# **Earth Observation**

# Land Cover Classification over Delhi-NCR using Remote Sensing and Deep Learning Project Summary

This project applies Earth Observation and Deep Learning techniques to classify land cover types over the Delhi-NCR region using high-resolution RGB satellite images. The pipeline involves spatial filtering using vector data, patch extraction from ESA WorldCover 2021 raster data, and classification using a ResNet18-based Convolutional Neural Network.

#### **Data Sources**

- ESA WorldCover 2021: 10m resolution land cover raster
- GeoJSON Boundaries: delhi\_ncr\_region.geojson and delhi\_airshed.geojson
- RGB Image Patches: 128×128 pixel PNGs named using lat/lon center coordinates

#### Workflow

#### 1. Spatial Preprocessing

- Loaded the Delhi-NCR region boundary and created a uniform 60x60 km grid over the region.
- Overlayed the grid on the boundary to filter out satellite patches based on whether their centers fall inside a grid cell.

#### 2. Label Generation

- For each image, a 128x128 pixel patch was extracted from the ESA WorldCover raster centered on the image's location.
- The most frequent land cover class (mode) within the patch was assigned as the image label.
- Mapped ESA class codes to human-readable names (e.g., Built-up, Cropland, Tree Cover).

#### 3. Dataset Preparation

- Stratified 60/40 train-test split was applied.
- Class imbalance was observed with Cropland and Built-up dominating.

### 4. Model Training

- A ResNet18 model was fine-tuned using PyTorch.
- Achieved ~93% training accuracy over 5 epochs.

#### 5. Evaluation

- Test accuracy: ~64%
- Macro F1 Score: ~0.22
- Performance was skewed toward dominant classes (Cropland, Built-up).
- Confusion matrix and class-wise F1 scores were plotted.
- Correct and incorrect predictions were visualized.

## **Key Results**

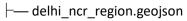
Train Accuracy: 92.9%
Test Accuracy: 64.0%
Macro F1 Score: 0.22

#### **Future Improvements**

- Incorporate NDVI or multispectral data for better land cover discrimination.
- Address class imbalance via data augmentation or synthetic oversampling.
- Explore temporal changes with multi-year imagery.

# **Repository Structure**





├— delhi\_airshed.geojson

— worldcover\_bbox\_delhi\_ncr\_2021.tif

├— rgb/ # RGB image tiles (128x128 PNGs)

— train\_eval.ipynb # Full notebook pipeline