Caspian Journal of Environmental Sciences
Online ISSN: 1735-3866
Print ISSN: 1735-3033

Economic impact assessment of land use change on the Hyrcanian Forests ecosystem services in Northern Iran

Shamim Khojasteh Deldar, Iraj Hassanzad Navroodi*, Sareh Hosseini

[1] *Forest Management, Department of Forest Science and Engineering, Faculty of Natural Resources, University of Guilan, Sowmeh Sara, Guilan, Iran*

**Corresponding author's Email: ehasanzadeh@guilan.ac.ir*

ABSTRACT
Land-use change has emerged as a primary driver of ecosystem degradation and the decline of ecosystem services worldwide, often resulting in substantial economic consequences. This study aims to (i) analyze the spatiotemporal dynamics of land use and land cover (LULC), (ii) investigate landscape pattern changes, and (iii) estimate the economic losses associated with forest land-use change in the Hyrcanian forests of Guilan Province, Iran, from 2012 to 2022. Five LULC classes were mapped: forest, built-up (residential), water, agriculture, and rangeland. LULC maps were generated using the Landsat 7 (ETM^+) and Landsat 8 (OLI) imagery on the Google Earth Engine platform. A supervised Random Forest (RF) classifier was applied, incorporating spectral indices including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Modified Normalized Difference Water Index (MNDWI) to enhance class separability. The classification achieved an overall accuracy exceeding 85% and a Kappa coefficient greater than 0.80, indicating substantial agreement. Landscape pattern changes were subsequently analyzed using Fragstats software. The results reveal considerable landscape transformation during the study period. Forest area declined from 621475 ha in 2012 to 611915 ha in 2022, while built-up areas expanded from 28937 ha to 38637 ha and agricultural lands increased from 343046 ha to 412768 ha. Conversely, water bodies decreased from 64397 ha to 45898 ha, and rangeland and barren land declined from 346545 ha to 295182 ha. Economic valuation, conducted using the Benefit Transfer method, revealed substantial losses resulting from forest area reduction, with the most severe decline occurring during 2012–2017 (12851 ha of forest loss). This loss represented approximately 5.1% of the provincial Gross Domestic Product (GDP), equivalent to approximately $ 308226.29 million. These findings underscore the critical importance of integrating ecosystem service valuation into regional land-use planning and sustainable forest management policies.

Keywords: Economic valuation, Forest degradation, Forest management, Random forest.

INTRODUCTION
Forests are widely recognized as a cornerstone of environmental, economic, and social sustainability, playing a pivotal role in human well-being by providing ecosystem services (Haq *et al.* 2020). These services encompass provisioning, regulating, and cultural functions that directly and indirectly influence the quality of human life (Hasan *et al.* 2020). Consequently, any changes in the structure and functioning of these ecosystems—particularly land use and land cover (LULC) changes play a critical role in forest degradation and undermine ecosystem sustainability. Such changes, primarily driven by urban development, infrastructure expansion, agricultural conversion, and population pressures,

alter the spatial structure and impair the functioning of ecosystems, leading to extensive environmental and economic consequences (Noh *et al.* 2022; Barati *et al.* 2023). At the global scale, deforestation remains one of the most significant threats to biodiversity, climate regulation, and food security. According to the Food and Agriculture Organization (FAO), forest resource degradation continues in many regions worldwide (FAO 2020). Recent studies indicate that the majority of research on LULC change has focused on identifying the spatial and temporal patterns of these changes using remote sensing data and classification algorithms such as Random Forest, Support Vector Machine, and Markov models (Liu *et al.* 2020; Baig *et al.* 2022). These studies have effectively documented patterns of land conversion, highlighting an expansion of human-modified land uses and a concurrent reduction in forested areas. Furthermore, the adoption of cloud-based processing platforms, such as Google Earth Engine, has significantly enhanced classification accuracy, computational efficiency, and the capacity for temporal analysis in LULC change research (Phan *et al.* 2020; Li *et al.* 2021; Mhanna *et al.* 2023).

However, the primary focus of these studies has been on monitoring spatial changes, with limited attention given to the direct economic consequences of such transformations. For instance, research on forest land use change has been conducted across diverse geographical contexts, including China (Zhou *et al.* 2020), Guangdong Province, China (Ye *et al.* 2021), North Korea (Piao *et al.* 2021), the Desha forests of Northern Ethiopia (Hishe *et al.* 2021), the Chalus watershed in Iran (Jalayer *et al.* 2022), Selangor, Malaysia (Baig *et al.* 2022), Binh Duong Province, China (Bui *et al.* 2023), Northern Punjab, Pakistan (Hussain *et al.* 2024), Binh Duong Province, Vietnam (Pham *et al.* 2024), and the Hyrcanian forests of Iran (Hosseini *et al.* 2025). The findings consistently indicate that land use changes (LUC) are primarily characterized by a reduction in forested areas, accompanied by an expansion of agricultural, residential, and barren lands.Within the domain of ecosystem services economic valuation, several studies have focused specifically on estimating the value of forests and other land cover types using Benefit Transfer methods, replacement cost approaches, or hybrid models (Hasan *et al.* 2020; Wu *et al.* 2020; Qiu *et al.* 2021). The studies have demonstrated that deforestation and the conversion of forests to agricultural or urban land uses are associated with substantial declines in ecosystem service values and increased social costs. However, most of the studies have been conducted at broad spatial scales or have focused on the total value of ecosystems, rather than quantifying the economic losses resulting from LULC changes within a specific ecosystem through detailed spatial analysis. Consequently, a systematic linkage between forest LULC change analysis and the quantification of its economic impacts at the regional scale remains a significant research gap.

The northern forests in Iran particularly the Hyrcanian forests in Guilan Province have in recent decades been increasingly affected by pressures from urban development, second-home construction, and tourism expansion (Ahmadlou *et al.* 2023). The forests, which form part of the world's natural heritage, play a crucial role in regional climate regulation, soil conservation, carbon storage, and hydrological sustainability (Omarzadeh *et al.* 2021). Studies conducted in the forested regions of Northern Iran have shown that LUC have led to a decline in forest cover and an expansion of residential and agricultural land uses (Omarzadeh *et al.* 2021; Garshasbi *et al.* 2025). Nevertheless, despite extensive documentation of spatial trends, precise quantification of the economic losses resulting from the changes at the scale of Guilan Province remains limited. In many studies conducted in Iran, the primary focus has been on identifying and monitoring LUC, while the quantitative assessment of associated economic impacts particularly at the regional scale has received comparatively little attention. This underscores a significant research gap in linking spatial analyses of LULC change with the economic valuation of ecosystem services.

Accordingly, the present study aims to conduct a detailed analysis of forest LUC in Guilan Province from 2012 to 2022 and to estimate the associated economic losses resulting from these changes. The novelty of the research lies in the integration of multi-temporal land use change analysis based on remote sensing and cloud-based processing with a regional-scale economic loss assessment framework, systematically quantifying the impact of forest conversion on the economic value of ecosystem services. The approach provides a scientific basis for strengthening sustainable management policies for the Hyrcanian forests and enhancing the integration between spatial analysis and natural resource economics.

MATERIALS AND METHODS

Study Area

Guilan Province is one of the northern provinces of Iran, located along the southern coast of the Caspian Sea, with a total area of approximately 14044 km². The province is located between 36°33′ and 38°27′ N latitude and 48°32′ and 50°36′ E longitude (Adel *et al.* 2014). It is bordered by the Caspian Sea and the Republic of Azerbaijan to the north, Ardabil Province to the west, Qazvin and Zanjan provinces to the south, and Mazandaran Province to the east. The Alborz Mountain Range, with an average elevation of approximately 3000 m, extends across the southern and western parts of the province, forming a natural barrier. The primary connection between this region and the Iranian Plateau is provided through the Manjil Valley (Omarzadeh *et al.* 2021).

The climate of Guilan Province is classified as humid Caspian, influenced by the Caspian Sea and the topographic conditions of the Alborz Mountains. Annual precipitation ranges from approximately 1200 to 1800 mm in the coastal areas of Bandar Anzali and Astara to about 800–1000 mm in the central and western regions (Fumanat). The forests of Guilan form part of the Hyrcanian forests, constituting a narrow mountainous belt along the northern slopes of the Alborz Mountains. The total area of the Hyrcanian forests exceeds 1.9 million hectares, of which approximately 610350.5 ha about 32% of the northern forests of Iran expansion (Ahmadlou *et al.* 2023).

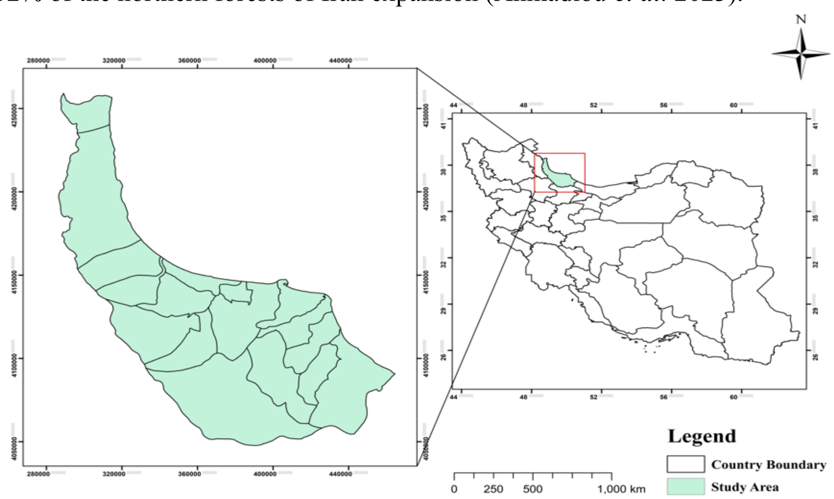

Fig. 1. Map of the study area.

Research methodology

The study was designed to analyze forest Land Use Changes (LUC) in Guilan Province and to estimate the associated economic losses over the period 2012–2022. The research employs an integrated framework that encompasses multi-temporal land cover monitoring, landscape structure analysis, and the quantification of economic losses based on environmental economics principles. All stages of spatial data processing, classification, and change detection were conducted using the cloud-based Google Earth Engine platform. As one of the most advanced platforms for remote sensing data analysis, Google Earth Engine provides direct access to satellite data archives from the United States Geological Survey (USGS) and has been widely applied in long-term LULC studies (Gorelick *et al*. 2017; Prochazka *et al.* 2023).

To analyze land use change trends, Landsat imagery was selected for the study period. Specifically, images from 2012 were acquired from the ETM+ sensor onboard Landsat 7, while images for 2017 and 2022 were acquired from the OLI sensor onboard Landsat 8. All data were obtained from the standard Collection 1 and Collection 2 datasets, which have undergone radiometric calibration and geometric correction to ensure data quality and consistency (Chen *et al.* 2020; Amindin *et al.* 2024). To minimize errors associated with cloud contamination, only satellite images with cloud cover of less than 5% were selected. When multiple images were available for a given year, the image with the highest spectral quality and the lowest cloud coverage was selected for analysis (Baig *et al.* 2022). All preprocessing procedures including the application of quality masks to remove cloud and cloud-shadow pixels and the refinement of datasets using the platform's built-in functions were performed within the Google Earth Engine environment (Wahap & Shafri 2020). To minimize phenological variability and ensure reliable interannual comparability, all selected images were acquired during the peak vegetation growing season, corresponding to the months of May and June (Liu *et al.* 2020). Subsequently, to minimize radiometric noise and short-term variability, annual image composites were generated using a median filter. To enhance spectral separability among land use classes, several spectral indices including the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Built-up Index (NDBI), and the Modified Normalized Difference Water Index (MNDWI) were calculated and incorporated as auxiliary bands in the classification process (Zhao *et al.* 2024). Land use classification was performed using the Random Forest (RF) algorithm. As a powerful supervised machine learning method, RF constructs an ensemble of independent decision trees and aggregates their outputs through majority voting, providing high classification accuracy and robustness when handling multidimensional and nonlinear data. This algorithm has been widely applied in remote sensing studies (Talukdar *et al.* 2020; Omarzadeh *et al.* 2021; Feng *et al.* 2022; Zhao *et al.* 2024). In the study, the Random Forest model was implemented using the ee.Classifier.smileRandomForest function within the Google Earth Engine (GEE) environment. For each year, 300 training samples were collected based on high-resolution image interpretation and field knowledge. Of these, 70% were used for model training and the remaining 30% served as independent validation data (Gündüz 2025). The model was trained with 300 trees, and the number of random variables considered at each node was set to the square root of the total number of input features (Shafizadeh-Moghadam *et al.* 2021).

The LUC included forest, agricultural land, rangeland and barren land (combined), built-up areas, and water bodies, defined in accordance with standard land use classification schemes (Hu *et al.* 2013). Following the generation of classified maps for 2012, 2017, and 2022, classification accuracy was assessed using error matrices and standard evaluation metrics. Overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient were calculated for each year to quantify the agreement between the classified maps and reference data (Macarringue *et al.* 2022; Zhao *et al.* 2024). The validation datasets were completely independent of the training data to minimize potential bias (Gündüz 2025).

To analyze landscape structural changes, the final classified maps were imported into FRAGSTATS version 3.3. The software, a standard tool for quantitative landscape pattern analysis, enables the calculation of spatial metrics at the class level and has been widely used to examine ecosystem fragmentation and connectivity patterns (Leitao & Ahern 2002; Leitão *et al.* 2012; Paonam & Chatterjee 2023). In this study, Class Area (CA), Percentage of Landscape (PLAND), Edge Density (ED), Total Edge (TE), and the Largest Patch Index (LPI) were calculated to assess the spatial and structural changes affecting the forest class over the study period (Bui *et al.* 2023). The economic losses resulting from LUC in the forest ecosystem of Guilan Province were estimated for three-time intervals: 2012–2017, 2017–2022, and the entire 2012–2022 period. The theoretical foundation of the analysis is based on environmental economics principles, which posit that the economic loss from LUC is equivalent to the value of ecosystem services provided by the ecosystem prior to conversion (Kumar 2012). To estimate the economic value of ecosystem services provided by the Hyrcanian forests in Guilan Province, the Benefit Transfer method was employed. The approach was selected due to time and budgetary constraints for conducting primary field-based studies, the high costs associated with direct valuation, and the availability of previous credible studies on ecosystem service valuation in the Hyrcanian forests (Hosseini *et al.* 2017).

Within this framework, a systematic literature review was conducted across domestic and international scientific databases. From an initial pool of 68 studies published between 2012 and 2023, only those meeting the following criteria were selected: (i) focusing on the Hyrcanian forests, (ii) providing monetary valuation of at least one ecosystem service, (iii) employing a clearly defined valuation method, and (iv) offering extractable quantitative data. Furthermore, selected studies had to be ecologically and socially compatible with the study region. To ensure conceptual consistency in defining ecosystem services, the Common International Classification of Ecosystem Services (CICES) framework was used as the basis for service classification (Haines-Young *et al.* 2018).

All extracted monetary values were adjusted to constant 2021 prices using the Consumer Price Index (CPI) obtained from the Statistical Center of Iran, thereby eliminating the effects of inflation and accounting for differences in publication years across studies. Subsequently, the values were transferred to the base year 2021 using Equation (1) (Yi *et al.* 2023).

Eq. 1:

$$Current\ Value = \frac{R}{(1+i)^t}$$

Following standardization, the average economic value per hectare of the Hyrcanian forests in Guilan Province (at constant 2021 prices) was estimate.

Eq. 2:

$$\begin{aligned} &\text{Economic Loss from Land Use Change} \\ &= \text{Area of Land Use Change (ha)} \times Economic\ Value\ per\ Hectare\ of\ Forest \end{aligned}$$

Eq. 3:

$$Share\ of\ Loss\ in\ Gross\ Domestic\ Product = \frac{Economic\ Loss\ from\ Forest\ Area\ Reduction}{Provincial\ GDP} \times 100$$

Data on provincial Gross Domestic Product (GDP) were obtained from official statistics published by the Statistical Centre of Iran (2022). Since the most recent available data corresponded to the year 2021, this year was designated as the base year, and all economic values are reported in constant 2021 prices.

RESULTS

In this study, land use maps were generated using the Random Forest algorithm, and classification accuracy was assessed using the Kappa coefficient. The Kappa values for 2012, 2017, and 2022 were 0.61, 0.63, and 0.68, respectively, indicating moderate to substantial agreement and confirming the reliability of the classified maps for subsequent analyses. LULC maps of the province were produced for five classes forest, residential areas, water bodies, agricultural land, and rangeland/barren land for the years 2012, 2017, and 2022, as illustrated in Fig. 2.

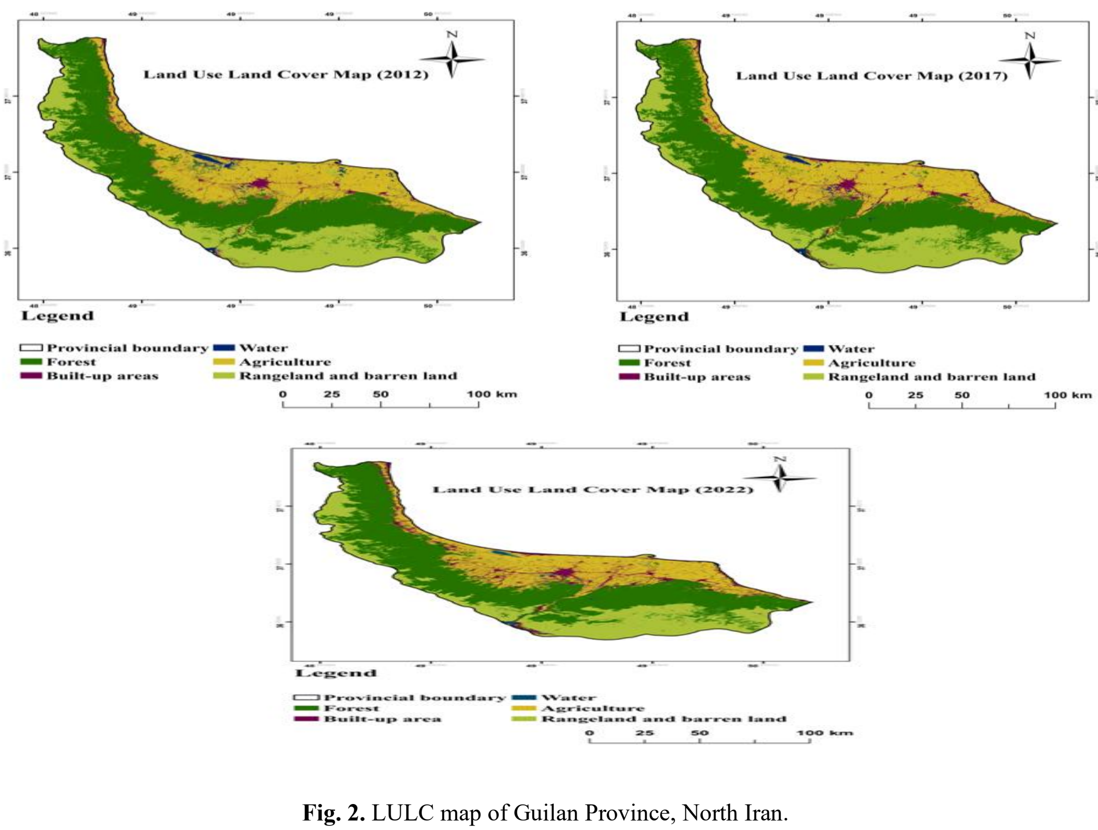

Fig. 2. LULC map of Guilan Province, North Iran.

The results of the spatiotemporal analysis of land use and land cover changes quantified using landscape metrics including CA, PLAND, LPI, ED, and TE reveal substantial landscape transformations over the study decade. The forest class covered 621475 ha in 2012, decreasing to 608624 ha in 2017 before increasing again to 611915 ha in 2022. The trend is mirrored by the PLAND metric, which declined from 44.4% in 2012 to 43.3% in 2017 and subsequently rose to 43.5% in 2022.

Although this slight increase suggests a partial recovery of forest cover, changes in LPI reveal fluctuations in patch cohesion, with the index decreasing from 26.81 in 2012 to 26.50 in 2017 and then rising to 27.72 in 2022. Similarly, both edge density and total edge exhibited increasing trends from 2017 to 2022, indicating greater edge creation and increased complexity of forest boundaries by the end of the period. These findings suggest that, despite the net increase in forest area by 2022, the spatial structure of forests became more fragmented. Such fluctuations reflect the combined influence of management interventions and anthropogenic pressures throughout the study period.

Built-up areas exhibited a consistently increasing trend in class area throughout the study period. The area expanded from 28937 ha in 2012 to 32880 ha in 2017, and further to 38637 ha in 2022. The PLAND increased from 2.1% in 2012 to 2.4% in 2017 and 2.8% in 2022. The continuous increase in the LPI from 0.38 in 2012 to 0.52 in 2022 indicates that the main urban patch not only expanded but also became more cohesive over time.

Alongside this expansion, TE increased from 10770510 m in 2012 to 16568370 m in 2022, while ED rose from 7.67 to 11.79 m ha^{-1}, reflecting rapid spatial expansion and increasingly scattered patterns of urban development. The trends highlight the growing encroachment of urban areas into the surrounding landscape and the intensifying pressure on natural ecosystems.

Water bodies experienced a substantial decline over the study period. The area of water decreased from 64,397 ha (4.6% of the total landscape) in 2012 to 56852 ha (4.1%) in 2017, and further to 45898 ha (3.2%) in 2022. Also, the LPI also declined from 0.39 to 0.17, indicating a reduction in the extent of individual water patches. Although TE increased over the study period, reaching 1572600 m in 2022, ED decreased from 3.39 to 1.11 m ha^{-1} over the same interval. This combination increasing total edge coupled with decreasing edge density suggests that while water boundaries became more complex, the overall area and connectivity of water bodies diminished considerably.

Agricultural land exhibited a non-linear trend over the study period. The area increased from 343046 ha (24.4% of the total landscape) in 2012 to 393234 ha (28.0%) in 2017, and further to 412768 ha (29.4%) in 2022. Changes in the LPI reflect this non-linear trajectory, increasing from 0.220 in 2012 to 0.248 in 2017, followed by a decline to 0.210 in 2022.

The TE increased from 17388990 m in 2012 to 18116010 m in 2022, while ED rose from 12.38 to 12.90 m ha^{-1} over the same period. These trends point to increased edge creation and reduced spatial cohesion of agricultural patches by the end of the study interval.

The combined area of rangeland and barren land decreased from 346,545 ha (24.5% of the total landscape) in 2012 to 312810 ha (22.2%) in 2017, and further to 295,182 ha (21.0%) in 2022. The LPI declined from 18.61 in 2012 to 15.66 in 2022, indicating a reduction in the size of the dominant rangeland patches and a corresponding loss of spatial cohesion.

Although total edge (TE) exhibited some interannual variability, it generally followed an increasing trajectory over the study period. Edge density (ED), however, decreased from 9.09 in 2017 to 8.61 in 2022. Collectively, these metrics suggest that rangeland and barren land experienced fragmentation in their spatial structure, albeit to a lesser degree than agricultural and built-up areas.

In summary, the landscape metrics reveal that over the past decade, the most pronounced changes occurred in built-up areas and water bodies the former undergoing rapid spatial expansion and the latter experiencing substantial areal loss. Forests, agricultural lands, and the combined rangeland/barren land class exhibited diverse patterns of quantitative and structural change, reflecting significant transformations in the overall landscape configuration of the region.

Table 1. Landscape structure changes in Guilan Province from 2012 to 2022.

Year	Land Use Class	Metrics				
		Class area (ha)	Percentage of landscape (%)	Largest patch index	Edge density (m ha^{-1})	Total edge (m)
2012	Forest	621475	44.4	26.81	12.51	17577600
	Urban	140360	9.9	0.38	7.67	10770510
	Water	194373	13.8	0.39	3.39	4765680
	Agricultural	221647	15.8	22.02	12.38	17388990
	Rangeland and barren land	226545	16.1	18.61	8.94	12564870
2017	Forest	608624	43.3	26.50	11.76	16514610
	Urban	193694	13.8	0.51	8.28	11636460
	Water	132668	9.4	0.24	1.35	1901580
	Agricultural	233234	16.6	24.08	11.88	16687830
	Rangeland and barren land	236180	16.9	15.95	9.09	12777180
2022	Forest	611915	43.5	27.72	11.87	16678020
	Urban	218413	15.6	0.52	11.79	16568370
	Water	119531	8.5	0.17	1.11	1572600
	Agricultural	217268	15.5	20.10	12.90	18116010
	Rangeland and barren land	237273	16.8	15.66	8.61	12100860

The results of the Benefit Transfer analysis indicated that the forest ecosystem service annual value per hectare in 2012, adjusted to constant 2021 prices was estimated at 6236 billion IRR (approximately $ 23.98 million). For 2017 and 2022, the estimated values were 6812 billion IRR ($ 26.2 million) and 22572 billion IRR ($ 82.9 million), respectively, all expressed in constant 2021 prices. The observed upward trend in these values over time is primarily attributable to changes in the general price level (inflation) rather than real changes in ecosystem service provision.

Based on the adjusted per-hectare value and the official forest area of the province, the ecosystem service total annual value of the Hyrcanian forests in Guilan Province for 2021 was estimated at approximately 1305566 billion IRR ($ 5021 million), underscoring the substantial contribution of natural capital to the regional economy.

The results of the economic loss assessment due to LUC, indicate that reductions in forest area over the study period exhibited notable temporal variability (Table 2). During the 2012–2017 interval, the highest forest loss was recorded (12851 ha), resulting in the largest economic loss from LUC, amounting to approximately $ 308226.29 million. The loss represented approximately 5.1% of the provincial GDP during this period, highlighting the significant economic impact of LUC at the regional scale.

During the 2017–2022 interval, the area of converted forest decreased markedly to 5291 ha, representing a substantial reduction compared to the previous period. This decline resulted in a correspondingly lower economic loss of approximately $ 138624.20 million, with its share of provincial GDP decreasing to 2.3%.

These results may reflect the relative effectiveness of management, regulatory, and control policies in mitigating LUC during specific intervals of the study period. However, from 2012 to 2022, a net forest loss of 9560 ha was recorded, indicating a continued upward trend in cumulative area loss compared to the preceding interval. Consequently, the total economic loss from LUC for the full decade amounted to $ 229293.69 million approximately. Despite this substantial absolute increase in economic loss, its share of provincial GDP remained relatively stable at 3.8% over the entire period, suggesting that the growth of the regional economy may have moderated the relative economic impact of LUC (Table 2).

Overall, the findings demonstrate a direct relationship between the magnitude of forest area reduction and associated economic losses. The observed temporal fluctuations further underscore the instability and inconsistent effectiveness of land management and control measures throughout the study period.

Table 2. Economic loss of forest ecosystems from 2012 to 2022[a].

Period	Area loss (ha)	Economic loss (Billion IRR)	Economic loss (Million $)	Share of national GDP (%)
2012–2017	12851	23.98	308226.29	5.1
2017–2022	5291	26.20	138624.20	2.3
2012–2022	9560	23.98	229293.69	3.8

Note: [a]: Values are converted to $ using the 2021 exchange rate (1 $ = 260000 IRR). Units are in million $.

Table 3. Economic loss of forest ecosystems from 2012 to 2022[b].

Period	Area loss (ha)	Economic loss (Billion IRR)	Economic loss (Million $)	Share of national GDP (%)
2012–2017	12851	15.52	199483.00	5.1
2017–2022	5291	16.95	89682.00	2.3
2012–2022	9560	15.52	148428.00	3.8

Note: [b]: Values are converted to $ using the 2024 exchange rate (1 $ = 401877 IRR). Units are in million $.

Table 4. Economic loss of forest ecosystems from 2012 to 2022[c].

Period	Area loss (ha)	Economic loss (Billion IRR)	Economic loss (Million $)	Share of national GDP (%)
2012–2017	12851	9.16	117623.00	5.1
2017–2022	5291	10.00	52935.00	2.3
2012–2022	9560	9.16	87502.00	3.8

DISCUSSION

The study results demonstrate that the landscape of Guilan Province underwent substantial structural transformations during the period 2012–2022. The observed changes were not limited to shifts in the areal extent of individual land use classes but also significantly influenced spatial configuration, ecological connectivity, and overall landscape cohesion. The findings align with the landscape ecology literature, which emphasizes that LUC assessments should consider not only area-based metrics but also spatial structure and fragmentation patterns (Liu *et al.* 2020; Hasan *et al.* 2020). The expansion of anthropogenic land use types and the decline of natural land cover constitute the dominant pattern of landscape transformation in the region. This trend, consistently documented across multiple studies, is primarily attributed to population growth, urban development, shifting livelihood strategies, and ongoing developmental pressures (Liu *et al.* 2020; Hasan *et al.* 2020). On a global scale, urbanization is widely recognized as one of the primary drivers of LUC, with profound implications for ecosystem services (Bui *et al.* 2023; Pham *et al.* 2024).

A notable finding of the present study is the observed decrease in connectivity and concurrent increase in fragmentation within forest and agricultural land use classes. The results indicate that an increase in the areal extent of a particular land use does not necessarily reflect an improvement in ecological condition; rather, landscape structure metrics offer a complementary perspective on ecosystem quality. The finding is consistent with theoretical perspectives in landscape ecology that emphasize the importance of spatial cohesion for ecosystem sustainability (Liu *et al.* 2021). The observed pattern of urban expansion in the study mirrors that of many cities in developing regions, characterized by horizontal and dispersed growth commonly referred to as urban sprawl. Over the long term, such a pattern drives excessive land consumption, accelerates the loss of agricultural land, and exacerbates pressure on natural resources (Khalid *et al.* 2023; Alshehri *et al.* 2025). Additionally, the decline in the spatial cohesion of agricultural land can compromise rural livelihoods and agricultural productivity, particularly in water-scarce regions (Aziz 2021; Hussain *et al.* 2024). Overall, the spatial analysis indicates that the region is undergoing a transition from a natural to a human-dominated landscape, accompanied by increased fragmentation and reduced spatial cohesion. This situation underscores the urgent need to reconsider land use policies and to more effectively integrate ecological considerations into development planning (Barati *et al.* 2023).

The findings related to economic losses indicate that LUC in forested areas have consequences extending beyond environmental dimensions, directly affecting the regional economic structure. According to the theoretical framework of ecosystem service valuation, forest area reduction results in the loss of non-market ecosystem services, thereby imposing welfare costs on society. In this research, economic losses were estimated based on the value of lost ecosystem services, and the results demonstrated that reductions in forest area across the study periods corresponded to increases in economic losses. This relationship aligns with environmental economic principles and natural capital theory (Kumar 2012). Moreover, Shiferaw *et al.* (2023) reported that forest degradation results in the loss of economic value from ecosystem services, which over the long term far exceeds the short-term benefits derived from land use conversion. Hasan *et al.* (2020) demonstrated that an increase in gross domestic product does not necessarily lead to higher ecosystem service values, and that the conversion of natural land cover to human-dominated uses reduces overall ecosystem value. Moreover, Zhou *et al.* (2020) highlighted that LUC are key determinants of ecosystem service provision and landscape functionality. The findings of the present study are consistent with these observations. The results regarding the relationship between economic losses and provincial GDP indicate that, while the relative share of these losses in GDP may appear modest, it nonetheless reflects a structural pressure on natural capital. The finding is consistent with Karimzadegan (2011) and related studies on the economic valuation of Hyrcanian forests, which emphasize the substantial importance of non-market forest services. Overall, the economic outcomes of the study suggest that forest LUC is not merely a spatial process but also an economic phenomenon with cumulative impacts. The observed increase in economic losses alongside reductions in forest area indicates that the region's natural capital is undergoing gradual depletion.

This situation aligns with the findings of Wu *et al.* (2020) and Zhang *et al.* (2020), which indicate that development pathways can exert a decisive influence on future economic losses. The findings of the present study provide empirical evidence supporting the necessity of integrating ecosystem service values into development decision-making. Neglecting natural capital within planning frameworks can simultaneously undermine both ecological and economic sustainability. Therefore, land use policies should be designed on the basis of an integrated spatial-economic assessment to prevent the escalation of long-term losses.

Economic sustainability. Therefore, land use policies should be designed on the basis of an integrated spatial-economic assessment to prevent the escalation of long-term losses.

CONCLUSION

The study employed an integrated framework encompassing land use and land cover change analysis, landscape structure assessment, and economic valuation of ecosystem services to comprehensively establish the link between spatial and ecological transformations and the economic consequences of forest loss and reduced spatial connectivity in Guilan Province, North Iran. The results revealed that the expansion of anthropogenic land uses, particularly urban development, coincided with decreased spatial connectivity, increased fragmentation, and structural degradation of the landscape a trend reflecting the gradual, cumulative, and structural nature of the changes occurring in the study area. Furthermore, the research findings indicated that reductions in forest area and spatial connectivity led to increased cumulative damages over time, with these effects exhibiting a time lag in the manifestation of their economic consequences. This suggests that the relationship between forest degradation and economic loss is neither linear nor immediate, but rather non-linear and contingent upon managerial and institutional frameworks. Accordingly, the effectiveness of conservation policies, the coherence of land use planning systems, and the approach to ecosystem service valuation play a decisive role in determining the magnitude of economic impacts. The primary contribution of the study resides in presenting an integrated approach for assessing structural changes in the landscape and quantifying their economic consequences within a unified analytical framework, which can serve as a foundation for evidence-based decision-making in land management. This framework facilitates an understanding of the interactions between spatial dynamics and ecosystem functions, underscoring the necessity of integrating ecological considerations into regional development planning. Despite the contributions of this study, the results are subject to certain limitations, including uncertainties inherent in remote sensing data, the assumptions underlying economic modeling, and the inherent challenges associated with ecosystem service valuation. Future research can contribute to extending these findings by employing data with higher spatial and temporal resolution, utilizing dynamic ecosystem service assessment models, and conducting scenario-based projections. Overall, the findings demonstrate that ensuring the economic and ecological sustainability of forested provinces in Northern Iran requires a transition from sectoral management to an integrated landscape management approach. This entails strengthening mechanisms for continuous land use change monitoring and incorporating the true value of ecosystem services into national accounts and decision-making processes. Such an approach can prevent the intensification of cumulative damages over the long term and enhance the resilience of both ecosystems and the regional economic system.

SUGGESTIONS

a. Policy Implications

- Given the cumulative and long-term nature of economic damages resulting from reductions in forest area and spatial connectivity, it is recommended that the value of ecosystem services be systematically incorporated into the assessment of development projects, the evaluation of land use change permits, and the formulation of urban development plans. Integrating these values into decision-making processes can help prevent the accumulation of long-term damages and support more sustainable land management practices.
- Given the significant role of anthropogenic land use expansion in driving landscape fragmentation, strengthening integrated landscape management at the regional level and enhancing coordination among land use planning authorities is essential. Such an approach would help prevent sectoral and uncoordinated decisions that contribute to the gradual degradation of forest ecosystems.
- It is recommended that continuous land use change monitoring systems grounded in remote sensing data and supported by periodic spatial analyses be developed as decision-support tools to enable the timely identification of trends in forest fragmentation and declining spatial connectivity.
- Furthermore, the design of deterrent economic instruments such as financial incentives for forestland conservation and compensatory fees for land use conversion can help curb incentives for degradation and ensure that the true environmental costs are reflected in economic processes.
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b. Research Recommendations

- Future studies could provide more detailed analyses of landscape structure dynamics and reduce uncertainty in economic damage estimations by utilizing data with higher spatial and temporal resolution. Additionally, integrating scenario-based modelling and incorporating ancillary data such as socioeconomic variables and land use policy frameworks would further strengthen the accuracy and applicability of findings for evidence-based decision-making.
- Moreover, the application of dynamic ecosystem service assessment models and scenario-based analyses could enhance understanding the non-linear and time-delayed effects of land use changes while enabling the simulation of alternative policy outcomes.
- Furthermore, undertaking comparative regional analyses across the forested provinces of Northern Iran could facilitate the identification of common spatial patterns and enhance the generalizability of findings, thereby contributing to more robust and transferable insights for land use policy development. Finally, it is recommended that future research investigate institutional variables, the quality of land governance, and the effectiveness of conservation policies as key determinants of the magnitude of economic damages, thereby contributing to a more holistic analytical framework.

ACKNOWLEDGEMENT

The article has been extracted from a Master of Science thesis conducted at the university of Guilan, with the financial support of the university. The authors would like to express their sincere gratitude to the Department of Forest Science and Engineering, University of Guilan, and Department of Natural Resources and Watershed Management in Guilan Province for their valuable cooperation in the execution of the study.

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DOI: Article type: Research

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Caspian J. Environ. Sci.
DOI:
Received:
Article type: Research

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Caspian J. Environ. Sci.
DOI:

Received:
Article type: Research