Land Use Land Cover & Change Detection in Bangalore

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Dataset

- Our dataset is limited to the city of Bengaluru in the state of Karnataka. The exact boundary for LULC and change detection are:
- Kannahalli in the west
- Devanahalli (near Airport) in the north
- Hoskote in the east
- Attibele(near the Tamil Nadu-Karnataka border) in the south

- Landsat 8's Collection 1 Surface Reflectance data captured between January 1, 2014, and September 30, 2014, January 1, 2016, and September 30, 2016, and January 1, 2016, and September 30, 2016, (similarly for 2020) filtered to include imagery intersecting a specific geographical region.

Introduction

- Land Use Land Cover (LULC) maps of an area provide information to help users to understand the current landscape.
- Change Detection (CD) is the method of examining multitemporal satellite images of a given geographic location obtained at different times.
- In the project, our aim is to provide details as to how the landscape of Bengaluru has changed from 2014 to 2016 and then to 2020.
- Annual LULC information on national spatial databases enable the monitoring of temporal dynamics of agricultural ecosystems, forest conversions, surface water bodies, etc. on annual basis for the better sustainable development and disaster management.

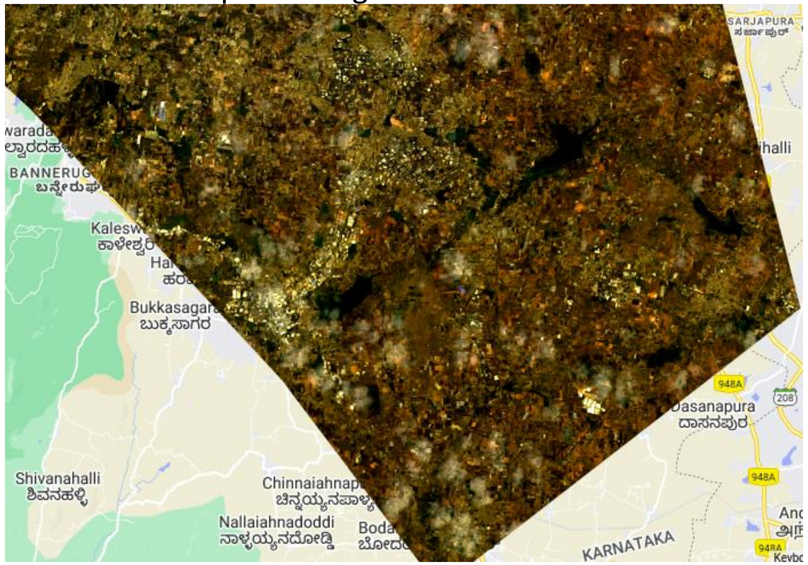
Methodology for Land Cover Detection

- We had utilized four classes for classification-green cover, settlements, water bodies and wastelands.
- For each classification, training polygons were demarcated using built-in geometry feature in google earth engine and for each class, a unique identifying variable was assigned to each class
- Each polygons were associated a color to it implying it’s class.
  - Red- Built-up area
  - Green- Green covers
  - Blue- Water Body
  - Yellow- Wasteland

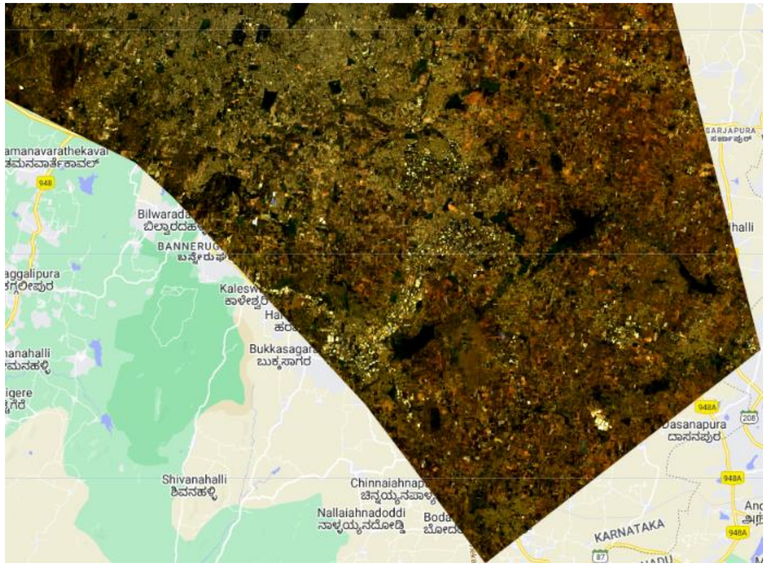
Preprocessing

- A collection of images in the given period range was taken, they were preprocessed to remove the cloud cover and cloud shadows.
- Mean of the remaining pixels was considered for further analysis.

Before Preprocessing



After Preprocessing



Training Polygons

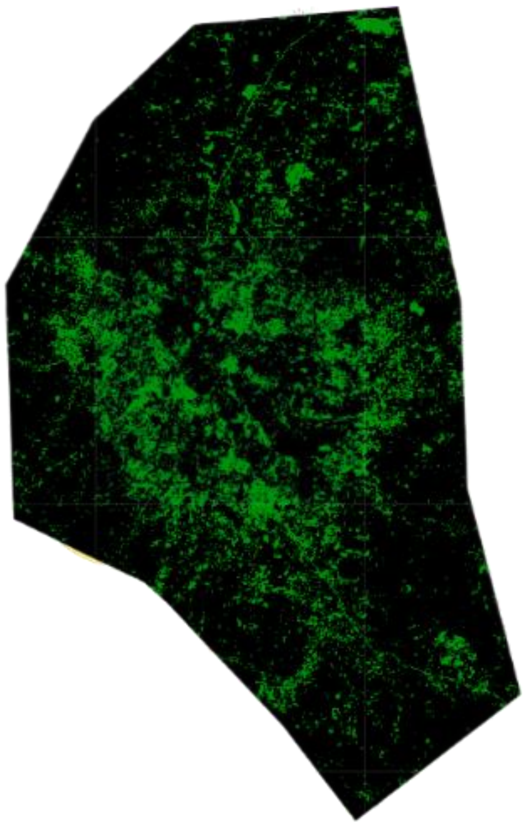

Built Up


Waste Land

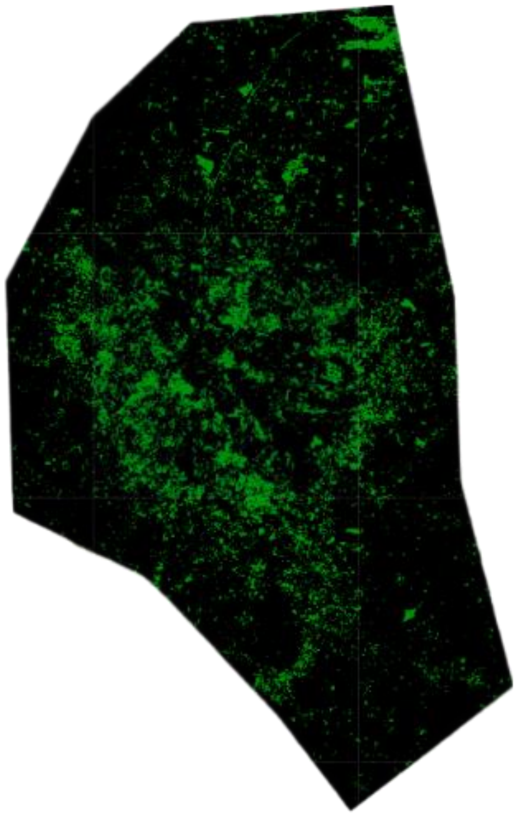

Green Cover

Water Body

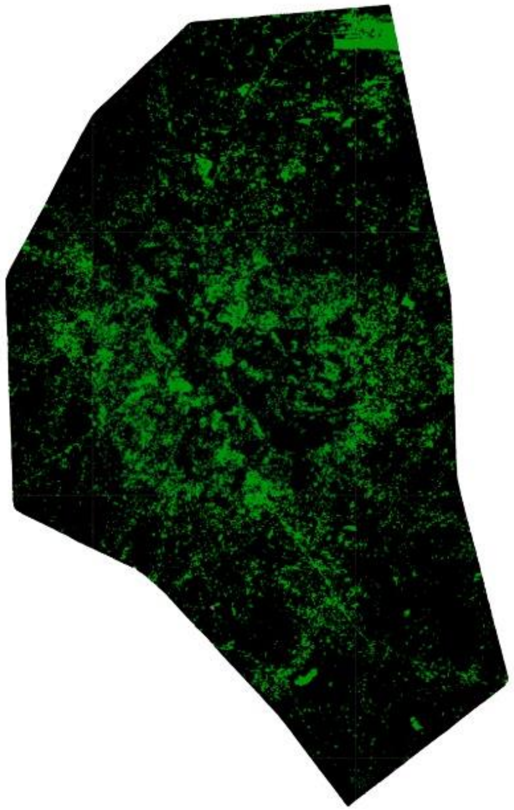
NDVI



2014



2016

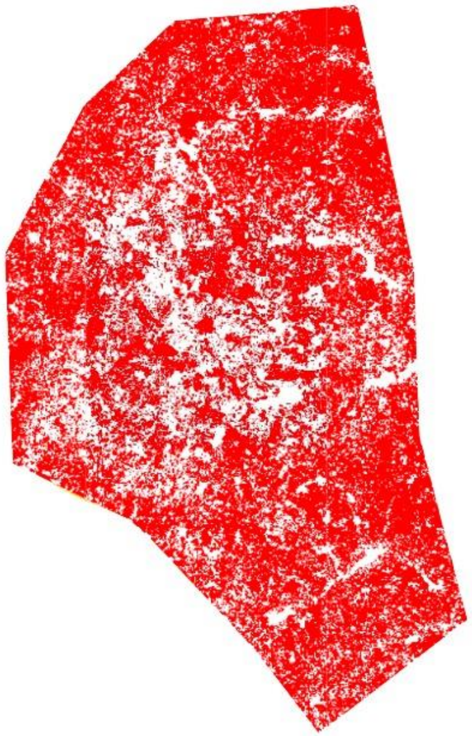


2020

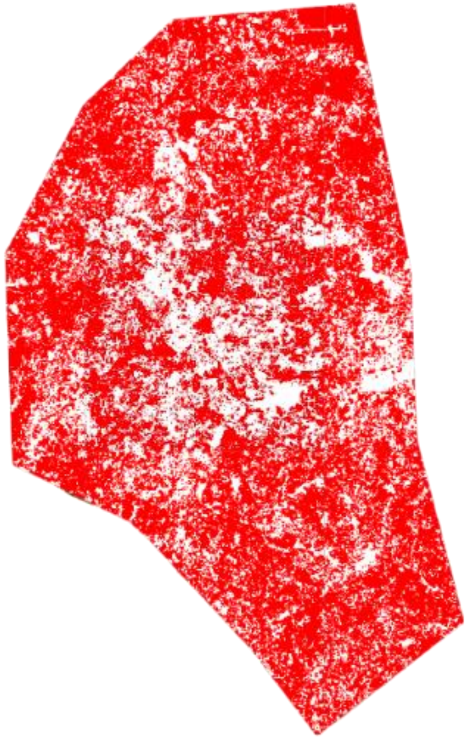
$$NDVI = \frac{NIR - Red}{NIR + Red}$$

- NDVI Range chosen between 0.1 and 1.
- Green Region = Green Cover, Very Dark green = Water Bodies
- Black Region = Built Up, Wasteland Region

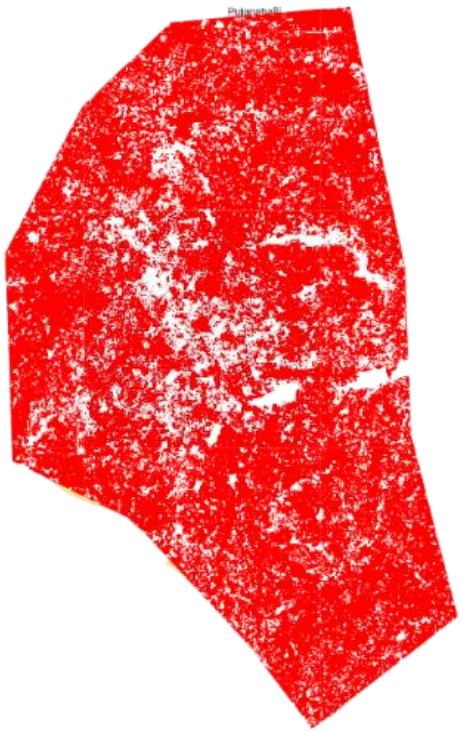
NDBI



2014



2016



2020

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

- NDBI Range chosen between 0 and 1.
- White Region = Green Cover, Water Bodies
- Red Region = Built Up, Wasteland Region

LULC Classified Maps for 2014 vs 2016 vs 2020

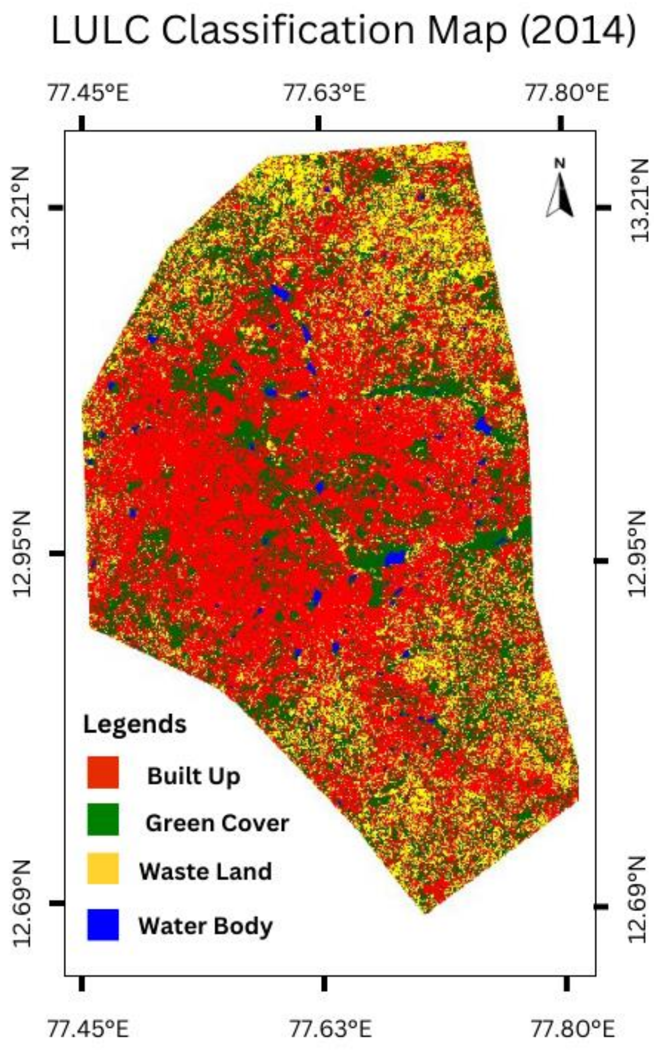


Fig 1:LULC for 2014

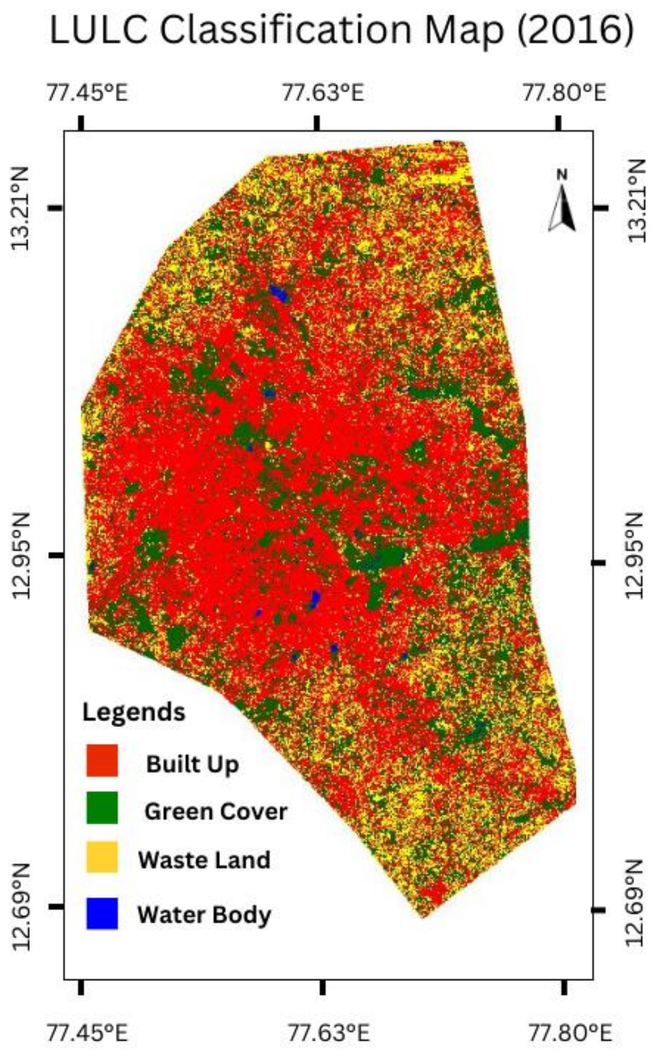


Fig 2:LULC for 2016

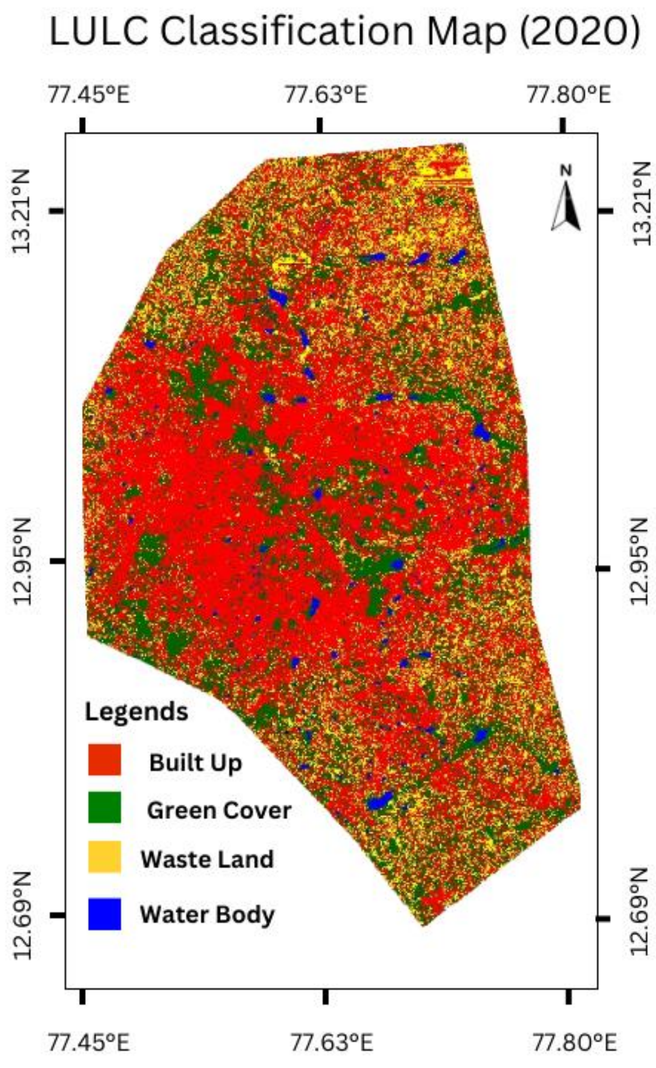


Fig 3:LULC for 2020

Methodology for Change Detection

After the three tif/tiff files were generated denoting LULC for 2014, 2016 and 2020 respectively, we applied change detection to find the change in the map from 2014 to 2016, 2016 to 2020 and 2014 to 2020.

To do this, we utilized PIL library to handle image loading, conversion, and basic image processing tasks such as converting images to grayscale and creating images from NumPy arrays.

NumPy: NumPy is employed to handle numerical operations and manipulate images as arrays, facilitating pixel-level operations and mathematical computations.

Thresholding and Colorization: It applies thresholding to the pixel-wise difference array to categorize differences into levels and colorizes the difference image accordingly to visualize varying levels of change using predefined color maps.

Difference Image Map based on Gray-Scale

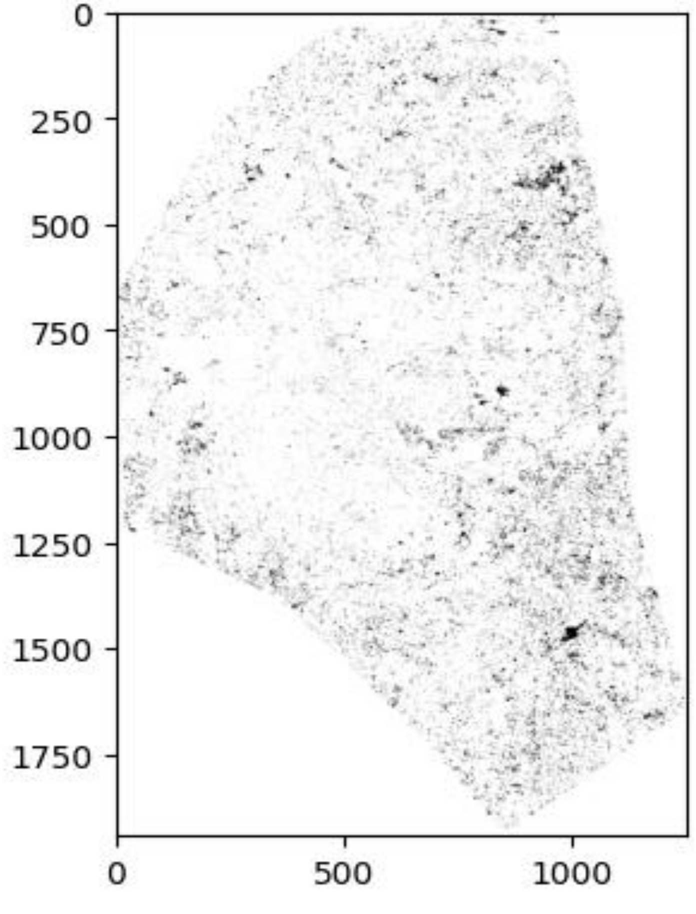


Fig 1:DI for 2014 vs 2016

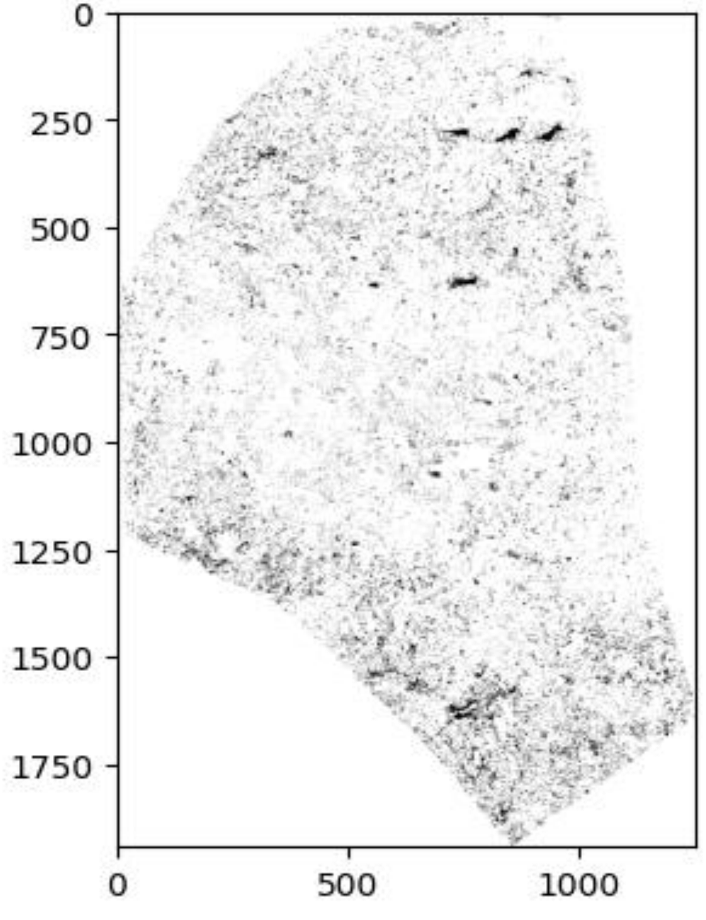


Fig 2:DI for 2016 vs 2020

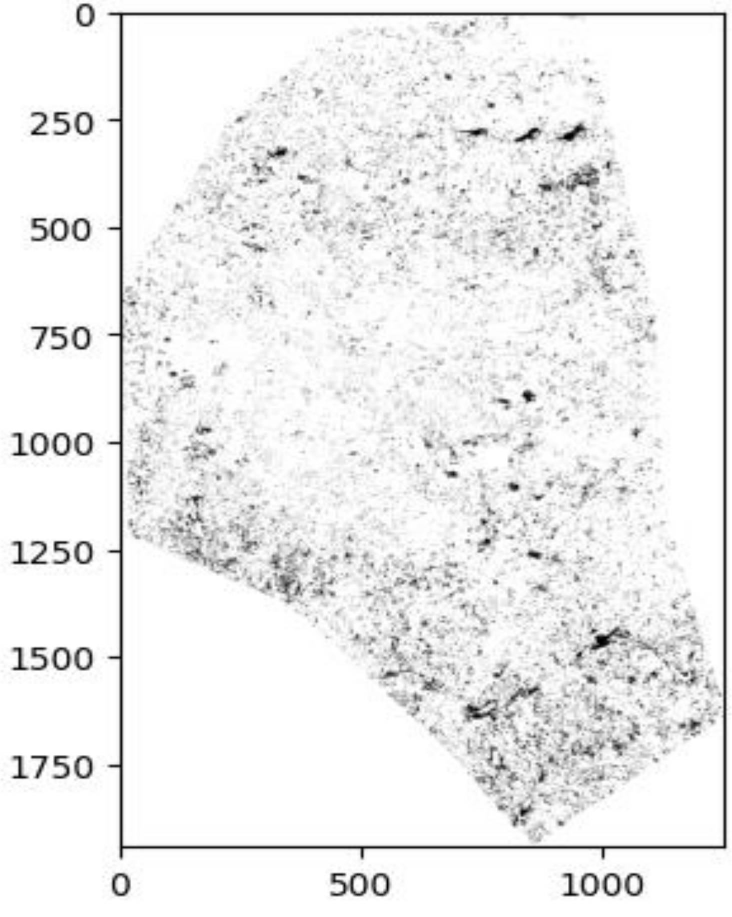
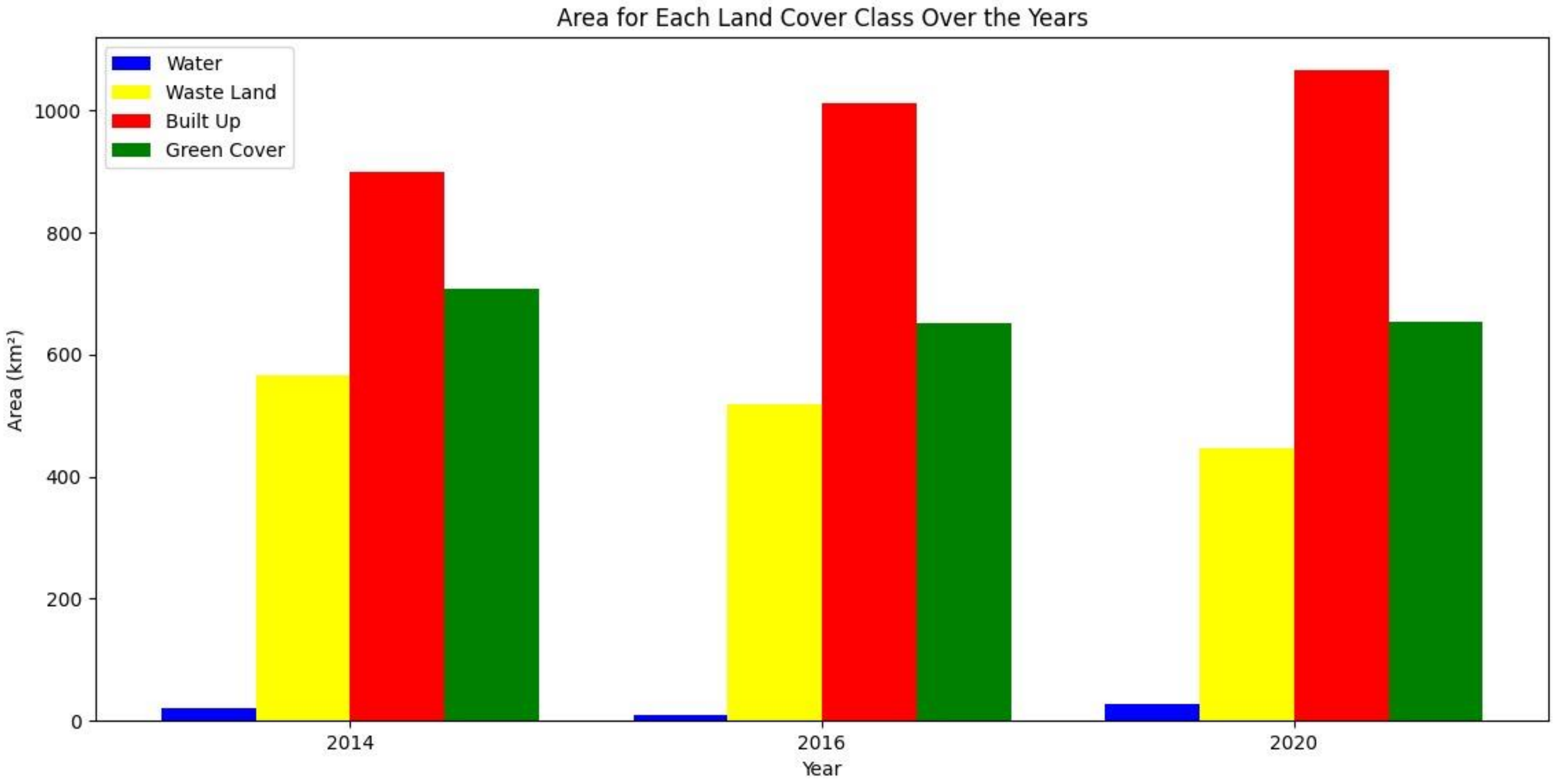


Fig 3:DI for 2014 vs 2020

Results

LULC for 2014	LULC for 2016	LULC for 2020
Validation accuracy for RandomForest=95.29%	Validation accuracy for RandomForest=94.65%	Validation accuracy for RandomForest= 95.43%
Validation accuracy for SVM=86.41%	Validation accuracy for SVM= 85.12%	Validation accuracy for SVM=87.01%
Validation error matrix(RF)=	Validation error matrix(RF)=	Validation error matrix(RF)=
List (5 elements) 0: [0,0,0,0,0] 1: [0,106,0,0,10] 2: [0,0,26,7,2] 3: [0,0,5,175,5] 4: [0,4,5,2,503]	List (5 elements) 0: [0,0,0,0,0] 1: [0,107,0,0,11] 2: [0,0,36,5,3] 3: [0,0,11,156,3] 4: [0,5,4,3,497]	List (5 elements) 0: [0,0,0,0,0] 1: [0,84,0,1,5] 2: [0,0,24,4,6] 3: [0,0,7,142,1] 4: [0,4,5,4,524]

Results


Area for Each Land Cover Class Over the Years
Water
Waste Land
Built Up
Green Cover
Area (km²)
0
200
400
600
800
1000
2014
2016
2020
Year

Challenges faced

- The tif files generated were hard to debug, as one would require tif file viewer and appropriate bands to perform change detection.
- The training samples were hand-picked and polygons were demarcated one-by-one which took up most of the time. We had to make sure that we do not underfit or overfit the model with training samples.
- The Google Earth Engine software takes a large amount of time in running the code:
  - The model trained using random forest took about 15 minutes to run.
  - The model trained using SVM took about 90 minutes to run.

Outcomes

In our training for LULC, random forest turned out to be efficient both in terms of accuracy and compute time as compared to SVM

The classification for the 4 land use classes are highly accurate(~95%).

Settlements in the central region are dense and consistent for all the years

Many of the regions having wastelands are converted to settlements from 2014 to 2020.

No significant change in the water bodies over the years.

Shortfalls

- The Landsat-8 in Google Earth Engine had data from 2014 onwards. Thus, we could not take previous years into consideration.

- The code takes too much time to run. Thus, it is not possible to track every change by running the code repeatedly.

- The resolution of Landsat-8 is of 30m, so it was not possible to distinguish elements belonging to different classes in a single pixel.

Research paper-1

- https://isprs-archives.copernicus.org/articles/XLIII-B3-2022/589/2022/
- This paper tells us how to utilize LULC maps of different years to find out percentage change in the classes like settlements, waterbody, wasteland , agriculture, fallow and forest regions.
- This paper also talks about NDBI(**Normalised Built-up index)** to extract built-up features,and utilising randomforest classifier for training and validation of the model.

Our project utilizes the above techniques. It utilizes the techniques for measurement of areas under various regions. It utilises the NDBI to find out to mitigate the effects of atmospheric effects and terrain illumination differences. It also utilizes randomforest classifier, as it provides the best results in minimum computation time and overall high accuracy.

Research paper-2 & 3 for Keshav Chandak

1. **Spatial Channel Attention based Change Detection in Synthetic Aperture Radar Images(Paper presentation-2)**
   - https://ieeexplore.ieee.org/document/10110172/
   - From this paper, we had learnt image differencing techniques for change detection, utilising bands for mapping changed and unchanged pixels, and accuracy measurement using confusion matrix
   - The above implementations helped us in our project for change detection implementation.

2. **Land Use/Land Cover Change Analysis using NDVI, PCA(Paper presentation-3)**
   - https://ieeexplore.ieee.org/document/9418025/
   - From this paper, we had learnt using NDVI(**Normalized Difference Vegetation Index)** to assess land cover changes in Landsat-8 satellite, and utilising various GIS software to measure the percentage of land covered by classes like forests, settlements, and water bodies.

   The above implementations helped us in our project for Land Use Land Cover(LULC) implementation.

Research paper-2 & 3 for Sunny Kaushik

1. **Remote sensing and GIS based approaches for LULC Change detection(Access here)**

   - Advantages and disadvantages of using SVM
   - The new model used was Random Forest on NDVI
   - Evaluation metrics – SSIM, MSE and Image differencing

2. Study on Land cover detection methods based on NDVI time series data and Noises affecting the change detection(Access here)

- In this paper the authors have conducted various experiments to show the affects of noises on change detection methods and the primary method used was based on spectral properties of object.
- Experiment 3: From This experiment sought to evaluate the influence of atmospheric variability (e.g., volcano ash) or climatic events, like cloudy conditions, on detection results.

Research paper-2 & 3 for Sunny Kaushik

Evaluation Metric	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%

Research paper-2 & 3 for Sunny Kaushik

```
var cloudShadowBitMask = ee.Number(2).pow(3).int();
var cloudsBitMask = ee.Number(2).pow(5).int();
```

- Two bit masks are defined. cloudShadowBitMask and cloudsBitMask are used to identify specific bits in the "pixel_qa" band of the input image that correspond to cloud shadow and cloud, respectively

```
var mask=qa.bitwiseAnd(cloudShadowBitMask).eq(0).and(qa.bitwiseAnd(cloudsBitMask).eq(0));
```

- The mask variable is created by performing bitwise operations (bitwiseAnd) between the "pixel_qa" band and the defined bit masks (cloudShadowBitMask and cloudsBitMask). It checks whether both the cloud shadow and cloud bits are equal to zero, indicating clear conditions.

Research paper-2 & 3 for Tanmay Jain

1. **Analysis of Various Change Detection Techniques Using Satellite Images(Paper presentation-2)**
    - https://ieeexplore.ieee.org/abstract/document/7489466
    - This paper provided key insights of change detection techniques like Image Differencing, performing NDBI, and NDVI in our project. These methods greatly enhanced our project's precision in detecting land cover changes.

2. **Land Use Land Cover Change Detection using LANDSAT Images: A Case Study(Paper presentation-3)**
    - https://ieeexplore.ieee.org/document/9250801
    - This paper provided us with the knowledge of using NDVI and performing LULC classification and then detecting changes by techniques like Image Differencing project. These methods gave us idea of how LULC Classification could be merged with change detection.