Journal of Architectural/Planning Research and Studies
(JARS) Vol.22(1).2025

https://doi.org/10.56261/jars.v22.268554

Predicting Urban Green Infrastructures of Ecosystem Services in Tehran Metropolitan Area Sprawl with Landsat Satellite time Series Data

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Received 25/2/2024 Revised 26/06/2024 Accepted 3/7/2024

Abstract

Urban green infrastructures play a crucial role in providing ecosystem services in metropolitan areas. However, the rapid urbanization and destruction of these infrastructures have become major concerns in the Tehran Metropolitan Region (TMR). This study focuses on analyzing the changes in Land Use and Land Cover (LULC) to highlight the significance of urban ecosystem services. The research utilized free Landsat time-series data from 2000, 2010, and 2020 to create a TMR development dataset. The study employed cellular automata and Markov chains to demonstrate the changes in LULC and the decline of urban green infrastructures in TMR. Six validated LULC classes were selected, including built up, garden, rainfed, soil and mountain, water, and cultivation. The data indicated that TMR's agricultural development and urban green infrastructures have increased by 21% since 2000, reaching 45% in 2020, and are expected to grow by 43% of the TMR's total LULC until 2040. The study highlights the potential risks of overusing lands for green infrastructure development which have been as results of human activities by rapid urbanization, industrialization, and population growth. Furthermore, the growth of green infrastructure at the provincial level does not fully support TMR's ecological capabilities. This study emphasizes the need for effective urban planning policies to ensure the sustainable development of urban green infrastructures and ecosystem services in metropolitan areas.

Keywords

Ecosystem services; Urban Green Infrastructures; Metropolitan; Land use; Land cover

1. Introduction

Urbanization has become a global trend, resulting in the expansion of built infrastructure while encroaching upon precious green spaces. This issue is particularly pronounced in developing countries' metropolises (Gomes et al., 2022). The loss of green spaces in cities poses a significant problem, impacting the overall quality of life for urban residents. Unfortunately, this problem is further aggravated in developing nations due to a lack of vision and interest from authorities in preserving and developing green areas (Dony et al., 2015; Lee & Hong, 2013). While there are isolated cases where a balance between built-up structures and green infrastructure has been achieved, it often falls short of compensating for the overall loss of green spaces (Feng et al., 2022; Gomes et al., 2022). Consequently, the availability and accessibility of urban green spaces remain limited in developing countries, making it challenging for city dwellers to benefit from the services provided by these areas. The relentless urbanization and disproportionate focus on built infrastructure at the expense of green spaces have led to stressed ecological systems within cities, significantly diminishing the quality of life for urban residents. Additionally, the strain on transportation systems exacerbates the problem by hindering safe and efficient movement throughout the city, thereby reducing accessibility to green spaces (Bettencourt et al., 2023; Fang et al., 2022). These issues pose significant challenges to urban planners striving to create healthy living environments in developing country metropolises. Therefore, it is of utmost importance to prioritize the development and maintenance of green spaces in urban planning processes, ensuring the well-being and satisfaction of urban residents (Sharifi et al., 2021; Vasiljević et al., 2018).

Urban ecosystems play a vital role in supporting human well-being and sustainable development by providing a wide range of services. Among these services, green areas stand out as the most valuable form of urban green infrastructure, especially in the face of rapid urbanization in developing countries. However, the degradation of natural resources resulting from changes in LULC poses a significant challenge to urban land management and sustainable development (Daba & You, 2022). Land cover refers to the natural features such as water bodies and trees that cover the soil, while land use encompasses human activities that impact the soil. Therefore, achieving sustainable urban development necessitates the monitoring of LULC trends across various categories (Ahmad et al., 2017). Regrettably, informal urbanization in developing countries has led to the loss of agricultural land, environmental degradation, decreased vegetation productivity, poor soil quality, and the emergence of heat islands. These LULC changes have also heightened the frequency and intensity of natural disasters, as well as increased air, water, and soil pollution levels (RoSohelGhalehteimourimero & Ordenes, 2004; Sejati et al., 2018). Moreover, urban green spaces play a critical role in delivering ecosystem services like air purification, water filtration, and carbon sequestration (Gómez-Baggethun et al., 2019). These services have profound implications for human health, well-being, and environmental sustainability. Urban ecosystems, particularly green areas, are indispensable for sustainable development, yet their degradation resulting from LULC changes presents significant challenges. Therefore, it is imperative to monitor LULC trends, manage land use effectively, and preserve green areas to ensure sustainable urban development and uphold the crucial ecosystem services provided by urban ecosystems.

Urban ecosystems possess the potential to generate ecologically sustainable responses to existing and future urban risks by producing ecosystem services. Urban areas pose both challenges and opportunities in addressing environmental issues, as human interactions are profoundly influenced by the process of urbanization (Russo & Cirella, 2020). As urban areas continue to evolve, they are increasingly recognized as unique ecosystems characterized by dynamic socio-ecological systems that exhibit adaptability in the face of change. The role of

LULC in enhancing the quality of urban environments through UESs is gaining recognition (Rosa et al., 2021). Preserving ecosystem patterns, mechanisms, and processes becomes crucial in comprehending the temporal and spatial changes in urban ecosystems over time and identifying the factors contributing to the degradation of service delivery. Given the highly dynamic nature of urban environments, the structure, processes, and functions of UESs are subject to both temporal and spatial variations (Kandziora et al., 2013; Sohel et al., 2015). LULC change are widely acknowledged as the primary drivers of ecosystem service alterations due to their distinct spatial characteristics. Accurately mapping LULC changes over time and comprehending their spatial and temporal dynamics can assist in addressing current and future hazards. With the aid of advanced tools and recent advancements in satellite data, it is now possible to create precise and reliable maps that assess changes in urban ecosystems and their potential impact on human well-being (Ghalehteimouri, 2024; Ghalehteimouri et al., 2024).

Recent research indicates that the utilization of remotely sensed data has significantly enhanced the level of sustainability in observing, evaluating, and managing urban ecosystems and their associated services (del Río-Mena et al., 2020). Despite the challenges posed by the dynamic nature of land dynamics and intricate environmental interconnections, remote sensing offers valuable Earth surface imagery, making it an indispensable tool in the understanding and implementation of ecosystem services concepts. Leveraging remote sensing capabilities enables the preservation of biodiversity and the enhancement of urban resilience (Angélica et al., 2022). In particular, CA-Markov matrix-based methods with dynamic simulation capabilities have proven effective in illustrating the interactions and spatial patterns of LULC across different temporal dimensions, including the past, present, and future. This geospatial modeling approach is renowned for its ability to integrate and predict various human and environmental elements, making it a powerful tool in analyzing urban dynamics (Matlhodi et al., 2021).

Over the past three decades, urban population growth has outpaced social, cultural, and environmental foundations, resulting in significant adverse impacts on the environment (Ghalehteimouri et al., 2021). The excessive and inefficient exploitation of urban natural resources has led to a decline in the overall quality of the urban environment. Particularly in developing countries, the lack of awareness among politicians and decision-makers regarding urban environmental issues, such as urban green infrastructure, remains a critical challenge. Their primary focus often revolves around land development and housing, neglecting the detrimental consequences in densely populated cities like Tehran, where open spaces and urban green infrastructure are lacking (Darvishi et al., 2020; Ghaalehteimouri et al., 2024). Tehran, one of the world's most densely populated capital cities, is experiencing the effects of climate change and environmental hazards, including air and water pollution, urban drought, and urban heat islands, leading to a substantial decline in urban environmental quality (Ardalan et al., 2019; Farhadi et al., 2019; Naddafi et al., 2012; Najafi et al., 2022). The rapid expansion of the urban population has significantly altered the spatial patterns of LULC in the TMR (Bokaie et al., 2016). It is commonly recognized that cities depend on strong links to their natural resources in order to prosper. (Seto et al., 2013).

The findings from this research focusing on the sustainable management of urban green infrastructure and water resources in the TMR hold significant global relevance as they offer valuable insights into achieving a harmonious balance between urban development and environmental sustainability. With the world's population steadily increasing and urbanization advancing rapidly, numerous cities will encounter similar challenges in effectively managing their natural resources while ensuring a high quality of life for their residents. The TMR can serve as an exemplary model that demonstrates how to foster sustainable urban development through the preservation and enhancement of green infrastructure, efficient water resource management, and inclusive stakeholder engagement in decision-making processes. In contrast to previous research primarily focusing on urban areas, this study takes a regional-scale approach to investigate the precise spatial growth and impact of urban ecosystem services. The findings shed light on the primary driver behind Tehran's environmental issues, pinpointing unanticipated LULC changes as the culprit. The hasty and inappropriate allocation of land to non-green infrastructure classes has resulted in a substantial reduction in urban green spaces within the metropolitan area. Studies conducted in Tehran and other cities worldwide underscore the critical role of urban green infrastructures in mitigating the adverse effects of environmental hazards and climate change. To comprehensively analyze the key ecological disturbances contributing to the decline in urban green infrastructure, this study leveraged an extensive dataset of NASA satellite imagery time series from Landsat 5, Landsat 7, and Landsat 8. By accurately simulating future changes in various land classes with respect to urban green infrastructures, we were able to identify the primary factors driving the decline in urban green infrastructure (Figure 1).

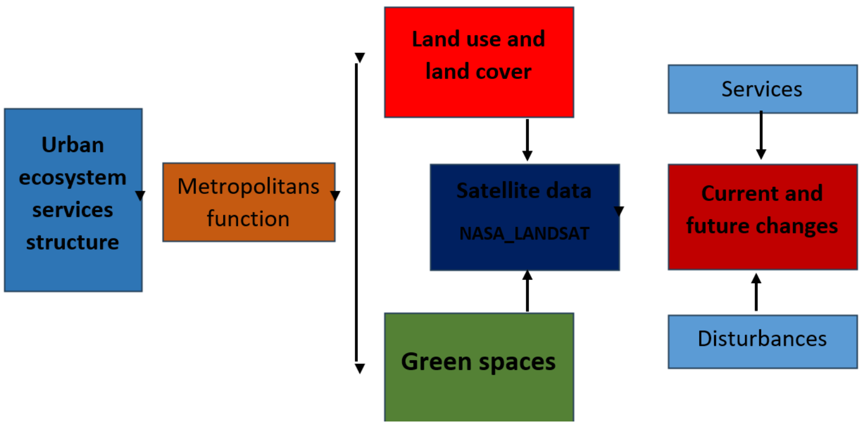

Figure 1. Conceptual framework

2. Materials and Methods

2.1 Study Area

According to the 2018 United Nations estimate, Tehran is the most populous city in West Asia and the 38th most populous city in the world, with a population of 8,693,706 people. The city is situated on two plains and the foothills of the Alborz Mountains, with an elevation ranging from 900 to 1800 meters above sea level. Tehran has a semi-arid climate, with the least amount of rainfall occurring in the summer, while winter contributes to almost half of the annual rainfall in the city (Erdösy, 1995; Statistical Center of Iran, 2021). Over the past decade, the population of Tehran has grown rapidly, as is evident from the overall population growth trend of Iran. The urban population has increased significantly, and it now constitutes a larger percentage of the total population compared to rural areas. The lack of adequate housing for all social groups is one of the most pressing issues in developing countries. Common housing policies in developing countries include lending, urban renewal, and affordable housing. One of Iran's housing protection policies was the housing component of its socioeconomic development plan (Hosseini & Hosseini, 2016) (Figure 2).

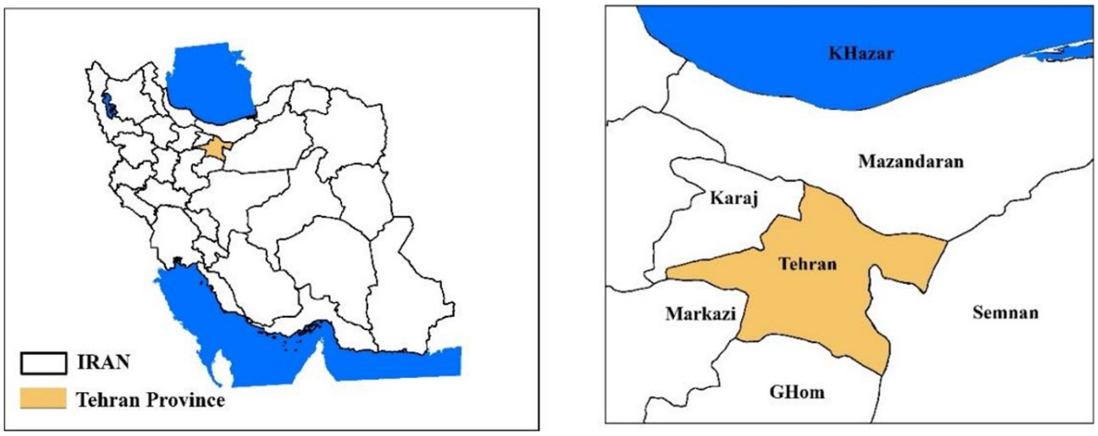

Figure 2. Tehran Metropolitan Area

2.2 Methodology

2.2.1 Data Collection and Process

Accurately assessing the historical and current trends of LULC requires the use of suitable images and a visualization tool that considers band knowledge and data selection. In this study, high-resolution satellite data from Landsat 5 (2000), Landsat 7 (2010), and Landsat 8 (2020) were utilized to visualize the region of interest. Once the images were combined, they were clipped to the study area's boundary and prepared for further analysis. To ensure reliable mapping, calibrated area and data from various satellite time series were employed using high-resolution operations.

The existing user map provided by Tehran and Google Earth were utilized, incorporating polygon imagery for reference. The study focused on six primary LULC classes: Built ups, gardens, rainfed areas, soil and mountain regions, water bodies, and cultivation areas. These classes were deemed crucial in the TMR as they significantly influenced the quality and extent of urban green infrastructure. To collect the LULC data for the TMR, the Maximum Likelihood supervised classification method was employed. Validation of the collected data involved comparing it with prepared satellite imagery and ground truth data collection. It is worth noting that satellite data time series inherently contain uncertainties that can pose challenges in assessment (Moghadam & Helbich, 2013). The widely accepted CA-Markov method was utilized to analyze and predict LULC tendencies, transformations, and future changes based on observed LULC patterns. The generated maps were imported into ArcGIS software for further calculations, such as determining the area and proportion of each LULC class. To assess the accuracy of the classification, two kappa coefficients and an overall accuracy measure were calculated (Ildoromi et al., 2017).

Markov Formulation

To assess the tendencies and changes in LULC, it is crucial to utilize appropriate images and a visualization tool that requires expertise in band knowledge and data selection. In this study, high-resolution satellite images were employed to visualize the specific region of interest under investigation. These images were carefully combined and then clipped to align with the study area boundary, ensuring the generation of reliable maps. The collection of LULC data in the TMR focused on six distinct classes: Built ups, gardens, rainfed areas, soil and mountain regions, water bodies, and cultivation areas. The Maximum Likelihood supervised classification method was employed to accurately delineate and classify these LULC classes. These classes were chosen due to their significant influence on the urban landscape and the extent of green infrastructure within the TMR.

To project and anticipate future changes in LULC based on the observed tendencies, the CA-Markov method was utilized. This method, known for its reliability, analyzed the current patterns to predict future LULC changes. The resulting LULC maps were imported into ArcGIS software, where various calculations, including the determination of the area and proportion occupied by each LULC class, were performed.

The accuracy of the collected LULC data was rigorously validated by comparing it with satellite images and ground data collection. Two kappa coefficients and an overall accuracy measure were calculated to assess the correctness of the LULC classification. These statistical measures provided a robust evaluation of the accuracy and reliability of the LULC classification results.

2.2.2 Cellular Automata (CA) Model

Mathematically, a cellular automata (CA) model can be represented as a dynamic system of spatial distribution that is discrete in both time and space. It consists of single automata (cells or locations) that are uniformly distributed over the points of a lattice in a discrete D-dimensional space (where D is usually 1, 2, or 3). Each automaton is a dynamic variable and its time changes are determined by the following equation:

$$St(x, t+1) \ = \ F[St(x-1, t), St(x, t), St(x+1, t)]$$

where St(x,t) represents the state of the cell in position x at time t, and F is a neighborhood transfer function that determines the new state of the cell based on its current state and the states of its neighboring cells. The most important characteristic and assumption of cellular automata is that the same state and neighborhood transfer function is uniformly applied to all spatial positions (Esfandeh et al., 2021; Maleki et al., 2020). Cellular automata have been recognized as an effective and appropriate model for displaying changes in various geographical features (Tobler, 1975).

The Cellular Automata (CA) model has been widely used for simulating future LULC changes in complex and dynamic systems, owing to its ability to capture spatial and temporal changes (Aburas et al., 2016). Its flexibility allows it to be easily integrated with other models, making it a valuable tool for urban prediction. CA models have been extensively employed in urban studies, investigating a wide range of urban phenomena, including traffic simulation, regional-scale urbanization, land-use dynamics, polycentric, historical urbanization, and urban growth. Furthermore, CA models have been developed to simulate urban redevelopment, discrimination, socio-spatial dynamics, and sprawl, as well as urban shape, growth, and location. SCA has many benefits for modeling urban phenomena, including its decentralized approach, connections to complexity theory, the relationship between form, function, pattern, and process, the ease with which model results can be visualized, flexibility, a dynamic approach, and affinities with RS-GIS (Sabzghabaei et al., 2018; Torrens, 2000). Nevertheless, the CA model has some drawbacks and advantages that should be combined with other types of models to overcome such gaps. CA models have excellent spatial resolution and the ability to be effectively computerized. However, the nonlinearity of the CA's repeating process tends to produce regular and organized patterns that can create comparable geometries at different scales (Falah et al., 2020; Santé et al., 2010). In summary, the CA model is a valuable tool for modeling complex urban phenomena, but its use should be coupled with other models to produce more accurate results.

2.2.3 Markov Chain Model

To determine the likelihood of a LULC changing or remaining unchanged, the MC analysis is commonly used. The degree of Markov change, which is equal to frequency in place, time, and space for the Markov model, is usually evaluated in most studies (Moradi et al., 2020). The chain states in MC analysis are the cover classes, and their changes are interdependent. Two land use maps of model inputs are necessary to determine the probability of change in this chain, typically obtained by processing satellite images (Afifi, 2020). The system illustrated in the figure below is always in one of the distinct states, and its state changes according to a set of possibilities at discrete times and regular intervals. To accurately describe the current system, it is necessary to know both the current state and all prior states. The probabilistic representation of a particular state of the first-order MC is solely determined by the current and prior states (as illustrated in Figure 2) (Rabiner, 1989). The Markov chain formula is a mathematical formula used to calculate the probability of transitioning from one state to another in a Markov chain. It is based on the principle of conditional probability and states that the probability of being in state j at time t+1, given that the Markov chain is currently in state i at time t, is equal to the sum of the probabilities of transitioning from all possible states to state j multiplied by their respective transition probabilities:

$$P(j|\, i) \;=\; \sum P(j \mid k)\; x\; P(k \mid i)$$

Where:

P(jl i) = probability of being in state j at time t+1, given that the Markov chain is currently in state i at time t

P(j l k) = probability of transitioning to state j from state k

P(k l i) = probability of being in state k at time t, given that the Markov chain is currently in state i at time t

The formula is used to calculate the probability of future states in a Markov chain based on the current state and the transition probabilities (Figure 3).

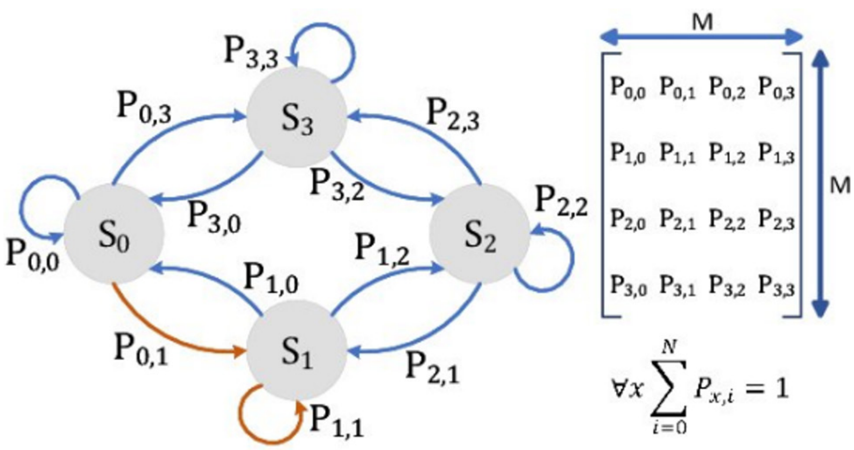

Figure 3. Markov Chain with matrix
Source: (Salamat et al., 2019)

A discrete stochastic process is characterized by a system that assumes a specific state at each stage and transitions to another state randomly. The stages can be considered as instances in time or any other discrete variable, such as physical distance. The Markov property governs the transitions between states and implies that the conditional probability distribution of the system's future state depends only on its present state and is independent of previous states. Although predicting the exact future state of the Markov chain is generally unfeasible due to its random nature, it is possible to forecast the statistical properties of the system that are crucial for various applications.

2.2.4 CA-Markov Model

A Cellular Automaton (CA) is a model consisting of a network of cells in a finite set of possible states, such as "On" or "Off," that can be of any finite size. Each cell is related to a set of neighboring cells, and an initial state is chosen by assigning a state to each cell at time t=0. On the other hand, a Markov Process (MP) is a probabilistic model that transitions from one state to another based on probabilistic rules. The essential feature of a MP is that the possible future states are constant regardless of how the process arrived at its current state (Ghoroghchian et al., 2019; Sharifi et al., 2021; Dravishi et al., 2020).

In this study, the CA-Markov method was used to predict future states by selecting past and current data. Stochastic processes, which are typically time-indexed, are one of the statistical and probability-based modeling approaches employed for data analysis. The term "Markov Process" or "MC" refers to a model that represents a sequence of random variables in which the probability of each event is solely determined by the preceding event. Therefore, the probability of occurrence of events in such a model is only dependent on the previous time, and the remaining events have no impact on the probability. This is commonly referred to as the "Memoryless" property of a random process (Ghalehteimouri et al., 2022; Nasiri et al., 2019).

The prediction of LULC is accomplished using two types of models: regression-based models and transition-based spatial models. While regression-based models cannot generate spatial expansions over time and space, CA-Markov and Monte Carlo models enable the spatial transformation of LULC over time. Moreover, due to the dynamic nature of LULC and the interdependence of their interactions, spatial assessment models must be used for evaluation purposes (Kumar et al., 2014; Rahnama, 2021). CA-Markov coupling is highly effective in assessing various changes in LULC interactions and identifying reliable spatial and temporal pattern changes by measuring transformation probabilities among classes (Kamusoko et al., 2009).

3. Results

3.1 Land use and Land Cover Types, Dynamics, and Rate of Changes Analysis

Tehran is one of the biggest and the most populated urban areas in Iran. We analyzed TMR LULC changes and transformations in last 20 years between years 2000-2010, 2010-2020, and then predicated for 2040. In this study 6 classes of lands identified to be analyzed including Built ups (e.g., Built ups, houses, factories), gardens(e.g., tree, shrubs), rainfed (e.g., seasonal cultivation based on rains seasons),soil and mountain (e.g., hills, mountains, mountain ranges., etc.,), water (e.g., rivers, ponds, lakes, swamps etc.,), cultivation (e.g., currently cultivated and based on ground or surface water). Since, the satellite data accuracy and access are more reliable and currently historical data is available. Therefore, we used Landsat historical data from Landsat 5, 7, and 8 with the highest level of accuracy (Table. 1)

Table 1. Data collection accuracy assessment

images	SVM classification images	
	overall accuracy	Kappa
2000 (Landsat 5)	94.68	0.93
2010 (Landsat 7)	98.66	0.99
2020 (Landsat 8)	98.60	0.98

The elevation of Tehran significantly influences its environmental regulation and subsequently impacts the overall environmental quality. Particularly, the Alborz mountain range and the presence of humid western winds contribute to improved rainfall, water resources, and green values in the northern and western parts of the city. However, the recent urban expansion of green infrastructures in Tehran has often neglected the ecological foundations that underpin its environmental well-being. Situated at the intersection of mountainous and plain regions, Tehran benefits from a moderate climate, characterized by mild and mountainous conditions in the north and semi-arid conditions in lower altitude areas. The city experiences abundant rainfall during winters, further enhancing its environmental dynamics. In 2000, the combined value of cultivation, rainfed, and garden LULC accounted for 23% of the total urban green infrastructure in Tehran. Among these categories, gardens represented 6%, cultivation accounted for 8%, and rainfed lands made up 7% of the urban green infrastructure. By 2010, the size of urban green infrastructures had doubled, comprising 46% of the total, with gardens occupying 24%, cultivation representing 7%, and rainfed lands accounting for 11%. However, in 2020, there was a significant decline in gardens, which dropped from 24% to 9%. Meanwhile, cultivation increased by 13% and rainfed lands increased by 23%.

Despite an increase in water resources, particularly a threefold increase from 8.64% in 2000 to 16.99% in 2010 and 20.36% in 2020, hydrological values such as surface water remain extremely low in Tehran. The combination of urban green infrastructures and improved hydrological values has the potential to greatly enhance the urban climate quality in the TMR. Based on reliable historical data, the LULC changes in the TMR have had a notable impact on the river basins, particularly in the Darband basin where there has been a significant transition from low to medium or high runoff production. Over time, the urban area has undergone changes, shrinking from 3 square kilometers in 1966 to 1.91 square kilometers in 1981 and further decreasing to 1.79 square kilometers in 2011. This transformation has seen a decline in barren lands and dense vegetation, which have been replaced by urban areas characterized by high runoff production and semi-dense or less dense vegetation. Comparing the years 2000, 2010, and 2020 in the TMR, there has been a noticeable expansion towards the southern parts of the region, leading to an increase in green values such as agricultural development and gardens. Despite the challenges posed by climate change and water resource issues, the urban green infrastructures in TMR have exhibited continuous spatial and temporal growth since 2000 (Figure 4).

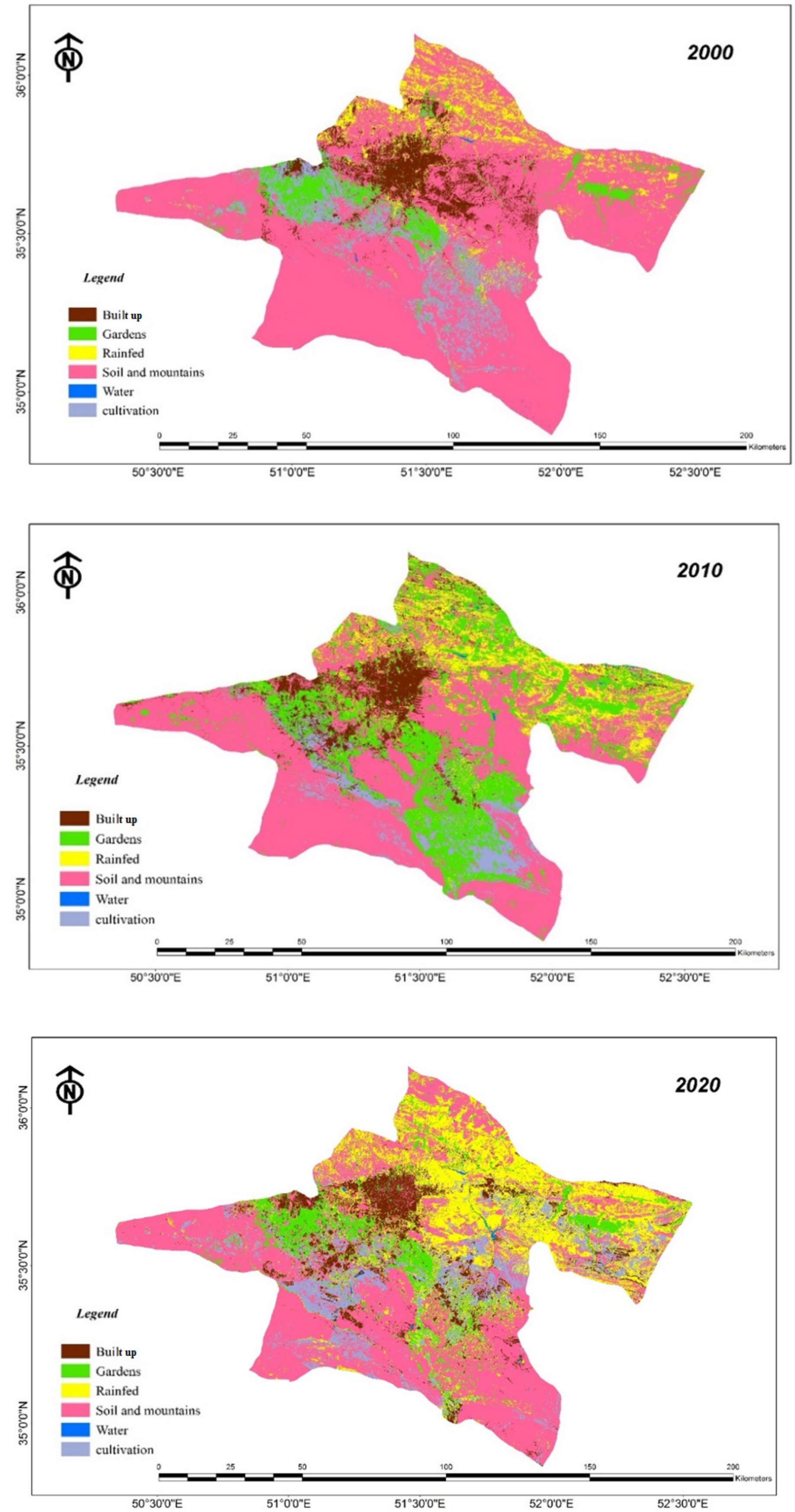

Figure 4. Land use and land cover transformation between 2000, 2010, and 2020

3.2 Cross-Tabulation Analysis

Over the past twenty years, the urban green infrastructure in the TMR has undergone significant transformations, witnessing a notable surge in agricultural practices such as gardens and farmlands. Notably, these changes have been most prominent in the traditionally less developed southern areas of TMR. This spatial pattern aligns with Tehran's hydrological and geomorphological model, which designates it as an orohydrological city. In this model, the northern regions of the Alborz Mountain Ranges receive higher levels of precipitation compared to the southern parts. Consequently, water flows southward, creating new opportunities for utilizing surface and ground water resources in the southern areas of TMR.

The importance of promoting a greener environment in the TMR is clearly demonstrated by the findings of cross-tabulation analysis comparing two time periods: 2000-2010 and 2010-2020. While the expansion of Built ups and non-urban green infrastructure continues to occur in various spatial and temporal directions, a notable shift in LULC can be observed between 2000 and 2010. Specifically, there has been a transformation where areas previously categorized as soil and mountains have been replaced by different forms of agricultural and urban green infrastructure lands. These changes are highlighted in Table 1 and Table 2, providing insight into the evolving nature of urban green infrastructure in the TMR.

Table 2. Cross-tabulation Results Using Landsat 2000 (columns) v.s. Landsat 2010 (rows)

Category	1	2	3	4	5	6	Total
1	150273	23532	38258	10866	145415	202	368546
2	26469	179020	211215	130450	531549	738	1079441
3	704	3922	32040	3660	256594	7	296927
4	23475	29992	13686	97492	322840	108	487593
5	128628	32270	60832	50796	1943097	971	2216594
6	169	294	21	675	4200	1370	6729
Total	329718	269030	356052	293939	3203695	3396	4455830

1: Built up, 2: gardens, 3: cultivation, 4: rainfed, 5: soil and mountains, 6: water

During the second assessment period from 2010 to 2020, the TMR has experienced significant urban development, leading to notable transformations in its LULC. Unlike many other developing cities, TMR has managed to undergo this development while preserving the quality of its agricultural lands. Although the proportion of Built up land is relatively lower compared to other LULC types, there has been a considerable increase in Built up construction. Furthermore, agricultural activities have continued to expand within the region, characterized by the presence of gardens, cultivated lands, and rainfed lands. lands. However, it is important to note that the area of soil and mountain coverage which present coverage is seasonal grass and sparse trees in TMR has decreased during this period, as depicted in Table 3.

Table 3. Cross-tabulation Results Using Landsat 2010 (columns) v.s. Landsat 2020 (rows)

Category	1	2	3	4	5	6	Total
1	186348	60615	20324	14159	124942	482	406870
2	27526	282570	8023	46584	40038	338	405079
3	8454	115574	55807	50732	334775	23	565365
4	77870	324835	12413	275444	340652	2106	1033320
5	67580	293145	200319	100357	1374979	1693	2038073
6	856	2968	38	455	1639	2096	8052
Total	368634	1079707	296924	487731	2217025	6738	4456759

1: Built up, 2: gardens, 3: cultivation, 4: rainfed, 5: soil and mountains, 6: water

Based on the CA-Markov prediction model, future projections indicate notable changes in the LULC composition of the TMR. The dominant LULC type is expected to be gardens, with a significant expansion that will see permanent trees replacing seasonal rainfed and fallow lands, primarily in the southern regions. Additionally, there will be a substantial increase in Built up development compared to previous decades. Validation of satellite images from Landsat time series confirms significant spatial shifts in Built up and garden developments. Looking ahead to 2040, the area dedicated to Built up is projected to increase by almost 30%, while gardens are expected to expand by over 50%, covering an estimated 2529.57 km2. Unfortunately, this expansion comes at the expense of rainfed LULCs, which are predicted to decrease by over 70% from 2618.61 km2 in 2020 to 720.73 km2 in 2040. Consequently, the proportion of rainfed lands in the total LULC is anticipated to decline from 23% in 2020 to 6% in 2040. On the other hand, cultivated lands are expected to experience a slight increase, growing from 1437.69 km2 in 2020 to 1641.61 km2 in 2040. These projections provide valuable insights into the future landscape composition of TMR, highlighting the trade-offs between urban development, green spaces, and agricultural activities.

A comparison between the years 2000 and 2040 in the TMR reveals a rapid transformation in LULC patterns, resulting in the depletion of natural resources. The proportion of soil and mountain areas has significantly declined from 72% in 2000 to 45% in 2040, indicating the extensive impact of urbanization on these crucial ecological components. While there has been an increase in urban green infrastructure, it has not been accompanied by a proportional increase in water bodies, which play a vital role in supporting a healthy ecosystem. Water bodies, despite their importance for sustaining green ecosystem services, remain the smallest LULC category in TMR. They accounted for only 8.64% in 2000, 16.99% in 2010, and 20.36% in 2020, with a projected increase to 24.24% by 2040 (as shown in Table 4 and Figure 5). These trends indicate a significant transformation in TMR's LULC composition, emphasizing the urgent need for sustainable development practices and conservation efforts to safeguard the region's natural resources. Efforts should be directed towards balancing urban expansion with the preservation of essential ecosystems, including the enhancement and restoration of water bodies. By prioritizing sustainable development practices, TMR can ensure the long-term resilience and ecological integrity of its urban green infrastructure, while effectively managing and conserving its valuable natural resources (Figure 5 and Figure 6).

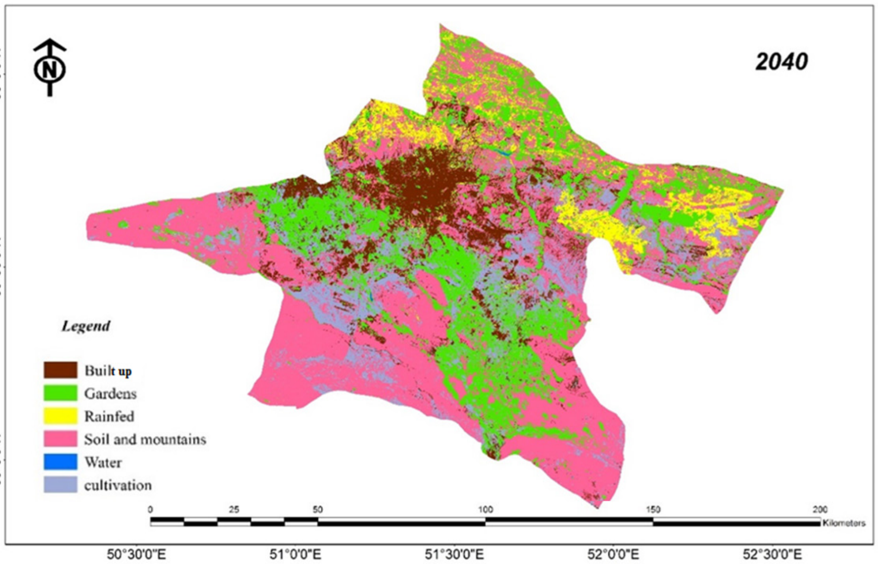

Figure 5. Spatial expansion of selected LULCs in 2040

Table 4. Land use and land cover transformation (2000, 2010, and 2020)

	area (km2)			
Land use	2000	2010	2020	2040
Built up	835.70	933.64	1032.15	1323.79
Gardens	682.83	2739.14	1027.13	2529.57
Cultivation	904.16	755.88	1437.69	1641.61
Rainfed	743.54	1237.23	2618.61	720.73
Soil and mountains	8141.54	5633.35	5180.34	5076.78
Water	8.64	16.99	20.36	24.24

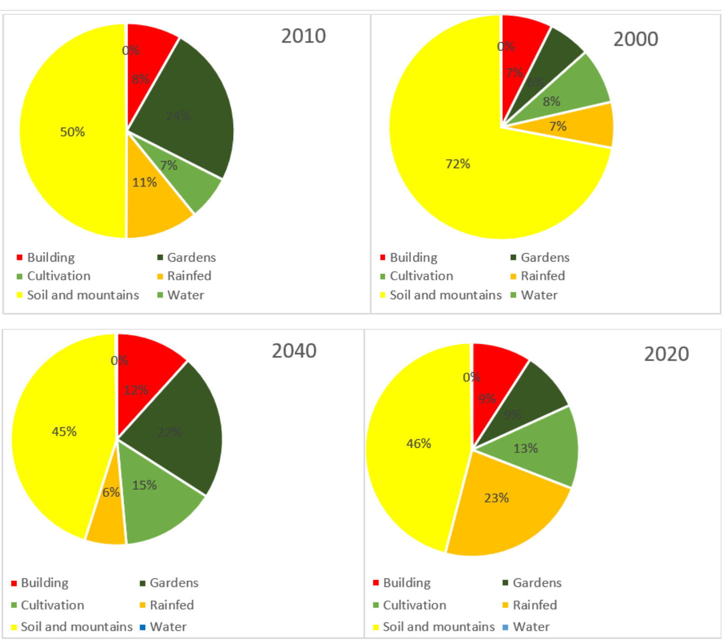

Figure 6. Percentage of land use and land cover changes in selected years

The TMR has witnessed significant changes in land use and land cover (LULC), driven by various developmental activities such as urban and industrial growth. Unfortunately, these processes have resulted in the destruction of valuable urban green infrastructures, particularly in areas where air currents and hydrological networks are limited, predominantly in the northern part of the TMR. The rapid urbanization of the region has played a significant role in shaping its current environmental landscape. The prevailing urbanization trend in the TMR, driven by population growth and increasing food demands, has led to the conversion of land for agricultural purposes, particularly for food production. Agricultural activities in the TMR are mainly concentrated in pre-urban areas, reflecting the consequences of pre-urbanization development. This emphasis on agricultural expansion comes at the expense of other rural or agricultural growth.

Despite the importance of water bodies for supporting urban green infrastructures, their area has not witnessed significant growth over time. In 2000, the water body area was measured at 8.64 km2, which increased to 16.99 km2 in 2010, 20.36 km2 in 2020, and is projected to reach 24.24 km2 by 2040. Water bodies are among the most fragile and sensitive LULCs, and their limited expansion raises concerns about the sustainability of urban green infrastructures. Efforts should be made to strike a balance between urban development and the preservation of valuable green spaces in the TMR. Sustainable land-use practices and the protection of water bodies are crucial for the long-term well-being of the region's urban environment. By prioritizing sustainable urban planning, the TMR can ensure the preservation and enhancement of its urban green infrastructures, fostering a more resilient and ecologically sound urban landscape.

The relationship between the TMR and urban green infrastructure is multifaceted, with distinct characteristics in different parts of the region. The northern areas are associated with aesthetics and cultural value, attracting affluent populations who appreciate the air-regulating and cultural aspects of urban green infrastructure. On the other hand, the southern parts of TMR are primarily linked to food production and rely on ecosystem services such as soil and water support, which are essential for sustaining local communities. The significance of urban green infrastructure in TMR goes beyond socio-economic factors. Given its geographical location in a dry and semi-dry region, with Tehran facing significant pollution challenges, the expansion of urban green infrastructure plays a crucial role in supporting regulating ecosystem services. It helps mitigate greenhouse gas emissions and supports environmental quality improvement, which directly impacts the health and well-being of citizens. Therefore, it is imperative to integrate the effectiveness of urban green infrastructure into urban planning systems and recognize the benefits of green development, particularly through the promotion of agricultural activities in TMR.

The development of sustainable LULC practices in agriculture is vital to meet the growing demand for food in urban areas, especially with the expanding population and the need for peri-urban agriculture. Urban green infrastructure should provide specific guidance to foster sustainable agricultural practices while preserving land with high agro-ecological value. This approach ensures the production of clean and locally sourced nutritious food while enabling the local population to enjoy and have access to the surrounding landscape. However, the challenge of urban sprawl remains a significant concern for regional planning in TMR, posing threats to sustainability goals and effective urban planning implementation. Unplanned LULC, driven by various factors, has profound economic, social, and environmental implications. The conversion of agricultural land into residential areas and informal urban development contributes significantly to sprawl, particularly noticeable in the southern parts of TMR. The need for urban expansion and the expansion of road networks in these areas disrupts the environment and further exacerbates the issue. To ensure sustainable urban development in TMR, it is crucial to address the challenges of urban sprawl, integrate effective land use planning strategies, and balance the socio-economic, environmental, and cultural aspects of urban green infrastructure. By considering the diverse needs of the population and promoting sustainable practices, TMR can create a harmonious and resilient urban landscape that enhances the well-being of its residents while preserving its natural resources

5. Conclusion

According to the precipitation data and surface water expansion analyzed by TMR, the area is not considered to be a wealthy urban district, with only 21% of agricultural operations in 2000. However, during the past 30 years, the urban green infrastructures in the TMR have grown significantly, with a gain of 45% by 2020, relates to the growth of agricultural lands. This indicates a positive trend towards sustainability in the region, with a focus on preserving and expanding natural resources. However, it is essential to note that the current green expansion tends to be one without taking the long-term impacts into account. As urban sprawl is a significant issue, the degree of land exposure, soil erosion, and water condemnation may only increase if there is more Built up and construction. This highlights the need for sustainable development and proper land use planning, as the TMR is anticipated to be significantly utilized by the building and construction industries. The data analysis for future LULC and urban green infrastructures in TMR also indicates that unsustainable urban expansion and rapid agricultural growth without the necessary natural resources, particularly water, will continue. This highlights the need for increased accountability from stakeholders and applying the best human and environmental techniques to achieve long-term allocation effectively and fairly. Moreover, surface water is one of the TMR's most vulnerable urban natural resources, with only 21% of agricultural operations in 2000, despite being essential to the creation of the urban green infrastructure in the region. To make sure that this development does not have a detrimental effect on the quality of urban water resources both now and in the future, water management needs to be enhanced with a focus on using urban green infrastructures properly. This indicates the need for sustainable development practices and proper management of natural resources for the long-term benefit of the region and its inhabitants.

Furthermore, the analysis of future land use and urban green infrastructure in the TMR highlights the persistence of unsustainable urban expansion and rapid agricultural growth without sufficient natural resources, notably water. This underscores the importance of increased accountability from stakeholders and the application of sound human and environmental techniques to achieve equitable and sustainable long-term resource allocation. Notably, surface water stands as one of the TMR's most vulnerable urban natural resources, despite its critical role in establishing urban green infrastructure. To safeguard the quality of urban water resources both presently and in the future, water management should be strengthened, with a specific focus on the proper utilization of urban green infrastructures. This necessitates the implementation of sustainable development practices and effective natural resource management for the region's long-term benefit and the well-being of its residents.

In conclusion, the data analysis underscores the imperative for a sustainable approach to urban development in the TMR, with a strong emphasis on preserving and expanding natural resources. By employing the best available human and environmental techniques, stakeholders can effectively and fairly allocate resources for long-term advantages, encompassing social, ecological, and economic dimensions. Adequate management of natural resources, particularly water, plays a pivotal role in the region's sustainable development and the overall well-being of its inhabitants. Therefore, enhancing water management practices with a specific focus on the proper utilization of urban green infrastructures is crucial. By adopting sustainable development practices and ensuring prudent resource management, the TMR can secure a prosperous and sustainable future.

Author Contributions

T. N. Coauthor, manuscript validation, K.J.G. main draft author, data validation, A.K. data collection and application of method M. N.M. managing team, data validation and A.R. resources, graphical design. All authors have read and agreed to the published version of the manuscript.

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