Land Use and Land Cover of Jnana Bharathi Campus Bangalore University, Bengaluru, Karanatka

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Abstract

This study examines the spatiotemporal dynamics of land use and land cover (LULC) within the Jnana Bharathi campus of Bangalore University over a two-decade period (2000–2020) using an integrated remote sensing and machine learning approach. Utilising multi-temporal Landsat imagery (Landsat 7 and 8) and Google Earth Engine (GEE), LULC classification was performed via the Random Forest (RF) algorithm. Five LULC classes—vegetation, water bodies, open land, barren land, and built-up areas—were delineated, yielding overall classification accuracies of 77%, 81%, and 82% for the years 2000, 2010, and 2020, respectively. The results reveal marginal net vegetation expansion (+0.56%) and a pronounced increase in open land (+23.94%), alongside significant declines in barren land (-55.70%) and water bodies (-9.47%). Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) time-series analyses (2000–2022) indicate a persistent trend of vegetation greening, with EVI consistently demonstrating higher sensitivity to canopy structural variations. The study also identifies classification uncertainties linked to canopy masking effects over built-up areas, highlighting limitations inherent to medium-resolution optical datasets. These findings underscore the utility of cloud-based geospatial platforms for long-term LULC monitoring in complex urban-forest landscapes and offer critical insights for evidence-based land management, biodiversity conservation, and urban ecological planning.

Keywords: LULC, EVI, NDVI, Random Forest, Landscape

1. Introduction

Land use and Land cover classification have been widely used for registering changes and tracking the trends of forest resources, as these changes are dynamic and continuous, usually influenced by key drivers originating from regional, local, and global environmental scenarios. India's contribution to the global vegetative area, at about 2.7%, is reported as the second highest, after China, and is primarily attributed to croplands (82%) with a minor contribution from forests (4.4%) (Chen, 2019). Persistent land use activities, such as the expansion of settlements, agriculture, urbanisation, and socio-economic growth, have contributed to tremendous landscape transformations through the degradation and deforestation of forests. The emerging application of Google Earth Engine techniques has been increasing to monitor the decadal changes in LULC. The emergence and development of satellite remote-sensing cloud storage and cloud computing platforms, represented by the Google Earth Engine (GEE), not only make it possible to integrate multi-source and multi-scale global remote-sensing images but also allow for full-band and high-intensity image calculation (Kaur *et al.,* 2023).

Changes in Land Use and Land Cover (LULC) is essential for managing and planning development. This information can be utilised to understand how land use patterns have changed over time, which aids in identifying potential environmental and socio-economic effects. Land use and land cover change (LULCC) are local and site-specific actions, but when all these changes are considered collectively, they are added to global environmental changes (Isufi *et al*., 2022).

Overall, this research paper will focus on the development of a GIS-based approach for LULC change detection at the Jnana Bharathi campus. The proposed approach will involve integrating remote sensing and GIS techniques to detect changes in land use patterns over the last decade using QGIS Software. The study will provide valuable insights into changes in land use patterns and help identify areas that have undergone significant land use changes, which can have implications for the environment.

2 Materials and Methods

2.1 Study area

The study was conducted at Bangalore University (Jnana Bharathi Campus), situated in the outskirts of the Bangalore Metropolitan City, with an area of 1111 acres, which is one of the largest universities in Asia. Out of 1111 acres, 400 acres are used for the construction of roads and buildings, and the remaining 800 acres of the original thorn forest were developed as a Biodiversity conservation area by the University without altering the original landscape and vegetation. It lies between 12°55'39'' to 12°57'33'' N Latitude and 77°29'45'' to 77°31'12'' E Longitude, covering the Arkavathi river basin and falls in an area of 6 km^2 in the village limits of Nayandahalli and Mudalapalya. The University campus has been categorised into eight sectors based on topography and watershed features. It lies at an elevation plateau 875–900 m asl (Rajashekar & Venkatesh, 2017) This campus is spread over an area of about 445.15 ha comprising undulating terrain and barren land with several vegetation patches with non-deciduous trees, weeds, shrubs, scrubs and herbs and ornamental plants and 98.38 ha is allotted for various organisations like institutions, buildings, hostels, offices, residential quarters etc. This campus also has several water bodies, most of which are seasonal, such as check dams, ponds of various departments, and the streams of the Vrishbhavathi River valley. The soil in the valleys is good and loamy, formed from fine particles of decomposed rock. The soil on the higher grounds is gravelly and reddish in colour (Kavana and Nagaraj, 2021).

The climate of the district is classified as a seasonally dry tropical savanna climate. The campus enjoys a climate typical of Bengaluru City, with an average maximum and minimum temperature of 36 °C and 14 °C, respectively, and humidity levels between 35% and 80%. The climate in Bengaluru from December to February is cold, March to May is hot, and from June to November is monsoon. It rains intermittently from June to December, and the city receives both southwest and northeast monsoon rains (Nagaraja *et al*., 2005).

Figure 1. Map of Bangalore University Campus, Bengaluru, showing study location

2.3 Methods

2.3.1 Data acquisition

In this study, LULC was mapped using top-of-the-atmosphere (TOA) reflectance data retrieved from the time series of Landsat 7 (LANDSAT/LE07/C01/T1_RT_TOA) and Landsat 8 (LANDSAT/LC08/C01/T1_RT_TOA) images, spanning 2000 to 2020, available on the GEE platform. Landsat Collection 2 Tier 1 and Real-Time data TOA Reflectance was used. Landsat data can improve our understanding of the land changes on Earth. This study applied machine learning algorithms, namely Random Forest (RF). The RF algorithm is a type of machine learning technique used for image classification. It is a robust algorithm that works through building multiple decision trees and merges them to produce accurate output.

The following major LULC classes were chosen: built-up area, water bodies, open space, vegetation, and barren land. This cloud-based platform implements three major steps outlined below:

- Image selection
- Collection of training samples
- Assembling features of a known class label and properties
- Running the classifier

Table 1. **Data source and its bands, year and resolution**

NAME	BANDS	YEAR	SPATIAL RESOLUTION (m)	Accuracy (%)
Landsat 7 collection 2 Tier 1 and real time data TOA reflectance	B3, B2, B1	Pre-monsoon (2000)	30m	77%
Landsat 7 collection 2 Tier 1 and real time data TOA reflectance	B3, B2, B1	Pre-monsoon (2010)	30m	81%
Landsat 8 collection 1 Tier 1 and real time data TOA reflectance	B5, B4, B3	Pre-monsoon (2020)	30m	82%

2.3.2 LULC classification

Land Use Land Cover (LULC) change detection is an important application of remote sensing that involves comparing two or more images of the same area taken at different times to identify changes in land use and land cover. There are two main methods for LULC change detection: Supervised Classification and Unsupervised Classification.

The land cover classification system categorises the land into distinct categories based on its objective. Barren land is characterised by a vegetation cover of less than 10%. It includes bare or exposed soil, sand and rocks. Vegetation land with more than 60% green cover and a height above two meters is termed a forest. Dams, pools, lakes, reservoirs, streams and rivers are categories as water bodies.

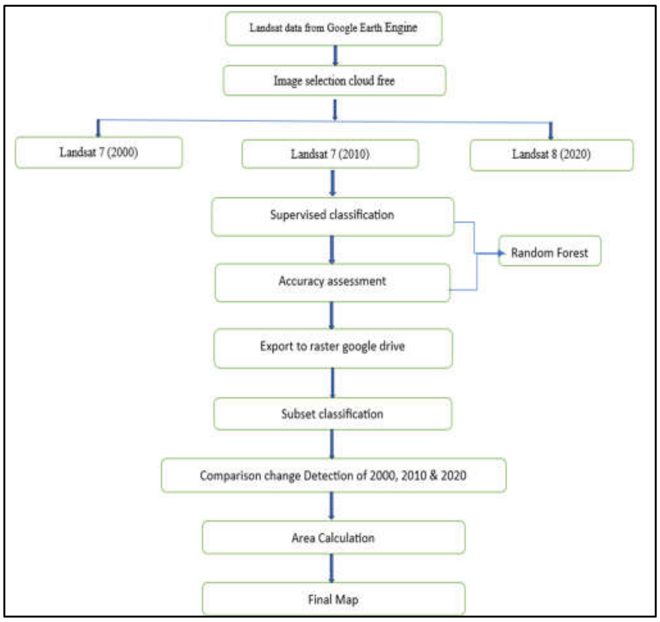


Figure 2. Flow chart depicting methodology adopted for the studies

The pre-processing was carried out in 8 steps; (1) creation of image data file; (2) cloud filtering; (3) creation of average image of study area; (4) selection of image bands and computation of NDVI (Normalised Difference Vegetation Index) and EVI (Enhanced vegetation Index) for classification; (5) preparation of LULC classes, followed by training and validation of samples; (6) classification LULC using the random forest approach; (7) accuracy assessment; (8) post-processing and analysis.The data processing stage has four parts.

First, data collection involved selecting Landsat data with cloud-free images from the GEE archive, followed by the use of Landsat 7 and Landsat 8 images. The spatial resolution of all Landsat dataset photos is 30 m. For all of the scenes, the photographs were taken with less than 10 % cloud cover. For image processing and remote sensing applications, QGIS was employed.

Second, pre-processed Landsat images available through GEE were used for image pre-processing to assess LULC change across the Bangalore University campus. All satellite pictures are georeferenced using the Universal Transverse Mercator (UTM) projection system and the World Geodetic System (WGS) 1984 datum. Using a standard shapefile, the region of interest is clipped with Q-GIS 3.28.3 software. Following that, certain multispectral bands are blended to create composite satellite pictures.

Third, supervised classification using Random Forest algorithms was employed to evaluate the classification of LULC, with overall accuracy assessed using a confusion matrix. Finally, a change detection comparison between 2000, 2010 and 2020 was evaluated to monitor the LULC. The time series were filtered to select images with cloud coverage below 70% and stored in the GEE platform. The filtered collection was reduced to a single median image per year to minimise the impact of clouds, cloud shadows, and noise. Training samples were created using the geometry import configuration. Training samples were collected from the GEE platform and ground truth data. The training samples were merged to present the land use and land cover. The samples were collected and validated based on manual visual analysis using Google Earth Engine.

Random forest (Machine learning model) forest classifier model combines the collective output for a new label based on the maximum votes from several decision-making processes. The random forest chooses a random subset of samples to create a single tree. Additionally, the RF model randomly selects variables from the training samples at each node to identify the optimal fraction for building a tree. RF was demonstrated to provide good results for classifying land use and land cover classes. Different random seeds were given to get the validation data. Then the result was filtered to get rid of any null pixels (tree and seed represent the class entity) (Baetens *et al.,* 2019).

2.3.2 Accuracy assessment

The accuracy was evaluated using a confusion matrix built into GEE. This matrix achieves this by contrasting the LULC linked to the validation points with the classifications produced. The overall accuracy can be calculated using a confusion matrix (Rana *et al.,* 2022).

2.4 NDVI and EVI time series analysis

2.4.1 Data collection

Google Earth Engine was employed to compute NDVI from an image using the red and near-infrared (NIR) frequency bands through raster calculations. The NDVI and EVI time series, spanning the years 2000-2022, of the Landsat 7 and 8 Collection 1 Tier 1 calibrated Top of Atmosphere (TOA) reflectance are employed. The band 4, band 3 and band 2 for Landsat 7 and band 5, band 4 and band 3 for Landsat 8, with an original spatial resolution, are used to carryout NDVI and EVI analysis. The GEE contains the Landsat-specific processing methods to compute at-sensor radiance, TOA reflectance, surface reflectance (SR), cloud score and cloud-free composites. On this platform, Landsat data processing is carried out using cloud computing technology for the study area (Schmid, 2017).

2.4.2 Methods of NDVI analysis

The value of NDVI lies between -1 and +1, and values less than zero are observed during the dormant season, i.e., when there is no vegetation cover, such as bare earth, clouds, water bodies, etc. Values greater than zero indicate the presence of vegetation cover. The NDVI is computed based on surface reflectance bands of Landsat 7 and 8. and is given by,

$$\mathbf{NDVI = (NIR - RED)/ (NIR + RED)}$$

The changes in vegetation over time are obtained with atmospheric correction (Zeng *et al.,* 2020). The GEE Code Editor scripts were used to extract Normalised Difference Vegetation

Index (NDVI) data from satellite images of the study areas. A feature is collected that inherits the coordinates of the plots as point features. Two NDVI functions for Landsat 7 and 8 are used to calculate NDVI from their respective satellite imagery. The image collections that specify which data from which timeframe and sensor will be used for NDVI calculations. The bands are selected from each dataset that are available for processing. The commands to create time series graphs for each image are collected. NDVI data can be downloaded from them as .csv-files. Commands are available to add NDVI data (image collection) and feature collections (plots) as map layers to the Google Maps base map.

2.4.3 Method of EVI analysis

EVI is a vegetation index obtained after optimising NDVI using the soil adjustment factor. It improves vegetation monitoring by cancelling the coupling of canopy background signals and reducing atmospheric influence. It can be calculated using blue, red, and NIR bands. In areas with high biomass, EVI exhibits higher sensitivity to topographical conditions. The EVI time series between 2000 and 2022, from the Landsat 7 and 8 Collection 1 Tier 1 calibrated Top of Atmosphere (TOA) reflectance, are employed.

EVI (Landsat 7) = 2.5∗ (NIR – RED)/ (NIR+6.0 ∗ RED – 7.5 ∗ BLUE+1)
EVI (Landsat 8) = 2.5 * ((Band 5 – Band 4) / (Band 5 + 6 * Band 4 – 7.5 * Band 2 + 1)

Landsat TOA data were collected from the GEE. They underwent pre-processing and the time series of the collections were filtered. The image filter function and the composite, and reducer functions were applied to determine the median values within the study region. The EVI function was used to determine the phases of the composite median imagery for Landsat 7 and 8, which calculates EVI from their respective satellite imagery. The image collections that specify data from which timeframe and sensor will be used for EVI calculations. The bands are selected from each dataset that are available for processing. The commands to create time series graphs for each image are collected. EVI data can be downloaded from them as .csv-files. Google Earth Engine-generated NDVI and EVI profiles were stored in comma-separated value (CSV) files, which we exported outside of GEE. Microsoft Excel was used for further statistical analysis.

3 RESULTS & DISCUSSION

3.1 LULC changes of Jnana Bharathi campus

LULC changes of Jnana Bharathi campus. The LULC classification was conducted for the Jnana Bharathi Campus for the years 2000, 2010, and 2020. These LULC studies utilised data from both Landsat 7 and Landsat 8 on the Google Earth Engine platform. The random forest (RF) model was used to prepare land use and land cover maps and the accuracy was assessed using confusion matrix method. The LULC changes from 2000, 2010, and 2020 are shown in Figures 3, 4, and 5, respectively. The figures show the LULC of five classes: vegetation, waterbodies, open land, barren land, and Built-up area. The statistical distribution of LULC in the research area is shown in the table below. Positive values indicate improved categorisations, whereas negative values indicate categorisations that have deteriorated.

Table 2. Distribution of LULC classes across Bangalore University, Jnanabharathi Campus

Sl. No.	LULC class	2000 Area (ha)	Area (%)	2010 Area (ha)	Area (%)	2020 Area (ha)	Area (%)	Percentage difference
1	**Vegetation**	218.97	47.65	218.49	47.55	220.19	47.92	0.56
2	**Waterbody**	34.83	7.58	32.4	7.05	31.53	6.86	-9.47
3	**Open land**	38.93	8.47	22.75	4.95	48.25	10.5	23.94
4	**Barren land**	1.58	0.34	2.88	0.63	0.7	0.15	-55.7
5	**Built-up**	165.2	35.95	182.99	39.82	158.83	34.57	-3.86
		459.51	100	459.51	100	459.5	100	0

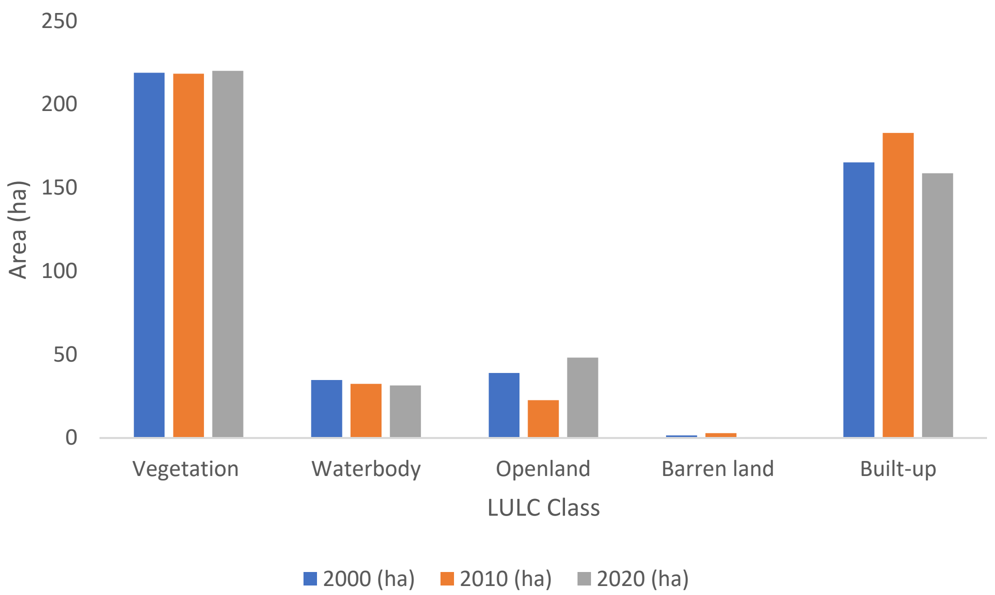
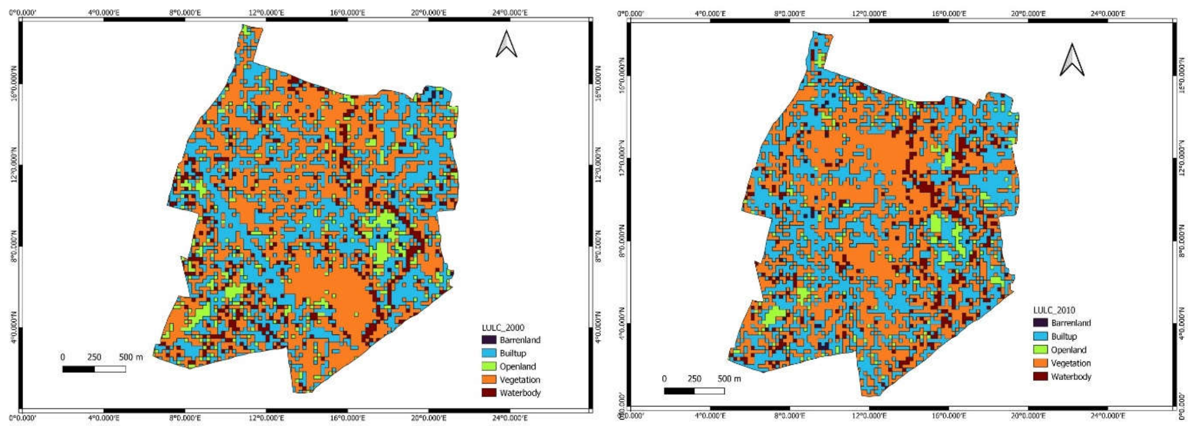


Figure 3. **Distribution of LULC classes across Bangalore University, Jnanabharathi Campus**

Mapping land-use and land-cover (LULC) changes plays a crucial role in the sustainable management of natural resources. An analysis of LULC over three decades reveals significant spatiotemporal variations, with notable implications for ecological balance and landscape functioning. Vegetation cover has remained relatively stable over the observed period, with a marginal increase from 218.97 ha (47.65%) in 2000 to 218.49 ha (47.55%) in 2010 and further to 220.19 ha (47.91%) by 2020. Although the net increase in vegetative cover is minimal (0.56%), it suggests a degree of ecological resilience, potentially indicating reforestation and natural regrowth in certain patches.

Conversely, the area under waterbodies has experienced a consistent decline, decreasing from 34.83 ha (7.58%) in 2000 to 32.4 ha (7.05%) in 2010, and further to 31.53 ha (6.86%) by 2020. This downward trend indicates increasing pressure on hydrological systems, potentially due to urban encroachment, changes in surface runoff, or climatic variability. The dynamics of open land exhibit a distinct fluctuation, decreasing from 38.93 ha (8.47%) in 2000 to 22.75 ha (4.95%) in 2010, followed by a sharp increase to 48.25 ha (10.49%) in 2020. This shift may reflect land conversion practices, abandonment of cultivated lands, or transitional phases of land development. The increase in open land, particularly in 2020, could also be attributed to changes in land management or seasonal land-use practices. Barren land increased from 1.58 ha (0.34%) in 2000 to 2.88 ha (0.63%) in 2010, which likely corresponds to construction activities or land degradation processes. However, by 2020, barren land reduced significantly to 0.7 ha (0.15%), possibly due to reclamation, vegetation regrowth, or land stabilisation efforts.

Built-up areas increased from 165.2 ha (35.95%) in 2000 to a peak of 182.99 ha (39.82%) in 2010, followed by a decrease to 158.83 ha (34.56%) in 2020. This apparent reduction in 2020 may not necessarily indicate a physical decline in built-up structures but could be attributed to increased vegetative canopy cover obscuring impervious surfaces in satellite imagery, especially given the 30-meter spatial resolution used in the analysis. As presented in Table 1, the expansion of built-up and open land is likely a contributing factor to the observed decline in waterbody extent, highlighting the trade-offs between development and natural ecosystem components. The percentage change across land cover classes over the study period shows a negative trend for waterbodies (-9.47%), barren land (-55.70%), and built-up areas (-3.86%), whereas open land demonstrated a substantial positive change (+23.94%). These shifts highlight the dynamic nature of land transformation processes and their implications for the sustainability of natural resources and the integrity of landscapes.



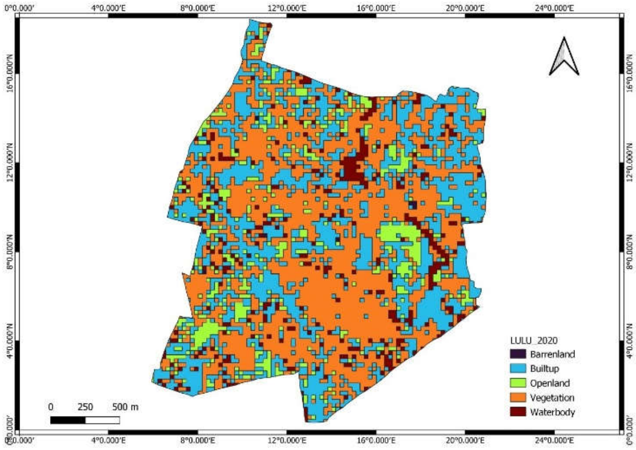


Figure 4. LULC changes of Bangalore University, Jnanbharathi Campus in 2000, 2010 to 2020

The random forest (RF) model was used to prepare land use and land cover maps for 2000, 2010, and 2020. In general, the overall vegetation has increased by 0.56% and the overall open land has increased by 23.94%. However, the waterbodies and barren land has decreased by 9.47% and 55.70% respectively over the years. The unusual trend in the built-up area can be due to the spike in the green cover/canopy cover during the pandemic due to restricted human interference that has been further justified in the studies related to NDVI and EVI. A total of seven check dams were built during 1998 to 2000, wherein the water spread to larger area was observed. Over the decade, vegetation cover along the check dam boundary is increased. The trees planted along the check dam and its fringes were grown up substantially, reducing the water cover area. It is also observed on the ground that these check dams were filled with silt, reducing the water storage.

Overall accuracy of Land cover classification

The LULC classification maps of the years 2000, 2010, and 2020 are shown in fig 3, 4 and 5, which were produced using random supervised classification. The RF classifier produced good overall accuracies for Jnana Bharati campus, with overall accuracy assessments of 77% (2000), 81% (2010), and 82% (2020).

Uncertainty of the result

There were certain uncertainties when using Landsat image data to draw LULC distribution maps of Jnana Bharathi campus were identified. The area calculation for built-up area showed a negative trend in contrary to the ground reality. This could have been due to the significant increase in the canopy cover due to less disturbance in the study area resulting in de-spiking. The reflection has caused distortion in the LULC determination. (Miller and Rogan, 2007; Rogan et al, 2008; Jacob et al., 2011; Shao & Wu, 2008)

The decrease in the water body can be observed due to a few reasons such as the increase of vegetation in the boundary of the check dams, siltation that reduces water storage and it can also be due to the algal blooms as a result of water pollution over the two decades.

The evidence shows that most of the vegetation during the initial stages of plantations was low and the built up was clearly visible. Over the years, with the increase in the canopy cover that sometimes covers two third of the building is evident. This typical domination of the vegetation over the built-up is a gap between the total reliance on the application of Google earth engine to the study. Its limitation to 2-dimensional data acquisition and lower resolution data that does not penetrate to should be modified. However, there are alternate technologies, that can be implemented to mask this overlap of vegetation over the built-up by obtaining the GPS point of the built-up area with the canopy covering it, visual inspection and following further procedure. Consistent with this hypothesis, this concludes the limitation and further scope of expansion of this study. However, we do know that the logic error in this was adding an artifact that would be particularly evident, and thus our goal is to document the impact of the application and its fix.
The NDVI and EVI were used as a measure to highlight the difference, it was also observed that it fits in the trend of the obtained results with LULC of the study area.

3.2 NDVI and EVI Time Series

NDVI varies between -1.0 and +1.0 of different vegetal density with +1 as high vegetal cover. It expresses pattern and trends of vegetal cover over a period of time. Satellite data for 23 years was acquired and the Normalised Difference Vegetation Index (NDVI) was calculated for the study area. The data used in this study were the enhanced vegetation index (EVI). EVI is responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant habitus, and canopy architecture. Java script code was developed for GEE. The EVI was mapped for the Jnana Bharati campus using google earth engine.

A comparative analysis of multitemporal EVI and NDVI data during 2000 to 2022 was estimated for the Bangalore university campus. The highest difference in the EVI and NDVI values are observed for the year 2015 when the NDVI was 0.193 while the EVI was 0.321. The EVI analysis is assumed to be slightly more accurate than the NDVI values because of atmospheric and background corrections. On the other hand, all the years shows higher value for EVI, except for the year 2003, the NDVI value is 0.29 that is greater than the EVI value that is 0.255. It can also be concluded from figure 10 that the NDVI time series analysis shows a slightly downward trend and the EVI time series analysis shows a very slight upward trend with the years 2001 and 2022 being more or less equal.

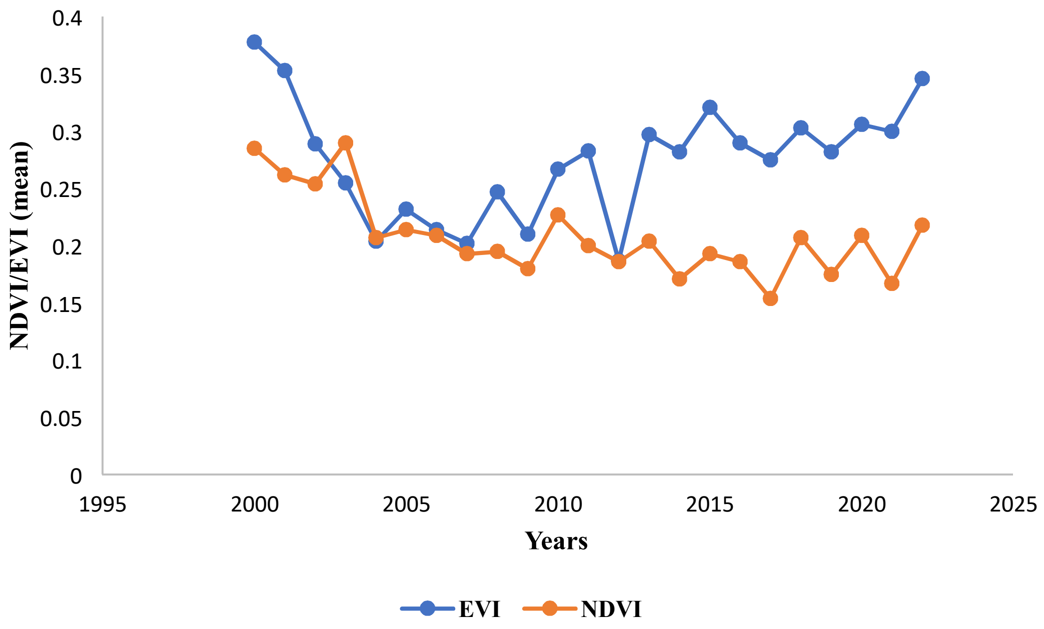


Figure 5. EVI and NDVI Time Series across Bangalore University, Jnanabharathi campus from 2000 to 2020

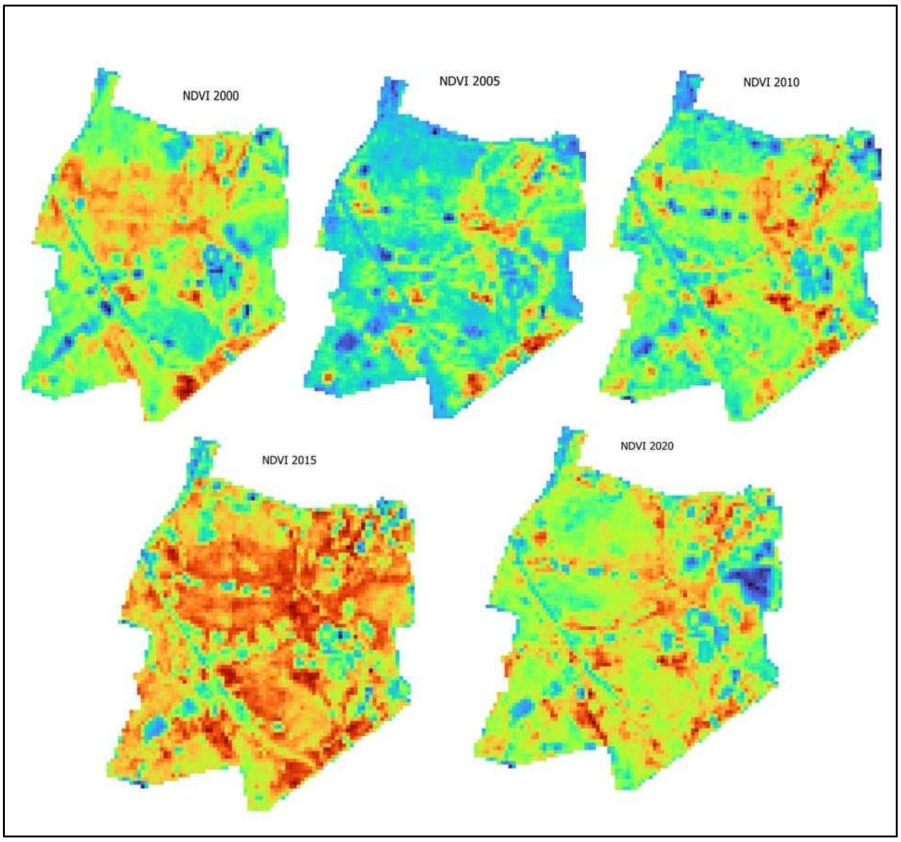


Figure 6. NDVI time series map of Bangalore University, Jnana Bharathi Campus

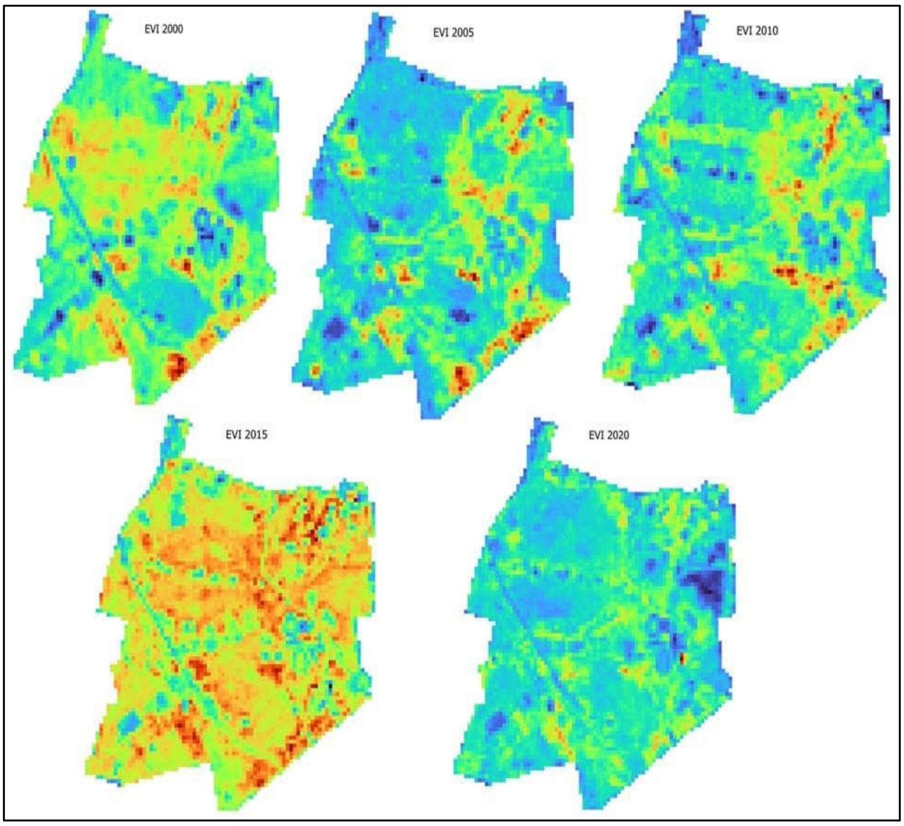


Figure 7. EVI time series map of Bangalore University, Jnana Bharathi Campus

4 Discussions and Conclusion

4.1 Discussions

The land use/land cover pattern of a region is an outcome of natural and socio-economic factors, as well as their utilisation by humans in time and space. Obtaining an accurately classified LULC map is of great importance in the remote sensing field. Land is becoming a more scarce resource due to immense anthropogenic pressure. Hence, information on land use and land cover is essential for the selection, planning, and implementation of land use and possibilities for its optimal use to meet the increasing demands for basic human needs. Land use change, as one of the main driving forces of global environmental change, and natural events such as flooding, fire, climatic fluctuations and ecosystem dynamics can also initiate modifications upon land cover.

The vegetation greenness over the Jnana Bharathi campus was investigated using two different vegetation indices, namely, the NDVI and EVI, for the twenty-two-year period. The highest mean NDVI recorded was 0.29 for the year 2003. And the EVI of 2022 is recorded to be 0.346. This shows that the Jnana Bharathi campus has experienced vegetation greening processes over the past two decades. It is noteworthy to mention that the EVI is consistently higher than NDVI values estimated from 2000 to 2022. The EVI results from this study support the LULC data, with a percentage difference increase of 29.58 from 2010 to 2020.

Bangalore University, Jnana Bharathi campus, attains a good vegetation cover and is seen as one of the 'green lungs' of Bangalore city. The built-up area was developed due to the expansion of infrastructure and new construction, factors that could lead to climate change resulting from the reduction of vegetation cover and the growing number of urban and bare surface areas. Bangalore University established a Biodiversity Park (Bio-Park) on its campus in 2000, covering 242.80 hectares of land. According to the records, around 5 lakh saplings belonging to 300 species have been planted on the campus from 1998 to date. Within the Bio-Park, several cultural mini-forests were developed.

The results of the LULC analysis show a percentage increase in open spaces, which is due to the increase in open spaces for sports activities. Additionally, SAI and other leased institutions have removed bushes to maintain the open area for sports and other amenities. The barren land shows a decrease in area due to its use for construction and other infrastructure. Several conservation initiatives have been put forth by the University to conserve the waterbodies within the campus. Bangalore Uunversity, with the help of the Central Ground Water Board (CGWB), constructed four check dams to harvest rainwater in 2004, which improved the microclimate of the campus. Later University has constructed another three check dams.

During the 2005 study, the total percentage of exotic species was 48.43%. During the same time period, the University has planted three lakh saplings, which are native to various habitats, ranging from high-altitude evergreen forests to scrub forests, thereby improving the microclimate of the bio-park area. Despite being human-inhabited, BUC premises are relatively safe from threats and devoid of hunting and timber extraction pressures. However, significant extents of habitat destruction and modification were noted due to the development of infrastructure of more construction of new buildings. Trespassers set fire to the grasslands annually during the dry season for cattle ranching, which rapidly spread to the grasslands on the campus. Felling trees for construction and firewood in BUC deters forest specialists and allows opportunistic predators and other invasive species to invade the campus areas. Thus, the fluctuations in NDVI are likely linked to both large- and small-scale changes in land use and associated declines in biodiversity, which are ongoing in the study area. The land being leased out to stakeholders within the campus has led to an increase in open lands prior to construction activities. Thus, several conservation measures were suggested, including the prohibition of setting fires on grasslands, less frequent and no complete mowing, etc. Garden waste should not be burned but disposed of sanitarily to encourage colonisation of invertebrate prey.

4.2 Conclusions

Land Use and Land Cover (LULC) mapping, along with vegetation indices such as the Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), provides critical insights into landscape dynamics and sustainability assessments. The analysis of the Bangalore University Campus (BUC) using multi-temporal remote sensing data from 2000 to 2022 reveals several notable trends. A marginal decline in built-up areas, along with stable NDVI and an increasing EVI trend, indicates that the green cover within the campus has been relatively well-preserved, with evidence of progressive vegetation greening. The superiority of EVI in capturing subtle changes in vegetation structure, particularly under dense canopy conditions, reinforces its utility for long-term ecological monitoring.

However, the decline in waterbody extent and the notable increase in open lands signal emerging ecological stressors that require strategic attention. These trends, if unaddressed, could lead to long-term degradation of ecosystem services. The shift in open land cover could be linked to land conversion, disturbance, or improper land-use planning, emphasising the need for integrated landscape management. To enhance environmental sustainability, the campus should prioritise vertical infrastructure development over horizontal expansion, thereby minimising further land surface sealing and habitat fragmentation. Moreover, Bangalore University is currently exposed to anthropogenic threats, including illegal encroachments, uncontrolled grazing, and fire hazards, all of which threaten the ecological integrity.

Effective habitat conservation strategies must include the restoration of native vegetation, the protection and rejuvenation of wetland areas, and the enhancement of floristic diversity. These actions would support biodiversity, improve ecological resilience, and contribute to the overall functioning of campus ecosystems. Reforestation initiatives, in particular, could play a pivotal role in ecological restoration and climate adaptation at the local level. In addition, improved sewage treatment and wastewater management are critical for safeguarding aquatic ecosystems within the campus. Protecting waterbodies from pollution will not only support biodiversity but also enhance the aesthetic and recreational value of the landscape. Ultimately, by adopting nature-based solutions, implementing sustainable land-use practices, and embracing holistic conservation strategies, Bangalore University has the potential to serve as a model for urban ecological stewardship. Scaling such efforts across the city of Bangalore could significantly contribute toward transforming it into a resilient and environmentally sustainable urban system.

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