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Mapping Urban Growth Through Landscape Expansion Index and Land Use Analysis: Evidence from Western Turkey

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Abstract

This study investigates the dynamics of Land Use and Land Cover (LULC) changes along the İzmir-Denizli Highway corridor in western Turkey from 1984 to 2025, utilizing remote sensing techniques and the Landscape Expansion Index (LEI) to analyze urban growth patterns. Employing cloud-free Landsat satellite imagery and the Random Forest classification algorithm within Google Earth Engine, the research identifies and quantifies built-up area expansion over four decades. The findings reveal a significant increase in built-up areas, particularly after 2000, with a total expansion from 45682 hectares in 1984 to 68869 hectares in 2025. The analysis highlights a predominance of edge-expansion growth (71.3%), with outlying growth (27.4%) and minimal infilling growth (1.3%). This trend indicates a shift towards urban sprawl, raising concerns about the sustainability of land use practices. The study underscores the importance of integrating spatial and temporal analyses in urban planning to promote more sustainable development patterns and mitigate the adverse effects of urbanization on the environment.

1. Introduction

Urbanization stands as one of the most transformative spatial processes of the 21st century, continuously reshaping landscapes, altering ecological balances, and redefining the relationship between human activity and the natural environment. Rather than remaining confined to compact cores, cities are increasingly expanding in outward, often fragmented patterns driven by demographic shifts, economic imperatives, environmental pressures, and infrastructural developments. Capturing this expansion, not only in terms of areal extent but also in terms of spatial form and configuration, is essential for sustainable land management and effective urban policy-making.

Traditional methods for analyzing urban growth have predominantly relied on static representations of land use, offering limited insight into the temporal and morphological dynamics of urban transformation. While such approaches are useful in identifying surface-level change, they often fail to reflect the evolving structure of urban growth. As cities develop, their spatial forms transition from scattered to clustered, from peripheral sprawl to inner densification. This dynamic process necessitates the use of temporally sensitive tools capable of depicting how urban areas interact with surrounding landscapes, infrastructure systems, and regulatory frameworks.

In this context, monitoring changes in land use and land cover (LULC), evaluating their impacts, and interpreting emerging spatial patterns have become central to informed urban planning [1–6]. Urban areas are inherently dynamic, and their continuous evolution is closely tied to LULC transformations [7]. Recent studies have emphasized the need to quantify the pace and typology of urban expansion, as these factors critically influence the distribution and ecological implications of built-up areas [1, 8, 9]. Temporal analyses that trace the evolution of land use provide important insights into the environmental consequences of urban growth [10, 11].

The forces driving spatial change are multifaceted, rooted in natural, social, economic, and technological dimensions [12]. Increasing urban populations place growing pressure on land resources, prompting the conversion of land for housing, industrial, commercial, and infrastructural uses. Additionally, the tendency to relocate from city centers to peripheral zones often intensifies urban sprawl—a process commonly attributed to economic motivations, demographic patterns, housing preferences, and improvements in transport infrastructure [13–15].

Urban expansion typically results in the conversion of agricultural and forested land into built-up areas. For instance, a two-decade study in Egypt revealed a marked increase in urban land at the expense of green areas [16]. Similarly, Chettry (2022) documented steady growth in built-up areas across multiple cities between 1991 and 2021, alongside the gradual disappearance of vegetated land, underscoring the urgent need for policies that strike a balance between development and ecological sustainability [17].

Among the most influential drivers of land conversion is transportation infrastructure. Expanding road networks, particularly highways, enhance accessibility to peripheral zones, thereby accelerating urban development and the conversion of open or agricultural lands into built-up areas [18]. Numerous studies have focused on buffer zones (typically within 10 km of highways) where land use changes are found to be especially pronounced [19–23]. Even more substantial transformations tend to occur in close proximity to highway exits, where accessibility and development pressure converge [22, 24, 25].

This trend has been observed across varied geographic contexts. For example, Müller et al. (2010) found that areas near highway exits in Switzerland experienced more rapid land conversion between 1985 and 1997 than other locations [22]. Similarly, Fiedeń (2019) reported that highway construction in Poland significantly reduced forest and agricultural lands while facilitating urban growth in adjacent areas [20]. In Turkey, Demirel et al. (2008) identified a strong correlation between increased road capacity in Istanbul's southeastern region and urban expansion [26]. Mothorpe et al. (2013) also demonstrated that the extension of the interstate highway system contributed substantially to suburban growth in Georgia during the latter half of the 20th century [27].

Population dynamics around transportation corridors have been equally influential. Chi (2010) observed that population growth rates were significantly higher in Wisconsin's highway-adjacent areas between 1970 and 2000, leading to further urban expansion [28]. In Barcelona, Garcia-López (2012) concluded that proximity to highway exits played a critical role in driving suburban growth between 1991 and 2006 [29]. A broader study by Duranton and Turner (2012) across 275 metropolitan areas in the U.S. affirmed that increases in road infrastructure directly fostered built-up area expansion [30]. Similarly, Zheng et al. (2016) showed that in China, the construction of a bay bridge accelerated the development of impervious surfaces along major transport routes between 1995 and 2009 [25].

As research interest in urban spatial dynamics deepens, scholars have increasingly emphasized the utility of impervious surface data and spatial metrics. Fan and Fan (2014), for instance, illustrated how newly urbanized districts shifted from fragmented to more consolidated configurations over time. This reflects a broader trend of early-stage sprawl followed by a densification phase—often referred to as the "filling-in" process—resulting in increased residential compactness [31].

Understanding urban growth also requires attention to landscape patterns and spatial heterogeneity. Landscape structure emerges through the aggregation and configuration of various land use types of different sizes and functions. Quantitative analysis of these patterns is crucial for monitoring urbanization and developing strategies to manage growth effectively.

Landscape metrics are commonly employed to assess spatial complexity, urban form, and land use dynamics, offering insight into how cities evolve in structure and intensity [2, 8, 32–34]. However, these conventional indices are generally static, limiting their capacity to represent long-term spatial processes.

To address this gap, the Landscape Expansion Index (LEI) has emerged as a robust method for characterizing urban growth trajectories. LEI allows researchers to differentiate between infilling, edge-expansion, and outlying growth types by analyzing the spatial context of new development. This typological distinction is critical for understanding the logic of urban expansion and its implications for infrastructure efficiency, resource management, and environmental impact. As a dynamic tool, LEI enables decision-makers to identify unsustainable patterns of sprawl and promote more resilient and compact forms of urbanization.

Given the accelerating pace of urban change, integrating spatial and temporal analyses is essential for building sustainable urban futures [35, 36]. Traditional models that rely solely on static land cover data fall short in capturing the complexity of urban transitions. This study addresses this gap by combining multi-temporal LULC data with LEI to provide a more comprehensive view of urban growth dynamics. By distinguishing between key growth forms—such as leapfrog, edge-expansion, and infill—this approach offers deeper insights into how urban landscapes transform over time.

The İzmir–Denizli Highway corridor in western Turkey presents a compelling case study for examining infrastructure-induced urbanization. Over the past four decades, this corridor has undergone significant change due to road investments, regional development pressures, and shifting population dynamics. By utilizing Landsat imagery and applying remote sensing and LEI-based classification between 1975 and 2025, this research identifies not only the spatial patterns but also the underlying processes that shape urban expansion. The findings aim to inform planners and policymakers by highlighting the interconnections between infrastructure, land use change, and sustainability—

ultimately contributing to more informed and adaptive urban planning frameworks.

2. Analysis Framework

The form of urban growth has been a phenomenon continually studied from past to present. In recent years, studies have focused on quantitatively measuring urban growth and determining growth types. However, Harvey and Clark (1965) were the first to define urban growth and sprawl in three different forms [9].

a. Low-Density Sprawl

This type of development generally occurs on the urban fringe for urban purposes, involving high land consumption. The observed pattern in this type of sprawl includes homogeneous, low-density construction.

b. Ribbon Development

This form of urban development extends from city centers to the periphery, following major transportation axes. Ribbon development is considered more costly than low-density sprawl during development. It usually concentrates along roads or transportation networks, while other surrounding areas remain vacant.

c. Leap-Frog Development

This type of sprawl creates separated yet compact urban use zones. Providing social and physical infrastructure services to newly formed areas is quite costly. The resulting land-use pattern is irregular.

Nas (2016) visualized the types of urban sprawl as shown in Fig. 1.

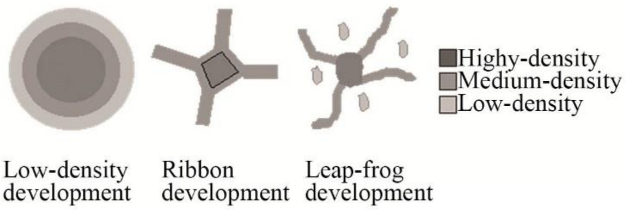

Figure 1. Types of urban sprawl [37]

Another type of development that is not synonymous with urban sprawl or considered a type of sprawl but still significant to evaluate is exurban development. This type of development generally consists of non-agricultural uses, predominantly residential areas, scattered in rural areas with agricultural and forest lands. Shands (1991) defined this as extended low-density development. Residents in these areas are often individuals seeking tranquility and peace, viewing rural areas as an escape or purchasing second homes for investment purposes [38]. However, these individuals' values differ from those of rural residents, leading to conflicts over land use and causing agricultural and forest lands to be used for unintended purposes [39].

In these developed approaches, only the physical characteristics were evaluated to determine the type of urban growth and sprawl, overlooking the pattern differences between the past and present. In this context, Liu et al. (2010) developed the Landscape Expansion Index (LEI), which allows for the analysis of dynamic change processes in spatial patterns using multi-temporal remote sensing data [1].

2.1. Traditional Landscape Indices and Their Limitations

In the context of landscape ecology and geographical analysis, an urban patch refers to a distinct, spatially separated, and homogeneous segment of urban land use or land cover type. Urban patches typically consist of areas serving specific urban functions, such as residential zones, commercial districts, industrial facilities, parks, or transportation corridors. Urban development areas can also be evaluated as urban patches.

Traditional landscape indices are employed to quantitatively analyze the spatial characteristics, distribution, and shapes of urban patches. These indices have been widely used to understand land use and land cover changes and examine spatial patterns. However, the sizes, distributions, and boundaries of urban patches are constantly changing due to urban growth processes and land use transitions.

Traditional landscape indices are limited in capturing temporal changes. These indices typically analyze spatial patterns at a specific point in time and fail to account for dynamic processes. Furthermore, they do not adequately consider spatial relationships and contextual interactions between patches [40], making them insufficient for understanding the temporal dynamics of urban growth.

Patch-level indices evaluate attributes such as patch area, geometric complexity (shape index), and edge-to-area ratio. Class-level indices examine the distribution and number of patches within a specific land cover class and analyze the connectivity between patches. Landscape-level indices, on the other hand, analyze the structure of the entire landscape [33, 41–43]. However, these traditional indices remain limited in reflecting temporal change processes.

To overcome the limitations of traditional landscape indices and better understand temporal dynamics, indices are needed that not only analyze patterns at a specific time but also provide insight into change processes occurring between two or more time periods [35].

2.2. Landscape Expansion Index (LEI)

Traditional landscape indices have significant limitations in analyzing urban expansion in rapidly growing areas. These indices generally only quantify landscape patterns and distributions at a specific time. To address these limitations, Liu et al. (2010) proposed the Landscape Expansion Index (LEI) to examine how urban patches change over time and identify expansion types over time [1].

LEI is based on buffer analysis, a key spatial analysis function in Geographic Information Systems (GIS). Buffer zones are areas created around a geographic feature based on a specified distance. This analysis determines which patches are located inside or outside a defined buffer zone. For accuracy, it is crucial to set the buffer zone at a distance of 1 meter during the analysis process [1].

LEI is calculated using the following formula:

$$LEI = 100\ x\ \frac{A_0}{A_0 + A_v}$$

LEI is the landscape expansion index for a newly grown patch,

A_o is the intersection between the buffer zone and the occupied category,

A_v is the intersection between the buffer zone and the vacant category.

LEI values range between 0 and 100 and are used to identify types of urban growth, each representing specific spatial characteristics and processes.

Infilling Growth – LEI: 50–100

This growth type occurs when new development areas fill in gaps within or around existing urban areas. In this case, the new development area is almost entirely surrounded by existing urban areas.

- The new development overlaps more than 50% with existing urban areas.
- Facilitates densification and the formation of a compact urban structure.
- Increases land use efficiency by utilizing vacant spaces.
- Infilling growth is considered ideal for sustainable urban development as it better integrates with existing infrastructure and reduces resource waste due to sprawl.

Edge-Expansion Growth – LEI: 0–50

This growth type occurs when new development areas expand outward from the edges of existing urban areas. In this case, the new development area touches both existing urban areas and vacant land.

- Less than 50% of the buffer zone of the new development overlaps with existing urban areas.
- Although it controls urban sprawl, it does not create a fully compact structure.

Outlying Growth – LEI: 0

This growth type occurs when new development areas emerge independently and are isolated from existing urban areas. These new areas are entirely surrounded by vacant land without any connection to old urban areas. Development is often irregular and unplanned, causing urban fragmentation.

Fig. 2 illustrates the three primary urban growth types—infill, edge-expansion, and outlying—identified through the Landscape Expansion Index (LEI) within a selected portion of the study area. The visual classification was derived from actual spatial patterns observed in the field and reinterpreted in accordance with the typological framework proposed by Liu et al. (2010). Black areas represent previously developed urban patches, while the gray tones indicate newly developed patches categorized by their spatial relationship to existing urban areas.

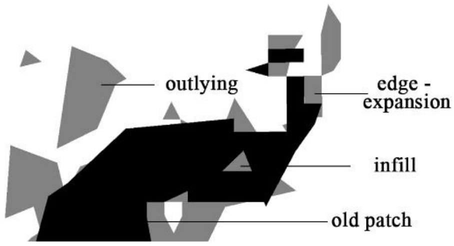

Figure 2. Urban growth types based on LEI

3. Methods And Data

3.1. Study Area and Image Classification

This study examines the changes in Land Use and Land Cover (LULC) within a 10 km buffer zone surrounding the İzmir-Denizli (O-31) Highway (Fig. 3) in western Turkey, covering the period from 1984 to 2025. The 10 km buffer zone was selected based on its widespread use in the literature for analyzing the spatial impacts of transportation infrastructure on land use dynamics [19–23, 44]. This radius provides a sufficient spatial extent to capture both direct and indirect effects of highway development on urban expansion, ensuring a comprehensive assessment of LULC changes over time.

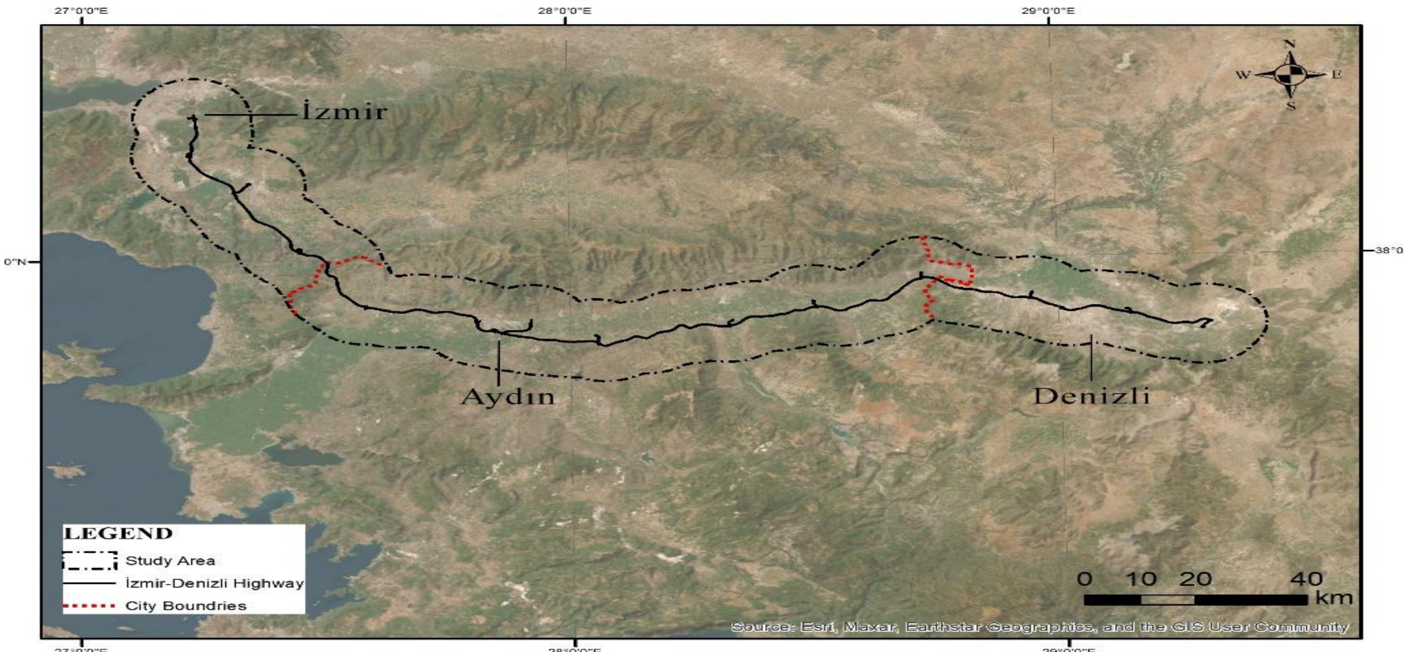

Figure 3. Study area

This study employed a temporal aggregation method to generate annual composite images, utilizing median metrics derived from time-series data [45].

Cloud-free Landsat satellite imagery was used to produce composite images for the years 1984, 1990, 2000, 2010, 2020, and 2025, all at a spatial resolution of 30 meters (Table 1) [46–48]. To ensure consistency in visual interpretation and the selection of training samples, RGB bands were used based on the sensor specifications: Bands 1, 2, 3 and 7 were utilized for Landsat 5 and 7, while Bands 2, 3, and 4 were employed for Landsat 8 imagery. However, during the classification process, a broader set of spectral bands was used to improve classification accuracy. Specifically, Bands 1–7 were used for Landsat 5, Bands 1–5, 7, and 8 for Landsat 7, and Bands 2–10 for Landsat 8. This approach ensured the inclusion of both visible and non-visible spectral information to enhance the detection of different land cover types and support more accurate LULC classification.

Table 1. General characteristics of satellite images and accuracy values for given years

Year	Satellite	Spatial Resolution	Cloud Cover	Acquisition Period	# images	Overall Accuracy	Kappa Coefficient
1984	Landsat 5 TM	30m	<1	03/06/1984 – 31/12/184	20	0.81	0.79
1990	Landsat 5 TM	30m	<1	01/01/1990 – 31/12/1990	30	0.84	0.81
2000	Landsat 7 ETM+	30m	<1	01/01/2000 – 31/12/2000	32	0.82	0.80
2010	Landsat 7 ETM+	30m	<1	01/01/2010 – 31/12/2010	12	0.88	0.85
2020	Landsat 8 OLI/TIRS	30m	<1	01/01/2020 – 31/12/2020	25	0.89	0.85
2025	Landsat 8 OLI/TIRS	30m	<1	01/01/2024 – 10/03/2025	39	0.90	0.88

Land use classification was conducted using the Random Forest (RF) algorithm implemented within the Google Earth Engine (GEE) platform, which is widely acknowledged for its high performance in remote sensing applications [45, 49–63]. The RF algorithm enabled the categorization of land use and land cover (LULC) into distinct classes and the extraction of urban areas for the selected years: 1984, 1990, 2000, 2010, 2020, and 2025. This methodological framework provided a robust basis for analyzing long-term LULC changes and understanding the spatial dynamics of urbanization over a nearly 40-year period.

3.2. Spatial and Temporal Analysis

The spatial and temporal analysis of LULC changes was conducted using the classified images to examine the transformation of built-up areas over time [64, 65]. To ensure a comprehensive assessment, built-up areas were extracted using both ArcMap 10.7 and GEE, integrating the strengths of both platforms for spatial analysis. While GEE was utilized for image classification, all subsequent calculations were performed within ArcMap 10.7 to quantify the extent and distribution of urban expansion. The classification results were analyzed to derive insights into urban growth patterns and their broader implications for land use dynamics in the study area.

3.3. Calculation of the Landscape Expansion Index (LEI)

The Landscape Expansion Index (LEI) and its variants were calculated using ArcMap 10.7 through custom programming. Initially, the land use data were converted into vector format to facilitate further analysis. Buffer zones for all new urban patches were generated by executing the program, allowing for the definition of these buffers with either constant or variable distances based on feature attributes. In this study, a constant distance of 1 meter was applied [1].

After obtaining the buffer zones for all growth patches, these zones were overlaid with the previous urban patches to calculate the area of old urban patches within the buffer zones. The LEI was then computed for each new urban patch using the established formula (Equation 1). The program automatically generated the buffer zones for new urban patches (Fig. 6), enabling the identification of different growth types, including infilling, edge-expansion, and outlying growth.

4. RESULTS

The temporal dynamics of built-up area expansion within the 10 km buffer zone surrounding the İzmir-Denizli Highway between 1984 and 2025 are illustrated through both the tabular data and spatial maps in Fig. 4 and Fig. 5. These representations collectively highlight the progressive urbanization trends influenced by transportation infrastructure and regional development dynamics.

The tabular data reveal a steady increase in built-up areas over the examined period. In 1984, the total built-up area was 45682 ha, which experienced a modest rise to 47585 ha in 1990. However, after 2000, a more pronounced acceleration in urban expansion is observed, with built-up areas reaching 53410 ha in 2000, 58923 ha in 2010, and 65204 ha in 2020. The most recent data from 2025 indicate a further increase to 68869 ha, demonstrating the continuing trend of urban sprawl in the region [16, 17, 19–23] .

The series of maps visually depict the spatiotemporal expansion of built-up areas along the highway corridor. The early periods (1984–1990) exhibit limited urban growth, with built-up areas mainly concentrated around existing urban centers. However, from 2000 onwards, significant expansion occurs, particularly near highway exits and along the corridor, indicating that improved accessibility has facilitated urban sprawl [20, 22, 23, 27–29, 66]. Unlike Fan and Fan, by 2020 and 2025, built-up areas have become increasingly widespread and interconnected, forming a more continuous urban fabric within the buffer zone [31].

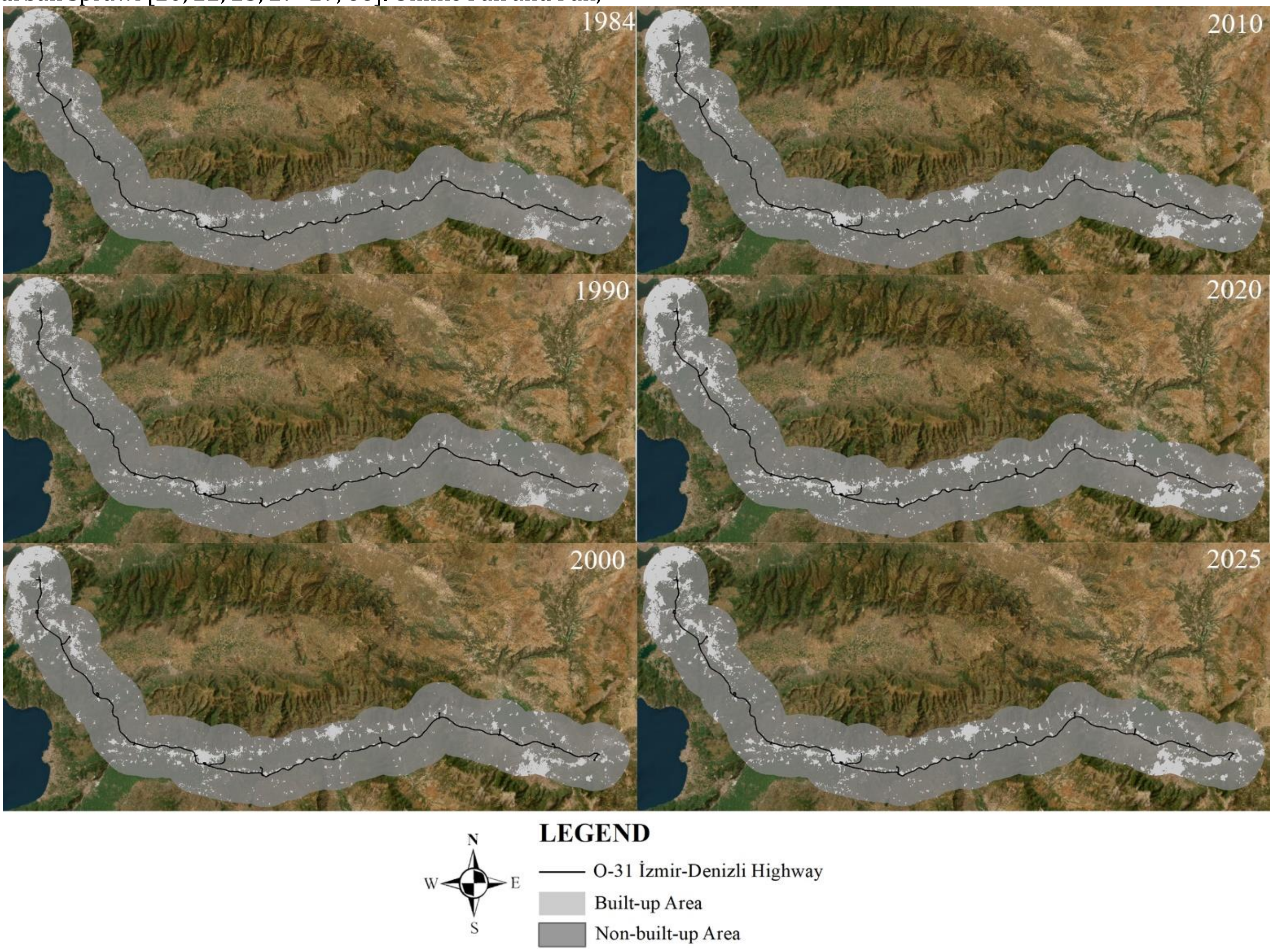

Figure 4. Built-up change between the years 1984-2025

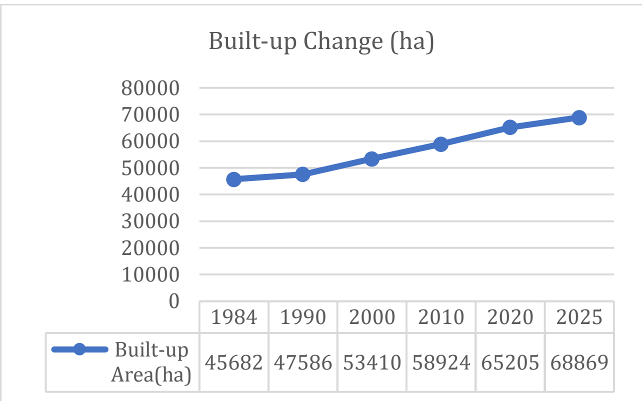

Figure 5. The temporal dynamics of built-up areas within the 10 km buffer zone of İzmir-Denizli Highway

Fig. 6 presents the newly developed patches and their growth types within the 10 km buffer zone surrounding the İzmir-Denizli highway after 1984. The studies conducted in the İzmir-Denizli corridor reveals a significant prevalence of edge-expansion growth, accounting for 71.3% of the newly developed patches identified in the area. Similarly Liu et al. (2010) observed similar patterns in Dongguan, China, where urban growth was primarily characterized by edge-expansion, indicating a common trend in rapidly urbanizing regions [1].

In addition, 27.4% of the patches are characterized by outlying growth, which promotes leapfrog development and reduces physical connectivity between patches. This scattered growth increases infrastructure costs and hinders the sustainable and planned development of cities.

Unlike Fan and Fan (2014), our findings highlight the low representation of infilling growth at just 1.3%. While Fan and Fan illustrate a significant transition in the built-up environment from sparse and irregular distributions to a denser, less fragmented configuration in newly developed districts—indicating a trend of urban sprawl followed by a "filling-in" process our findings raise concerns about the insufficient utilization of existing urban areas [31].

This analysis provides a framework for better understanding the spatial characteristics of growth types in the study area. The proportions of growth types underscore the need to reassess urban and rural planning strategies to promote more sustainable development patterns [1].

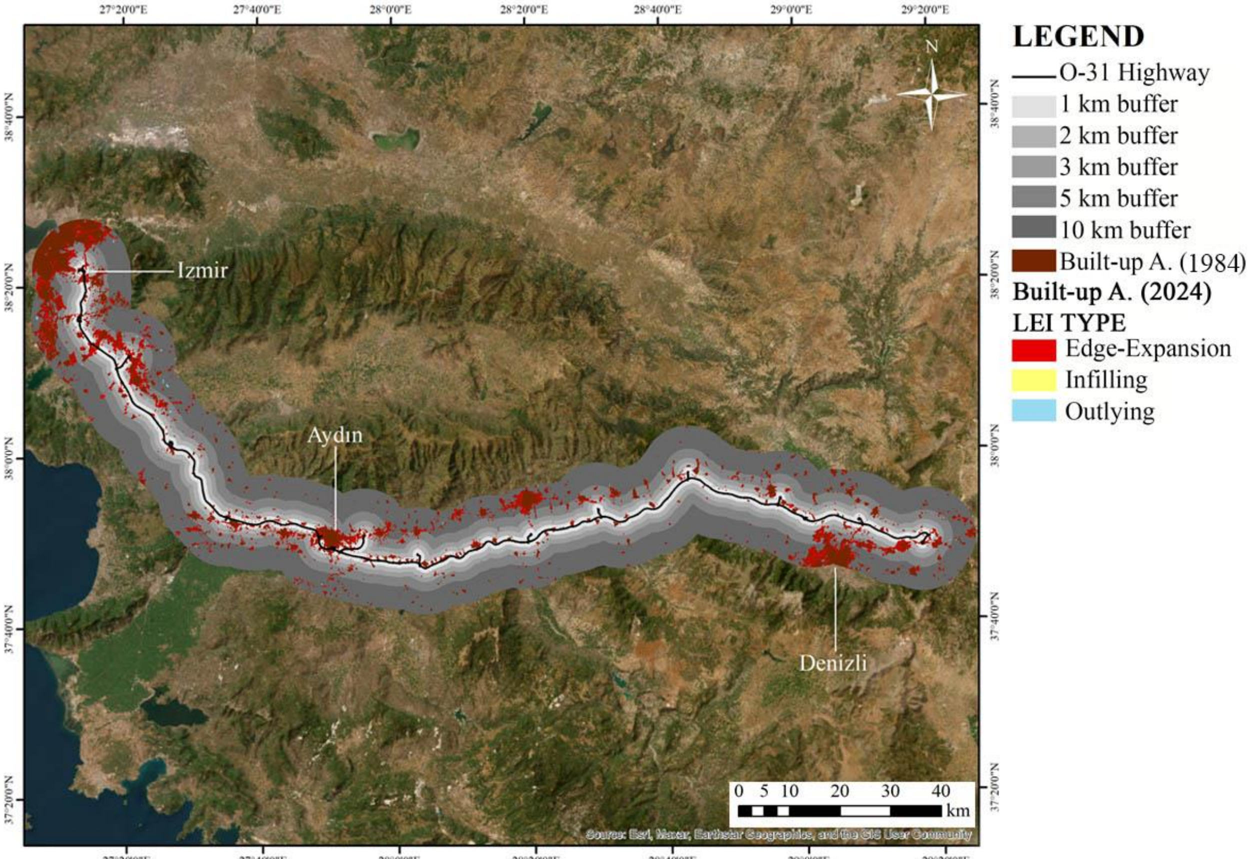

Figure 6. Spatial distribution of growth patterns along the İzmir-Denizli highway corridor

Table 2 illustrates the growth patterns along O-31 Higway. The analysis of built-up area expansion along the İzmir-Denizli Highway Corridor reveals significant urbanization trends across different buffer zones (1 km, 2 km, 5 km, and 10 km). The total new built-up area is highest within the 10 km buffer zone (32,534 ha), indicating that urban expansion is not confined to the immediate highway surroundings but extends into the peri-urban landscape. This result differs from the existing literature, which often emphasizes more concentrated urban growth in proximity to major transportation corridors [16, 18, 19].

Table 2. Growth patterns of built-up areas across different buffer zones (ha)

	1 km			2 km			5 km			10 km		
(ha)	Izmir	Aydın	Denizli	Izmir	Aydın	Denizli	Izmir	Aydın	Denizli	Izmir	Aydın	Denizli
Edge-expansion	2382	4400	1020	2068	3291	1211	8605	5685	4230	17705	6881	7366
Outlying	72	96	28	65	80	8	193	144	52	228	217	79
Infill	18	10	8	2	4	3	4	15	9	5	30	23
Total	2472	4506	1056	2135	3375	1223	8802	5845	4291	17938	7127	7468
Total in buffers		8034			6733			18937			32534	

5. Discussion

This study provides a comprehensive analysis of land use and land cover (LULC) changes along the İzmir-Denizli Highway corridor from 1984 to 2025, utilizing remote sensing techniques and the Landscape Expansion Index (LEI) to assess urban growth patterns. The findings reveal a significant increase in built-up areas, with a total expansion of 32,534 ha within the 10 km buffer zone, indicating that urbanization is extending beyond immediate highway surroundings into the peri-urban landscape. This trend contrasts with existing literature that often emphasizes concentrated growth near transportation corridors [22, 24, 25]. The results suggest that urban expansion is not merely a localized phenomenon but rather a broader transformation affecting the entire region.

The analysis highlights a predominance of edge-expansion growth, which accounts for 71.3% of newly developed patches. This finding aligns with observations made by Liu et al. (2010) in rapidly urbanizing regions, where edge-expansion is often the primary mode of urban growth. The transition from sparse and irregular distributions to a denser, less fragmented configuration in newly developed districts reflects a trend of urban sprawl, followed by a "filling-in" process that leads to increased residential density [31]. However, the low representation of infilling growth at just 1.3% raises concerns about the inefficient utilization of existing urban areas. This indicates a missed opportunity for sustainable development, as infilling is widely regarded as a more environmentally friendly approach that optimizes land use and reduces the need for new infrastructure.

The implications of these findings are significant for urban planning and policy-making. The predominance of edge-expansion growth suggests that current development practices may be contributing to urban sprawl, which can lead to increased infrastructure costs, environmental degradation, and social fragmentation. As highlighted by Chettry (2022), the continuous transformation of land use due to urban expansion necessitates policies that balance growth with environmental sustainability [17]. Policymakers must prioritize strategies that encourage infilling and the efficient use of existing urban spaces to mitigate the adverse effects of sprawl and promote more sustainable urban forms.

Moreover, the study underscores the critical role of transportation infrastructure in shaping urban growth patterns. Improved accessibility along the İzmir-Denizli Highway has facilitated urban sprawl, particularly near highway exits, where built-up areas have expanded at a much higher rate. This finding is consistent with previous research that emphasizes the influence of transportation networks on land use transformations [18, 28]. As urban areas continue to grow, it is essential to consider the long-term impacts of transportation infrastructure on land use dynamics and to implement planning measures that promote connectivity and accessibility while minimizing environmental impacts.

This study not only identifies the spatial patterns of urbanization but also provides insights into the driving forces behind these changes. Understanding these long-term urbanization trends is essential for urban planners and policymakers, as it enables them to anticipate future development trajectories, mitigate uncontrolled sprawl, and promote more sustainable land use strategies.

6. Conlusion

Understanding the spatial and temporal dynamics of urban growth is crucial for effective urban planning and management. By employing advanced remote sensing techniques and quantitative analysis, this study contributes valuable insights into the complex interactions between urbanization and landscape change, guiding efforts toward sustainable urban development in the İzmir-Denizli corridor and similar contexts.

Future research should continue to explore the implications of different growth types on infrastructure, resource allocation, and environmental sustainability, ensuring that urban expansion aligns with broader sustainability goals. Additionally, integrating community input and stakeholder engagement in the planning process will be vital for creating resilient urban environments that meet the needs of current and future populations while preserving ecological integrity. By fostering a deeper understanding of urban growth dynamics, this research aims to inform policies that promote sustainable, equitable, and resilient urban futures.

Future research can expand on this methodology by applying the LEI process across different time series and urban contexts. Incorporating high-resolution LULC data and advanced geospatial techniques, such as machine learning and remote sensing, can enhance the precision and applicability of such analyses. Policymakers and urban planners should use LULC and LEI insights to prioritize strategies that balance urban growth with ecological sustainability. Specifically, promoting infill growth and mitigating outlying expansion can help optimize infrastructure usage while minimizing the ecological and social costs of urban sprawl.

Ultimately, this research contributes to the broader discourse on urban sustainability by demonstrating how advanced spatial analysis techniques can enhance our ability to monitor, interpret, and manage urban growth in rapidly developing regions

Author contributions

Gülsüm Ecem Demirdağ: Data curation, Conceptualization, Methodology, Software, Writing-Original draft preparation, Visualization, **Kemal Mert Çubukçu:** Validation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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