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Spatial Landscape and Ecosystem Services Assessment of a Dryland Reservoir–Watershed System

Bahman Veisi Nabikandi[1], Zhale Amini [2], Mohammad Nikzad[3], Mohammad Hossein Sayadi[4*]

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ABSTRACT

Dryland reservoir–watershed systems face multiple environmental pressures, including water scarcity, anthropogenic land conversion, and increasing demands for sustainable ecosystem management. Nevertheless, ecological assessments of these systems frequently remain disconnected from their surrounding landscape context, limiting their relevance for integrated watershed management. To address this gap, this study employs a spatially explicit ecosystem-service assessment framework to quantify carbon storage and habitat quality across the Shahid Shahcheraghi reservoir–watershed system in northeastern Iran. A seven-class land use/land cover (LULC) map for 2025 was generated and used as the primary input for the InVEST Carbon and Habitat Quality models. Total carbon storage was estimated at approximately 39.37 million Mg C, with soil organic carbon constituting the dominant pool (74.3%), followed by belowground biomass (17.1%) and aboveground biomass (8.4%). Spatially, carbon storage was generally higher in areas with greater vegetation cover. Habitat quality, by contrast, revealed a markedly asymmetric distribution: the mean habitat quality index was 0.27, with 70.7% of the study area classified as having very poor habitat quality, whereas 22.9% fell within the good to excellent categories. High-quality habitats were predominantly concentrated in mountainous areas characterized by extensive grasslands and tree/shrub cover, while low-quality areas were concentrated in developed and highly accessible zones subject to greater anthropogenic disturbance. These findings reveal pronounced spatial heterogeneity in ecological condition and demonstrate that integrating readily available geospatial data with the InVEST modelling framework can provide a replicable and cost-effective approach for assessing ecosystem condition in data-limited dryland environments.

KEYWORDS:
Carbon Storage, Dryland Reservoirs, Ecosystem Services, Environmental Monitoring, Habitat Quality

[1] *Landscape Architecture Department, Faculty of Agriculture, University of Tabriz, Tabriz, Iran.*
[2] *Wetland Planning and Management Group, Deputy of Marine and Wetlands, Department of Environment, Tehran, Iran.*
[3] *Department of Habitat Protection and Management and Protected Areas Affairs, Semnan Provincial Department of Environment, Semnan, Iran.*
[4] *Iranian National Institute for Oceanography and Atmospheric Science, Tehran, Iran.*
[*] *Corresponding Author: Email: Mh_sayadi@inio.ac.ir/ORCID: 0009-0003-3972-6933*

1. Introduction

Dryland reservoir–watershed systems are important coupled socio-ecological landscapes that support a range of regulating, provisioning, supporting, and cultural ecosystem services (Rahdari et al., 2026). Reservoirs provide essential functions related to water storage, supply, flood regulation, and agricultural production, while the surrounding watershed contributes to water regulation, soil retention, carbon storage, habitat provision, and other ecosystem functions (Gooden and Pritzlaff, 2021). The condition and functioning of these systems are closely linked to the spatial configuration of land use/land cover (LULC), vegetation condition, hydrological processes, and interactions between terrestrial and aquatic components (Hu et al., 2018). These relationships are particularly important in water-limited regions, where reservoirs and their contributing watersheds can provide critical ecological and socioeconomic functions within otherwise dry landscapes. However, increasing pressures from land-use conversion, agricultural expansion, infrastructure development, water scarcity, and climate variability can alter landscape structure and ecosystem processes, potentially reducing the capacity of reservoir–watershed systems to maintain ecological functions and ecosystem services (Jahangeer et al., 2026; Kaden et al., 2026).

These pressures are particularly important in dryland environments, where low and highly variable precipitation coincides with high evaporative demand and chronic water scarcity. Dryland ecosystems are sensitive to changes in climate and land management, and their ecological processes can respond rapidly to changes in water availability, vegetation cover, and human land use (Wang et al., 2022). LULC change can reshape the spatial configuration of ecosystems while altering hydrological pathways, carbon dynamics, soil properties, and habitat structure (Veisi Nabikandi et al., 2025a; Shoja et al., 2025). Agricultural expansion, urban development, infrastructure, and vegetation degradation can therefore generate effects that extend beyond individual land-cover classes and influence broader landscape functioning (Shoja et al., 2026). Climate change may further intensify these effects through increasing temperatures, shifts in precipitation regimes, and higher evaporative losses (Abel et al., 2023). Together, these interacting pressures make assessing ecological condition in dryland landscapes particularly challenging.

Within this context, LULC provides an important link between environmental pressures and ecosystem condition. The composition and spatial arrangement of vegetation, agricultural land, built-up areas, barren surfaces, and water bodies influence the distribution of ecological resources and the capacity of landscapes to store carbon and support suitable habitats (Veisi Nabikandi and Shahbazi, 2024). LULC change can generate multiple ecological responses simultaneously rather than affecting individual ecosystem functions in isolation. For instance, the conversion or degradation of vegetated land can reduce carbon stocks while increasing habitat fragmentation and exposure to anthropogenic disturbance (Veisi Nabikandi et al., 2025b). Conversely, areas with greater vegetation cover and lower human pressure may retain higher carbon stocks and provide more suitable habitat conditions. The relationship between LULC structure, carbon storage, and habitat quality is therefore relevant to landscape-scale assessments of ecosystem services and ecological condition (Ren et al., 2023).

Carbon storage is particularly relevant in dryland landscapes because soil and vegetation carbon represent important components of ecosystem functioning and can be sensitive to land degradation and changes in vegetation cover. Although drylands generally support lower aboveground biomass than humid ecosystems, their extensive spatial coverage and substantial belowground carbon pools make them important components of the global carbon cycle. Land-use change, vegetation degradation, and inappropriate land management can alter carbon stocks and contribute to broader processes of ecosystem degradation (Shang et al., 2026). Dryland reservoir–watershed systems may be especially important carbon reservoirs because their soils, sediments, and vegetation can contain substantial carbon pools.

However, the persistence of these stocks depends on hydrological and ecological conditions, and wetland drying or degradation may substantially modify carbon dynamics (Zhang et al., 2023). Habitat quality represents a complementary dimension of ecological condition. Whereas carbon storage reflects an important regulating function associated with ecosystem structure, habitat quality describes the capacity of land-cover types to provide suitable ecological conditions under the influence of surrounding anthropogenic pressures (Bai et al., 2019). Habitat quality is inherently spatial, depending not only on the suitability of individual land-cover classes but also on their exposure to disturbance sources such as built-up areas, cropland, roads, and railways (Zhuo et al., 2022). Assessing carbon storage and habitat quality together can therefore provide complementary information on the ecological condition of heterogeneous landscapes and reveal spatial patterns that may not be captured by a single indicator.

Despite growing research on ecosystem services and LULC change, important gaps remain in the assessment of inland wetland–watershed systems in dry and semi-arid environments, particularly where water bodies are strongly influenced by human regulation. Many existing studies have focused either on individual ecosystem services or on broad-scale assessments of LULC dynamics (Wernberg et al., 2025; Bhushal and Lal, 2026), while fewer have examined carbon storage and habitat quality together within human-regulated watershed systems and their contributing watersheds. Moreover, dryland reservoir–watershed systems assessments are frequently conducted in relative isolation from the surrounding landscape, despite the fact that hydrological, ecological, and anthropogenic processes operate across connected spatial scales (Rawat et al., 2025). This limitation is particularly relevant to artificial reservoirs in drylands, where the ecological condition of the water body is closely linked to upstream land cover, downstream agricultural dependence, surrounding habitat structure, and regional climatic stress. A watershed-scale assessment that integrates these dimensions can therefore provide a more comprehensive understanding of ecological condition in human-regulated dryland systems (Gacu et al., 2025). The Shahid Shahcheraghi Dam reservoir in northeastern Iran represents such a coupled human–environment system. The reservoir is located within a dry to semi-arid watershed characterized by pronounced topographic gradients, extensive barren and grassland areas, localized agricultural and built-up development, and increasing pressure on water resources. Its ecological condition is influenced by climatic variability, high evaporative demand, water abstraction, agricultural dependence, hydrological regulation, and landscape transformation. Despite its importance for water supply, irrigation, flood regulation, and local ecological and recreational functions, the spatial distribution of ecological condition across the reservoir–watershed system has not been comprehensively quantified. In particular, the spatial relationship between the existing LULC structure, carbon storage, and habitat quality remains insufficiently understood.

To address this gap, this study develops an integrated spatial assessment of the Shahid Shahcheraghi reservoir and its contributing watershed using readily available spatial data and the InVEST modelling framework. Specifically, the study aims to: (i) quantify the spatial distribution of carbon stocks across major LULC classes using the InVEST Carbon Storage model; and (ii) evaluate the spatial pattern of habitat quality and degradation in relation to major anthropogenic threats using the InVEST Habitat Quality model. By integrating these complementary dimensions within a common spatial framework, the study provides a landscape-scale assessment of current ecological conditions and demonstrates the potential of readily available spatial data for ecosystem assessment in data-limited dryland environments.

2. Data and Methodology

Research Framework and Workflow

This study employed a quantitative and spatially explicit framework to assess carbon storage as an ecosystem service and habitat quality as an indicator of ecological condition within the Shahid Shahcheraghi reservoir–watershed system. The research workflow comprised five main stages: (1) data acquisition and preparation, (2) development of a harmonized GIS-based spatial database, (3) ecosystem-service and ecological-condition assessment using the InVEST–CS and HQ models, (4) spatial analysis and synthesis of model outputs, and (5) generation of the final spatial and analytical outputs (Figure 1).

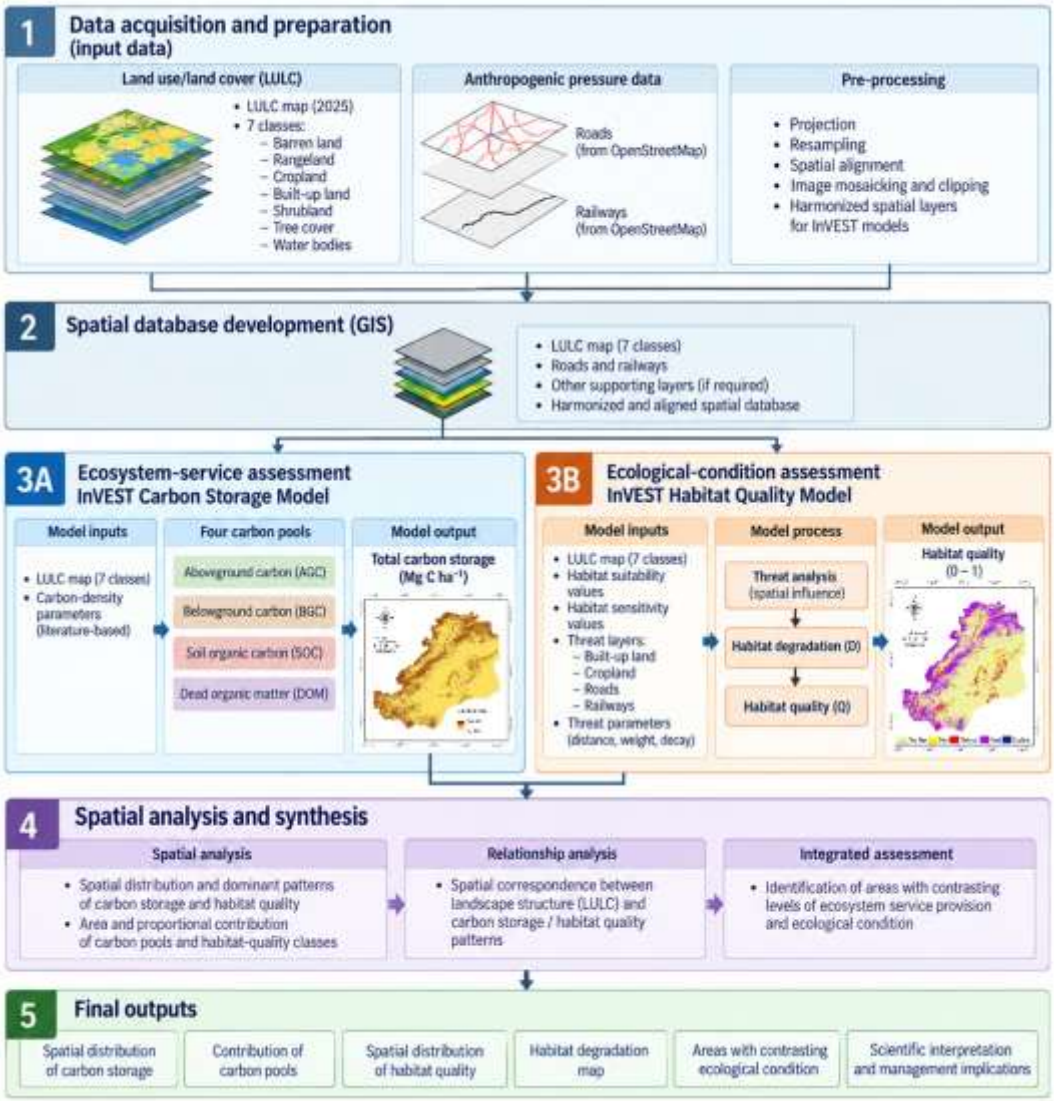


Figure 1. Research framework and workflow

In the first stage, the required spatial datasets were collected and pre-processed. The 2025 LULC map included seven classes: barren land, grassland, cropland, built-up land, shrubland, tree cover, and water bodies. Roads and railways, representing major anthropogenic pressures, were obtained from OpenStreetMap. All datasets were projected, resampled, spatially aligned, mosaicked where required, and clipped to the study area. In the second stage, the processed datasets were integrated into a harmonized spatial database for InVEST modelling. In the third stage, the InVEST-CS model was used to estimate total carbon storage across four carbon pools, including aboveground carbon (AGC), belowground carbon (BGC), soil organic carbon (SOC), and dead organic carbon (DOC). In parallel, the InVEST-HQ model was applied to estimate modeled habitat degradation and habitat quality based on LULC, habitat suitability and sensitivity, and major anthropogenic threats, including built-up land, cropland, roads, and railways. In the fourth stage, the model outputs were analyzed separately to characterize the spatial distribution of carbon storage and modeled habitat quality, quantify the contribution of individual carbon pools and habitat-quality classes, and interpret their spatial patterns in relation to the underlying LULC configuration. Finally, the results from the two complementary assessments were synthesized to identify areas with different levels of modeled ecosystem condition and to derive management implications for the dryland reservoir–watershed system.

Study area

The Shahid Shahcheraghi Dam reservoir is located in Damghan County, Semnan Province, northeastern Iran (Figure 2). It was formed by impounding the Cheshmeh-Ali River and represents a human-regulated

freshwater system within the drylands of the Central Iranian Plateau. The reservoir lies at approximately 252,424 m E and 4,012,825 m N (UTM Zone 40N) and covers a surface area of about 280 ha, with an estimated storage capacity of 40–41 million m³. The climate is arid to semi-arid, with a mean annual precipitation of about 100 mm at the Damghan synoptic station (2003–2025), concentrated in late winter and spring and highly variable between years (41.7–162.2 mm). The study year (2025) was among the driest on record (57.5 mm; SPI = −1.33) (IRIMO, 2025). Hydrologically and ecologically, the reservoir is connected to upstream mountain catchments and downstream agricultural plains, making the watershed–reservoir system a suitable spatial unit for assessing landscape-level changes in carbon storage and habitat condition.

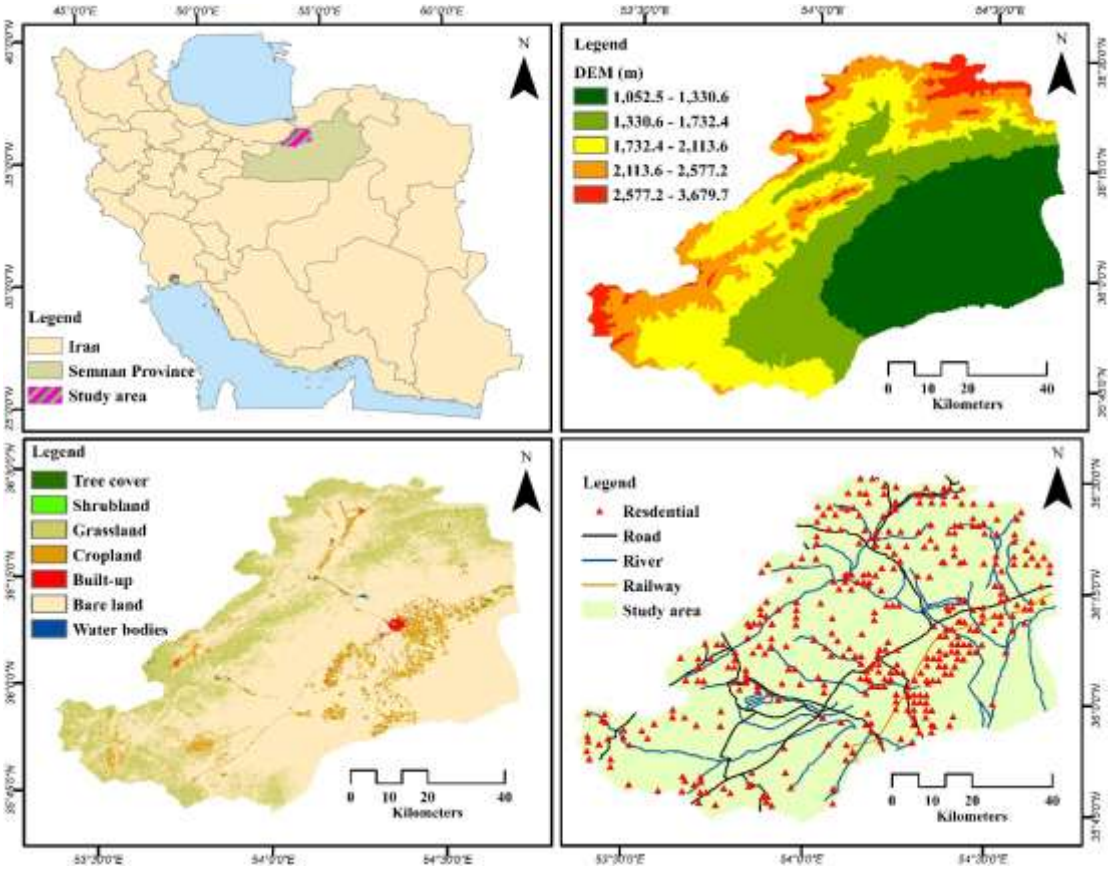


Figure 2. Location of the study area in Iran, digital elevation model (DEM), land use/land cover (LULC) classes, and geographic features of the study area

LULC in the study area reflects the combined influence of topography, water availability, climatic constraints, and human activities. The study area covers approximately 5,917 km², and its LULC map distinguishes seven classes: barren land, grassland, cropland, built-up land, shrubland, tree cover, and water bodies (Fig. 1). Barren land dominates the landscape (4,151.43 km²; 70.2%), followed by grassland (1,397.24 km²; 23.6%) and cropland (303.51 km²; 5.1%). Built-up areas cover approximately 36.90 km² (0.6%), while shrubland (17.38 km²), tree cover (8.19 km²), and water bodies (1.92 km²) account for relatively small proportions. These classes follow a pronounced elevation gradient: grasslands and tree- and shrub-dominated areas are concentrated in mountainous sectors, whereas cropland and built-up land are mainly found in lower-elevation plains and along accessible corridors. The reservoir and its riparian zone form a small but functionally important aquatic–terrestrial interface within this predominantly dry landscape. The combination of a water-limited climate, strong topographic gradients, heterogeneous LULC, agricultural dependence, and increasing anthropogenic and climatic pressures makes the Shahid Shahcheraghi watershed–reservoir system particularly suitable for examining landscape-scale ecological condition. In this study, the LULC configuration provides the spatial basis for estimating carbon storage and habitat quality using the InVEST framework, allowing

ecological condition to be evaluated in relation to the distribution of vegetation, agricultural land, built-up areas, and other landscape components.

Land use/land cover mapping

Because no suitable LULC map with sufficient thematic detail was available for the study area, a new LULC map was prepared as a primary input for the InVEST-Carbon and InVEST-Habitat Quality models. Landsat satellite imagery acquired on July in summer 2025, with a spatial resolution of 30 m, was used to characterize the land-cover conditions of the study area. The imagery was processed and classified using the Google Earth Engine (GEE) platform. A supervised classification approach based on the Random Forest (RF) algorithm was applied to distinguish seven LULC classes: tree cover, shrubland, grassland, cropland, built-up land, bare land, and water bodies. The accuracy of the resulting LULC map was assessed using reference samples derived from high-resolution imagery available through Google Earth. The classification accuracy was evaluated using the Kappa coefficient, which provides a quantitative measure of agreement between the classified LULC map and the reference data (Bogale et al., 2025). The resulting LULC map was subsequently used as the primary spatial input for the InVEST-Carbon and InVEST-Habitat Quality models.

InVEST Carbon Storage Model

The InVEST-CS model was used to estimate the spatial distribution of carbon stocks across the study area. The model was selected because it provides a spatially explicit assessment of ecosystem carbon storage while requiring relatively limited input data compared with process-based carbon models (Rachid et al., 2024). The analysis was conducted within a GIS-based framework to integrate LULC information with carbon-density estimates for the major carbon pools associated with each LULC class. For the 2025 assessment, total carbon storage was estimated across four carbon pools: aboveground carbon (AGC), belowground carbon (BGC), soil organic carbon (SOC), and dead organic carbon (DOC). The total carbon stock associated with each LULC class was calculated based on the carbon density assigned to each pool and the corresponding area of that LULC class. The model calculations were based on Eqs. 1 and 2 (Jiang et al., 2017; Zhao et al., 2018):

$$C = AGC + BGC + SOC + DOC \quad (1)$$

$$C_{total} = \sum_{k=1}^{n} A_k \times C_{k,} \, (k = 1, 2, \ldots n) \quad (2)$$

where Ck represents the total carbon density per unit area for the kth LULC class, Ak denotes the area occupied by that LULC class, and Ctotal represents the total carbon stock associated with the corresponding LULC class.

The carbon-density values required by the model can be derived from field measurements, habitat-specific meta-analyses, or published studies conducted in environmentally comparable regions. Because spatially explicit measurements of carbon stocks were not available for the study area, carbon-density values were compiled from published studies conducted in Iran and other regions with comparable environmental conditions. The selection of reference studies was primarily based on the similarity of LULC or vegetation classes to those represented in the study area and, where available, on similarities in climatic conditions, ecosystem type, and geographic setting. Studies providing carbon-density estimates for comparable land-cover or vegetation types were therefore prioritized. This approach is consistent with previous InVEST-based carbon assessments conducted in Iran and other dryland or semi-arid environments (Rachid et al., 2024; Veisi Nabikandi et al., 2024).

Importantly, no previous study was identified that specifically quantified the carbon-storage capacity of the Shahid Shahcheraghi reservoir–watershed system for the LULC classes considered in this study. Therefore, the adopted carbon-density parameters should be regarded as literature-based estimates derived from ecologically comparable settings rather than site-specific field measurements. This limitation introduces uncertainty into the estimated carbon stocks, particularly because carbon density can vary within the same LULC class according to local environmental conditions. The sources of the carbon-density parameters used for each LULC class and carbon pool are explicitly reported in Table 1. All carbon-density values were expressed as megagrams of carbon per hectare (Mg C ha^{-1}) and used as the corresponding model inputs.

Table 1. Carbon density of each LULC type across the study area (in Mg ha-1)

LULC classes	AGC	BGC	SOC	DOC	Source
Tree cover	63.68	53.25	122.91	1.96	Zhang et al., 2024
Shrubland	8.96	10.7	33.3	0.07	Bai et al., 2025
Grassland	19.92	39.74	90.57	0.47	Ma et al., 2026
Cropland	9.59	37.08	80.60	0.47	Ma et al., 2026
Built-up	0.17	0	61.21	0	Ma et al., 2026
Bare land	0.47	0	33.30	0	Ma et al., 2026
Water bodies	1.42	0	0	0	Bai et al., 2025

InVEST Habitat Quality Model

The InVEST-HQ model was applied to quantify the spatial variation in habitat degradation and habitat quality across the study area. The model was selected because of its relatively limited data requirements and its ability to represent the spatial effects of anthropogenic pressures on habitat conditions (Wang et al., 2025). The model estimates habitat degradation and habitat quality by integrating LULC patterns, the spatial distribution and intensity of threat sources, the sensitivity of different habitat types to individual threats, and the relative suitability of each LULC class as habitat (Lei et al., 2022). In the model framework, habitat degradation increases with greater exposure to anthropogenic threats and with decreasing distance from threat sources. For each LULC class, the cumulative degradation score is determined by the combined influence of the identified threat sources, their relative weights, the sensitivity of habitat types to each threat, and the spatial decay of threat effects with distance. The principal equations used by the model are presented in Eqs. 3–5.

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

$$Linear\ decay:\ i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\ max}} \right) \tag{4}$$

$$Exponential\ decay:\ i_{rxy} = exp\left[- \left(\frac{2.99}{d_{r\ max}} \right) \times d_{xy} \right] \tag{5}$$

In Eq. 3, D_{xj} denotes the cumulative degradation of pixel x belonging to LULC class j; R represents the total number of threat sources; r denotes an individual threat; Y_r is the set of pixels associated with threat r; w_r is the weight assigned to threat r, and S_{jr} represents the sensitivity of habitat type j to threat r. The parameter β_x represents the level of habitat protection or resistance to disturbance at pixel x. The spatial influence of each threat is determined by i_{rxy}, which describes the effect of threat r at threat-source pixel y on focal pixel x. This effect is represented using either linear or exponential distance-decay functions, depending on the specified characteristics of the threat (Eqs. 4 and 5). The term d_{xy} represents the Euclidean distance between the focal pixel x and threat-source pixel y, while $d_{r\ max}$ denotes the maximum effective distance of threat r. Habitat quality was subsequently derived from the estimated level of habitat degradation using the following relationship (Tang et al., 2023):

$$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z + k^z} \right) \right] \tag{6}$$

where Q_{xj} represents habitat quality at pixel x for LULC class j, H_j denotes the habitat suitability score of LULC class j, and k is the half-saturation constant. The model uses a default value of 0.5 for k, while z, the normalization parameter controlling the shape of the habitat-quality response, was set to the default value of 2.5. Based on the characteristics of the study area and evidence from previous studies, four anthropogenic threat sources were considered: built-up land, cropland, roads, and railways. These threats were selected because they represent the main spatially explicit sources of anthropogenic disturbance identifiable from the available LULC and geospatial datasets. Built-up land and cropland represent land-use pressures associated with urban development and agricultural activities, respectively,

whereas roads and railways represent transportation infrastructure that can affect habitat conditions through direct land disturbance and increased accessibility. Other potential pressures, such as grazing intensity and localized resource extraction, were not included because spatially explicit and sufficiently reliable datasets were not available for the study area.

Road and railway networks were obtained from OpenStreetMap and converted into spatial threat layers compatible with the InVEST model. The maximum effective distance, relative weight, and distance-decay function assigned to each threat were determined based on InVEST parameterization guidance and previous studies conducted in comparable environmental settings. The selected parameters were further evaluated in relation to the spatial characteristics of the study area and the relative intensity and extent of each threat. The resulting parameterization is presented in Table 2. Because these parameters were derived primarily from published studies and expert-based model parameterization rather than site-specific calibration, the resulting habitat-quality estimates may contain parameter-related uncertainty. This uncertainty is therefore acknowledged as a limitation of the present assessment.

Table 2. Threat sources and parameters used in the InVEST Habitat Quality model

Threat source	Maximum effective distance	Weight	Distance-decay function	Source
Built-up land	5 km	1	Exponential	Zhang et al., 2020
Cropland	4 km	0.5	Exponential	Zhang et al., 2020
Roads	2 km	0.5	Linear	Veisi Nabikandi et al., 2025b
Railways	5 km	0.6	Linear	Chu et al., 2018; Zhang et al., 2020

The habitat suitability and threat-sensitivity parameters assigned to each LULC class were based on previously published InVEST-HQ applications and the ecological characteristics of the corresponding land-cover types (Table 3). To improve transparency and reproducibility, the source of each parameter set is explicitly reported in Table 3. Habitat suitability represents the relative capacity of each LULC class to provide habitat, whereas threat-sensitivity values represent the expected relative response of each habitat type to the identified anthropogenic threats. Built-up areas were assigned a habitat suitability value of zero because they were considered non-habitat in the model. In contrast, tree cover, shrubland, grassland, cropland, barren land, and water bodies were assigned different suitability and sensitivity values according to their ecological characteristics and reported parameterizations in previous studies. These parameters were not calibrated using field-based habitat observations and should therefore be interpreted as literature-supported model inputs rather than site-specific empirical measurements.

Table 3. Habitat suitability and sensitivity of LULC classes to the identified threat sources

LULC classes	Habitat	Built-up	Cropland	Roads	Railways	Source
Tree cover	1.0	1.0	0.5	0.6	0.8	Veisi Nabikandi et al., 2025b
Shrubland	0.9	0.8	0.4	0.8	0.9	Wang and Cheng, 2022
Grassland	0.8	0.6	0.5	0.5	0.55	Yang, 2021
Cropland	0.5	0.9	0.3	0.6	0.7	Yang, 2021
Built-up	0.0	0.0	0.0	0.0	0.0	Dashtbozorgi et al., 2023
Bare land	0.1	0.1	0.1	0.2	0.2	Wang and Cheng, 2022
Water bodies	0.9	0.75	0.65	0.6	0.7	Yang, 2021

The resulting habitat-quality index is dimensionless and ranges from 0 to 1, with higher values representing more favorable habitat conditions and lower values indicating greater degradation. For spatial interpretation, the continuous habitat-quality surface was reclassified in ArcGIS 10.8 into five classes: very poor (0–0.15), poor (0.15–0.30), moderate (0.30–0.60), good (0.60–0.80), and excellent (0.80–1.00), following the classification adopted by Veisi Nabikandi et al. (2025b).

3. Results

3.1. Accuracy of prepared LULC map

To evaluate the accuracy of supervised classification, the kappa statistic was used in this research. Veisi Nabikandi et al. (2025c) reported that kappa is a suitable indicator for evaluating the performance of multi-class classification. After classifying LULC changes, a total of 212 points were randomly selected

based on their available coordinates, covering the six LULC classes examined across the study area. Because the areal extent varied among the classes, the number of selected points differed for each class. The value of each random point was then verified using Google Earth for accuracy assessment. The classification accuracy for 2025, based on the kappa coefficient and overall accuracy, was 0.84 and 89.0%, respectively.

3.2. Carbon storage

Figure 3 shows the spatial distribution of total carbon storage estimated using the InVEST-CS model across the study area. Carbon storage exhibited a clear spatial pattern, with the lowest values concentrated mainly in the central and southern parts of the study area. These areas are characterized predominantly by built-up and barren land and are subject to relatively greater anthropogenic pressure. In contrast, higher carbon stocks were spatially associated with areas supporting greater vegetation cover. Overall, the model estimated a total carbon stock of approximately 39.37 million Mg C across the study area.

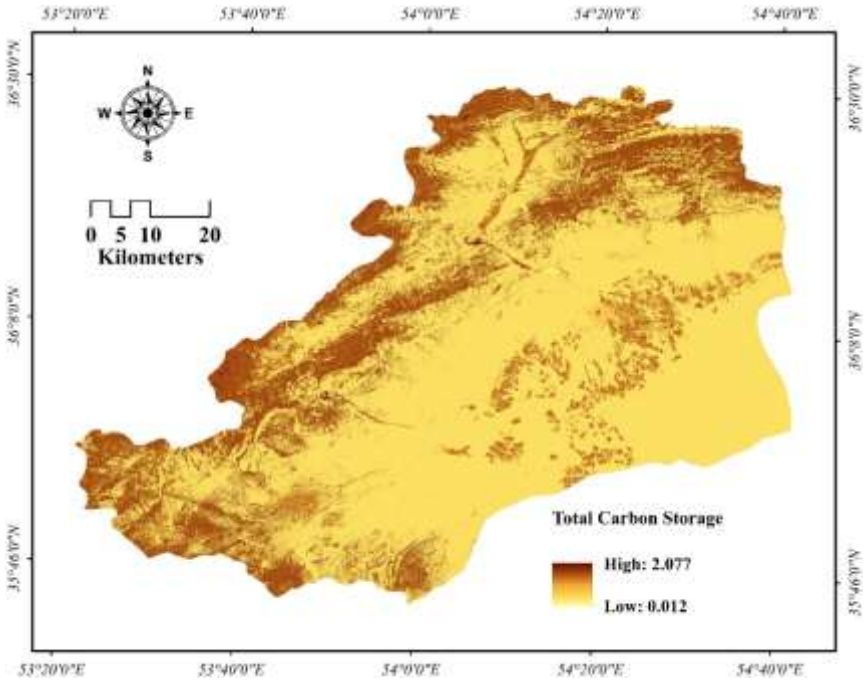


Figure 3. Spatial distribution of total carbon storage estimated using the InVEST-Carbon Storage model

To further examine the contribution of individual carbon pools, total carbon storage was partitioned into AGC, BGC, SOC, and DOC. The results revealed a pronounced difference in the contribution of the four pools to total carbon storage (Figure 4). SOC accounted for by far the largest proportion of the total carbon stock, with an estimated 29,244,735 Mg C. BGC represented the second-largest carbon pool, storing approximately 6,741,350 Mg C, followed by AGC with 3,306,074 Mg C. In contrast, DOC accounted for only 81,644 Mg C, representing the smallest carbon pool in the study area.

The relative contribution of the four carbon pools indicates that approximately 74.3% of the total carbon stock was stored in SOC, while BGC and AGC accounted for approximately 17.1% and 8.4%, respectively. DOC contributed less than 0.3% of the total carbon stock. Thus, the carbon-storage profile of the study area was strongly dominated by soil carbon, with substantially smaller contributions from above- and belowground vegetation biomass and a negligible contribution from dead organic matter.

3.3. Habitat quality and degradation

The InVEST-HQ model was subsequently used to assess the spatial distribution of habitat quality and habitat degradation across the study area for 2025. The resulting habitat quality map (Figure 5) showed considerable spatial variation across the study area. The mean habitat quality index was 0.27, indicating generally low habitat quality across the study area.

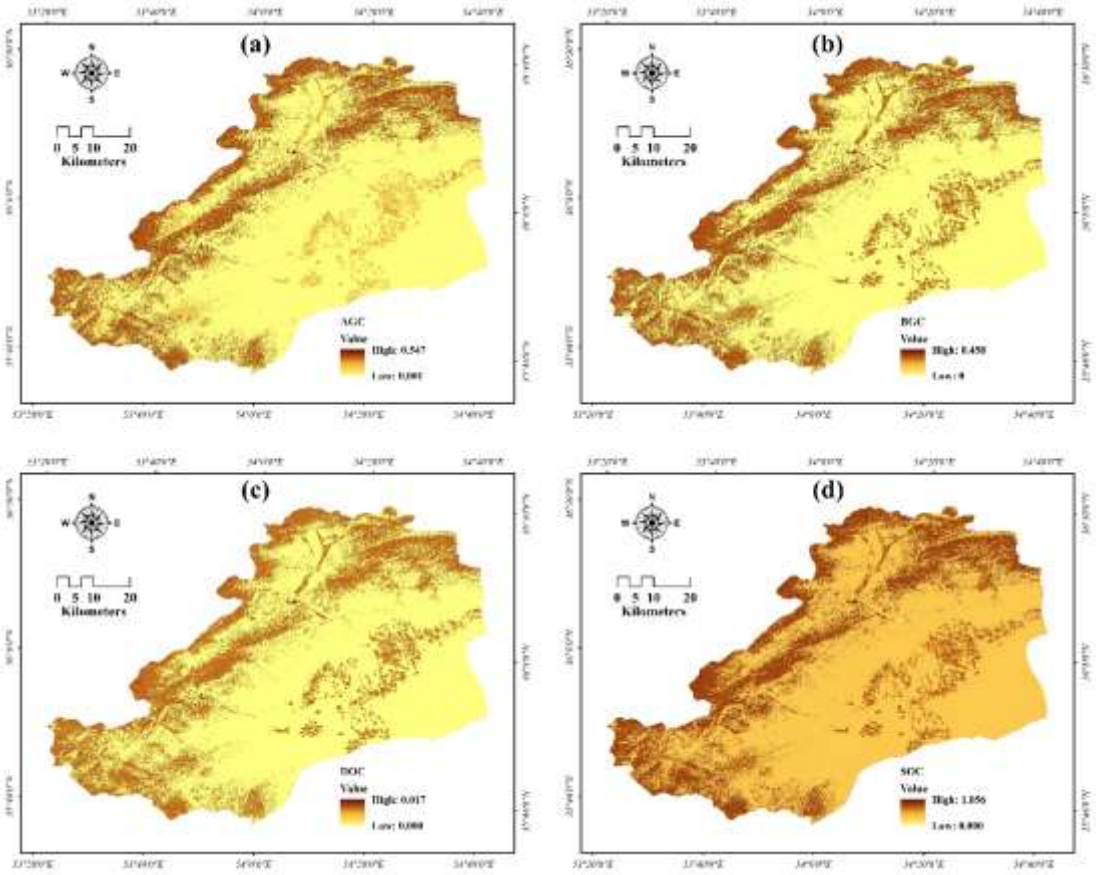


Figure 4. Spatial distribution of carbon storage in the four carbon pools

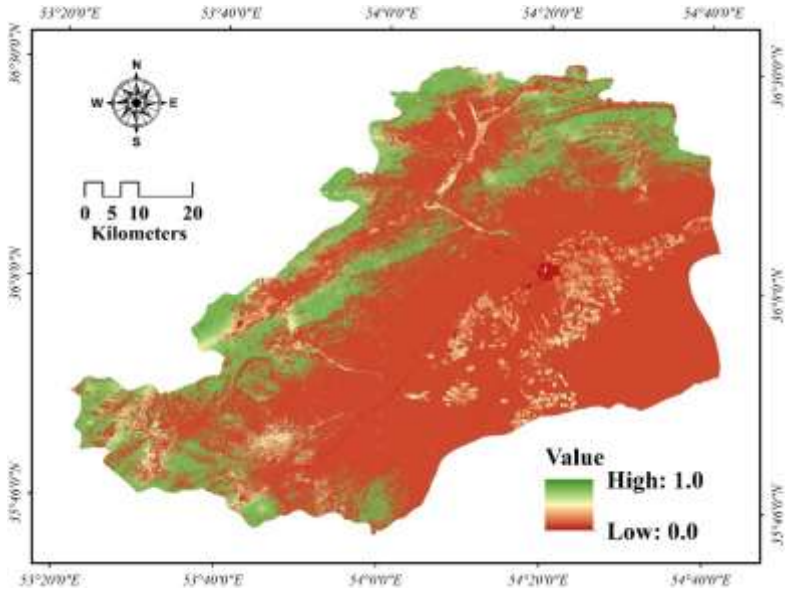


Figure 5. Spatial distribution of habitat quality across the study area

Higher habitat quality values were concentrated primarily in the northern and western parts of the study area, particularly across mountainous areas characterized by greater coverage of tree and grassland habitats. In contrast, lower habitat-quality values were predominantly observed in the southeastern part of the study area, where built-up areas and transportation infrastructure are more extensively distributed.

The spatial pattern therefore indicates a clear contrast between relatively intact ecological areas and landscapes exposed to greater anthropogenic pressure. The habitat quality surface was further classified into five categories using ArcGIS 10.8: very poor (0–0.15), poor (0.15–0.30), moderate (0.30–0.60), good (0.60–0.80), and excellent (0.80–1.00). The resulting spatial distribution of these classes is presented in Figure 6.

The area statistics showed that the very-poor habitat-quality class occupied the largest proportion of the study area, covering 4,184.54 km², followed by the good class (1,334.63 km²), moderate class (289.04 km²), poor class (90.52 km²), and excellent class (17.76 km²). Overall, approximately 70.7% of the study area was classified by the model as having very poor habitat quality, while the good, moderate, poor, and excellent classes accounted for approximately 22.6%, 4.9%, 1.5%, and 0.3% of the total area, respectively. However, this distribution should be interpreted in relation to the underlying LULC composition and the habitat-suitability parameters used in the InVEST-HQ model. In particular, barren land accounts for approximately 70.2% of the study area and was assigned a relatively low habitat-suitability value (0.1). Therefore, the large extent of the very-poor habitat-quality class partly reflects the dominance of low-suitability barren land in the landscape and should not be interpreted directly as evidence of widespread anthropogenic habitat degradation or biodiversity loss. Rather, the results represent a model-based assessment of relative habitat condition under the specified LULC, threat, and suitability parameters. Figure 7 presents the spatial distribution of habitat degradation estimated by the InVEST-HQ model, which showed spatial heterogeneity, with higher degradation values occurring predominantly around the boundaries between human-dominated land uses and relatively natural habitats.

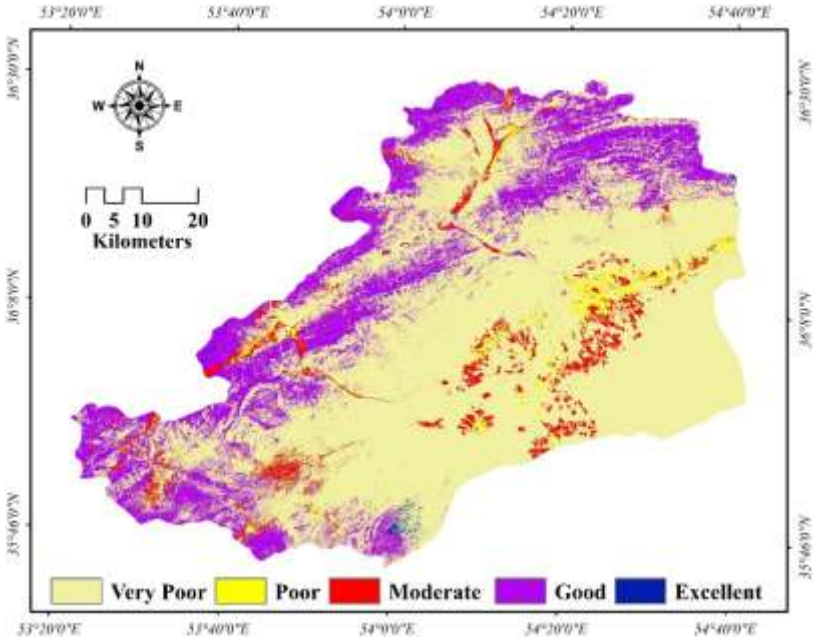


Figure 6. Spatial distribution of habitat-quality classes across the study area

The most pronounced degradation was concentrated along interfaces between agricultural land and ecological habitats, particularly shrubland and grassland. These transition zones showed greater exposure to anthropogenic pressures than areas located farther from human-dominated land uses. The spatial pattern of degradation was therefore particularly evident at the boundaries between agricultural areas and natural or semi-natural habitats, identifying these interfaces as important spatial concentrations of habitat pressure within the reservoir–watershed systems.

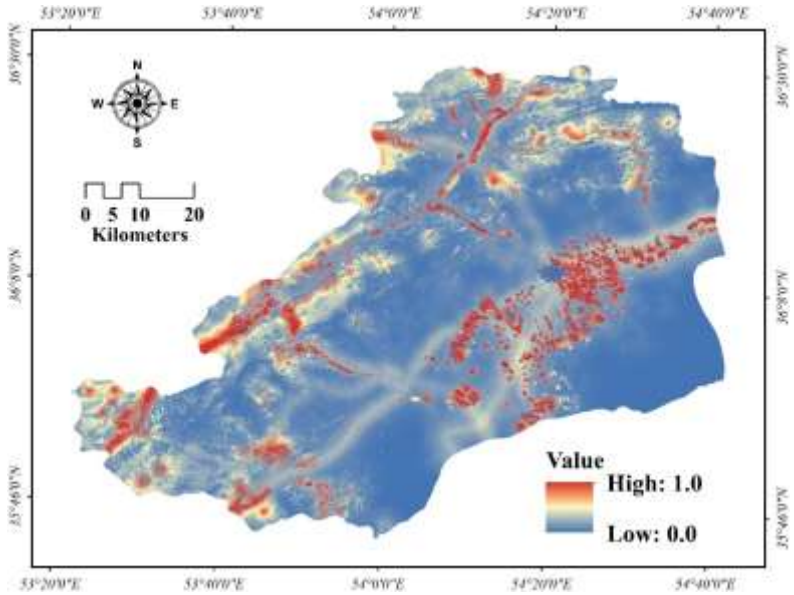


Figure 7. Spatial distribution of habitat degradation in study area

4. Discussion

Carbon storage and its landscape drivers

The spatial pattern of carbon storage indicates that vegetation cover and land-cover condition are important controls on carbon retention within the Shahid Shahcheraghi reservoir–watershed system. The greater carbon-storage capacity of vegetated mountainous landscapes can be attributed to their higher biomass inputs and greater soil-carbon accumulation compared with barren and highly disturbed areas. This interpretation is consistent with previous InVEST-based studies showing that vegetation loss and conversion to human-dominated land uses generally reduce ecosystem carbon-storage capacity (Liu et al., 2015; Feitosa et al., 2023). In the context of this dryland system, maintaining existing grassland, shrubland, and tree cover is therefore important not only for preserving above- and belowground biomass but also for maintaining soil carbon. The dominance of soil organic carbon in the estimated carbon pool further highlights the importance of belowground carbon in dryland ecosystems. Similar patterns have been reported for arid and semi-arid landscapes in Iran and China, where SOC represented the largest component of total ecosystem carbon (Veisi Nabikandi et al., 2024; Ma et al., 2019; Li et al., 2021). This dominance suggests that carbon-management strategies in the study area should extend beyond vegetation restoration and include measures that reduce soil disturbance and carbon loss. Sustainable agricultural practices, erosion control, and the conservation of soil cover may therefore be particularly relevant for maintaining carbon stocks in the watershed (Wiesmeier et al., 2019). From a landscape-management perspective, the concentration of higher carbon-storage capacity in relatively natural mountainous areas suggests that these areas provide an important carbon-conservation function despite their relatively limited spatial extent. Conversely, the lower carbon-storage capacity associated with developed and highly disturbed areas illustrates the potential carbon consequences of continued land conversion (Lorenz et al., 2019; Fan et al., 2023). These patterns support a management strategy that prioritizes the conservation of existing natural and semi-natural land covers while reducing unnecessary conversion of vegetated areas. In dryland reservoir–watershed systems, such an approach may provide a practical means of maintaining carbon stocks while simultaneously supporting broader ecosystem functions.

Habitat quality and anthropogenic pressures

The spatial pattern of modeled habitat quality suggests that land-cover composition and exposure to anthropogenic threats are important controls on the spatial variation of habitat conditions within the study area. The predominance of barren land, together with the distribution of built-up areas, croplands, roads, and railways, contributes to the relatively low modeled HQ values across large parts of the

landscape. However, these results should be interpreted as a model-derived index rather than a direct measure of biodiversity, species richness, or empirically observed habitat condition. In particular, the extensive very-poor category is partly influenced by the low habitat-suitability value assigned to barren land and therefore should not be interpreted as evidence of equivalent levels of biodiversity loss or ecological degradation.

The relatively higher modeled HQ values in mountainous areas can be interpreted in relation to the greater presence of grassland, shrubland, and tree cover and their lower exposure to some anthropogenic pressures. Similar spatial patterns have been reported in Iranian landscapes, where agricultural expansion, urbanization, infrastructure development, and vegetation loss have been associated with lower modeled habitat quality and greater habitat fragmentation (Hasani et al., 2017; Dezhkam et al., 2014; Ansari et al., 2023). Roads and developed areas may further influence modeled habitat quality by increasing the spatial exposure and accessibility of relatively natural areas, consistent with previous InVEST-HQ applications (Meng et al., 2023; Chen et al., 2024).

From a management perspective, the concentration of modeled degradation near interfaces between agricultural land and natural or semi-natural habitats identifies these transition zones as potential priorities for targeted intervention. Maintaining vegetation buffers, improving agricultural management, and limiting unnecessary expansion of infrastructure could help reduce modeled exposure to anthropogenic threats. However, because the present assessment does not include field-based biodiversity observations or species-distribution data, these management implications should be considered spatial planning priorities rather than evidence of measured biodiversity responses. Future studies incorporating multi-year LULC and environmental data together with field-based biodiversity or species-distribution observations could provide stronger evidence of temporal ecological change and allow the modeled HQ patterns to be evaluated against empirical ecological indicators.

Implications for dryland reservoir–watershed management

The findings of this study have several implications for the integrated management of dryland reservoir–watershed systems. First, the pronounced spatial heterogeneity in carbon storage and habitat quality highlights the need for spatially targeted management. Areas with relatively high carbon storage and habitat quality, mainly located in the mountainous northern and western sectors, should be prioritized for conservation because they simultaneously support important ecosystem functions. In contrast, areas with low carbon storage and poor habitat quality, particularly in the central and southern parts of the watershed, may require restoration and rehabilitation to improve ecological condition and carbon-storage capacity. Second, the dominance of SOC in total carbon storage emphasizes the importance of soil conservation in the study area. Agricultural practices, overgrazing, and construction activities that increase soil disturbance should therefore be carefully managed to reduce carbon losses. Sustainable agricultural practices, erosion control, and maintenance of vegetation cover can help conserve soil carbon (Wiesmeier et al., 2019). In particular, protecting grasslands and shrublands is important because these land covers occupy substantial parts of the watershed and contribute to the dominant soil-carbon pool. Third, the concentration of habitat degradation around agricultural–natural habitat interfaces suggests that these transition zones should be considered priority areas for management. Establishing ecological buffers, promoting wildlife-friendly agricultural practices, and restoring degraded transitional habitats could reduce anthropogenic pressure and improve habitat connectivity. Combining GIS, remote sensing, and ecosystem-service modelling with scenario-based approaches can further support the identification of priority areas and evaluation of alternative land-use strategies (Veisi Nabikandi et al., 2025b). Finally, the integration of easy-to-acquire geospatial data with the InVEST framework provides a practical and relatively cost-effective approach for assessing ecosystem condition in data-limited dryland environments. This is particularly relevant in regions such as Iran, where obtaining consistent ecological data remains challenging (Veisi Nabikandi et al., 2025a, b). The framework can be adapted to other reservoir–watershed systems with similar environmental characteristics and can support spatial prioritization for conservation, restoration, and sustainable land-use planning (D'Auria et al., 2018). More broadly, linking ecosystem-service assessment with local land-use planning can help decision-makers balance ecological conservation with agricultural and development needs in increasingly water-limited dryland systems.

Limitations and future directions

While this study provides a spatial assessment of carbon storage and habitat quality in the Shahid Shahcheraghi reservoir–watershed system, several limitations should be acknowledged. First, the carbon-density parameters used in the InVEST-CS model were compiled from previous studies conducted in Iran and other environmentally comparable regions rather than from site-specific field measurements. Differences in soil properties, vegetation structure, and land-management practices may therefore introduce uncertainty into the estimated carbon stocks. Future research should prioritize field measurements across different LULC classes to validate and refine the estimates. The integration of remote sensing and soil spectral information may also provide a cost-effective approach for improving SOC mapping in data-limited regions (Velazquez et al., 2022). Second, the InVEST-HQ model depends on literature-supported and model-recommended parameters, including threat weights, sensitivity values, maximum effective distances, distance-decay functions, and habitat-suitability scores. These parameters may not fully represent local ecological responses, particularly where site-specific ecological observations are limited. In addition, the selection of built-up land, cropland, roads, and railways as threat sources was constrained by the availability of reliable spatially explicit datasets. Other potential pressures, such as grazing intensity and localized resource extraction, could not be incorporated consistently because sufficiently reliable spatial data were unavailable. Future studies should therefore incorporate field-based habitat assessments and species-distribution data, together with sensitivity and uncertainty analyses, to evaluate the robustness of HQ estimates and improve site-specific parameterization. Importantly, the HQ values reported in this study represent a model-derived index based on LULC composition, habitat suitability, and exposure to selected anthropogenic threats, rather than direct measurements of biodiversity, species richness, or observed habitat degradation. This distinction is particularly relevant in the present study because the extensive barren land cover and its relatively low habitat-suitability value contribute substantially to the spatial distribution of modeled HQ classes. Future research combining field-based biodiversity observations with the InVEST-HQ framework could provide stronger empirical evaluation of the modeled patterns. Third, the present assessment represents a single time period and therefore does not quantify temporal changes in LULC, climate variability, drought conditions, or climate-driven ecosystem responses. Moreover, 2025 was drier than average at the Damghan station (57.5 mm versus a 2003–2025 mean of 100.4 mm; SPI = −1.33), so vegetation-dependent classes such as grassland and cropland may partly reflect short-term moisture deficits rather than long-term conditions. Extending the framework to multi-temporal LULC and climate datasets would allow changes in carbon storage and modeled habitat quality to be examined over time. Scenario-based approaches, such as PLUS and CA–Markov models, could further be used to explore potential ecosystem-service changes under alternative development and conservation pathways (Ma et al., 2026; Cesur et al., 2026). Such temporal and scenario-based analyses would provide a stronger basis for distinguishing persistent spatial patterns from changes associated with land-use and climatic dynamics. Fourth, the study focused on carbon storage and habitat quality, although dryland reservoir–watershed systems provide a broader range of ecosystem services. Water yield, soil conservation, sediment retention, flood-risk mitigation, food production, and cultural services may also be important for sustainable management. Future research could integrate these services with climatic, topographic, and socioeconomic variables and quantify their trade-offs and synergies to identify multifunctional areas and improve spatial prioritization for conservation and restoration. Finally, the analysis focused on a single reservoir–watershed system in northeastern Iran, which may limit the direct transferability of the findings to other dryland environments. Nevertheless, the spatially explicit framework combines LULC, GIS, and InVEST with relatively accessible datasets, making it potentially useful for ecosystem assessment in data-limited regions. Applying the framework across multiple dryland reservoir–watershed systems with contrasting climatic, topographic, and land-use conditions would help evaluate its robustness and identify context-specific drivers of carbon storage and modeled habitat quality. Such comparative assessments could support the development of more transferable strategies for ecological conservation, restoration, and sustainable land-use management.

5. Conclusion

This study provides a spatially explicit assessment of carbon storage and habitat quality in the Shahid Shahcheraghi reservoir–watershed system, demonstrating the utility of the InVEST modeling framework for evaluating ecosystem services in data-limited dryland environments. The results reveal pronounced spatial heterogeneity in both carbon storage and habitat quality, with SOC dominating the total carbon stock and habitat quality being strongly skewed toward the very-poor category. The spatial patterns of carbon storage and habitat quality are closely linked to LULC distribution, with higher values concentrated in vegetated mountainous areas and lower values in human-dominated lowland areas. The identification of agricultural–natural habitat interfaces as hotspots of habitat degradation highlights the need for spatially targeted management interventions. The framework employed in this study can be adapted to other dryland reservoir–watershed systems, providing a replicable and cost-effective approach for assessing ecosystem condition and informing integrated watershed management. Future research should prioritize field-based measurements of carbon stocks, incorporate temporal dynamics and scenario analysis, evaluate multiple ecosystem services, and apply the framework to multiple reservoir–watershed systems to enhance its generalizability and policy relevance.

Authors' Contributions
All authors participated equally in formulating the core concept, developing the methodology, conducting the research, and drafting as well as revising the manuscript.
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Data Availability Statement
The climate action plans analyzed in this study are publicly available from the official websites of the respective municipalities, as cited in the reference list. The coded dataset generated during the study is available from the corresponding author upon reasonable request.
Declaration of AI Use
The authors used AI-based language tools to improve the language, clarity, and readability of the manuscript. All scientific content, interpretations, and conclusions are solely the responsibility of the authors.
Conflict of Interest
The authors declare that there is no conflict of interest regarding the publication of this article.

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