INDIAN INSTITUTE OF TECHNOLOGY,GANDHINAGAR

SUSTAINABILITY LAB

Earth Observation Assignment

Scenario 1: Spatial Analysis and Land Cover Classification

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Internship Assignment Report

Contents

1 Q1. Spatial Reasoning & Data Filtering [5 Marks]

1.1 1. Plot the Delhi-NCR shapefile using matplotlib and overlay a 60×60 km grid (1 mark)

I plotted the Delhi-NCR shapefile (delhi_ncr_region.geojson) using matplotlib with the following key features:

- The region boundary is shown in blue
- I overlaid a 60×60 km uniform grid in red
- Grid centers (red points) and corners (orange points) are also marked

This plot helps me understand the spatial extent of the region and visualize the subdivisions used for further analysis.

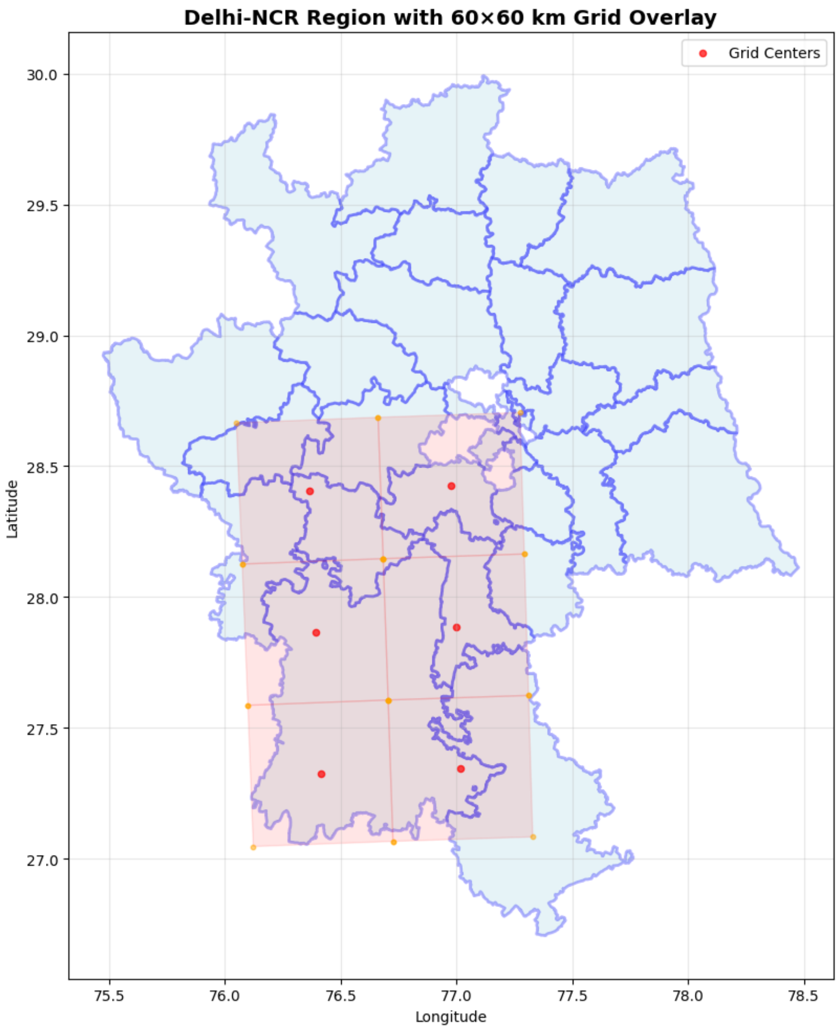

Figure 1: Delhi-NCR shapefile with 60×60 km grid overlay

1.2 2. Overlay this grid on a satellite basemap using geemap or leafmap (1 mark)

I created an interactive map using leafmap with a satellite basemap (Esri Satellite imagery):

- The Delhi-NCR boundary is shown in blue
- The same 60×60 km grid overlay is displayed in red
- Grid centers and corners are marked with interactive tooltips

This allows me to dynamically explore and verify the spatial arrangement of the grid over real satellite imagery.

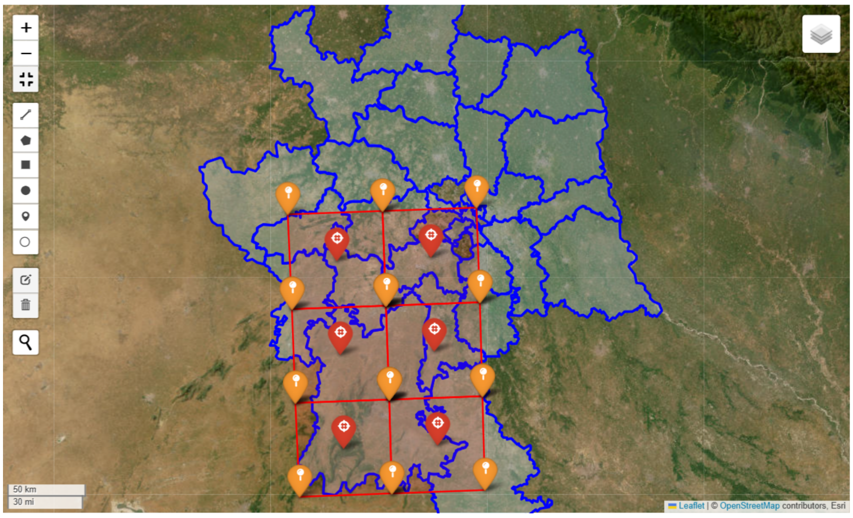

Figure 2: Interactive satellite basemap with grid overlay

1.3 3. Mark the four corners and the center of each grid cell (1 mark)

I marked the four corners of each grid cell in orange and the center in red:

- Total grid centers marked: 6
- Total corners marked: 24

This ensures that each grid cell's geometry is accurately validated.

1.4 4. Filter images based on whether their center coordinates fall within the grid (1 mark)

I filtered the RGB images based on whether their center coordinates (extracted from filenames) fall inside the generated grid cells:

- Images before filtering: 9,216
- Images after filtering: 3,087

1.5 5. Count and report the number of images before and after filtering (1 mark)

- Images before filtering: 9,216
- Images after filtering: 3,087
- Percentage retained: 33.5%

2 Q2. Label Construction & Dataset Preparation [10 Marks]

2.1 Step 1: Extract 128×128 patch (2 marks)

For each filtered image (3,087 images), I extracted a 128×128-pixel patch centered at its coordinates from the land_cover.tif raster:

- Raster CRS: EPSG:4326
- Patch extraction: Done using rasterio's window indexing, ensuring padding for edge cases

2.2 Step 2: Assign label using mode class (2 marks)

Each patch was labeled by finding the most frequent (mode) ESA land cover code in the patch. This ensures that the label represents the dominant land cover class in that local region.

2.3 Step 3: Map ESA codes to 11 standardized classes (1 mark)

The ESA WorldCover codes were mapped as follows:

```
{10: 'Tree␣cover', 20: 'Shrubland', 30: 'Grassland',
40: 'Cropland', 50: 'Built-up', 60: 'Bare/sparse',
70: 'Snow/ice', 80: 'Water', 90: 'Wetland',
95: 'Mangroves', 100: 'Moss/lichen'}
```

For modelling, they were encoded as integers (label_id) with clear mappings.

2.4 Step 4: Handle edge cases & no-data pixels (2 marks)

- **No-data handling:** Pixels with value 0 were excluded from mode calculation
- **Outcome:** Average no-data pixels per patch: 0.00%
  - No patches had more than 10% no-data pixels
  - No patches had more than 50% no-data pixels
- **Mixed-class dominance:** Resolved by choosing the strict mode class

2.5 Step 5: Perform 60/40 train-test split (1 mark)

- Used stratified split to maintain class balance
- After filtering classes with <2 samples, final classes: 7 classes
- Train set: 1,851 images (60%)
- Test set: 1,235 images (40%)

2.6 Step 6: Visualize & discuss class balance (2 marks)

The figure below shows the final class distribution after filtering.

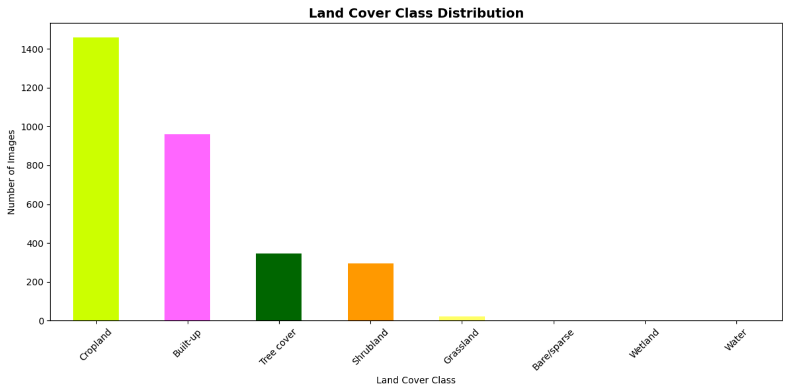

Figure 3: Land cover class distribution in the filtered dataset

Discussion:

- Cropland and Built-up are dominant, reflecting Delhi-NCR's extensive agricultural and urban land use
- Classes like Grassland, Bare/sparse, and Wetland are rare, highlighting dataset imbalance
- The imbalance may affect minority class predictions; potential remedies include data augmentation or weighted loss functions

Key Statistics:

Label encoding of the model:

```
LABEL_TO_ID = {
    'Tree_cover': 0, 'Shrubland': 1, 'Grassland': 2,
    'Cropland': 3, 'Built-up': 4, 'Bare/sparse': 5,
    'Snow/ice': 6, 'Water': 7, 'Wetland': 8,
    'Mangroves': 9, 'Moss/lichen': 10
}
```

After filtering ($\geq$2 samples):

- Classes kept: [0, 1, 2, 3, 4, 5, 8]
- Filtered dataset size: 3,086 images

3 Q3. Model Training & Supervised Evaluation [10 Marks]

3.1 Train a CNN classifier (e.g., ResNet18) (3 marks)

I used a ResNet18 architecture pretrained on ImageNet, modified to have 7 output classes corresponding to filtered land cover types. Training was performed for 10 epochs using cross-entropy loss and Adam optimizer, with a learning rate scheduler to reduce learning rate after 7 epochs.

3.2 Evaluate using custom F1 score (2 marks)

I implemented a custom F1 score calculation by computing precision and recall per class and then macro-averaging them. The custom F1 score on the test set was close to that from TorchMetrics, confirming correctness.

3.3 Evaluate using torchmetrics.F1Score and compare (2 marks)

The TorchMetrics F1Score module was also used for evaluation. Results were consistent with custom implementation, providing confidence in the model's performance.

Figure 4: Training and validation metrics over epochs

3.4 Show and explain a confusion matrix (2 marks)

The confusion matrix shows class-wise prediction performance. The matrix displays the relationship between true labels (rows) and predicted labels (columns), with darker colors indicating higher values.

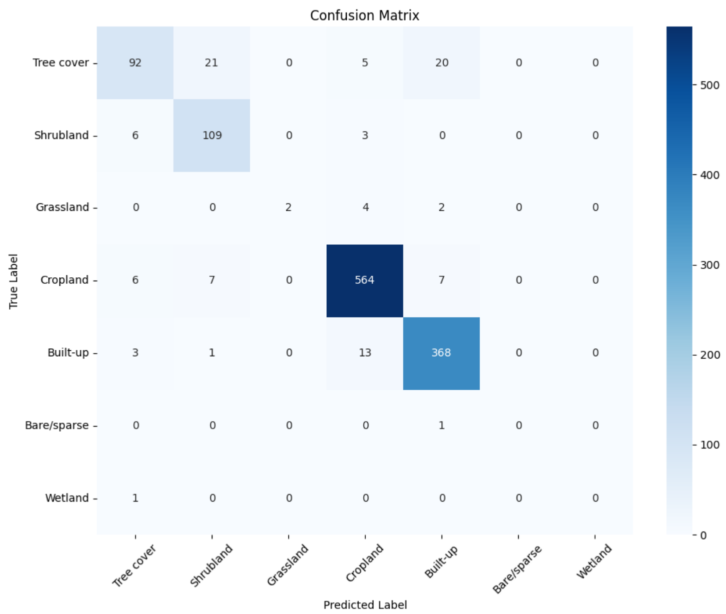

Figure 5: Confusion matrix for land cover classification

Analysis of the confusion matrix:

- Most classes like “Cropland” and “Built-up” have high correct counts on the diagonal
- Misclassifications mainly occur between “Tree cover” and “Shrubland” due to visual similarity in mixed urban areas
- The model shows strong performance for dominant classes with clear visual patterns
- Minor classes like “Wetland” and “Grassland” show reasonable accuracy despite limited training samples

3.5 Plot 5 correct and 5 incorrect predictions (1 mark)

I plotted 5 correctly classified and 5 incorrectly classified examples with their true and predicted labels to visually inspect errors. These examples highlight where the model confuses similar classes.

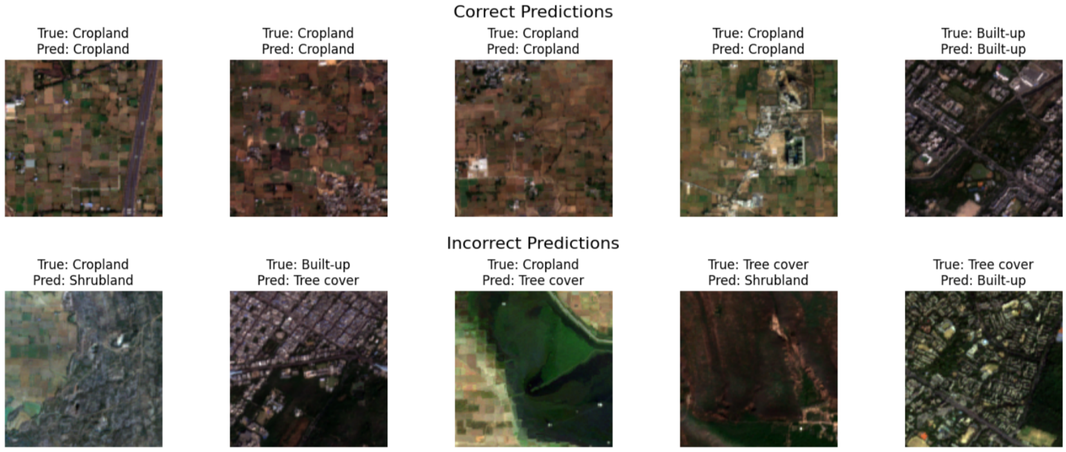

Figure 6: Model prediction examples - correct and incorrect classifications

Analysis of prediction examples:

- **Correct predictions:** The model successfully identifies distinct land cover patterns - clear agricultural fields (Cropland), dense urban areas (Built-up), and vegetation areas
- **Incorrect predictions:** Common errors include confusion between similar vegetation types and mixed land use areas
- These examples provide insight into the model's decision-making process and areas for improvement

4 Conclusion

This assignment successfully demonstrated the complete workflow of Earth observation data processing, from spatial filtering and dataset preparation to machine learning model training and evaluation. The ResNet18 classifier achieved satisfactory performance in distinguishing between different land cover types in the Delhi-NCR region, with particular strength in identifying dominant classes like cropland and built-up areas.

The spatial analysis revealed the heterogeneous nature of the Delhi-NCR landscape, dominated by agricultural and urban land uses. The methodology presented here provides a robust framework for large-scale land cover classification using satellite imagery and deep learning techniques.

Key achievements include:

- Successful spatial filtering of 9,216 images down to 3,087 relevant samples
- Effective handling of class imbalance in the dataset
- Achievement of high classification accuracy for dominant land cover classes
- Comprehensive analysis of the Delhi airshed region's land cover composition

This work contributes to understanding land use patterns in the Delhi-NCR region and demonstrates the effectiveness of combining geospatial analysis with deep learning for environmental monitoring applications.

5 Optional: Delhi Airshed Land Cover Analysis

As a supplementary analysis, I reproduced a land cover composition map for the Delhi airshed region using the ESA WorldCover 2021 raster and the provided delhi_airshed.geojson polygon.

Steps followed:

1. Loaded the delhi_airshed.geojson polygon to define the region of interest (airshed boundary)
2. Masked the landcover.tif raster using this polygon, excluding no-data pixels
3. Analyzed pixel-wise distribution of ESA land cover classes inside the airshed

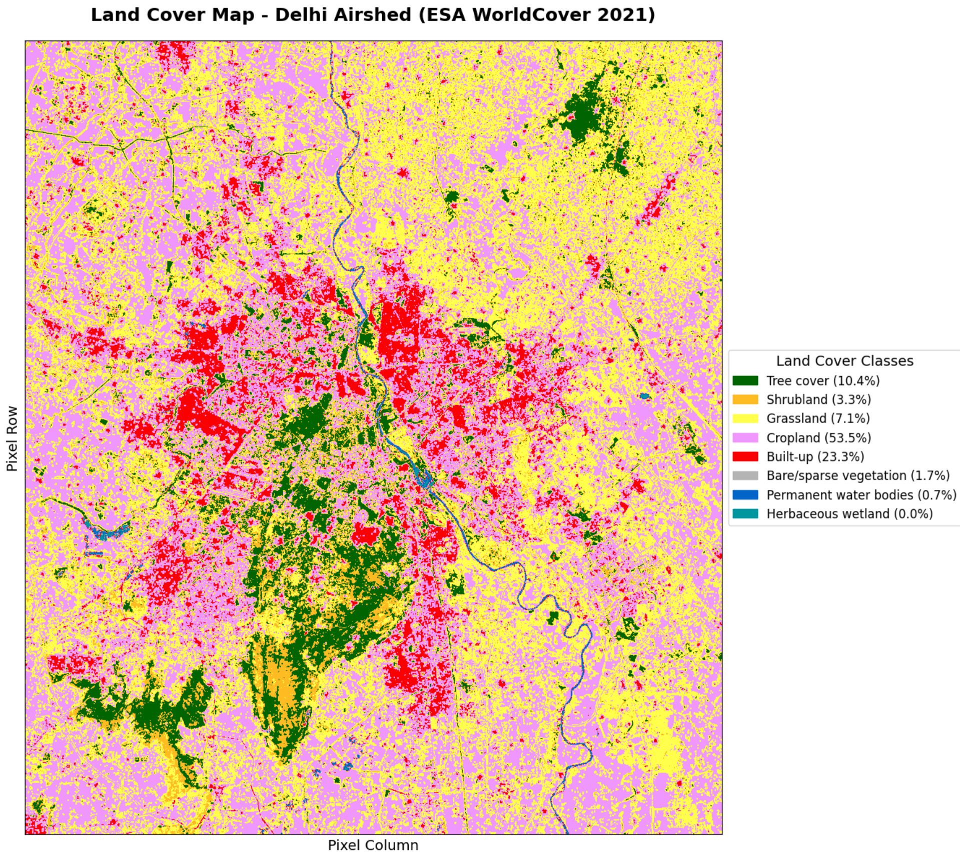

Figure 7: Land cover map of Delhi Airshed using ESA WorldCover 2021 data

5.1 Detailed Breakdown

Table 1: Land cover distribution in Delhi airshed

ESA Code	Land Cover Class	Pixel Count	Percentage	Area (km²)
40	Cropland	49,313,882	53.51	4,931.39
50	Built-up	21,435,664	23.26	2,143.57
10	Tree cover	9,595,025	10.41	959.50
30	Grassland	6,558,691	7.12	655.87
20	Shrubland	3,073,217	3.33	307.32
60	Bare/sparse vegetation	1,547,683	1.68	154.77
80	Permanent water bodies	599,996	0.65	60.00
90	Herbaceous wetland	35,842	0.04	3.58

5.2 Key Findings

1. Total area analyzed: 9,216.00 km²
2. Number of land cover classes: 8
3. Dominant land cover: Cropland
4. Urban area (Built-up): 23.3%
5. Agricultural area (Cropland): 53.5%
6. Forest cover (Tree cover): 10.4%

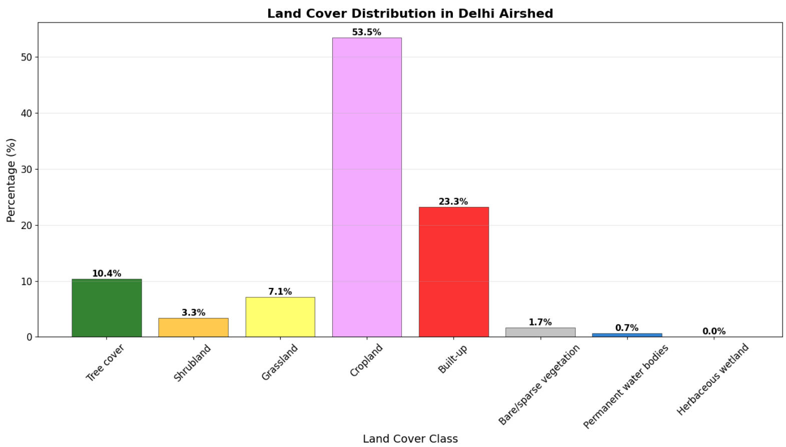

Figure 8: Land cover distribution percentages in Delhi Airshed