# AN EVALUTION OF LANDSAT-8, SENTINEL-2 AND MODIS DATA FOR VEGETATION COVERAGE MAPPING IN DHAKA CITY

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## ABSTRACT

Bangladesh faces severe vegetation degradation due to inadequately managed protected areas, climate changes and poor coordination between government and non-government sectors, exacerbated by rapid population growth and unplanned urbanization. Dhaka, the capital, bears the brunt of these issues, causing a significant disruption in its ecological balance. Acknowledging the dynamic and unavoidable nature of these changes, obtaining precise data on the extent and geographic shifts in vegetation coverage is crucial for effective implementation of sustainable urban planning strategies. In this study, the utility of Landsat-8, Sentinel-2 and the Moderate Resolution Imaging Spectroradiometer (MODIS) has been evaluated for mapping vegetation coverage within Dhaka city. This study has involved a series of classification experiments utilizing these satellite datasets, where manually digitized data from Google Earth with a scale of 1:1000 is used as a reference for accuracy assessment. Multiple tests have been conducted with the data from each satellite sensor to determine their respective potential accuracy levels in vegetation mapping. Results have shown that data from Sentinel-2 could achieve 89.4–92.6% accuracy and data from Landsat could achieve 81.2–84.7% accuracy whereas the coarse-resolution MODIS could produce about 86.4% accuracy with respect to the manually digitized data from Google Earth. Sentinel-2 is identified as the preferred satellite for vegetation coverage due to its finer spatial resolution of 10m and exceptionally low cloud coverage of just 0.048%, meeting the criterion of minimal deviation from ground truth data.This study suggests that, in the absence of constraints related to training data availability, currently accessible moderate-resolution satellite data like Landsat-8, Sentinel-2, and MODIS can potentially achieve accuracy levels exceeding 90% for mapping vegetation coverage which is beneficial for formulating plans and policies for development across extensive industrial zones, such as the Dhaka city.

***Keywords:*** *Land Use/Land Cover (LULC), normalized difference vegetation index(NDVI),supervised classification, remote sensing, urban growth*

## 1. INTRODUCTION

Vegetation consists of various plant species and the ground coverage provided by those plants. It acts as a natural linkage between the atmosphere, hydrosphere and pedosphere. Quantitative and qualitative evaluation of vegetation coverage and determining its changes is essential for various ecological studies(Yuan et al., 2019). Unplanned urbanization of Dhaka City has resulted in severe environmental consequences. The rate of population growth of the city has simultaneously increased making it one of the most populous megacities in the world. Because of this ever-fluctuating population growth rate, the physical characteristics of Dhaka city are gradually changing as open spaces, vegetation areas and water bodies are being converted into built-up areas triggering environmental instability of the area. Therefore, it is necessary to track the morphological changes of Dhaka city- especially the changes in the vegetation land use pattern of the city(Ullah, 2019). The vegetation area was measured using the classification technique of remote sensing images which is basically a pattern recognition technique. The technique recognizes and classifies ground cover information in remote sensing images and extracts the required information corresponding to the Ground Truth(Li et al., 2010). The Ground Truth data in the study was considered to be the manually digitized data as it is the real or true data.

Access to high resolution satellite imagery is progressively becoming freely available for wide range of applications such as agriculture, urban planning, and natural resource management, both at regional and global scales. To identify changes on the earth surface more rapidly than conventional ground survey techniques, the accessibility of remotely sensed data has provided a diverse array of images, with both high spectral and spatial resolution (Aneesha Satya et al., 2020; Chen et al., 2013).This study has been conducted by using supervised and NDVI classification on these remotely sensed data. The land use detection method discussed in this study can be utilized to generate data related to modifications in land usage including monitoring changes in land use and degradation. Landsat–8 OLI launched in 2013, is an earth observational satellite which is easily accessible and usable. Landsat-8 exhibits enhanced spectral resolution compared to its previous Landsat instruments which will further advance the use of Landsat-8 for analyzing both local and global data analysis (Ahmadian et al. 2016). For investigating better classification accuracy, Several methods have been developed to extract Land Use Land Cover (LULC) images from Landsat–8 OLI data (Jia et al., 2014; Taufik & Ahmad, 2016). In the study, Landsat-8 OLI was used as all the bands are of same resolution (30m), so the most accurate value could be obtained by converting all bands into a composite band. MODIS is playing an important role to predict environmental changes accurately to assist experts in making decisions concerning the protection of the planet (Justice et al., 1998). The global MODIS vegetation indices, generated every 16 days with band resolutions of 250, 500, and 1000 meters, offer reliable spatial comparisons of greenness in terrestrial vegetation. (Chen et al., 2003). For the study, NDVI classification was done using the 250m band. NDVI (Normalized Difference Vegetation Index) is a measure to determine the photosynthetic capability of leaves as it can detect changing illumination conditions and viewing angle. It is especially useful for continental- to global- scale vegetation monitoring(Hil Baky et al., 2017). Studies show that vegetation indices are useful in vegetation studies (Huete, 1988) which includes normalized difference vegetation index (NDVI) (Wang & Maduako, 2018). European Space Agency (ESA) successfully launched a trio of satellite sensors (Sentinels-1, 2, and 3A) through the Copernicus program that supplies finer resolution free satellite images (Bertini et al., 2012).Sentinel-2 sensor was used in this case as its objective is land monitoring**.** Recent studies have shown that Sentinel-2 outperforms Landsat-8 and earlier Landsat sensors, in terms of spectral capabilities. Sentinel-2 has been proven effective with finer band resolution of 10m, in distinguishing rangeland management practices (Sibanda et al., 2016) estimating forest canopy cover and leaf area index (LAI) (Korhonen et al., 2017) and improving the accuracy of classifying built up areas (Pesaresi et al. 2016).

The aim of the study is to detect the total vegetation coverage of Dhaka Metropolitan Area. The specific objectives are:

i. Manually digitized the vegetation area in Google Earth Pro. for the year 2023

ii. Comparing multi-sensor remote sensing data with the manually digitized data (Ground Truth)

Dhaka Metropolitan Area (DMA) was settled on the eastern bank of the Buriganga River in the heart of the Bengal Delta. It is located at the geographical center of Bangladesh showing in figure 01, between 23.55°N and 90.23° E and 23.39°N and 90.26°E respectively (Alam, 2019). DMA covers the total area of 300.95 sq.km which is the study area for the research.

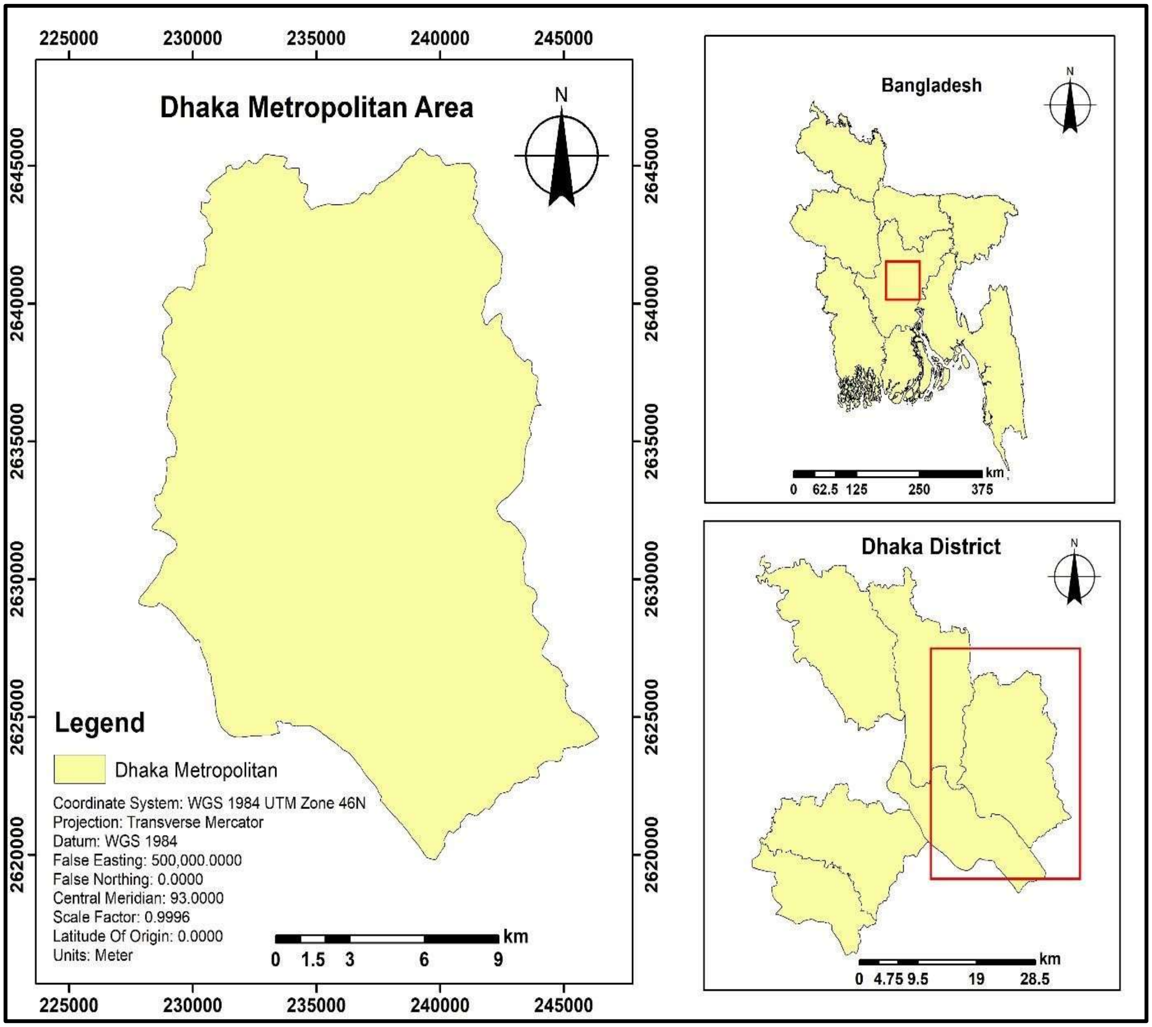


Figure 01: Schematic Diagram of Study Area

## 2. METHODOLOGY

### 2.1 Remote Sensing Data Collection and Image Processing

In this study, a high-resolution remote sensing dataset was utilized for vegetation mapping, and its outcomes were cross-referenced with manually digitized data from Google Earth Pro. The study's working principle, involved the collection of images from Landsat-8, Sentinel-2 and MODIS with varying image resolutions. To ensure temporal coherence and enhance accuracy, these images were acquired nearly simultaneously. Attention was paid to the cloud coverage to keep it to minimum for better classification. Additionally, efforts were made to refine the classification process through techniques such as band sharpening, image enhancement, and atmospheric correction applied uniformly across all satellite images, demonstrating a comprehensive approach to improve the overall accuracy of vegetation mapping.

Table 01: Satellite images used for the study

| Acquisition Date | Data Category | Spatial Resolution (meter) | Band Properties | Cloud Coverage |
|---|---|---|---|---|
| 02 March 2023 | Sentinel-2 | 10 m | RGB and NIR | 0.048% |
| 17 March 2023 | Landsat-8, OLI | 30 m | Multispectral | 0.36% |
| 21 March 2023 | MODIS | 250 m | 16 days NDVI | 0% |
| February,2023 | Ground Truth | 1:1000(scale) | --- | --- |

At the very beginning, remote sensing data was meticulously collected and geo-referenced, with layers systematically stacked in preparation for subsequent analysis using ArcMap 10.5. The study employed the WGS-1984 UTM Zone 46N as the projected coordinate system for consistency. For Landsat-8, classification efforts focused on all bands except Band-9, Band-10, and Band-11, while Sentinel-2, offering bands at 10m, 20m, and 60m resolutions, underwent experimentation involving the stacking of all bands and the use of only the 10m bands. Significantly improved results emerged with the latter approach, leading to the selection of four bands (Band-2, Band-3, Band-4, Band-8) for continued analysis. For MODIS, the Vegetation Indices 16 days L3 Global 250m dataset was employed for classification, and a normalization process, applying a scale factor of 0.0001, was undertaken. Subsequently, the study area was delineated through cropping from this satellite image to facilitate more focused and detailed analysis.

## 2.2 Vegetation Area Detection Method

In this study, the classification of land use was undertaken with a focus on distinguishing between two major categories: vegetation and non-vegetation, aligning with the primary objective of quantifying the total vegetation coverage within the designated DMA. Two distinct methods, supervised classification and the Normalized Difference Vegetation Index (NDVI) were employed to achieve a refined and comprehensive conclusion. Supervised classification can be visualized from the following diagram:

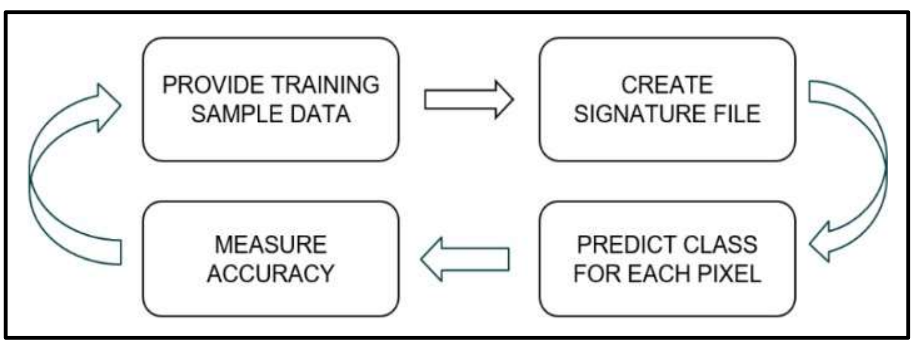


Figure 02: Flow diagram of supervised classification

In the realm of supervised classification in figure 02, ArcMap 10.5 was utilized as the analytical platform. The process involved the generation of a signature file, where pixel values were selected along with their corresponding labels. This signature file was then utilized by the model to conduct supervised image classification, employing the Maximum Likelihood algorithm. Within this algorithm, a function was derived to calculate the highest probability of a pixel matching the values in the signature file, subsequently assigning an appropriate label. This method allowed for a detailed and accurate classification of the raster images into distinct groups based on the provided sample data, contributing to a more nuanced understanding of the land use patterns within the DMA.

In the final phase of the study, NDVI classification was employed to delineate areas of healthy vegetation, offering valuable insights into the distribution of vegetation based on reflectance patterns from incoming waves detected by the sensor. NDVI, a dimensionless indicator widely used for assessing vegetation presence remotely (Rouse et al. 1973), was calculated using the formula:

$$NDVI = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \quad (1)$$

The specific band values used for NDVI calculations varied among different sensors. For Landsat-8, Band-4 and Band-5 were utilized, while Sentinel-2 employed Band-8 and Band-4. In the case of the MODIS dataset, the 250m_16days_NDVI band was instrumental, involving the multiplication of a scale factor of 0.0001 to obtain the NDVI range. The study rigorously tested different NDVI threshold values (0.15, 0.2, 0.3, 0.35, 0.4)(Gandhi et al., 2015) on these bands to optimize the results, ensuring a thorough exploration of the dataset for the most accurate depiction of vegetation coverage within the study area. Methodological approach can be visualized from the following diagram Figure 03:

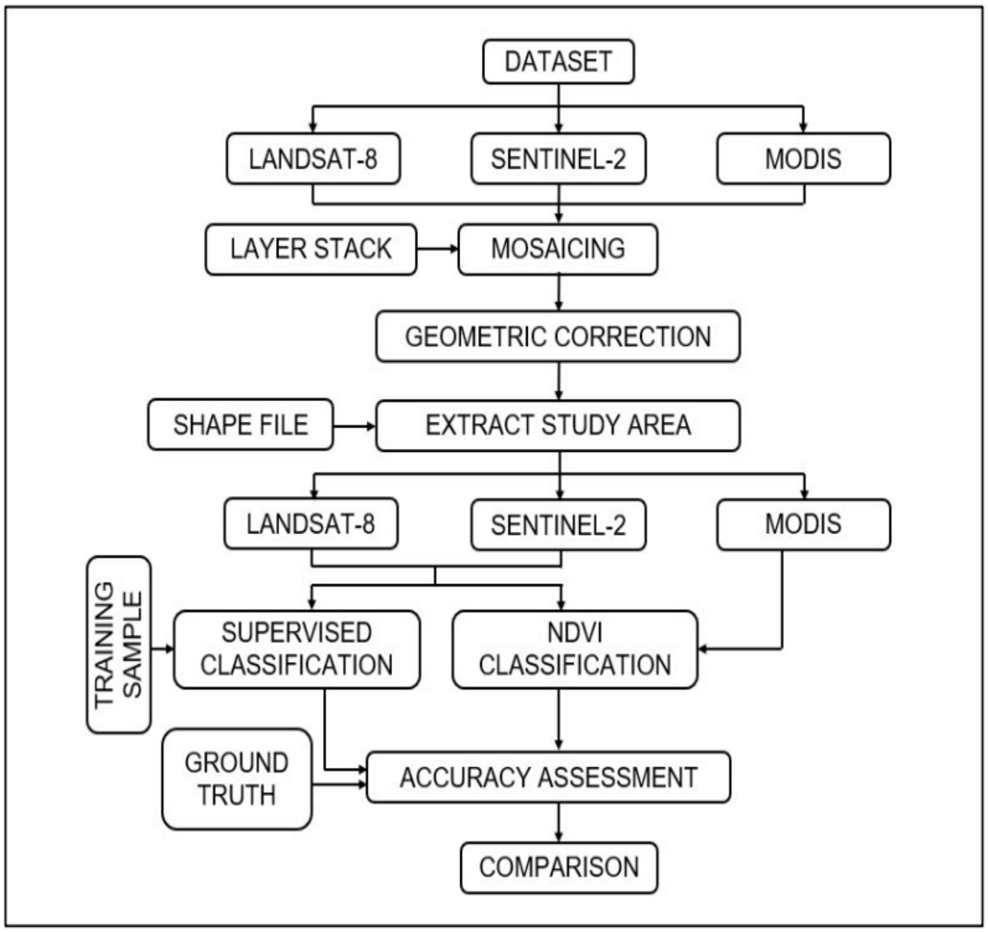


Figure 03: Overview of methodological approach

For the acquisition of Ground Truth data in figure 05, a manual digitizing approach was meticulously employed utilizing Google Earth Pro. The objective was to delineate vegetation areas from bare lands, water bodies, and built-up areas by creating polygons. Maintaining an average elevation of 800 feet during polygon drawing aimed at enhancing resolution for more precise segmentation. Notably, the digitization process excluded floating plants and algae, as their occurrence is seasonal and does not directly align with land use considerations. Additionally, patchy dark artificial pavements were excluded from the digitization process. The resulting digitized files, in KML format, underwent conversion into shapefiles within ArcMap 10.5. Subsequently, these shapefiles underwent further processing to calculate the exact area, establishing them as the ground truth dataset for the study. This rigorous manual digitization process ensured a reliable and accurate reference for validating and refining the results of the remote sensing and classification methodologies employed in the study.

### 2.3 Change Detection and Accuracy Assessment

Post-classification comparisons were used to detect the accuracy of vegetation area by comparing classified images individually with ground truth. Accuracy assessment measures the degree of closeness to true values. Error matrix is a common method in the accuracy assessment process, including overall accuracy, producer's accuracy, user's accuracy. Randomly distributed points were identified on the reference image and attributed to different categories where high-resolution field data are used as reference data to assess the image classification accuracy. IOU (Intersection over Union) accuracy check is a metric commonly used in object detection tasks. It measures the overlap between predicted and ground truth bounding boxes, providing a numerical evaluation of the model's localization accuracy. A higher IOU score indicates better alignment between predicted and actual object boundaries.

## 3. RESULTS AND ANALYSIS

### 3.1 Vegetation detection

The vegetation area of DMA was detected by Sentinel-2 NDVI Classification using the following equation:

$$NDVI_{S2} = \frac{(band8-band4)}{(band8+band4)} \quad (2)$$

Where, $band8$ signifies the reflectance in the near infrared (NIR) band and $band4$ and signifies the reflectance in the red band. A threshold of 0.35 was taken to get the best vegetation classification from the Sentinel-2 remote sensing image in figure 06. Total vegetation area through Sentinel-2 NDVI Classification was found to be 74.2754 sq.km. After relative comparison with the Ground Truth vegetation area of 68.6129 sq.km, 7.6% deviation had been seen in total vegetation area. To detect the vegetation area of DMA by Sentinel-2 Supervised Classification, a signature file was created with 73 samples for vegetation and 131 samples for non-vegetation area to train the model using Maximum Likelihood algorithm. After that raster calculator was used to separate vegetation and non-vegetation area and total vegetation area was calculated. Total vegetation area through Sentinel-2 Supervised Classification was found to be 76.5457 sq.km. in figure 07. After relative comparison with the Ground Truth vegetation area of 68.6129 sq.km, 10.4% deviation had been seen in total vegetation area. The vegetation area of DMA was detected by MODIS NDVI Classification using 250m_16Days_NDVI band which is previously classified according to the study requirement and the band range was brought into NDVI range by multiplying a scale factor of 0.0001. A threshold of 0.4 was taken to get the best vegetation classification from the MODIS remote sensing image. Total vegetation area through MODIS NDVI Classification was found to be 80.7117 sq.km in figure 08. After relative comparison with the Ground Truth vegetation area of 68.6129 sq.km, 15% deviation had been seen in total vegetation area. To detect the vegetation area of DMA by Landsat-8 Supervised Classification, initially pan sharpening tool of ArcMap 10.5 was used for finer resolution by reducing the cell size of 30m to 15m. Then a signature file was created with 38 samples for vegetation and 73 samples for non-vegetation area to train the model using Maximum Likelihood algorithm. After that, raster calculator was used to separate vegetation and non-vegetation area and total vegetation area was calculated. Total vegetation area through Landsat-8 Supervised Classification was found to be 86.6268 sq.km in figure 09. After relative comparison with the Ground Truth vegetation area of 68.6129 sq.km, 20.8% deviation had been seen in total vegetation area. The vegetation area of DMA was detected by Landsat-8 NDVI Classification using the following equation:

$$NDVI_{L8} = \frac{(band5-band4)}{(band5+band4)} \quad (3)$$

Where, $band5$ signifies the reflectance in the near infrared (NIR) band and $band4$ and signifies the reflectance in the red band. A threshold of 0.15 was taken to get the best vegetation classification from the Landsat-8 remote sensing image. Total vegetation area through Landsat-8 NDVI Classification was found to be 90.2934 sq.km in figure 10. After relative comparison with the Ground Truth vegetation area of 68.6129 sq.km, 24% deviation had been seen in total vegetation area.

Table 02: Vegetation Coverage Calculation by different Remote Sensing Technique

| Categories | Non-Vegetation Area (sq km) | Vegetation Area (sq km) | Deviation (%) |
|---|---|---|---|
| Ground Truth | 232.34 | 68.61 | 0 |
| Sentinel-2 NDVI | 226.67 | 74.28 | 7.6 |
| Sentinel-2 Supervised | 224.40 | 76.55 | 10.4 |
| M0DIS | 220.24 | 80.71 | 15.0 |
| Landsat-8 Supervised | 214.32 | 86.63 | 20.8 |
| Landsat-8 NDVI | 210.66 | 90.29 | 24.0 |

The table 02 denotes the deviation of the calculated vegetation area with respect to the Ground Truth data. The "Deviation" values quantify the disparities between predicted and actual land cover. Landsat-8 NDVI exhibits the highest deviation at 24% indicating notable differences while Sentinel-2 NDVI has a lower deviation of 7.6% suggesting closer alignment with the ground truth in terms of total vegetation area.

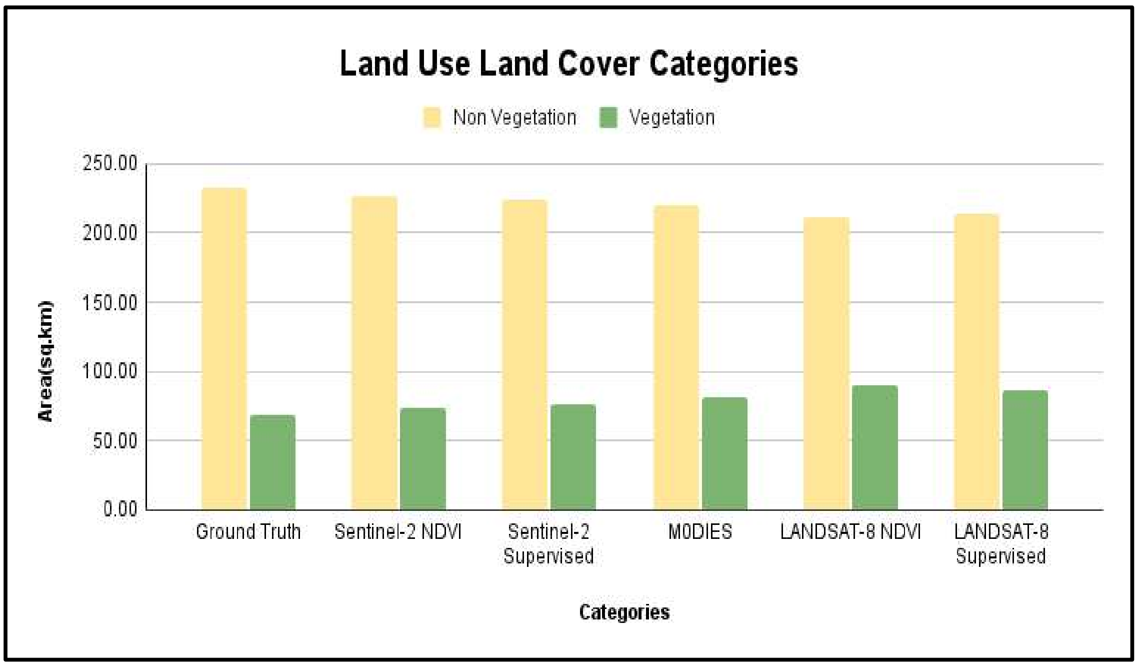


Figure 04: Land Use Land Cover Categories

The chart depicts the distribution of non-vegetation and vegetation in different land cover categories, comparing ground truth data with various remote sensing methods. Ground truth values serve as a reference, showing 232.34 sq km for non-vegetation area and 68.61 sq km for vegetation area. Notably, Landsat-8 NDVI reports the highest non-vegetation area quantity 210.66 sq km, while MODIS indicates the highest vegetation area quantity 80.71 sq km. The chart visually illustrates the variations in land cover assessments among methods, providing insights into their effectiveness in distinguishing non-vegetation and vegetation, crucial for environmental monitoring and resource management.

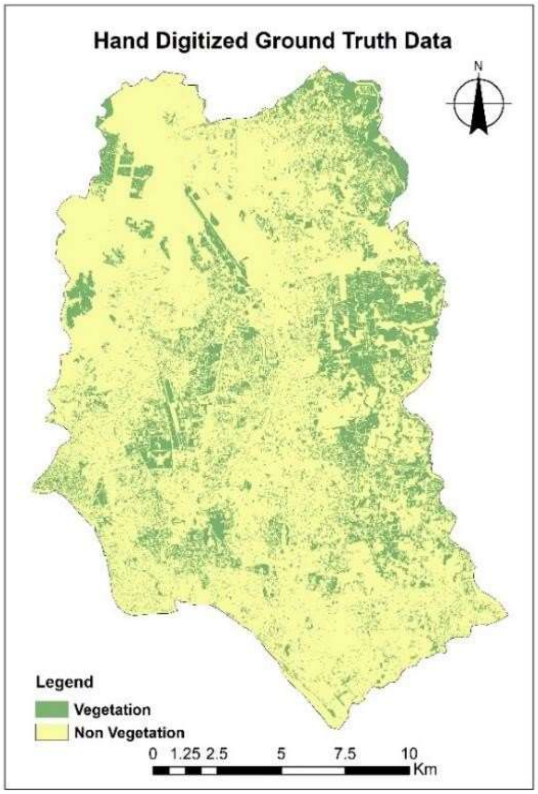


Figure 05: Ground Truth

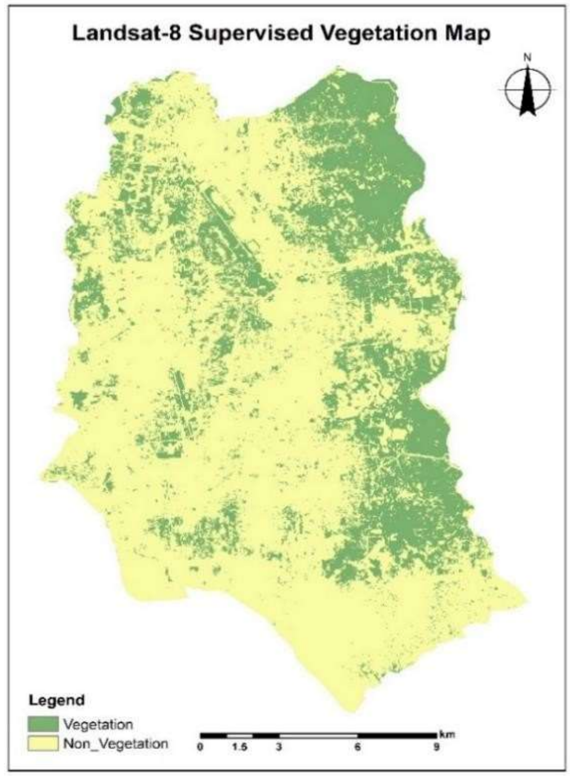


Figure 06: Landsat-8 Supervised Classification

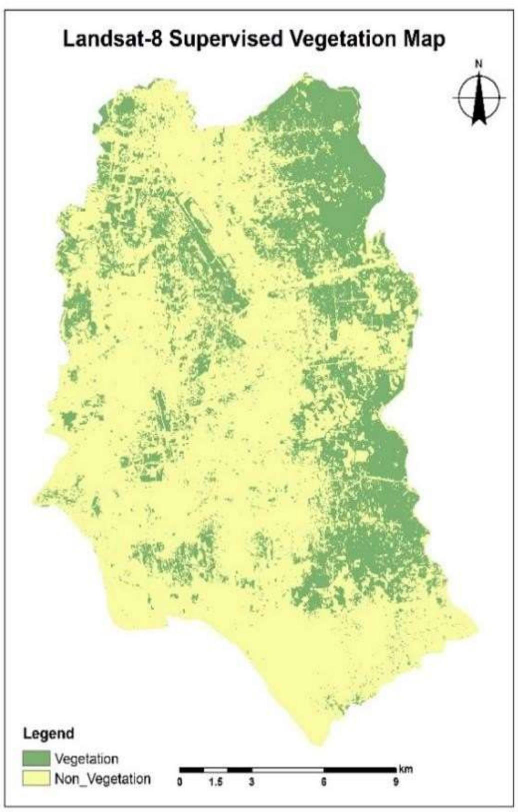


Figure 07: Landsat-8 NDVI Classification

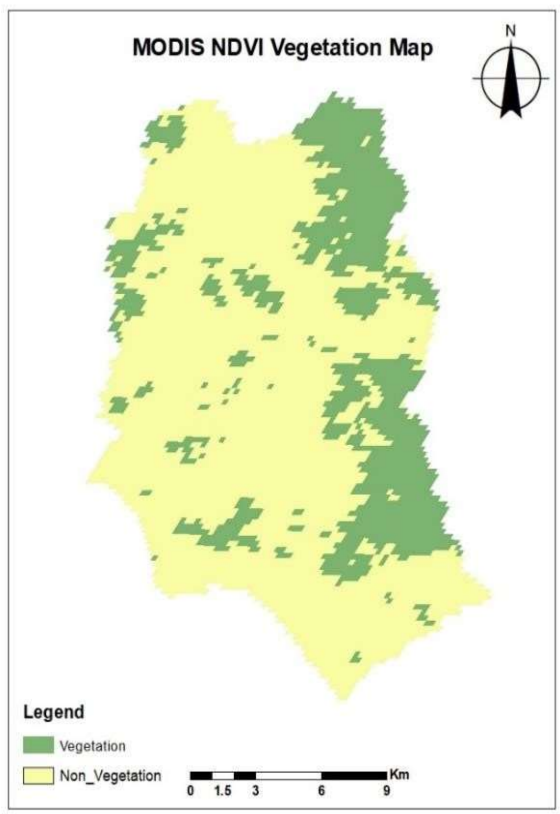


Figure 08: MODIS NDVI Classification

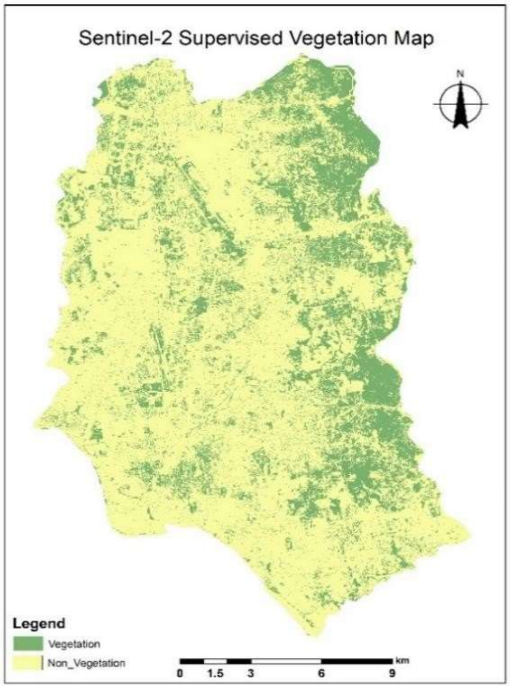


Figure 09: Sentinel-2 Supervised Classification

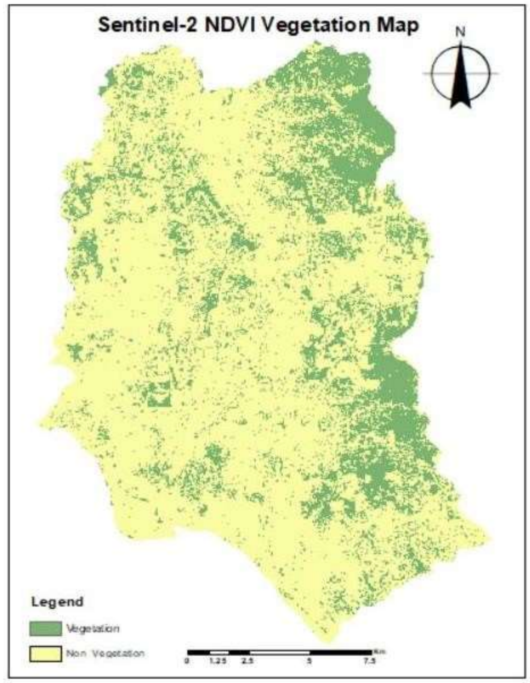


Figure 10: Sentinel-2 NDVI Classification

### 3.2 Accuracy Assessment of the Classified Image:

To evaluate the accuracy of the image data, this study has conducted a confusion matrix operation and union over intersection method. The results indicate that most land use types were classified with a level of accuracy making the study reliable for planning purposes. Table 03 provides a summary of the accuracy assessment for the satellite imagery. Starting with the Sentinel-2 approach it achieved an overall accuracy rate of 92.6% indicating that nearly 93% of the pixels were correctly classified. The IoU value of 0.86 further confirms the agreement, between the predicted and actual land cover classes suggesting that this supervised classification method using data is highly effective in accurately identifying different types of land cover. The Sentinel-2 NDVI technique, which likely incorporates Normalized Difference Vegetation Index also performed well with an accuracy rate of 89.4% and an IoU value of 0.82. This method takes advantage of information related to vegetation health showcasing its capability to distinguish between land cover classes. Moving on to Modis it achieved an accuracy rate of 86.4% with an IoU value of 0.78. Although slightly lower than the Sentinel-2 methods Modis still demonstrates performance in classifying land cover and can be a viable option depending on specific application requirements. In both the NDVI contexts Landsat-8 displayed overall accuracy compared to Sentinel-2 and Modis. Landsat-8 Supervised achieved an accuracy rate of 84.7% with an IoU value of 0.81 while Landsat-8 NDVI had an accuracy rate of 81.2% with an IoU value of 0.76. Despite their accuracies these methods may still be suitable, for applications or regions where other satellite data sources may be limited.

Table 03: Accuracy Assessment for Vegetation Detection

| Category | Overall Accuracy (%) | IoU value |
|---|---|---|
| Sentinel-2 supervised | 92.6 | .86 |
| Sentinel-2 NDVI | 89.4 | .82 |
| Modis | 86.4 | .78 |
| Landsat-8 supervised | 84.7 | .81 |
| Landsat-8 NDVI | 81.2 | .76 |

## 4. CONCLUSION

This study aimed to explore the effectiveness of freely accessible satellite data in mapping land use over extensive areas. The main focus was on highlighting the benefits of utilizing satellite imagery sources and to evaluate sensing-based method for mapping the vegetation coverage in Dhaka city. Google Earth Pro played a vital role in offering top notch images which were crucial for mapping the vegetation zones in the designated monitoring area. The investigation revealed that although manually digitizing data ensures its authenticity, the process is quite time consuming. Therefore, it becomes necessary to strike a balance, between accuracy and efficiency. Among the sensing datasets considered, Sentinel 2 emerged as the preferred choice due to its unmatched high resolution spatial and spectral data. This study performed an evaluation of accuracy by utilizing confusion matrix operations and intersection over Union methods. These techniques were found to be reliable for planning purposes as confirmed by the study. With the maximum IoU of 0.86 and accuracy of 92.6% , Sentinel 2 Supervised Classification demonstrated the accuracy proving its effectiveness in accurately identifying different land cover classes. Moreover, the research indicates that utilizing Sentinel 2 NDVI Classification which offers information regarding both the spectral aspects of vegetation identification in various regions. The effectiveness of Supervised classification heavily depends on collection of accurate samples and ensuring a balanced representation of classes for each classification type. Insufficient sample size can result in degradation in accuracy. In that context, Sentinel-2 NDVI Classification is positioned as another solution with an accuracy of 89.4% which effectively balance between accuracy and efficiency. Without prior knowledge of a vast, intricate, and diverse area, unsupervised classification may yield more precise outcomes than supervised classification. With the aid of a decision support system and the integration of expert knowledge and additional GIS data, the accuracy of the supervised classification can be noticeably enhanced in every instance. Although this method holds great potential, its usefulness is contingent upon the accessibility of dependable ancillary data. Drawing conclusions from the analysis, the study posits that current freely available, moderate-resolution satellite data, particularly from Sentinel-2, holds the potential to achieve accuracy levels exceeding 90% in mapping vegetation coverage across large industrial regions like Dhaka city. The approach utilized in this research can also be applied to wetland delineation, build up area detection which can then be utilized to make decisions regarding urban planning and the implementation of smart cities.

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