BIO Web of Conferences **228**, 09004 (2026) https://doi.org/10.1051/bioconf/202622809004
Biospectrum 2025

Assessing and detecting spatiotemporal land use/cover changes in Uzbekistan using sentinel-2 imageries

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Abstract. Understanding Land use and Land cover (LULC) change is important in environmental modification and natural resource management. This study analyzed the dynamic changes of LULC in the Syrdarya province of Uzbekistan from 2017 to 2024 by applying AI-based classification Sentinel-2 data. The results of the study indicate that certain LULC categories have experienced shifts in extent. While the built-up areas expanded from 40,082 ha to 47,670 ha and the water bodies increased from 13,785 ga to 16,912 ha between 2017 and 2024, other LULC types such as bare land exhibited a substantial decrease from 1,136 ha to 305 ha with the cropland and rangeland experiencing moderate decline to fluctuations. Also, a correlation analysis was performed to better understand the interrelationship between these LULC categories. The flooded vegetation and water bodies (R = 0.62), built-up areas and water bodies (R = 0.69), bare land and cropland (R = 0.56) showed a strong positive relationship. However, the strong negative correlations between cropland and water bodies (R = –0.60), built-up areas and cropland (R = –0.58), bare land and water bodies (R = –0.84), bare land and built-up areas (R = –0.85), and rangeland and cropland (R = –0.88) were detected. As one of the primary driving factors of the LULC types, the province's population has been considered. The most positive correlation (R=-0.96) was found between population and built-up areas.

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1 Introduction

Land use refers to the use of land by humans for various purposes, including agriculture, residential construction, industrial activity, recreation, transportation, and nature conservation. Land cover refers to the physical materials found on the earth's surface, such as vegetation, water bodies, territories, and open spaces. These terms are often used together because land use and land cover are inextricably linked and cannot be fully understood in isolation [1]. As a result, the LULC represents the outcomes of anthropogenic environmental interactions that are shaped by the dynamics of climate change and socioeconomic factors in a given region [2]. For sustainable land resource management and implementing environmental protection strategies, understanding temporal and dynamic variations in LULC is important as its aim is to reconcile human development with ecological equilibrium [3]. The conversion of green areas into residential or industrial zones, the designation of ecologically important areas for state protection are a few examples of common LULC transformation [4]. These changes are intensifying by the increased human activity at the local, regional, and international scales. As a result, they have a significant impact on ecosystem functions and ultimately human well-being [5]. Thus, a proper understanding and analysis of the dynamics of the LULC is more important than ever to ensure a sustainable future in the areas where agricultural systems are being transformed by rapid population growth and climate change should be prioritized in LULC analyses [5, 6].

Central Asia, in particular, is notable for its historical dependence on irrigated agriculture and large-scale cotton cultivation throughout the last century, making it a critical region for LULC and environmental change analysis [7]. During the Soviet era, the conversion and expansion of unused arable areas, known as “Virgin Land campaign”, into irrigated agricultural land made Central Asia one of the leading wheat and cotton- producing regions worldwide [8]. For example, between 1954 and 1963, approximately 23 million hectares of grassland were converted into cropland in northern Kazakhstan [9], as part of a broader effort that transformed an estimated 45 million hectares (Mha) across the Eurasian steppe, comprising areas in western Siberia and the Ural region [10]. However, inefficient water and land management strategies during this period made the successor states of the Soviet Union in Central Asia vulnerable to further environmental degradation and a range of associated challenges. This led to significant transformations in LULC following the Union’s collapse in 1990s [9, 10].

Similarly, Uzbekistan, among the other Central Asian, has experienced significant LULC changes across its vast territory long before 1991. Since the country was mostly designed to cotton production during the Soviet Union, the bare lands and forest areas were converted to irrigated areas [11]. To meet the needs of a mounting population, particularly in rural areas and major cities, urban areas have expanded at the expense of grasslands, bare lands, and agricultural lands. At the same time, the poorly managed agricultural system inherited from the Soviet era, Aral Sea disaster, large-scale pollution, and the other problems linked to climate change all have significantly contributed to land degradation and salinization, further exacerbating environmental stress in arid and semi-arid regions of the country [12, 13]. Accordingly, recent projections indicate that by 2050, Uzbekistan, Turkmenistan, Kyrgyzstan, and countries in the Middle East, North Africa, and South Asia, will be among the most severely affected by increasing water stress driven by climate change and rising water demand [14]. Therefore, the sustainable protection and efficient management of land resources should be considered a national priority for Uzbekistan in addressing future environmental challenges.

In recent decades, using remote sensing (RS) and geographic information systems (GIS) for evaluating various spatial and temporal interactions has become common techniques in environmental studies [15]. Due to their historical and extensive observation coverage and fast update cycle, the remote sensing datasets are viewed an effective and valuable source of information for the evaluation and detection of LULC changes [16]. Specifically, wide-area, high-resolution, multispectral imagery from the Landsat (NASA/USGS) [7, 9] and Sentinel (ESA/Copernicus) satellite missions is widely utilized. Sentinel-1 comes with synthetic aperture radar (SAR) data, while Sentinel-2 and Landsat provide multispectral optical imagery [17]. This set of satellite systems has proven to be effective in detecting soil salinity, monitoring large-scale vegetation cover dynamics, and analyzing LULC changes over various time scales [18]. Landsat and Sentinel-2 satellite data are commonly used to assess and detect LULC variations. Since Sentinel-2 has a high precision in space (10-60 m) and time (5-day re-visit), it is better suited for analysis of near-period and micro-scale changes [19]. Landsat imageries provide continuous historical data from 1972, which is suitable for long-term analysis [20]. However, Sentinel images are being commonly used with machine learning techniques and integrated with artificial intelligence algorithms to improve classification accuracy. Once combined with these modern tools, they are capable of identifying subtle and negligible changes in land cover [21].

Using these images and data sets, a number of LULC assessment studies have been conducted by local scientists in Uzbekistan. For example, Juliev and et al. studied the detection of LULC changes based on Landsat 5 TM and 8 OLI satellite imagery in the Bustanliq district of the Tashkent province of Uzbekistan, and found that significant changes occurred in forest cover, built-up areas, bare soil and snow cover over 28 years [22]. Similarly, Alikhanov and et al. conducted an analysis of the entire Tashkent region, which consists mainly of mountainous terrain, and their results were almost identical to those of Juliev's research, showing a significant reduction in the area of glaciers and an expansion of urban areas associated with population growth in Tashkent, the capital of Uzbekistan [23]. Additionally, Edlinger and and et al. reconstructed the spatiotemporal evolution of irrigation systems in the Kashkadarya province (also a mountainous region) using Landsat time series data to analyze historical land use changes and agricultural land dynamics. They found a significant expansion and intensification of agricultural land, from 134,775 hectares in 1972/73 to 469,685 hectares in 2009 [7]. In a recent study by Alikhanov and et al. the vegetation cover change in Ugam-Chatkal National Park during the post-Soviet period (1991-2022) was assessed using several statistical methods and remote sensing data. The results showed that the maximum and minimum values of vegetation cover in the study area were significantly related to the air temperature [24]. Alikhanov and et al. also assessed land use and land cover (LULC) changes in the province between 1993 and 2022, but this time used advanced CA–Markov modeling and Random Forest machine learning algorithms to predict future LULC scenarios. According to their projections, glaciers will continue to shrink in area, while tree cover, rocky areas, pastures, agricultural land, and urban areas are expected to expand [25]. Aslanov et al. applied remote sensing data, Landsat 5 TM and 8 OLI, for monitoring green areas in the Tashkent city, since the city is experiencing a rapid urbanization and increased environmental pressure. According to their results, between 1990 and 2019, there were significant changes in land use in Tashkent, in particular, agricultural land decreased from more than 12,000 hectares in 1990 to only 2,661 hectares in 2019. As expected, urban (building) areas expanded from 20,497.95 hectares to 31,596.48 hectares, mainly due to agricultural land reduction [26].

In conclusion, the studies above show that significant changes occurred in land use in urban and rural areas, especially in mountainous regions, are associated with population growth and the effects of climate change. However, the dynamics of LULC in irrigated areas of Uzbekistan are poorly studied, and there is no comprehensive study dedicated to the spatial and temporal aspects of these changes. This suggests that there is a significant scientific gap in the current literature. In this regard, this study aims to fill this scientific gap by analyzing the spatial and temporal dynamics of land use and land cover (LULC) changes in irrigated regions of Uzbekistan. The results of the study are expected to serve as an important scientific basis for supporting sustainable management of land and water resources in the country.

2 Materials and methods

2.1 Study area

In this study, the Syrdarya province of Uzbekistan is selected as the study area owing to its agro-economic importance in the country. Located on the left bank of the Syrdarya river, the province shares borders with the Republics of Tajikistan, Kazakhstan, and Jizakh and Tashkent provinces of Uzbekistan (Figure 1) [27]. It covers approximately 4,300 km² (equivalent to around 430,000 ha), with the Mirzachul steppe comprising a substantial portion of the landscape

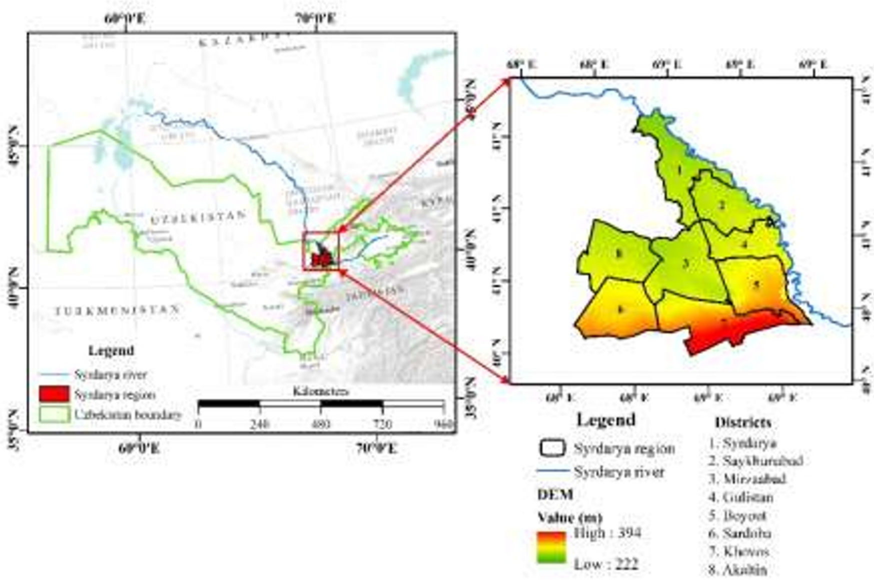

Fig. 1. The location of the study area

Administratively, the province is divided into eight districts; Syrdarya, Saykhunabad, Mirzaabad, Gulistan, Boyout, Sardoba, Khovos, and Akaltin [28]. As of 1 July 2025, the total population is 930,800 people [29]. The climate in the province is semi-arid, characterized by dry and hot summers, which makes agriculture possible only through irrigation. Based on climate data from the past decade (2009 and 2019), the average annual temperature is approximately 14.8°C, recorded extremes ranging from a maximum of 15.8°C to a minimum of 13.7°C. A parching wind, locally known as garmsil, is prevalent throughout the province [30], and evaporates soil moisture loss, impedes plant development. Due to the semi-aridic climate, atmospheric precipitation predominantly occurs during the winter and spring seasons, which makes the province reliant on the Syrdarya River for irrigation [27]. The irrigated area is 2872 km2 (or 287,200 ha), which makes up 70.6% of the provincial area [31]. The soils of irrigated lands are predominantly classified as Anthrosols, Technosols, Solonchaks, Arenosols, and Cambisols. These soils have relatively low organic matter, on average 1.0%, with reserves of nearly 40 tons per hectare [31].

2.2 Dataset

Integration of artificial intelligence and machine learning into remote sensing data and GIS environment have enhanced the mapping techniques. Different high-resolution satellite imagery datasets from different sources are now available for free online, which facilitates comprehensive spatial analysis for the given area. In this study, high-resolution (10 m) LULC data were taken from the Land Cover Explorer platform (https://livingatlas.arcgis.com/landcoverexplorer/), developed by Esri and Microsoft. This platform uses AI-based classification algorithms to produce consistent global land cover maps. Specifically, the classification is performed using Impact Observatory's deep learning land classification model, which has been trained on billions of human-labeled image pixels from over 20,000 globally distributed sites representing all major biomes, in partnership with the National Geographic Society. The model is applied to Sentinel-2 Level-2A imagery through Microsoft's Planetary Computer, processing over 400,000 Earth observations annually. The resulting dataset categorizes the land surface into nine LULC classes (water, trees, flooded vegetation, crops, built areas, bare ground, snow/ice, clouds, and rangeland) and covers the time span from 2017 to 2024 [32]. For the purpose of this study, the LULC data were downloaded the platform above and spatially clipped to match the boundaries of the Syrdarya Province study area. During the research, out of nine LULC classes, only seven types were identified (Table 1).

Table 1. Description of classified LULC in the Syrdarya Province

LULC class	Description
Water	Areas where water was predominantly present throughout the year
Trees (or forest)	Any significant clustering of tall (~15 feet or higher) dense vegetation, typically with a closed or dense canopy
Flooded Vegetation	Areas of any type of vegetation with obvious intermixing of water throughout a majority of the year; seasonally flooded area that is a mix of grass/shrub/trees/bare ground
Crops (or cropped areas/cropland)	Human planted/plotted cereals, grasses, and crops not at tree height
Built Area	Human made structures; major road and rail networks; large homogenous impervious surfaces including parking structures, office buildings and residential housing
Bare ground	Areas of rock or soil with very sparse to no vegetation for the entire year; large areas of sand and deserts with no to little vegetation
Rangeland	Open areas covered in homogenous grasses with little to no taller vegetation; wild cereals and grasses with no obvious human plotting (i.e., not a plotted field)

2.3 LULC change detection

For LULC change detection, the first (2017) and last (2024) periods were selected to reveal how LULC types have changed over eight years. Each raster containing 7 LULC types was converted to polygon, and the area (in ha) for each class type was calculated. Afterwards, two files were intersected and the major changes identified. The basic calculations were performed using Excel, while change detection was performed using ArcGIS 10.8 software.

2.4 Pearson's correlation

In this study, Pearson correlation coefficient was utilized to assess the interrelationships among various LULC types, with the relationship between LULC types and total population. The Pearson correlation coefficient (r) is a statistical measure that quantifies the strength and direction of the linear relationship between two continuous variables. Its value ranges from −1 to +1, where +1 represents a perfect positive linear relationship (both variables increase together), −1 represents a perfect negative linear relationship (one variable increases while the other decreases), and 0 indicates no linear relationship. For interpretation, correlation values of 0.0–0.1 suggest no correlation, 0.1–0.3 a low correlation, 0.3–0.5 a moderate correlation, 0.5–0.7 a strong correlation, and 0.7–1.0 a very strong correlation [33].

The correlation coefficient (r) could be computed as :

$$r = \frac{\sum(x - m_z)(y - m_y)}{\sqrt{\sum(x - m_z)^2 \quad \sum(y - m_y)^2}}$$

Where is r is the correlation coefficient, m_z and m_y illustrate the means of the x and y variables. The correlation values presented for the analysis of the multiple LULC types, and relationship between LULC types and total population were tested on a confidence level of 95%, which is used to calculate the significance of the correlation.

3 Results and discussion

3.1 Spatiotemporal changes of LULC in the Syrdarya province

Using AI-classified Sentinel-2 Level-2A LULC data imagery, seven LULC classes were identified in the study area and they are as follows Water, Forest, Flooded vegetation, Cropland, Built-up area, Bare land, and Rangeland. Although the classification algorithm is designed to indentify nine classes, only seven were observed due to the absence of Ice/Snow and cloud cover. Figure 2 presents the major spatial and temporal shifts in LULC within eight districts of the province from 2017 to 2024.

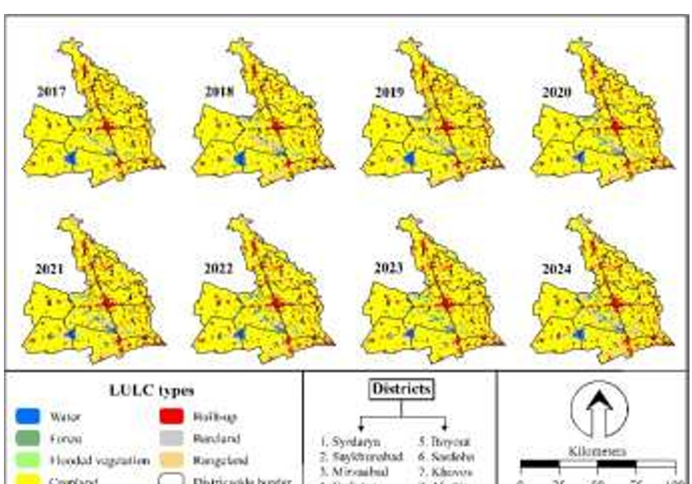

Fig. 2. The spatial and temporal dynamics changes of LULC types.

Indubitably, the cropland areas have been the dominant land use type from 2017 to 2024. This showcases how the important irrigated agriculture is in all districts. The water bodies showed minor fluctuations in extent, with a noticeable reduction between 2020 and 2021, which is particularly visible in the Mirzaabad district. This decline could be attributed to the Sardoba reservoir failure occurred in 2020, which resulted in the release of a large amount of water, and shrunk in size [34]. The area covered by forest is quite negligible and is primarily located in the upper part of the Syrdarya district, near the Syrdarya River, where the environment is suitable for their growth and development. The flooded vegetation and bare land are seen nearly invisible types on the LULC spatial map, appearing only in small areas around the water bodies such as the Sardoba reservoir and Mirzaabad district [34]. However, the built-up areas could be spotted easily, showing expansion in the central part of the province, particularly in the Gulistan district, across all periods. Similarly, the rangeland is also eye-catching in the Mirzaabad, Boyovut, Sardoba, and Khovos district. Due to their closeness to the international borders with Kazakhstan and Tajikistan, the rangeland in the districts of Mirzaabad and Khovos could not have been exploited for either agriculture or residential purposes. Overall, the spatial LULC map of the Syrdarya Province reveals moderate to significant changes in water bodies and built-up areas, whereas changes in forest and flooded vegetation are negligible. Meanwhile, the cropland and bare land areas have undergone moderate to significant reductions in extent, due to population growth and the residential area expansion.

The changes of LULC types in hectare from 2017 to 2024 was calculated and shown in the Figure 3. It could provide insights into land transformation trends across the study area. The province's landscape is dominantly cropland, which occupied the largest portion of the territory. Its area ranged from 329,857 ha in 2024 to a peak of 348,948 ha in 2017. Despite minor annual fluctuations, the cropland remained the dominant type of land use on agriculture.

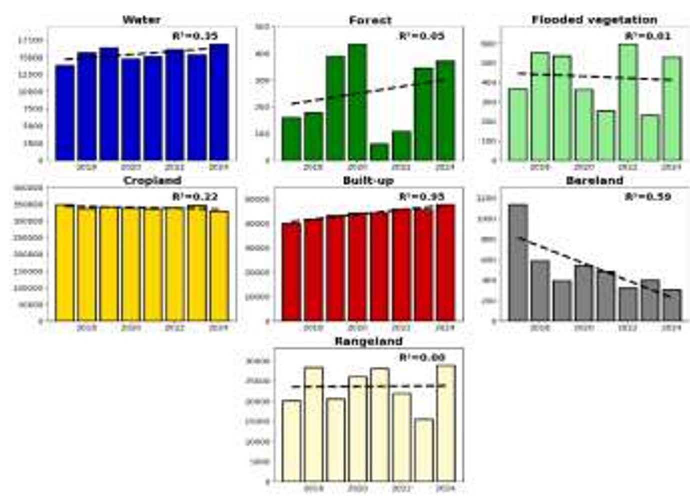

Fig. 3. LULC dynamics over the eight years.

The water bodies have demonstrated a consistent increasing trend (R=0.35) with 13,785 ha in 2017 to 16,911 ha in 2024, gaining more than 3,100 ha over the study period. This is linked to the Sardoba reservoir that had an impact on water bodies in 2020. The forest areas, in total, increased from 155 ha in 2017 to 349 ha in 2024, with sharp fluctuations between 2019 and 2020. Meanwhile, the flooded vegetation varied between 232 ha (2023) and 597 ha (2022), which follows seasonal and hydrological water cycles. As mentioned above, the cropland was the dominant land use type, accounting for the majority of land cover across all years. Although it declined a little bit from 348,948 ha in 2017 to 329,857 ha in 2024, it seemed to have remained the backbone of the local economy and food production. The built-up areas exhibited a constant increase from 40,081 ha in 2017 to 47,670 ha in 2024, highlighting a significant urban expansion. The bare land, in contrast, declined sharply, being just 305 ha in 2024 from 1,136 ha in 2017. The rangeland, although some fluctuations were observed, presented no increasing trend, with a minimum of 15,581 ha in 2023 and a maximum of 28,923 ha in 2024.

3.2 LULC detection from 2017 to 2024

The LULC detection map is shown in the Figure 4. The dominant yellow color, which represents persistent cropland (Cropland–Cropland), shows that a large portion of agricultural land remained unchanged over time. However, significant areas marked in red (Cropland–Built-up) and blue (Cropland–Water) indicate alarming patterns of urban encroachment and hydrological shifts on previously cultivated lands. One of the most notable transitions is from cropland to built-up areas, which appears widespread, particularly around urban centers and along major transportation routes. This pattern aligns with the quantitative findings showing a 1.79% increase in built-up land and a corresponding 4.5% decrease in cropland (Table 2). These observations suggest a direct link between urban expansion and the declining agricultural land due to population growth.

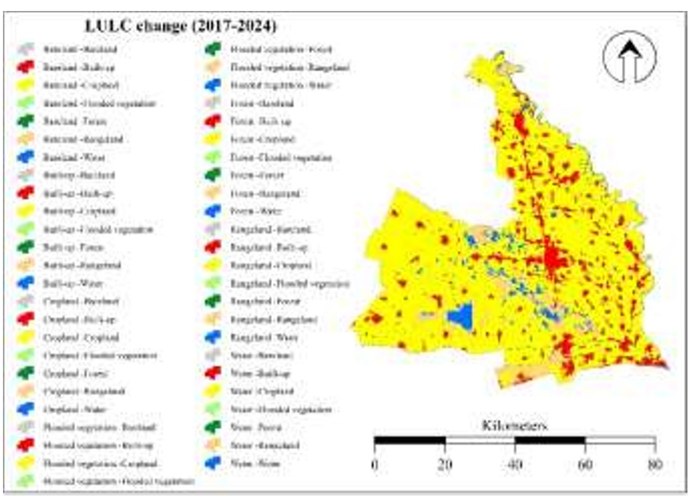

Fig. 4. LULC change detection map.

The blue patches in the map in formerly cropland-dominated areas highlight a visible increase in water bodies, possibly due to water infrastructure building, or changes in water management systems. This is also supported by the 0.73% (3126.79 ha) increase in total water area recorded in the table 2. The map also reveals the conversion of bare lands and rangelands into cropland or urban areas, especially in the southwestern parts of the region, reflected either land reclamation efforts or natural succession processes. Conversely, there are other instances of cropland reverting to rangeland or forest. This could indicate land abandonment, salinization, or degradation issues that gave a rise to forest areas. The small-scale transitions, for instance built-up to water or bare land to forest, although limited in extent, might have been caused by the local ecological restoration projects such as afforestation activities, or improved water allocation for agriculture.

The analysis of LULC dynamics from 2017 and 2024 reveals notable shifts in the study area (Table 2). The cropland experienced a substantial decline from 348948.6 ha (82.19%) in 2017 to 329857.5 ha (77.69%) in 2024. This reduction, approximately 19,091 ha (or 4.5%), reflects increasing pressures from urbanization, land degradation, and shifts in land management practices. Simultaneously, the built-up areas undergone a marked expansion, which grew from 40081.76 ha (9.44%) to 47670.5 ha (11.23%), an increase of over 7,500 ha (or 1.79%.) The rangeland also increased significantly, from 20090.34 ha (4.73%) to 28923.49 ha (6.81%), suggesting a reversion of some cropland or bare land into extensive grazing areas, which may be associated with land abandonment.

Table 2. The area of each LULC and proportion of total area from 2017 to 2024 (hectare, %)

Years	2017		2024		Change	
LULC types	Area	Proportion	Area	Proportion	Area	Proportion
Water	13785.12	3.25	16911.91	3.98	3126.79	0.73
Forest	159.22	0.04	371.55	0.09	212.33	0.05
Flooded vegetation	367.05	0.09	527.94	0.12	160.89	0.03
Cropland	348948.6	82.19	329857.5	77.69	-19091.1	-4.5
Built-up	40081.76	9.44	47670.5	11.23	7588.74	1.79
Bare land	1136.38	0.26	305.6	0.08	-830.78	-0.18
Rangeland	20090.34	4.73	28923.49	6.81	8833.15	2.08

Interestingly, the area of water bodies rose from 13785.12 ha (3.25%) to 16911.91 ha (3.98%). This 0.73% increase indicate hydrological changes, including reservoir expansion after the Sardoba incident, or climatic factors such as increased precipitation. Smaller but important increases should be also noted in the forest cover, which grew from 159.22 ha (0.04%) to 371.55 ha (0.09%), and the flooded vegetation, with an increase from 367.05 ha (0.09%) to 527.94 ha (0.12%). These changes could suggest the reforestation efforts and natural vegetation recovery implemented by the government. In contrast, the bare land area dramatically decreased from 1136.38 ha (0.26%) to 305.6 ha (0.08%). This could have been caused by urban expansion.

3.3 Intercorrelation of LULC classes and the influence of population growth

The intercorrelation among the identified LULC classes and the influence of population growth as a driving factor were evaluated using Pearson's correlation coefficient (Figure 5). This analysis could support decision-making by providing a better understanding of how LULC classes have been interrelated and how population growth has had influence on land use dynamics. A strong positive correlation between water and built-up areas ($r = 0.69$) was detected, which suggests that urban growth and water body expansion have occurred at the same time. But it does not imply the urban areas have expanded at the expense of water bodies. However, the water bodies were negatively correlated with cropland ($r = –0.60$) and strongly negatively correlated with the bare land ($r = –0.84$), showcasing that the water body expansion in the last 8 years have taken place in decreased croplands and also the bare lands could have been used for water conservation. Meanwhile, the forest area showed a low correlation with most other land types, although a weak positive correlation with built-up areas (r = 0.30) has been detected. This could be explained by the fact that the urban development could have incorporated the areas covered by the forest and green spaces. Therefore, the result might have been a low relationship.

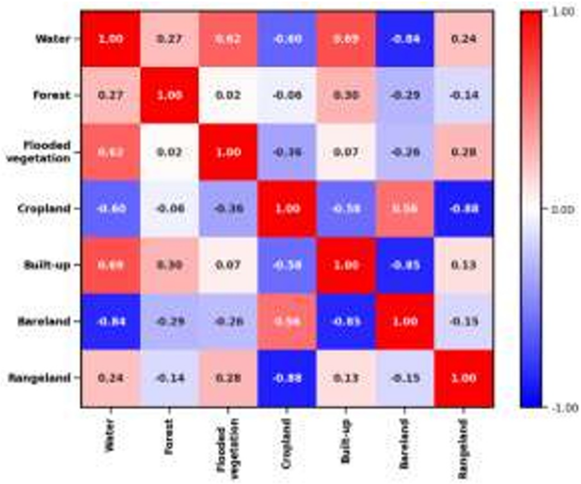

Fig. 5. Intercorrelation between LULC types.

The flooded vegetation exhibited a moderate positive correlation with water bodies (r = 0.62). This reflects the interdependence of flooded vegetation with water bodies. The weak correlations with other classes imply that the flooded vegetation areas do not significantly interact with other LULC types such as cropland or built-up. Also, the cropland revealed strong negative correlation with rangeland (r = –0.88). This means that the cropland has been increasing not because of the rangeland. Similarly, the cropland had negative correlations with water bodies (r = –0.60) and built-up areas (r = –0.58). This could be explained that the areas near to water bodies have not been suitable for cultivating agricultural crops and the built-up area have increased at the expense of bare lands.

As mentioned above, the built-up areas revealed strong correlations with several other types, including a positive correlation with water bodies (r = 0.69) and negative correlation with bare land (r = –0.85). These results suggest that the urban development could have grown in size with water bodies and at the same time. It has expanded at the expense of previously unused and barren land areas. Similarly, the built-up areas have shown a negative correlation of -0.58 with cropland areas. This also reflects the same pattern that the urban areas have been built on previously cropped areas, thereby leading to a shrinkage in cropland areas. The bare land, as shown in the Figure 3, has lost approximately 830 ha over eight years, which could be attributed to its strong negative correlation with both built-up (r = –0.85) and water bodies (r = –0.84). This relationship also suggests that the bare lands in the province have been increasingly transformed into developed areas by people or occupied by the areas covered with water. Over the years, the bare land and cropland have moderately decreased, thus showing a positive correlation (r = 0.56) with each other.

The demographic trends of Syrdarya province have seen a steady increase over the past eight years, as evidenced by the consistent increase in both total population and population density (Table 3). According to statistics [29], the population in the province increased from

803.1 thousand in 2017 to 914.0 thousand in 2024, showing an absolute increase of 110.9 thousand people in the last eight years. In parallel, the population density rose from 187.6 to 213.6 persons per km², which is equivalent to an increase of 26.0 persons/km² over the same period.

Table 3. Total population and population density trends

Year	Total Population (thousand)	Change from Previous Year	Population Density (persons/km²)	Change from Previous Year
2017	803.1	–	187.6	–
2018	815.9	+12.8	190.6	+3.0
2019	829.9	+14.0	193.9	+3.3
2020	846.3	+16.4	197.7	+3.8
2021	860.9	+14.6	201.1	+3.4
2022	878.6	+17.7	205.3	+4.2
2023	896.6	+18.0	209.5	+4.2
2024	914.0	+17.4	213.6	+4.1

Year-on-year changes indicate a moderate yet accelerating demographic trend. The highest annual population growth was recorded between 2022 and 2023 (+18.0 thousand), followed closely by 2023 to 2024 (+17.4 thousand). The lowest increase occurred in 2017–2018 (+12.8 thousand), suggesting an upward momentum in demographic expansion in recent years. Similarly, population density increased at an average rate of approximately 3.7 persons/km² per year, with the highest yearly increments also observed in 2022–2024. These numbers suggest a stable and continuous population growth trajectory, with an average annual population growth rate of approximately 1.9%. This sustained rise reflects natural population growth linked to economic opportunities, infrastructure development, or urban expansion policies in the region. It is known that an increasing population leads to spatial and temporal changes in LULC dynamics. Considering that we conducted a correlation analysis to better understand how a mounting population has affected LULC dynamics over the period 2017–2024. The correlation coefficients area shown in the Figure 6.

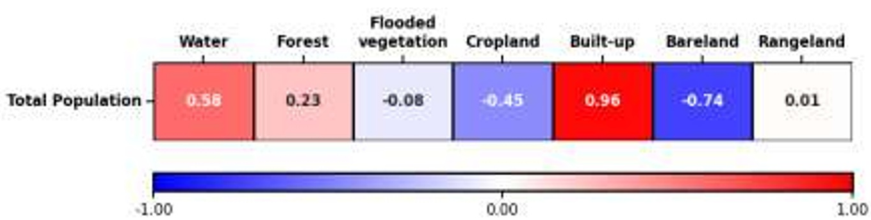

Fig. 6. A correlative relationship between total population and LULC types.

As expected, the strong positive correlation between total population and built-up areas (r = 0.96) have been found. This highlights the urban expansion has been a dominant process that has accompanied with demographic increase in the province. To put it simply, as the population rises, more land is converted into residential areas. Such findings align with global trends where population growth is considered one of the primary drivers of LULC changes, particularly in developed countries. A moderate positive correlation was also found between total population and water bodies (r = 0.58). This, as discussed above, reflect the increase in water infrastructure such as irrigation channels, reservoirs in the province. However, further investigation should be conducted to distinguish between natural and anthropogenic water expansion. The weakly positive relationship between the population and forest cover (r = 0.23) was detected. This possibly suggests that the minor afforestation practices, and green spaces within or around growing settlements have been implemented by the local governments since Uzbekistan is on the way of combating desertification and advocating sustainable development goals. Conversely, the bare land and cropland exhibited strong (r = –0.74) and moderate (r = –0.45) negative correlations with total population. These values mean that as population density increases, the bare lands are tended to be transformed, likely into urban and industrial uses. The negative relationship with cropland should be taken seriously into consideration, as it might indicate a loss of productive agricultural land to urban encroachment. As indicated, no correlation has been found between total population and flooded vegetation/rangeland. This no correlation implies that flooded vegetation and rangeland have not been influenced by demographic changes in this context. Based on these results, population dynamics could be considered one of the key drivers of LULC changes in the Syrdarya province, particularly through urban expansion at the expense of agricultural land and bare land.

4 Conclusion

In this paper, LULC changes in the Syrdarya province of Uzbekistan were evaluated and mapped using Sentinel-2 data from 2017 to 2024 period. The research results reveal that the built-up areas have significantly expanded with forest areas and water bodies experiencing a moderate increase over the last eight years, while bare land has exhibited a substantial decline. The cropland, although, remained the dominant land use type, its overall extent decreased negligibly. Other LULC types such as flooded vegetation and rangeland remained unchanged, exhibiting a stable trend over the observed years.The correlation between LULC classes revealed that built-up areas had the highest correlation (0.69) with water bodies and the lowest correlation (0.07) with flooded vegetation, suggesting that urban growth has expanded with water bodies in extent. Also, flooded vegetation presented a similar strong correlation (0.62) with water bodies, implying its interdependence. The cropland has demonstrated a moderate correlation (0.56) with bare land, while rangeland has shown a low correlation with built-up areas (0.13), flooded vegetation (0.28), and water (0.24). In addition, the population in the province has substantially grown since 2017 and exhibited a very strong correlation (0.96) with built-up areas, a moderate correlation with water bodies, and a weak correlation with forest areas. These results highlight that the population growth is inextricably tied to the expansion of built-up areas in the province. Lastly, it should be noted that there are some limitations that were not considered in this research. First of all, this study did not use long-term datasets, and just considered only eight consecutive years of data that may not fully capture the actual dynamics of LULC. If possible, incorporating spatial data spanning several decades will be necessary in future work to obtain a better understanding of LULC changes and implement better land management strategies. In addition, only the total population has been considered as the sole driver of LULC change. The inclusion of other driving forces such as natural (e.g., precipitation, temperature, GDP, spatial indices) and human activities (e.g., agricultural practices, land use policy, water allocation) will augment the significance and applicability of this work. Also, the outcomes from Pearson's correlation could not fully specify the intercorrelation between LULC types, because LULC changes are affected by multiple factors. Finally, more advanced approaches, particularly machine learning techniques such as CA-Markov model, should be considered while assessing long-term changes to gain more precise results and predict future LULC scenarios under changing climate. Considering these shortcomings and using advanced approaches for future work not only in the Syrdarya province but also across other regions of Uzbekistan would provide more accurate insights and strengthen the generalizability of the findings.

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