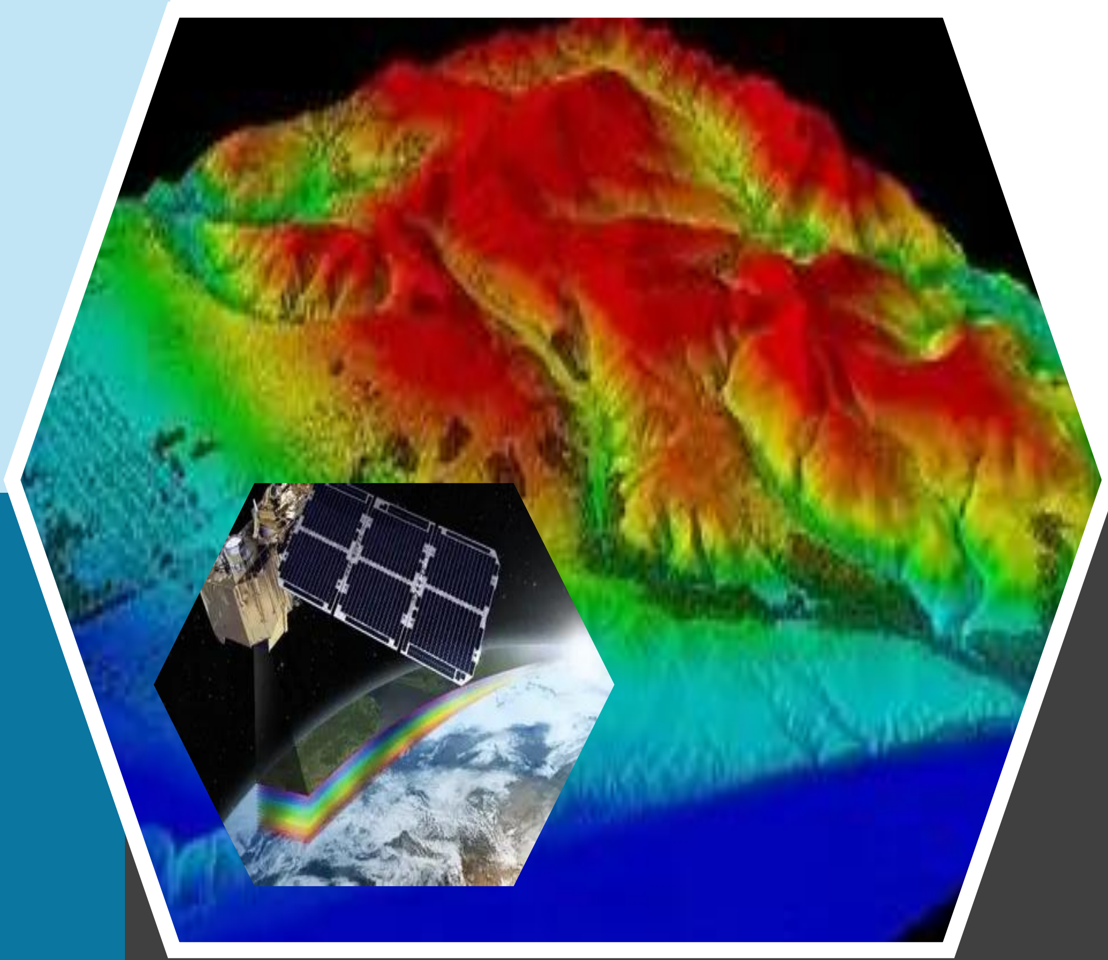
Indian Institute of Technology(Indian School of Mines),Dhanbad



Land Use Land Cover Classification

P3

(Generating Land Use Land Cover Map Using Supervised Classification Techniques)

Submitted By

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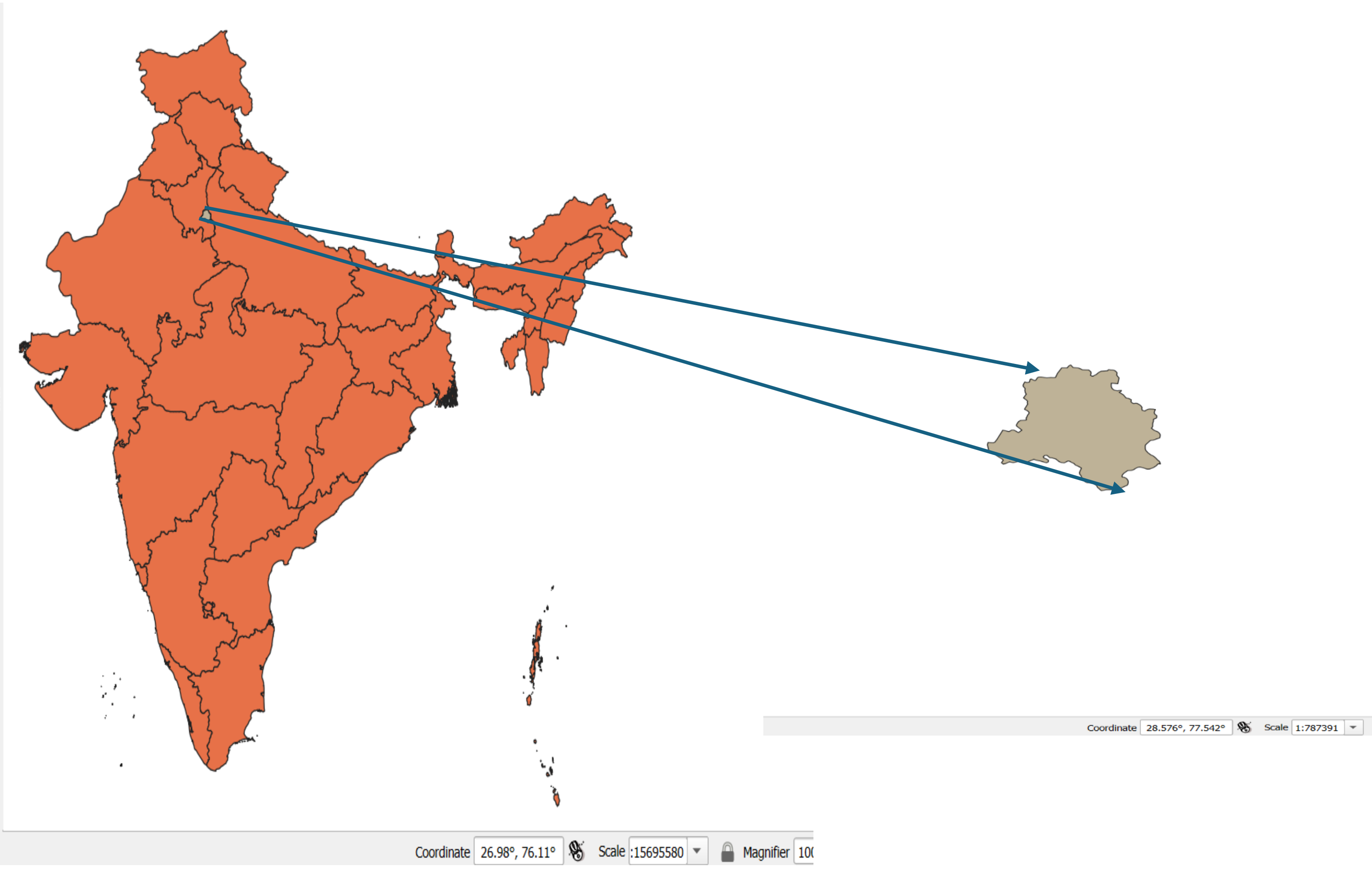
OBJECTIVES

- To classify satellite imagery of the Delhi region into distinct land use/land cover (LULC) categories using supervised classification techniques.
- To generate a final LULC map in both raster and vector formats for versatile analysis and cartographic presentation.
- To calculate the spatial extent (in km^2) and percentage share of each LULC class within the study area.
- To prepare high-quality map layouts and thematic outputs suitable for reporting and decision-making.
- To evaluate the classification accuracy using a confusion matrix, Overall Accuracy (OA), and Kappa coefficient for reliability assessment.

STUDY AREA

- Place – Delhi NCR, India
- Longitude – 28° 36′ 36″
- Latitude - 77° 13′ 48″

Fig.1. Study Map of Delhi (QGIS)



DATA USED

Satellite – Landsat 8-9 OLI/TIRS C2 L1

Source -

Google Earth Engine. (2025). *Google Earth Engine Documentation*. Retrieved from https://earthengine.google.com/

QGIS Development Team. (2025). *QGIS Geographic Information System*. Open Source Geospatial Foundation Project. https://qgis.org/

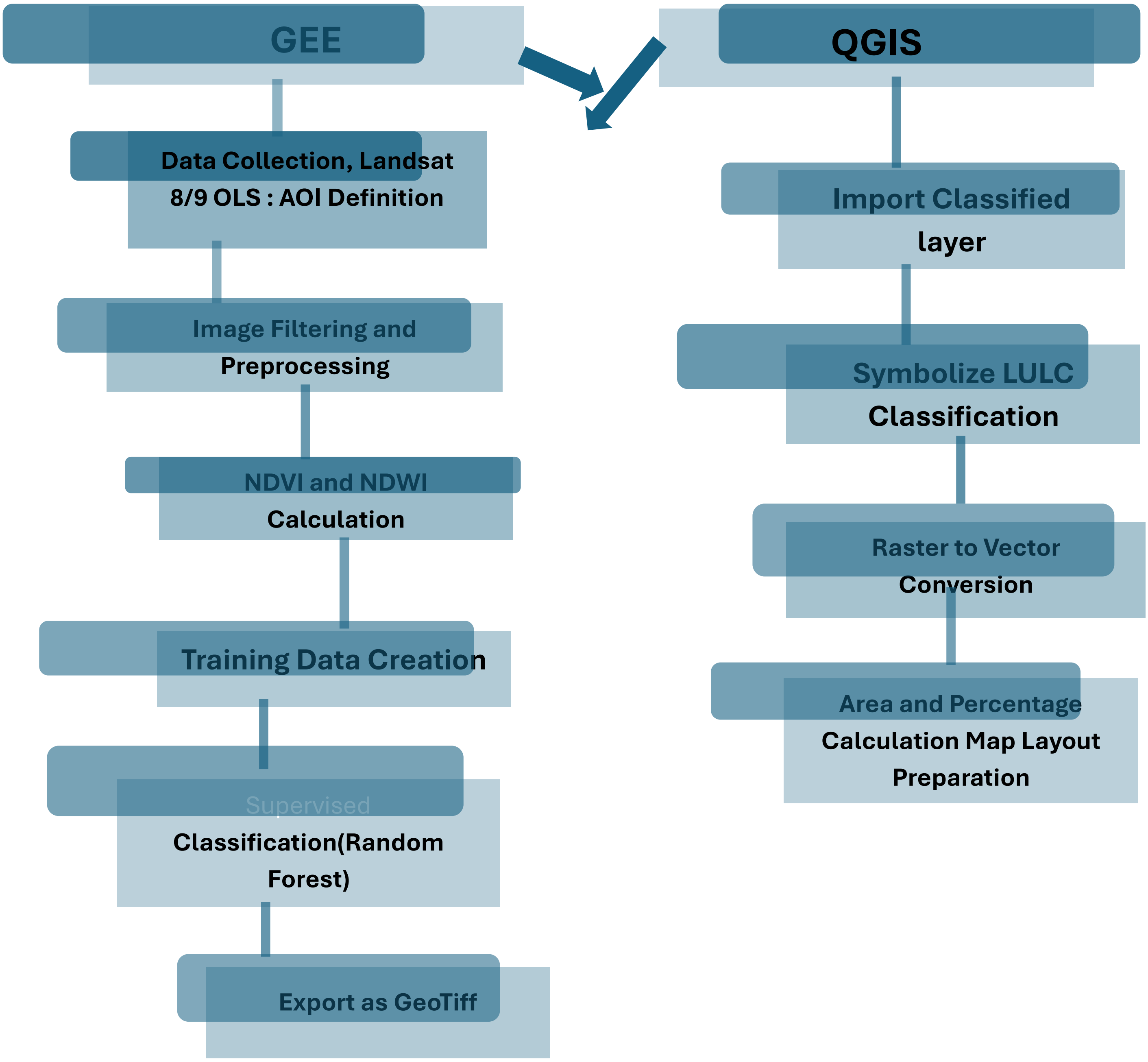
Bands – B2 (Blue), B3 (Green), B4 (Red), and B5 (Near Infrared)

Date Range of Imagery – 01 July 2025 to 31 July 2025

Spatial Resolution – 30 m (OLI Bands)

METHODOLOGY

GEE and QGIS offer reliable, scientific workflows for satellite data analysis.
GEE enables fast cloud-based processing, while QGIS supports detailed visualization and mapping, together aiding in LULC change detection and natural resource conservation.



STEP-1:

The area of interest (AOI) was defined as a 15 km buffer around the point coordinates (77.18° E, 28.63° N) located in Delhi. Landsat 8 and Landsat 9 Collection 2 Level 2 surface reflectance imagery for July 2025 was obtained from the Google Earth Engine (GEE) data catalog. The imagery was filtered by AOI and date range to ensure cloud-free conditions.

```
Imports (2 entries)
  var aoi: Point (77.18, 28.63)
    type: Point
    coordinates: [77.17943275921547,28.62858192731989]
  var imageVisParam: SR_B4, SR_B3 and SR_B2 from 0 to 0.3
```

```
// Define AOI
var aoi = ee.Geometry.Point([77.18, 28.63]).buffer(15000); // 15 km buffer

// Load Landsat 8-9 SR data
var image = ee.ImageCollection("LANDSAT/LC09/C02/T1_L2")
  .merge(ee.ImageCollection("LANDSAT/LC08/C02/T1_L2"))
  .filterBounds(aoi)
  .filterDate('2025-07-01', '2025-07-31')
  .map(function(img) {
    // Apply scale factor for surface reflectance
    var scaled = img.select(['SR_B.']).multiply(0.0000275).add(-0.2);
    return img.addBands(scaled, null, true);
  })
  .median()
  .clip(aoi);

// Visualization (scaled range)
var visParamsTrue = {
  bands: ['SR_B4', 'SR_B3', 'SR_B2'],
  min: 0,
  max: 0.3,
  gamma: 1.4
};

// Display
Map.centerObject(aoi, 10);
Map.addLayer(image, visParamsTrue, "Landsat 8/9 July 2025 True Color");
Map.addLayer(ee.Geometry.Point([77.18, 28.63]), {color: 'red'}, 'Reference Point');
```

Fig.2. GEE Code-1

STEP-2

NDVI (Normalized Difference Vegetation Index) was computed using Landsat near-infrared (NIR) and red bands:

NDVI = (NIR – RED) / (NIR + RED)

NDWI (Normalized Difference Water Index) was computed using green and near-infrared bands:

NDWI = (GREEN-NIR) / (GREEN + NIR)

These indices highlight vegetation and water bodies respectively.

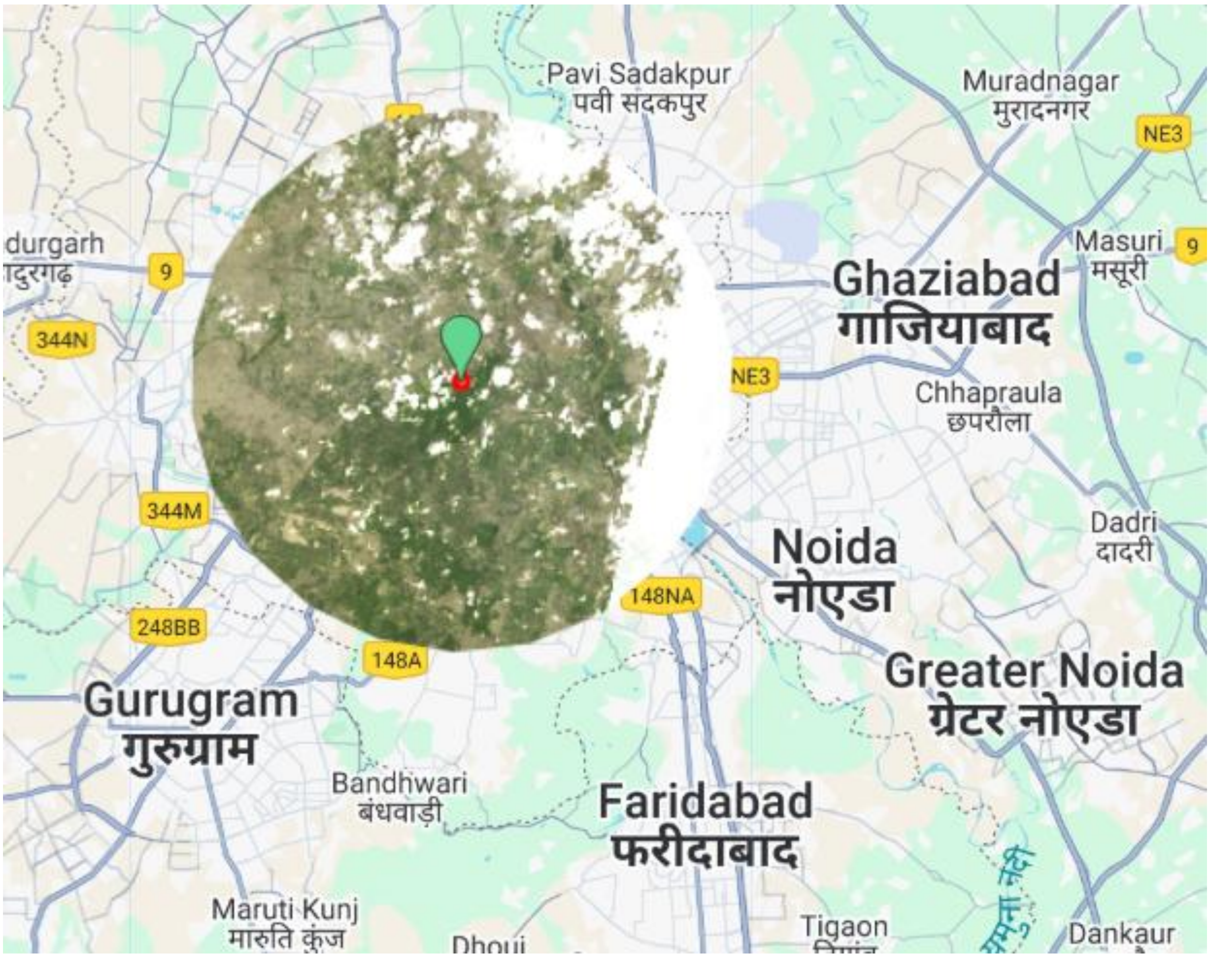


Fig.3.GEE MAP showing AOI Boundary + True-Color Landsat Image

NDVI Stats: Object (4 properties)

NDVI_max: 0.9154957105661774

NDVI_mean: 0.34865495340517016

NDVI_min: -0.045399607867713576

NDVI_stdDev: 0.2033602322994091

NDWI Stats: Object (4 properties)

NDWI_max: 0.1399256289675978

NDWI_mean: -0.32753665556912964

NDWI_min: -0.728126141015047

NDWI_stdDev: 0.17364507465580986

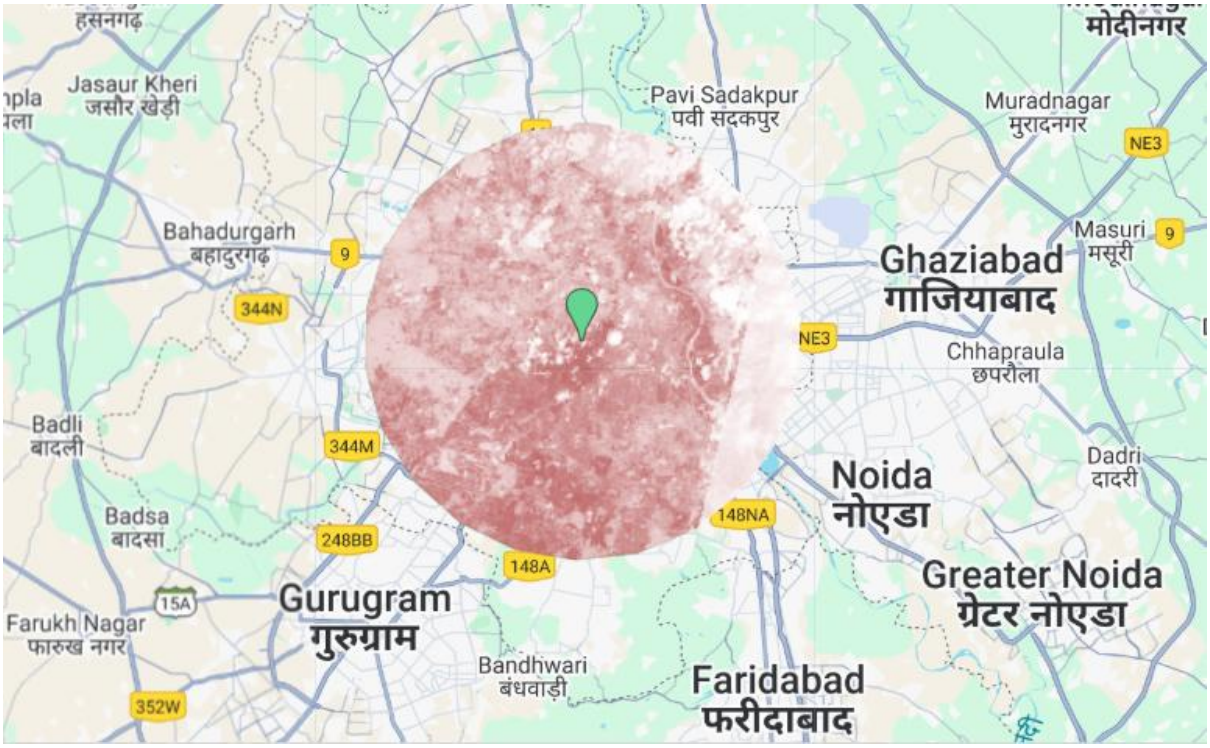


Fig.4. NDWI MAP

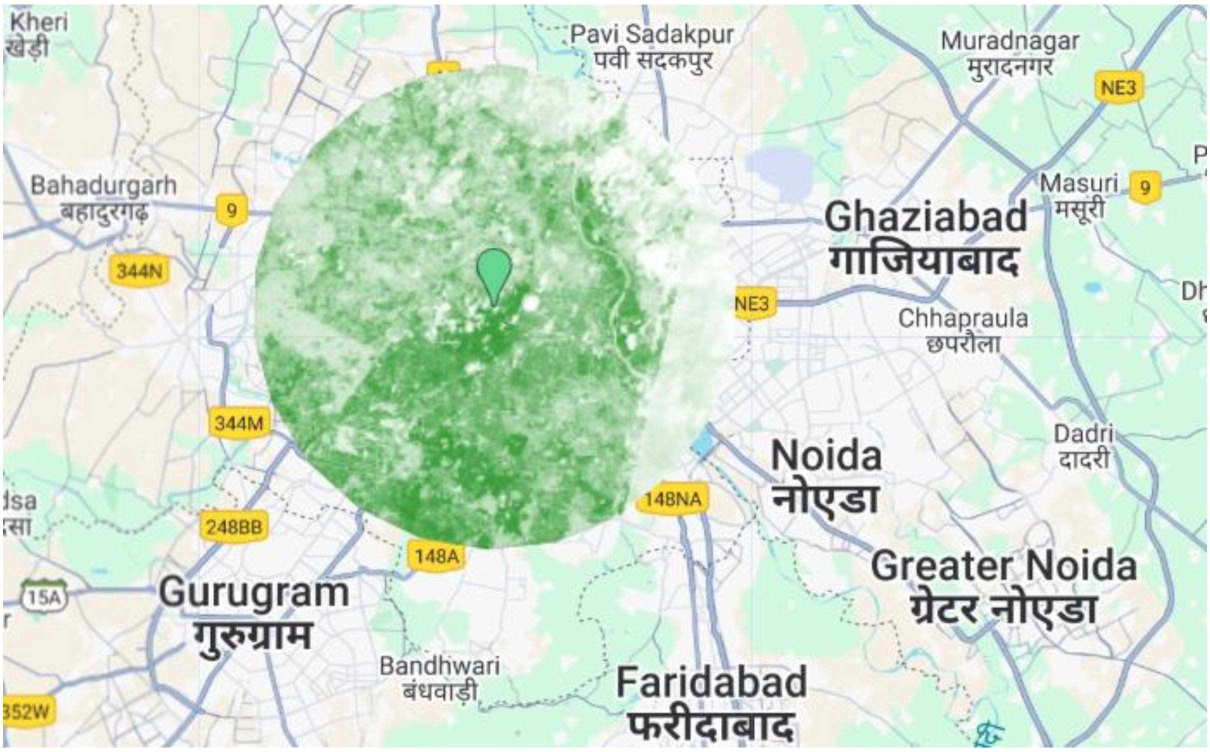


Fig.5. NDVI MAP

STEP-3

Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were computed in Google Earth Engine using the respective Landsat bands. The resulting raster images were exported as GeoTIFF files to Google Drive and imported into QGIS for further analysis.

In QGIS, the Raster Calculator was used to refine index values and perform threshold-based classification. Appropriate color ramps were applied in the Symbology settings to enhance visual interpretation—green shades for vegetation in NDVI, and blue tones for water features in NDWI—facilitating clearer thematic representation.

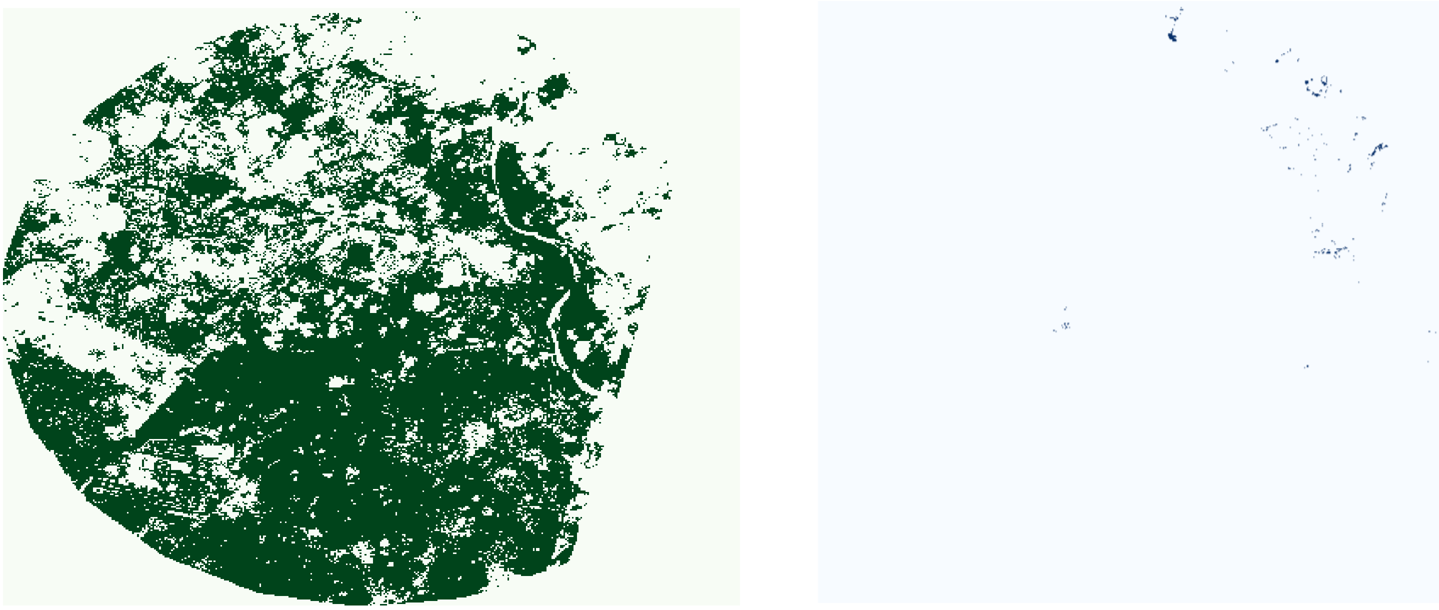


Fig.4. NDVI and NDWI raster Images (0 &1 : light & dark colors)

In NDWI, Dark blue is the detected water bodies and the light background is everything else.

Similarly, Dark green is the detected vegetation and the light is everything else.

STEP-4

The classified LULC raster exported from Google Earth Engine was imported into QGIS for further processing and visualization. The raster was symbolized using the Categorized renderer, assigning distinct colors and labels to each class: 0 – Built-up (light red), 1 – Vegetation (green), 2 – Water (blue), and 3 – Barren land (brown/yellow). The classified raster was then converted into a vector polygon layer using the Polygonize tool to enable precise area calculations. The layer was reprojected to EPSG:3857 to ensure accurate measurements, and an attribute field (Area) was created in the Field Calculator by dividing the polygon area (in m^2) by 1,000,000. Additional fields were generated for Total_Area and Percentage Share of each class. Statistical representation of the land cover distribution was prepared using the Data Plotly plugin, generating both bar charts (class vs. area) and pie charts (percentage share of each class). This allowed for visual interpretation of the spatial extent of each category, facilitating both quantitative and qualitative assessment of the LULC distribution.

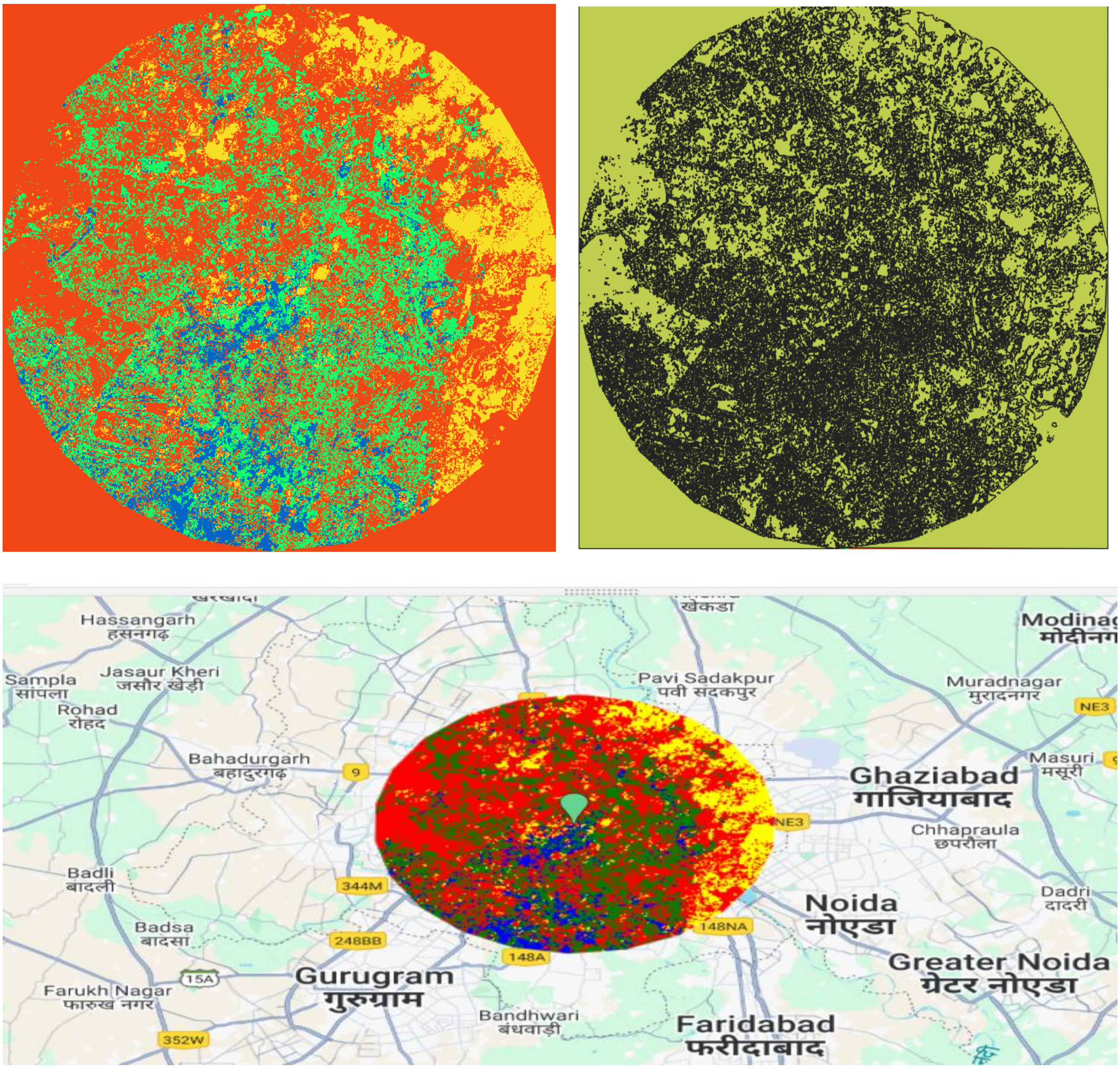
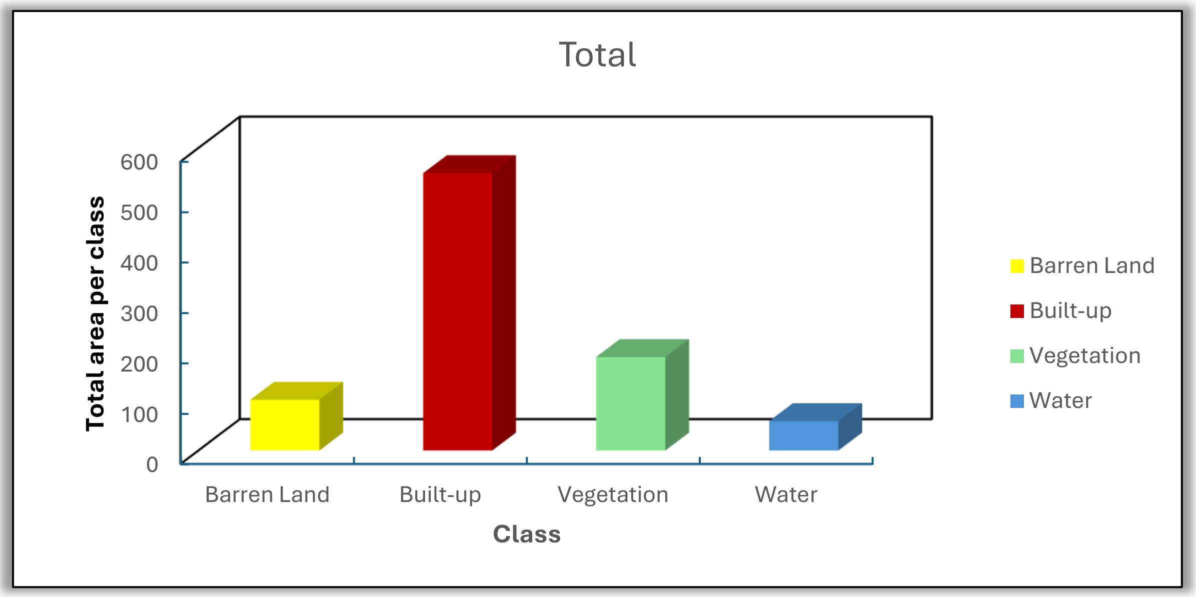


Fig.5. Raster and Vector classified images of Delhi region(QGIS),GEE Classified image.

Class	Sum of area
Barren Land	100.5055824
Built-up	550.1885706
Vegetation	185.4404825
Water	58.35195503
Grand Total	894.4865906



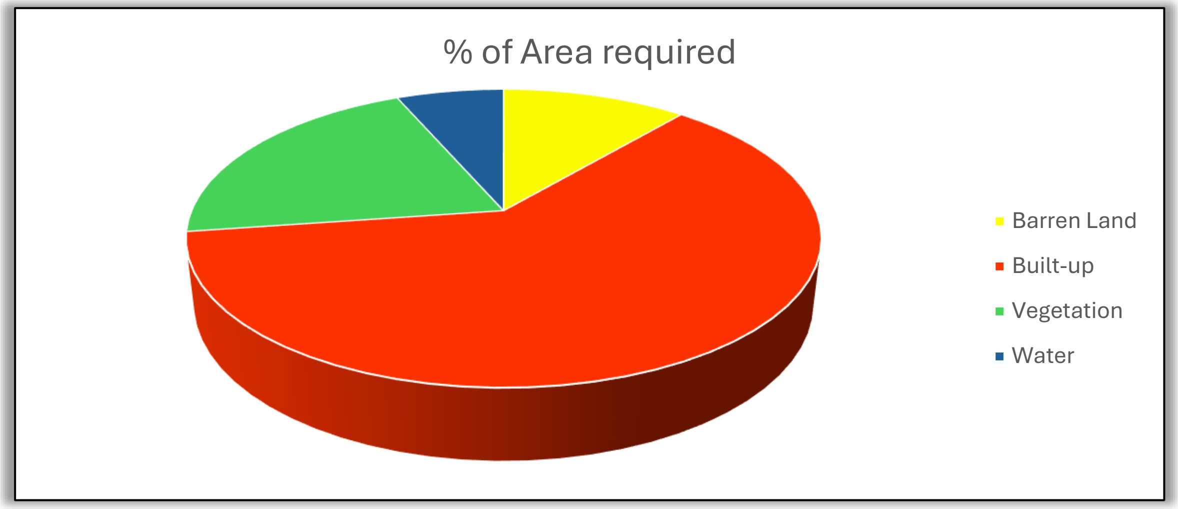


Fig.6. LULC classification versus % area occupied (bar and pie-chart)

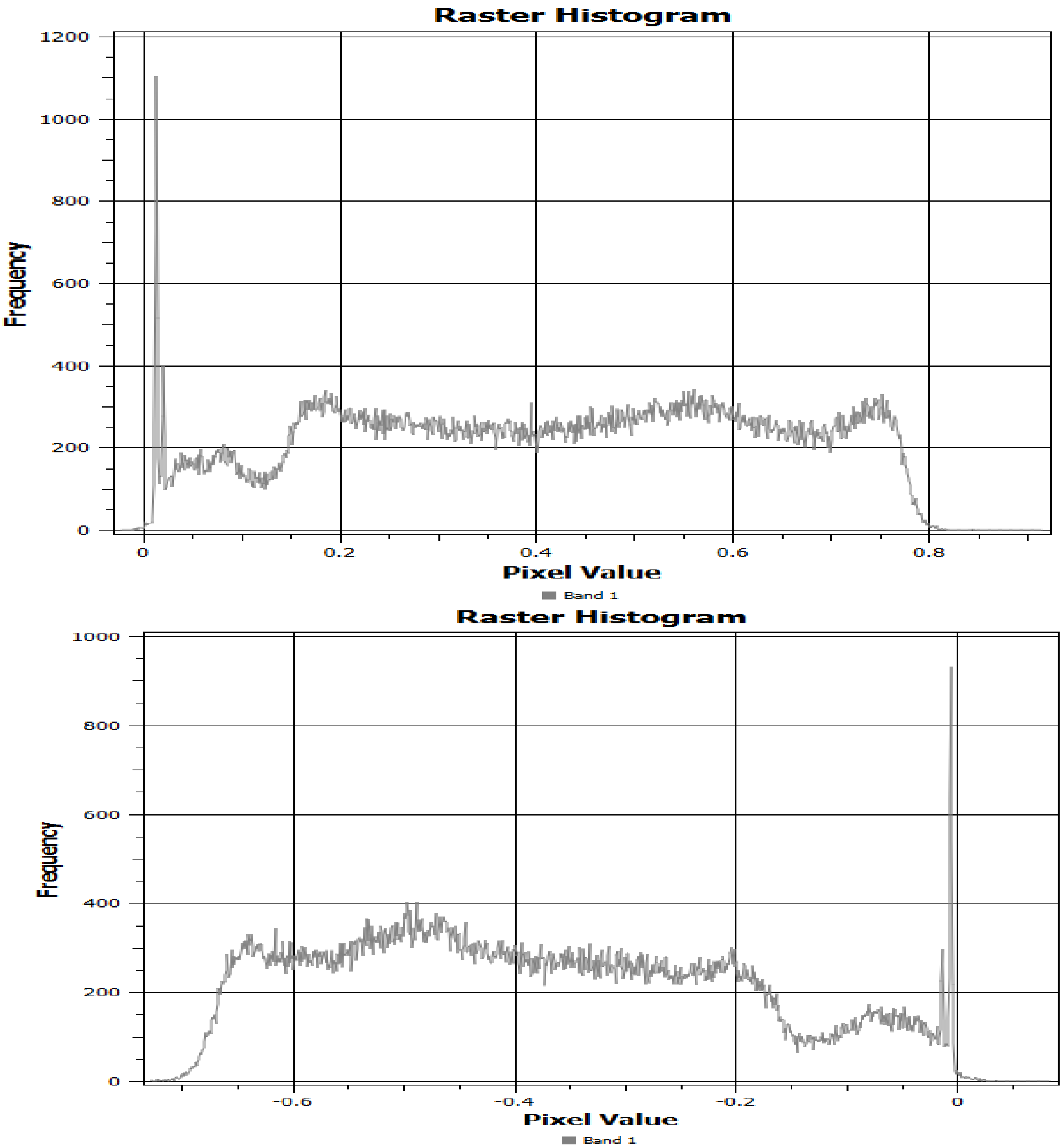


Fig.7. NDVI & NDWI Raster Histograms (QGIS)

RESULTS

- LULC Classified Map: The supervised classification produced four distinct land cover classes for the study area--Barren Land, Built-up, Vegetation, and Water.
- Area Statistics (sq. km):
  Barren Land: 100.51
  Built Up:550.19
  Vegetation:185.44
  Water:58.35
  Total Area:894.49
- The NDVI values ranged from -0.045 to 0.915, with a mean of 0.349 indicating overall healthy vegetation cover.
- NDWI values ranged from -0.728 to 0.140, with a mean of -0.328 suggesting limited surface water presence in the area.
- Map Outputs**:** The classification outputs and layout maps were exported and integrated into the methodology section, including class legends and visual interpretation.

CONCLUSION

The supervised classification successfully mapped the major land cover categories in the study area, with the largest portion being Built-up land (over 61% of the total area), followed by Vegetation, Barren Land, and Water bodies. This spatial distribution highlights the dominance of urban development in the region.

Supervised classification is an effective method for LULC analysis when accurate and representative training data are used. In this study, the method was able to clearly differentiate between the four chosen land cover types. While this approach is efficient in both QGIS and Google Earth Engine, mixed pixels and spectrally similar classes remain potential sources of error. Combining classification outputs with ground-truth validation and post-classification refinement can further enhance accuracy and reliability.

GEE complete Source Code:
https://code.earthengine.google.com/44ee0c3d91ad0b37c8f20031c7f7210c?noload=1