TerraScan: AI Land Use Classifier from Satellite Imagery

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1. Introduction

1.1 Problem Definition

With our ecosystem and environment changing rapidly due to many factors such as global warming, urbanization, and deforestation, it is increasingly important to understand how land is being used and how it changes over time. Today, land use and land cover maps are often created through manual inspection or infrequent surveys, which are slow, expensive, and hard to update at scale. As a result, decision-makers may be working with outdated or incomplete information about what is actually happening on the ground.

Accurate and up-to-date land use information is critical for multiple stakeholders:

- Environmental agencies need it to monitor deforestation, loss of green space, and habitat change.
- City planners and governments rely on it to plan infrastructure, zoning, and sustainable urban growth.
- Businesses and utilities use it to assess risk (agricultural expansion, flood-prone areas, etc.) and plan investments.
- Policymakers and researchers depend on data to model climate impacts and evaluate environmental policies.

By automating land use classification from satellite imagery with deep learning, we can help provide faster, more scalable, and more consistent insights into how land is being used.

1.2 Objectives

- Goal 1: Develop a deep learning model that classifies satellite images into meaningful land use/cover categories using the EuroSAT dataset.
- Goal 2: Evaluate the model's performance and analyze which land use types are easier or harder to classify, using both quantitative metrics and qualitative examples.

2. Background & Related Work

2.1 Related Work / Existing Solutions

Remote sensing and land use/cover (LULC) mapping have traditionally relied on manual photo-interpretation or classical machine learning methods applied to satellite imagery. Analysts often use tools like GIS software to visually inspect satellite images and label regions as agricultural, urban, forest, or water. While accurate at small scales, these approaches are time-consuming, expensive, and difficult to scale to large geographic areas or frequent updates.

With the increasing availability of satellite data from platforms like Sentinel-2 and Landsat, researchers have explored automated classification methods such as support vector machines (SVMs), random forests, and k-means clustering on hand-crafted features (e.g., spectral indices like NDVI). These methods improved automation but still require careful feature engineering and often struggle to capture complex spatial patterns.

2.2 Motivation for Deep Learning

A deep learning approach is appropriate for this problem because land use patterns in satellite imagery are inherently visual and spatial. Different classes (such as residential areas, forests, crops, and water bodies) have distinct textures, shapes, and color distributions that are not always easily captured with simple statistical features. For our approach, we chose to use a convolutional neural network (CNN), which is designed to learn hierarchical features from images, making it ideal for our use.

By fine-tuning ResNet50 on EuroSAT, TerraScan obtains a model that can map satellite tiles to 10 land use classes. The model's output probabilities for vegetation-related classes are then used as a vegetation risk component in the wildfire score. This shows a practical way to integrate deep learning-based land use classification with traditional fire risk features.

3. Data

3.1 Datasets

EuroSAT (RGB)

EuroSAT is a land use/cover dataset derived from Sentinel-2 satellite imagery. It consists of small image patches (tiles) representing different land use categories such as agricultural fields, forests, urban areas, and water bodies. In this project, we use the RGB version of EuroSAT, where each image is a 64x64 pixel patch with three color channels (red, green, blue).

EuroSAT contains 10 classes, which include:

- Annual Crop
- Forest
- Herbaceous Vegetation
- Highway
- Industrial
- Pasture
- Permanent Crop
- Residential
- River

- Sea/Lake

Other Data Sources:

In addition to satellite imagery, TerraScan uses current weather data from the Open-Meteo API for a specific geographic location (lat 34.1189, long -118.3004 in our prototype). From the hourly forecast endpoint, we retrieve:

- Temperature
- Relative Humidity
- Wind Speed
- Soil Moisture

The data is then loaded into a pandas DataFrame, and the most recent hour is used as the current weather condition. These weather features are then normalized and combined into a weather risk score, which is blended with the vegetation risk score from the EuroSAT CNN. The final output of TerraScan is a wildfire risk score from 0 to 100, where higher values indicate higher estimated wildfire risk based on both land use and current weather conditions.

3.2 Preprocessing

Before training, each image from the dataset is preprocessed to make it compatible with the ResNet50 backbone and to improve training efficiency:

Resizing

All images are resized from their original 64x64 resolution to 224x224 pixels to match the default input size of ResNet50.

Normalization

We apply the preprocess input function from the keras library, which scales pixel values and centers them according to the statistics that were used for the original ImageNet training. This helps the pretrained weights transfer better for our task.

Data pipeline

Using the TensorFlow tf.data API, we did the following:

- Mapped the preprocessing function over the training and test datasets
- Shuffle the training data with a buffer size of 1000
- Batch examples into batches of 32

This pipeline ensures that the EuroSat tiles are in the correct format and that training runs efficiently.

4. Methodology

4.1 System Overview

TerraScan combines satellite imagery–based land use classification with current weather data to estimate a simple wildfire risk score. First, a EuroSAT RGB tile is preprocessed and passed through a ResNet50-based convolutional neural network to predict one of ten land use classes. Then the predicted probabilities for vegetation-related classes are used to estimate how flammable the area is. At the same time, TerraScan retrieves current weather conditions for a fixed geographic location from the Open-Meteo API. Finally, the vegetation signal and weather signal are combined into a single wildfire risk score on a 0–100 scale.

4.2 Model Architecture

For land use classification, TerraScan uses a convolutional neural network based on ResNet50 with transfer learning. We start from a ResNet50 model pretrained on ImageNet, with an input size of 224x224x3 and the original classification head removed. The base of REsNet50 uses a frozen feature extractor, so only the newly added layers are trained. On top of the base, we add a global pooling layer and a final Dense layer with 10 units and softmax activation to output class probabilities. This architecture allows us to reuse powerful features learned from large-scale natural images while keeping the training manageable.

4.3 Training Setup

We train the TerraScan land use classifier using the following setup:

- **Data Split**
    - EuroSAT is split into a training set and a test set using the TensorFlow Datasets split for training and testing. We did an 80/20 split for training and evaluation. However, we used the test set as both the validation set during training and reporting for final accuracy, so this would need to be changed in a fully fledged system for better results.
- **Preprocessing and batching**
    - Images are resized from 64x64 to 224x224 pixels and preprocessed with the ResNet50 preprocess_input function.
    - We use the tf.data API to map preprocessing, shuffle the training set, batch the examples, and prefetch the batches.
- **Optimization**
    - Loss function: sparse categorical cross-entropy
    - Optimizer: Adam
    - Metrics: accuracy
- **Training configuration**

- Number of epochs: 10
- Hardware: Training in Google Colab with T4 GPU

4.4 Wildfire Risk Scoring

To connect the land use model to wildfire risk, we define a simple scoring function that combines vegetation and weather:

1. **Vegetation component**

From the model's softmax output over the 10 EuroSAT classes, we focus on vegetation-related classes such as AnnualCrop and Pasture. The predicted probabilities for these classes are then summed to get a vegetation risk score between 0 and 1, where values closer to 1 indicate more flammable vegetation.

2. **Weather component**

We retrieve the most recent hourly values of temperature, relative humidity, wind speed, and soil moisture from Open-Meteo for a fixed location. Each variable is then normalized into a risk value (higher temperature and wind increase risk, higher humidity and soil moisture decrease risk). A weighted sum of these normalized values yields a weather risk score between 0 and 1, with more weight on humidity and wind if they are present.

3. **Final wildfire risk score**

The final wildfire risk is computed as a weighted combination of the weather score and vegetation score, then scaled to a score from 0-100. We have a 60% weight on weather while we have a 40% weight on vegetation.

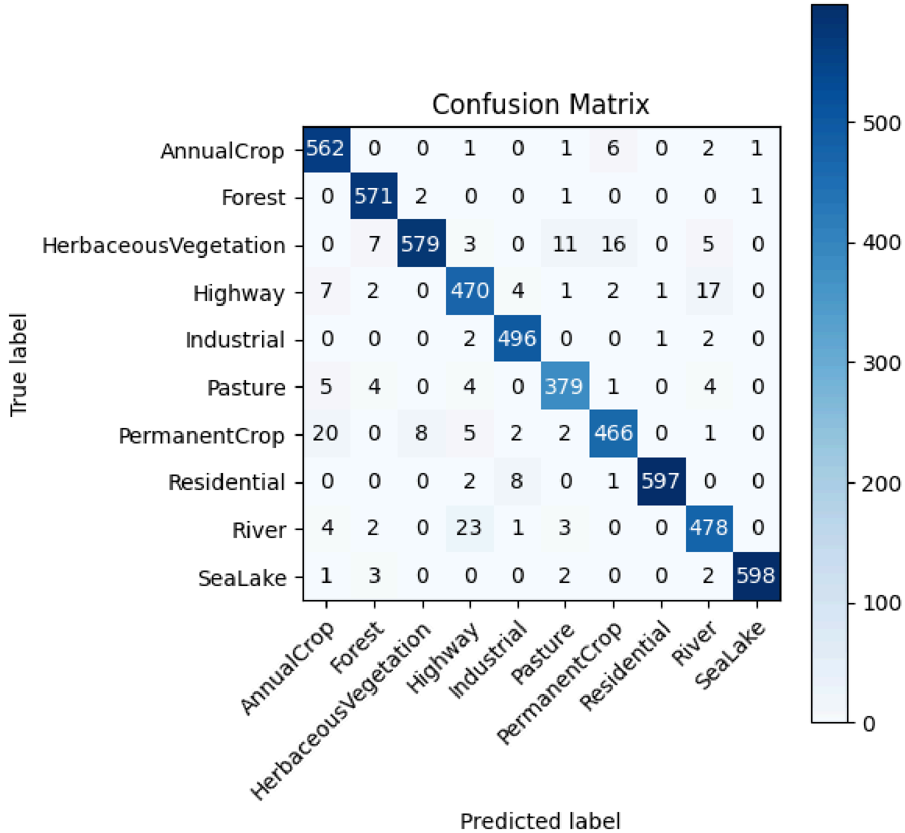
This formula is not meant to replace fire danger indices, but to demonstrate how deep learning based land use classification can be integrated with real-time weather data in a prototype system.

5. Experiments & Evaluation

5.1 Quantitative Results

We evaluate TerraScan on the 20% EuroSAT split that is used as the validation set during training. Due to time constraints, we did not maintain a completely separate held-out test set, so all reported metrics come from this validation split. The final model reaches a validation accuracy of approximately 96–97% depending on training, indicating that it correctly classifies the vast majority of land use tiles.

The confusion matrix below shows that performance is especially strong for visually distinctive classes such as Forest, Sea/Lake, and River, where most examples fall along the diagonal. Most remaining errors occur between visually similar vegetation classes, for example, AnnualCrop, Pasture, HerbaceousVegetation, and PermanentCrop, which often share similar textures and colors in satellite imagery. This pattern suggests that while TerraScan captures the broad land use structure well, fine-grained distinctions between similar vegetation types remain challenging for our prototype.



5.2 Qualitative Analysis

To complement the quantitative metrics, we visually inspected individual predictions from the validation split. For many tiles containing large water bodies or dense tree cover, the model confidently predicts Sea/Lake, River, or Forest, and these predictions match the ground-truth labels. In contrast, some mixed or edge cases, such as agricultural areas near roads, are occasionally misclassified. For example, predicting 'Residential' instead of 'Industrial' or confusing 'AnnualCrop' with 'Pasture'. These qualitative examples are consistent with the confusion matrix and highlight that TerraScan is reliable for clear, homogeneous land use patterns but can struggle when classes have overlapping visual characteristics or when multiple land uses appear within a single tile. This might be a problem on a larger scale, but for the amount of training, it will suffice for our prototype.

6. Business Applicability & Impact

6.1 Target Users / Stakeholders

Potential users for TerraScan include:

- Environment
- City
- Utility
- Researchers

6.2 Use Cases

Scenario: Regional wildfire risk monitoring

A regional planning agency wants to monitor wildfire risk in areas near residential communities and power lines. Currently, they rely on static land cover maps and general fire danger indices that do not account for recent land use changes.

With this prototype, the agency can use recent satellite imagery to classify land use into the different categories, such as Forest. Next, they could identify the tiles with high vegetation-reduced probabilities near critical infrastructure. Combining this information with real-time weather data would then allow them to generate a wildfire risk score. By taking this wildfire risk score into account, they could prioritize inspection, management, or public alerts in zones that have an elevated risk.

6.3 Benefits & Limitations

Benefits

- Automates land use classification that would otherwise be manual
- Scales to large geographic areas and frequent satellite image updates on a large-scale application
- Combines current weather with land use in a single, interpretable risk score
- Built on widely used open datasets and tools (EuroSAT, TensorFlow, Open-Meteo)

Limitations

- The model is trained only on the EuroSAT dataset and may not generalize perfectly to all regions or sensors
- Accuracy is moderate, and some visually similar classes are frequently confused
- In the prototype, weather data is fetched for a single fixed location rather than a full spatial grid, and must be implemented differently on a bigger scale
- The wildfire risk score is a simplified heuristic and not a replacement for operational fire danger models

6.4 Prototype/MVP

Our current prototype runs as a Google Colab notebook. A user can load the trained model and the latest weather data from Open-Meteo. Then they can select or upload a satellite image tile from EuroSAT or a similar source. Then they can run the model to get the predicted land use class ,which is combined with our scoring function to output a wildfire risk score from 0-100 based on multiple components.

7. Conclusion

In this project, we developed TerraScan, a deep learning–based system that classifies land use from satellite imagery and combines it with real-time weather data to estimate a simple wildfire risk score. Using a ResNet50 model fine-tuned on the EuroSAT dataset, TerraScan can distinguish between ten land use classes and provide useful vegetation information for downstream risk estimation.

Although the current prototype has limitations in accuracy, generalization, and spatial coverage, it demonstrates the feasibility of integrating AI-based land use classification with weather-driven risk modeling. In future work, TerraScan could be extended by using a more powerful or fine-tuned model, incorporating additional data sources, and deploying the workflow as a web-based dashboard that supports real-world environmental monitoring and planning.