

Article

Driving Factors of Habitat Quality and Degradation Revealed by GeoDetector-Based Analysis: A Coastal District of Çeşme, İzmir (Türkiye)

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Abstract

Habitats are fundamental for maintaining biodiversity, supporting ecological processes, and delivering essential ecosystem services such as carbon sequestration, water regulation, and soil conservation. Habitat degradation has become an increasingly critical environmental concern, particularly in coastal regions where anthropogenic pressures intersect with natural dynamics under the accelerating impacts of climate change. (1) This study explores the spatially stratified heterogeneity and underlying driving factors of habitat quality and degradation in Çeşme, a rapidly developing coastal district in western Türkiye. (2) The InVEST Habitat Quality model was applied to assess both habitat quality and habitat degradation across the study area for the years 2017 and 2024. The GeoDetector method was applied to analyze the spatial heterogeneity in habitat quality and degradation, enabling the assessment of dominant environmental and anthropogenic drivers, including urban development pressure, tourism activities, energy-related infrastructure, road density, and vegetation conditions. (3) Night-time light intensity showed the highest explanatory power among the tested variables, although its absolute explanatory power for habitat degradation remained limited, while protection status represented a contrasting human-related factor associated with higher habitat quality. (4) These findings underscore the importance of carefully directing human interventions to balance development pressures with effective conservation strategies.

Keywords: human–environment relations; ecosystem services; ecological connectivity; land use and land cover change; spatial stratified heterogeneity

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1. Introduction

Achieving urban climate resilience requires the integration of ecosystem service analysis with spatially informed planning strategies. The consideration of ecosystem services within planning frameworks is fundamental to promoting urban sustainability [1]. In urban planning, such insights allow for the development of context-sensitive strategies that

protect ecological assets while supporting human well-being [2,3]. Urban resilience refers to the capacity of cities to anticipate, absorb, adapt to, and recover from various stresses, including those caused by climate change [2].

One of the most pressing challenges to urban resilience is habitat degradation, which denotes a gradual decline in ecosystem quality due to both natural and human-induced pressures [4]. Rapid urban expansion has significantly altered landscapes, leading to problems such as habitat loss, biodiversity decline, and ecological imbalance. Addressing these issues requires spatially explicit tools to assess and manage the drivers of environmental change [5,6].

It is crucial to identify ecosystem services and the spatially explicit factors influencing them in order to build climate-resilient cities, particularly in rapidly urbanizing coastal districts. Understanding these drivers enables planners and policymakers to develop targeted interventions and implement spatial instruments that are tailored to local ecological dynamics [1]. In this context, the present study investigates the spatial drivers of habitat degradation using the GeoDetector method. This method enables the assessment of both the individual and interactive effects of various anthropogenic and natural factors contributing to habitat loss [7].

The GeoDetector method has been increasingly applied in recent years to investigate the spatial determinants of various environmental and ecological phenomena. Rooted in the concept of spatial stratified heterogeneity (SSH), the GeoDetector model provides a robust statistical framework to identify spatially explicit driving factors behind environmental phenomena [8]. Unlike traditional methods, GeoDetector does not require strict assumptions, making it well-suited for analyzing heterogeneous and complex spatial data [9]. GeoDetector has been widely applied to explore the spatiotemporal drivers of environmental variables such as land surface temperature by providing a quantitative and objective framework for detecting spatial heterogeneity and evaluating the explanatory power of different influencing factors [10,11]. GeoDetector has been employed to examine spatial heterogeneity in habitat quality and eco-environmental quality in several recent studies [7,9,12,13]. Similarly, vegetation change characteristics and the spatial factors influencing the ecological footprint have been analyzed using GeoDetector [14,15]. In the context of disaster risk, the method has been utilized to investigate the driving forces behind the spatial distribution of landslides [16]. Furthermore, GeoDetector has been integrated into advanced modeling frameworks. It has been applied to identify key predictors of PM_{2.5} in the Pearl River Delta, combining principal component analysis (PCA) with an augmented geographically weighted regression (GWR) model to reduce multicollinearity and improve performance [17]. Apart from environmental studies, GeoDetector has also been applied to analyze diverse spatial factors, including theft crime patterns [18] and the spatial distribution of data centers [19]. Thus, studies highlight the versatility of GeoDetector in quantifying the explanatory power of both natural and anthropogenic variables across diverse environmental applications. Additionally, the interaction detector component of the GeoDetector model allows for the exploration of synergistic or non-linear effects between variables, offering deeper insights into the complex dynamics of ecological degradation [7,13].

Although many studies have utilized the GeoDetector model to investigate environmental variables, there remains a significant gap in the literature concerning its application to Mediterranean coastal cities, particularly in relation to habitat degradation driven by both natural and anthropogenic factors. This study seeks to fill this gap by examining spatial drivers of habitat loss in a rapidly transforming coastal landscape.

Building on the expanding body of literature, this study aims to identify the spatial drivers of habitat degradation in Çeşme, Türkiye, a Mediterranean coastal district experiencing intense development pressure. Çeşme is representative of a broader category of

small- to medium-sized, tourism-oriented Mediterranean coastal settlements, characterized by strong seasonal population fluctuations, increasing second-home development, and a landscape that remains largely shaped by natural and semi-natural systems. To achieve this, the GeoDetector method is employed, using habitat quality as the dependent variable. This spatially explicit approach seeks to provide an evidence-based understanding of landscape fragmentation and to inform the development of resilience-oriented urban planning strategies applicable to similar coastal contexts. In this context, the study specifically investigates how both natural dynamics and human-induced activities contribute to habitat degradation in Çeşme, a Mediterranean coastal district characterized by ecological sensitivity and increasing development pressure. Çeşme, located on the western coast of Türkiye, is a prominent Mediterranean district known for its rich biodiversity and ecologically valuable landscapes with encompass several protected natural areas [20]. However, despite its ecological significance, Çeşme faces increasing land-use pressures driven by anthropogenic activities.

The expansion of urban areas, the proliferation of tourism infrastructure, and the growing prevalence of mining and wind energy installations have contributed to the fragmentation and degradation of natural habitats. These pressures pose significant challenges to conservation efforts and threaten the ecological balance of the region. Among these pressures, the proliferation of secondary housing developments, particularly along the coastal areas, has led to the fragmentation of natural landscapes [21]. In this process, the completion of the Çeşme-İzmir highway has been a key factor in facilitating accessibility to the region and intensifying development pressure [22]. Nevertheless, despite all these pressures, it is considered a positive outcome that the natural vegetation, although fragmented, still maintains its dominance in the landscape [21].

In light of these challenges, understanding the spatial patterns and driving factors of habitat degradation in Çeşme is essential for developing informed and resilient planning strategies that safeguard its natural heritage. To guide this investigation, the study addresses the following research questions:

1. How did land use and land cover change between 2017 and 2024?
2. What are the spatial clustering and distribution of habitat quality and habitat degradation in 2017 and 2024?
3. What are the primary factors influencing habitat quality and habitat degradation in the study area for 2017 and 2024?

2. Materials and Methods

This study employed a four-step methodological framework to analyze land use/land cover change, habitat quality dynamics, spatial patterns of degradation, and their potential driving factors. The overall workflow is presented in Figure 1.

First, land cover data were prepared by adapting ESRI land cover maps for 2017 and 2024. The total area of each land use/land cover class was calculated, and changes between the two years were assessed to identify spatial patterns of transformation within the study area.

Second, analysis units were generated by creating a fishnet grid across Çeşme district. A change detection analysis was then conducted to assess variations in habitat quality and degradation between 2017 and 2024 across the study area. To further examine the spatial characteristics of degradation, Hot Spot Analysis (Getis-Ord G_i^*) was performed in ArcGIS Pro version 3.6.1 using Euclidean distance to identify statistically significant clusters. This technique enabled the identification of statistically significant clusters where habitat degradation was particularly concentrated.

Third, a set of potential driving factors was identified through a combination of literature review and local context-specific knowledge. These factors included both natural

and anthropogenic variables. The selection process was informed by previous studies employing the GeoDetector model in similar ecological and urban contexts [7,9,13].

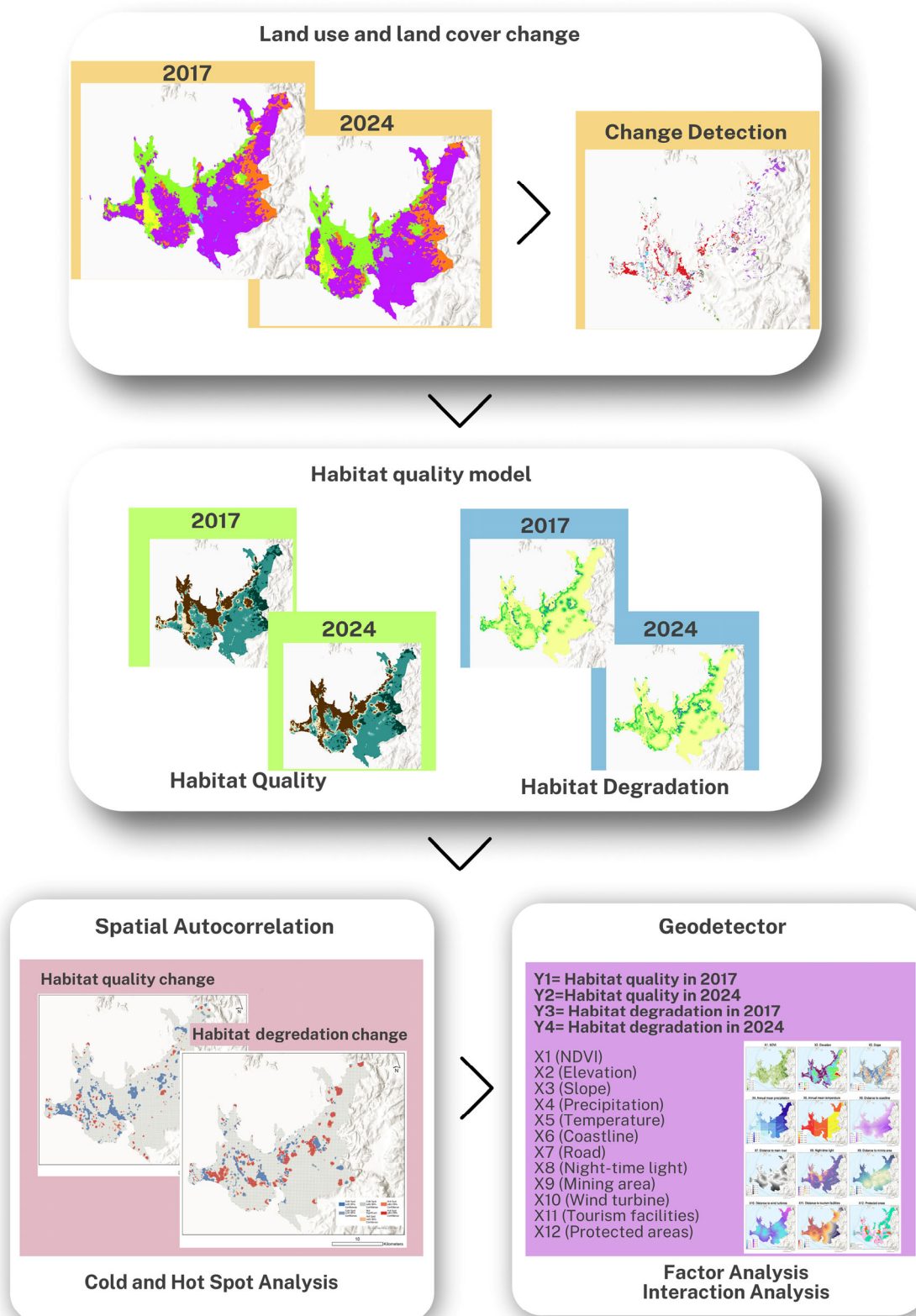


Figure 1. Flowchart of the study.

Finally, in the fourth step, the GeoDetector model was applied by treating habitat quality and the degradation index as dependent variables (Y), and the selected natural and anthropogenic variables as independent factors (X). The model was used to assess both the individual explanatory power of each factor through the factor detector and the interactive effects between pairs of variables through the interaction detector.

2.1. Study Area

Çeşme District is located in the western part of Türkiye, within İzmir Province, and lies along the Aegean Sea coastline (Figure 2). It is situated approximately between latitudes $38^{\circ}15'$ and $38^{\circ}25'$ N, and longitudes $26^{\circ}15'$ and $26^{\circ}30'$ E. Covering an area of around 260 km², the district had an estimated population of 48,500 as of 2024 [23]. Çeşme experiences a typical Mediterranean climate, with hot, dry summers and mild, wet winters. The average annual precipitation in İzmir is approximately 700 mm and although the region is relatively arid compared to other parts of western Türkiye, it supports shrubland, fragmented forests, and agricultural landscapes [24].

In this study, Çeşme was selected as the study area due to its unique combination of diverse anthropogenic pressures and ecological significance. The district hosts intensive tourism activities, extensive wind energy infrastructure, and widespread quarrying operations, making it a representative coastal region where multiple land use conflicts and environmental stressors converge. This diversity provides an ideal context to assess how overlapping drivers impact habitat quality and degradation patterns.

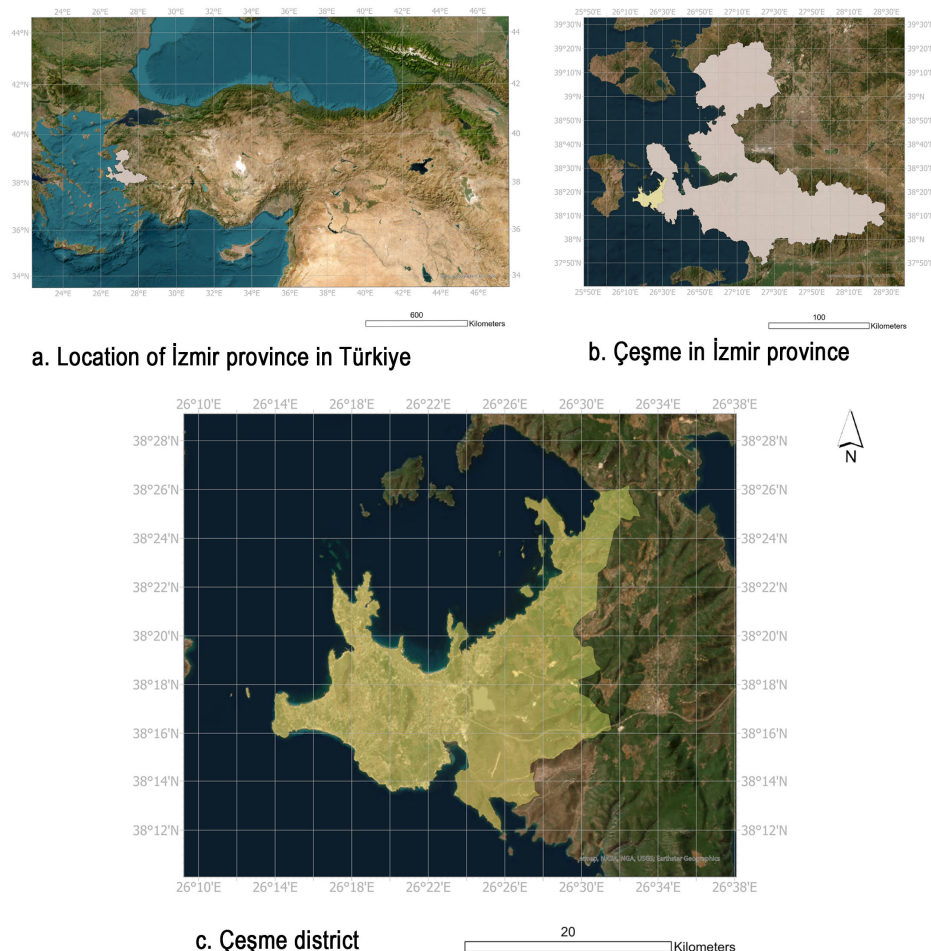


Figure 2. Location of Çeşme in Türkiye.

2.2. Data Preparation

The land use and land cover (LULC) data for the years 2017 and 2024 were obtained from the ESRI Land Cover dataset [25] which provides consistent, high-resolution global land cover information at a spatial resolution of 10 m. The year 2017 was selected as the baseline as it represents the earliest year for which ESRI Land Cover maps derived from Sentinel-2 imagery are consistently available, while 2024 was chosen to capture the most recent land cover conditions. This eight-year interval was selected to capture recent LULC changes under a consistent data source, spatial resolution, and classification framework, allowing the analysis to reflect contemporary development pressures and recent landscape transformations. Therefore, this dataset was preferred to minimize user-induced classification errors and to ensure methodological consistency across temporal analyses. Nevertheless, an independent accuracy assessment was conducted for both years, and the resulting confusion matrices, overall accuracy, producer's accuracy, user's accuracy, and Kappa index values are provided in Supplementary File S1. For spatial alignment, both datasets were clipped to match the administrative boundaries of the Çeşme.

To detect the spatially stratified heterogeneity of habitat quality model in the study area, a regular grid-based spatial analysis unit was adopted. A 2 km × 2 km fishnet grid was applied to investigate vegetation Dynamics [14,26]. Similarly, a 1.5 km × 1.5 km evaluation grid was applied to examine the spatial and temporal dynamics of oasis migration [13]. However, this approach has been considered suitable for basin-scale studies; for finer scales, a 300 m grid cell resolution was applied in a case study on National Nature Reserves in Hubei Province [9]. Therefore, the finer resolution, the 100 m × 100 m resolution in this study was deliberately chosen to reflect the district-level planning scale of the Çeşme Peninsula and to enable more precise detection of localized changes. Specifically, a 100 m × 100 m fishnet was created across the Çeşme Peninsula, serving as the fundamental unit of spatial analysis for the GeoDetector model. This spatial resolution was selected to provide a meaningful balance between ecological significance and analytical precision. Thus, it is finer spatial resolution allows for a more detailed analysis of habitat degradation patterns and enhances the model's ability to capture subtle anthropogenic and ecological variations relevant to small-scale coastal environments.

In this study, habitat quality and habitat degradation for the years 2017 and 2024 were selected as the dependent variables (Y) to evaluate the spatial heterogeneity of ecological disturbance. Habitat quality and degradation outputs were analyzed separately for each year in order to capture year-specific spatial patterns and the underlying driving mechanisms of ecological pressure. A synthesis of previous studies demonstrates that explanatory variables have been employed for a range of analytical objectives, including habitat degradation, landscape fragmentation, and ecological disturbance (see Supplementary File S2). This body of literature indicates that the selection of explanatory variables is inherently purpose-driven and context-dependent, and therefore requires adaptation to both the analytical framework and the site-specific characteristics of the study area. Building on this perspective, the independent variables (X) were identified based on a combination of insights from the existing literature and the specific characteristics of the study area [7,12,14,16]. While commonly used drivers such as elevation, slope, and NDVI (Normalized Difference Vegetation Index) were included in alignment with previous studies, additional location-specific factors were integrated to better reflect the ecological pressures unique to the Çeşme Peninsula. These included the proximity of wind turbines and mining activities, both of which are known to contribute significantly to landscape fragmentation and habitat quality decline in the region (Table 1).

Table 1. Independent variables.

Code	Category	Factor	Reference	Data Source
X1	Natural	NDVI	[7,12,26]	Maximum NDVI composites derived from Sentinel-2 imagery using the Maximum Value Composite (MVC) method in Google Earth Engine (2017 and 2024)
X2	Natural	Elevation	[12,14,26,27]	Copernicus Digital Elevation Model (DEM, 30 m) processed in Google Earth Engine
X3	Natural	Slope	[9,13,14]	Slope derived from the DEM using the Slope tool in ArcGIS Pro
X4	Natural	Precipitation	[7,9,13,14,26]	Annual mean daily precipitation derived from the CHIRPS daily dataset by averaging daily precipitation values for each reference year in Google Earth Engine (2017 and 2024)
X5	Natural	Temperature	[9,13,14,28]	Annual mean air temperature derived from ERA5-Land ERA5 and hourly temperature data by averaging hourly values over each year in Google Earth Engine (2017 and 2024)
X6	Natural	Distance to coastline	[13]	Euclidean distance to the coastline was generated as a continuous proximity surface derived from a coastline polyline obtained from OpenStreetMap (OSM). The distance layer was produced consistently for both the 2017 and 2024 analyses.
X7	Anthropogenic	Distance to main roads	[9]	Euclidean distance to main roads was calculated as a continuous distance surface based on the main road network derived from OpenStreetMap (OSM) and Google Earth Pro, and applied identically for both 2017 and 2024.
X8	Anthropogenic	Night-time light	[7]	Night time light was extracted from GEE
X9	Anthropogenic	Mining area ¹		Google Earth Pro, 2025 and Open Street Map (2017 and 2024)
X10	Anthropogenic	Distance to wind turbine ¹		Google Earth Pro, 2025 and Open Street Map (2017 and 2024)
X11	Anthropogenic	Distance to touristic facilities	[9]	İzmir Planning Agency, Google Earth Pro, and Open Street Map (2017 and 2024)
X12	Policy regulation	Protected areas	[29]	İzmir Metropolitan Municipality (2025)

¹ Factor based on local knowledge.

In addition to factor sets commonly adopted in the GeoDetector literature, local environmental pressures specific to the study context were also incorporated to better capture the underlying spatial processes. In particular, mining and stone-crushing activities were included as explanatory variables due to their significant and locally observed environmental impacts, as these activities generate substantial amounts of particulate matter on an annual basis, directly affecting soil properties, vegetation health, surface temperature dynamics, and nearby water bodies, thereby contributing to habitat degradation [30].

2.3. InVEST Habitat Quality Model

Habitat quality is quantified by analyzing the spatial distribution of habitats and the effects of threat factors [31]. Habitat Quality model was used to evaluate biodiversity by integrating land use and land cover data with habitat threat intensity. The model assumes that all defined threats negatively impact the landscape [32]. In addition to the habitat quality index, the model also generates a habitat degradation output, which highlights areas under greater anthropogenic pressure based on proximity to and intensity of threats.

The habitat quality module provides a dimensionless indicator ranging from 0 to 1. The primary calculation formula is presented as follows:

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

where Q_{xj} represents the habitat quality of grid cell x within land cover type j ; H_j denotes the habitat suitability of land cover type j , and z and k constant is the half-saturation constant [33]. Further details on the model equation and assumptions can be found in the InVEST Habitat Quality Model Guidebook [32].

Prior to conducting the habitat quality analysis using the InVEST model version 13.7.0, it is essential to define the required parameters, including the current land cover data, threat data, a threat table specifying the weight, distance of influence, and decay function for each identified threat, and a sensitivity table assigning habitat sensitivity values to each land cover type. In this study, land use and land cover data adapted from the ESRI Land Cover maps for 2017 and 2024 were used as input data.

To ensure temporal comparability, the same threat parameters and habitat sensitivity values were applied to the 2017 and 2024 model runs. Urban areas were considered as the only threat factor in the InVEST Habitat Quality model, as the analysis focused on habitat degradation associated with urban land expansion. The maximum distance of influence, threat weight and exponential decay function assigned to the urban threat are presented in Table 2.

Table 2. Threat factor and parameters used in the InVEST Habitat Quality model (adapted from [32,34,35]).

Threat Factor	Source	Maximum Distance of Influence	Weight	Decay Function
Urban area for 2017	Derived from the ESRI Land Cover map for 2017	0.8	0.9	Exponential
Urban area for 2014	Derived from the ESRI Land Cover map for 2024	0.8	0.9	Exponential

In the InVEST Habitat Quality model, the sensitivity table is a required CSV input that links each LULC class to its habitat suitability and sensitivity to each threat factor. Habitat suitability values range from 0 to 1, where 0 indicates that the land cover class is not suitable as habitat and 1 indicates complete habitat suitability. Threat sensitivity values also range from 0 to 1, where 1 represents high sensitivity to the specified threat and 0 indicates no sensitivity [32]. In accordance with the InVEST input requirements, sensitivity values were specified for all LULC classes. In this study, habitat suitability scores and sensitivity values were assigned according to land cover types, and the full sensitivity matrix used in the model is provided in Table 3.

Table 3. Habitat suitability scores and sensitivity values used in the InVEST Habitat Quality model (Adapted from [32,34,35]).

Land Use and Landcover Type	Habitat Suitability	Sensitivity to Urban Threat
Water	1.00	1.00
Forest	0.95	1.00
Agriculture	0.50	0.70
Artificial surfaces	0.05	0.00
Bare land	0.40	0.60
Shrubland	0.80	0.90
Wetland	1.00	0.90

Following the habitat quality assessment, spatial autocorrelation analysis was conducted using the Hot Spot Analysis (Getis-Ord Gi) to identify statistically significant clusters of high and low habitat quality values across the study area.

2.4. GeoDetector Model

The GeoDetector model is a spatial statistical method used to detect and quantify the influence of explanatory variables (factors) on the spatial distribution of a dependent variable. Developed by Dr. Jinfeng Wang and colleagues [36], the model aims to identify the extent to which spatial stratified heterogeneity in a dependent variable can be explained by one or more factors. It is particularly useful in environmental science, geography, urban studies, and public health for exploring spatial heterogeneity and uncovering the driving forces behind spatial patterns [8,36,37]. The GeoDetector model includes four detectors which are factor detector, risk detector, interaction detector, and ecological detector [7,8]. In the interaction detector analysis, bivariate enhancement indicates that the combined explanatory power of two factors is greater than that of each factor acting independently, whereas nonlinear enhancement denotes a synergistic interaction in which the joint effect of two factors exceeds the sum of their individual effects [38].

GeoDetector model analyzes the correlations among different factors based on grid data [7]. Several recent studies have employed the GeoDetector model to investigate the spatial heterogeneity of ecological variables and to identify the driving factors influencing habitat quality change [7,9], habitat quality [12] and environment quality [13]. Moreover, the same approach has been used to examine the spatial heterogeneity of land surface temperature and its sensitive regions [11]. On the other hand, the model has been applied to quantitatively analyze vegetation change characteristics and their associated driving forces [14]. These studies highlight the effectiveness of the GeoDetector model in identifying natural and anthropogenic drivers of spatial ecological variation. Accordingly, the use of the GeoDetector model in this study is well-suited to the research aim of identifying the spatial drivers of habitat quality and degradation in Çeşme. By focusing on both habitat degradation and habitat quality, this study contributes to the literature by identifying the spatial driving factors of degradation, offering a more targeted perspective on ecosystem vulnerability and land-use pressures.

In this study, habitat quality and degradation was used as the dependent variables (Y1–Y4), represented by a continuous (numeric) dataset derived from the InVEST Habitat Quality model output for 2017 and 2024. In this context, four dependent variables were defined: Y1 (habitat quality, 2017), Y2 (habitat quality, 2024), Y3 (habitat degradation, 2017), and Y4 (habitat degradation, 2024).

The explanatory variables (X), treated as categorical data, included a combination of natural and anthropogenic factors: X1 (NDVI), X2 (Elevation), X3 (Slope), X4 (Annual mean precipitation), X5 (Annual mean temperature), X6 (Distance to coastline), X7 (Distance to roads), X8 (Night-time light), X9 (Distance to mining area), X10 (Distance to wind

turbines), X11 (Distance to tourism facilities) and X12 (Protected areas). Where applicable, these variables were prepared separately for 2017 and 2024 in order to match the temporal coverage of the dependent variables. Static variables, including elevation, slope, distance to coastline, and protected areas, were kept constant across both years. These variables were selected based on their ecological relevance, their ability to represent both natural and anthropogenic pressures, and the availability of consistent spatial data across the study period.

GeoDetector requires independent variables to be in categorical form in order to measure spatial stratified heterogeneity (SSH) [10,14]. GeoDetector literature evaluates discretisation performance based on q-statistics and frequently applies unsupervised classification methods such as Natural Breaks and Equal Interval [39]. Among these, Natural Breaks is widely preferred for heterogeneous environmental variables in GeoDetector-based studies [28].

Therefore, the Natural Breaks (Jenks) method available in ArcGIS was mainly applied to variables with heterogeneous spatial distributions, including NDVI, elevation, slope, night-time light intensity, distance to mining areas, distance to wind turbines, and distance to tourism facilities. Equal Interval classification was used for annual mean precipitation and annual mean temperature, as these climate variables were derived as gridded continuous surfaces and required comparable value ranges across the study area. For distance to coastline and distance to roads, proximity-based Equal Interval classes were used to represent gradually increasing distance bands from these linear features in a consistent and interpretable way. Protected areas were classified according to their existing categorical status.

The number of classes was determined by considering both previous GeoDetector studies and the representativeness of each variable in the Çeşme case. Since the explanatory variables differed in their value ranges and spatial patterns, a fixed number of classes was not imposed on all variables. Detailed information on the classification method, number of classes, and rationale for each explanatory variable is provided in Supplementary File S4.

Thus, all variables were discretized into categorical classes prior to analysis. Following the mapping of each explanatory factor, a spatial grid (100 × 100 m) was overlaid across the study area, and the values of each factor were prepared accordingly. Usually, the natural breakpoint methods were adapted to test and select the best model [7,27,40]. The GeoDetector analysis was then conducted by integrating the dataset into ArcGIS Pro through the GeoDetector toolbox, enabling the assessment of both individual and interactive effects of the selected factors on habitat degradation.

3. Results

3.1. Land Use and Land Cover Change and Habitat Quality Model

According to land use and land cover change in Çeşme, the vast majority of the area (87.33%) remains unchanged, indicating relatively stable land cover across the region (Figure 3). However, the remaining 12.67% of the landscape has undergone transformations, with several dominant transition types standing out. The most substantial change is from Shrubland to Artificial land, covering over 1069 hectares and accounting for 4.02% of the total area. Another major transition is Shrubland to Forest (2.55%), possibly due to reforestation or natural succession processes. Conversely, Forest to Shrubland (2.48%) suggests some degree of vegetation degradation, deforestation, or ecological disturbance. (see Supplementary File S1 for detailed percentages).

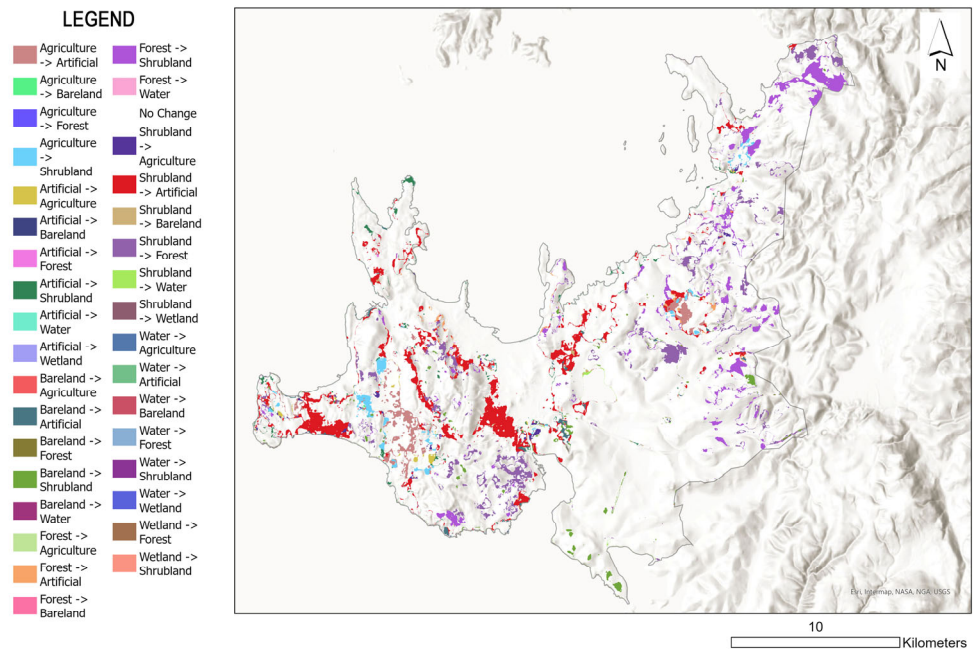


Figure 3. Land use and land cover change in Çeşme.

The InVEST Habitat Quality model generates two key outputs: a habitat quality map and a habitat degradation map. Figure 4 illustrates the spatial distribution of habitat quality and habitat degradation across the Çeşme in 2017, while Figure 5 represents the same analyses in 2024. The eastern part of the region exhibits relatively high habitat quality, represented. In contrast, low habitat quality is concentrated along the northern coastal strip, particularly stretching from the northwest to the south. An increase in areas with low habitat quality has been observed from 2017 to 2024. In 2017, the mean habitat quality value in Çeşme was 0.62, whereas in 2024 it decreased to 0.58.

The spatial pattern of habitat degradation, as depicted in the map, shows a clear concentration along the transition zones between high and low habitat quality areas. This is consistent with the logic of the InVEST model, which calculates degradation based on the proximity and intensity of anthropogenic threats in relation to existing habitat patches. In areas with high habitat quality that are adjacent to threats such as urban development or intensive agriculture, degradation values tend to be higher. In contrast, locations that already exhibit low habitat quality such as urban centers or bare land show little to no degradation, as these areas are no longer functioning habitats and thus do not register additional ecological loss both in 2017 and 2024.

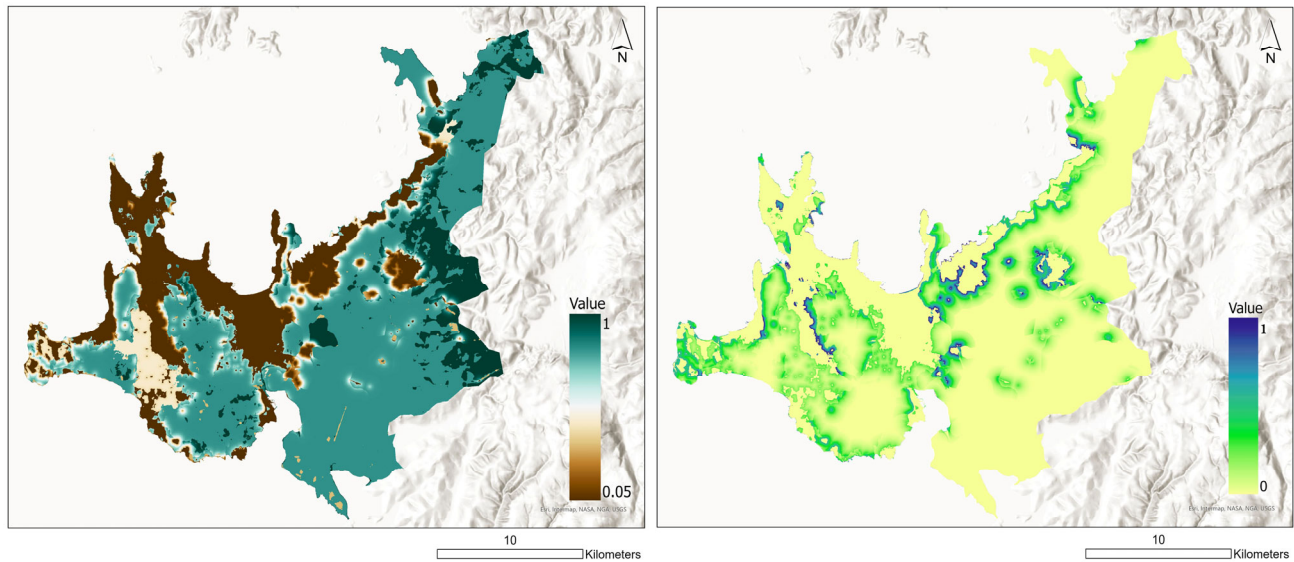


Figure 4. Habitat quality (left) and habitat degradation (right) maps in 2017.

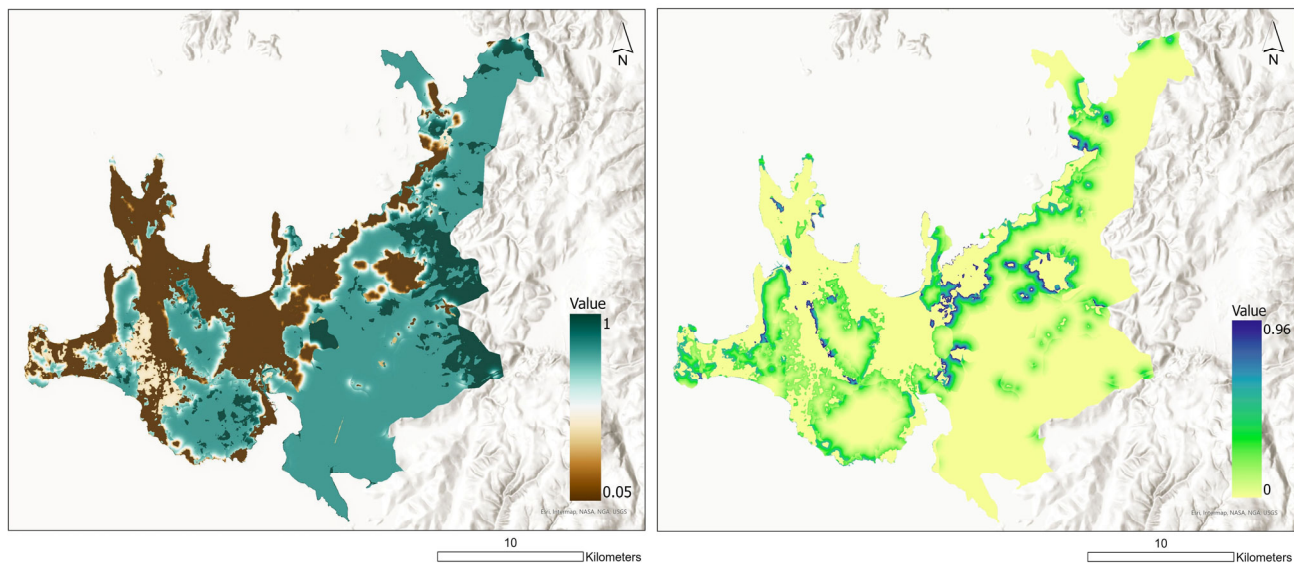


Figure 5. Habitat quality (left) and habitat degradation (right) maps in 2024.

The spatial autocorrelation analysis of habitat quality reveals meaningful geographic patterns, offering statistically supported insights into spatial clustering [41]. As previously described in the methodology section, the study area was divided into 100×100 m grid cells. The mean values of normalized habitat quality and degradation were assigned to each grid cell and subsequently used to perform the spatial autocorrelation analysis. As shown in Figure 6, the hot spot analysis conducted based on the mean values within the 100×100 m grid cells produced results that closely align with the outputs of the habitat quality and degradation assessments. In the habitat quality change map, cold spots represent areas where a significant decrease in habitat quality has occurred over time, indicating clusters of degradation. Conversely, hot spots indicate regions where habitat quality has significantly improved, showing clusters of positive ecological change from 2017 to 2024. As shown in Table 4, the majority of the area (75.45%) shows no significant clustering pattern. Cold spot areas, represented by light and dark blue tones on the map, account for a total of 9.85% of the study area, including 6.86% classified as very cold spots, 1.85% as cold spots, and 1.14% as slight

cold spots. Additionally, the majority of the study area (82.36%) exhibits no significant clustering pattern in terms of habitat degradation. Cold spots, which signify areas with lower degradation levels, constitute a total of 8.67%, including 4.71% as very cold spots, 1.74% as cold spots, and 1.22% as slight cold spots, whereas hot spot areas indicating zones of high ecological degradation cover 9.97% of the area, with 1.65%, 2.44%, and 5.88% respectively classified as slight, moderate, and very hot spots.

The hotspot–cold spot analysis reveals distinct spatial patterns in habitat quality and degradation changes. The habitat quality change map indicates that cold spots are predominantly concentrated within existing urban areas and their immediate surroundings, reflecting a significant decline in habitat quality associated with urban influence. In contrast, hot spots are more fragmented and spatially limited, mainly occurring in semi-natural areas and transition zones where urban pressure is relatively lower. The habitat degradation changes map shows a more clustered and pronounced distribution of hot spots, highlighting areas where degradation processes are intensifying. This difference in total grid counts results from the removal of null values after transferring the raster outputs to the fishnet grid using Zonal Statistics. The partial spatial mismatch between habitat quality decline and degradation increase suggests that habitat quality is influenced not only by degradation intensity but also by fragmentation, cumulative environmental stressors, and the broader land-use context.

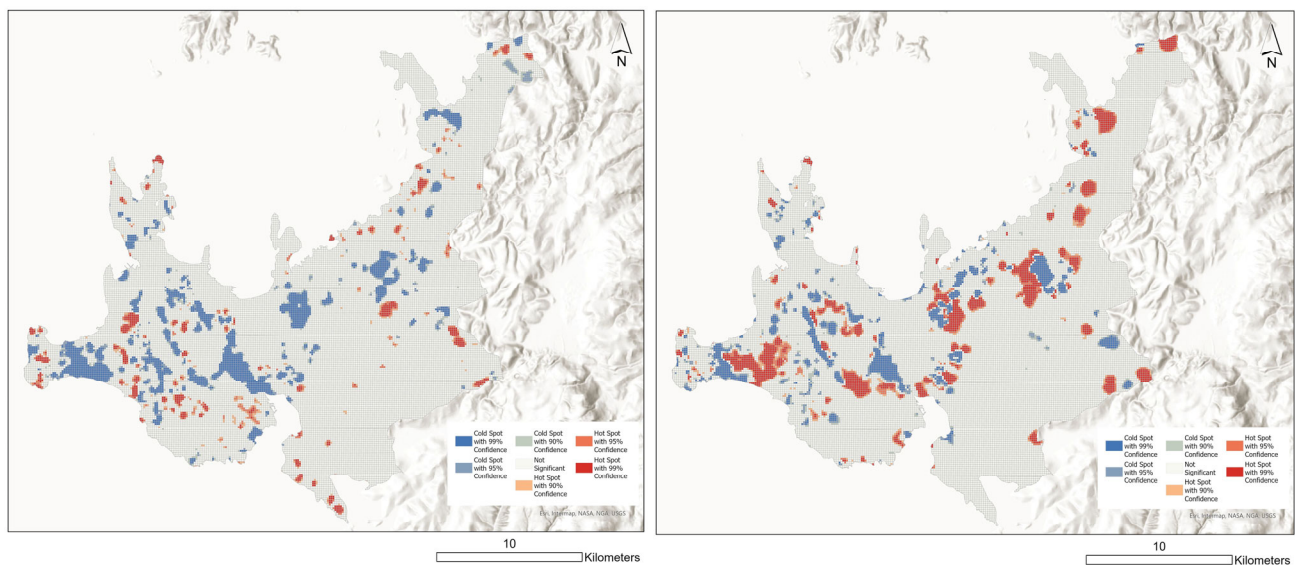


Figure 6. Distribution of difference in cold and hot spots, habitat quality (left) and habitat degradation (right).

Table 4. Area of Cold and Hot Spots (%).

Name	Habitat Quality		Habitat Degradation	
	Count	%	Count	%
Cold Spot with 99% confidence	2157	6.86%	1326	4.71%
Cold Spot with 95% confidence	583	1.85%	490	1.74%
Cold Spot with 90% confidence	359	1.14%	343	1.22%
No Significant Change	23,710	75.45%	23,188	82.36%

Hot Spot with 90% confidence	379	1.21%	465	1.65%
Hot Spot with 95% confidence	404	1.29%	687	2.44%
Hot Spot with 99% confidence	552	1.75%	1654	5.88%
TOTAL	31,144	100%	28,153	100%

3.2. Detection and Interaction Analysis of Driving Factors Using GeoDetector

3.2.1. Spatial Distribution of Driving Factors

NDVI values derived for 2017 and 2024 reveal both increases and decreases in vegetation cover across the study area. The NDVI data were classified into five categories, ranging from 1 (lowest vegetation intensity) to 5 (highest). Despite localized variations, grid cells belonging to the medium NDVI category (Class 3) constituted the largest proportion in both years. Within the administrative boundaries of the study area, the mean NDVI value was slightly higher in 2024 than in 2017, indicating the persistence of moderately vegetated landscapes under spatially heterogeneous change patterns.

Elevation and slope are treated as static topographic variables and therefore remain constant across both study years. Both variables were classified into seven categories using the Natural Breaks method, with higher classes representing greater elevation and steeper slopes, respectively. The spatial distribution reveals a clear coastal–inland gradient, where lower elevation and gentler slopes dominate along the coastline and central lowland areas, while higher elevation levels and steeper slopes are predominantly concentrated in the eastern parts of the study area.

Annual mean precipitation was analyzed separately for 2017 and 2024, revealing a broadly consistent spatial pattern across both years. Precipitation values were classified into 10 categories, with lower values predominantly observed in the western and southwestern coastal parts of the study area. In contrast, higher precipitation levels were concentrated in the eastern and northeastern inland zones. Although interannual variability was evident, the overall east–west gradient remained stable.

Annual mean temperature values for 2017 and 2024 exhibit a consistent spatial pattern across the study area. Higher temperature classes are predominantly observed in the western and southwestern coastal zones, while relatively lower temperatures are concentrated in the eastern and inland areas, reflecting the influence of elevation and distance from the coast. Although an overall increase in temperature levels is evident in 2024 compared to 2017, the underlying spatial gradient remains stable, indicating persistent coastal–inland contrasts in thermal conditions.

Figure 7 presents the spatial distribution of the driving factors for 2024 as a representative and compact visual summary of the explanatory variables used in the GeoDetector analysis. Detailed information on the classification, temporal characteristics, and data sources of each variable is provided in Supplementary File S4.

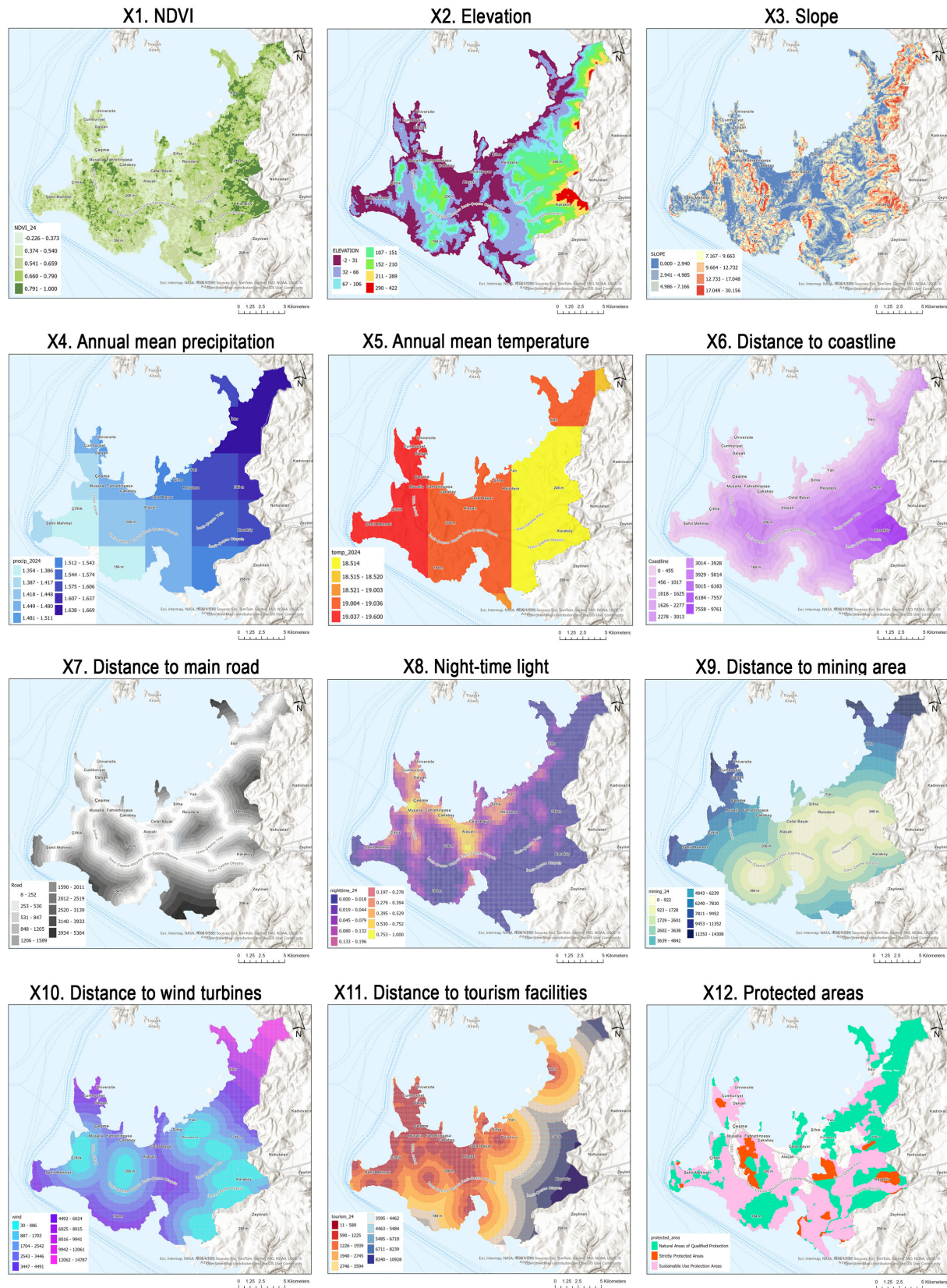


Figure 7. Spatial distribution of independent variables/driving factors (detailed information on the reference, data source, and variable type of each independent variable is provided in Table 1).

3.2.2. Factor Detector of Habitat Quality and Habitat Degradation

The q value ranges from 0 to 1, with higher values indicating stronger explanatory power for each driving factor. The GeoDetector output also provides q -statistics and corresponding p -values, which were used to assess the explanatory power and statistical significance of each factor. (see Supplementary File S3). The detection results for habitat quality are presented in Table 5 and the results for habitat degradation are presented in Table 4, for the years 2017 and 2024.

According to the results of the factor analysis of habitat quality in 2017, night-time light intensity was found to be the most influential driving factor, with a Q value of 0.5699 indicating strong spatial explanatory power. This was followed by tourism-related activities ($q = 0.3625$), protection status ($q = 0.2932$) and elevation ($q = 0.2576$). Climatic variables, particularly temperature ($q = 0.1929$) and precipitation ($q = 0.1510$), had a moderate influence. Proximity to roads ($q = 0.1587$) also highlighted the importance of accessibility-related pressures. In contrast, mining ($q = 0.0609$) and wind energy infrastructure ($q = 0.0962$) showed relatively weak associations with habitat quality. Slope was not statistically significant ($p > 0.05$), indicating negligible explanatory power.

A similar pattern emerged in 2024, with night-time light intensity continuing to be the primary driver of habitat quality ($q = 0.5589$), followed by tourism ($q = 0.3956$), protection status ($q = 0.3142$), and elevation ($q = 0.2635$). Notably, the explanatory power of climatic variables increased in 2024, with temperature ($q = 0.2235$) and precipitation ($q = 0.2002$) overtaking road proximity ($q = 0.1607$). NDVI made a relatively low but statistically significant contribution in both years, reinforcing the idea that vegetation greenness alone is not a sufficient indicator of habitat quality. As in 2017, slope remained statistically insignificant in 2024.

Cross-year comparisons indicate minor rank shifts among secondary drivers, particularly between elevation, precipitation, and road proximity, alongside a modest increase in the influence of temperature and NDVI. Despite these changes, the overall pattern remained stable, with urbanization-related pressure, protection status, elevation, precipitation, and road proximity consistently emerging as the dominant drivers of habitat quality.

Table 5. Factor detector results for habitat quality in 2017 and 2024.

Comparing Ranking ¹	2017		2024	
	Variable	q Value	Variable	q Value
O	X8_nighttime	0.5699	X8_nighttime	0.5589
O	X11_tourism	0.3625	X11_tourism	0.3956
O	X12_protected	0.2932	X12_protected	0.3142
O	X2_elevation	0.2576	X2_elevation	0.2635
O	X5_temperature	0.1929	X5_temperature	0.2235
X	X7_road	0.1587	X4_precipitation	0.2002
X	X4_precipitation	0.1510	X7_road	0.1607
O	X6_coastline	0.1501	X6_coastline	0.1495
O	X1_NDVI	0.1155	X1_NDVI	0.1227
O	X10_wind	0.0962	X10_wind	0.0969
O	X9_mining	0.0609	X9_mining	0.0519
O	X3_slope	0.0004	X3_slope	0.0001

¹ O: no change ranking; X: change ranking.

According to the results of the factor detector analysis of habitat degradation, the explanatory power of all driving factors was substantially lower than that observed for habitat quality. This indicates a more fragmented and spatially heterogeneous degradation process. In 2017, night-time light intensity had the highest q -value among the tested

variables ($q = 0.1335$), emphasizing the impact of urbanization on habitat degradation patterns. This was followed by precipitation ($q = 0.0734$) and protection status ($q = 0.0648$), while tourism, wind energy and mining exerted moderate, yet still statistically significant, influences. By 2024, night-time light intensity again had the highest q -value among the tested variables ($q = 0.1128$). The relative importance of mining had increased markedly ($q = 0.0726$), rising to second place, followed by precipitation ($q = 0.0584$) and protection status ($q = 0.0540$). Temperature also showed a relatively higher position ($q = 0.0329$) in 2024, surpassing road proximity and elevation. These changes indicate a reordering among secondary explanatory factors, rather than a strong increase in explanatory power (Table 6). A cross-year comparison reveals that, apart from night-time light intensity and NDVI, which maintained similar relative positions, the ranking of most explanatory factors shifted considerably between 2017 and 2024. The increased prominence of mining and temperature suggests an intensification and diversification of degradation pressures over time. Nevertheless, despite these rank shifts, the absolute explanatory power of individual factors remained low, underscoring that habitat degradation is driven by the combined and spatially overlapping effects of multiple pressures rather than by any single dominant factor.

Table 6. Factor detector results for habitat degradation in 2017 and 2024.

Comparing Ranking ¹	2017		2024	
	Variable	q Value	Variable	q Value
O	X8_nighttime	0.1335	X8_nighttime	0.1128
X	X4_precipitation	0.0734	X9_mining	0.0726
X	X12_protected	0.0648	X4_precipitation	0.0584
X	X11_tourism	0.0455	x12_protected	0.0540
X	X10_wind	0.0450	X11_tourism	0.0459
X	X9_mining	0.0364	X10_wind	0.0365
X	X7_road	0.0319	X5_temperature	0.0329
X	X2_elevation	0.0271	X6_coastline	0.0253
X	X6_coastline	0.0214	X7_road	0.0198
X	X3_slope	0.0131	X2_elevation	0.0160
X	X5_temperature	0.0125	X3_slope	0.0124
O	X1_NDVI	0.0124	X1_NDVI	0.0088

¹ O: no change ranking; X: change ranking.

3.2.3. Interaction Detector

The interaction detector evaluates whether the combined influence of two factors strengthens, weakens, or remains independent in explaining the spatial distribution of a dependent variable [28]. According to study's outputs, habitat quality analysis (2017 and 2024) and habitat degradation analysis (2017 and 2024) have bivariate enhance and non-linear enhance outputs (Figures 8–11). Thus, it compares the joint effect of two individual risk factors with their separate effects, showing whether their combined influence is stronger, equal to, or weaker than the sum of their individual contributions [39].

The Interaction Detector results show that the strongest bivariate interaction affecting habitat quality in 2017 was observed between protected areas and night-time lights ($q = 0.68$). While protected areas have a positive influence on habitat quality, nighttime lights represent anthropogenic pressure and are usually linked to lower levels of habitat quality. The significant impact of this combined effect highlights the crucial role of protection status in offsetting human-induced disturbances, particularly in areas characterized by low night-time light intensity. Similar interaction patterns were identified between night-time lights and tourism areas, wind energy facilities, and mining areas. This suggests that the

impact of these activities on habitat quality is more pronounced when considered alongside human activity intensity. Overall, night-time lights interacted significantly with almost all explanatory variables, underscoring their central role in shaping the spatial variability of habitat quality. In 2024, a broadly comparable interaction structure was observed, although the magnitude of the q-values varied, indicating changes in the strength of the interactions over time rather than changes in the underlying patterns.

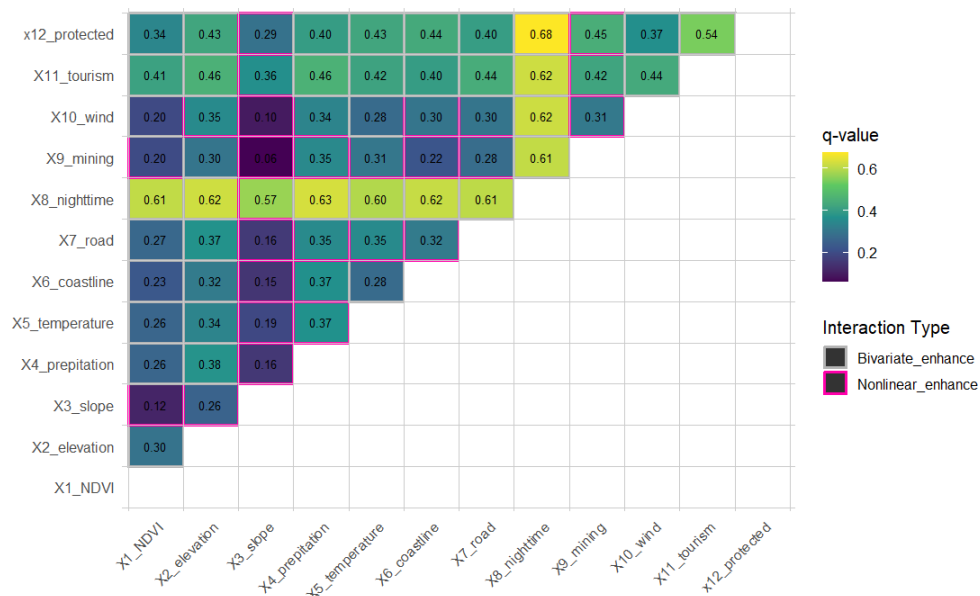


Figure 8. Interaction factors on habitat quality in 2017, visualized as a heatmap in R Studio v2024.12.1+563.

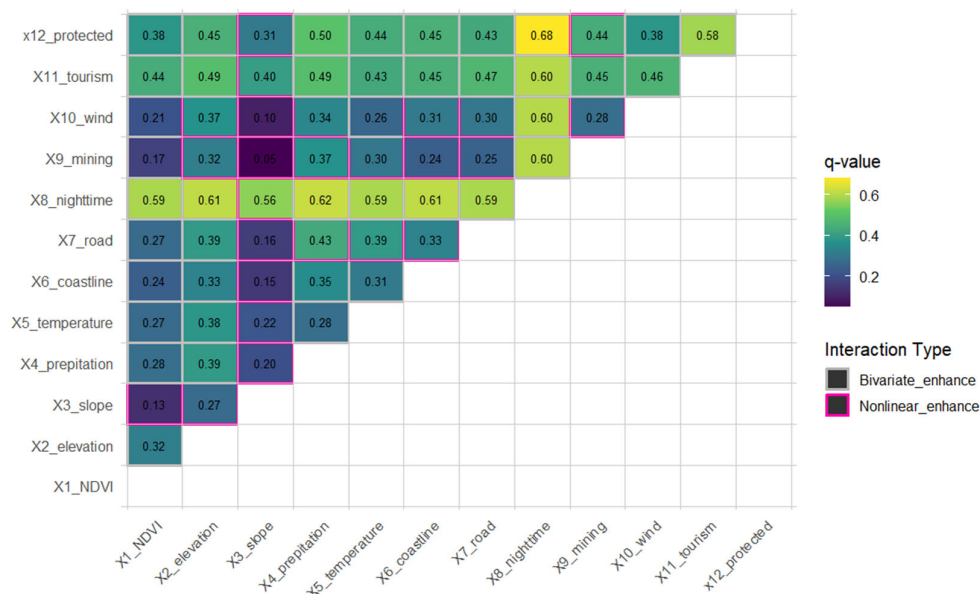


Figure 9. Interaction factors on habitat quality in 2024, visualized as a heatmap in R Studio v2024.12.1+563.

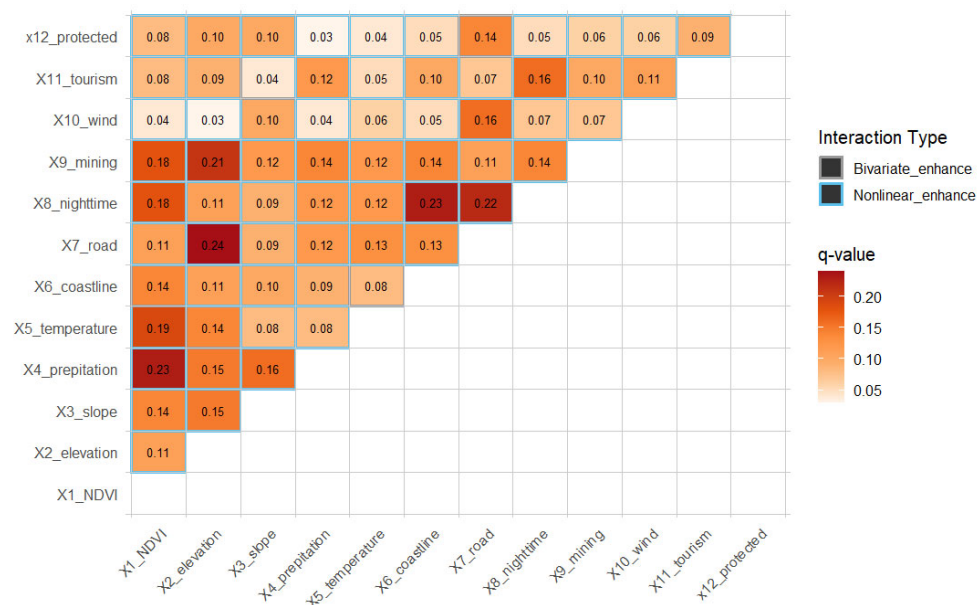


Figure 10. Interaction factors on habitat degradation in 2017, visualized as a heatmap in R Studio v2024.12.1+563.

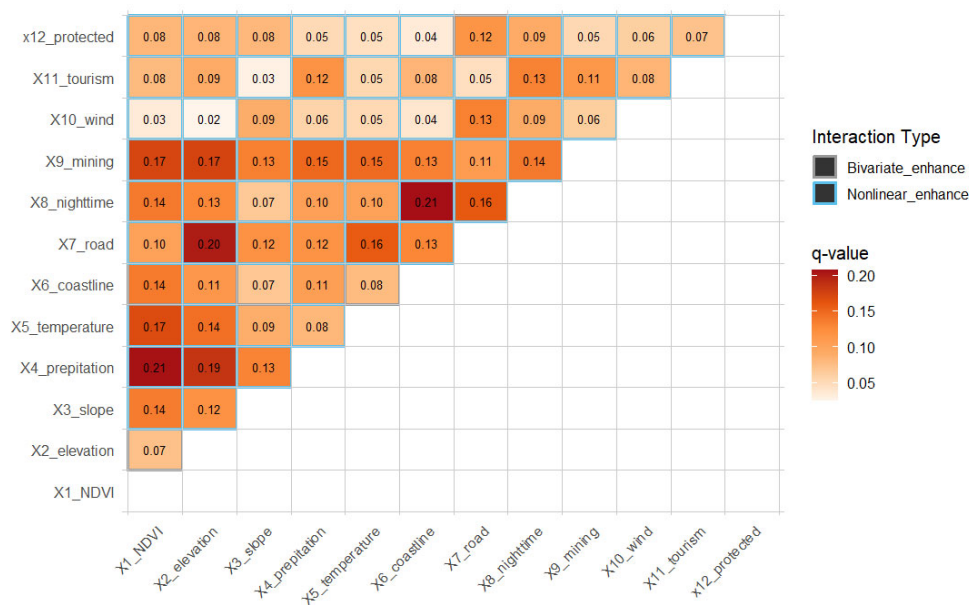


Figure 11. Interaction factors on habitat degradation in 2024, visualized as a heatmap in R Studio v2024.12.1+563.

4. Discussion

The research examined habitat quality (HQ) and habitat degradation (HD) simultaneously in the different years. This dual approach provides a more comprehensive understanding of ecosystem integrity, identifying not only the current state of habitats but also the underlying causes of their deterioration. Recently, there has been growing interest in analyzing these causal mechanisms, and the GeoDetector model has emerged as one of the most popular methods for this purpose thanks to its ability to handle complex spatial relationships [7]. Compared with classical regression techniques, the GeoDetector model

is more flexible in detecting spatial heterogeneity and identifying the interactive effects of influencing factors [8,9].

Overall, anthropogenic pressures consistently dominate habitat quality dynamics across both study periods (2017–2024). The consistently strong explanatory power of night-time light intensity highlights the enduring role of urbanization and human activity intensity in shaping ecological stress patterns, particularly in densely built and functionally active areas. Tourism-related development and proximity to protected areas further underscore the dual nature of human influence, where land-use intensification contributes to habitat degradation, while conservation designations mitigate these effects.

The interaction among driving factors highlights the need to strengthen policy implementation through the integrated consideration of socioeconomic and climatic dimensions [12]. Within this framework, human influence cannot be reduced to a purely degrading force, but should be recognized as simultaneously shaping both habitat loss and ecological recovery. This dual role calls for the advancement of more precise and flexible conservation and restoration policies capable of actively responding to context-specific pressures rather than relying on uniform management approaches.

Given the dual role of human influence in driving degradation and enabling ecological recovery, a policy-oriented interpretation is particularly important. From a policy perspective, variations in the intensity and consistency of land management and conservation measures can significantly impact the spatiotemporal dynamics of habitat quality [9]. Therefore, maintaining stable yet adaptive policy frameworks is essential to ensure long-term ecological resilience. In this context, protected areas play a critical role in sustaining ecological quality. Consistent with previous findings, mean habitat quality is significantly higher within and around protected zones [41]. The present study further reinforces this relationship, confirming that increasing levels of protection are associated with improved habitat quality. However, persistent pressures in unprotected or weakly protected areas highlight the continued need to strengthen and expand conservation efforts.

Furthermore, interactions involving urbanization-related pressures and natural factors, such as elevation and precipitation, consistently exhibited stronger explanatory power than natural–natural interactions alone. This finding supports the interaction hierarchy, in which natural–socioeconomic interactions exert the greatest influence, followed by socioeconomic–socioeconomic interactions, and finally natural–natural interactions [9]. The results emphasize that spatial patterns of habitat quality and degradation cannot be attributed to a single driver. Instead, these patterns emerge from the interplay of ecological, climatic, and human-induced processes, which can be either synergistic or antagonistic.

Overall, the GeoDetector interaction analysis shows that the combined factors' explanatory power often exceeds the sum of their individual effects. This reinforces the importance of adopting an integrated, non-linear analytical framework. Failing to consider these interactions can lead to oversimplifying ecological processes and underestimating the cumulative effects of land-use regulation, human activity, and environmental constraints on habitat integrity.

Çeşme is a typical Mediterranean coastal district where ecological sensitivity and intensive development pressures coexist. The presence of natural conservation zones, residential areas, tourist infrastructure, wind farms and quarries creates a complex spatial mosaic. Of these, urbanization, particularly in the form of secondary housing, is the most significant driver of habitat quality decline. Planning reports confirm that several neighborhoods, particularly in coastal areas such as Alaçatı experience significant seasonal population fluctuations due to the prevalence of second homes [42].

Also, between 2017 and 2024, the population of Çeşme increased by approximately 23% [23] while the built-up area expanded by 25%. Although the difference between these

growth rates is not substantial, the figures suggest that urban expansion has largely kept pace with population increase. However, when interpreted together with the seasonal nighttime light analysis, a different dynamic becomes evident: illumination intensity shows a pronounced summer peak indicating that a significant share of the built-up expansion is related to temporary or seasonal residential use.

To better discuss the dynamics, a seasonal nighttime light analysis was employed not merely as a population proxy but as an analytical tool to disentangle different forms of urbanization particularly secondary housing development and tourism-related activities (Figure 12). In this context, potential secondary housing areas were identified based on seasonal fluctuations in nighttime light intensity, with particular emphasis on summer peaks. This methodological choice is supported by studies demonstrating that VIIRS/DNB data can reveal settlement dynamics and mobility patterns not captured in official demographic records, and that seasonal variations in light intensity provide a reliable proxy for tourism-driven population dynamics [43,44].

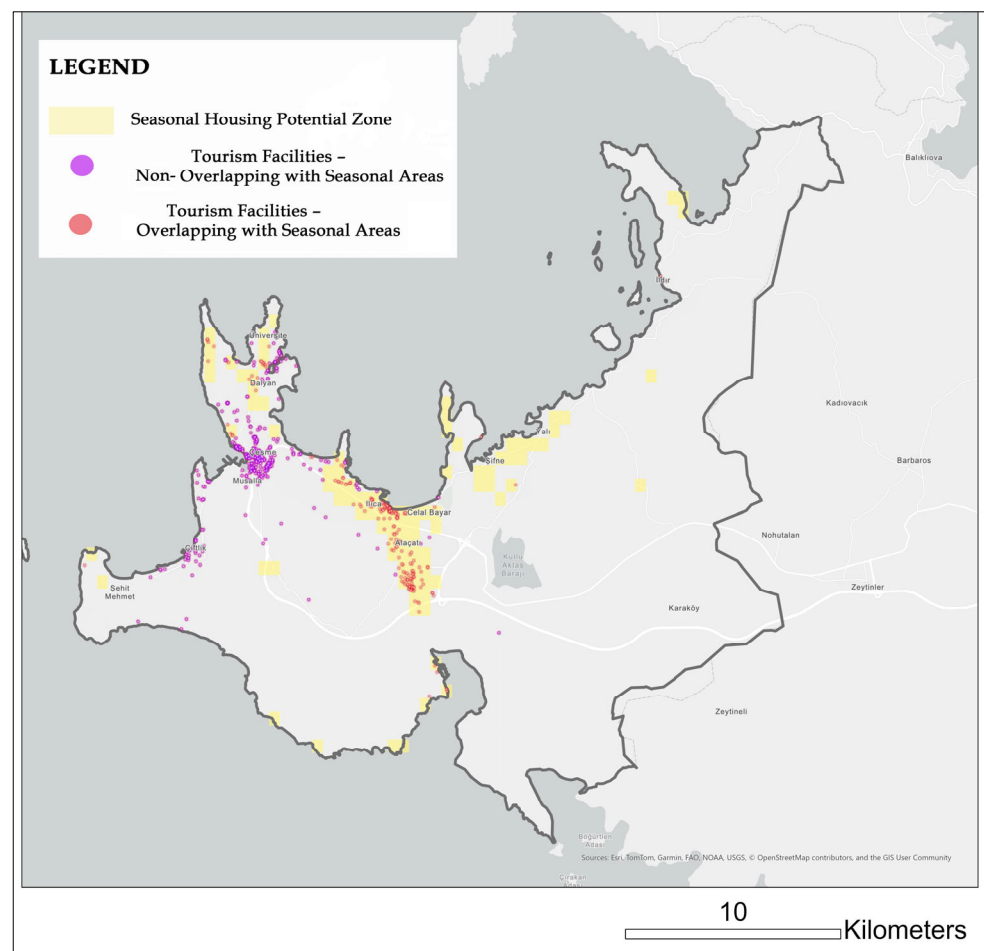


Figure 12. Spatial relationship between tourism facilities and potential seasonal residential areas.

In Çeşme, the analysis revealed pronounced summer illumination peaks in areas such as Alaçatı, İlica, and Celal Bayar neighborhoods, which spatially coincide with zones designated in local planning documents as secondary housing concentrations. When interpreted alongside field observations and planning data, these findings suggest that seasonal urbanization associated with secondary housing and tourism activities may contribute to habitat degradation patterns in Çeşme, underscoring the importance of temporally sensitive indicators in coastal Mediterranean planning contexts.

Overall, while aggregate urban growth rates broadly mirror demographic trends, their spatial and temporal configurations reveal that second-home development and tourism-related urbanization represent important contextual pressures behind habitat degradation. Integrating local qualitative evidence with quantitative modeling helped clarify the mechanisms behind observed spatial patterns of degradation. Such integrated, spatially explicit analytical frameworks enhance interpretability and can function as effective decision-support systems for sustainable urban and environmental planning [12].

5. Conclusions

This study aimed to jointly assess habitat quality and habitat degradation in order to better capture both the cumulative condition of ecosystems and the processes driving their deterioration under multiple anthropogenic and environmental pressures. By integrating spatial indicators with the GeoDetector framework, the analysis demonstrates that habitat quality and habitat degradation respond to different sets of dominant drivers and interaction mechanisms.

Both habitat quality and degradation are influenced by long-term human decisions regarding land use and protection. However, degradation is more strongly associated with anthropogenic pressures, as measured by dynamic indicators. These findings demonstrate that human intervention can have both a degrading and a protective effect on ecosystems, highlighting the importance of planning and management decisions. It is therefore essential to consider not only static land-use configurations, but also ongoing spatial reconfigurations and temporally concentrated human activities when evaluating ecological vulnerability.

Within this broader analytical framework, Çeşme emerges as a case study illustrating how human-driven spatial dynamics can simultaneously shape habitat quality and drive habitat degradation in ecologically sensitive coastal environments. The findings demonstrate that conservation measures, seasonal urbanization, and tourism-related land-use practices intersect in complex ways, generating cumulative pressures that cannot be explained by permanent urban growth alone. Rather than long-term demographic change, temporally concentrated human activities play a decisive role in driving habitat degradation, even within areas subject to protection regimes. This case study underscores the importance of incorporating temporal sensitivity and local planning considerations into ecosystem assessments, thereby reinforcing the broader conclusions of the study.

This study presents analytical results on habitat quality and degradation, and critically reflects on the planning decisions that have contributed to these patterns. It emphasizes that past and ongoing urban development practices, particularly those disregarding ecological thresholds and coastal sensitivity, have resulted in substantial habitat loss and fragmentation. These findings emphasize the need for planning approaches that move beyond conventional land consumption models and prioritize the protection of ecological assets instead. The analysis encourages planners and decision-makers to question which strategies have failed, which actions should be avoided in future, and how spatial planning can better integrate habitat quality as a core criterion. Looking ahead, it is imperative to adopt landscape-sensitive, adaptive planning frameworks that address urban growth and biodiversity conservation together.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071193/s1>, Supplementary File S1: Land Use/Land Cover (LULC) Results; Supplementary File S2: Literature Review for Variables; Supplementary File S3: GeoDetector Analysis Results; Supplementary File S4: Explanatory Variables Used in the GeoDetector Analysis.

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Abbreviations

The following abbreviations are used in this manuscript:

SSH	Spatially Stratified Heterogeneity
HQ	Habitat Quality
HD	Habitat Degradation
NDVI	Normalized Difference Vegetation Index
PCA	Principal Component Analysis
GWR	Geographically Weighted Regression
CIs	Confidence Intervals

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