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Determining Land Use/Land Cover (LULC) Changes Using Remote Sensing Method in Lüleburgaz and LULC Change's Impacts on SDGs

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Abstract
Urbanization is among the human activities that affect the quality of urban life and sustainable urban development at a global scale. For monitoring human-induced changes in cities, studies on the changes in land use/land cover (LULC) based on a series of satellite images along with geographic information systems (GIS) are widely used. This study aims to evaluate the LULC changes in Lüleburgaz between 2001 and 2021. For this purpose, the impacts of urban growth on natural areas and how these areas are handled in the context of sustainable development goals are examined, and the effects of urbanization on land use change are evaluated. The accuracy of the LULC maps was evaluated by means of the general accuracy index and the Kappa index. The overall accuracy rates of the land use maps for 2001, 2010, and 2021 were 96.32%, 93.66%, and 95.91%, respectively, while Kappa values were 0.95, 0.91, 0.94. These results indicate that, due to the effect of rapid urbanization and population growth over the last two decades, the built environment increased by 4.82% and the agricultural land has decreased by 4.88%. This result is a testament to the upward trend in the built environment at the expense of depleting a significant amount of agricultural land. The findings of the study provide useful data that can aid authorities in making conscious decisions to achieve sustainable urban planning and to improve environmental conditions.

Keywords: Urbanization, Land use/land cover change, Agricultural land, Sustainable development goals (SDGs), Remote sensing.

1. Introduction

Urbanization is a complex issue that affects land use/land cover systems for many reasons including economic development and population growth (Almdhun et al., 2018). Over the past two centuries, urbanization and industrialization has led to changes in land use/land cover (LULC), thus deteriorating sustainability for the future (Abijith & Saravanan, 2021; Halefom et al., 2018). The midyear of 2009 marked a milestone where the world's population was transformed from rural to more urban. The urban population (3.42 billion) exceeded the population that lives in the countryside (3.41 billion); thus more than half of the world's population began living in cities (ISOCARP, 2010; United Nations, 2009). By 2050, the world's population, is expected to reach about 10 billion, and cities will be the major contributor in this increase (Davis, 2007; United Nations, 2009).
In addition to affecting economic and social change, urbanization also adversely affects the loss of agricultural land (Macedo et al., 2013), the increase in construction in natural areas around cities (Cavailhes & Wavresky, 2003; Liu, Yue, & Fan, 2011; Pribadi & Pauleit, 2015), land degradation and biodiversity (Butt et al., 2015). In order to accommodate increasing in population, agricultural lands and forests rapidly turn into built-up areas

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(Dadashpoor et al., 2019; Liu et al., 2011). LULC changes prove to affect ecology, land degradation, wetland decline, climate (Akinyemi et al., 2016; Karki et al., 2018; Moradi et al., 2020; Niya et al., 2020; Purswani et al., 2019; Tolessa et al., 2017). In particular, it is stated that the conversion of first-class agricultural land around cities into residential areas has negative effects on agriculture and food security (Bristow & Kennedy, 2013; Livanis et al., 2006). Food and agricultural security are highlighted as critical elements of sustainable development (Adelaja & George, 2021). For this reason, data on changes in land use/land cover are important to setting policy priorities for the efficient use of natural resources and sustainable development (Adelaja & George, 2021; Bristow & Kennedy, 2013; Hou et al., 2019; Livanis et al., 2006; Motlagh et al., 2020).
In 1987, the concept of "sustainable development" was defined in “Brundtland Report” and this concept required redefining the basic priorities of planning’s quest for the future of urban settlements (Brundtland, 1987, Ersoy, 2016). In 2015, the United Nations (UN) adopted the 2030 Agenda for sustainable development, which establishes the foundation for 17 global goals and 230 indicators (Sustainable Development Goals, 2022). When the Sustainable Development Goals are examined in terms of land use/land cover change for the protection of natural areas at local scale, SDG 2, SDG 6, SDG 11, SDG 12, SDG 13, and SDG 15 draw attention (Table 1).

Table 1. The relationship between LULC and SDGs (United Nations, 2022)

LULC Class	Sustainable Development Goals and Objectives	
Vegetation	SDG 12	Responsible production and consumption • **Sustainable management and use of natural resources**
	SDG 15	Terrestrial life • **Conserving and restoring terrestrial and freshwater ecosystems** • **Stopping deforestation and restoring degraded forests** • **Stopping desertification and restoring degraded land** • **Conserving biodiversity and natural habitats**
Water body	SDG 6	Clean water and sanitation • **Safe and affordable drinking water** • **Improving water quality, wastewater management and safe reuse** • **Protecting and restoring aquatic ecosystems**
	SDG 15	Terrestrial life • **Conserving and restoring terrestrial and freshwater ecosystems**
Agricultural land	SDG 2	End hunger • **Universal access to reliable and nutritious food** • **Sustainable food production and resilient agricultural practices**
	SDG 12	Responsible production and consumption • **Promoting a universal understanding of a sustainable way of life**
	SDG 13	Climate action

		• **Integrating climate change-related measures into policies and plans**
	SDG 15	Terrestrial life • **Conserving and restoring terrestrial and freshwater ecosystems** • **Stopping desertification and restoring degraded land** • **Conserving biodiversity and natural habitats**
Built-up land	SDG 11	Sustainable cities and communities • **Inclusive and sustainable urbanization** • **Reducing the environmental impact of cities** • **Strong national and environmental development planning**
	SDG 12	Responsible production and consumption • **Promoting a universal sustainable way of life**
	SDG 13	Climate action • **Integrating climate change-related measures into policies and plans**

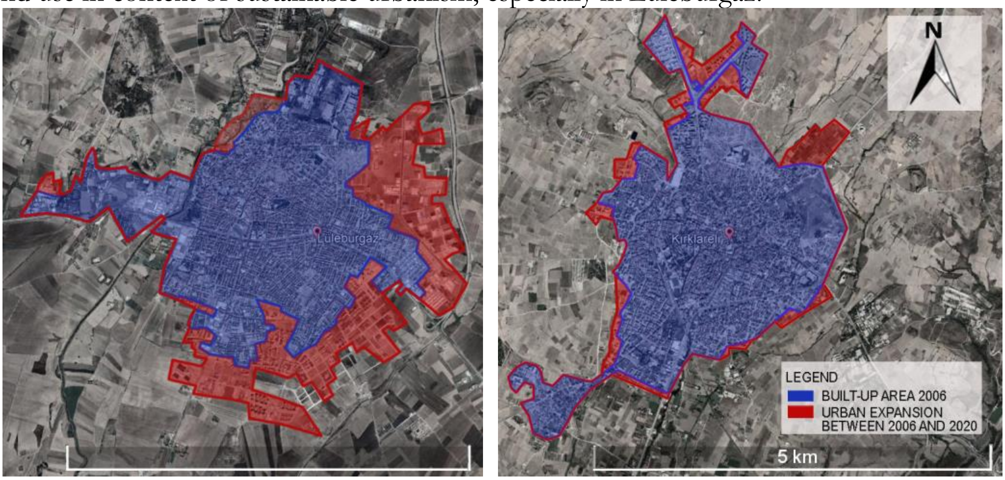
The aims and objectives towards the protection of the vegetation class are directly met in SDG 12 and SDG 15. While SDG 12 emphasizes universal sustainable ways of life, SDG 15 focuses on efforts to protect terrestrial ecosystems, halt deforestation and restore degraded forests, halt desertification and restore degraded soils, and protect biodiversity and natural habitats. The aims and objectives of the water body class are addressed in SDG 6 and SDG 15. It is discussed around the principles of providing safe and affordable drinking water, improving water quality, wastewater management and safe reuse, protecting and restoring aquatic ecosystems, and protecting and restoring terrestrial and freshwater ecosystems. Agriculture is at the heart of SDG 2, which aims to achieve zero hunger. It is also addressed in SDG 12, SDG 13, and SDG 15 to different extents. SDG 11, SDG 12, and SDG 13 are particularly relevant to the goals and objectives of the built-up land class. The goals and objectives related to the built environment include ensuring inclusive and sustainable urbanization, reducing the environmental impacts of cities, realizing a strong national and environmental development planning, promoting a universal sustainable lifestyle understanding, and integrating climate change-related measures into policies and plans.

In this context, the emergence of remote sensing techniques and geographic information systems (GIS) provides useful and detailed mechanisms that enable monitoring the changes in LULC (Abbas et al, 2021; Baig et al, 2022; Butt et al., 2015; Hegazy & Kaloop, 2015; Muhammad et al, 2022). LULC examines provides guidance for local decision-makers and urban planners to know where change is happening, to identify and measure spatial changes, to reduce the future impacts of urban growth and LULC changes, to improve environmental conditions and to protect natural areas (Alexander et al., 2017; Feng et al., 2020; Gharbia et al., 2016; Li et al., 2017; Reddy et al., 2018). The aim of this study, which is focused on the Lüleburgaz district in Turkey, is to analyze the land use/land cover (LULC) change from 2001 to 2021 by utilizing the remote sensing method, to examine the effects of population growth on this change, and to evaluate the relationship between LULC change and Sustainable Urbanization Goals. Located in the Thrace region, Lüleburgaz has fertile agricultural lands, and the pressure urban growth has put on agricultural areas due to the population growth over the last 20 years is emphasized in the upper-scale plans. Additionally, the development axis of the Istanbul metropolitan area, which is the most important city on a global scale in Turkey, includes the Thrace region. This requires taking into account the ecological balance in the land use decisions of Lüleburgaz, a medium-sized city facing rapid urban growth. Thus, the findings of the study will help decision makers and authorities to make urban plans that duly consider sustainability. Also, revealing potential changes for the years to come will contribute to urban quality of life and agricultural policy decisions. For this reason, the evaluation and reporting of LULC changes in Lüleburgaz is of great importance in terms of taking the necessary measures on time.

2. Method

2.1. Study Area

In Kırklareli, agricultural lands make up approximately 60% of the province's surface area. Kırklareli is among the provinces with an important share in paddy, wheat, and sunflower production. According to 2022 data, Kırklareli ranks fourth among the provinces with the largest share in sunflower production in Turkey with a rate of 10.2% (Ministry of Agriculture and Forestry, 2022). Lüleburgaz (32.4%) has the highest amount of agricultural land within the province (Ministry of Environment and Urbanization, 2009). In addition, its agricultural production, Kırklareli central district and Lüleburgaz district attract attention in terms of industrial and service sectors and population attracting potential. When these two settlements are examined using the google earth images in terms of the increase in the built-up area between 2006 and 2020, it is seen that the most changes in urban macroform have taken place in Lüleburgaz district (Figure 1). It is observed that there is an intense urban expansion in the direction of agricultural land. The urban macroform change requires a close examination in the terms of the balance of protection and use in context of sustainable urbanism, especially in Lüleburgaz.



Lüleburgaz Kırklareli

Figure 1. Urban expansion between 2006 and 2020

Lüleburgaz is a southern district of the Kırklareli province, and it is 58 km away from the Kırklareli city center. Located on the Ergene Plain at the heart of the Thrace, Lüleburgaz is a district with high accessibility not only with its favorable location but also with its D100, TEM and railway facilities (Ministry of Environment and Urbanization, 2005). Lüleburgaz (Figure 2) has experienced a rapid industrialization in recent years, and it is the fastest developing district in Kırklareli. Accordingly, there is a rapid population growth (Figure 3) caused by internal migration to a large extent. As shown in Table 2, it is apparent that the population of the central district increased by 121% between 1980 and 2000 and that the increase in population has continued between 2010 and 2020.

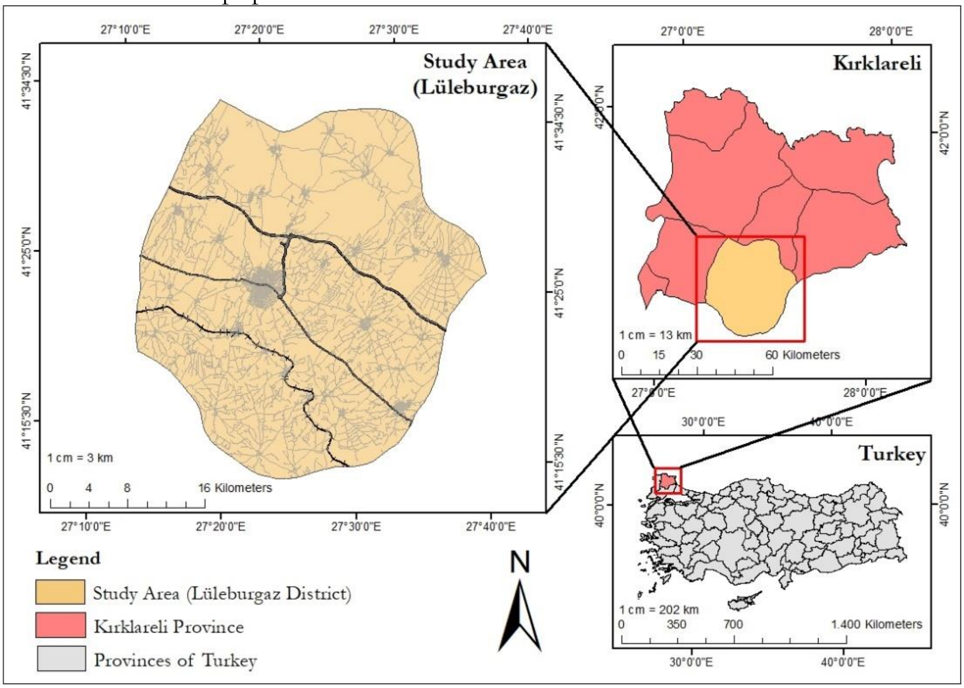


Figure 2. Location of Lüleburgaz, Turkey

Table2. Population change in Lüleburgaz (Kirklareli Provincial Planning and Coordination Directorate, 2022)

Settlement	1970	1970-1980 % change	1980	1980-2000 % change	2000	2010-2020 % change	2010	2010-2020 % change	2020
Lüleburgaz District	64,378	%15	74,129	%59	117,606	%14	134,073	%14	152,192
Center	27,808	%28	35,689	%121	79,002	%27	100,412	%22	122,635

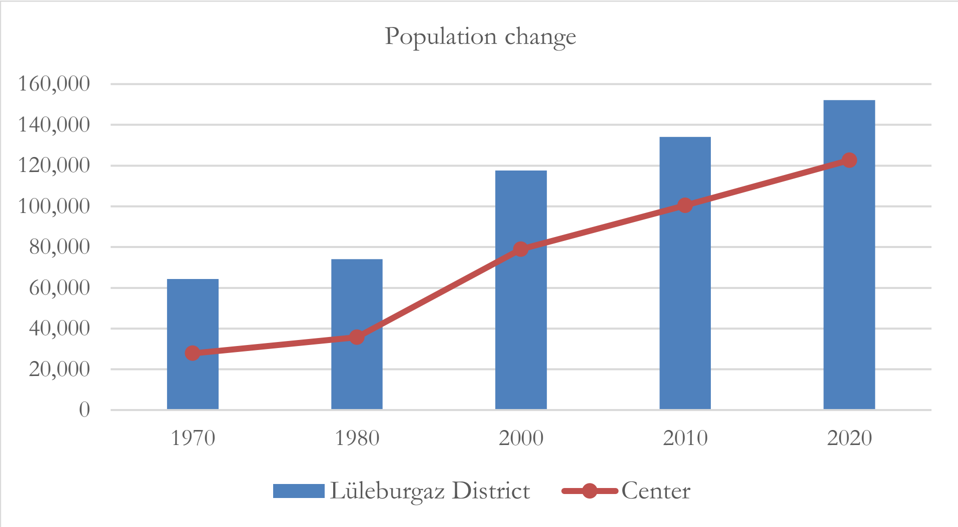


Figure 3. Population change

Industrialization, population growth, developments in transportation and communication technologies results in urban sprawl and urban decentralization (Hoyt, 1940; Bullard, 2000; von Hoffman & Felkner, 2002). New neighborhoods that formed in peri-urban areas have with plenty of light and air (Hoyt, 1940), low density (von Hoffman & Felkner, 2002), new buildings, more affordable land and housing options compared to the city center (Hoyt, 1940). Also give opportunity individuals to live in the same region together that have same socio-economic status (Hoyt, 1940). Decision makers choose the tendency of expansion rather than the reconstruction of the city center (Hoyt, 1940). However, urban sprawl contradicts to sustainable urbanization (Gordon & Richardson, 1997). Because it causes increased service delivery, infrastructure and transportation costs, land speculation, waste of land, tax increase, reduction of natural areas (Clawson, 1962; Bullard, 2000) and unplanned growth (Bullard, 2000). Istanbul's Metropolitan decentralization (decentralization of industry) has also contributed to such a formation in Lüleburgaz. There is an urban growth process that results in industrial migration and the increase in housing areas, the need for rapid transportation due to the daily journey of business owners to their facilities from Istanbul, and the land occupation of the roads. In addition, the construction of the High Speed Railway Project (Halkalı-Kapıkule) and Airport Projects is on the agenda in order to improve the transportation infrastructure between the Thrace Region and Istanbul (Ministry of Environment and Urbanization, 2019). Similar to many other cities, growth in Lüleburgaz did not occur in accordance with the plans. The occupation of agricultural lands in Lüleburgaz by industrial facilities, transportation infrastructure, expanding urban areas is one of the most important problems brought about by urbanization and industrialization (Timor, 1992).

When the 1/100,000 Provincial Environmental Plan Decisions of the Thrace Ergene Basin Sub-Region and the 1/25,000 Kırklareli Provincial Environmental Plan Decisions for the Lüleburgaz District Center are examined, it is evident that measures to protect the natural habitat of the district are emphasized in order to withdraw from the agricultural lands that were opened to various land uses with lower-scale plans, to restore the quality of agricultural lands, and to control the construction pressure on agricultural lands. In the 1/25,000 Kırklareli Provincial Environmental Plan, the 2023 population for Lüleburgaz is foreseen as 180,000 people, and the population for Lüleburgaz district center is forecasted as 135,000 people, whereas the current plan of Lüleburgaz Municipality is designed for a population of 155,000 people. In the current plan for Lüleburgaz District Center, it is understood that the population foreseen in the plan is higher than the 2023 population projection suggested in the 1/25,000 Kırklareli Provincial Environmental Plan. Due to this discrepancy, areas that are opened to development with approved plans but that are typically absolute agricultural land are prevented from being used for agriculture, and such areas are depleted for no reason. This situation also results in an exponential increase in the cost of infrastructure and services. From this point of view, it has been observed that a large amount of absolute agricultural lands throughout the province had to be opened to construction with lower-scale plans. A district-by-district analysis of the agricultural areas and pastures that should be strictly protected and that were designated for non-agricultural uses in lower-scale plans reveals that Lüleburgaz is the most problematic district (total 1555.2 ha) in this respect (Ministry of Environment and Urbanization, 2009; Ministry of Environment and Urbanization, 2011). With the examination of the upper-scale plans, it becomes evident that urbanization and population increase caused the changes in land use/land cover. Therefore, in Lüleburgaz, extra caution about urban growth and construction is necessary, and lower-scale plans should be used to limit urban development in parallel with the upper-scale plans to achieve sustainability in agricultural production, and attention should be paid to correctly specify the population size that will be served. The aforementioned facts reveal that it's necessary to detect the LULC changes in Lüleburgaz.

2.2. Problem Statement and Research Questions

This study strives to reveal the land use/land cover changes in Lüleburgaz over the last twenty years by using remote sensing data, to examine the effect of population growth on these changes, and to evaluate the link between LULC change and Sustainable Urbanization Goals. Within this context, this study explores the answers to the following research questions:

- **In the last 20 years, has there been a significant change in land use/land cover in the study area? In which land use class has the highest rate of change occurred? In which direction did the city expand?**
- **What is the impact of population growth on LULC changes?**
- **What is the link between LULC change with the policy frameworks towards achieving the SDGs?**

A graphical abstract of the study is provided in Figure 4.

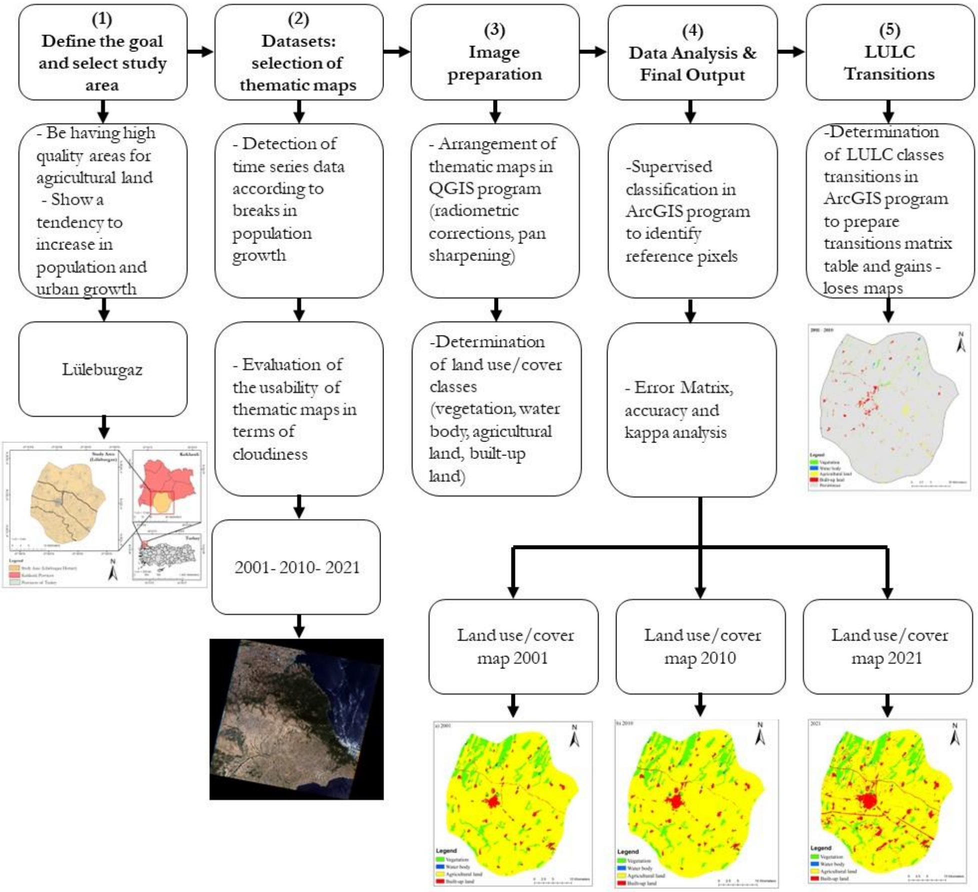


Figure 4. Graphical abstract of the study

2.3. Data Collection and Processing

Landsat satellite images (TM, OLI) for 2001, 2010, and 2021 were used to create the land use change maps. Landsat satellite imagery is widely used for the identification and monitoring of LULC changes, given that images with a relatively high spatial resolution (30 meters) from previous years can be obtained free of charge (Khwarahm, Qader, Ararat, & Al-Quraishi, 2020) (Li, et al., 2020). Landsat satellite imagery was downloaded from the United States Geological Survey (USGS) Earth Explorer portal. When maps were selected, two principles were considered: First of all, based on the fluctuations in the urban population growth (Table 2), it was aimed to examine the years 2000, 2010, and 2020. Subsequently, in order to accurately make the land cover classification, it was decided that the Landsat satellite image scenes should have the lowest percentage of cloud cover (less than 5%). Since the data for 2000 and 2020 did not fulfill the low cloud percentage rule, satellite images for 2001 and 2021 were used instead. Details of the Landsat satellite imagery selected for the study are provided in Table 3.

Table3. Details of satellite datasets used in the study (Source: https://earthexplorer.usgs.gov)

Satellite data	Acquisition date	Spatial resolution (m)	Reference System/Path/Row
Landsat 4-5 TM	07.20.2001	30	WGS-84/181/031
Landsat 4-5 TM	09.15.2010	30	WGS-84/181/031
Landsat 8 OLI/TIRS	07.27.2021	30	WGS-84/181/031

For the classification of LULC, the conventions provided by Anderson et al. (1976), and Kisamba and Li (2022) were utilized. It is widely accepted that the use of five land cover classes corresponds to an average value (Pontius et al., 2008). Accordingly, LULC is classified into four main groups: (1) vegetation, (2) water body, (3) agricultural land, and (4) built-up land (Table 4).

Table4. Description of the LULC classes

LULC classes	Description
Vegetation	All areas covered by any vegetation such as forest (deciduous forest land, evergreen forest land and mixed forest land), shrubs, grasses, trees.
Water body	All areas covered by water, these includes lakes, dams, river, ponds all kinds of reservoir and streams.
Agricultural land	All areas covered by agricultural/farm land, pasture area and bare fields.
Built-up land	All artificial surfaces including residential, industrial areas and commercial and services as well as all roads and railway networks.

In order to achieve an accurate classification, image correction pre-operations such as atmospheric correction and sharpen were performed in the QGIS software. Afterwards, the ArcGIS (version 10.8) software was used to classify satellite images into four categories. Landsat image layers were combined with the composite bands tool. In order to clip the merged layers according to the district boundaries, the administrative boundaries map was downloaded from the website of the Ministry of Defense General Directorate of Mapping (https://www.harita.gov.tr/urun/turkiye-mulki-idare-sinirlari/232). The merged images were georeferenced to the World Geodetic System 84 (WGS84) that was projected into the Lüleburgaz UTM coordinate system (UTM-Zone 35 N). Clipping was then performed to obtain study area limits. The 'supervised classification' method was used to identify LULC changes. Finally, the accuracy assessment of the obtained maps was carried out. The steps performed to obtain the LULC map is shown in Figure 5.

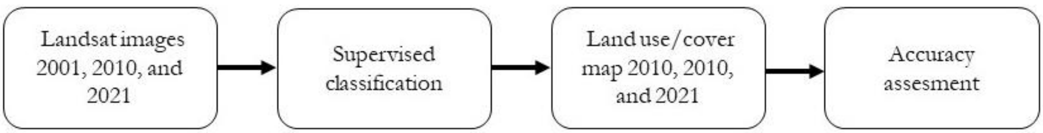


Figure 5. Steps to prepare the LULC maps

2.4. Land Use Classification and Accuracy Assessment

Accuracy assessment is an important step when analyzing remote sensing data. Remote sensing studies can provide a basis when policies are formulated. For this reason, potential users should know how reliable the maps obtained are (IIASA, 1998). Accuracy assessment provides to comprehend how certainty the maps are so that they can be used correctly and effectively. The error matrix is created for verification points. The Kappa coefficient (KC) is used to evaluate the accuracy of the image classification. The overall accuracy (OA), producer accuracy (PA) and consumer accuracy (CA) that are obtained from the error matrix must be analyzed for each LULC classes (Abdi, 2020; Foody, 2002; IIASA, 1998). It is suggested that if the area exceeds 500 km^2, or the number of categories is more than 12, at least 75-100 samples per class should be taken (Congalton, 1991). This suggestion coincides with the sample size recommended by Hay (1979) and Fenstermaker (1991) (IIASA, 1998). In this study, a sample of 100 verification points for each class was taken.

Preparing an error matrix proves to be the most common method to express the accuracy of the classification. This matrix shows crosstab of classified LULC and actual LULC (IIASA, 1998). The minimum overall accuracy value obtained from the error matrix should be 85% (Arono, 1985). Equations (1), (2), (3) below are used to calculate the accuracy values (IIASA, 1998).

$$\text{Overall Accuracy} = \frac{\text{Total number of correct pixels (Sum of the values in the main diagonal)}}{\text{Total number of pixels}} \quad (1)$$

Producer’s accuracy measures how well a particular area is classified (IIASA, 1998).

$$\text{Producer's Accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels}} \quad (2)$$

User's accuracy informs the user how well the map really represents what is on the ground (IIASA, 1998).

$$\text{User's Accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels in a category}} \quad (3)$$

The Kappa coefficient is a measure of the overall fit of a matrix (Roseneld & Fitzpatrick-Lins, 1986). The Kappa coefficient, developed by Cohen (1960) for classification accuracy, is widely used (IIASA, 1998; Mallick, 2014). According to Cohen (Table 5), any Kappa value below 0.60 indicates insufficient compliance, and the results of the study in question are highly unreliable. A Kappa value between 0.60-0.79 indicates a reasonable relationship, while a Kappa value between 0.80-0.90 points to a strong relationship. A Kappa value of 0.91 or higher indicates that there is an almost perfect fit and the reliability of the data obtained ranges between 82-100% (Cohen, 1960; McHugh, 2012).

Table5. Interpretation of Cohen's Kappa

Value of Kappa	Level of Agreement	% of Data that are Reliable
0-.20	None	0-4%
.21-.39	Minimal	4-15%
.40-.59	Weak	15-35%
.60-.79	Moderate	35-63%
.80-.90	Strong	64-81%
Above.90	Almost Perfect	82-100%

2.5. Annual Rate of Change (ARC) Analysis

ARC is the annual rate of change in LULC categories. The following equation is used to obtain the annual rate of change for each land use class (Abbas et al., 2021; Muhammad et al., 2022).

$$ARC\ (\%) = \frac{A2 - A1}{A1 \times t} \times 100$$

A1 and A2 refer to the areas in the first year and the last year, respectively, and *t* is the time interval.

2.6. Transition Matrix

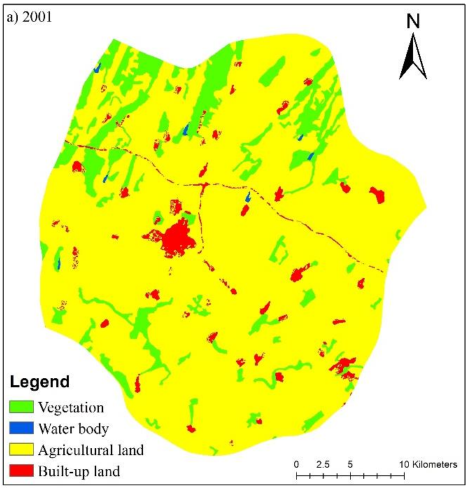
The transition matrix is the most common approach used to compare maps of different periods as it provides detailed class of change information (Teferi, 2013; Zhang B, 2017). The transition matrix is calculated using the overlay functions (intersect of geoprocessing tools) in ArcGIS software and the Pivot Table function in Excel to analyze LULC transitions (Teferi, 2013).

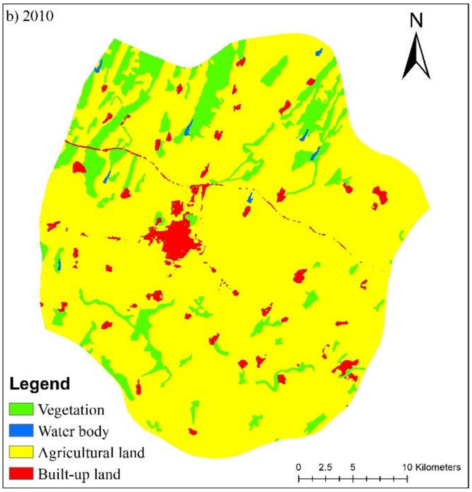
3. Results and Discussion

3.1. LULC Changes

The 2001, 2010, and 2021 satellite images of the study area were divided into four main classes: vegetation, water body, agricultural land, and built-up land.

In Figure 6, the spatial distribution of LULC classes created for the years 2001, 2010, and 2021 are shown. As a result of the urban growth that occurred over the course of twenty years, a considerable increase in the built-up areas is observed. It is understood that during period from 2001 to 2021, urban growth in Lüleburgaz occurred particularly in the east, south-east direction.





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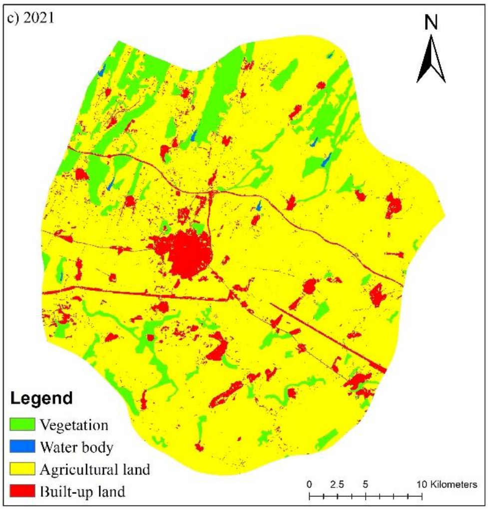

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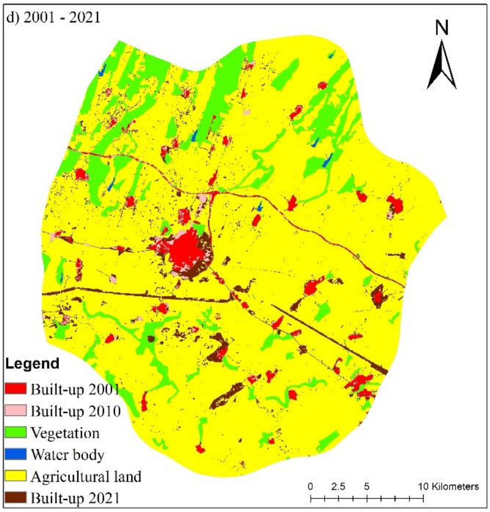

Urban expansion between 2001 and 2021

Figure 6. LULC classification maps and urban expansion map

In Table 6 the areas and ARC values of LULC maps for 2001, 2010, and 2021 are presented. Over the last two decades, there has been a significant increase in the built-up land with an annual increase rate of 7.58%. It is observed that there has been a *continuous* increase in the built areas from 32.23 km² in 2001 to 37.26 km² in 2010 and 81.13 km² in 2021. Especially between 2010 and 2021, there is a remarkable change of 43.87 km² in the built environment (Table 7). In agricultural land, there was an average annual decrease of 0.29% (from 862.05 km² to 812.39 km²). The vegetation class decreased during the time period between 2001-2010 (–2.33 km²) and increased between 2010–2021 (2.85 km²). The water body class increased during the time period between 2001–2010 (0.86 km²) and decreased between 2010–2021 (-0.69 km²). When the vegetation and water surface classes are evaluated respectively in the twenty-year period between 2001-2021, there was an increase from 119.93 km² to 120.45 km² (+0.52 km²), and from 1.52 km² to 1.69 km² (+0.17 km ²). These increases correspond to 0.02% and 0.56% respectively on an annual basis (Table 6, Table 7).

Table 6. Total area cover by different LULC classes and the percentage of cover

LULC Classes	2001		2001-2010	2010		2001-2021	2021		2001-2021
	Area (km²)	%		Area (km²)	%		Area (km²)	%	
Vegetation	119.93	11.81	-0.22	117.60	11.58	0.22	120.45	11.86	0.02
Water Body	1.52	0.15	6.29	2.38	0.23	-2.64	1.69	0.17	0.56
Agricultural Land	862.05	84.87	-0.05	857.92	84.51	-0.48	812.39	79.99	-0.29
Built-up Land	32.23	3.17	1.73	37.26	3.67	10.7	81.13	7.99	7.58

Table 7. Changes in the total area of different LULC classes

	2001-2010		2010-2021		2001-2021	
	Area (km²)	%	Area (km²)	%	Area (km²)	%
Vegetation	-2.33	1.94	72.85	2.42	0.52	0.43
Water Body	0.86	56.58	-0.69	28.99	0.17	11.18
Agricultural Land	-4.13	0.48	-45.53	5.31	-49.66	5.76
Built-up Land	5.03	15.6	43.87	117.74	48.9	151.72

The results for the 20 years between 2001 and 2021 show a remarkable growth in the built environment (+48.9 km²) and a significant decrease in agricultural land (-49.66 km²) (Table 7). The built-up land class, which was 32.23 km² in 2001 (Table 6), increased by 5.03 km² (Table 7) and reached 37.26 km² in 2010. Between 2010-2021, it has increased by 43.87 km² and reached 81.13 km² with a rapid hike. During the twenty-year period, there has been an increase of 0.52 km² in vegetation and 0.17 km² in the water surface. The highest increase was observed (48.9 km²) is observed in the built-up land class. It is also evident that a significant decrease of 49.66 km² occurred in agricultural lands. While the increase in the built-up land was 15.6% between 2001 and 2010, it was 117.74% between 2010 and 2021 (Table 7). While the annual built-up rate of change (ARC) was 1.73% between 2001 and 2010, it was 10.7% between 2010 and 2021. Agricultural land loss was 0.48% between 2001 and 2010, and 5.31% between 2010 and 2021. In addition, while the rate of loss of agricultural land (ARC) was 0.05% annually between 2001 and 2010, it was 0.48% between 2010 and 2021 (Table 6). These findings show us that the increase at the built-up land class, the losses at the agricultural land class accelerated between 2010 and 2021.
Based on the graph showing the percentage of the changes for all four LULC classes in the study area between 2001 and 2021 (Figure 7), it is apparent that the exchange has occurred largely between built-up lands and agricultural lands.

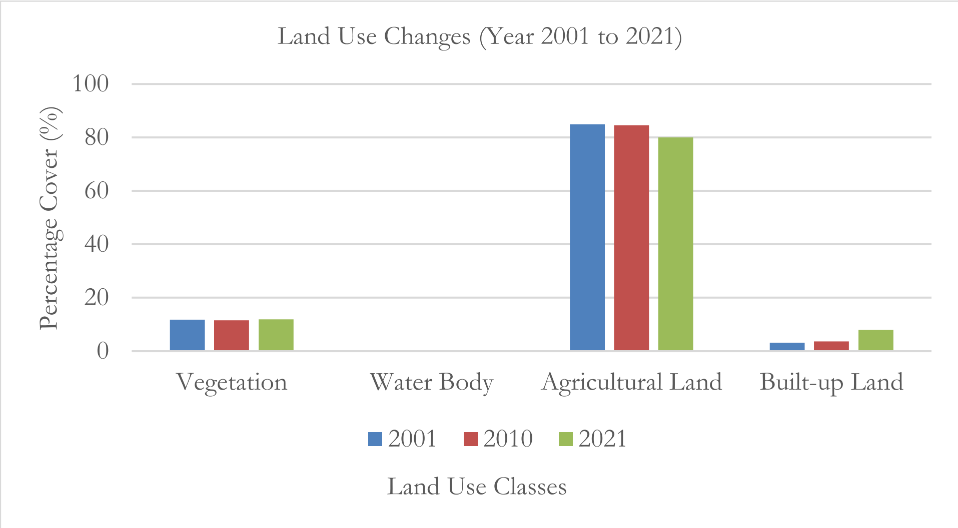

Figure 7. Changes in different LULC classes

Figure 8 shows the distributions of transition categories in the LULC classes in the different period from 2001 to 2021, and Table 8 shows the detailed composition of the gain and loss values of these transitions. Transitions between LULC classes for 2001, 2010 and 2021 were analyzed for two time intervals and three time points. The data in the main diagonal (underlined) shows the non-transition field value. In the transition matrix, the rows show the values (bold) of classes from the first time period (2001-2010), while the columns show the values (italic) of the classes from a later time interval (2010-2021). While the built-up land gain was 10.88 km² between 2001-2010, it was 46.06 km² between 2010-2021. While the amount of loss area in vegetation was 8.76 km² between 2001-2010, it was 3.63 km² between 2010-2021. While the water body loss was 0.08 km² between 2001-2010, it was 0.76 km² between 2010-2021. While the loss of agricultural land was 16.85 km² between 2001-2010, it was 50.65 km² between 2010-2021. The total area of the category transition that took place in the two time periods was determined as 90.23 km². While agricultural lands emerged as the class that loss the most land with a total of 67.50 km² between 2001 and 2021, it is seen that a total of 56.94 km² gain was realized in the built-up land (Table 8).

Table 8. LULC Transition Matrix

	Final year of time interval				Initial Total	Gross Loss
	Vegetation	Water Body	Agricultural Land	Built-up Land		
Initial year of time interval						
Vegetation	*113.95*	*0.03*	*2.77*	*0.83*	*117.58*	*3.63*
	111.04	**0.78**	**7.72**	**0.26**	**119.8**	**8.76**
Water Body	*0.7*	*1.62*	*0.06*	*0*	*2.38*	*0.76*
	0.04	**1.44**	**0.04**	**0**	**1.52**	**0.08**

Agricultural Land	*5.38*	*0.04*	*<u>807.33</u>*	*45.23*	*857.98*	*50.65*
	6.08	**0.15**	**<u>844.95</u>**	**10.62**	**861.8**	**16.85**
Built-up Land	*0.23*	*0*	*3.58*	*<u>33.34</u>*	*37.15*	*3.81*
	0.41	**0**	**5.28**	**<u>26.27</u>**	**31.96**	**5.69**
Final Total	*120.26*	*1.69*	*813.74*	*79.4*	*1015.1*	*58.85*
	117.57	**2.37**	**857.99**	**37.15**	**1015.1**	**31.38**
Gross Gain	*6.31*	*0.07*	*6.41*	*46.06*	*58.85*	
	6.53	**0.93**	**13.04**	**10.88**	**31.38**	

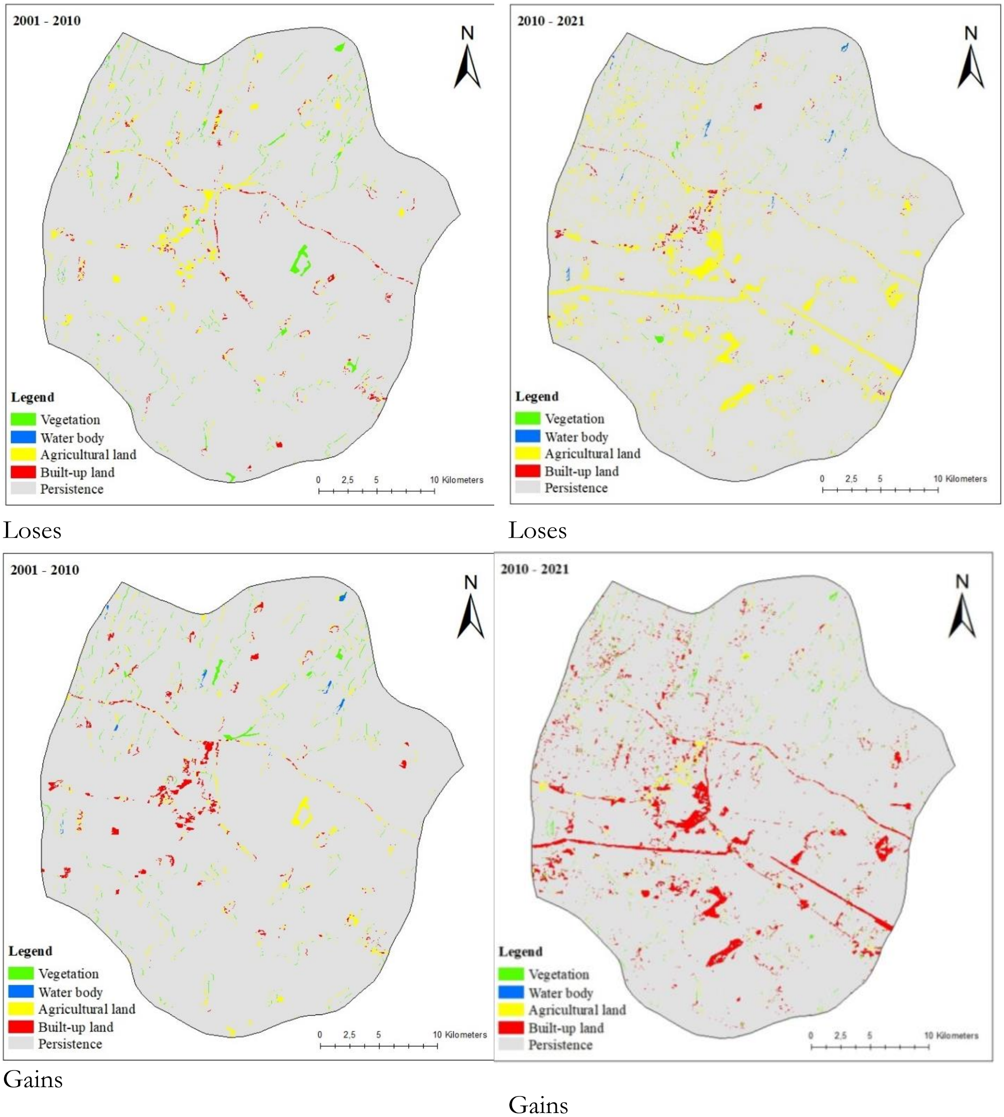

Figure 8. Loses and gains maps

3.2. Accuracy Assessment

The LULC classification of satellite images was performed by applying a pixel-based supervised classification technique. For accuracy analysis, a total of 400 random ground point samples (100 ground points samples to each class) were taken from the land use maps prepared by using Landsat satellite images (Table 9). The ground point sample was evaluated by making a comparison with Google Earth images. Overall accuracy values and Kappa coefficient were calculated to determine the accuracy of the classification of LULC maps. According to Anderson (1976), when defining LULC classes from remote sensor data, the minimum overall accuracy should be at least 85% (Anderson, 1976). The details on the Error Matrix for 2001, 2010, and 2021 are provided in Table 9.

Table 9. Error Matrix

2001					
Category	Vegetation	Built-up land	Water body	Agricultural land	Total (user)
Vegetation	96	0	9	0	105
Built-up land	2	99	0	1	102
Water body	0	0	91	0	91
Agricultural land	2	1	0	99	102
Total (producer)	100	100	100	100	400
2010					
Category	Vegetation	Built-up land	Water body	Agricultural land	Total (user)
Vegetation	95	2	8	5	110
Built-up land	0	95	0	3	98
Water body	0	0	92	0	92
Agricultural land	5	3	0	92	100
Total (producer)	100	100	100	100	400
2021					
Category	Vegetation	Built-up land	Water body	Agricultural land	Total (user)
Vegetation	95	1	0	0	96
Built-up land	0	90	0	2	92
Water body	0	0	100	0	100
Agricultural land	5	9	0	98	112
Total (producer)	100	100	100	100	400

The CA value of the built-up land class was the highest in 2021 (97.83%), while the highest rate of PA value (99.00%) was observed in 2001. In 2021, both the CA and PA values for the water surface were 100% (Table 10).

Table 10. CA and PA

LU/LC	CA (%)			PA (%)		
	2001	2010	2021	2001	2010	2021
Built-up land	97.06	96.94	97.83	99.00	95.00	90.00
Agricultural land	97.06	92.00	87.50	99.00	92.00	98.00
Vegetation	91.43	86.36	95.00	96.00	95.00	95.00
Water body	100.00	100.00	100.00	91.00	92.00	100.00

Based on the LULC images, the OA and Kappa index accuracy values were calculated for each one of the three years that were analyzed (Table 11). OA has been more than 90% for all of them. While Kappa index accuracy has the highest accuracy range for all of the years that were analyzed, the highest value (0.95) is observed for 2001. Based on the explanation of Cohen's Kappa intervals in Table 5, these results – which are 0.91 or above - prove to be a near-perfect match, and the data provides a reliability rate between 82-100%.

Table 11. OA and Kappa statistics

Year	Overall accuracy (OA) (%)	Kappa index accuracy
2001	96.32	0.95
2010	93.66	0.91
2021	95.91	0.94

3.3. Changes in LULC With Population

The R^2 value was examined to reveal the relationship between population and LULC (Inalpulat & Genc, 2021; Rahman, 2022). In order to obtain the R^2 value, the population values and LULC classes for 2001, 2010, and 2021 were normalized and then regression analysis was performed in the SPSS software. When the R^2 values for each class are examined, the highest R^2 values are observed in the built-up land and agricultural land classes (Table 12). The R^2 value for the built-up land class is 0.856, and the R^2 value for the agricultural area class is 0.843. According to the graph, there is a directly proportional relationship between population growth and the built-up land class and an inversely proportional relationship between population growth and the agricultural land class. On the other hand, the R^2 values for the water body and vegetation classes ($R^2 = 0.022$, $R^2 = 0.045$, respectively) were slim in these classifications. The total population of Lüleburgaz has increased by about 35 thousand people over the period of 20 years (Table 2). Population growth appears to have a strong correlation with the changes in the built-up areas and agricultural lands ($R^2 = 0.856$, $R^2 = 0.843$) (Figures 9 & 10).

Table 12. R^2 values of LULC classes

LULC Classes	R^2
Built-up land	0.856
Agricultural land	0.843
Vegetation	0.045
Water body	0.022

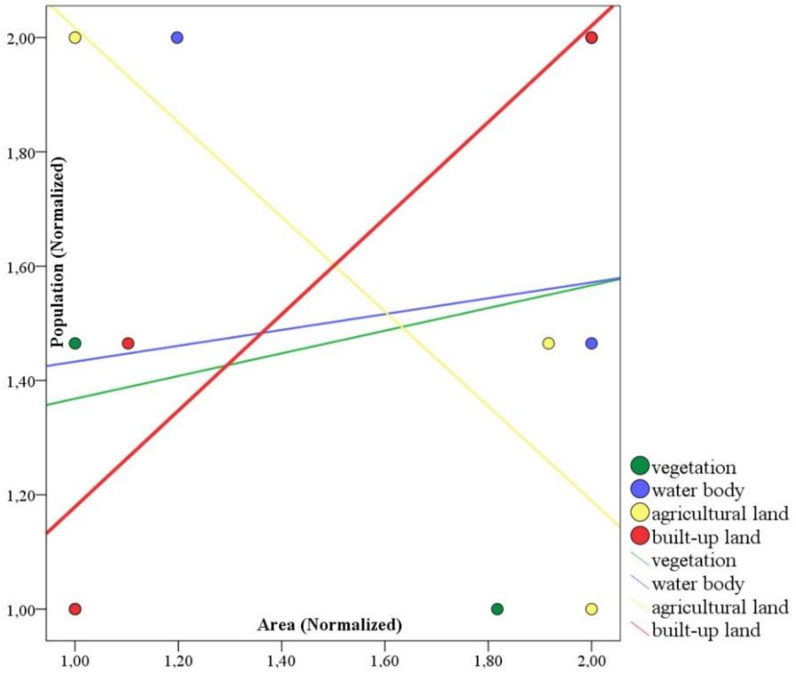

Figure 9. The relationship between population and LULC changes

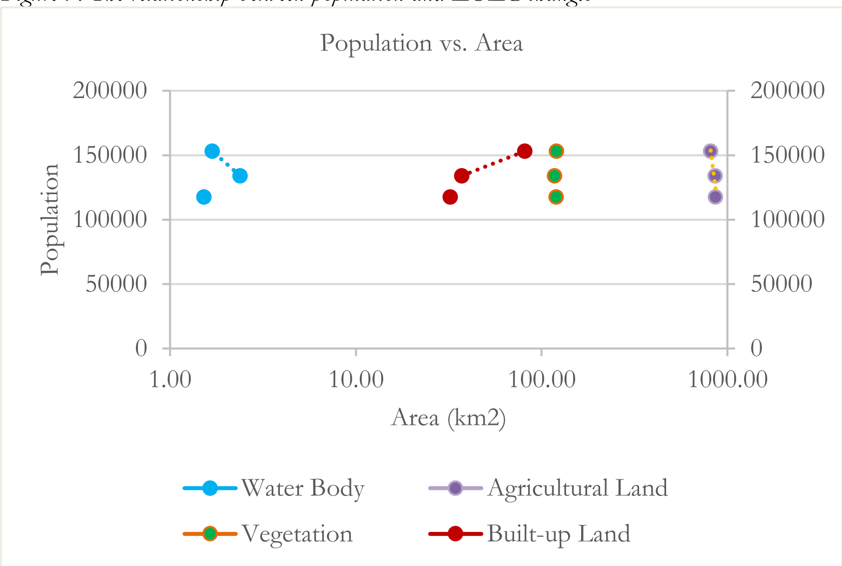

Figure 10. Changes in population and land use classes

3.4. Discussion

Urban growth leads to the conversion of natural land cover to built-up areas, thus both affecting ecosystem services adversely and hindering to achieve the Sustainable Development Goals (Shao et al., 2021). In order to ensure that urban planning is performed in line with the achievement of sustainable development goals, it is necessary to know the negative trends that have been going on since the past and that may persist in the future. Various studies emphasize that population growth and economic development are the underlying reasons behind why built-up areas expand (Reza, 2016; Wu et al., 2021). Increased construction adversely affects the natural ecosystem, water quality, and biodiversity (Seto et al., 2012). This raises concerns about the fragmentation of natural areas, climate change, food insecurity, and scarcity of natural resources (Abbas et al., 2021). In this study; important changes in LULC in Lüleburgaz over the last twenty years and which land use classes experienced the highest rate of change were evaluated. The direction of urban growth, the effects of population growth on the LULC changes, and the relation between SDG policy frameworks and LULC changes were examined. (In the study,) The LULC classification for 2001, 2010, and 2021 were presented, providing accurate representations of LULC changes and relevant trends. The LULC maps obtained by means of the supervised classification of Landsat satellite images were found to have high reliability with an overall accuracy value of 93.66% at the lowest. By performing comparisons between the classified maps for 2001–2010 and 2021, significant LULC changes in Lüleburgaz were observed from 2001 to 2021. Between 2001- 2021 While the built-up land class had the highest growth rate (reaching 7.99% in 2021 from 3.17% in 2001), the agricultural land class had the highest rate of decline (declining to 79.99% in 2021 from 84.87% in 2001). Minimal changes were observed in the vegetation and water body classes. The vegetation class increased from 11.81% in 2001 to 11.86% in 2021, and the water surface increased from 0.15% to 0.17%. Between the 2001-2010, the built-up land growth rate (ARC) was 1.73% and the agricultural land decrease rate was 0.05%. Between the 2010-2021, the urban growth rate was 10.7% and the decrease in agriculture was 0.48% (Table 6). While an increase of 6.29% was observed in the water surface between 2001-2010, there was a decrease of 2.64% between 2010-2021. The changes between LULC classes is clearly visible from the transition matrix. While the built-up land gain was 10.88km2 and the agricultural land loss was 16.85km2 between 2001-2010, the built-up land gain was 46.06km2 and the agricultural land loss was 50.65km2 between 2010-2021. The amount of lost area in vegetation has decreased relatively (while 8.76km2 was lost between 2001-2010, 3.63km2 was lost between 2010-2021). The area lost on the water surface, which was 0.08km2 between 2001-2010, increased to 0.76km2 between 2010-2021. These data reveal that the built-up land increase and the loss of agricultural land and water surface between the years 2001-2010 accelerated between the years 2010-2021. The analysis of R^2 values demonstrates that built-up areas ate up the agricultural land class. It was observed that the main trend between 2001 and 2021 was a rapid reduction in agricultural lands as a consequence of rapid urban growth. These findings indicate that the natural land classes such as vegetation, water body, and agricultural lands has decreased, while there has been a significant increase in in built-up areas. In summary, Lüleburgaz, which sits on high quality agricultural land, has lost a significant amount of agricultural land.

Based on the analysis that reveal the relationship between population growth and LULC, it is possible to suggest that the increase in the built-up land, the significant decrease in agricultural land over the last 20 years are due to the population increase according to the R^2 value. The decline of vegetation around the city's peripheries is the primary obstacle against achieving SDG 15, which is focused on supporting sustainable use of terrestrial ecosystems, combating desertification, halting land degradation, and curbing biodiversity loss. The increase in the built environment and the decline of agricultural land will result in straying from the path to achieve SDG 2, which aims to end hunger, achieve food security and good nutrition, and support sustainable agriculture by 2030. In addition, this outlook will cause a deviation from the path to achieve SDG 11, SDG 12, SDG 13, which aim to make settlements inclusive, safe, resilient and sustainable.

These findings indicate that natural resources, ecology, and food security may be endangered due to urban growth and the fragmentation of agricultural areas. Increased urbanization and degradation of vegetation will significantly affect the quality of groundwater as well as the use of natural resources. In addition to making it difficult to reach the SDGs, this situation is also at odds with with the quality of urban life. The expansion of urban areas poses a challenge for local governments worldwide (Marans, 2012). As noted by Myers (1988), rapid urban growth is negatively changing the quality of life (Myers, 1988). The increase in built-up areas leads to adverse effects such as traffic congestion, pollution, unsustainable land changes, reduced public open green spaces, and heightened pressure on public services (Shao et al., 2021). Rapid urban growth hinders local governments' ability to adequately provide required infrastructure and facilities, thus leading to poor quality of life, which is particularly in conflict with SDG 11.

From this perspective, planning helps to mitigate the damaging effects of growth, while promoting economic development. Development of environmental possibilities is a strategy aimed at improving the overall quality of life by offsetting the deterioration of other components (Myers, 1988). Studies focused on the quality of urban life provide the opportunity to overcome these challenges (Marans, 2012). These relationships make it clear that quality of life requires closer examination (Myers, 1988). Therefore, as a prerequisite for sustainable urban management, it is important to control urban sprawl (Shao et al., 2021) and improve the quality of urban life in line with the pace of urbanization. These data demonstrate that lower-scale plans should be prepared in line with the principles that will be adopted to minimize the loss of natural land cover in the face of the pace of urbanization. Findings of this study can assist decision makers in adopting a planning approach that considers environmental protection, improved urban service delivery, and sustainable development in accordance with sustainable development goals. This study reveals the need to control urban growth that leads to the loss of agricultural land. If ending hunger, providing clean water and sanitation, achieving sustainable cities and communities, ensuring responsible production and consumption, climate action and terrestrial life, which are the requirements of the SDGs, will be set as a target for the people of Lüleburgaz at a local scale, adopting planning trends that prevent the loss of natural land due to urban growth/urbanization will be a critical decision.

4. Conclusion

In this study; the changes in land use and land cover in Lüleburgaz, which has fertile agricultural land and where a tendency to rapid urbanization has occurred, were analyzed by using the remote sensing method. The results revealed that the agricultural lands in Lüleburgaz face a tremendous pressure due to construction. The results of the analysis show that the built-up land gains the most land and these gains are mostly obtained from agricultural lands. The findings reveal that there was a significant change between agricultural land and built-up land in LULC between 2001 and 2010, and the speed and intensity of this change increased in the period between 2010 and 2021. The transition matrix reveals a steady increase from the agricultural land class to the built-up land, implying that the LULC trend is towards artificial surfaces. It is apparent that a planning perspective based on population growth and growth is also embraced in Lüleburgaz. This leads to the destruction of natural areas and the emergence of ecological negative effects. Lüleburgaz faces problems including rapid urban growth and environmental degradation as a result of the fragmentation of natural land classes, the decline in the water quality, and the decrease in agricultural lands. This outlook is not in rapport with the Sustainable Development Goals. These factors will further exacerbate the challenges associated with sustaining regional development and protecting the environment. It is thought that the implementation of the High-Speed Railway Project and the Airport Projects will even more accelerate the urban growth/sprawl in Lüleburgaz. In order for big cities not to negatively affect small and medium-sized cities around metropolitan areas, urban growth should be realized within the framework of the three main components of sustainable urbanism, namely economic, environmental and social components. This framework will ensure the strengthening of economic prosperity and employment, the sustainable use of renewable/non-renewable resources in the urban production-consumption chain, and the livability of cities on the basis of the principle of social justice and equality.

Adequate food, water, and clean air are not only one of the Sustainable Development Goals but are also among the physiological needs according to Maslow's hierarchy of needs. These needs are the very basic requirements for the survival of an individual, and all other needs are secondary until these basic needs are met. In this respect, the transformation of first-class agricultural lands into built-up land results in the deterioration of the ecological balance, and it affects numerous issues ranging from quality of life, economy, food security, employment opportunities, land prices, and local production. For this reason, when making plans that must prioritize public interest, it is critical that local governments do not adopt policies that do not comply with the SDGs, and thus, jeopardize the quality of urban life.

Although rapid urbanization and LULC changes have an impact on various topics including urban quality of life, economy, food security, job opportunities, land prices, loss of goods produced, exports and local consumption, this study is only focused on analyzing the existing LULC. Considering the fact that in Lüleburgaz has been a rapid increase in the built-up land over the last twenty years and that this trend will continue in the years to come, it is necessary to examine the current urban quality of life in urban service delivery. Further studies should be carried out to investigate the current outlook and the effects of urban growth on the quality of urban life.

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