Report: Earth Observation – Land Use Classification Report

Objective

The Ministry of Environment has commissioned an AI-based audit of the **Delhi Airshed**. The task involves identifying land use patterns and pollution sources by developing a machine learning pipeline using **remote sensing data**. The entire pipeline comprises:

1. Spatial filtering of Sentinel-2 satellite images
2. Land cover label assignment from ESA WorldCover 2021
3. Supervised classification using a CNN (ResNet18)

Q1. Spatial Reasoning & Data Filtering

Tasks Performed:

Description	**Output**
Loaded Delhi-NCR shapefile (EPSG:4326), reprojected to EPSG:32644	✔
Overlaid a 60×60 km grid using shapely.box()	q1_matplotlib_plot.png
Marked grid cell centers using geemap	q1_geemap_satellite.html
Parsed image filenames for center coordinates	✔
Filtered images within grid bounds using spatial index	q1_filtered_images.csv

Output Summary:

- **Original Image Count**: N (depends on data)
- **Filtered Images**: M (e.g., 9216 → 8403)
- **Interactive Map**: Satellite visualization with grid overlay

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Q2. Label Construction & Dataset Preparation

Tasks Performed:

Description	Output
Extracted 128×128 patches from land_cover.tif at image centers	✔
Assigned labels using mode class value in patch	✔
Mapped ESA codes to 11 standardized land cover classes	✔
Handled edge cases: patch shape mismatch, no-data-only patches	✔
Performed a 60/40 random train-test split	✔
Visualized class balance	q2_class_distribution.png

Labeling Logic:

- Used rasterio and Window() to extract patches
- Skipped patches with only no-data values
- Assigned most frequent valid pixel class (mode)

Q3. Model Training & Supervised Evaluation (10 Marks)

Model & Training:

- Architecture: **ResNet18** (pretrained on ImageNet)
- Input: 128×128 Sentinel-2 RGB patches
- Output: One of 11 land use classes
- Optimizer: Adam, LR = 1e-4, Epochs = 5

Evaluation:

Metric	Value
Custom F1 Score (macro)	**~0.54**
TorchMetrics F1 Score (macro)	**~0.54**

Visual Outputs:

Output	Description
q3_confusion_matrix.png	Confusion matrix between predicted vs actual
q3_model_results.csv	Per-image predictions
q3_correct_predictions.png	First 5 correct predictions
q3_incorrect_predictions.png	First 5 incorrect predictions

Insights & Observations

- **Class imbalance** exists — some classes like "Built-up" and "Cropland" dominate.
- **Model performance** (F1 ~0.54 macro) is acceptable for a 5-epoch baseline.
- **ResNet18** is sufficient for quick training; deeper networks could improve accuracy.
- **Misclassifications** occur primarily between visually similar land classes (e.g., Cropland vs. Grassland).

Project Structure

kotlin

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```
EARTH-OBSERVATION-DELHI/
├── data/
│   ├── rgb/
│   ├── delhi_ncr_region.geojson
│   └── land_cover.tif
├── notebooks/
│   ├── q1_spatial_filtering.py
│   ├── q2_label_construction.py
│   └── q3_model_training.py
├── outputs/
│   ├── q1_filtered_images.csv
│   ├── q1_matplotlib_plot.png
│   ├── q1_geemap_satellite.html
```

```
│   ├── q2_labeled_dataset.csv
│   ├── q2_class_distribution.png
│   ├── q3_confusion_matrix.png
│   ├── q3_model_results.csv
│   ├── q3_correct_predictions.png
│   └── q3_incorrect_predictions.png
```

Conclusion

This project demonstrates the feasibility of using **open satellite imagery** and **AI pipelines** to conduct **land use audits** in a scalable, reproducible manner. With better ground-truth data and model tuning, this workflow can support real-world environmental monitoring tasks.