

Geospatial modelling of land use-based habitat quality changes and predicting its degradation using the InVEST model

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Abstract

The quality of habitats determines ecosystem integrity and is associated with its structure, functioning and components, reflecting the degradation degree, serving as the basis for assessing sustainable landscape development. Urbanization in Karaj County endangers ecosystems, requiring spatial planning to prevent habitat loss. The objective of this study is to evaluate habitat quality and degradation in Karaj County from 2013 to 2032, with predictions for the near future. Landsat images from 2013, 2018, and 2023 were obtained, and after LULC classification for the respective years, the InVEST model's habitat quality ecosystem service model was utilized to determine habitat quality. Based on existing threats to habitats, habitat quality was assessed by selecting six threats, including agriculture, urban areas, rural areas, railways, main roads, and secondary roads. Threat layers were weighted between zero and one. According to the results, the urban areas information layer was assigned the highest weight due to causing the most habitat destruction. The predictive results indicated a decrease in habitat quality from 2013 to 2032, with an increase in landscape degradation. During the study period, the area classified as "severe degradation" increased by 51.752 km², nearly doubling from 2023 to 2032. The InVEST model, using LULC maps and habitat threats, effectively assessed habitat quality and predicted future changes. High-accuracy LULC classification ($Kappa > 90\%$) ensured reliability. Integrating the CA-Markov model improved land use change predictions. Habitat quality declined from 2013 to 2032, with the greatest loss in human-built areas, while mountainous regions remained less affected. Accessible natural habitats underwent LULC conversion. Urban expansion from 2013 to 2023 reduced agricultural and natural areas, a trend expected to continue, increasing habitat threats. These results indicate the need for limiting urban expansion, preserving ecological corridors, and adopting targeted nature-based solutions, particularly in rapidly urbanizing zones like Karaj County, to mitigate projected degradation and maintain ecosystem integrity by 2032.

Key words:

geospatial modelling,
habitat degradation,
ecosystem service,
CA-Markov model,
land use change

1 INTRODUCTION

Human activities and climate change are altering Earth's ecosystems in ways that threaten their well-being and sustainability (Steffen et al., 2011). These changes have significant implications for ecology and environmental integrity at local, regional, and global scales (Deng & Quan, 2022). Habitat quality (HQ) is a crucial factor affecting the life of living organisms, biodiversity, ecosystem services, and human uses (Wang & Cheng, 2022). Habitat quality, indicative of landscape pattern dynamics and regional biodiversity, has become increasingly vulnerable to both human-induced and natural destructive factors. The composition and structure of habitats are altered, ultimately affecting the material cycle and energy flow among habitat patches (Gharehaghaji et al., 2012; Liu et al., 2014; Zhao et al., 2015). Habitat quality defined as the ability of the environment in a particular spatial and temporal conditions

supporting the life, survival and development of plant and animal communities and the livelihoods of dependent communities (Sun et al., 2019; Lei et al., 2022). Habitat quality considered as an indicator of ecosystem stability and is associated with biota biodiversity, indicating the extent of degradation and ecological habitat status, thus serving as the basis for LULC and sustainable land development and assessment (Chen et al., 2016; Sun et al., 2019; Wu et al., 2022).

Key factors contributing to habitat degradation include agricultural expansion, urban development, infrastructure construction, overgrazing, and unsustainable resource use. Habitat fragmentation, pollution, and climate change further accelerate this degradation. Understanding these drivers is essential for effective biodiversity conservation. Geo-spatial methods for habitat quality assessment include remote

sensing to detect land cover changes, GIS for modeling spatial factors, and process-based models like InVEST to assess human impacts. Machine learning models predict species distribution, while land-use change models like CA-Markov simulate future habitat trends, supporting effective conservation planning.

Currently, the most used models and approaches for habitat quality assessment includes ARIES, HSI, SolVES, LDI, HQI, and InVEST models (Aneseyee et al., 2020; Raji et al., 2022; Wang & Cheng, 2022). InVEST model is among the most commonly used models due to its comprehensive evaluation of ecosystem services and exchanges, along with advantages such as appropriate visualization, easy and fast data processing, and user-friendly interface, developed by Stanford University and WWF (Wei et al., 2022). Therefore, considering the importance of habitat quality assessment as a basis environmental governance improvement and sustainable planning of ecosystems it is of particular attention (Hou & Wu, 2024). LULC change as a multifaceted process influenced by human activities, economic growth, climate variations, and various factors (Wu et al., 2022; Talebi Khiavi et al., 2022). The impact of land use change on habitat quality degradation has been evaluated in various studies and confirmed (Wei et al., 2022; Sobhani & Danekar, 2023). LULC change affects the spatial configuration of habitats through altering the flow of material and energy cycles among habitat patches and matrix, consequently impacting habitat quality (Jin et al., 2022; Raji et al., 2022). A multidimensional understanding of LULC change impact on habitat quality requires the recognizing of interactive mechanisms and connections resulting from land use change intensity, extent and type of changes (Li et al., 2020). However, studies on the temporal and spatial mechanisms of land use change and their assessment on habitat quality/degradation are limited. LULC change predictions are often made through modelling platforms, using common prediction models including FLUS, CA-Markov, CLUE-S, and PLUS. In land use change prediction

models, the intensity and extent of land use change over a series of long-term time frames are forecasted, and spatial and temporal land use changes are simulated with acceptable accuracy (Liang et al., 2021; Shi et al., 2021).

Wu et al. (2022) assessed habitat quality in the Weihe River Basin, indicating socioeconomic and meteorological drivers of land use change and stressing the need to balance development and conservation. Lei et al. (2022) used InVEST and CA-Markov models to predict habitat quality decline on Hainan Island by 2040, with national parks maintaining higher quality. Huang et al. (2023) analyzed the Yangtze River Basin using the PLUS-InVEST model, finding rapid urban expansion and identifying NDVI, DEM, GDP, and population as key factors affecting habitat quality. He et al. (2023) investigated landscape habitat quality changes in the Yangtze River Basin, noting significant expansion of construction land and marginal improvements in habitat quality indices, especially under ecological protection scenarios. Zhao et al. (2023) focused on sustainable land use in the Beijing–Tianjin–Hebei region, projecting a substantial increase in construction land area by 2030. They developed the imperative of tailored strategies to reverse the declining trend in habitat quality and promote sustainable land use practices. Nie et al. (2023) assessed how LULC change affected quality of habitat in the Lhasa River Basin, Tibetan Plateau, finding that ecological restoration countered urban expansion, improving natural habitat quality from 2000 to 2020. However, under cropland protection scenarios, habitat quality was projected to deteriorate due to increased urban expansion, particularly in Chengguan District. Hou and Wu (2024) forecasted land use and habitat quality from 2000 to 2020, revealing a decline in habitat quality, especially between 2010 and 2020, due to human land development and forest-to-agriculture conversion. Louis et al. (2024) modeled habitat quality in Malaysia using InVEST and Sentinel-2 imagery under forest degradation and non-degradation scenarios,

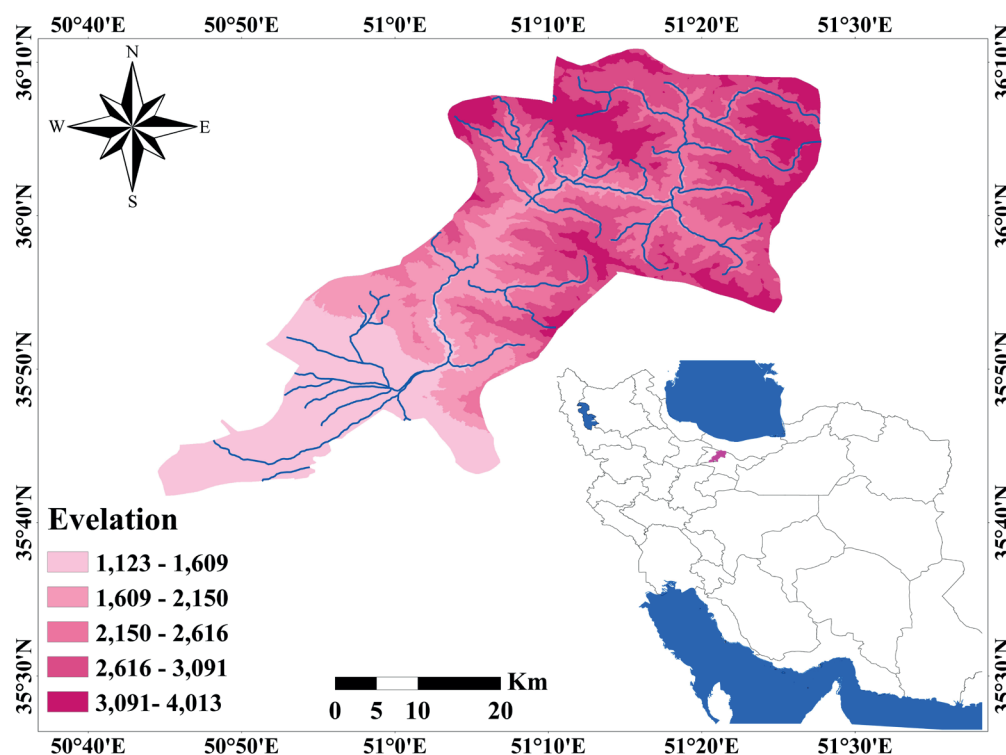


Fig. 1. Geographical location of the studied area in Iran

finding decreased landscape biodiversity. Chen et al. (2025) studied land use and habitat quality changes in China over 40 years. Using InVEST and FLUS models, they projected land use to 2050 and found high-quality habitats declining and low-quality ones growing, with further degradation likely without better land management. Xu et al. (2025) analyzed habitat quality in the Yellow River Basin from 2005 to 2020. They found farmland and grassland decreased, while forest and construction land increased. Habitat quality declined then improved, with construction areas having the lowest quality.

In conclusion, the reviewed studies have offered significant attention on the dynamics of habitat quality and its correlation with LULC change, indicating the importance of sustainable development for preserving ecosystem health and resilience. These frameworks can predict future habitat quality trends and evaluate the efficacy of conservation measures across different LULC scenarios. By focusing on modeling approaches that account for the intricate interactions between LULC change and habitat quality dynamics, we can enhance our understanding and improve the accuracy and reliability of habitat quality assessments. This, in turn, will enable evidence-based decision-making for ecosystem conservation and management, ultimately aiding in the promotion of sustainable development and biodiversity conservation amidst ongoing global environmental changes.

Assessing habitat degradation is crucial in environmental studies, as habitat quality indicates ecosystem health and is affected by land use changes and human activities. This evaluation helps identify vulnerable areas, track degradation trends, and plan effective conservation and restoration. Assessing and analyzing the prediction of ecological habitat quality in Karaj County due to its proximity to the metropolis of Tehran is crucial for achieving ecological conservation and coordinated development with high quality. The aim of the present study is to model habitat quality using the InVEST model under the influence of spatial and temporal evolution of LULC within the study area. Furthermore, future LULC changes are predicted, and the intensity of habitat degradation in the future is forecasted through analyzing the factors affecting habitat destruction. This study improves habitat assessment by combining LULC projections (CA-Markov) with ecosystem service valuation (InVEST), quantifying anthropogenic pressure on habitat quality in semi-arid mountains. It establishes region-specific conservation thresholds and multi-decadal degradation trends, offering tools for adaptive land-use zoning, especially in rapidly urbanizing, ecologically fragile areas.

2 MATERIAL AND METHODS

Geographical Setting of the study area

Karaj, the capital of Alborz Province, covers an area of 1,420 km² at the southern foothills of the Alborz Mountains (Figure 1). Geographically, it lies at 51 degrees' east longitude and 35 degrees 48 minutes' north latitude, with a mean elevation of 1321 meters above sea level, located 36 km northwest of the capital city of Iran (Meshkini et al., 2020). According to the 2016 census by the Statistical Center of Iran, the population of Karaj was 1.59 million (www.amar.org). Based on recent growth trends, it is estimated to have reached around 1.9 million. Karaj County's favorable location near Tehran, industrial zones, and economic importance make it highly prone to migration. Influenced by the Alborz Mountains, Chalous Valley,

and Karaj River, it has cooler, more humid conditions than Tehran. Urban growth, traffic, and industry have degraded air quality, especially in autumn and winter. Karaj's proximity to Tehran, metro connection, and provincial capital status have driven rapid suburbanization, making it Iran's largest residential city and centralizing industrial and service sectors, resulting in higher provincial budget allocations.

Methodology

Spatial data preparation and analysis

To assess habitat quality, it is necessary to first identify the LULCs in the study region. In the current years, a decrease in rainfall and the onset of drought conditions have led to habitat quality deteriorating from natural conditions. Additionally, urban population growth significantly impacts habitat quality; therefore, satellite images for the past 15 years, with 5-year intervals, were selected. The Landsat images have a resolution of 30 meters, which, when combined with the panchromatic image, results in a resolution of 15 meters. This high resolution and a kappa coefficient of over 90% in land cover mapping are responsive to the needs of land cover change analysis in multiple time series (Naseri & Mostafazadeh, 2023). Since this study aims to examine changes in habitat quality over time, LULC maps were prepared for three periods: 2013, 2018, and 2023. For this purpose, after obtaining satellite images and conducting necessary atmospheric and radiometric corrections, the images were preprocessed, and the information on the images used is presented in Table 1.

Tab. 1. Information on satellite images for the study periods in LULC change assessment

Year	Satellite/ Row and Path	Data
2013	LC08_L1TP_165035	20130731
2018	LC08_L1TP_165035	20180703
2023	LC09_L1TP_165035	20230810

To prepare LULC maps for the study years, ENVI software was utilized, employing the Support Vector Machine (SVM) classification method. Sample training points were selected from Google Earth images based on sufficient familiarity with the study area and were chosen in an adequate number to cover the extent of LULC types. Subsequently, LULC maps for the study area were generated for each of the study years. The accuracy of classification was estimated using Cohen's kappa coefficient (κ), (Equation 1).

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (1)$$

Where, p_o is the proportion of cases correctly classified (overall accuracy), and p_e is the proportion of cases expected to be correctly classified by random chance. The κ value ranges from -1 to +1, with higher values indicating higher classification accuracy and lower values indicating agreement due to chance (Li et al., 2017).

LULC prediction using the CA-Markov Model

The CA-Markov model, as a commonly used for LULC prediction has been used in this study (Hamad et al., 2018). The cellular automata (CA) and Markov chain-based approach combined to predict the overall trend of LULC changes over time (Nouri et al., 2014). The Markov model describes LULC changes among studied periods to predict future changes (Burnham, 1973; Kumar et al., 2014; Behera et al., 2012), while

CA simulations demonstrate the dynamic process of LULC (Parsa et al., 2016). The Markov chain precisely determines the transition probability of different LULC classes from the last period to the future predicted time. The LULC change among two periods, LULC maps at a past time (T1), and LULC maps at a recent time (T2) are used to predict LULC maps in recent years (T3) (Nehzak et al., 2022). The transition probability matrices obtained from the Markov procedure represent the likelihood of each LULC class at time T1 transitioning to any other class at time T2, with probabilities shifting closer to zero (low transition probability) or closer to one (high transition probability) (Kumar et al., 2014; Hyandye & Martz, 2017). For model validation, the simulated LULC map at time T3 is compared with the classified LULC map for the same time span (T3). Once satisfactory validation results are obtained, the model is then used for future predictions (Mostafazadeh & Talebi Khiavi, 2024). To predict the LULC map for the year 2032, the CA-Markov model was executed in Terrset software using the LCM extension. For this purpose, images from 2013 were used for algorithm calibration, while the 2018 image was utilized for validating the CA-Markov predictions.

The CA-Markov model was applied to predict LULC changes using 2013 and 2018 satellite images in Terrset with the LCM module. Images from 2013 calibrated the algorithm, while 2018 images validated it. The transition probability matrix, based on changes from 2013 (T1) to 2018 (T2), was used with a 3×3 neighborhood Cellular Automata to predict 2018 (T3) LULC, which was then compared to actual data. This matrix also served to simulate future changes for 2032. Upon validation confirmation, the CA-Markov model was employed for simulating future predictions for the year 2032.

Habitat Quality (HQ) Ecosystem Service Model

The InVEST Habitat Quality model utilizes habitat quality as an indicator to represent biodiversity within a landscape, estimate habitat extent and types of vegetation cover across a landscape, and assess their degradation status. This model combines land use and land cover (LULC) maps with habitat threats and response data. Habitat quality modeling, alongside ecosystem services, enables users to compare spatial patterns and identify areas where protection yields the highest benefits for natural ecosystems and conserves threatened vegetation species. In this model, no monetary value is assigned to biodiversity (Polasky et al., 2011).

The InVEST Habitat Quality model was chosen for its alignment with the study's goals, enabling spatial-temporal assessment of habitat degradation. It integrates LULC and threat data to quantify human impacts and identify sensitive areas, supporting targeted conservation and sustainable land use planning. Therefore, by employing the Habitat Quality module in the InVEST model, the indices of habitat degradation and habitat quality for each LULC are evaluated considering information related to biodiversity threats, ecological numerical parameters, and LULC patterns. In the present study, the habitat quality index is calculated as follows (Wang & Cheng, 2022):

$$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z K^z} \right) \right] \quad (2)$$

where, Q_{xj} represents the habitat quality degree of raster x for LULC type j , K considered as the half the resolution of raster data in the given area, generally corresponding to half the maximum habitat

degradation value and ranging from zero to one. Additionally, Z refers to the normalization constant, typically set to 2.5. Furthermore, D_{xj} denotes the stress level experienced by raster x under LULC type j , indicating the habitat degradation degree which reflects the intensity of habitat alteration by threat agent and is obtained as follows (Hou & Wu, 2024; Wang et al., 2024).

$$D_{xj} = \sum_{r=1}^R \sum_{y=1}^R \left(\frac{\omega_r}{\sum_{r=1}^R \omega_r} \right) r_y i_{rxy} \beta_x S_{jr} \quad (3)$$

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}} \right) \text{(Linear Decay)} \quad (4)$$

$$i_{rxy} = \exp \left(\frac{-2.99d_{xy}}{d_{rmax}} \right) \text{(Linear Decay)} \quad (5)$$

in which, D_{xj} represents the habitat degradation degree; R equals the stressor numbers; y is the number of networks in the stressor factor r raster layer. Also, Y_r considered as the number of networks occupied by stressor factors. ω_r is the weight of the stressor factor, r_y is the stress value of raster y . β_x is the availability of raster x , meanwhile, S_{jr} is the j 's habitat sensitivity to stressor factor r , i_{rxy} is the stress coefficient value of y raster's stress level on raster x , d_{xy} is the linear distance between raster x and raster y , d_{rmax} is the maximum distance of stress from the threat source r . The higher the calculated score, the greater the level of threat from the habitat threat factor, and the greater the habitat degradation (Louis et al., 2024).

In this study, habitat quality assessment covers both natural (forests, grasslands, water bodies) and human-made habitats (agriculture, urban/rural areas, roads). The InVEST model uses LULC maps and threat factors to analyze habitat quality across the entire study area. The study area includes all of Karaj County (not just the city) and satellite data and LULC analyses reflect this full coverage. According to the guidelines of the InVEST model (<https://naturalcapitalproject.stanford.edu/>) and considering previous research results on habitat quality assessment in similar areas to the study area conditions, six threats in urban, rural, main roads, secondary roads, agricultural lands, and railways were selected (Sharma et al., 2018; Bai et al., 2019; Xu et al., 2019; Zhou et al., 2020; Gomes et al., 2021). The "Ecological Threat Agents" in Table 2 were selected based on their significant impact on habitat quality in Karaj County, following the InVEST model framework. These factors (agriculture, urban and rural settlements, railways, and roads) are the main human activities causing habitat loss and fragmentation, as supported by previous studies in similar regions. Their weights and impact distances reflect their intensity and spatial influence, ensuring an accurate assessment of habitat degradation.

Table 2 presents the types of ecological threats considered in the present study and their characteristics.

Tab. 2. Ecological threat agents, their weights, and maximum distance of impact in habitat quality assessment

Threat	Max_Dist/ km	Decay	Weight
Agriculture	8.0	linear	0.7
Urban	10.0	exponential	1.0
Village	6.0	exponential	0.5
Main road	3.0	linear	1.0
Secondary road	1.0	linear	0.7
Railroad	5.0	exponential	0.6

Table 3. Types of habitats and the sensitivity of habitats to various threats

LULC	Name	Habitat	Agriculture	Railroad	Urban	Village	Main road	Secondar road
1	Barren plain land	0.00	0.30	0.50	0.50	0.20	0.50	0.60
2	Outcrop	1.00	0.60	0.50	0.60	0.50	0.60	0.50
3	Man- made water body	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	Natural water body	1.00	0.50	0.50	0.60	0.30	0.60	0.50
5	Agriculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	Rangeland	1.00	0.60	0.50	0.60	0.20	0.50	0.50
7	Forest	1.00	0.50	0.60	0.60	0.20	0.60	0.50
8	Industrial sites	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	Rural land	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	Urban land	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The „maximum influence distance“ and „decay type“ parameters in the InVEST model were selected based on prior knowledge and familiarity with the study area. Despite some limitations, their applicability is supported by alignment with local environmental and land use conditions, high land use classification accuracy (Kappa > 90%), use of detailed maps, CA-Markov predictions, and consistency with observed trends. Future studies should include more extensive fieldwork and local data collection to better calibrate and validate these parameters regionally, thereby improving model accuracy and reliability.

The sensitivity values of LULCs were also considered for examination based on the importance of each habitat relative to threats, as presented in Table 3.

If each LULC is considered as a habitat, the number one is assigned, and if it is not a habitat, the number zero is assigned. The sensitivity level of each habitat to threat maps ranges between zero and one, where the number one corresponds to the habitat with the highest sensitivity to the considered threat, and zero corresponds to the habitat with the lowest sensitivity (<https://naturalcapitalproject.stanford.edu/>). In this regard, He et al. (2023) investigated the sensitivity and stability of each habitat to threat sources, with habitat sensitivity ranging from 0.3 to 0.75. Furthermore, Wang and Cheng (2022) examined the effects of LULC on habitat quality considering various geomorphic conditions using the InVEST model, considering threats from agricultural, residential, mining, industrial and barren lands. Among these, urban and industrial-mining lands were considered the most significant threats to habitat quality, allocating the highest weight for quality reduction, as human-made LULCs have the greatest impact on habitat quality reduction.

3 RESULTS

The results of the accuracy assessment of LULC maps are presented in Table 4.

Tab. 4. Results of the accuracy assessment of LULC maps in the study area

Year	Kappa coefficient %	Overall Accuracy %
2013	0.9657	97.3380
2018	0.9141	93.4721
2023	0.9322	94.4052

Accuracy assessment showed a Kappa of 0.9141 and Overall Accuracy of 93.47% for 2018, confirming the model's reliability for future predictions.

Spatio-temporal LULC change

Spatio-temporal LULC changes and classification maps of Karaj County are presented in Figure 2, Figure 3, and Tables 5.

Analysis of Habitat Quality and Degradation

Habitat quality maps based on the InVEST model for the years 2013 to 2032 are presented in Figure 4 and Figure 5.

The results of the assessment of habitat degradation in Karaj County for the study years, as well as the predicted scenario for the year 2032, are presented in Figure 6 and Figure 7.

4 DISCUSSION

According to Figure 2 and Figure 3, by classifying and mapping LULC in Karaj County for the years 2013, 2018, and 2023, it was determined that the predominant LULC in the region, covering the largest area, consists of mountainous and plain barren lands, as well as rangelands. Given that the upper parts of the study area are located in a mountainous region; it is expected that the largest area of this region is related to the outcrop land cover.

According to the information provided in Table 5, during the study years, the extent of rural, urban, and agricultural LULC has increased, while the area of natural grassland and water bodies has decreased. The urban area increased from 1.95 km² in 2013 to 34.39 km² in 2023 and is predicted to reach 54.77 km² by 2032 based on the Markov chain model. The agricultural area increased from 7.36 km² to 29.27 km² in 2023 and is projected to reach 30.35 km² by 2032. The area of human-made water bodies was 10.33 km² in 2013, which increased to 21.81 km² in 2023, while the area of natural water bodies decreased from 0.83 to 0.59 km². In 2023, the predicted areas for human-made and natural water bodies are 7.10 and 60.36 km², respectively. Forested land increased from 15.86 km² in 2013 to 18.76 km², and a significant increase is expected by 2032 according to the Markov chain model and previous period maps. It's worth noting that some changes may result from classification errors, potentially affecting the accuracy of the observed changes and land cover reality.

Efforts were made to select images from the region's vegetation growth period to improve classification accuracy and assess LULC changes accurately. However, limited availability of suitable images at certain times may affect image selection and the interpretation of results. The satellite images with classification accuracy above 90% were used, ensuring acceptable quality for land cover determination. Although differences in the years of image acquisition may introduce some errors,

Tab. 5. Area of LULCs in Karaj County (km²) for the study years and predicted future

LULC	2013	2018	2023	2032
Barren land	254.17	215.78	207.68	178.81
Outcrop	852.77	862.86	922.97	760.53
Man- made water body	10.33	26.84	21.81	60.36
Natural water body	0.83	1.59	0.59	7.10
Agriculture	7.36	23.71	29.27	30.35
Rangeland	255.99	184.58	177.88	164.15
Forest	15.86	67.70	18.76	148.47
Industrial sites	14.34	5.80	5.66	6.90
Rural area	8.26	2.23	2.86	10.42
Urban land	1.95	30.77	34.39	54.77
Sum	1421.86	1421.86	1421.87	1421.86

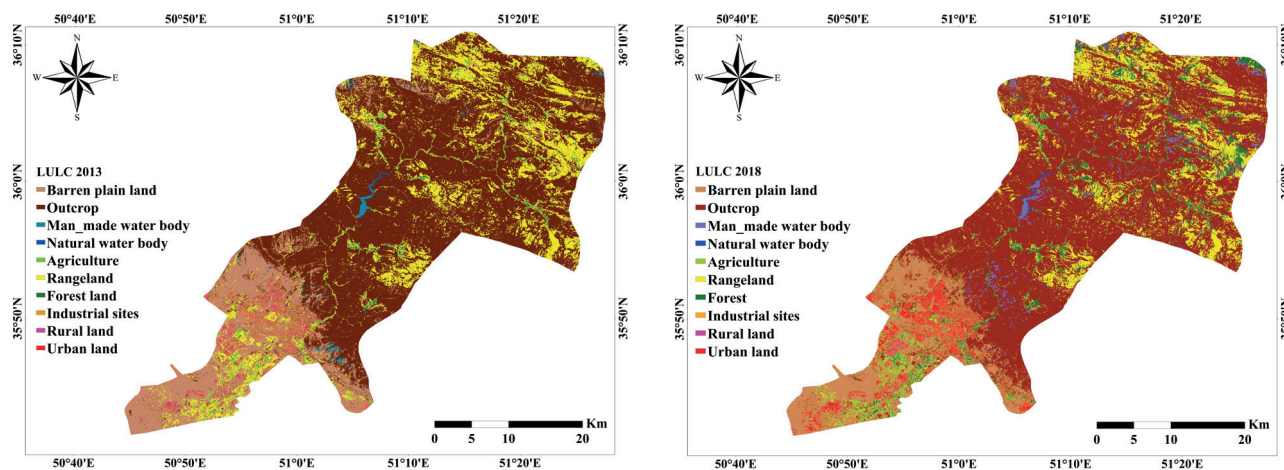


Fig. 2. The LULC map of the studied area in 2013 (left) and 2018 (right).

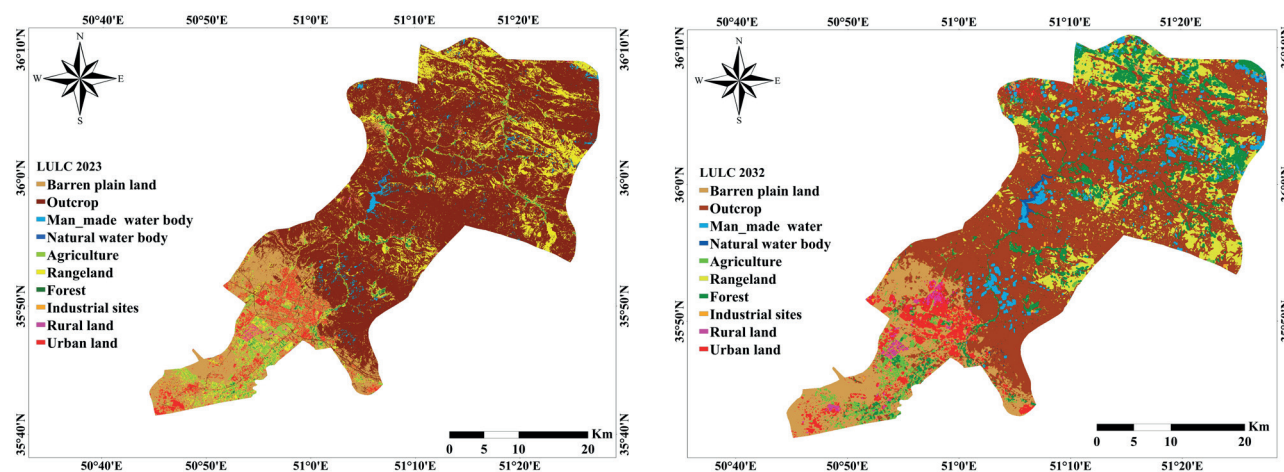


Fig. 3. The LULC map of the studied area in 2023 (left) and future prediction in 2032 (right).

atmospheric corrections and SVM classification have minimized these inaccuracies. The 2032 prediction was made using the CA-Markov model, which is validated based on actual trends and historical data. Despite the possibility of errors and the influence of temporal differences, due to limitations in field data and higher-resolution imagery, these results are considered a realistic estimation of the overall habitat change trends. These limitations have been explicitly acknowledged in the manuscript.

Regarding the land use prediction, the CA-Markov model was calibrated with 2013 data and validated using 2018 data, showing high accuracy in predicting land use changes. A Kappa coefficient above 90% confirms the reliability of the input data and model

outputs. The study also explains transition probabilities and model implementation with Terrset and the LCM plugin. Overall, the well-calibrated and validated model provides a strong basis for forecasting future land cover changes and assessing habitat quality.

Using the InVEST ecosystem services software as a comprehensive tool, various ecosystem services have been analyzed, encompassing 22 types of ecosystem services, among which the habitat quality model is considered one. Habitat quality maps are divided into four classes: poor, low, moderate, and natural (Figure 4 and Figure 5). In 2013, the areas of habitat quality classes were 296.4, 852.7, 185.1, and 87.5 km² respectively. These figures changed to 301.7, 922.8, 19.2, and 178.0 km² in 2023. By 2032, the areas will

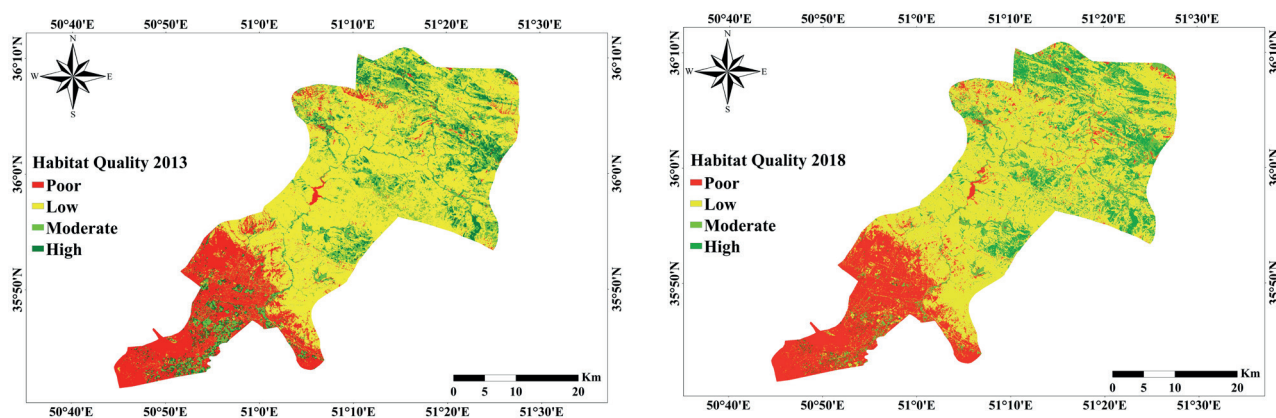


Fig. 4. Habitat quality map within the study area for the study period in 2013 (left) and in 2018 (right)

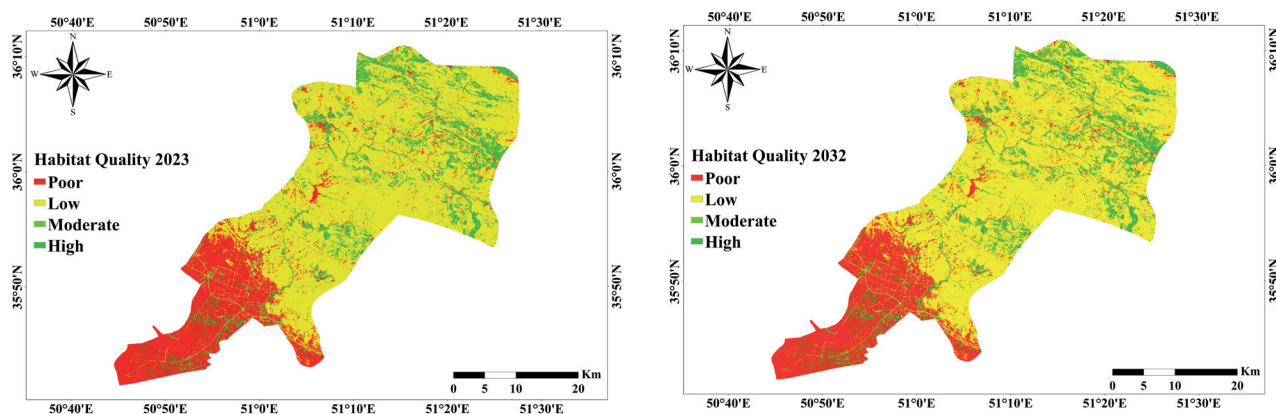


Fig. 5. Habitat quality map within the study area for the study period in 2023 (left) and predicted future in 2032 (right)

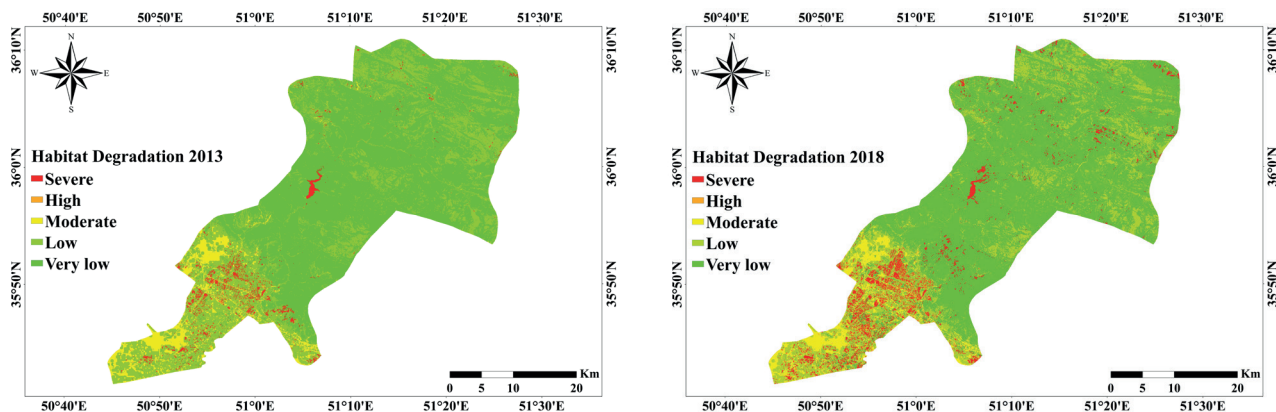


Fig. 6. Habitat degradation map of Karaj County for the study years - 2013 (left) and 2018 (right)

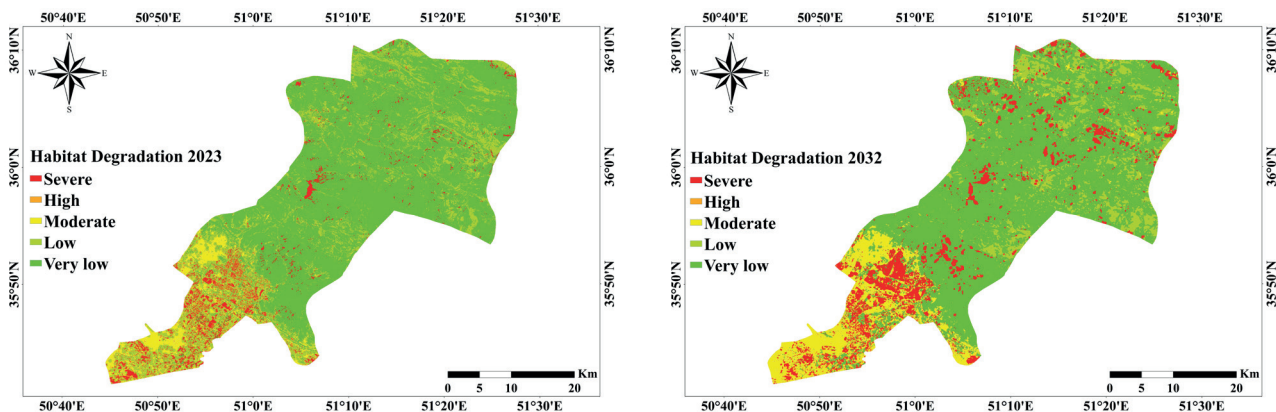


Fig. 7. Habitat degradation map of Karaj County for the study year 2023 (left) and the predicted future in 2032 (right)

be 341.6, 760.4, 153.8, and 165.9 km², respectively, with the low-quality class occupying the largest area and the natural-quality class the smallest. The habitat quality of Karaj County declined from 2013 to 2023, with the most significant decline observed in urban, rural, industrial, and agricultural human-made LULC areas, while the habitat quality remained relatively favorable in other LULC categories. Furthermore, according to simulated modeling, habitat quality is expected to decrease by 2032. In line with this, Hou and Wu (2024) concluded in their assessment of river habitat quality that construction and residential areas have the greatest negative impact on habitat quality, with areas with more construction having lower habitat quality levels. Since LULC has a close relationship with HQ, human activity intensity is the main factor driving LULC change. Urban areas and major roads are considered the most significant threats to habitat quality due to the use of various human-made materials. According to the study by Lin et al. (2024) examining the spatial and temporal evolution and mechanisms of habitat quality in 18 protected natural areas in Hubei Province, China, among the influencing factors, single-factor effects such as land use intensity and distance to roads and county slopes have a strong negative linear relationship with habitat quality, with land use intensity being the most important human activity factor.

The InVEST model not only has the capability to analyze habitat quality but also can calculate the level of degradation in each habitat. Therefore, habitat degradation maps were generated for the study years. As depicted in Figure 6 and Figure 7, the level of habitat degradation has increased over the study periods. Degradation in each of the maps was classified into five categories: very low, low, moderate, high, and severe degradation. In 2013, Karaj County had the lowest level of degradation, while in 2023, it had the highest, and in 2032, degradation will reach its peak. Additionally, the area of each category in 2013 ranged from severe degradation to very low degradation, with 42.2, 86.1, 424.0, 16.7, and 825.6 km², respectively. In 2023, the corresponding areas are 94.0, 78.0, 307.5, 19., and 922.8 km², with an increase of 51.7 km² in the severe degradation category from 2013 to 2023. In 2023, the area of severe degradation is 162.8 km², nearly doubling compared to the previous period.

Each of the threats leads to fragmentation and loss of integrity of natural habitats. Nematollahi et al. (2020) concluded that habitat fragmentation and road networks can negatively impact natural habitats by reducing their core area and quality. The effects of habitat quality reduction include the loss of plant species, subsequently intensified the disappearance of ecosystem species and habitats for many life forms and the extinction of rare and endangered species. Soil degradation, erosion, and loss of landscape aesthetics result from habitat loss. Urban growth and road development, driven by population increase, accelerate habitat destruction and reduce ecosystem services.

This study used InVEST and CA-Markov to model land use and habitat quality, showing urban areas grew from 1.95 km² (2013) to 34.39 km² (2023), projected to reach 54.77 km² by 2032 due to population and economic growth. While human factors are indirectly reflected in the models, the study offers a tool to assess human impacts on landscapes. Future research should directly incorporate socio-economic variables to better connect development with environmental change and improve habitat conservation.

Future land use and habitat conditions may be influenced by unexpected factors like climate change and new urban policies, causing deviations from current predictions. The 2032 forecasts assume stable conditions and should be updated if major changes occur. Policy shifts without environmental safeguards could also rapidly alter land use. Predictions should consider multiple scenarios, from pessimistic to optimistic. Future research should use scenario-based and dynamic climate models (e.g., IPCC, RCP) for improved accuracy. Climate change impacts habitats directly (temperature rise, vegetation loss, species shifts, drought) and indirectly (greater resource pressure, land conversion), increasing degradation risk. Although this study focused on habitat quality changes driven by LULC, the role of climate change is also important. Reduced rainfall and frequent droughts have accelerated degradation in semi-arid areas like Karaj, indirectly promoting urban growth and agricultural expansion. Future research should integrate climate variables to better assess their combined effect with land use on habitat quality.

Limitations and future directions:

This study assessed LULC change and habitat degradation trends in Karaj but is limited by Landsat imagery's inability to capture fine-scale habitat changes, possibly causing inaccuracies in habitat quality assessment. Moreover, the study did not incorporate socio-economic factors and local stakeholder perspectives, which could influence habitat changes and conservation outcomes. The temporal resolution of available data may also limit the detection of short-term fluctuations and sudden disturbances affecting habitat quality. The InVEST model simplifies complex ecological processes, which may oversimplify habitat quality assessment, especially in dynamic urban areas. Threat selection and weighting can also introduce subjectivity and bias. Future research should examine cumulative threat effects, develop targeted conservation strategies, and explore community engagement and traditional knowledge to improve habitat resilience. Future studies should quantify the impacts of different threat factors on habitat quality using methods like geographically weighted regression or variance decomposition to better understand their interactions and effects.

Implications:

The results showed habitat quality decline in Karaj County due to LULC changes, mainly from urban expansion and infrastructure development. The study showed the need to integrate habitat conservation into urban planning. Policymakers and land managers must implement sustainable land-use and restoration measures to protect ecosystem health and resilience amid increasing landscape degradation. Habitat degradation in Karaj County's semi-arid, mountainous region is driven by rapid urban growth and land use changes. Fragile vegetation, drought, and complex mountain-valley topography make conservation difficult. Protecting key mountain-valley corridors is vital for connectivity and ecosystem resilience. Effective preservation requires spatial planning, growth limits, corridor prioritization, and nature-based solutions. To ensure practical policy application, it is important to balance urban growth restrictions with local socio-economic needs. Sustainable planning should allow regulated development in controlled zones, integrating green infrastructure and ecological corridors to reduce

habitat fragmentation. Collaboration among stakeholders, planners, and authorities is key to aligning conservation with development goals, promoting adaptive land-use policies that support both ecological health and community needs. This balance will improve long-term habitat sustainability amid urbanization pressures.

6 CONCLUSIONS

This study assessed habitat quality and degradation in Karaj County (2013–2023) using LULC maps and the InVEST model. Land use changes, especially urban and agricultural expansion, caused habitat decline, driven mainly by urban growth, agriculture, and roads. LULC maps were classified with over 90% accuracy (Kappa coefficient). Combining the CA-Markov and InVEST models effectively predicted land use changes and their impact on habitat quality. Based on the habitat quality model in the respective software, maps of degradation and habitat quality for four periods were generated. The results indicated a decrease in habitat quality from 2013 to 2032, with the greatest decline observed in human-built LULCs, while natural land cover areas, due to their mountainous terrain and limited human access, experienced less habitat quality degradation. Meanwhile, natural habitats in areas suitable for human land use development underwent transformation and LULC conversion.

From 2013 to 2023, urban areas grew significantly while agricultural and natural lands declined, a trend expected to continue until 2032 with more urban and industrial expansion. Urban growth, driven by population increase, construction, and rangeland and forest degradation, has intensified habitat threats. The area's favorable climate, amenities, and proximity to Tehran have attracted migration and development, while weak regulations have accelerated habitat loss. The InVEST model quantifies threat factors by assigning each (e.g., urban development, agriculture, roads) a numeric weight and impact distance. These, combined with habitat sensitivity, allow calculation and comparison of each threat's impact on habitat quality. The model also implicitly considers spatial interactions by aggregating combined effects based on proximity and intensity. While this study lacks direct statistical analysis of interactions, the model's parameters effectively capture multi-factor interactions. Habitat degradation in Karaj County from 2013 to 2032, driven by urban growth and agriculture, reduces habitat quality and fragments ecosystems. This threatens biodiversity and ecosystem services. Without action, degradation will worsen, emphasizing the need for conservation and sustainable planning. Drought and climate change have caused water loss, vegetation decline, and soil erosion, worsening habitat quality in Karaj County. Conservation efforts like expanding green spaces, managing water, and restricting development near natural areas can help protect habitats. The study recommends limiting urban expansion in Karaj County to protect natural habitats and preserve green corridors. Nature-based planning can reduce human impact, while ongoing monitoring of land use and habitats is essential. Educating local communities and officials on conservation is also key to success. Urbanization has led to „severe degradation“ in some areas, indicating the importance of future urban planning to preserve sensitive regions and prevent land use change and habitat destruction.

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