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Urban Development Impacts on Ecosystem Services: Modeling and Valuation of Carbon Storage in the Tehran Metropolis

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Abstract

The rapid growth of urbanization in Iranian metropolises, especially Tehran, has caused significant changes in land use and cover, and consequently, a decrease in ecosystem services, including carbon storage. This study aimed to model and value changes in carbon storage in Tehran's ecological metabolism over three decades (1994–2024). Multi-temporal Landsat satellite images, advanced processing in Google Earth Engine, and the Random Forest algorithm were used for land use/cover classification. In addition, 66 urban soil samples were collected and analyzed to estimate soil organic carbon. The InVEST model was used to simulate changes in four main carbon pools (aboveground biomass, belowground biomass, soil, and dead organic matter). In addition, using economic valuation frameworks and global market reference rates, losses and benefits from carbon changes were calculated in the form of monetary indices. The results showed that over the study period, the area of green spaces decreased from 14.19% in 1994 to 11.87% in 2024. These changes, along with the conversion of wasteland to construction, led to a significant reduction in carbon storage. Specifically, about 280,000 tonnes of carbon (equivalent to $7.62 million) were lost between 1994 and 2004, and more than 151,000 tonnes of carbon (equivalent to $4.11 million) between 2014 and 2024. Field-based models revealed several localized zones of carbon decline along with areas that could feasibly be restored. The results suggest that rapid urban growth and the steady loss of vegetation cover have greatly weakened the city’s capacity to retain carbon, and in turn, reduced its economic and ecological value. These observations highlight the importance of incorporating ecosystem service valuation into broader planning practices, ensuring that urban development does not undermine environmental integrity and contributes to climate resilience in large cities.

Introduction

Modern metropolitan regions face a growing set of interconnected challenges, many of which are rooted in human activity. Rapid population increases, unplanned urban expansion, and the overuse of natural resources have together placed severe stress on urban environments (Talkhabi et al., 2024). These pressures appear in multiple ways—from worsening air and water pollution to heavier traffic congestion and the gradual loss of ecological systems. Over the past few decades, Tehran, the capital and largest city of Iran, has shown a clear decline in environmental quality, a trend that reflects the cumulative effects of these human-driven changes (Mohaqeq et al., 2020).

Urbanization remains one of the main causes of land use and land cover change (LULCC). Such changes reshape both the structure and function of ecosystems, particularly in fast-growing cities such as Tehran (Feddema et al., 2005; Newbold et al., 2015; Li et al., 2019). Expansion of the built environment alters landscapes through habitat fragmentation, increased greenhouse gas emissions, and the disturbance of hydrological cycles—each of which weakens the natural resilience of urban ecosystems (Zipperer et al., 2012).

Ecosystems possess their own structures and processes that depend on the interaction between living organisms and physical conditions (Meng et al., 2025). These interactions give rise to a wide range of ecosystem services—the direct and indirect benefits people obtain from nature—which play an essential role in maintaining human well-being (Costanza et al., 1998). An important regulating services is carbon sequestration, which contributes to climate stabilization by capturing atmospheric CO_2 through photosynthetic processes in vegetation (Georgiou et al., 2025; Sharma et al., 2020; Baro *et al*., 2015).

Urban and peri-urban green spaces, particularly trees, parks, and forests play a vital role in the delivery of ecosystem services for city dwellers (Bolund and Hunhammar, 1999; Gomez-Baggethun and Barton 2013; Berghlin and Gomez-Baggethun 2021), including carbon sequestration and climate regulation, (McPherson 1998; Nowak and Crane 2002; Baró *et al*. 2012; Estruch et al., 2024; Hazrati *et al*., 2019; Lisboa et al., 2024; Yin et al., 2022). However, these carbon stocks are vulnerable to anthropogenic disturbances such as deforestation, land degradation, and LULC changes (Khachoo et al., 2024; Lal et al., 2024; Zhang *et al*., 2025).

Over the last three decades, Tehran has undergone substantial urban expansion, resulting in a significant decline in its natural vegetation cover. According to available data, between 1994 and 2024, green spaces in the city were experienced a substantial loss—a trend largely attributed to construction booms, suburban sprawl, and deforestation (Talkhabi et al., 2024; Malekzadeh et al., 2025). These land use changes have disrupted microclimates and diminished Tehran's ecological potential for absorbing atmospheric carbon.

Another pressing environmental issue in Tehran is the continuous rise of carbon dioxide concentrations, particularly within its crowded residential districts and industrial zones. Since the mid-2000s, measurements from several urban monitoring stations have shown CO_2 levels consistently exceeding the limits proposed by the World Health Organization (WHO), with little sign of meaningful improvement over time (Hazrati *et al*., 2019). When combined with the steady loss of vegetation and open space, this trend highlights why Tehran serves as a critical example for examining carbon sequestration strategies and potential policy interventions.

Understanding how land use transformations influence carbon storage is central to evaluating the city's environmental trajectory. By linking remote sensing and GIS analyses with ecological and economic modeling, researchers can explore how different patterns of urban growth shape the capacity of ecosystems to capture and store carbon (Felzer, 2025). Such integrated approaches also help visualize future scenarios, revealing where targeted management or restoration efforts might offer the greatest benefit.

InVEST (Integrated Valuation of Ecosystem Services and Trade-Offs) is an open-source software model for mapping and valuing ecosystem services that uses biophysical data to examine how ecosystem change affects ecosystem services (Arcidiacono et al., 2015). The InVEST model has emerged as a widely used tool for assessing carbon storage due to its simplicity, spatial explicitness, and ability to integrate with land use simulation models like CA–Markov and PLUS (He et al., 2016; Lei et al., 2024;

Sharp et al., 2015). This model also allows for scenario-based analysis, enabling policymakers to evaluate trade-offs and synergies between development and conservation (Wang et al., 2025; Tariq and Mumtaz, 2023).

Moreover, the economic valuation of carbon storage—using tools such as the Social Cost of Carbon (SCC)—provides a framework for comparing ecological benefits with development costs (Stern, 2007; Tol, 2005). This approach supports evidence-based decision-making and can inform strategies for internalizing environmental costs (Nguyen et al., 2024).

Despite growing interest in urban ecosystem services, few studies have comprehensively modeled and economically valued the impacts of land use change on carbon storage in rapidly urbanizing cities like Tehran (Malekzadeh et al., 2025; Varshney et al., 2022). Most existing research has focused on either current carbon stocks or historical land use trends, with limited attention to future scenarios and integrated valuation approaches.

To fill existing gaps in understanding how rapid urbanization affects carbon storage over time and space in megacities such as Tehran, this study applies a cloud-based analytical framework designed to improve both accuracy and scalability. In semiarid urban regions like Tehran, where the pace of development has often outstripped integrated modeling efforts, such an approach is particularly valuable. The analysis was conducted using the Google Earth Engine (GEE) platform, which is well known for its ability to combine large volumes of satellite data with machine learning algorithms while avoiding the heavy computational demands of conventional desktop processing (Phan et al., 2020).

Land use and land cover (LULC) changes were identified across four decades—1994, 2004, 2014, and 2024—by applying the Random Forest classifier to high-resolution Landsat imagery, enhanced through spectral indices and topographic variables. Compared with traditional supervised methods such as maximum likelihood classification, the Random Forest approach achieved notably higher accuracy, consistent with findings from other urban studies (Amani et al., 2020). Beyond improving processing efficiency, this workflow supports rapid and automated assessment of Tehran’s landscape dynamics and provides insight into challenges related to informal urban expansion and climate vulnerability.

Building on this foundation, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is utilized to simulate variations in carbon stocks across key reservoirs—aboveground and belowground biomass, soil organic matter, and dead organic material—under evolving urban scenarios (Sharp et al., 2020). Economic valuation is then performed by incorporating global carbon market benchmarks, translating biophysical changes into monetary terms to highlight trade-offs and opportunities for low-carbon development. Outputs are visualized through detailed spatiotemporal maps for each period and LULC category, facilitating granular insights into urban expansion's impacts on ecosystem services. This holistic approach advances beyond static inventories by providing a predictive, policy-oriented toolset that empowers urban planners and decision-makers to embed sustainability into growth strategies, ultimately fostering resilience in emerging megacities.

The primary objective of this study is to develop and validate a replicable framework for assessing and valuing the effects of urban development on carbon storage services, with a specific focus on Tehran. To achieve this, the research integrates remote sensing and machine learning techniques within the Google Earth Engine platform to produce multi-temporal land use and land cover maps, capturing long-term patterns of urban expansion. The InVEST carbon model is then employed to simulate the dynamics of carbon pools and estimate both sequestration potential and associated losses. In parallel, the study aims to derive economic valuations and actionable recommendations, such as incentive-based green infrastructure strategies, to mitigate environmental degradation while advancing broader climate and urban sustainability goals.

Materials and methods

Study area

Tehran, the capital of Iran, lies between the rugged Alborz Mountains to the north and the vast Markazi Desert to the south, forming an urban landscape that has evolved through both its distinctive topography and a long historical process of expansion. The city now covers approximately 733 square kilometers, and its elevation varies sharply—from about 900 meters in the southern plains to nearly 1,800 meters in the foothills. This steep gradient produces noticeable differences in climate and environmental conditions between the northern and southern districts, shaping patterns of development, vegetation, and air quality across the metropolis (Zarandi et al., 2021; Afarideh et al., 2023).

Figure 1 illustrates the geographic location of the Tehran metropolis that situated between 35° 35' to 35° 51' N latitude and 51° 4' to 51° 33' E longitude, Tehran is flanked by the plains of Shahriar and Varamin to the south and southwest, and bordered by steep mountain ranges in the north and east (Ramyar et al., 2019). Hydrologically, the Karaj and Jajroud rivers demarcate the western and eastern edges of the urban expanse, converging toward the southeastern drylands near the Namak Desert. Tehran’s evolution from a modest pre-Qajar town into Iran’s largest city has been marked by rapid demographic growth. Historical census data reflects a surge from approximately 1.56 million inhabitants in 1946 to 9.1 million residents by 2024, as reported by the Tehran Province Planning and Management Organization (Management and Planning Organization, 2024; Iran Statistical Center, 2016). Tehran contains over 56,000 hectares of green spaces, both within and surrounding its built-up areas. Presently, urban green space per capita stands at 16.33 m², complemented by 6.9 m² per capita of parks and recreational zones distributed among 2,366 public spaces across the metropolis (Tehran City Statistical Yearbook, 2024). This distinctive interplay between natural topography, urban expansion, and ecological structures situates Tehran as a pivotal subject for research in metropolitan resilience, urban planning, and sustainability—particularly within the context of rapidly transforming Middle Eastern megacities.

Research methodology

This research is conducted based on the stages and phases outlined briefly in Fig. 2. The model and methods used are summarized below.

Preparation of Land Use/Land Cover map

To construct a comprehensive Land Use/Land Cover (LU/LC) profile for Tehran spanning the period 1994 to 2024, a multi-temporal analysis of Landsat satellite datasets was performed using Google Earth Engine (GEE). This included imagery from the Thematic Mapper (TM) for 1994 and 2004, Enhanced Thematic Mapper Plus (ETM+) for 2014, and Operational Land Imager (OLI) for 2024, all accessed via the United States Geological Survey (USGS) Earth Explorer catalog integrated within GEE (Table 1).

Table 1
Image processing information

Year	Image source	Sensor	Training sample number	Kappa cofficient
1994	USGS Landsat 5 Level 2, Collection 2, Tier 1	TM	3536	0.8
	ALOS DSM: Global 30m v4.1			
2004	USGS Landsat 5 Level 2, Collection 2, Tier 1	TM	36525	0.92
	ALOS DSM: Global 30m v4.1			
2014	USGS Landsat 7 Level 2, Collection 2, Tier 1	ETM+	3579	0.86
	ALOS DSM: Global 30m v4.1			
2024	USGS Landsat 8 Level 2, Collection 2, Tier 1	OLI/TIRS	2059	0.94
	ALOS DSM: Global 30m v4.1			

The preprocessing stage was carried out entirely within the Google Earth Engine (GEE) environment. It began with automated atmospheric correction using the Surface Reflectance (SR) products supplied by the USGS. These datasets apply the LEDAPS algorithm for Landsat 5/7 and LaSRC for Landsat 8/9, helping to normalize pixel values and reduce the influence of atmospheric noise (Shrestha et al., 2019; Vermote et al., 2016; Balist et al., 2022). To further refine image quality, cloud masking was performed using the CFMask procedure, followed by temporal compositing to create median, cloud-free mosaics and geometric co-registration to maintain spatial alignment among scenes (Gorelick et al., 2017). Together, these steps ensured that the multi-decadal imagery was consistent and reliable for subsequent machine-learning analysis.

Following preprocessing, an initial unsupervised classification using the Iterative Self-Organizing Data Analysis Technique (ISODATA) was applied within GEE to delineate preliminary LU/LC clusters. To refine feature extraction, index-based segmentation was performed leveraging multiple spectral indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Bare Soil Index (BSI) and Normalized Difference Water Index (NDWI), facilitating the accurate identification of Regions of Interest (RoIs) for training samples across ecological and urban land features.

Following the preprocessing stage, supervised classification was carried out using machine learning techniques, with a particular focus on the Random Forest (RF) algorithm. This model, originally developed by Breiman (2001), uses an ensemble of decision trees to assign pixels to land-cover categories based on their spectral, textural, and topographic attributes (Bilotta et al., 2025; Bill Donatien et al., 2024). Within the GEE JavaScript API, the RF model was trained using a balanced set of regions of interest (RoIs)—typically ranging from 500 to 1,000 samples per class—derived from high-resolution reference imagery. The model employed 100 decision trees, a minimum leaf size of five, and out-of-bag error estimation to fine-tune performance and minimize overfitting. This approach allowed for the clear separation of four dominant land-use categories: urban built-up areas, barren or unvegetated lands, vegetated green zones, and water bodies.

Classification outputs were validated through a protocol, cross-referencing with high-resolution Google Earth imagery, geolocated GPS checkpoints, and existing LU/LC maps for Tehran. Accuracy assessments, including overall accuracy, user's and producer's accuracies, and the Kappa coefficient, were computed using GEE's built-in confusion matrix tools. Kappa values exceeding 0.85 indicated strong agreement between the machine learning-derived maps and ground truth data, validating the robustness of the GEE-based workflow (Tesfaye et al., 2024; Shoja et al., 2025). This section details the modeling of land use and land cover changes within the Tehran metropolitan area. The analysis for the years 1994, 2004, 2014, and 2024 was conducted using the Google Earth Engine and a machine learning approach.

Carbon Reservoirs and Soil Organic Carbon Estimation

To investigate the spatial distribution of soil organic carbon (SOC) reservoirs across Tehran’s urban landscape, a total of sixty-six soil samples were systematically collected from various public parks and green spaces, as depicted in the accompanying Fig. 4. These samples served as the foundation for generating a detailed SOC mapping layer.

The organic carbon content of each sample was quantified under controlled laboratory conditions and expressed as mass per unit surface area (tons per hectare). SOC content was calculated as Eq. 1 (Yu et al., 2009):

$$\text{SOC (ton/ha)} = \frac{\%OC * BD * D}{100} * 10{,}000\ \text{m}^2\ \text{ha}^{-1} \quad (1)$$

Where:

- **%OC** refers to the percentage of organic carbon in the soil sample,
- **BD** denotes the bulk density of the soil (measured in Mg/m^2),
- **D** represents soil depth (in millimeters).

This equation ensures the integration of both compositional and physical soil characteristics, enabling precise estimation of carbon stocks within the surface soil layer. The derived SOC values contribute to understanding the carbon sequestration capacity of urban green spaces and their potential role in climate mitigation strategies.

Carbon sequestration and storage ecosystem service model

Terrestrial carbon storage potential is predominantly determined by four primary reservoirs: above-ground biomass, below-ground biomass, soil organic carbon, and dead organic matter. The InVEST carbon sequestration and storage model quantifies carbon stored within these pools based on user-supplied Land Use/Land Cover (LU/LC) maps and classifications.

Above-ground biomass comprises all living vegetation above the soil surface, including stems, branches, and leaves. Below-ground biomass consists of living root systems. Soil organic carbon, representing the most substantial terrestrial carbon reservoir, reflects the organic fraction of soil. Dead organic matter includes decomposing litter, fallen leaves, and standing deadwood.

Leveraging spatial land cover data, the model estimates the net carbon accumulation over time and its monetized ecosystem value, accounting for changes in land cover types and carbon content per reservoir. However, it operates under simplifying assumptions, such as a linear rate of sequestration, a fixed discount rate, and exclusion of biophysical parameters like photosynthetic intensity or soil microbial activity. These omissions may constrain ecological accuracy.

Raster-based LU/LC inputs such as forest, cropland, and pasture enable pixel-level estimation of carbon storage density. The model outputs include: (1) total carbon stock, (2) net carbon sequestration, (3) economic valuation, and (4) aggregated raster maps. Accuracy improves when data on multiple reservoirs are available for each LU/LC class.

The model compares current and future landscape scenarios to compute sequestration dynamics, producing per-pixel change maps that reflect carbon stock fluctuations and their associated societal valuation.

Model Equations

Carbon inventory estimation follows established carbon accounting principles (Ortas et al., 2016). The annual change in carbon stock across all LU/LC categories is calculated as Eq. 2:

$$\Delta C_{AFOLU} = \Delta C_{FL} + \Delta C_{CL} + \Delta C_{GL} + \Delta C_{WL} + \Delta C_{SL} + \Delta C_{OL} \quad (2)$$

Where:

- ΔC = Total annual carbon change
- AFOLU = Agriculture, Forestry, and Other Land Uses
- FL, CL, GL, WL, SL, OL = Land use categories: Forest, Cultivation, Grassland, Wetland, Settlement, and Others

Carbon change per LU/LC type is determined via reservoir-level aggregation is calculated as Eq. 3:

$$\Delta C_{LUi} = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta C_{SO} \quad (3)$$

- AB = Above-ground biomass
- BB = Below-ground biomass
- DW = Dead wood
- LI = Leaf litter
- SO = Soil organic matter

Net carbon sequestration across a temporal span is calculated using the inventory-difference technique as Eq. 4:

$$\Delta C = \frac{(C_{t2} + C_{t1})}{(t_2 - t_1)} \quad (4)$$

Where:

- ΔC = Annual carbon change (tons/year)
- C$_1$, C$_2$ = Carbon inventory at the start and end of the period

Required Input Data

All spatial datasets must be in projected coordinate systems and use meters for linear units.

- Current LU/LC Raster: A geospatial raster where each pixel is assigned an integer representing a distinct LU/LC class. These codes must match entries in the Carbon Pool table.
- Reference Calendar Year: Indicates the temporal scope of the current LU/LC data for valuation and sequestration calculation.
- Carbon Reservoir CSV Table: Contains carbon densities for four reservoirs for each LU/LC class. If certain data are unavailable, placeholder zeroes may be used (Table 2).

Table 3
CSV Table

Column	Description	Unit
LUcode	Unique integer per land cover class	Integer
c_above	Above-ground biomass density	Mg/hectare
c_below	Below-ground biomass density	Mg/hectare
c_soil	Soil organic carbon density	Mg/hectare
c_dead	Dead organic matter density	Mg/hectare

For valuation purposes, a base price of US$35 per tonne of carbon was chosen. This figure was chosen based on average global values for carbon and was consistent with previous studies in developing countries (Goulder and Williams., 2012). A discount rate of 2% (Rennert & Kingdon., 2019) was used to account for the time value of money as well as perceptions of intergenerational equity (i.e., the value of money today compared to the future). It was also assumed that the price of a unit of carbon would increase by 3% annually (Pache et al., 2020)—an assumption adjusted for global trends of increasing carbon regulations, the growth of carbon markets, and likely inflation. With this set of assumptions, the economic value of carbon storage is reflected in a way that takes into account both current market conditions and future expectations.

Results and discussion

Land use/Land cover change

Figure 3 presents a visual representation of land use and land cover (LU/LC) dynamics across the study period from 1994 to 2024.

Table 3 provides a quantitative breakdown of LU/LC transitions over four decadal intervals. During this thirty-year period, green spaces in Tehran experienced a noticeable decline—from 14.19% of the total urban area in 1994 to 11.87% in 2024. This reduction was more pronounced in the initial decades: approximately 700 hectares were lost between 1994 and 2004, followed by a similar loss over the second ten-year interval. However, in the final decade (2014–2024), the rate of decline slowed considerably, with green space reduction amounting to only 10 hectares. These findings suggest that the pressure on green spaces was highest during the early phases of urban expansion.

Barren lands, primarily located in peri-urban zones and interstitial spaces with minimal vegetation, also diminished considerably over the study period. These areas were progressively repurposed to accommodate urban infrastructure, becoming the principal source for land conversion. Notably, approximately 7,000 hectares of barren land underwent transition to built-up uses between 1994 and

2004. This figure decreased to 4,000 hectares between 2004 and 2014, and slightly increased to 4,300 hectares in the final period, indicating continued but gradually tapering urban land demand.

Table 3
Land use changes in Tehran city from1994-2024

	1994 ha	%	2004 ha	%	2014 ha	%	2024 ha	%
Water Bodies	59	0.09	95	0.15	41	0.06	168	0.2
Green Areas	8706	14.1	8012	13	7295	11.8	7284	11.8
Built-Up Area	22907	37.3	30677	50	35520	57.9	39726	64.7
Bare land	29673	48.3	22560	36.7	18488	30.1	14166	23
Sum	61345	100	61345	100	61345	100	61345	100

Urban expansion into previously undeveloped or ecologically functional land has been the predominant driver of LU/LC transformation. Built-Up areas expanded by approximately 7,500 hectares in the first decade (1994–2004), followed by 5,000 hectares in the second, and 4,000 hectares in the final ten-year interval. Apart from minor allocations of land to water bodies, most land conversion activities drew from barren lands initially, with increasing encroachment into green areas—particularly private gardens and semi-natural zones—in later years.

These patterns reveal the cumulative impact of rapid urbanization on natural and semi-natural landscapes, highlighting the need for robust land management strategies to safeguard remaining green infrastructure in Tehran metropolis.

Carbon sequestration model

Figure 4 illustrates the spatial distribution of soil organic carbon (SOC) across the study area, modeled as a function of soil depth, bulk density, and organic carbon percentage. These input parameters were derived from empirical data.

Carbon Reservoirs and Land Cover Typologies

Table 4 outlines the estimated carbon densities within four principal carbon reservoirs—above-ground biomass, below-ground biomass, soil organic matter, and dead organic material—across distinct land use/land cover (LU/LC) classes. Each value is expressed in metric tons per hectare (Mg/ha).

Table 4
Carbon Pool Densities per LULC Class (Mg/hectare)

LUcode	LU/LC class	C_above (Mg/ha)	C_below (Mg/ha)	C_soil (Mg/ha)	C_dead (Mg/ha)
1	Water	0	5.00	0	0
2	Green area	11.00	2.00	65.00	1.10
3	Built-up	4.00	5.00	15.00	1.00
4	Bareland	0.40	0.83	58.00	0

The outputs of the InVEST carbon storage and sequestration model are presented in raster format, with each pixel representing a cell-specific carbon stock expressed in Mg/cell. These maps reveal the spatial variation in carbon sequestration potential throughout the Tehran metropolis. Values ranged from 0.45 Mg/cell at the lower end, typically associated with barren or impervious surfaces, to 7.119 Mg/cell in areas with dense vegetation and high organic soil content. Comparative analysis of the carbon maps highlights areas of significant carbon accumulation versus regions with minimal sequestration capacity. These spatial patterns are crucial for identifying priority zones for conservation and strategic urban planning, especially in the context of enhancing urban carbon sinks (Fig. 5).

Spatiotemporal Variations in Carbon Sequestration

Figure 6 illustrates the dynamic changes in carbon sequestration across four distinct intervals between 1994 and 2024. The quantified values—expressed in metric tons—reflect both positive and negative fluctuations. Positive values denote net carbon uptake through vegetative or ecological restoration processes, whereas negative values indicate carbon loss attributable to anthropogenic activities such as deforestation, land conversion, or urban expansion. Spatial distribution patterns of carbon change closely correspond with significant alterations in land use and land cover. Areas exhibiting the most extreme values—either positive or negative—highlight regions of pronounced ecological transition. As demonstrated in Fig. 6, green-shaded zones represent enhanced carbon sequestration and storage, while red-shaded areas reveal net reductions in stored carbon due to environmental degradation. This analysis provides critical insight into the influence of land management practices on atmospheric carbon dynamics and offers an evidence-based foundation for targeted climate mitigation strategies at the regional scale.

Changes in the Economic Value of Carbon Sequestration

As mentioned in the methodology section, the economic valuation of carbon stocks was based on $35 per ton, which is consistent with regional conditions and the global average for carbon markets. This value was considered to be the midpoint between the highly variable global market prices—from over $80 in the formal EU markets to less than $1 in voluntary markets—to maintain comparability with international studies. Also, to account for the time dimension of carbon value, a discount rate of 2% and

an annual growth rate of 3% were used to reflect changes in economic value over the assessment period (Goulder & Williams, 2012; Pache et al., 2020; World Bank, 2023).

Figure 7 presents the spatial distribution of changes in carbon-related economic value across the study intervals. The map highlights areas where the monetary value of carbon stocks has fluctuated due to ecological transitions and land-use dynamics. Purple-shaded regions denote a decline in economic value, either from reduced carbon storage or complete carbon loss. Across the landscape, these changes span a spectrum between USD − 181 and USD + 181, reflecting variations in sequestration performance and ecosystem service delivery.

This spatially explicit evaluation provides crucial insight into the interplay between environmental management and carbon market economics. Despite using an economic valuation approach to quantitatively compare changes in ecosystem services, it should be noted that monetizing these services is a controversial issue and cannot replace broader environmental and social values. As Gómez-Baggethun and Ruiz-Pérez (2011) have pointed out, linking ecosystem management to market logic may ignore non-economic aspects of sustainability. Therefore, the results of this study should be interpreted within a balanced and multidimensional framework in which economic value is only one dimension of environmental decision-making.

Impacts of Land Use Dynamics on Carbon Loss and Economic Valuation

Over the three-decade span from 1994 to 2024, extensive land use transformations within Tehran have resulted in substantial carbon emissions. Specifically, the release of > 280,000 metric tonnes of carbon, corresponding to an economic loss of approximately USD 7,600,000, has been recorded. During the 2004–2014 interval, ~ 177,000 tonnes of carbon were emitted, translating into USD > 4,800,000 in foregone sequestration value. The period from 2014 to 2024 saw an additional loss of 151,000 tons, valued at > USD 4,100,000 (Table 5).

These figures underscore the profound influence of unregulated urban expansion and construction activities, which have systematically encroached upon green spaces and previously undeveloped lands. Despite municipal initiatives aimed at restoring urban vegetation and promoting green infrastructure, the scale and intensity of built-area development have largely offset potential ecological gains.

The data presented herein reinforces the urgency of implementing land use policies that prioritize carbon-sensitive planning and integrate ecosystem service valuation into urban development frameworks. Without corrective action, the economic and environmental costs associated with unchecked expansion may continue to rise, undermining Tehran’s climate resilience strategies.

Table 5
Decadal Trends in Carbon Sequestration and Its Economic Valuation

Description/year	1994	2004	2014	2024
Total Sequestered Carbon (1000 Mg of C)	3017	2737	2560	2409
Change in Carbon (1000 Mg of C)	-280	-176	-151	
Net present value (USD)	-7626000	-4814000	-4112000	

The results of this study, compared with similar studies in other cities around the world, show that the reduction of green spaces and the subsequent decline in carbon sequestration and storage capacity is a global phenomenon, but its severity is more significant in Tehran. In this study, the reduction in the share of green spaces from 14.19% to 11.87% over three decades (1994 to 2024) caused a significant decrease in carbon storage and an economic loss of more than $7.6 million. In Shenzhen, China, Wang et al. (2024) used the CASA and InVEST models to show that the total carbon storage of green spaces between 2008 and 2022 was in the range of 7.17 to 7.42 million tons, with significant spatial variations between the western and eastern parts of the city; while the InVEST model is less accurate in built-up areas. In Noida, India, Sharma et al. (2024) reported using multitemporal satellite imagery and the InVEST model that the rapid expansion of construction between 2011 and 2019 significantly reduced the carbon sequestration capacity and its economic value in the projected scenario of 2027. In Beijing, Cao et al. (2025) showed that the carbon density of urban green spaces is strongly dependent on the vegetation structure, and increasing the density of trees and shrubs improves the accuracy of modeling and carbon estimation. Overall, while cities such as Shenzhen, Noida, and Beijing have also faced a decrease or fluctuation in carbon storage due to urban development, the intensity of the conversion of wasteland to construction and the gradual encroachment of development into private gardens and semi-natural spaces in Tehran, along with heavy economic losses, indicate a more critical situation for this city. The findings of this study, in line with global literature, emphasize the need for careful land use policymaking and the development of green infrastructure to restore urban carbon sinks, especially in semi-arid regions.

Moreover, the application of the InVEST model allowed for a spatially explicit valuation of carbon reservoirs and highlighted zones where conservation or restoration efforts could yield tangible climate benefits. The sharp decline in net present value of carbon stocks—exceeding USD 7.6 million over the study period—illustrates how development-driven carbon emissions erode not only environmental stability but also economic opportunities tied to ecosystem services. The consistency of carbon loss in areas undergoing artificial land conversion further reinforces the importance of strategic planning and data-driven environmental management to balance urban growth with climate mitigation objectives.

Conclusions

This study provides a comprehensive understanding of the dynamics of land use change across the Tehran urban region over a 30-year period. The accelerated decline of green and barren lands,

particularly between 1994 and 2014, coincided with rapid population growth, rural-to-urban migration, and intense demand for urban expansion. The geographical constraints imposed by mountainous terrain, limited land availability, and saturation of development capacity have emerged as critical challenges for horizontal growth in recent years. Consequently, urban vertical expansion—through high-rise construction—has gained prominence as a compensatory strategy. Moreover, demographic shifts and economic pressures have further impacted the city's developmental trajectory, with slower population growth and fiscal constraints contributing to reduced construction intensity.

In parallel, the increasing prioritization of urban green spaces reflects a strategic pivot toward environmental sustainability. Green infrastructures not only mitigate air pollution and heat island effects, but they also enhance overall urban livability. A key contribution of this study lies in its application of the InVEST carbon sequestration and storage model, which spatially quantifies ecosystem services and highlights the value of vegetated landscapes. These patterns reveal the cumulative impact of rapid urbanization on natural and semi-natural landscapes, highlighting the need for robust land management strategies to safeguard remaining green infrastructure in Tehran metropolis. The substantial decrease in carbon stock and its economic valuation underscore the pressing need for data-driven urban planning strategies that integrate climate resilience. As terrestrial ecosystems act as critical carbon reservoirs, their preservation plays a pivotal role in achieving sustainable development goals. Hence, the findings of this research can inform land use scenarios, policy interventions, and ecological restoration efforts that reinforce Tehran's capacity to adapt to climate challenges and maintain ecosystem functionality.

Declarations

Conflict of Interest

The authors declare no conflict of interest.

References

1. Afarideh F, Ramasht MH, Mortyn G (2023) Air pollution and topography in Tehran. AUC Geogr 58(2):157–171. https://doi.org/10.14712/23361980.2023.12
2. Alibakhshi Z, Ahmadi M, Farajzadeh Asl M (2020) Modeling biophysical variables and land surface temperature using the GWR model: case study—Tehran and its satellite cities. J Indian Soc Remote Sens 48(1):59–70. https://doi.org/10.1007/s12524-019-01062-x
3. Amani M, Ghorbanian A, Ahmadi SA, Kakooei M, Moghimi A, Mirmazloumi SM, Moghimi P, Sobhan M, Ebrahimy H, Khosravi H, Brisco B (2020) Google Earth Engine cloud computing platform for remote sensing big data applications: A comprehensive review. IEEE J Sel Top Appl Earth Observations Remote Sens 13:5326–5350. https://doi.org/10.1109/JSTARS.2020.3021052
4. Arcidiacono A, Ronchi S, Salata S (2015) Ecosystem Services assessment using InVEST as a tool to support decision making process: critical issues and opportunities. In Computational Science and

Its Applications–ICCSA 2015: 15th International Conference, Banff, AB, Canada, June 22–25, 2015, Proceedings, Part IV 15 (pp. 35–49). Springer International Publishing

5. Balist J, Malekmohammadi B, Jafari HR, Nohegar A, Geneletti D (2022) Detecting land use and climate impacts on water yield ecosystem service in arid and semi-arid areas. A study in Sirvan River Basin-Iran. Appl Water Sci 12(1):4. https://doi.org/10.1007/s13201-021-01545-8
6. Baró F, Chaparro L, Gómez-Baggethun E, Langemeyer E, Nowak DJ, Terradas J (2014) Contribution of Ecosystem Services to Air Quality and Climate Change Mitigation Policies: The Case of Urban Forests in Barcelona, Spain. Ambio 43:466–479
7. Baró F, Haase D, Gómez-Baggethun E, Frantceskaki N (2015) Mismatches between ecosystem services supply and demand in urban areas: A quantitative assessment in five European cities. Ecol Ind 55:146–158
8. Berglihn E, Gómez-Baggethun E (2021) Ecosystem services from urban forests: the case of Oslomarka, Norway. *Ecosystem Services* 51 (2021) 101358
9. Bill Donatien LM, Clobite B, B., Lemvo M, Midel M (2024) Comparing Sentinel-2 and Landsat 9 for land use and land cover mapping assessment in the north of Congo Republic: a case study in Sangha region. Int J Remote Sens 45(22):8015–8036. https://doi.org/10.1080/01431161.2024.2394238
10. Bilotta G, Barrile V, Bibbò L, Meduri GM, Versaci M, Angiulli G (2025) Enhancing land cover classification: Fuzzy similarity approach versus random forest. Symmetry 17(6):929. https://doi.org/10.3390/sym17060929
11. Bolund P, Hunhammar S (1999) Ecosystem services in urban areas. Ecol Econ 29:293–301
12. Breiman L (2001) Random forests. Mach Learn 45:5–32. https://doi.org/10.1023/A:1010933404324
13. Cao Y, He X, Wang C, Fang Y (2025) Estimation of carbon density in different urban green spaces: Taking the Beijing main district as an example. Land 14(2):270. https://doi.org/10.3390/land14020270
14. Costanza R, d'Arge R, De Groot R, Farber S, Grasso M, Hannon B, Van Den Belt M (1998) The value of ecosystem services: putting the issues in perspective. Ecol Econ 25(1):67–72. https://doi.org/10.1016/S0921-8009(98)00019-6
15. Estruch C, Curcoll R, Morguí JA, Segura-Barrero R, Vidal V, Badia A, Villalba G (2024) Exploring how the heterogeneous urban landscape influences CO2 concentrations: The case study of the Metropolitan Area of Barcelona. Urban Forestry Urban Green 99:128438. https://doi.org/10.1016/j.ufug.2024.128438
16. Feddema JJ, Oleson KW, Bonan GB, Mearns LO, Buja LE, Meehl GA, Washington WM (2005) The importance of land-cover changes in simulating future climates. Science 310(5754):1674–1678. https://doi.org/10.1126/science.1118160
17. Felzer BS (2025) Modeling the future carbon sink: Land-use and climate change may offset CO2 fertilization in the United States. Plants People Planet 7(3):763–775. https://doi.org/10.1002/ppp3.10582

18. Georgiou K, Angers D, Champiny RE, Cotrufo MF, Craig ME, Doetterl S, Wieder WR (2025) Soil carbon saturation: what do we really know? Glob Change Biol 31(5):e70197. https://doi.org/10.1111/gcb.70197
19. Gómez-Baggethun E, Ruiz-Pérez M (2011) Economic valuation and the commodification of ecosystem services. Progress Phys Geography: Earth Environ 35(5):613–628. https://doi.org/10.1177/0309133311421708
20. Gómez-Baggethun E, Barton DN (2013) Classifying and valuing ecosystem services for urban planning. Ecol Econ 86:235–245
21. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens Environ 202:18–27. https://doi.org/10.1016/j.rse.2017.06.031
22. Goulder LH, Williams RC III (2012) The choice of discount rate for climate change policy evaluation (NBER Working Paper No. 18301). National Bureau of Economic Research. https://doi.org/10.3386/w18301
23. Hazrati M, Malakoutikhah Z (2019) An unclear future for Iranian energy transition in light of the Re-imposition of sanctions. Oil Gas Energy Law, *17*(1)
24. He C, Zhang D, Huang Q, Zhao Y (2016) Assessing the potential impacts of urban expansion on regional carbon storage by linking the LUSD-urban and InVEST models. Environ Model Softw 75:44–58. https://doi.org/10.1016/j.envsoft.2015.09.015
25. Iran Statistical Center (2016) (4 pages). (Persian) https://amar.org.ir/statistical-information/statid/51044
26. Khachoo YH, Cutugno M, Robustelli U, Pugliano G (2024) Impact of land use and land cover (LULC) changes on carbon stocks and economic implications in Calabria using Google Earth Engine (GEE). Sensors 24(17):5836. https://doi.org/10.3390/s24175836
27. Lal P, Thakur P, Nayak L, Adavi SB, Behera L, Altaf MA, Lal MK (2024) Advancing Urban Forest Resilience: Strategies, Challenges, and Innovations in the Face of Climate and Environmental Change. Urban Forests, Climate Change and Environmental Pollution. Springer, Cham, pp 469–480. https://doi.org/10.1007/978-3-031-67837-0_22
28. Lei J, Zhang L, Chen Z, Wu T, Chen X, Li Y (2024) The impact of land use changes on carbon storage and multi-scenario prediction in Hainan Island using InVEST and CA-Markov models. Front Forests Global Change 7:1349057. https://doi.org/10.3389/ffgc.2024.1349057
29. Li S, Bing Z, Jin G (2019) Spatially explicit mapping of soil conservation service in monetary units due to land use/cover change for the Three Gorges Reservoir Area, China. Remote Sens 11(4):468. https://doi.org/10.3390/rs11040468
30. Lisboa MAN, da Silva LVA, da Silva Nascimento A, de Oliveira Silva A, Teixeira MRA, Ferreira MFR, Júnior JTC (2024) Diversity, structure, and carbon sequestration potential of the woody flora of urban squares in the Brazilian semiarid region. Trees Forests People 16:100561. https://doi.org/10.1016/j.tfp.2024.100561

31. Malekzadeh S, Jafari H, Nazari R, Blaschke T, Hof A, Karimi M (2025) Modeling the cooling effect of urban green infrastructures with an ecosystem services approach (case study: Tehran metropolis). Int J Hum Capital Urban Manage 10(2):199–214. https://doi.org/10.22034/IJHCUM.2025.02.01
32. Management and planning organization (2024) (4 pages). (In Persian) https://amar.thmporg.ir/main-topic/99264-population-and-labor/population
33. McPherson EG (1998) Atmospheric carbon dioxide reduction by Sacramento's urban forest. J Arboric 24:215–223
34. Meng N, Wang NA, Zhao L, Liu X, Liu J, Lee SC (2025) Water Use Efficiency of Grassland Ecosystem in Badain Jaran Desert and Its Relations to Biometeorological Variables. Ecosystems 28(3):1–21. https://doi.org/10.1007/s10021-025-00977-6
35. Mohaqeq MS, Mobarghei Dinan N, Vafaeinejad A, Sobhan Ardakani S, Monavvari SM (2020) Assessing the Changes in Tehran'Ecosystems Using the Landscape Metrics and Carbon Sequestration Rates. J Environ Stud 46(1):1–22. https://doi.org/10.22059/jes.2019.282612.1007871
36. Newbold T, Hudson LN, Hill SL, Contu S, Lysenko I, Senior RA, Purvis A (2015) Global effects of land use on local terrestrial biodiversity. Nature 520(7545):45–50. https://doi.org/10.1038/nature14324
37. Nguyen TB, Bahzad HY, Leonzio G (2024) Economic and environmental optimization of a CCUS supply chain in Germany. Processes 12(8):1–23
38. Nowak DJ, Crane DE (2002) Carbon storage and sequestration by urban trees in the USA. Environ Pollut 116:381–389
39. Ortas E, Gallego-Álvarez I, Álvarez I, Moneva JM (2016) Carbon accounting: A review of the existing models, principles and practical applications. Corp carbon Clim Acc 77–98. https://doi.org/10.1007/978-3-319-27718-9_4
40. Pache R-G, Scholz M, Dieterle M (2020) Economic valuation of carbon storage and sequestration in forest ecosystems. Forests 12(1):43. https://doi.org/10.3390/f12010043
41. Phan TN, Kuch V, Lehnert LW (2020) Land cover classification using Google Earth Engine and Random Forest classifier—The role of image composition. Remote Sens 12(15):2411. https://doi.org/10.3390/rs12152411
42. Ramyar R, Zarghami E, Bryant M (2019) Spatio-temporal planning of urban neighborhoods in the context of global climate change: Lessons for urban form design in Tehran, Iran. Sustainable Cities Soc 51:101554. https://doi.org/10.1016/j.scs.2019.101554
43. Rennert K, Kingdon C (2019), August 1 Social cost of carbon 101. Resources for the Future. https://www.rff.org/publications/explainers/social-cost-carbon-101/
44. Sharma R, Pradhan L, Kumari M, Bhattacharya P (2020) Assessment of carbon sequestration potential of tree species in Amity University Campus Noida. *Environmental Sciences Proceedings*, *3*(1), 52. https://doi.org/10.3390/IECF2020-08075
45. Sharma R, Singh A, Kumar P (2024) Spatio-temporal assessment of urban carbon storage and its monetary value in a fast-growing Indian city (Noida). Land 13(9):1387.

https://doi.org/10.3390/land13091387

46. Sharp R, Douglass J, Wolny S, Arkema K, Bernhardt J, Bierbower W, Chalastani VI, Cohen E, DiMarco M, Duarte CM, Dunford R, Heady W, Hunt L, Kennedy E, Knowlton M, Kwon P, Lazzaro S, Lee A, Lippiatt S, Vogl AL (2020) InVEST 3.8.9 user's guide. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund. https://invest-userguide.readthedocs.io/en/latest/
47. Sharp R, Tallis HT, Ricketts T, Guerry AD, Wood SA, Chaplin-Kramer R, Bierbower W (2015) InVEST 3.2. 0 user's guide. Nat capital project, 133
48. Shoja F, Nabikandi V, B., Feizizadeh B (2025) Spatiotemporal analysis of urbanization-driven land use changes in Tehran Province using novel technologies. J Geoscience Environ Prot 8(2). Article 11630. https://doi.org/10.24294/jgc11630
49. Shrestha M, Leigh L, Helder D (2019) Classification of north Africa for use as an extended pseudo invariant calibration sites (EPICS) for radiometric calibration and stability monitoring of optical satellite sensors. Remote Sens 11(7):875. https://doi.org/10.3390/rs11070875
50. Stern N (2007) The economics of climate change: the Stern review. Cambridge University Press
51. Talkhabi H, Ghalehteimouri J, K., Toulabi Nejad M (2024) Integrating Tehran metropolitan air pollution into the current transport system and sprawl growth: an emphasis on urban performance and accessibility. Discover Cities 1(1):6. https://doi.org/10.1007/s44327-024-00008-4
52. Tariq A, Mumtaz F (2023) A series of spatio-temporal analyses and predicting modeling of land use and land cover changes using an integrated Markov chain and cellular automata models. Environ Sci Pollut Res 30(16):47470–47484. https://doi.org/10.1007/s11356-023-25722-1
53. Tesfaye W, Elias E, Warkineh B, Tekalign M, Abebe G (2024) Modeling of land use and land cover changes using google earth engine and machine learning approach: Implications for landscape management. Environ Syst Res 13(31). https://doi.org/10.1186/s40068-024-00366-3
54. Tol RS (2005) The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. Energy policy 33(16):2064–2074. https://doi.org/10.1016/j.enpol.2004.04.002
55. Varshney K, Pedersen Zari M, Bakshi N (2022) Carbon Sequestration and Habitat Provisioning through Building-Integrated Vegetation: A Global Survey of Experts. Buildings 12(9):1458. https://doi.org/10.3390/buildings12091458
56. Vermote E, Justice C, Claverie M, Franch B (2016) Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sens Environ 185:46–56. https://doi.org/10.1016/j.rse.2016.04.008
57. Wang R-Y, Zhou H, Zhang J, Du M (2024) Comparison of the CASA and InVEST models' effects for estimating spatiotemporal differences in carbon storage of green spaces in megacities: A case of Shenzhen, China. Sci Rep 14:55858. https://doi.org/10.1038/s41598-024-55858-0
58. Wang Y, Jiang X, Gao S, Jiang Q, Du H, Han N (2025) Multi-scenario carbon storage analysis based on PLUS model and InVEST model: a case study of Zhejiang province, China. Earth Sci Inf 18(2):192. https://doi.org/10.1007/s12145-024-01683-y

59. World Bank (2023) Carbon pricing dashboard. World Bank Group. https://carbonpricingdashboard.worldbank.org
60. Yearbook of Tehran City Annual Statistical Yearbook of Tehran City 2023. (In Persian)
61. Yin S, Gong Z, Gu L, Deng Y, Niu Y (2022) Driving forces of the efficiency of forest carbon sequestration production: Spatial panel data from the national forest inventory in China. J Clean Prod 330:129776. https://doi.org/10.1016/j.jclepro.2021.129776
62. Yu Y, Guo Z, Wu H, Kahmann JA, Oldfield F (2009) Spatial changes in soil organic carbon density and storage of cultivated soils in China from 1980 to 2000. Glob Biogeochem Cycles 23(2). https://doi.org/10.1029/2008GB003428
63. Zarandi SM, Shahsavani A, Nasiri R, Pradhan B (2021) A hybrid model of environmental impact assessment of PM2. 5 concentration using multi-criteria decision-making (MCDM) and geographical information system (GIS)—a case study. Arab J Geosci 14(3):177. https://doi.org/10.1007/s12517-021-06474-z
64. Zipperer WC, Foresman TW, Walker SP, Daniel CT (2012) Ecological consequences of fragmentation and deforestation in an urban landscape: a case study. Urban Ecosyst 15:533–544. https://doi.org/10.1007/s11252-012-0238-3

Figures

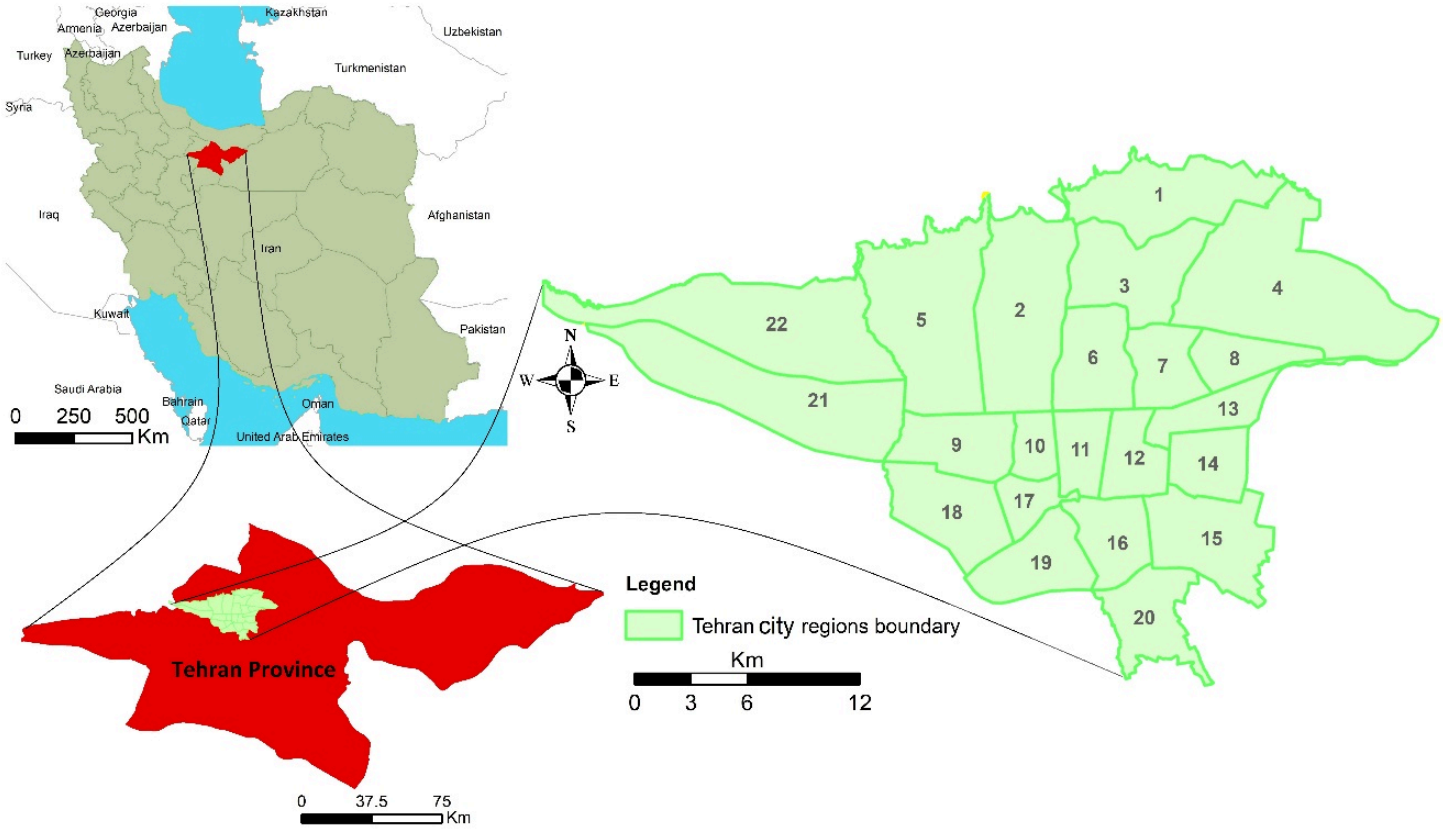


Figure 1

Geographical location of the study area and Tehran’s 22 urban districts

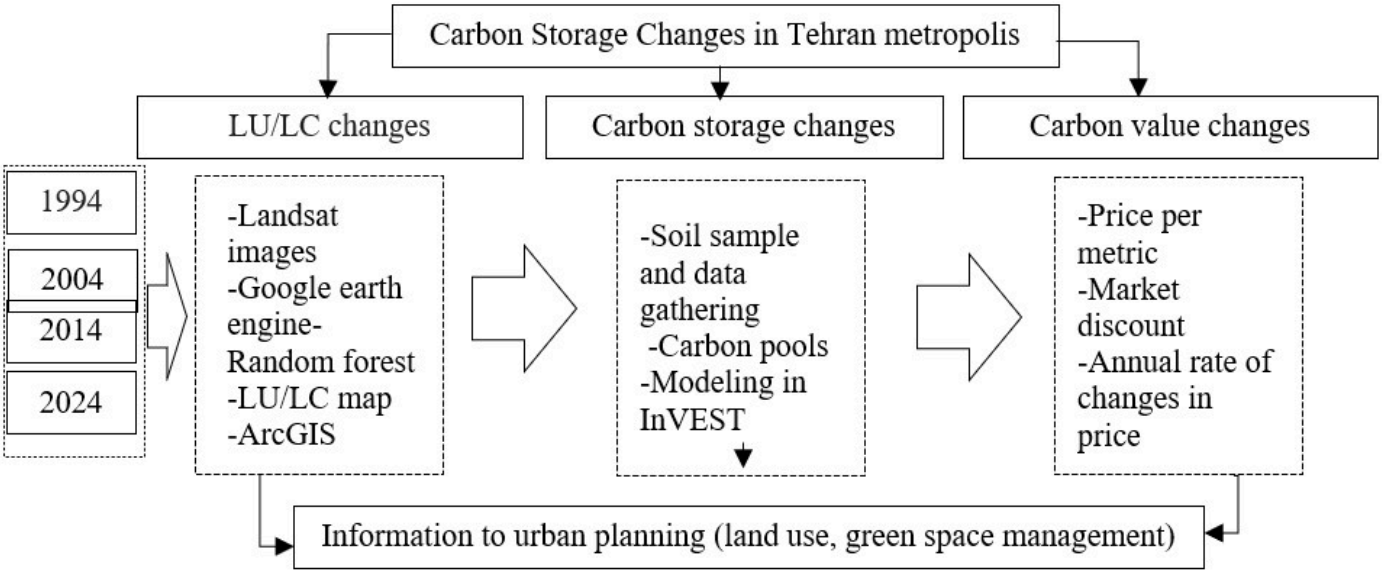


Figure 2

conceptual research model

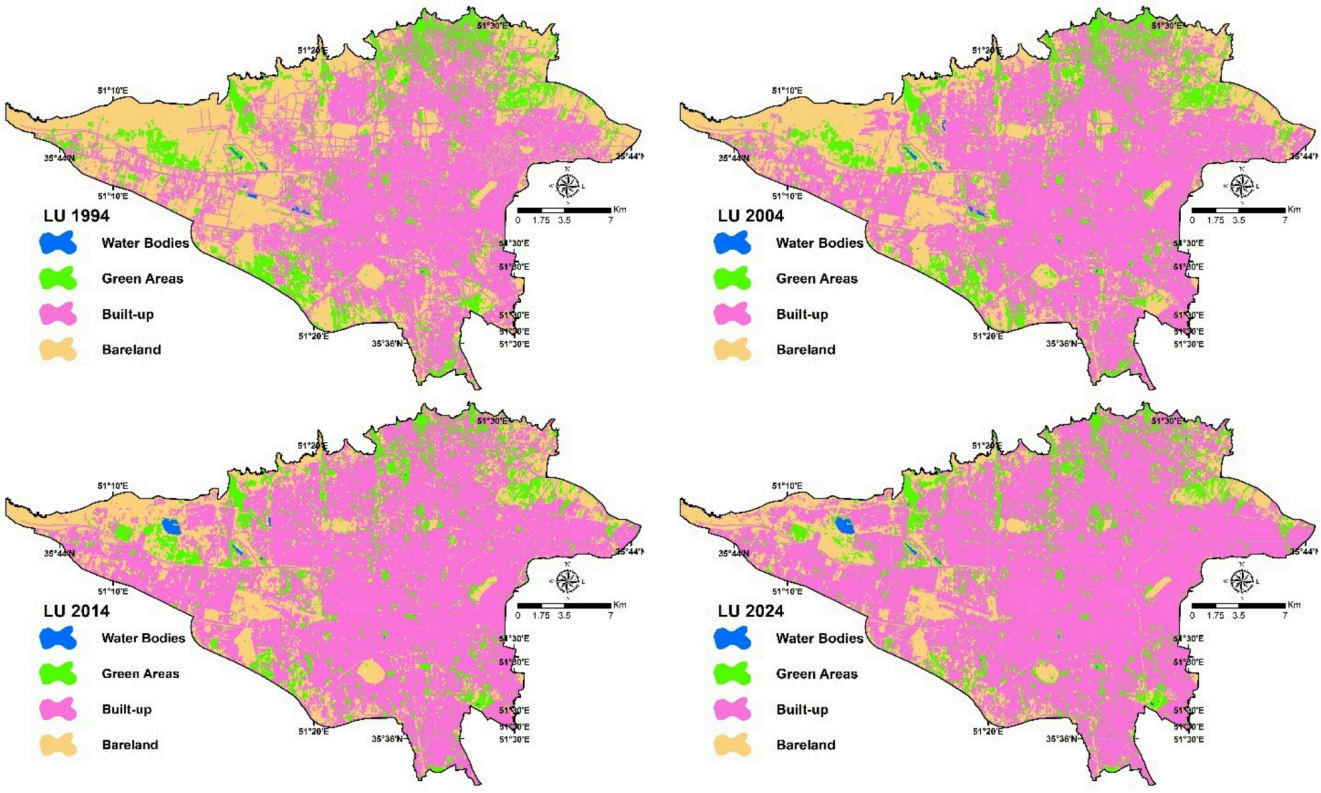


Figure 3

Land use maps of Tehran city from 1994 to 2024

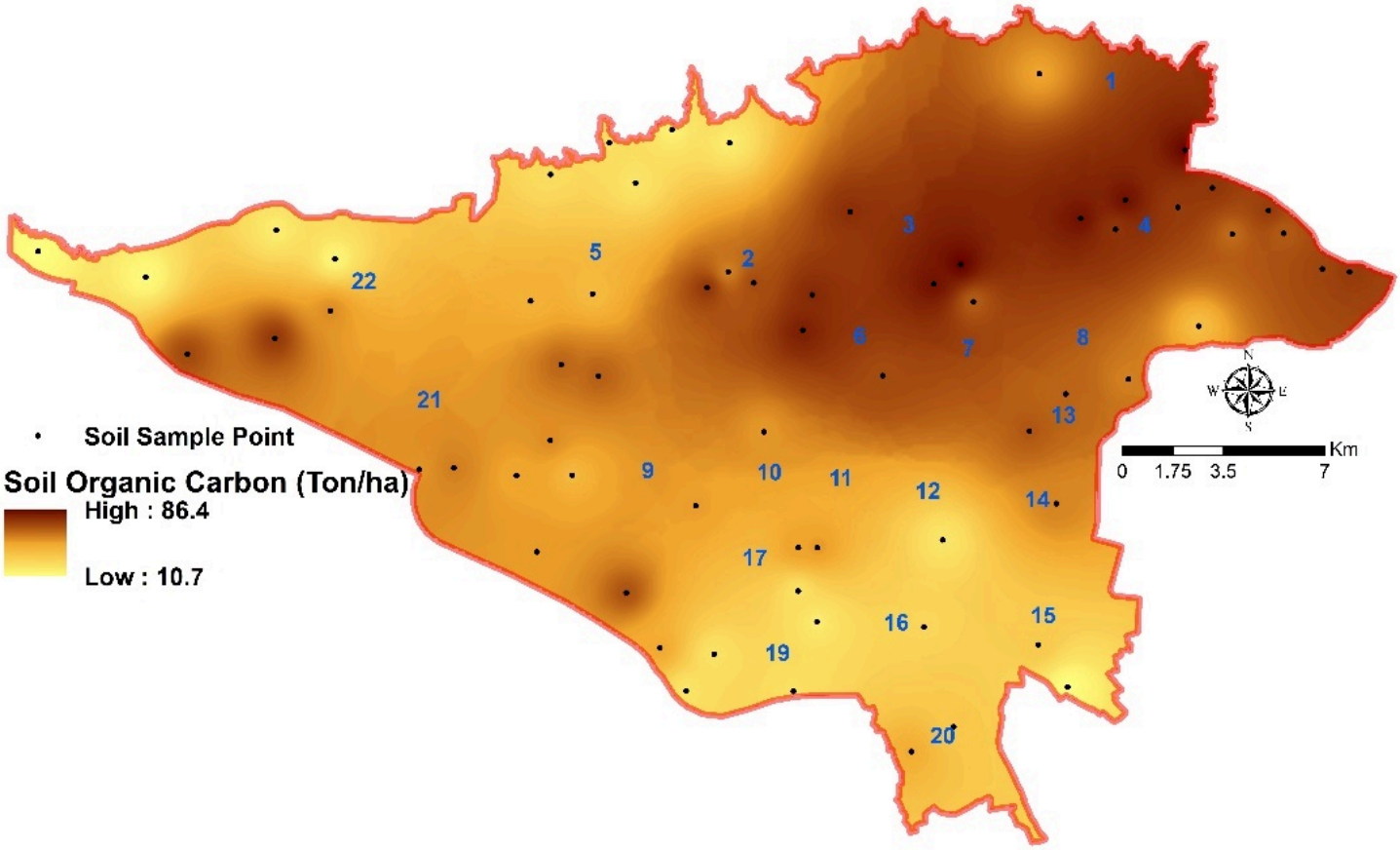


Figure 4

Soil organic carbon map in Tehran city

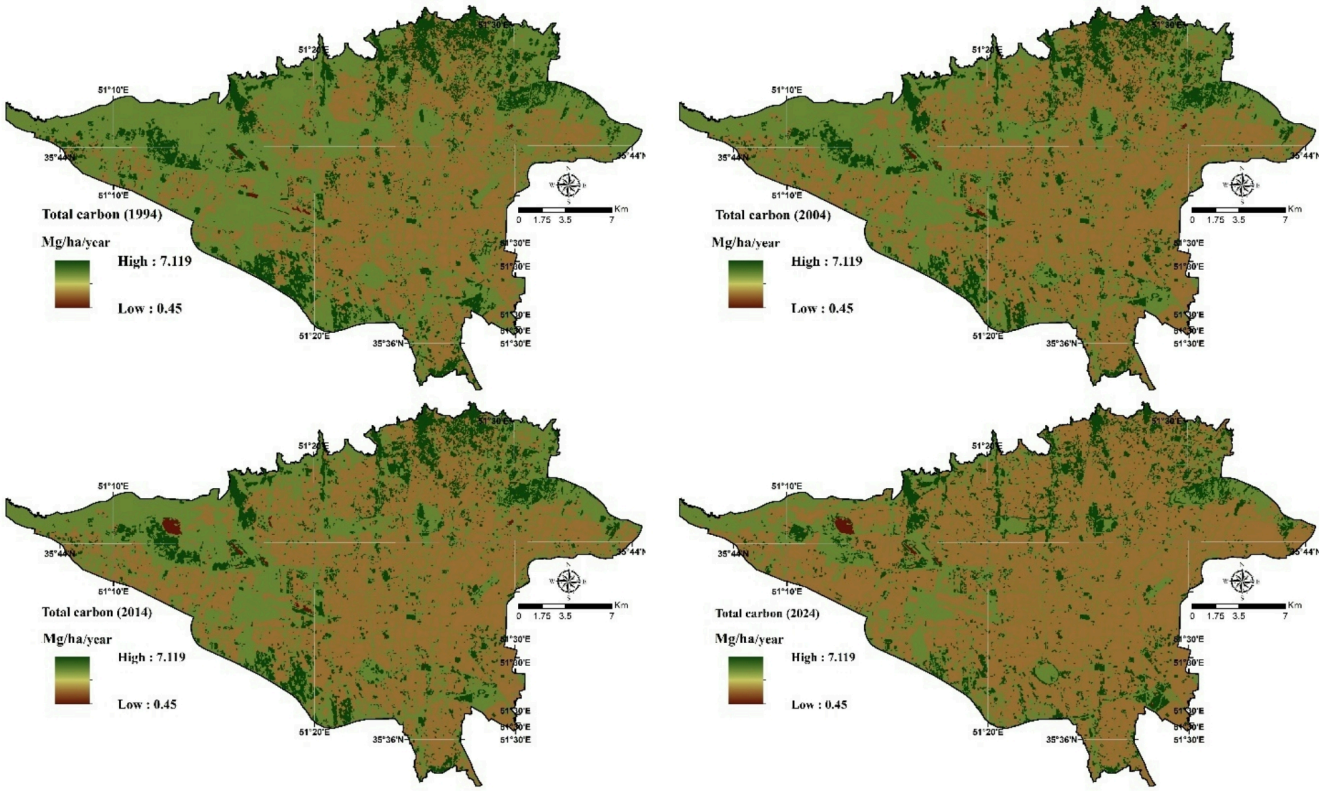


Figure 5

Carbon sequestration potential map in Tehran city from 1994 to 2024

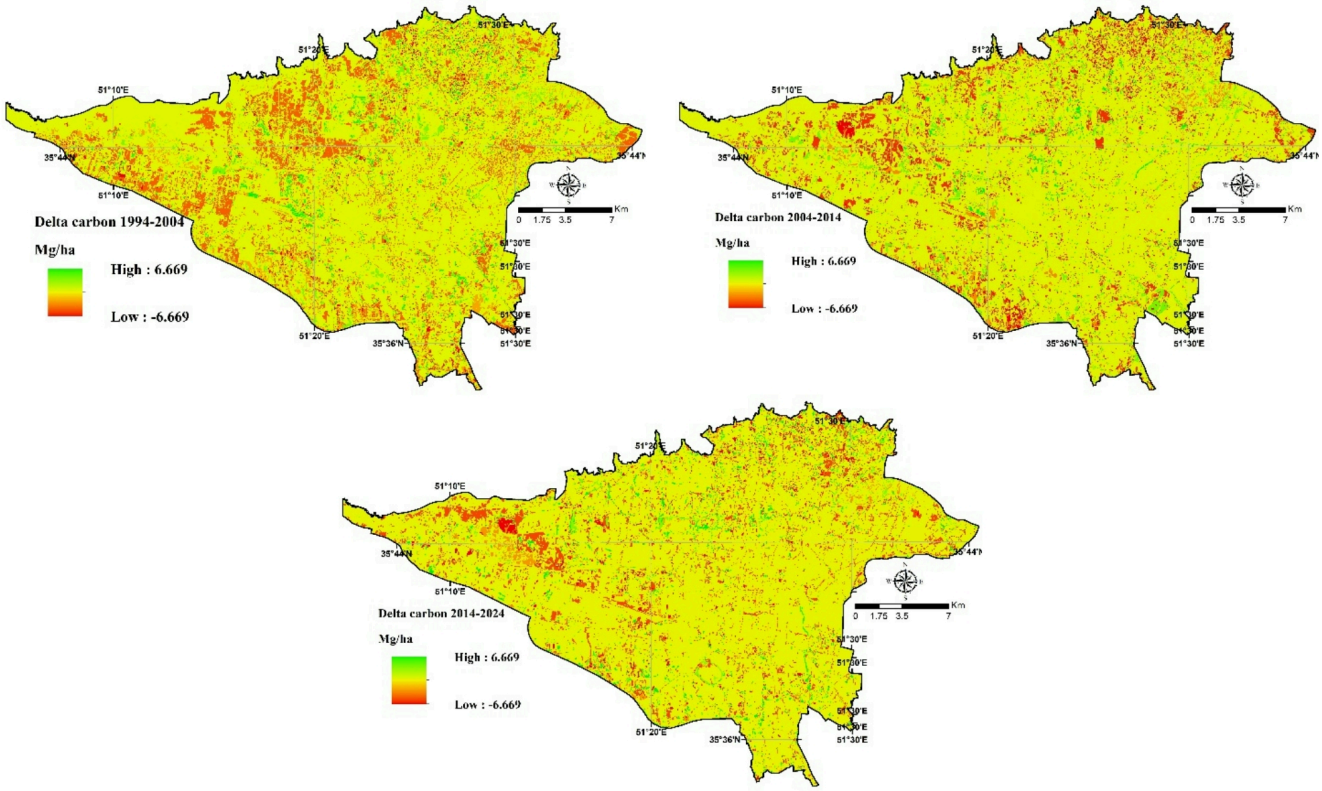


Figure 6

Decadal Carbon changes over every two consecutive periods

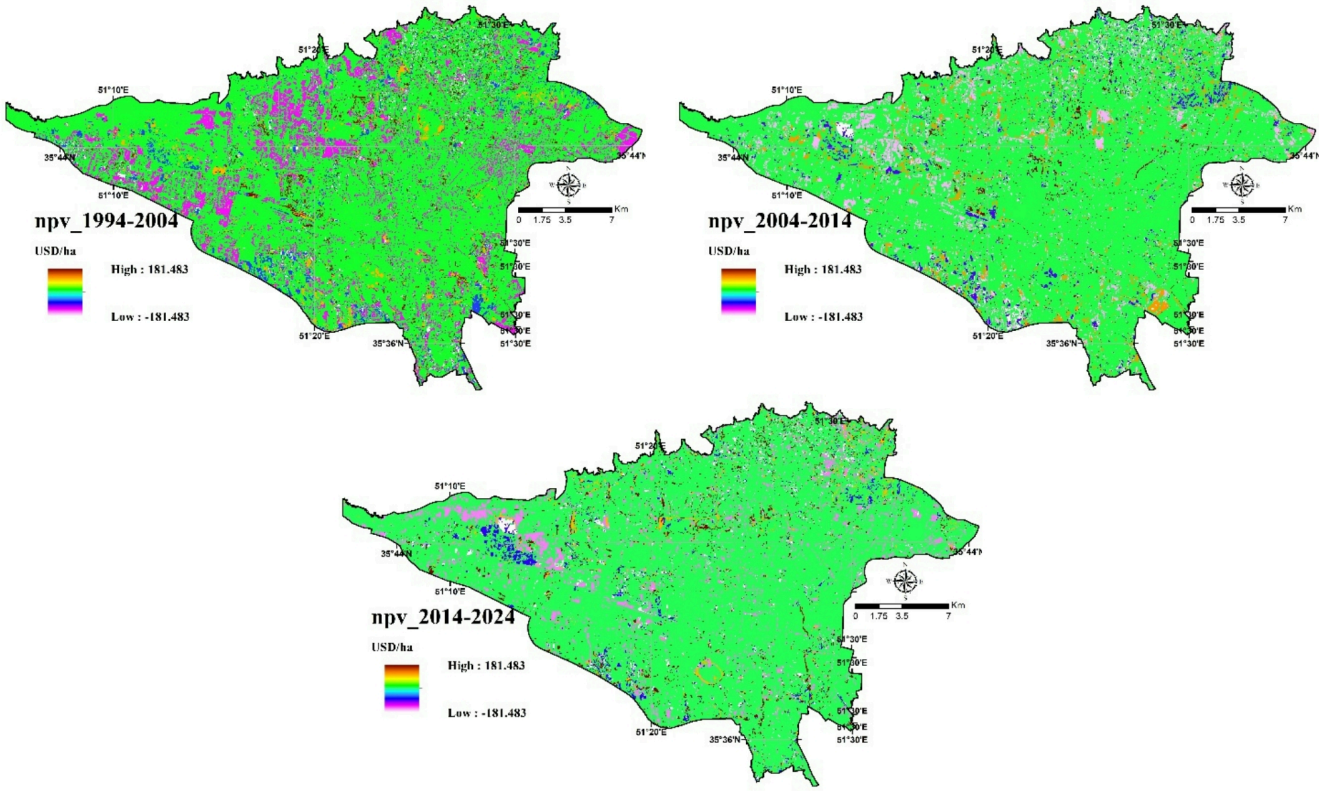


Figure 7

Spatial distribution of changes in economic value of sequestrated carbon

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