Land Cover Change Analysis: A Case Study of Suryabinayak Municipality

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KEYWORDS

Land cover, Spatial pattern analysis, Urbanization, Remote sensing

ABSTRACT

This research examines how the Land cover (LC) have consistently changed in past eight years of timeframe from 2016 to 2024 in Suryabinayak Municipality with the help of remote sensing and GIS techniques. This study employed Sentinel-2 imagery, which underwent pre-processing, followed by the application of the random forest algorithm to classify land cover for the years 2016, 2020, and 2024 using Google Earth Engine. After classifying the images, accuracy assessments were conducted to evaluate the reliability of these classifications. Subsequently, spatial pattern analyses were performed on the classified images to examine land cover changes over time. Additionally, a literature review was conducted to identify the causes and impacts of urbanization within the study area, drawing from various research studies. The results show from 2016 to 2024, vegetation suffered the most loss, with built-up areas experiencing increase along the roads and minimal change in agricultural land. This analysis showed a conversion trend where vegetation was primarily transformed into agricultural land, which was then developed into urban areas. At the ward level, wards 2 & 3 (Balkot) and wards 5 & 6 (Katunje) exhibited pronounced urbanization, with built-up areas exceeding those of other wards. The rising number of parcels in Chitpol and Sipadol underscores the increasing demand for land, reflecting ongoing urban growth. Internal migration was identified as a key driver of urbanization, with individuals relocating to urban areas for better opportunities. This research underscores the significant changes in LC within the Suryabinayak Municipality, largely driven by urbanization. This rapid urban growth not only threatens environmental sustainability but also triggers demographic changes, resulting in a decline in rural populations.

1. INTRODUCTION

The rapid conversion of rural regions into low-density urban areas, often separated by undeveloped land, significantly impacts the socioeconomic and environmental sustainability of communities (Mubea et al., 2011). Land-use and land-cover (LULC) changes are central to global environmental change and sustainable development debates. These modifications can alter water and air quality, ecosystem functions, and the climate system through greenhouse gas fluxes (Lambin et al., 2003).

While land cover describes the physical state of the earth's surface—such as forests, wetlands, or human structures—land use refers to the purpose for which land is managed, such as agriculture or urban development (Ellis & Pontius, 2007). In developing countries like Nepal, major towns are experiencing a rapid shift where core areas, previously devoted to agriculture, are being transformed into built environments (Muzzini & Aparicio, 2013). Nepal is projected to be one of the top ten rapidly urbanizing countries by 2050, with its urbanization level expected to exceed 30% (Desa, 2015). The Kathmandu Valley, including Suryabinayak Municipality, serves as a primary hub for this intense population concentration and urban growth.

Increasing population and economic activities drive unprecedented land-use changes that are often neglected by administrations (Nepal et al., 2020). In Suryabinayak Municipality, rapid urban sprawl is occurring in an unplanned manner, leading to the loss of natural vegetation and agricultural land. This study is necessary to provide data for future urban planning and decision-making. The primary goal of this research is to identify and analyze land cover (LC) changes within Suryabinayak Municipality between 2016 and 2024.

2. DATASETS AND PREPROCESSING

2.1 Datasets

This study utilized multispectral satellite imagery from European Space Agency's Sentinel-2 (Level-2A) products for the years 2016, 2020, and 2024 to analyze temporal land cover (LC) changes in Suryabinayak Municipality. The images (cloud cover <10%) include 12 spectral bands with spatial resolutions ranging from 10 m to 60 m. Additional data such as administrative boundaries were obtained from the Survey Department of Nepal, and parcel information from the Department of Land Management and Archive (DOLMA).

Table 1: Sentinel-2 images used

S.N.	Image	Resolution	Date
1	Sentinel-2	10 m	2016-04-13
2	Sentinel-2	10 m	2020-03-11
3	Sentinel-2	10 m	2024-03-05

2.2 Software Used

The analysis was carried out using Google Earth Engine, ArcGIS, and FRAGSTATS. Google Earth Engine was used for processing and analyzing satellite imagery in a cloud-based environment, ArcGIS supported spatial data management and map preparation, while FRAGSTATS was applied to compute landscape metrics for assessing spatial patterns and land cover structure (Singh et al., 2014).

2.3 Data pre-processing

Data preprocessing involved both spatial and spectral filtering to ensure accurate analysis. In the spatial filtering stage, Sentinel-2 images were clipped using the boundary of Suryabinayak Municipality to extract only the area of interest. In the spectral filtering stage, instead of using all available bands, only the most relevant bands—Band 2 (Blue), Band 3 (Green), Band 4 (Red), and Band 8 (Near-Infrared)—were selected, as these bands are particularly effective for distinguishing vegetation, water bodies, built-up areas, and other land cover types (Nhemaphuki, et. al., 2021).

3. METHODOLOGY

The initial phase involved the collection of essential remotely sensed datasets for the year 2016, 2020 and 2024. Also, primary field data was collected about the land cover for the verification of LC for the year 2024.

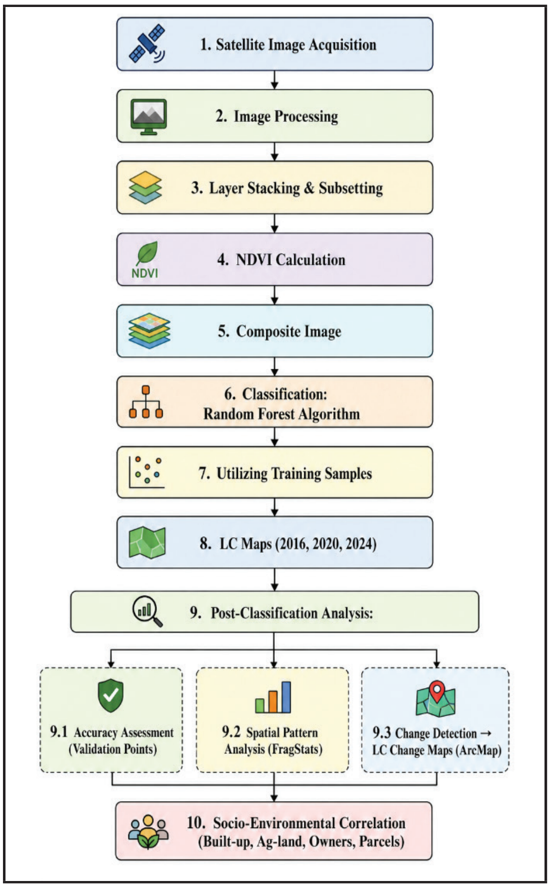

Figure 1: Research methodology

Google Earth Engine (GEE) which was used for processing and then the classification of satellite images using Random Forest Algorithm (RFA) to obtain LC for the corresponding year. It contains five classes which are agricultural land, built-up area, water body, vegetation and barren land. The accuracy assessment of these classifications was performed to ensure the quality, reliability of the data and its suitability for various applications. Change detection analysis was conducted for agricultural, built-up and vegetation area for three time periods: 2016 to 2020, to 2024, and the cumulative change from 2016 to 2024. Furthermore, Spatial Pattern Analysis (SPA) was conducted using Fragstat to gain a more comprehensive understanding of the changing landscape and how various LC categories were distributed and structured over the specified time periods (Weng, 2007).

3.1 Study area

The study area lies in Suryabinayak Municipality of Bhaktapur District, located on the eastern rim of the Kathmandu Valley in Nepal. Covering 42.45 km² with elevations ranging from about 1,372 m to 2,025 m.

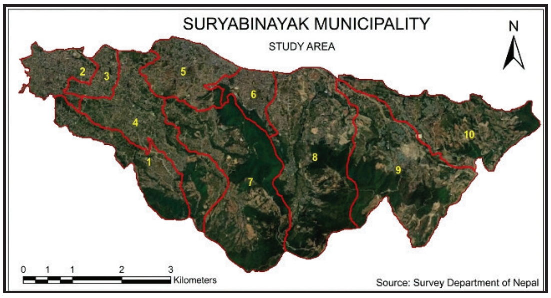

Figure 2: Study area

The municipality has experienced rapid urbanization and significant population growth, increasing from 78,845 in 2011 to 140,085 in 2021.

3.2 Data preparation

NDVI was calculated using Band 8 (Near-Infrared) and Band 4 (Red) from Sentinel-2 imagery through the standard formula

$$NDVI = (NIR - Red) / (NIR + Red)$$

which helps distinguish vegetation from non-vegetated surfaces based on reflectance characteristics. After computing NDVI for each study year, composite images were generated by stacking the selected spectral bands—Blue (B2), Green (B3), Red (B4), and NIR (B8)—together with the derived NDVI layer. These multi-band composite images enhanced the spectral information and were used as the final input dataset for land cover classification (Gitelson et al, 1996).

3.3 Land cover classification

Land cover classification in this study was performed using the Random Forest algorithm, an ensemble machine learning technique widely applied in remote sensing analysis (Naghibi et al., 2017). The model constructs multiple decision trees from randomly selected training samples and input features, and the final classification is determined by aggregating the predictions of all trees, thereby improving accuracy and reducing overfitting. Due to its ability to handle high-dimensional multispectral data and capture complex nonlinear relationships (Zhang et al., 2021), Random Forest is well suited for LULC mapping (Congalton & Green, 2019). In this research, the model was trained using 20 trees with default feature settings and applied to classify land cover for the years 2016, 2020, and 2024.

3.4 Spatial pattern analysis

LC patterns were analyzed using spatial metrics to calculate metrics at patch, class, and landscape levels in order to assess spatial and temporal changes. In this study, six key metrics were used: Number of Patches (NP), Class Area (CA), Patch Density (PD), Largest Patch Index (LPI), Edge Density (ED), and Mean Patch Area (AREA_MN). CA measures the total area occupied by a specific land cover class, while NP and PD describe the fragmentation and spatial distribution of patches. ED reflects the extent of edges between different land cover types, indicating landscape complexity. LPI identifies the dominance of the largest patch within the landscape, and AREA_MN represents the average size of patches, helping to understand changes in landscape structure over time.

3.5 LC change analysis

LC change analysis was carried out for the periods 2016–2020, 2020–2024, and the overall span from 2016–2024 to assess both short-term and long-term transformations in the study area. Change detection maps were generated to examine micro-level changes within specific locations as well as macro-level trends (Kafi et al., 2014) across the entire municipality. The analysis particularly focused on agricultural land, vegetation, and built-up areas, identifying patterns such as urban expansion, agricultural fragmentation, and vegetation loss. This approach provided a comprehensive understanding of the extent, direction, and intensity of land cover transitions over time.

4. RESULT AND DISCUSSION

LC analysis for 2016, 2020, and 2024 reveals that agricultural land consistently dominated the study area, covering 53.53% (22.82 km²) in 2016, 56.39% (24.04 km²) in 2020, and 56.91% (24.26 km²) in 2024. Vegetation showed a gradual decline from 34.32% (14.56 km²) in 2016 to 27.66% (11.79 km²) in 2024, while built-up areas increased steadily from 10.38% (4.42 km²) to 13.71% (5.84 km²) over the same period.

Table 2: Land cover for different year

Land Cover Type	2016 Area (km²)	2020 Area (km²)	2024 Area (km²)
Vegetation	14.56	12.14	11.79
Agricultural Land	22.82	24.04	24.26
Water Body	0.08	0.14	0.01
Built-up Area	4.42	5.06	5.84
Barren Land	0.54	1.05	0.51

Change detection analysis (2016–2024) highlights that the major land transitions occurred between agricultural land and built-up areas.

Table 3: Change from other LC to built-up

Change Type	2016-2020	2020–2024	2016–2024
Vegetation → Built-up	0.22	0.22	0.42
Agriculture → Built-up	3.78	3.15	4.02
Water → Built-up	0.00	0.10	0.03
Barren → Built-up	0.32	0.29	0.16

Table 4: Change from built-up to other LC

Change Type	2016–2020	2020–2024	2016–2024
Built-up → Vegetation	0.06	0.14	0.32
Built-up → Agriculture	1.29	2.59	2.62
Built-up → Water	0.05	0.00	0.01
Built-up → Barren	0.17	0.10	0.00

Approximately 4.02 km² of agricultural land was converted into built-up areas, demonstrating strong urban growth pressure. Conversely, 2.62 km² of built-up land reverted to agriculture, largely due to the reclassification of former brick factory areas as shown in Table 3 and Table 4. Vegetation loss was mainly driven by conversion to agriculture, while minor shifts occurred toward built-up land.

Table 5: Spatial metrics for the year 2016

TYPE	CA	NP	PD	LPI	ED
Agricultural Land	2485.67	1206	15.21	25.22	148.58
Barren Land	88.71	1354	17.08	0.05	19.5
Built up	264.63	4377	55.23	0.44	61.2
Vegetation	1424.88	2111	26.63	11.98	80.12
Water Body	1.87	123	1.5	0.00	0.8

Table 6: Spatial metrics for the year 2024

TYPE	CA	NP	PD	LPI	ED
Agricultural Land	2v437.39	2150	27.13	15.4469	215.63
Barren Land	51.67	1028	12.97	0.04	11.85
Built up	588.26	7366	92.95	1.0473	132.92
Vegetation	1187.34	5114	64.53	3.30	123.59
Water Body	1.1	104	1.3	0.00	0.5

Spatial metrics computed using FRAGSTATS (Table 5 and 6) shows increasing fragmentation of built-up and vegetation classes between 2016 and 2020, followed by partial consolidation in 2024. Agricultural land maintained the highest Largest Patch Index (LPI), confirming its dominance, whereas built-up areas exhibited high patch density, reflecting urban sprawl.

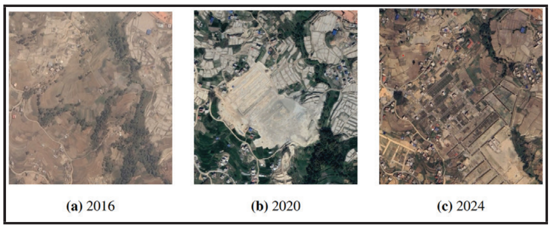

Figure 3: LC change in Sipadol region

Figure 3 illustrates satellite images of a portion of the Suryabinayak Municipality area in the Sipadol region, covering the years 2016, 2020, and 2024. The images clearly depict a transformation: agricultural land in 2016 was converted into barren land by 2020, as the area was cleared for housing development. By 2024, only a few plots have been developed with houses, while the remaining plots remain vacant and are being used for agricultural purposes.

Urban expansion was primarily concentrated in the northern part of Suryabinayak Municipality along the Araniko Highway, indicating a ribbon development pattern (Doan & Oduro, 2012).

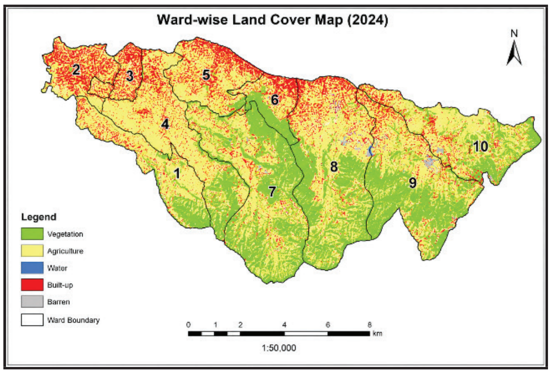

Figure 4: Ward-wise LC for 2024

Ward-wise analysis shows that Wards 2 and 3 (Balkot) and Wards 5 and 6 (Katunje) are highly urbanized, with greater built-up coverage than other areas, likely due to their proximity to the Araniko Highway as indicated earlier. In contrast, the southern wards (1, 4, 7, 8, and 9) are less urbanized, with more vegetation and lower built-up presence.

Table 7: Ward-wise percentage coverage of built-up area

Ward	2016	2020	2024
1	3.22	6.40	10.39
2	16.73	33.44	43.55
3	13.32	34.67	41.94
4	2.97	9.04	11.86
5	15.21	21.55	27.15
6	15.45	24.96	26.18
7	1.27	6.12	12.45
8	3.92	8.22	12.07
9	3.38	5.27	9.26
10	8.73	11.16	12.10

Figure 5 (a) and 5 (b) shows the number of land owners and number of parcels from 2016 to 2024. In every location, both the number of land owners and the number of parcels shows an upward trend. Areas like Katunje, Dadhikot, and Sipadol consistently lead in both metrics, indicating they are the primary hubs of land activity and urbanization, whereas Sirutar remains the least active despite following the same upward trajectory.

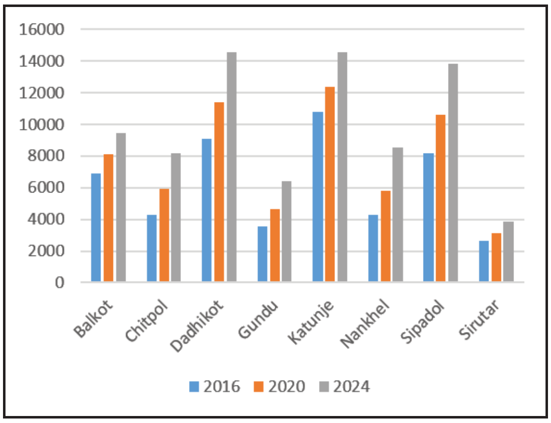

Figure 5 (a): Number of land owners

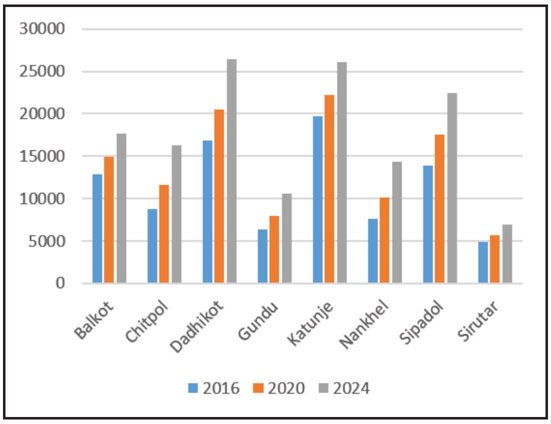

Figure 5 (b): Number of parcels

Furthermore, a strong positive correlation was observed between built-up area and number of parcels as well as land owners, confirming that land subdivision and ownership growth are closely linked to urbanization as shown in Table 8 below.

Table 8: Interrelationship between Parcels, Ownership, and Built-up Area

	Number of parcels	Owners	Built-up
Number of parcels	1		
Owners	0.99	1	
Built-up	0.75	0.76	1

Migration data further supports this trend, with higher inward migration recorded in rapidly urbanizing wards, demonstrating that population movement is a key driver of land cover transformation in the municipality as indicated by Twayana et al. (2021) in Banepa Municipality.

5. CONCLUSION

The study shows that Suryabinayak Municipality has undergone substantial land cover changes from 2016 to 2024, driven mainly by rapid urbanization along the Araniko Highway. Significant losses in vegetation and agricultural land were observed, with these areas progressively converting into built-up zones. This transition follows a clear pathway vegetation converting into agriculture and agricultural land further transforming into urban areas. Wards 2, 3, 5, and 6 show the most intense urban growth, while the sharp increase in parcel numbers in Ward 8 and Ward 10 reflects rising land demand and active land development.

Specific locations such as Sipadol, Nankhel, and Chitpol have experienced notable transformations, including land reclamation from brick manufacturing sites and expansion of settlement areas. These shifts are strongly influenced by internal migration, political instability, and natural disasters, which have pushed people toward urban centers like Suryabinayak. As a result, rural areas face a declining and aging population, while urban expansion continues to put pressure on natural landscapes.

Overall, the findings highlight accelerating urban growth in Suryabinayak Municipality at the cost of vegetation and agricultural land, signaling urgent concerns for environmental sustainability and balanced regional development.

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