obtained map and mapping other threats. (Fig. 6).

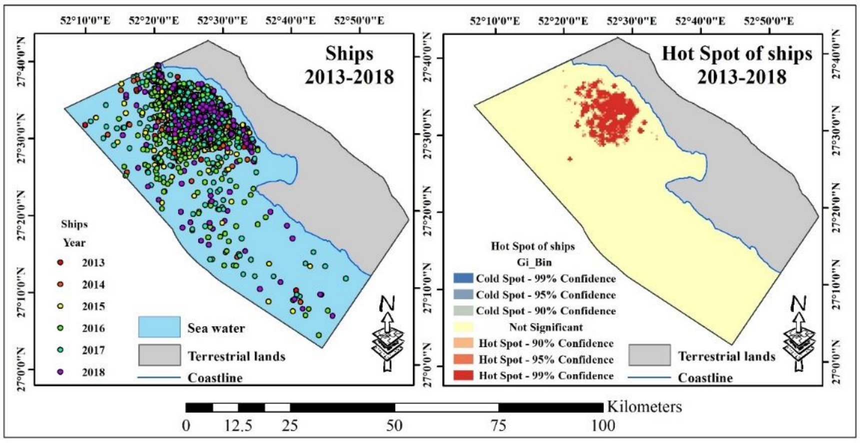

Fig. 5: Identified ships from 2013-2018 and the hotspot analysis to provide a map of the traffic of ships

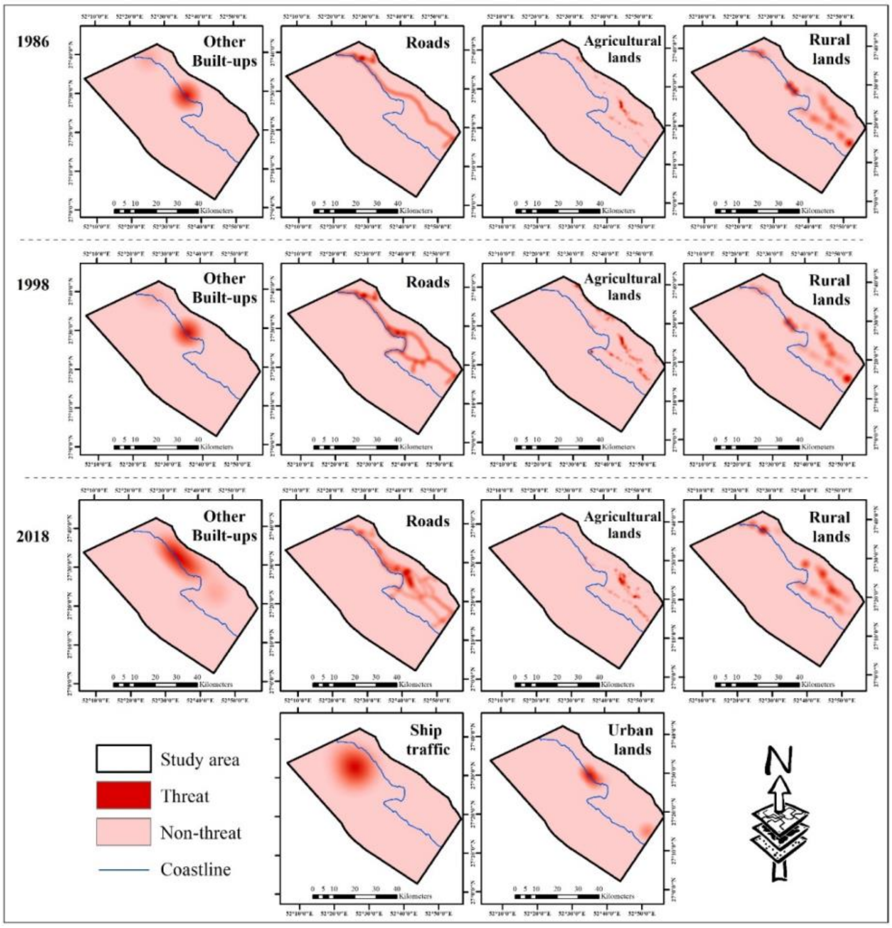

Fig. 6: Spatial distribution of threats in 1986, 1998 and 2018 (Since there were no urban areas prior to the establishment of the PSEEZ and the traffic of ships was not detected by remote sensing images, the ship traffic and urban land threat maps were used only in 2018 based on the InVEST habitat quality model).

Habitat Degradation and Quality Maps

The InVEST habitat quality model outputs included habitat degradation and quality maps in the span0 to 1. The mean of habitat degradation for 1986, 1998 and 2018 is 0.0007, 0.0012 and 0.0128, respectively (Table 5). These results indicate that the degradation trend after the establishment of the PSEEZ was 18 times higher. However, from 1986 to 1998, before the establishment of the PSEEZ, the trend of degradation doubled. The results also indicate that 3464 ha (1.16%), 9335 ha (3.15%) and 80593 ha (27.40%) of habitats in the studied area were affected by degradation in 1986, 1998 and 2018, respectively. The degradation map of the habitat in 2018 shows a hot spot within the study region, and thus illustrates the location of the main threats to the habitat. (Fig. 7). The concentration of oil and gas refineries and industries, the existence of several ports and the traffic of ships on the coasts of this region, the existence of two urban areas and abundant roads are the main reasons for this hot spot. Fig. 7 shows that the effects of habitat degradation in 2018 have reached and threatened Naybond National Marine Park.

Table 5: Habitat degradation in 1986, 1998 and 2018

Year	Area (ha)	Min	Max	Range	Sum	Mean*	SD	Habitat (ha)	Non-habitat (ha)
1986	300347	0	0.0432	0.0432	2426.9086	0.0007	0.0022	297197	3150
1998	300347	0	0.0477	0.0477	3914.5720	0.0012	0.0031	295879	4469
2018	300347	0	0.1333	0.1333	42800.0946	0.0128	0.0256	294099	6249

*The mean values are low due to the fact that the area of the study area is high and a significant part of it is habitat.

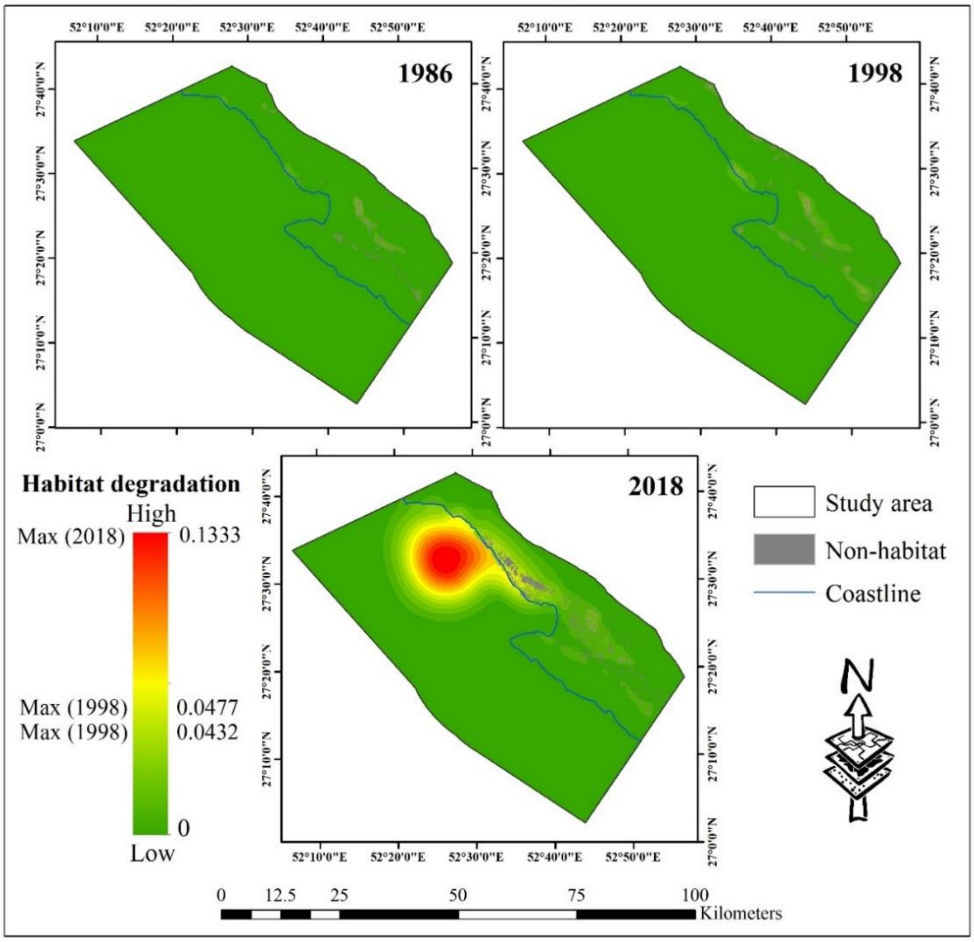

Fig. 7: Spatial distribution of habitat destruction in 1986, 1998 and 2018

The average habitat quality for the years 1986, 1998, and 2018 is 0.9895, 0.9851, and 0.9779, respectively. (Table 6). These high values are because a significant portion of the studied area is regarded as a protected habitat. The results suggest that the habitat quality declined significantly following the establishment of the PSEEZ compared to the period before. The habitat quality maps show that a large part of the study area had a high-quality habitat in 1986 and 1998. However, in 2018, the habitat quality experienced a decrease, particularly in the western part of the study area. (Fig. 8). The analysis of habitat quality's spatial distribution reveals that the habitat threats in 1986 and 1998 affected the study area's east. These threats, with the establishment of the PSEEZ, have affected the study area from the east to the west. Fig. 9 (stacked column chart) compares the trend of habitat degradation and quality changes in 1986, 1988, and 2018.

Table 6: Habitat quality in 1986, 1998 and 2018

Year	Area (ha)	Min	Max	Range	Sum	Mean	SD	Habitat (ha)	Non-habitat (ha)
1986	300347	0	1	1	3302179.59	0.9895	0.1019	297197	3150
1998	300347	0	1	1	3287517.20	0.9851	0.1211	295879	4469
2018	300347	0	1	1	3263381.35	0.9779	0.1426	294099	6249

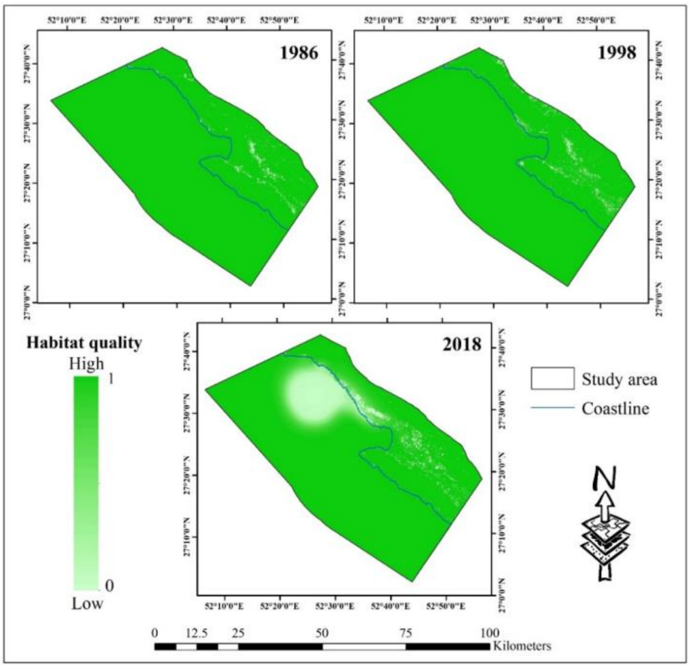

Fig. 8: Spatial distribution of habitat quality in 1986, 1998 and 2018

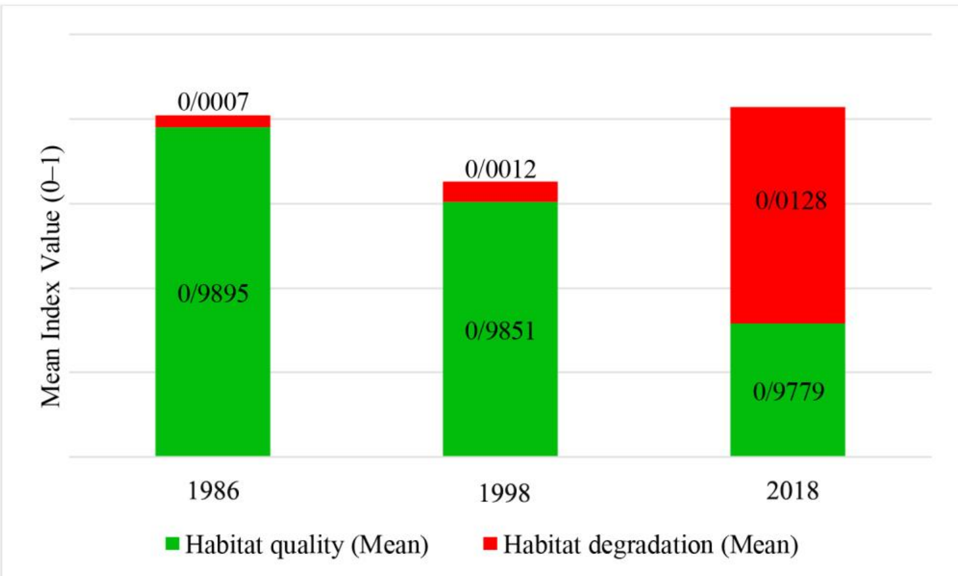

Fig. 9: Comparison of changes in habitat quality and degradation in 1986, 1998 and 2018

Discussion

In comparison with previous studies that investigated habitat quality changes resulting from dam construction, agricultural land conversion, mining, and urbanisation (Ntshane and Gambiza, 2016; Liang and Liu, 2017; Zarandian et al, 2017; He et al, 2017; Chu et al, 2018), the results of the present study demonstrate that the establishment and rapid development of the Pars Special Economic Energy Zone (PSEEZ) have caused more rapid and extensive habitat degradation. This finding is consistent with the intensive industrialisation of the region, where oil and gas extraction, petrochemical industries, transportation infrastructure, and associated environmental pollution have substantially altered natural ecosystems (Davoodi et al, 2017; Rostami et al, 2019; Aghadadashi et al, 2019). Unlike many other development projects that affect relatively limited areas, the concentration of multiple industrial activities within the PSEEZ has generated cumulative pressures on terrestrial and coastal ecosystems, particularly around the Nayband National Marine Park. Similar to previous habitat quality assessments that employed Landsat imagery for long-term environmental monitoring (Nie et al, 2016; Zarandian et al, 2016; Terrado et al, 2016b; Liang and Liu, 2017; Chu et al, 2018), this study integrated Landsat imagery with Sentinel-2 observations and other remote sensing datasets to monitor habitat quality changes over 32 years. The capability of Earth observation data for biodiversity monitoring has been widely recognised (Vihervaara et al, 2017). Moreover, the continuous development of global Earth observation programs such as the Earth Observing System (EOS) and Copernicus has significantly improved the availability of freely accessible satellite imagery with enhanced spatial and temporal resolution (King and Platnick, 2018; Jutz and Milagro-Pérez, 2020). The Sentinel-2 imagery used in this study represents one of the major outcomes of the Copernicus programme, enabling more detailed monitoring of habitat changes in recent years. Although the InVEST Habitat Quality model provides a practical and cost-effective proxy for biodiversity assessment over large areas compared with traditional field-based approaches (Sharma et al, 2018), its underlying assumptions should be carefully considered when interpreting the results. The model assumes that higher habitat quality corresponds to greater biodiversity potential (Sharp et al, 2018). Therefore, habitat quality should be interpreted as an indicator of the capacity of an ecosystem to support biodiversity rather than as a direct measure of species richness or abundance. Furthermore, the model parameters used in this study were derived from the InVEST User Guide, published literature, and expert knowledge because locally calibrated ecological parameters and comprehensive field observations were not available. Consequently, the results should be interpreted as a relative assessment of spatial and temporal habitat quality changes. Nevertheless, the consistent application of the same modelling framework, input criteria, and parameterisation across all study periods provides a reliable basis for evaluating long-term habitat quality trends within the study area. The findings of this study have important implications for environmental management and sustainable land-use planning in the Pars Special Economic Energy Zone. The considerable increase in habitat degradation, particularly in and around the Nayband National Marine Park, highlights the necessity of integrating biodiversity conservation into future industrial development strategies. Priority management actions should include establishing ecological buffer zones around environmentally sensitive habitats, limiting further industrial expansion in ecologically critical areas, restoring degraded coastal ecosystems such as mangrove forests, and strengthening long-term biodiversity monitoring through remote sensing and habitat quality modelling. Furthermore, the habitat quality maps produced in this study can support environmental impact assessment (EIA), land-use planning, biodiversity conservation strategies, and sustainable development policies by identifying areas where conservation and development objectives require careful balancing.

Conclusion

This study presents the first long-term spatio-temporal assessment of habitat quality in the Pars Special Economic Energy Zone (PSEEZ) by integrating the InVEST Habitat Quality model with remote sensing data. The results demonstrate that the establishment and rapid industrial development of the PSEEZ have significantly reduced habitat quality and accelerated habitat degradation, particularly after its establishment in 1998. The findings also reveal that biodiversity threats have increasingly affected the Nayband National Marine Park, highlighting the vulnerability of this ecologically important coastal ecosystem to large-scale industrial development. These findings provide valuable spatial evidence to support biodiversity conservation, land administration, and sustainable land-use planning in the region. To protect the remaining natural habitats and mitigate further habitat degradation, future development plans should integrate ecological considerations into industrial expansion. Priority should be given to protecting ecologically sensitive areas, establishing ecological buffer zones around the Nayband National Marine Park, restoring degraded coastal ecosystems, and incorporating habitat quality assessments into environmental impact assessment (EIA), land administration, and regional planning to support evidence-based environmental decision-making. Although the InVEST Habitat Quality model proved to be an effective and cost-efficient tool for long-term habitat quality assessment over large areas, the results should be interpreted in light of the model assumptions, the use of literature-based parameters, and the lack of locally calibrated ecological parameters and comprehensive field observations. Nevertheless, the consistent application of the same modelling framework, input criteria, and parameterisation across all study periods provides a robust basis for evaluating long-term spatial and temporal changes in habitat quality. Future research should integrate the InVEST Habitat Quality model with land-use change simulation models (e.g., PLUS, FLUS, or CA–Markov) to evaluate alternative development scenarios and their potential impacts on biodiversity and habitat quality. Further studies should also investigate the influence of model parameterisation, spatial scale, and input data characteristics through comprehensive sensitivity analyses, while incorporating field-based ecological observations to calibrate and validate the model. Such efforts will improve the robustness and reliability of habitat quality assessments and support evidence-based biodiversity conservation and sustainable environmental management in rapidly developing coastal regions.

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