# Mapping Urban Evolution: A Case Study of Bengaluru's Land Use Land Cover Dynamics


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***Abstract*—Rapid urbanization in Bangalore, India, has raised concerns about its sustainability. This study analyzes land-use and land-cover (LULC) changes from 2014 to 2020 using Landsat-8 imagery and machine learning. The random forest algorithm classified built-up areas, wastelands, green cover, and water bodies with high accuracy. Image differencing techniques[4,6] have also been utilized for change detection to show the regions with maximum changes and highlighting the growth in those regions.**
**Results show significant urban sprawl primarily at the expense of wastelands, highlighting the need for sustainable planning strategies. Notably, green cover and water bodies remained stable despite urban expansion, emphasizing the importance of conserving these vital resources.**



***Index Terms*—LULC, change detection, NDVI, NDBI, change detection and image differencing**


## I. Introduction

Land use and land cover represent integral components of the Earth's surface, encapsulating the diverse ways in which human activities and natural processes interact and shape the environment[1]. Understanding the dynamics of land use and land cover change has become increasingly crucial in comprehending the evolving landscape patterns and their implications on ecological systems, societal development, and resource management.

**Land Use** refers to the human utilization of land for various purposes such as residential, agricultural, industrial, commercial, recreational, and institutional activities. It encompasses the spatial distribution, intensity, and arrangement of these activities on the Earth's surface.

**Land Cover**, on the other hand, encompasses the physical and biological cover over the Earth's surface, encompassing vegetation, water bodies, bare soil, urban infrastructure, and other natural or artificial elements. Land cover often embodies the visible or tangible characteristics of the landscape.

The dynamic interplay between land use and land cover is a subject of immense importance. Human activities continuously alter land use patterns, resulting in changes to land cover, whether through deforestation, urbanization, agricultural expansion, or natural processes such as erosion and succession. Understanding these changes and their impacts requires sophisticated tools and methodologies, often involving remote sensing, geographic information systems (GIS), and advanced data analysis techniques.

This article aims to delve into the analysis of land use and land cover change detection, highlighting methodologies, key findings, and the implications of these changes. By investigating the shifts in land use and cover over time, this study endeavors to contribute valuable insights into the dynamic nature of landscapes and aid in informed decision-making for sustainable land management and environmental conservation.

## II. Study Area and Dataset

The study area for this land use and land cover change detection project is focused on the vibrant city of Bengaluru, situated within the state of Karnataka, India. Specifically, the analysis concentrates on a delineated geographical boundary encompassing key landmarks: Kannahalli in the west, Devanahalli in the north adjacent to the airport, Hoskote in the east, and Attibele near the Tamil Nadu-Karnataka border in the south, covering a total area of 2192.86 $km^2$. This spatial demarcation serves as the defined region for the investigation of land use and land cover changes over specific periods.

The dataset utilized in this study is derived from Landsat 8's Collection 1 Surface Reflectance data, with the Red, Green, Blue, Near Infrared and Short Wave Infrared bands, acquired by the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). The dataset covers multiple temporal windows, capturing imagery from January 1st to September 30th of the years 2014, 2016, and 2020. These selective timeframes were chosen strategically to assess land surface changes at different intervals, allowing for the observation of variations over time within Bengaluru's evolving landscape.

**Study Area Boundary :**

- West: Kannahalli
- North: Devanahalli (near Airport)
- East: Hoskote
- South: Attibele (near the Tamil Nadu-Karnataka border)

This demarcated boundary serves as the geographic confines for the investigation, delineating the area under scrutiny for land use and land cover change detection within Bengaluru.

## III. Methodology

### A. Data Pre-processing

In the process of preparing the data for analysis, a critical step involved mitigating the impact of atmospheric interference, primarily clouds and their shadows, on the satellite im-

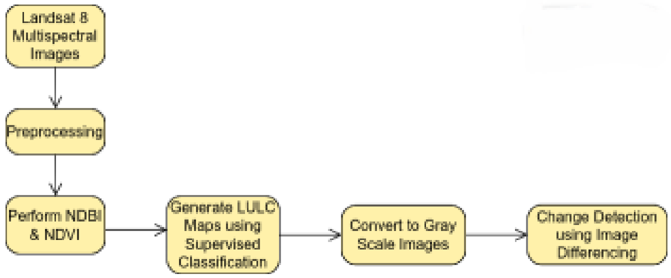



Fig. 1: Overall Methodology at a High Level

agery[5]. To accomplish this, a method known as bit masking was applied. This method effectively identified and masked out areas in the images where clouds or their shadows were present. By employing specific bit patterns associated with cloud cover within the imagery, these areas were systematically identified and removed from consideration.

Moreover, to ensure a comprehensive analysis of the land use and land cover changes, a range of dates was selected rather than solely relying on a single day's image. This selection encompassed a timeframe between January and September for the specified year. Utilizing multiple images over this period facilitated a more comprehensive understanding of the landscape dynamics, enabling the observation of seasonal variations and detecting alterations in land features over time. The selection criteria for these images also included filtering out data with cloud cover less than 10 percent, ensuring a higher quality dataset for the analysis. This rigorous data preprocessing laid the foundation for a more accurate and detailed assessment of land use and cover changes during the specified timeframe.

### *B. NDBI (Normalized Difference Built-up Index )*

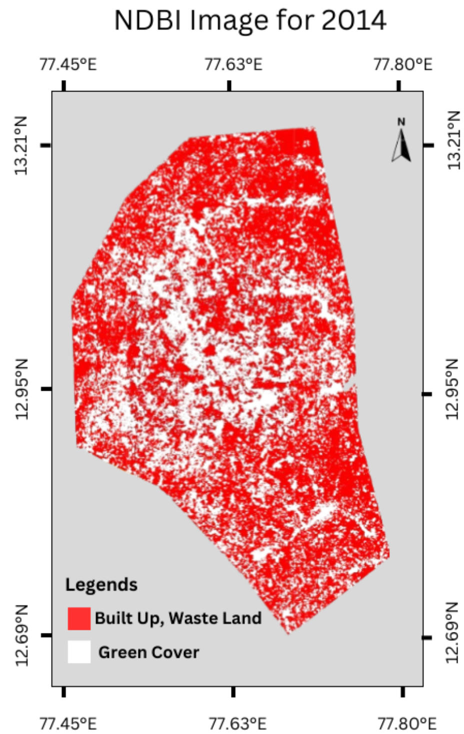
The application of the Normalized Difference Built-up Index[4] (NDBI) played a pivotal role in capturing built-up areas within the study region. The chosen range of NDBI values between 0 and 1 effectively discriminated built-up features from non-built-up features, with high positive values indicating the presence of built-up areas. Each pixel has been assigned a particular NDBI value which has later been used to classify each pixel. It is calculated using the formula:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

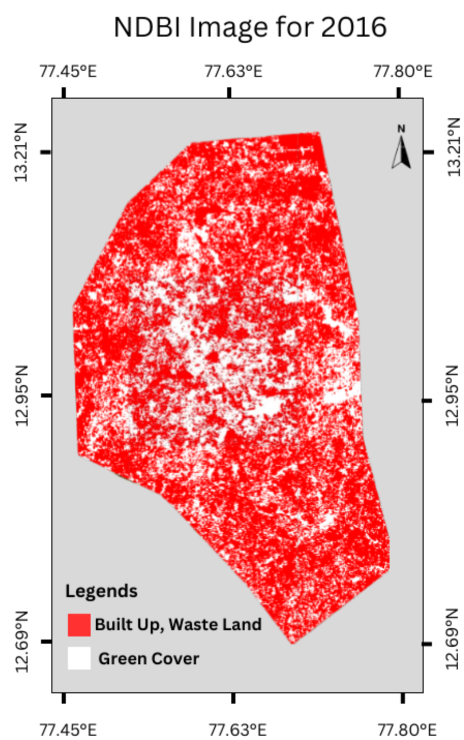
where $SWIR$ is Short Wave Infrared Region, and $NIR$ is Near Infrared Region.

### *C. NDVI (Normalized Difference Vegetation Index)*

The NDVI[4] value is used to capture the spectral characteristics associated with green cover and healthy vegetation [6]. A threshold of 0.275 was strategically chosen to filter pixels with substantial vegetative content, optimizing the classifier's ability to differentiate vegetated areas from other land cover classes.



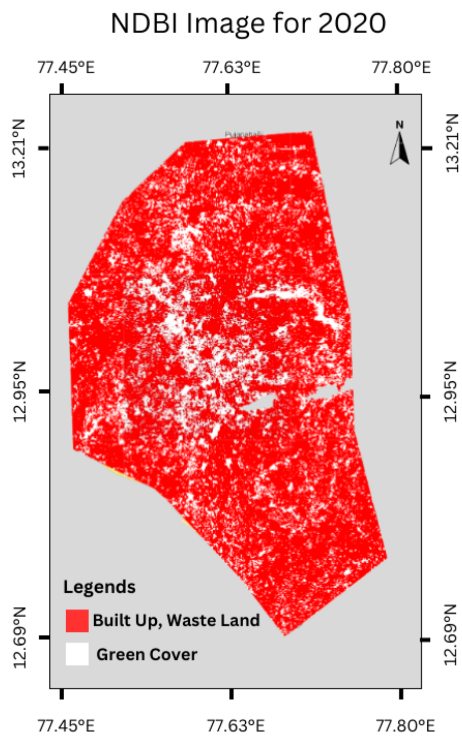

(a). 2014




(b). 2016

It is calculated using the formula:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$




(c). 2020

Fig. 3: NDBI Images for the selected years of study

where $NIR$ is Near Infrared Region, and $RED$ is visible red light.

*D. Training the Model with Polygons and Pixel Classification:*

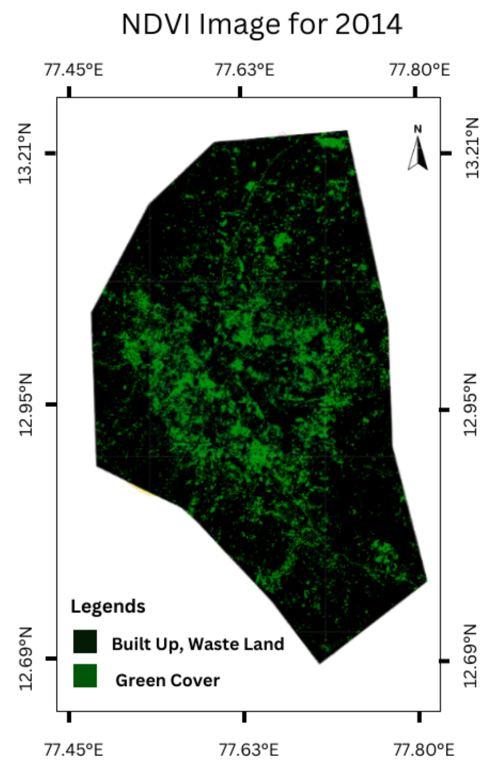
In the process of land cover classification, supervised classification models Random Forest and Support Vector Machine(SVM)[4] have been used which involves training on labeled datasets, which has been achieved by demarcation of regions of interest using polygons. The four classes considered are Built-Up, Water Body, Waste Land, and Green Cover.

Upon successful training, the model was applied to the entire study area, classifying each pixel based on its spectral characteristics. The resulting land cover map provided a detailed representation of the distribution of built-up areas, water bodies, waste lands, and green cover as shown in figures below [6].

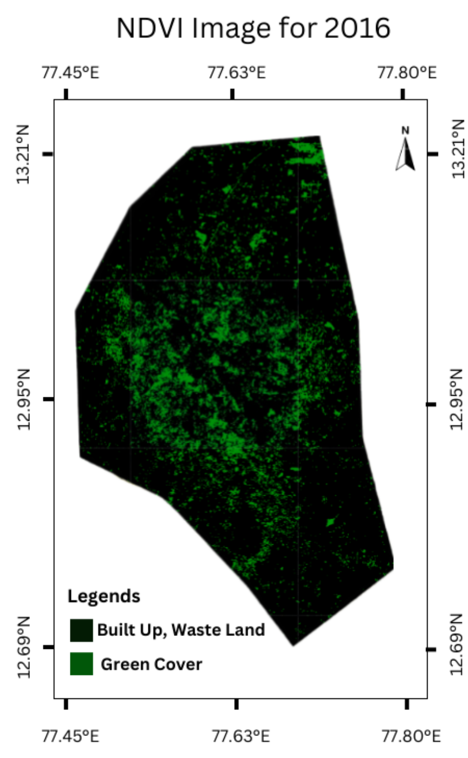
*E. Change Detection through Image Differencing*

To perform change detection, we used Google Earth Engine (GEE) to export land use land cover (LULC) maps for 2014, 2016, and 2020 in GeoTIFF format. Employing a straightforward image differencing technique, we calculated pixel-wise absolute differences between consecutive years, yielding change maps for 2014-2016, 2016-2020 and 2014-2020.

The change maps, representing the magnitude of alterations, were converted to grayscale images for clarity. Using Numpy and PIL, we chose a threshold value such that pixels in the

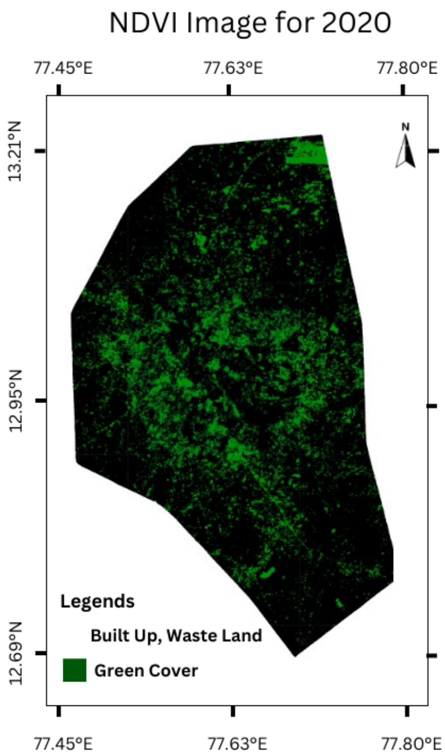



(a). 2014




(b). 2016

difference image, with magnitude greater than the threshold were rendered black, while stable regions remained white.




(c). 2020

Fig. 5: NDVI Images for the selected years of study

The pixel values in grayscale images ranged from 0 to 255 and that in the difference image ranged from -255 to 255.

The absolute difference between two images $A$ and $B$ is given by:

$$D(x, y) = |A(x, y) - B(x, y)|$$

$A(x, y)$ : Pixel value in the first image at position $(x, y)$

$B(x, y)$ : Pixel value in the second image at position $(x, y)$

$D(x, y)$ : Pixel value in the difference image at position $(x, y)$

Careful consideration of the grayscale image's dynamic range guided the selection of an optimal threshold. The resulting binary difference images visually highlighted areas undergoing substantial land cover modifications [7]. This approach provided a robust means to identify and quantify temporal changes in LULC patterns, contributing to a comprehensive understanding of landscape dynamics. The difference images for various years are as in Fig.7 with the axes showing number of pixels.

### F. Models for LULC Change Mapping

Two machine learning models, Random Forest (RF) and Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel, were employed for accurate LULC change mapping in Bengaluru, whose validation accuracies in subsequent years have been tabulated in Table.III. These models were trained on predefined polygons, utilizing NDBI and NDVI indices for enhanced feature extraction. The models were evaluated by dividing the training data such that 80% of the data were used for training, and 20% for validation.

*1) Random Forest (RF):* Random Forest, an ensemble learning method, proved highly effective in capturing intricate relationships within Bengaluru's dynamic LULC changes. Its ability to handle complex spatial patterns resulted in superior classification accuracy.

*2) Support Vector Machine (SVM) with RBF Kernel:* SVM, known for its capacity to perform non-linear classification, demonstrated satisfactory performance but exhibited lower accuracy compared to RF.

## IV. Results

The analysis of LULC changes for the years 2014, 2016 and 2020 in Bengaluru reveals notable transformations in different land classes. The area covered by water bodies witnessed a substantial decrease from 2014 to 2016 from 20.59 km² in 2014 to 10.21 km² in 2016 and then increased to 27.06 $km^2$ in 2020, indicating dynamic changes in the city's water features. In contrast, waste land areas experienced a continuous decline from 565.18 km² in 2014 to 445.60 km² in 2020, suggesting potential urbanization or repurposing of previously unused land. The built-up areas displayed consistent growth, expanding from 899.45 km² in 2014 to 1065.81 km² in 2020, indicating urban development and infrastructure expansion. Green cover areas, while showing fluctuations, remained relatively stable, with a slight decrease from 707.64 km² in 2014 to 654.39 km² in 2020. A detailed analysis has been tabulated in I

To evaluate the correspondence between land cover change representations generated by distinct predefined classifications, established metrics like Mean Squared Error (MSE), Structural Similarity Index (SSIM), and percentage MSE are employed. While MSE measures the average squared differences between corresponding pixels, percentage MSE scales this by the average value of the pixels, offering a normalized measure of error, thus accounting for the magnitude of the data.These methods serve as vital tools in the evaluation of land cover change assessments. MSE quantifies the average error magnitude, providing a numerical measure of dissimilarity between images. SSIM, by contrast, offers a more comprehensive assessment, considering luminance, contrast, and structure, providing a perceptual similarity index. Additionally, percentage MSE normalizes errors relative to pixel values, enabling a comparative analysis that isn't influenced by varying image intensities. Together, these metrics offer a nuanced understanding of similarity, guiding decision-making processes in land cover analysis, environmental monitoring, and resource management, facilitating informed policy and planning strategies.

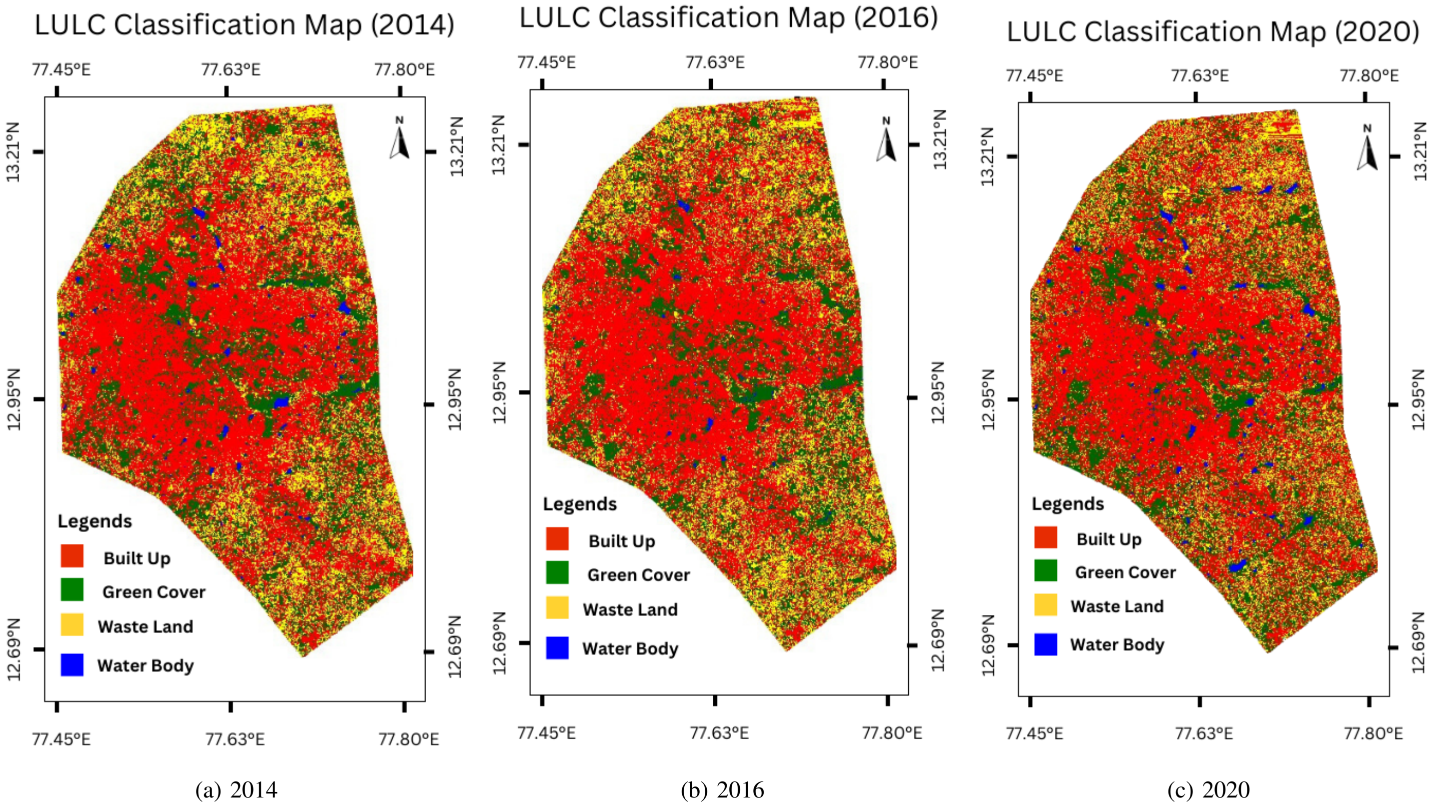



Fig. 6: LULC Maps for the chosen years of study

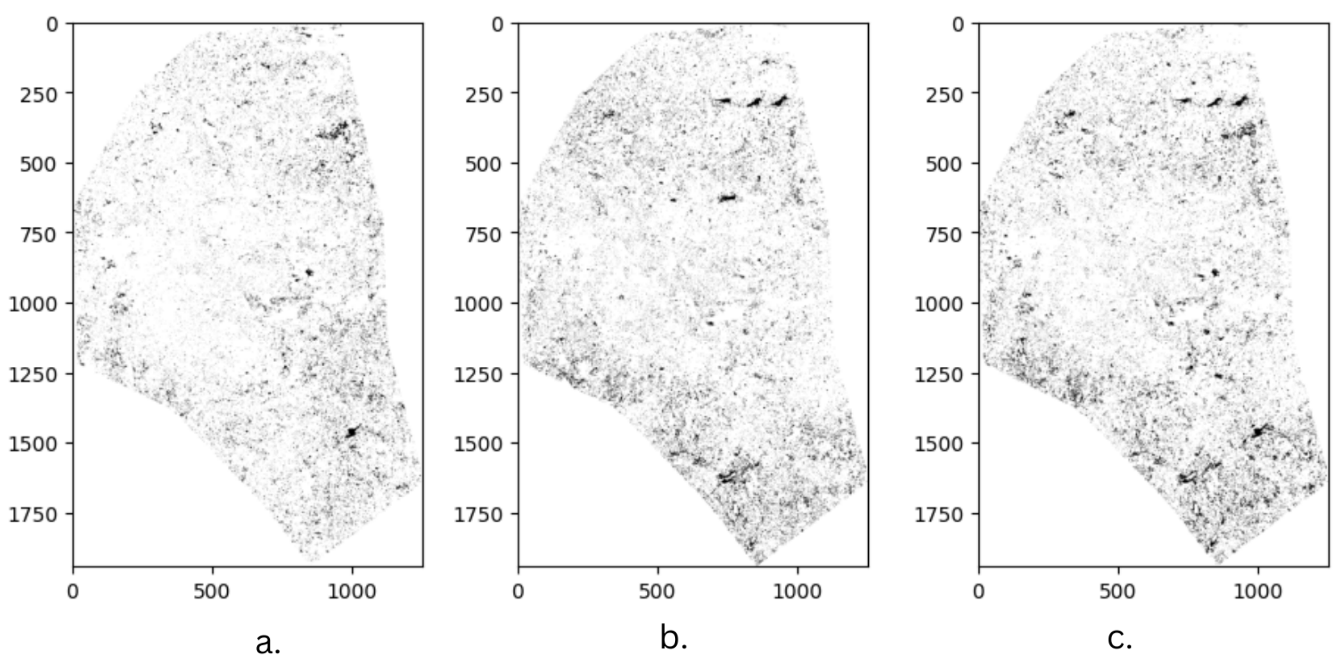



Fig. 7: Difference Image for the years (a). 2014 and 2016. (b). 2016 and 2020. (c). 2014 and 2020.

TABLE I: Land Use and Land Cover (LULC) Class Areas

| **Class** | **2014** | | **2016** | | **2020** | |
|---|---|---|---|---|---|---|
| | **Area ($km^2$)** | **% Area** | **Area ($km^2$)** | **% Area** | **Area ($km^2$)** | **% Area** |
| Water Body | 20.59 | 0.94 | 10.21 | 0.47 | 27.06 | 1.23 |
| Waste Land | 565.18 | 25.77 | 517.98 | 26.32 | 445.60 | 20.32 |
| Built Up | 899.45 | 41.02 | 1012.58 | 46.18 | 1065.81 | 48.60 |
| Green Cover | 707.64 | 32.27 | 652.09 | 29.74 | 654.39 | 29.84 |

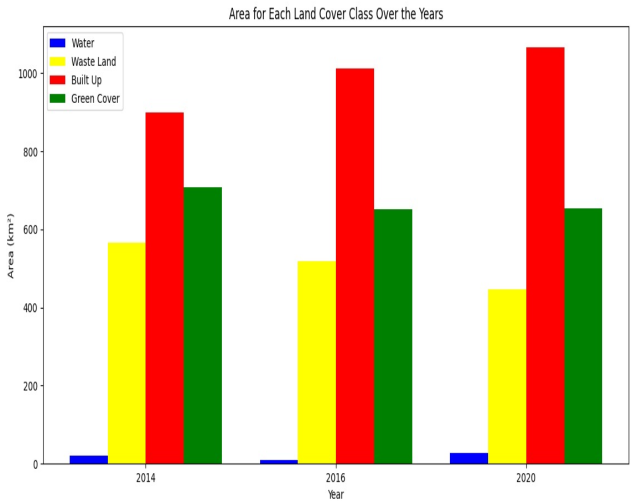



Fig. 8: Bar chart showing the area for each land cover class over the years

The comparisons between different years exhibit distinct trends:

the Mean Squared Error (MSE) consistently rises across the comparisons—2014 vs 2016, 2016 vs 2020, and 2014 vs 2020—indicating an increasing divergence in pixel-wise differences. Conversely, the Structural Similarity Index (SSIM) consistently declines, signifying a decreasing level of structural resemblance between the land cover images over time. Additionally, the Percentage Change on MSE shows a progressive increase with a widening temporal span, reflecting an escalating average error relative to pixel values. These collective trends underscore a noticeable amplification in dissimilarity, both in pixel-wise variance and structural correspondence, as the temporal gap between the compared land cover images extends.

TABLE II: Evaluation Metrics

| Metric | Comparison | | |
|---|---|---|---|
| | 2014 vs 2016 | 2016 vs 2020 | 2014 vs 2020 |
| MSE | 247.4377 | 293.8139 | 318.9108 |
| SSIM | 0.7155 | 0.6667 | 0.6480 |
| % Change on MSE | 0.38% | 0.45% | 0.49% |

These shifts in land classes reflect the evolving landscape of Bengaluru, highlighting the complex interplay between urbanization, environmental factors, and land management strategies.Predicting land use changes across years remains a formidable challenge, as evidenced by the persisting discrepancies between anticipated outcomes and actual observations in numerous studies conducted over time.[15]

TABLE III: Different Model Accuracy for LULC Maps for various years of study

| **Year** | **Random Forest Accuracy** | **SVM Accuracy** |
|---|---|---|
| 2014 | 95.29% | 86.41% |
| 2016 | 94.65% | 85.12% |
| 2020 | 95.43% | 87.01% |

## V. Conclusions

Utilizing Landsat-8 imagery and machine learning, this study delved into the land-use and land-cover (LULC) transformations of Bangalore from 2014 to 2020. The analysis revealed several key insights. Firstly, the random forest algorithm was proved to be better for LULC classification, because it provided us with high accuracy (around 95%) and computational efficiency compared to its SVM counterpart. Secondly, we can see that the built-up areas are rapidly increasing, primarily at the cost of wastelands. Thirdly, the central region of Bangalore had high urban density with majority of the built-up around that region. Lastly, we had observed that green cover and water bodies remained relatively stable, highlighting the crucial role of conservation efforts in safeguarding these vital natural resources.

These findings solidify the importance of remote sensing and geospatial analysis in comprehending urban growth dynamics and paving the way for sustainable urban planning strategies.

## VI. Future Works

While this study offers valuable insights into the rapid urban transformation of Bangalore, further research can broaden its scope and impact. Expanding data acquisition through multi-sensor integration, including higher-resolution imagery and alternative sources like radar or socio-economic information, could enhance land cover identification and deepen our understanding of urban dynamics.

Additionally, utilizing cloud-based computing and optimizing algorithms can significantly improve efficiency and enable large-scale LULC analyses over longer timeframes. By refining accuracy through advanced cloud masking and uncertainty quantification, we can build a more robust foundation for future assessments and predictions. These potential advancements in data acquisition, computational efficiency, and accuracy assessment pave the way for more comprehensive LULC mapping, empowering sustainable urban planning initiatives and shaping a resilient future for Bangalore and beyond.

## REFERENCES


[1] H. Dehingia, R. R. Das, S. Abdul Rahaman, P. Surendra, and A. D. Hanjagi, "Decadal Transformation of Land Use-Land Cover and Future Spatial Expansion in Bangalore Metropolitan Region, India: Open-Source Geospatial Machine Learning Approach," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 43, pp. 589–595, 2022.

[2] L. Khandelwal, V. N. Sujit Vudattu, and U. C. Pati, "Spatial Channel Attention based Change Detection in Synthetic Aperture Radar Images," in *2023 International Conference on Device Intelligence, Computing and Communication Technologies (DICCT)*, pp. 537–541, 2023, IEEE.

[3] V. K. A. Somayajula, D. Ghai, and S. Kumar, "Land Use/Land Cover Change Analysis using NDVI, PCA," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 849–855, 2021, IEEE.

[4] A. Kumar and S. Srivastava, "Remote Sensing GIS based Approaches for LULC Change Detection - A Review," *Remote Sensing Applications: Society and Environment*, vol. 12, pp. 144–152, 2018.

[5] Y. Xue, X. Yang, Z. Liu, and S. Qin, "Study on land cover change detection method based on NDVI time series datasets: Change detection indexes design," *Journal of Remote Sensing*, vol. 9, no. 2, pp. 125–134, 2005.

[6] S. Mishra and S. Jabin, "Land Use Land Cover Change Detection using LANDSAT images: A Case Study," in *2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA)*, Greater Noida, India, 2020, pp. 730-735, doi: 10.1109/ICCCA49541.2020.9250801.

[7] S. R. Kotkar and B. D. Jadhav, "Analysis of various change detection techniques using satellite images," in *2015 International Conference on Information Processing (ICIP)*, Pune, India, 2015, pp. 664-668, doi: 10.1109/INFOP.2015.7489466.

[8] Masroor Hussain, Dongmei Chen, and Angela Cheng, "Change detection from remotely sensed images: From pixel-based to object-based approaches," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 80, pp. April 2013.

[9] Dandan Xu and Xulin Guo, "Compare NDVI extracted from Landsat 8 imagery with that from Landsat 7 imagery," *American Journal of Remote Sensing*, vol. 2, no. 2, 2014.

[10] J. S. Rawat and M. Kumar, "Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India," *The Egyptian Journal of Remote Sensing and Space Science*, vol. 18, no. 1, pp. 77-84, 2015.

[11] A. Arshad, A. Arif, and S. K. Singh, "Study of urban land use dynamics in Srinagar city using geospatial approach," *Bulletin of Environmental and Scientific Research*, vol. 1, no. 2, pp. 18-24, 2012.

[12] T. Liu, R. Luo, L. Xu, D. Feng, L. Cao, S. Liu, and J. Guo, "Spatial channel attention for deep convolutional neural networks," *Mathematics*, vol. 10, no. 10, p. 1750, 2022.

[13] V. Sujit and U. C. Pati, "Gabor and PCA feature-based unsupervised change detection in SAR images," in *2021 IEEE International India Geoscience and Remote Sensing Symposium (InGARSS)*, IEEE, 2021, pp. 82–85.

[14] K. Winkler, R. Fuchs, M. Rounsevell, et al., "Global land use changes are four times greater than previously estimated," *Nat Commun*, vol. 12, no. 1, article 2501, 2021, doi: 10.1038/s41467-021-22702-2.