Research Article GU J Sci 39(1): 59-80 (2026) DOI: 10.35378/gujs.1643528

Gazi University

Journal of Science

http://dergipark.org.tr/gujs

Spatial Dynamics of Land Use and Land Cover Change around the İzmir–Aydın Highway (1993–2023)

Gulsum Ecem DEMIRDAG[1,2,*], Kemal Mert CUBUKCU[1]

[1]Dokuz Eylul University, Faculty of Architecture, 35000, İzmir, Türkiye
[2]Mersin University, Faculty of Architecture, 33000, Mersin, Türkiye

Highlights

- Long-term LULC changes analyzed around the İzmir–Aydın Highway (1993–2023).
- Built-up areas doubled, while agricultural and forest lands declined significantly.
- Kernel Density and buffer analyses reveal clustered growth near highway exits.
- Highway accessibility drives peri-urban expansion and agricultural land loss.

Article Info

Received: 20 Feb 2025
Accepted: 24 Oct 2025

Keywords

Google earth engine
LULC change
Remote sensing
Spatio-temporal analysis
Kernel density

Abstract

This study aims to examine the effects of increased accessibility caused by the O-31 Highway on Land Use and Land Cover (LULC) changes within a 10 km buffer zone between 1993 and 2023. Using multi-band Landsat satellite imagery, LULC classifications were performed through the Random Forest (RF) machine learning algorithm on the Google Earth Engine (GEE) platform. To enhance classification accuracy, remote sensing indices and the pan-sharpening method were integrated. Results show a significant transformation in land cover over the 30-year period. Built-up areas doubled, increasing from 8% in 1993 to 16% in 2023, while bare land expanded from 27% to 45%. Conversely, agricultural areas declined from 35% to 22%, and forest areas from 31% to 16%. Spatial analysis, including transition matrices and kernel density estimation, revealed that the most intense LULC changes were concentrated within the 1–5 km buffer zone and particularly around highway interchanges (entry/exit points). These findings highlight how accessibility-driven development tends to cluster in strategically connected peri-urban areas, aligning with broader observations in urban expansion literature while offering context-specific insights. The study underscores the limitations of current urban planning practices in managing peri-urban growth and protecting agricultural land.

1. INTRODUCTION

Since the dawn of civilization, agriculture and related activities have constituted a fundamental part of human existence. While the relationship between land and humans was historically balanced, recent increases in population, urbanization, and urban growth have disrupted this equilibrium. Soil, a resource that takes centuries to form, is easily depleted and difficult to restore once degraded or misused. In this context, soil is recognized as a vital and limited resource for sustaining human life [1]. Industrialization, rapid population growth, and various planning decisions have collectively accelerated urbanization and contributed to the outward expansion of cities, thereby increasing pressure on agricultural areas. Uncontrolled urban growth, particularly prevalent in industrialized and industrializing countries, has resulted in severe environmental consequences. Over the past century, the combined effects of industrialization and intensified human activity have led to environmental degradation, unplanned urban development, and the misuse of fertile agricultural land [2].

The development of urban areas and the rising global population demand a comprehensive and strategic evaluation of land use. With the advancement of satellite technologies, remote sensing (RS) has emerged as a powerful tool, offering rapid and reliable access to diverse datasets without the need for physical contact [3]. This capability makes RS particularly valuable for monitoring and analyzing land use changes.

*Corresponding author, e-mail: ecemyuksel@mersin.edu.tr

In recent years, the availability of medium- and high-resolution satellite imagery has significantly enhanced the applicability and accuracy of remote sensing methods [4–6]. Moreover, land use land cover (LULC) maps derived from remote sensing data have become indispensable tools in land resource management, urban planning, agricultural land conservation, and change detection studies [7–10].

Given the increasing urban pressure on agricultural lands and their ongoing conversion for non-agricultural purposes, there is a growing need to evaluate how effectively current urban planning practices respond to these transformations. Rather than being inherently inadequate, planning policies often suffer from limited access to consistent spatial data and analytical tools that can capture long-term land-use dynamics. The inability to accurately assess and interpret these changes constrains evidence-based decision-making and reduces the adaptability of planning interventions. As a forward-looking discipline, urban planning should bridge past and future developments through a robust understanding of spatial and temporal patterns of urban growth. Therefore, advancing spatial analysis techniques and integrating them into planning practice are crucial for achieving sustainable land management and informed policy development.

2. REVIEW OF RELATED LITERATURE

The main drivers of urban sprawl are primarily economic, particularly factors related to cost and rent. Cities tend to expand more readily toward areas that are accessible and economically favorable. As a result, mountainous or steep regions often act as natural barriers to urban growth. In contrast, extended transportation networks, supportive public policies, and lower taxes in peripheral areas encourage urban expansion. Improved transportation infrastructure facilitates access to distant regions from city centers, while lower land prices and fiscal incentives in outlying areas make these locations more attractive for development. This pattern of expansion frequently occurs on the peripheries of cities and often affects fertile agricultural land, gradually reducing agricultural activity [11]. Initially, the spatial impact on farmland may appear limited or dispersed; however, as urban growth continues over time, these scattered changes accumulate, ultimately leading to significant losses in agricultural areas and reductions in food production capacity. Such trends have raised growing concerns among planners and agricultural professionals.

Investigating the spatial transformations caused by urban sprawl, analyzing changes in land use patterns, developing strategies to alleviate pressure on agricultural lands, and managing non-agricultural uses of farmland are essential for ensuring sustainable development. It has been emphasized that one of the primary reasons for the ineffectiveness of urban planning policies lies in the limitations of tools and techniques used to monitor and interpret spatial change over time. To support well-informed planning decisions, it is necessary to examine past land use trends and current dynamics through analytical and evidence-based approaches that can inform long-term strategies [12, 13].

Studies examining land use and land cover (LULC) changes between 2000 and 2020 have revealed substantial decreases in agricultural lands alongside increases in built-up areas [14]. These findings underscore a consistent trend of urban expansion occurring at the expense of agricultural resources and reinforce the need for planning practices that promote a balance between urban development and the preservation of fertile land. Other analyses using satellite imagery from the early 1990s to 2020 have also documented consistent increases in built-up areas and declines in surrounding green spaces across multiple cities, demonstrating the persistent pressure that urban expansion places on nearby agricultural and forested lands [15].

Transportation infrastructure plays a central role in facilitating urban sprawl. Improvements in road transport systems have been shown to exert significant influence on spatial development patterns [16]. As population densities increase, investments in transportation tend to follow, enhancing accessibility to peripheral regions and accelerating land use change [17, 18]. Researchers often focus on areas located within a 10-kilometer buffer around highways [19–23]. To assess the influence of highways more precisely, areas in close proximity to highway exits have received special attention, as they exhibit more direct exposure to development pressures [22]. Over time, these areas often experience a marked decline in the significance of agricultural land [24, 25].

Changes in land cover are generally more pronounced near highway exits. Studies reviewed in the literature indicate that areas in close proximity to highway exits tend to experience faster and more intense land transformations compared to other regions [20, 22, 23, 26–29]. These studies consistently report that the construction of highway infrastructure is associated with losses in forest and agricultural lands, while built-up areas expand considerably in these zones [20, 22, 30]. The expansion of transport networks has also been linked to widespread urban growth and a corresponding decline in barren and agricultural lands in metropolitan regions [29, 30]. Furthermore, the likelihood of urban development increases significantly in areas located near major roads [31, 32].

Research focusing on population dynamics around highways has also demonstrated that demographic growth tends to be concentrated in these areas. These trends reflect patterns of spatial development and increased land demand near major transport corridors [26, 27, 33]. Infrastructure developments such as bridges and interregional road networks have been shown to significantly influence the spatial extent and density of urbanized surfaces, facilitating concentrated patterns of urban expansion along highway corridors [25].

Remote sensing is widely recognized as a cost-effective and efficient method for producing LULC maps. Classification techniques in remote sensing are generally divided into categories such as supervised, unsupervised, semi-supervised, reinforcement learning, and machine learning algorithms [34]. A recent review of hundreds of peer-reviewed studies has shown that Google Earth Engine (GEE) has become the most frequently used platform in global remote sensing research, with the Random Forest (RF) algorithm identified as the most widely applied classification method [35]. In accordance with these findings, the LULC maps in this study were produced using the RF algorithm on the GEE platform, utilizing a supervised classification approach.

While existing studies have largely focused on land-use changes, suburbanization, and population increases near transportation infrastructure, the primary objective of this research is to quantify agricultural land loss and the conversion between land use types. Quantitative assessments of agricultural land reduction near highways, the expansion of bare land, and the growth of urban areas around highway exits remain limited. This study extends the literature by providing a long-term (1993–2023) and broad-scale (10 km buffer) analysis, capturing the cumulative impacts of highway infrastructure on multiple land-cover types, including agricultural, forest, bare, and built-up areas. By applying kernel density analysis, the study identifies zones where land transformation is most intense, highlighting the spatial concentration and continuity of urban expansion over time. Although spatial analysis alone cannot fully account for socio-economic and demographic drivers, it provides a crucial framework for understanding the temporal and spatial dynamics of land-use change and guiding evidence-based planning strategies in peri-urban areas. These methodological and analytical contributions provide new insights into the extent, intensity, and spatial patterns of land transformation, thereby refining and complementing previous studies in the field.

3. MATERIALS AND METHODS

Land Use Land Cover (LULC) maps are crucial for understanding, assessing, and addressing the degradation of natural and cultural resources caused by urban land use changes, especially within the framework of sustainability. They serve as one of the most widely used indicators for examining environmental changes and degradation, as land use alterations are directly influenced by both natural phenomena and human activities [36]. In this study, LULC maps were generated from satellite imagery to analyze temporal changes within the study area [7–10].

3.1. Land-use Analysis

Satellite image processing was conducted using Google Earth Engine (GEE) and ArcGIS software. GEE is a cloud-based geospatial data processing platform that enables rapid execution of various analyses. Supported by Google, the platform provides open access to extensive datasets globally. Through GEE, it is possible to assess changes in features such as vegetation, forests, water bodies, and the condition of

agricultural lands. The platform offers access to over 40 years of global-scale data, along with robust analytical tools [37, 38].

3.2. Study Area

The İzmir-Aydın highway (O-31) is among the oldest highways in Turkey. This highway traverses the Büyük Menderes Basin, one of the world's largest drainage basins and a key fertile agricultural region in Turkey. Given that the main focus of this study is the evaluation of agricultural lands surrounding the highway, the O-31 and its vicinity were selected as the study area [39].

The study area includes a 10 km buffer zone around Highway O-31, which connects the cities of İzmir and Aydın in Turkey [21–23]. The initial segment of the highway was completed in 1993, with most parts (except for the tunnel leading to the Aydın North interchange) becoming operational in 1996. The highway reached its current form in 2017. Figure 1 illustrates Highway O-31 alongside the 10 km buffer zone used in this study.

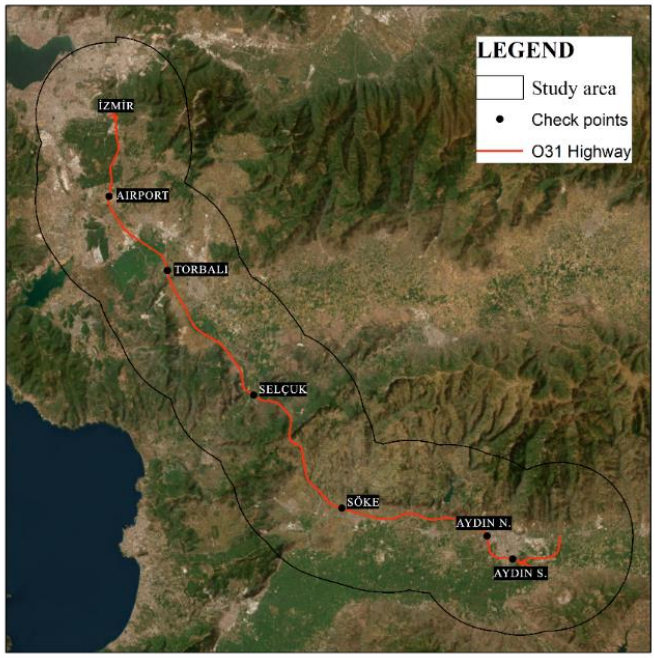


Figure 1. *Study area (10 km buffer of O-31 highway) (Source: Author)*

3.3. Materials

Satellite imagery utilized in this study was sourced from the United States Geological Survey (USGS) through the Google Earth Engine (GEE) platform. The analysis focused on median data from Landsat 5 imagery collected from January 1 to December 31, 1993, and Landsat 8 collected from January 1 to December 31, 2023. For effective land cover mapping using Landsat data, it is recommended to select imagery with cloud cover below 10% [40, 41]. In this research, the GEE cloud masking tool was employed to ensure that only Landsat images with cloud cover below 1% were included.

The analysis incorporated bands 1 through 8 from both Landsat 5 and Landsat 8. Additionally, several indices were integrated into the analysis to enhance land cover classification, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), Built-up Index (BUI), and Built-up Surface Index (BSI), utilizing the random forest machine learning algorithm.

Table 1 summarizes the characteristics of the satellite images used in this study. The Landsat 5 imagery from 1993 consisted of 26 images, achieving an overall accuracy of 0.81 and a Kappa coefficient of 0.80,

and the Landsat 8 imagery from 2023 included 23 images, with an overall accuracy of 0.93 and a Kappa coefficient of 0.89 indicating a high level of reliability in the classification results. The differences in overall accuracy and Kappa coefficients between the 1993 and 2023 classifications suggest potential challenges in land cover classification, which may be attributed to variations in land use patterns, environmental conditions, or atmospheric influences over the intervening years. Additionally, these discrepancies may also result from differences in sensor characteristics and spatial resolution between Landsat 5 and Landsat 8 satellites. In this context, the use of pan-sharpening technique to Landsat 8 imagery contributes to improving spatial detail and enhancing classification accuracy, thereby partially mitigating the limitations caused by resolution differences. Figure 2 illustrates the data processing flow employed in this analysis.

Table 1. *Characteristic of Satellite images used*

Year	Satellite	Spatial Resolution	Cloud Cover	Acquisition Period	# of images	Overall Accuracy	Kappa Coefficient
1993	LANDSAT 5 TM	30m	<1	01.01.1993 – 31.12.1993	26	0.81	0.80
2023	LANDSAT 8	30m > 15m	<1	01.01.2023 – 31.12.2023	23	0.93	0.89

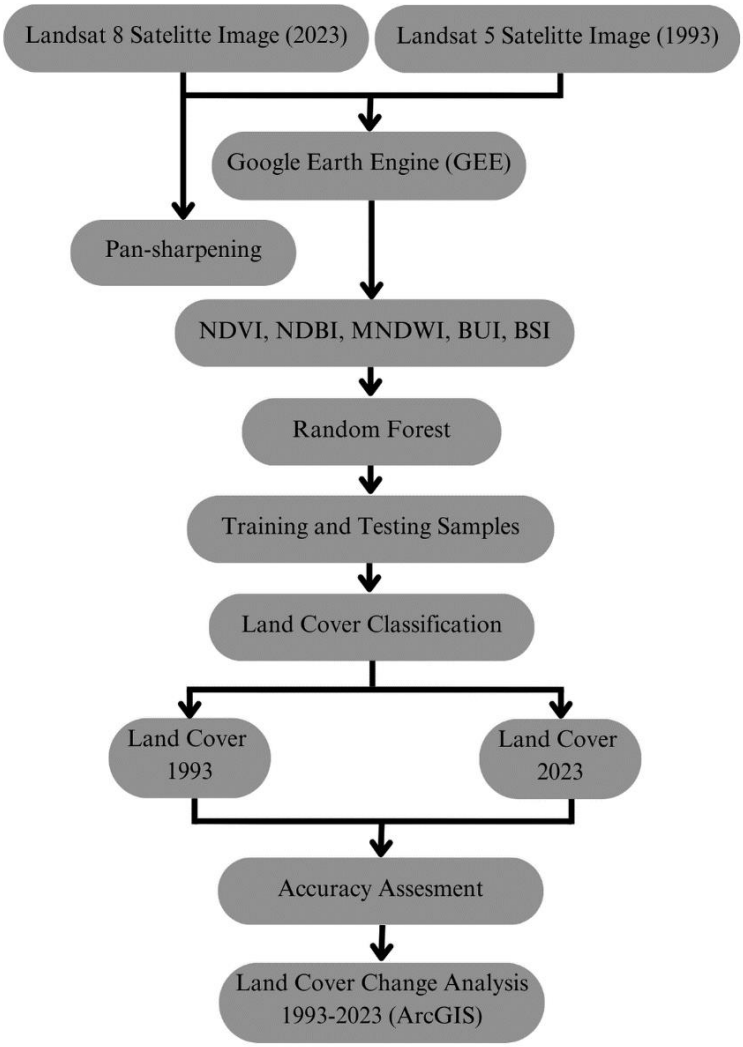


Figure 2. *Data processing (Source: Author's work)*

3.4. Pan Sharpening

In this study, the Hue-Saturation-Value (HSV) pan-sharpening technique was applied to Landsat 8 imagery to enhance spatial resolution. Pan-sharpening is a method that merges multispectral images (30-meter resolution) with panchromatic images (15-meter resolution) and aims to improve the spatial quality of remotely sensed data [42, 43]. The improvement in visual clarity can be observed in Figures 3 and 4. Figure 3 shows the central area of Aydın Province before pan-sharpening, while Figure 4 illustrates the same area after the application of the technique, with spatial resolutions of 30 m and 15 m, respectively.

The combined use of different sensors (e.g., Landsat 5 and Landsat 8) and the application of advanced image processing techniques such as pan-sharpening can introduce potential sources of uncertainty that may affect classification outcomes. Differences in spectral, radiometric, and temporal characteristics between sensors, as well as image processing steps, may influence land cover interpretation. Nevertheless, the pan-sharpening technique applied particularly to Landsat 8 images has significantly improved spatial detail and contributed to an increase in classification accuracy and Kappa coefficient values.



Figure 3. *Landsat 8 image without pan-sharpening (30m resolution) (Source: Author, using USGS Landsat 8 imagery)*



Figure 4. *Landsat 8 image with pan-sharpening (15m resolution)* (*Source: Author, using USGS Landsat 8 imagery*)

3.5. Land Cover Classification

In the classification phase, the Random Forest (RF) algorithm (a supervised machine learning method) was implemented on the Google Earth Engine (GEE) platform [34, 35]. Bands 1 through 8 of Landsat 5 and Landsat 8 images were used along with a set of spectral indices to enhance classification accuracy: NDVI, NDBI, MNDWI, BUI, and BSI. The land use/land cover (LULC) in the study area was categorized into five classes: Built-up areas, Forest areas, Agricultural areas, Water surface, and Bare lands. Among the vegetation indices, the Normalized Difference Vegetation Index (NDVI) is one of the most widely utilized. It effectively identifies vegetation vitality, dry areas, and water bodies, and has been frequently applied in studies on agricultural change, climate variability, and vegetation dynamics [35, 44].

The Normalized Difference Built-up Index (NDBI) is used to detect urban features and building density by comparing reflectance in the shortwave infrared (SWIR) and near-infrared (NIR) bands [45]. Values range from -1 to 1; higher positive values indicate denser built-up areas, while negative values typically indicate vegetation or water.

The Modified Normalized Difference Water Index (MNDWI) improves water surface detection by using the difference between green and SWIR reflectance. Compared to NDWI, it better distinguishes water bodies from built-up environments, with water typically yielding higher positive values and urban areas appearing with negative values [46].

The Built-up Index (BUI), calculated as NDBI minus NDVI, uses SWIR, NIR, and red bands to more precisely distinguish between urban surfaces and bare soil. Although this semi-automatic approach can improve classification accuracy by more than 20% compared to NDBI alone, it is still dependent on the quality of training samples and may not fully separate bare land from built-up areas [47].

The Bare Soil Index (BSI), derived from red, blue, NIR, and SWIR bands, is particularly effective for identifying bare ground surfaces. It combines components of both NDVI and NDBI. Positive values indicate exposed soil and land surfaces, whereas negative values are associated with vegetation or water bodies [48-50].

The calculations used are presented in the following.

$$NDVI = (NIR-Red)/(NIR+Red) \quad (1)$$

$$NDBI = (SWIR-NIR)/(SWIR+NIR) \quad (2)$$

$$MNDWI = (Green-SWIR)/(Green+SWIR) \quad (3)$$

$$BUI = NDBI-NDVI \quad (4)$$

$$BSI = ((SWIR+Red)-(NIR+Blue))/((SWIR+Red)+(NIR+Blue)) \quad (5)$$

To ensure reliable classification performance, the dataset was randomly divided into training and testing subsets, with 60% used for training and 40% for validation. This approach aligns with standard practices found in the literature, where various studies have applied similar or slightly different data partitioning strategies depending on the nature of the classification task and the dataset characteristics [51–56].

4. RESULTS

To achieve better accuracy, multiple indices and the pan-sharpening method were used. In this context, the inputs obtained were combined with LANDSAT satellite images from 1993 and 2023. Using the RF method on the processed images, the LULC characteristics in the study area were classified, and changes in LULC conditions were evaluated. The LULC classes analyzed in the research area include "Built-up Areas," "Forest Areas," "Agricultural Areas," "Water Surface," and "Bare Lands". The spatial distribution of the LULC status in the research area for 1993 is shown in Figure 5, and for 2023 in Figure 6.

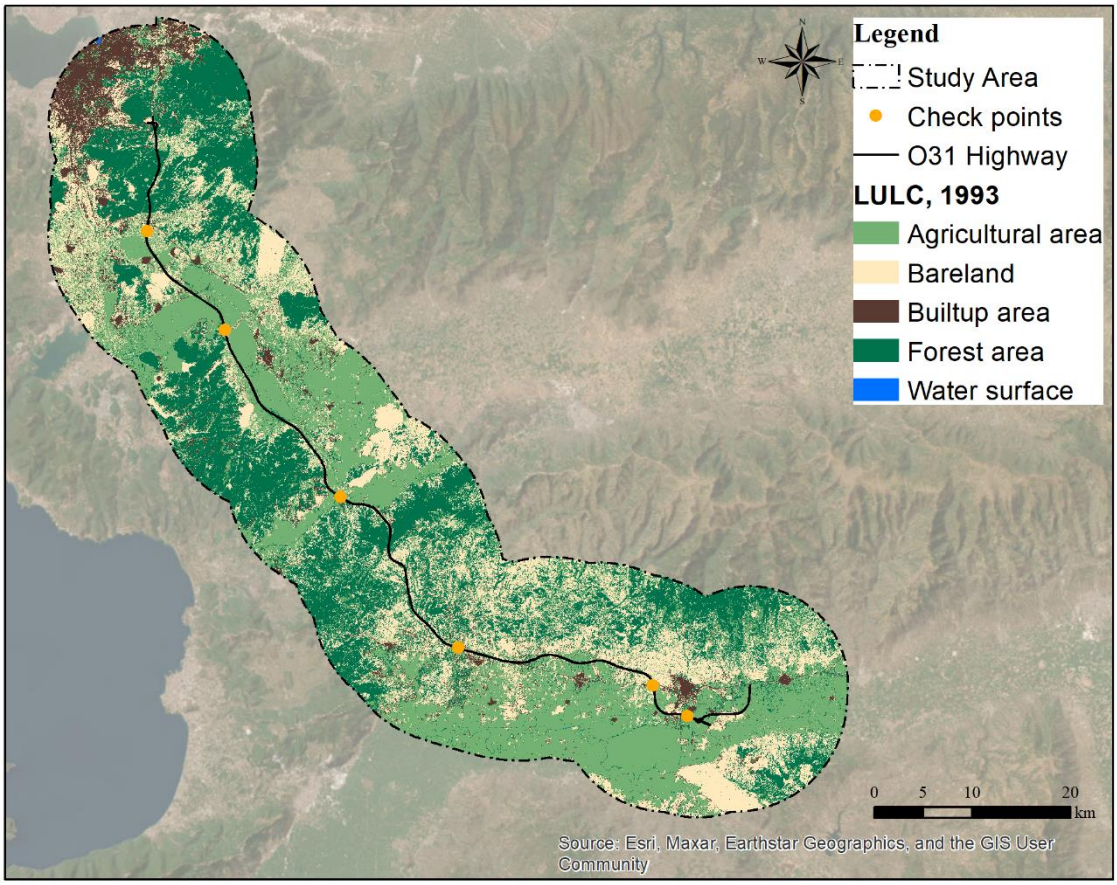


Figure 5. *Land use land cover map of study area, 1993 (10km buffer of O-31 Highway) (Source: Author)*

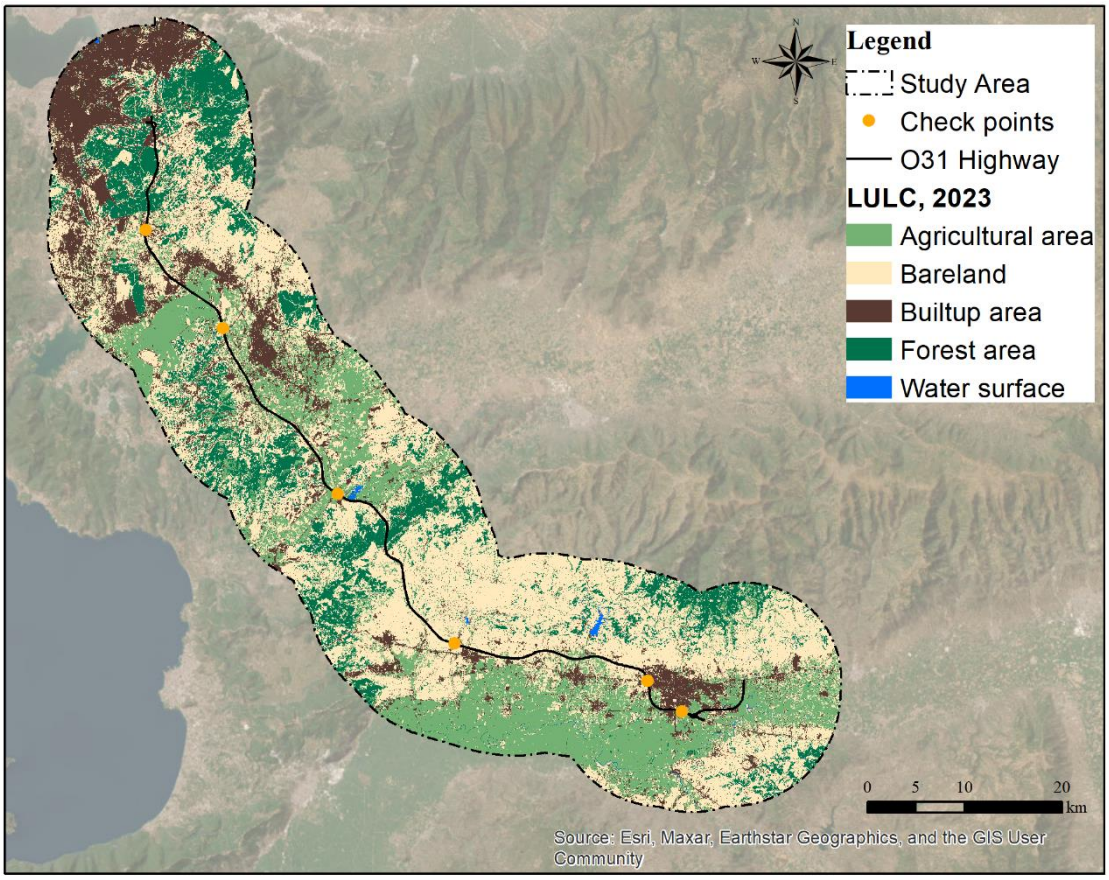


Figure 6. *Land use land cover map of study area, 2023 (10km buffer of O-31 Highway) (Source: Author)*

In 1993, agricultural areas (35%) and forested areas (31%) comprised the majority of the land cover, while built-up areas accounted for 8% (Table 2). By 2023, agricultural and forest areas had decreased significantly to 22% and 16%, respectively while built-up and bare lands increased, the latter reaching 45% of the total area. Notably, bare lands saw the largest growth, increasing by approximately 41,805 ha. Built-up areas grew by about 20,474 ha.

Table 2. *LULC values 1993-2023*

LU Type	1993 - Ha	1993 - %	2023 - Ha	2023 - %
Built-up	17811	8	38285	16
Agriculture	81320	35	52911	22
Forest	73136	31	38576	16
Bare	63343	27	105148	45
Water	34	0,01	722	0,3

The LULC transfer matrix (Table 3) for the 10 km buffer surrounding the O-31 Highway between 1993 and 2023 reveals significant spatial transformations, particularly in agricultural and forested landscapes. The most notable losses occurred in agricultural and forest areas, with net decreases of approximately 28,403 hectares and 34,548 hectares, respectively. These losses reflect a broader trend of land conversion driven by expanding built-up and bare land categories.

Agricultural land exhibited considerable transitions primarily into bare land (26,824 ha) and built-up areas (11,178 ha). This pattern indicates increasing pressure from both urban expansion and land degradation processes. Forested areas experienced the highest rate of conversion into bare land (30,661 ha), signaling widespread deforestation and ecosystem disruption. The transition from forests to built-up areas, although

smaller in magnitude (3,625 ha), still represents a critical loss of natural land cover, particularly near highway access points where urban growth is more concentrated.

Conversely, built-up areas increased substantially, gaining approximately 20,471 ha, a clear indicator of urban sprawl associated with improved accessibility and infrastructure development along the highway corridor. A significant portion of this increase originated from bare lands (12,024 ha), demonstrating the prioritization of undeveloped or transitional lands for urban development. Bare land itself showed the most substantial net gain (+41,792 ha), which may be attributed to the degradation of formerly vegetated or cultivated areas and potential delays in land conversion to structured urban forms.

Table 3. *Transfer matrix from 1993 to 2023*

10km buffer of O-31 Highway (ha)		2023						
		Agriculture	Builtup	Bareland	Forest	Water	Total	Gains(+)/Loses(-)
1993	Agriculture	40560	11178	26824	2475	269	81306	-28403
	Builtup	1715	11445	4366	233	48	17807	20471
	Bareland	4728	12024	43266	3169	141	63328	41792
	Forest	5897	3625	30661	32690	244	73117	-34548
	Water	3	6	3	2	19	33	688
	Total	52903	38278	105120	38569	721		

Figure 7 illustrates the spatial distribution of land use transitions from forest, bare land, and agricultural land to built-up areas along the O-31 highway corridor. Tables 4 and 5 complement these visualizations by quantifying the total area (in hectares) and proportional distribution of land cover conversions within 1 km, 2 km, 5 km, and 10 km buffers from the highway. These tabular results clearly demonstrate that a significant portion of urban expansion - particularly for bare land and agricultural areas - occurs within the first 5 kilometers of the transportation corridor, aligning with findings in existing literature emphasizing proximity as a critical driver of land use change.

However, while these numerical tables provide a useful overview of the magnitude and distribution of changes, they fall short in illustrating the spatial intensity and clustering dynamics of land transformation. The kernel density maps, in contrast, offer a more nuanced perspective by identifying concentrated hotspots of change, which are particularly prominent near highway exits in the north and southwest sections of the study area. This analytical approach distinguishes the current study from previous works that primarily relied on buffer-based or zonal statistics, allowing for a finer-grained understanding of urban expansion patterns and their spatial determinants.

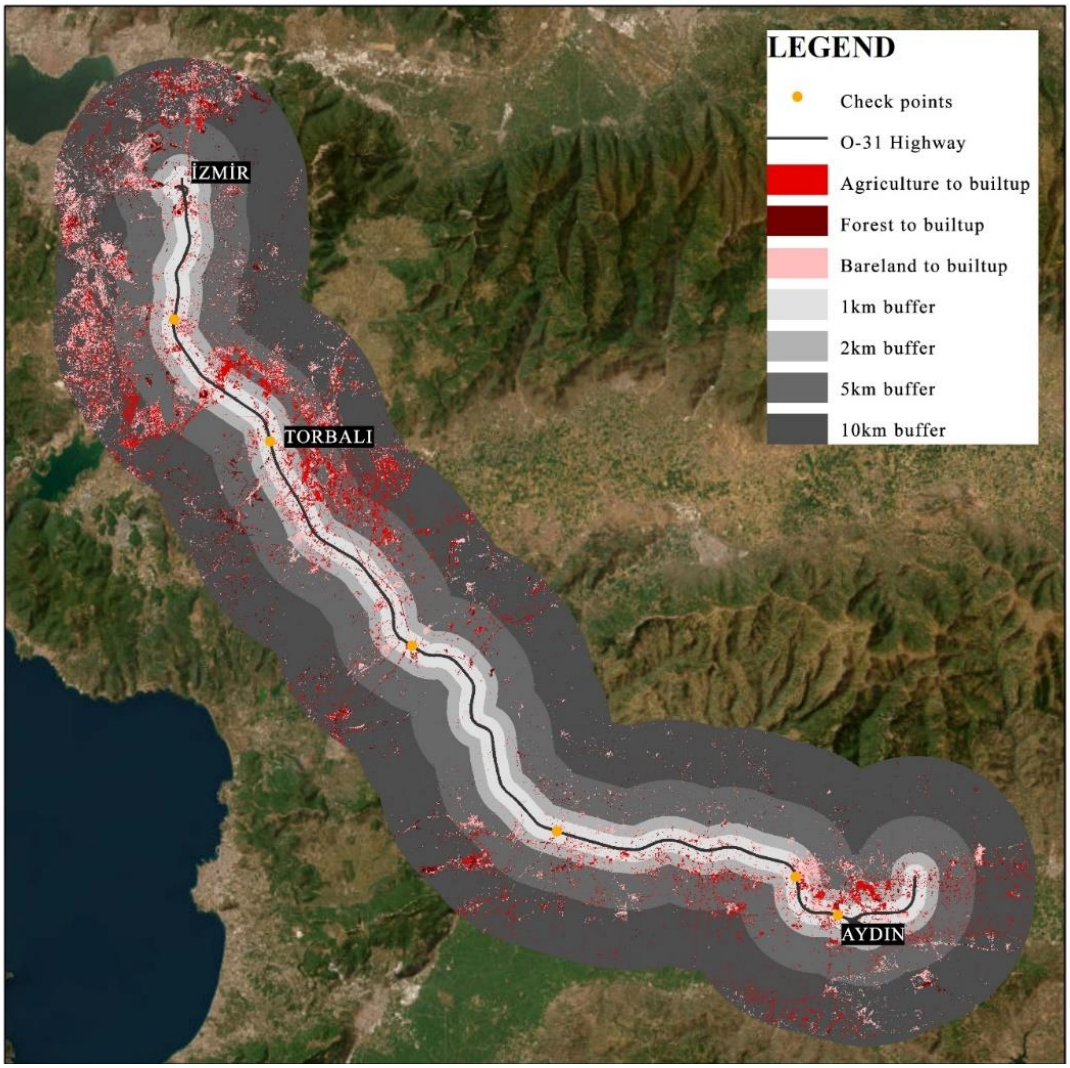


Figure 7. *Change map with buffers (Source: Author)*

Table 4. *Change in buffers*

Change (Ha)	Within 1km	Within 2km	Within 5km	Within 10km	Total
Agriculture to Built-up	1464	1379	3626	4698	11167
Forest to Built-up	362	415	1243	1601	3621
Bare land to Built-up	1612	1234	3314	5851	12010
Total	3438	3029	8183	12149	

Table 5. *Change table according to buffers*

% change in buffers (km)	Within 1km	Within 2km	Within 5km	Within 10km	Total
Agriculture to Built-up	13	12	32	42	100
Forest to Built-up	10	11	34	44	100
Bare land to Built-up	13	10	28	49	100

To enhance the understanding of these spatial dynamics, Kernel Density Estimation (KDE) was employed. For this analysis, a representative point was assigned to each polygon that underwent a land use conversion to built-up area. KDE was then applied to these points to quantify the density of transformation events across the study area. The resulting density surfaces offer a more nuanced view of spatial concentration, allowing the identification of hotspots and areas with intensified land use change. The kernel density maps

for forest-to-built-up, bare land-to-built-up, and agriculture-to-built-up transitions are presented in Figures 8, 9, and 10, respectively.

Kernel density analyses conducted for the O-31 Highway corridor highlight distinct spatial dynamics across different land use transitions, particularly from bare land, agricultural land, and forest areas to built-up areas. The conversion from bare land to urban land exhibits the most spatially extensive and homogeneous pattern, with high-density clusters especially evident around major highway exits in the northern and southwestern sectors of the study area. Kernel density values ranging between 61 and 110 are most concentrated within a 1 to 5 km radius from these access points, underscoring the influence of high accessibility in accelerating urban development over previously unused lands.

When compared to forest-to-urban transitions, which display more fragmented and localized patterns due to topographic constraints and ecological protections, bare land conversions reflect a more opportunistic and unconstrained development logic. These lands, often lacking formal land cover or legal restrictions, are more susceptible to rapid transformation. This is particularly evident in the western corridor near İzmir's urban boundary and in the south near Aydın, both emerging as transformation hotspots experiencing strong urban expansion pressure.

Similarly, transitions from agricultural land to urban areas also concentrate around highway infrastructure, yet show a more localized and selective spatial pattern compared to bare land. Kernel density values for these transitions (ranging between 64 and 114) again peak in 1 to 5 km buffers, but with greater clustering and less spatial spread than bare lands. These patterns likely reflect the influence of land tenure, agricultural productivity, and existing rural economic structures, which collectively introduce greater resistance to conversion than in bare lands. Nonetheless, the proximity of agriculture to transport corridors still makes them vulnerable to speculative development.

In contrast, forest land conversions exhibit the lowest spatial density and are limited to discrete clusters, particularly in areas with lower slope and less ecological sensitivity. Their distribution is primarily shaped by natural barriers and legal protection status, further confirming their relatively high resilience to infrastructure-driven urban pressures.

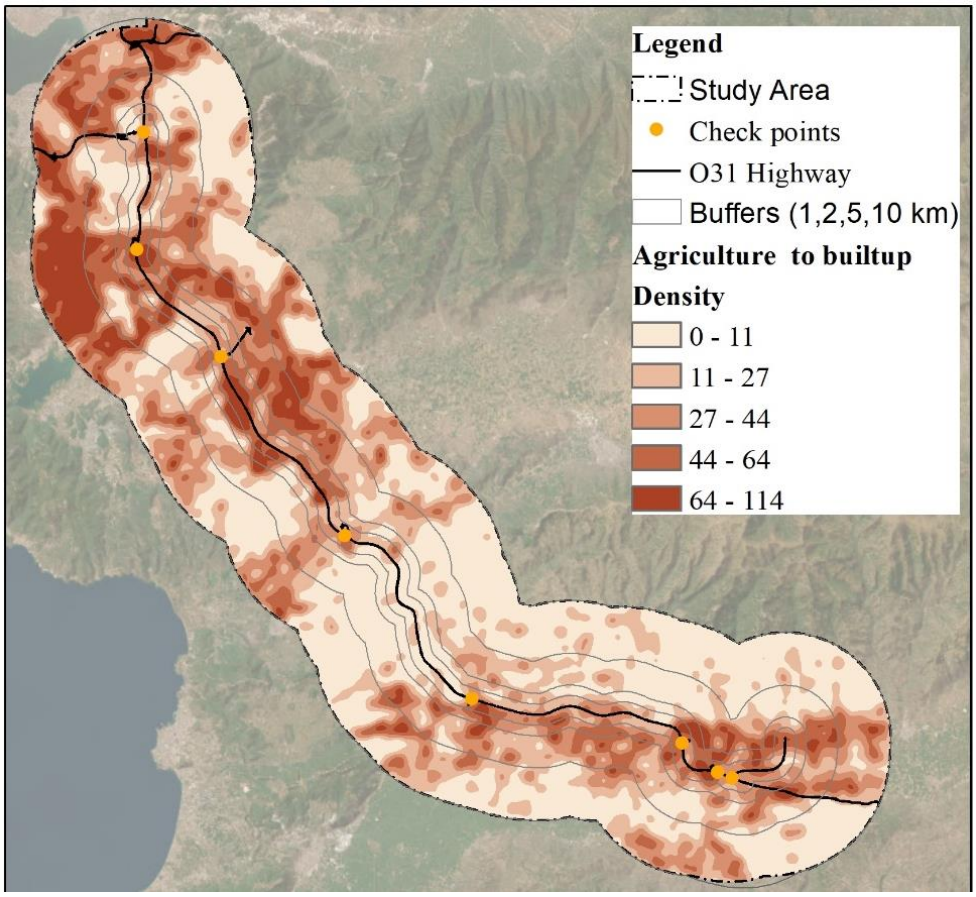


Figure 8. *Kernel density map of transitions from agricultural areas to builtup (Source: Author)*

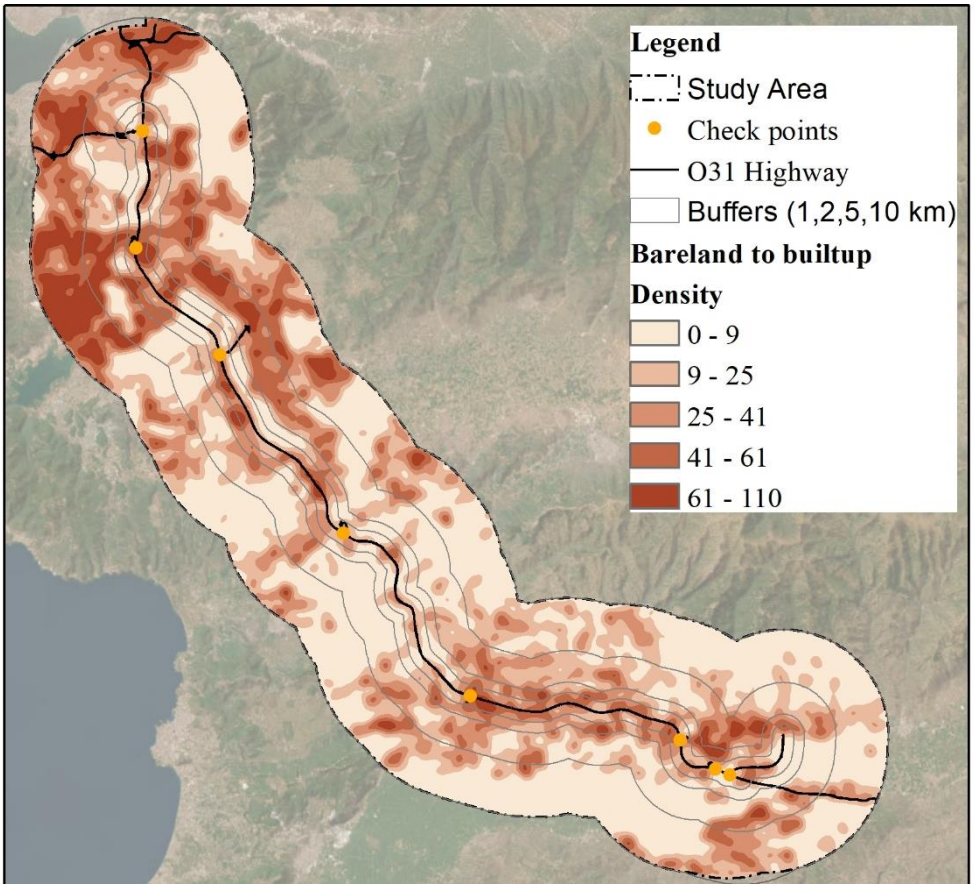


Figure 9. *Kernel density map of transitions from bare lands to builtup (Source: Author)*

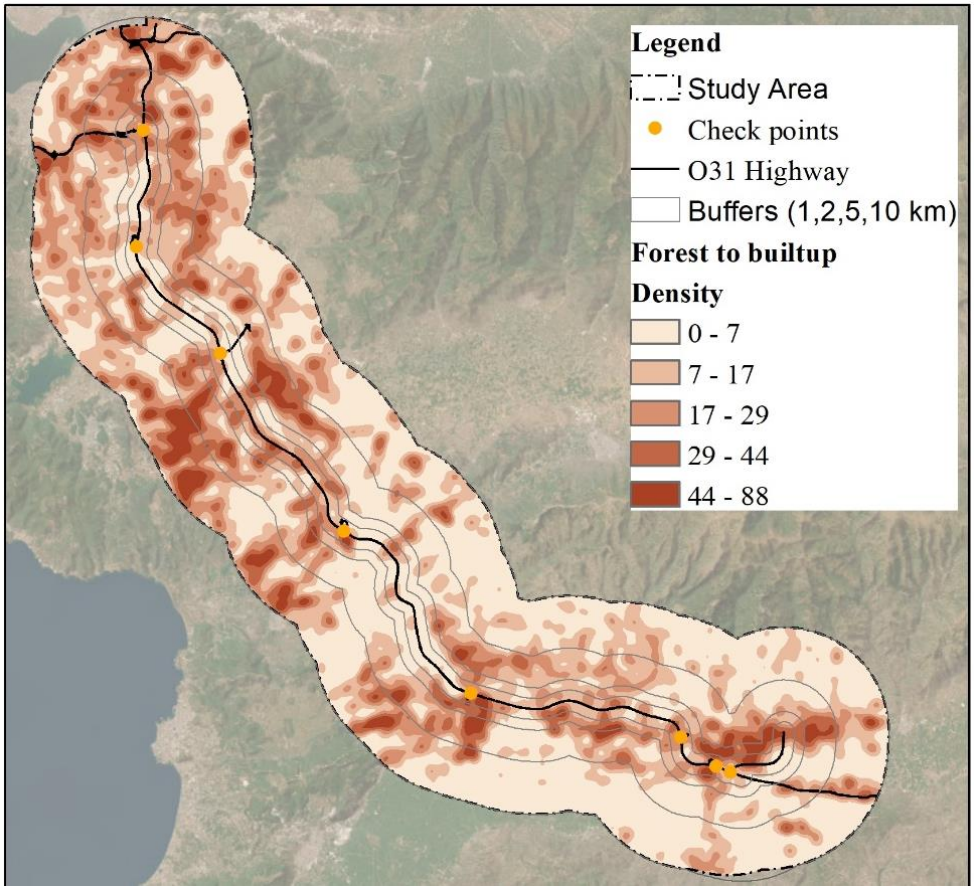


Figure 10. *Kernel density map of transitions from forest areas to builtup (Source: Author)*

These patterns collectively indicate a typical sprawl progression, where development initially occurs on marginal and unregulated lands before extending into more regulated or protected categories such as agricultural or forest areas. Particularly concerning is the tendency to perceive bare lands as suitable for construction due to the apparent absence of legal restrictions or visible ecological constraints. However, such areas frequently serve as critical ecological buffers, hydrological corridors, or potential sites for environmental restoration, underscoring their strategic importance in achieving sustainable urban development.

The differential resilience of land use types against urban encroachment also points to the need for land-use-specific planning strategies. For instance, while forest areas already benefit from certain legal protections, agricultural zones require stronger planning tools, especially in buffer zones with high accessibility. Likewise, proactive zoning is essential to regulate the conversion of bare lands, which currently follow a trajectory of unregulated, infrastructure-driven development.

Ultimately, this study's integration of kernel-based spatial intensity analysis with buffer-based quantification presents a novel methodological approach that surpasses simple proximity assessments. The findings suggest that land use transitions near major transport infrastructure are neither uniform nor random, but instead highly structured by accessibility, legal status, and ecological characteristics, each of which should inform future regional planning decisions.

5. DISCUSSION

This study provides a comprehensive spatial-temporal analysis of land use/land cover (LULC) changes between 1993 and 2023 within a 10 km buffer of the O-31 Highway corridor in western Turkey. The findings confirm many trends highlighted in the existing literature, particularly the concentration of built-

up expansion around transportation infrastructure and the increasing pressure on agricultural and forest lands.

One of the most striking results is the increase in built-up areas, which doubled from 8% in 1993 to 16% in 2023. This trend is consistent with similar findings in Switzerland, Poland, Istanbul, Georgia, Atlanta, New Jersey, and China [20, 22, 25, 29-32]. The expansion of built-up areas has been accompanied by the loss of both forest and agricultural lands, an outcome aligned with patterns observed in Poland and Istanbul. However, unlike most previous studies that reported more intense land use changes within a 1 km buffer, this study found more significant changes in the 5 km and 10 km buffers, suggesting that development pressures extend far beyond the immediate vicinity of the highway.

The results show that built-up areas increased by approximately 20,474 ha over the 30-year period, with significant portions of this growth occurring within 5 km of the highway. This pattern supports the notion that proximity to highways is a major driver of urbanization, consistent with studies emphasizing the influence of transportation infrastructure on development intensity [19, 22, 25, 26]. Particularly around highway exits, the transformation from agriculture and bare land to built-up areas is both rapid and spatially clustered, validating earlier findings that these nodes serve as focal points of development [20, 22, 27, 29].

The decline of agricultural land (28,403 ha) and forested areas (-34,548 ha) further confirms the vulnerability of productive and ecologically valuable lands to urban encroachment, especially under weak regulatory frameworks or insufficient land-use planning. As noted by previous research [11, 14, 30], these losses are not simply localized events but part of a broader, cumulative process that erodes the spatial integrity of rural landscapes over time. The continued expansion of bare lands (+41,792 ha) points to both ecological degradation and the transformation of previously undeveloped land into transitional or abandoned states awaiting future construction.

A key contribution of this study lies in the integration of buffer-based statistics with Kernel Density Estimation (KDE), which together provide a layered understanding of spatial transformation. While buffer analyses show how much change occurred at various distances from the highway, KDE identifies where the changes are most intense. This combination helps to uncover the clustering patterns that simple proximity analysis would overlook, echoing the call in recent literature for more nuanced spatial tools in urban and environmental planning [12, 13, 35].

The KDE maps reveal that the densest transformation hotspots are located around major exits near İzmir in the north and Aydın in the south. These areas, marked by flat topography and prior infrastructure investment, demonstrate the “path dependency” of urban sprawl, wherein prior development encourages further expansion [16, 17]. Bare land-to-built-up transitions, in particular, display a homogeneous and aggressive spread, consistent with studies showing that such areas, often lacking ecological or legal restrictions, are the first to be targeted for development [29, 30].

In contrast, forest-to-built-up transitions are limited in spatial scope and intensity, supporting findings that topographic barriers and legal protections slow forest conversion [24, 26]. Similarly, the conversion of agricultural land to built-up areas is more selective and clustered, reflecting ongoing productive use, land ownership structures, and possible resistance to speculative conversion. However, even this relative resilience is under threat, as demonstrated by the steady decline of agricultural land near transportation corridors [14, 25, 31].

The spatial differentiation in transformation intensity also has critical planning implications. Agricultural lands, unlike forests, often lack stringent legal protections and are highly susceptible to speculative development near infrastructure. The findings strongly support the need for land-use-specific policies that go beyond buffer-based zoning. While proximity is a key determinant of pressure, the response capacity of each land type differs depending on legal, ecological, and economic factors.

This study also highlights the importance of identifying not just the amount of change but the form and spatial logic of that change. The data show that urban expansion is not random; it follows predictable

patterns influenced by accessibility, pre-existing infrastructure, topography, and land type. These observations align with global trends in urbanization but also underscore the need for context-specific strategies that reflect local development pressures and planning considerations.

Lastly, while remote sensing and machine learning tools such as Random Forest (RF) offer substantial advantages in classification accuracy, the real power of these tools lies in how they are applied to spatial planning questions. By combining supervised classification with KDE and buffer analysis on the GEE platform, this study demonstrates a scalable methodology for monitoring and anticipating LULC transitions, particularly in rapidly changing peri-urban and infrastructural zones.

6. CONCLUSION

This study evaluated long-term land use and land cover (LULC) changes in the 10 km buffer surrounding the O-31 highway between 1993 and 2023, with a particular focus on the loss of agricultural areas. The results reveal a substantial increase in built-up and bare lands, accompanied by a corresponding decrease in agricultural and forested areas, underscoring the considerable spatial impact of highway infrastructure on surrounding landscapes. These findings align with previous studies that demonstrate the concentration of urban expansion near transportation nodes and the vulnerability of productive and ecologically valuable lands to development pressures.

Highways not only facilitate mobility but also enhance the accessibility and attractiveness of peripheral lands, particularly near interchanges, leading to intensified development pressures. These dynamics highlight the importance of proactive land-use management in peri-urban areas to prevent uncontrolled expansion and the loss of productive soils.

In the case of the İzmir-Aydın Highway, the results indicate a gradual conversion of agricultural and bare lands, especially within the first 5 km buffer. This pattern highlights the importance of proactive land-use control in peri-urban areas. Priority agricultural zones within high-pressure buffers should be identified and safeguarded through targeted planning regulations and development restrictions. Incorporating remote sensing–based monitoring tools into regular planning practice would allow continuous tracking of urban expansion and provide timely guidance for policy interventions. Additionally, implementing ecological buffer strategies along major transport corridors could help balance accessibility with environmental protection, ensuring a more resilient and adaptive land-use planning framework.

Integrating remote sensing–based monitoring tools more broadly into planning practice can provide continuous tracking of urban expansion trends and early warning signals for policy intervention. These measures are essential for preserving landscape connectivity while mitigating the risks posed by rapid infrastructure-driven development.

While this study primarily focuses on spatial and quantitative patterns of land transformation, economic, social, and demographic factors also play a crucial role in shaping land use change. Future research integrating these variables would provide more comprehensive insights into the multifaceted nature of urban expansion and further strengthen evidence-based planning strategies.

Overall, the findings emphasize the need for forward-looking, adaptive, and evidence-based planning approaches that bridge historical trends with future development considerations. The combination of spatial analysis, remote sensing data, and machine learning classification offers a robust framework for guiding land-use planning, particularly in areas experiencing rapid infrastructural growth. By applying these tools, planners can design sustainable land management strategies, mitigate risks to agricultural and ecological resources, and implement timely policy interventions that anticipate and manage the pressures of urbanization.

ACKNOWLEDGEMENTS

This study was derived from a doctoral thesis titled “Karayolu Yatırımlarının Tarımsal Alanlar Üzerindeki Etkilerinin Mekânsal Analizi” in the Department of City and Regional Planning Institute of Science, University of Dokuz Eylul.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

[1] Sezgin, D., “Kentsel saçaklanmanın verimli tarım topraklarının amaç dışı kullanımına etkisi: Ankara örneği”, MSc.Thesis, Gazi University Institute of Science and Technology, Ankara, (2010).

[2] Simmons, I.G., Global environmental history: 10,000 BC to AD 2000, Edinburgh University Press, (2008).

[3] Jensen, J.R., Remote Sensing of the Environment An Earth Resource Perspective, Second Edition, United States of America, (2014).

[4] Cai, G., Ren, H., Yang, L., Zhang, N., Du, M., Wu, C., “Detailed urban land use land cover classification at the metropolitan scale using a three-layer classification scheme”, Sensors, 19:1-24, (2019). DOI: https://doi.org/10.3390/s19143120

[5] Li, L., Chen, Y., Yu, X., Liu, R., Huang, C., “Sub-pixel flood inundation mapping from multispectral remotely sensed images based on discrete particle swarm optimization”, ISPRS Journal of Photogrammetry and Remote Sensing, 101: 10-21, (2015). DOI: https://doi.org/10.1016/j.isprsjprs.2014.11.006

[6] Vaighan, A.A., Talebbeydokhti, N., Bavani, A.M., “Assessing the impacts of climate and land use change on streamflow, water quality and suspended sediment in the Kor River Basin, southwest of Iran”, Environmental Earth Science, 76: 1-18, (2017). DOI: https://doi.org/10.1007/s12665-017-6880-6

[7] Hussein, K., Alkaabi, K., Ghebreyesus, D., Liaqat, M.U., Sharif, H.O., “Land use/land cover change along the Eastern Coast of the UAE and its impact on flooding risk”, Geomatics, Natural Hazards and Risk, 11: 112-130, (2020). DOI: https://doi.org/10.1080/19475705.2019.1707718

[8] Lu, D., Weng, Q., “A survey of image classification methods and techniques for improving classification performance”, International Journal of Remote Sensing, 28: 823-870, (2007). DOI: https://doi.org/10.1080/01431160600746456

[9] Martinuzzi, S., Gould, W.A., Ramos González, O.M., “Land development, land use, and urban sprawl in Puerto Rico integrating remote sensing and population census data”, Landscape and Urban Planning, 79: 288-297, (2007). DOI: https://doi.org/10.1016/j.landurbplan.2006.02.014

[10] Zhang, X., Han, L., Han, L., Zhu, L., “How well do deep learning-based methods for land cover classification and object detection perform on high resolution remote sensing imagery?”, Remote Sensing, 12: 1-29, (2020). DOI: https://doi.org/10.3390/rs12030417

[11] Harvey, R.O., Clark, W.A.V., “The Nature and economics of urban sprawl”, Land Economics, 41: 1-9, (1965). DOI: https://doi.org/DOI: https://doi.org/10.2307/3144884

[12] Eyoh, A., Olayinka, N., Nwilo, P., Okwuashi, O., Udoudo, D., "Modelling and predicting future urban expansion of Lagos, Nigeria from remote sensing data using logistic regression and GIS", International Journal of Applied Science and Technology, 2: 116-124, (2012).

[13] Nduwayezu, G., "Modeling Urban Growth in Kigali City Rwanda", MSc.Thesis, University of Twente Faculty of Geo-Information Science and Earth Observation, Enschede, (2015).

[14] Atef, I., Ahmed, W., Abdel-Maguid, R.H., "Modelling of land use land cover changes using machine learning and GIS techniques: a case study in El-Fayoum Governorate, Egypt", Environmental Monitoring and Assessment, 195: 637, (2023). DOI: https://doi.org/10.1007/s10661-023-11224-7

[15] Chettry, V., "Geospatial measurement of urban sprawl using multi-temporal datasets from 1991 to 2021: case studies of four Indian medium-sized cities", Environmental Monitoring and Assessment, 194, (2022). DOI: https://doi.org/10.1007/s10661-022-10542-6

[16] Elburz, Z., Cubukcu, K.M., "Spatial effects of transport infrastructure on regional growth: the case of Turkey", Spatial Information Research, 29: 19-30, (2021). DOI: https://doi.org/10.1007/s41324-020-00332-y

[17] Baum-Snow, N., "Did highways cause suburbanization?", The Quarterly Journal of Economics, 122: 775-805, (2007).

[18] Khisty, C.J., Lall, B.K., Transportation Engineering: An Introduction, Third Edition, Prentice Hall (2003).

[19] Abelairas-Etxebarria, P., Astorkiza, I., "Farmland prices and land-use changes in periurban protected natural areas", Land Use Policy, 29: 674-683, (2012). DOI: https://doi.org/10.1016/j.landusepol.2011.11.003

[20] Fiedeń, Ł., "Changes in land use in the communes crossed by the A4 motorway in Poland", Land Use Policy, 85: 397-406, (2019). DOI: https://doi.org/10.1016/j.landusepol.2019.04.025

[21] Liang, Y., Zeng, J., Sun, W., Zhou, K., Zhou, Z., "Expansion of construction land along the motorway in rapidly developing areas in Cambodia", Land Use Policy, 109: 1-15, (2021). DOI: https://doi.org/10.1016/j.landusepol.2021.105691

[22] Müller, K., Steinmeier, C., Küchler, M., "Urban growth along motorways in Switzerland", Landscape and Urban Planning, 98: 3-12, (2010). DOI: https://doi.org/10.1016/j.landurbplan.2010.07.004

[23] Villarroya, A., Puig, J., "Urban and industrial land-use changes alongside motorways within the Pyrenean area of Navarre, Spain", Environmental Engineering and Management Journal, 11: 1213-1220, (2012). DOI: https://doi.org/10.30638/eemj.2012.145

[24] Keken, Z., Sebkova, M., Skalos, J., "Analyzing land cover change—The impact of the motorway construction and their operation on landscape structure", Journal of Geographic Information System, 06: 559-571, (2014). DOI: https://doi.org/10.4236/jgis.2014.65046

[25] Zheng, Q., He, S., Huang, L., Zheng, X., Pan, Y., Shahtahmassebi, A.R., Shen, Z., Yu, Z., Wang, K., "Assessing the impacts of Chinese sustainable ground transportation on the dynamics of urban growth: A case study of the Hangzhou Bay Bridge", Sustainability, 8: 1-20, (2016). DOI: https://doi.org/10.3390/su8070666

[26] Chi, G., "The impacts of highway expansion on population change: An integrated spatial approach", Rural Sociology, 75: 58-89, (2010). DOI: https://doi.org/10.1111/j.1549-0831.2009.00003.x

[27] Garcia-López, M., Àngel, "Urban spatial structure, suburbanization and transportation in Barcelona", Journal of Urban Economics, 72: 176-190, (2012). DOI: https://doi.org/10.1016/j.jue.2012.05.003

[28] Kasraian, D., Maat, K., Stead, D., Van Wee, B., "Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies", Transport Reviews, 36: 772-792, (2016). DOI: https://doi.org/10.1080/01441647.2016.1168887

[29] Mothorpe, C., Hanson, A., Schnier, K., "The impact of interstate highways on land use conversion", Annals of Regional Science, 51: 833-870, (2013). DOI: https://doi.org/10.1007/s00168-013-0564-2

[30] Demirel, H., Sertel, E., Kaya, S., Zafer Seker, D., "Exploring impacts of road transportation on environment: a spatial approach", Desalination, 226: 279-288, (2008). DOI: https://doi.org/10.1016/j.desal.2007.02.111

[31] Hu, Z., Lo, C.P., "Modeling urban growth in Atlanta using logistic regression", Computers, Environment and Urban Systems, 31: 667-688, (2007). DOI: https://doi.org/10.1016/J.COMPENVURBSYS.2006.11.001

[32] Conway, T.M., "Current and future patterns of land-use change in the coastal zone of New Jersey", Environment and Planning B: Planning and Design, 32: 877-893, (2005). DOI: https://doi.org/10.1068/b31170

[33] Duranton, G., Turner, M.A., "Urban growth and transportation", Review of Economic Studies, 79: 1407-1440, (2012). DOI: https://doi.org/10.1093/restud/rds010

[34] Cihlar, J., "Land cover mapping of large areas from satellites: Status and research priorities", International Journal of Remote Sensing, 21: 1093-1114, (2000). DOI: https://doi.org/10.1080/014311600210092

[35] Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., Brisco, B., "Google Earth Engine for geo-big data applications: A meta-analysis and systematic review", ISPRS Journal of Photogrammetry and Remote Sensing, 164: 152-170, (2020). DOI: https://doi.org/10.1016/j.isprsjprs.2020.04.001

[36] Vivekananda, G.N., Swathi, R., Sujith, A.V.L.N., "Multi-temporal image analysis for LULC classification and change detection", European Journal of Remote Sensing, 54: 189-199, (2021). DOI: https://doi.org/10.1080/22797254.2020.1771215

[37] Koskinen, J., Leinonen, U., Vollrath, A., Ortmann, A., Lindquist, E., d'Annunzio, R., Pekkarinen, A., Käyhkö, N., "Participatory mapping of forest plantations with Open Foris and Google Earth Engine", ISPRS Journal of Photogrammetry and Remote Sensing, 148: 63-74, (2019). DOI: https://doi.org/10.1016/j.isprsjprs.2018.12.011

[38] Mirelva, P.R., Nagasawa, "Application of Sentinel-1 data for classifying croplands using Google Earth Engine", International Journal of Geoinformatics, 15: 21-31, (2019).

[39] Büke, A., Gültekin, M., Aksoy, A., Dıvrak, B.B., Göcek, Ç., Berke, M.Ö., Çeşmeci, H., Büyük Menderes Havza Atlası, İstanbul, (2013). DOI: https://doi.org/10.3390/s19143120

[40] Sano, E.E., Ferreira, L.G., Asner, G.P., Steinke, E.T., "Spatial and temporal probabilities of obtaining cloud-free Landsat images over the Brazilian tropical savanna", International Journal of Remote Sensing, 28: 2739-2752, (2007). DOI: https://doi.org/10.1080/01431160600981517

[41] Wahelo, T.T., Mengistu, D.A., Merawi, T.M., "Spatiotemporal trends and drivers of forest cover change in Metekel Zone forest areas, Northwest Ethiopia", Environmental Monitoring and Assessment, 196: 1170, (2024). DOI: https://doi.org/10.1007/s10661-024-13294-7

[42] Prayogi, H., Setiadi, H., Supriatna, S., Dewayany, D., "Land cover change analysis in Majalengka Regency using the pan-sharpening method and random forest machine learning algorithm", Jurnal Pendidikan Geografi: Kajian, Teori, dan Praktek dalam Bidang Pendidikan dan Ilmu Geografi, 28: 178-192, (2023). DOI: https://doi.org/10.17977/um017v28i22023p178-192

[43] Hidayati, I.N., Susanti, E., Utami, W., "Analisis pan-sharpening untuk meningkatkan kualitas spasial citra penginderaan jauh dalam klasifikasi tata guna tanah", Bhumi, 3: 122-135, (2017).

[44] Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., "Monitoring vegetation systems in the Great Plains with ERTS", III. ERTS Symposium, Washington, DC, 309-317, (1973).

[45] Zha, Y., Gao, J., Ni, S., "Use of normalized difference built-up index in automatically mapping urban areas from TM imagery", International Journal of Remote Sensing, 24: 583-594, (2003). DOI: https://doi.org/10.1080/01431160304987

[46] Xu, H., "Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery", International Journal of Remote Sensing, 27: 3025-3033, (2006). DOI: https://doi.org/10.1080/01431160600589179

[47] He, C., Shi, P., Xie, D., Zhao, Y., "Improving the normalized difference built-up index to map urban built-up areas using a semiautomatic segmentation approach", Remote Sensing Letters, 1: 213-221, (2010). DOI: https://doi.org/10.1080/01431161.2010.481681

[48] Roy, P., Miyatake, S., Rikimaru, A., "Biophysical spectral response modeling approach for forest density stratification", The 18th Asian Conference on Remote Sensing, Dehra, (1997).

[49] Zhao, H., Chen, X., "Use of normalized difference bareness index in quickly mapping bare areas from TM/ETM+", International Geoscience and Remote Sensing Symposium (IGARSS), Seoul, 1666–1668, (2005). DOI: https://doi.org/10.1109/igarss.2005.1526319

[50] Danacıoğlu, Ş., Öngül, H.C., "Güzelhisar havzasında endüstriyel gelişmenin arazi kullanımı ve arazi örtüsü özellikleri üzerindeki etkisinin bulut tabanlı makine öğrenme teknikleri ile değerlendirilmesi", Ege Coğrafya Dergisi, 32: 135-150, (2023). DOI: https://doi.org/10.51800/ecd.1224255

[51] Amini, S., Saber, M., Rabiei-Dastjerdi, H., Homayouni, S., "Urban Land Use and Land Cover Change Analysis Using Random Forest Classification of Landsat Time Series", Remote Sensing, 14, (2022). DOI: https://doi.org/10.3390/rs14112654

[52] Breiman, L., "Random Forests", Machine Learning, 45: 5-32, (2001). DOI: https://doi.org/10.1023/A:1010933404324

[53] Lasaponara, R., Abate, N., Fattore, C., Aromando, A., Cardettini, G., Di Fonzo, M., "On the Use of Sentinel-2 NDVI Time Series and Google Earth Engine to Detect Land-Use/Land-Cover Changes in Fire-Affected Areas", Remote Sensing, 14, (2022). DOI: https://doi.org/10.3390/rs14194723

[54] Millard, K., Richardson, M., "On the importance of training data sample selection in Random Forest image classification: A case study in peatland ecosystem mapping", Remote Sensing, 7: 8489-8515, (2015). DOI: https://doi.org/10.3390/rs70708489

[55] Quintero, N., Viedma, O., Urbieta, I.R., Moreno, J.M., "Assessing landscape fire hazard by multitemporal automatic classification of landsat time series using the Google Earth Engine in West-Central Spain", Forest, 10, (2019). DOI: https://doi.org/10.3390/f10060518

[56] Wessels, K.J., Bergh, F. van den, Roy, D.P., Salmon, B.P., Steenkamp, K.C., MacAlister, B., Swanepoel, D., Jewitt, D., "Rapid land cover map updates using change detection and robust random forest classifiers", Remote Sensing, 8, (2016). DOI: https://doi.org/10.3390/rs8110888