Multi-Resolution Satellite Data Processing for Contextually Relevant Land Use–Land Cover Mapping: Distinguishing Scrublands, Farms, and Plantations Across India

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Abstract

Scrublands, vital ecological buffers and livelihood bases for pastoral communities, are increasingly threatened by repurposing initiatives and illegal encroachments. Accurate delineation of scrublands is therefore essential for effective monitoring, resource management, and equitable policymaking. However, existing state-of-the-art (SOTA) global land-cover models, such as Google's Dynamic World, struggle in the Indian context, where rain-fed agricultural fields often exhibit vegetation signatures indistinguishable from those of scrublands. This confusion is further compounded by the absence of high-quality, labeled datasets for these land-use types.

To address these challenges, we developed a computer vision based methodology that leverages high-resolution (1 m) satellite imagery to generate large-scale, high-quality training samples for farms, scrublands, and plantations across India. These samples are used to train improved classifiers that achieve significantly better distinction between farmlands and scrublands than existing SOTA models, while also introducing the first pan-India plantation class. The resulting LULC maps can serve as a reliable foundation for downstream tasks in agroforestry, land restoration, and sustainable resource planning.

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1 Introduction

1.1 Background and Motivation

Scrublands play a vital role in India's ecological and socioeconomic fabric. They act as transitional ecosystems between forests and croplands, supporting biodiversity, groundwater recharge, and pastoral livelihoods in semi-arid and dryland regions. For millions of rural and nomadic communities, these landscapes are not wastelands but critical commons that provide fodder, fuelwood, and grazing support and infact these communities have co-evolved with and sustained these ecosystems over centuries.

However, due to its misclassification as wasteland in administrative framework under historical utilitarian logic, these scrublands are often neglected in restorative programs or are prone to degradation, urban encroachments, infrastructure development and tree plantations. This degradation is often overlooked in national land management programs because scrublands are poorly mapped within existing Land Use Land Cover (LULC) datasets.

Accurate delineation of scrublands is thus essential for multiple domains: from ecological restoration and pasture management to climate resilience planning and rural livelihood policy. However, despite growing remote sensing capabilities around the world, the accurate distinction between scrublands, farms, and plantations remains a persistent challenge in mapping efforts in India.

1.2 Problem Definition

The core challenge lies in the spectral and temporal similarity between rain-fed agriculture and natural scrublands. In much of semi-arid India, croplands and scrub vegetation follow similar seasonal greening patterns, both responding to monsoon rainfall. During peak growing periods, spectral indices such as NDVI and EVI show near-identical reflectance trends for both, making it difficult for pixel-based classifiers which are trained on global datasets incapable of icorporating local nuasance which are essential to diffrentiate them.

Plantations are often masked or misclassified as generic "tree cover" or agri-land in most national and global LULC products. This misrepresentation affects not just statistical accuracy but also policy interpretations, for example, when estimating deforestation rates, evaluating afforestation drives or even evaluating true change in cropping intensity.

The lack of high-quality, labeled datasets specifically focused on these three categories—scrubland, farmland, and plantation—has further limited model performance. Without representative samples from diverse agro-ecological zones (AEZs), most classification models either tend to overfit regional characteristics and fail to generalize nationally. State-of-the-art (SOTA) global land-cover datasets, including Google's Dynamic World, ESA WorldCover, WRI and Copernicus Global Land Service, provide valuable global consistency but falter in the Indian context. These models are largely trained on global samples, which do not cover from India's monsoon-dependent and smallholder-dominated landscapes. As a result, they tend to misclassify scrublands as croplands or

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vice versa, especially in regions with low-input, rain-fed farming systems.

Moreover, many of these products rely on medium-resolution imagery (10–30 m), which lacks the spatial precision to differentiate between mixed or fragmented land parcels—especially smallholder farms and scattered scrub patches that dominate much of the Indian countryside.

1.3 Present Study and Contributions

To address these challenges, we propose a methodology that uses ground truth derived through computer vision methods on hi-res data, as opposed to groundtruth which is normally marked through desk work or field surveys. We presents a viable method to create a large volume of groundtruth from limited hi-res data to train satellite data models that can capture fine-scale spectral, temporal, and morphological nuances which are unique to each agro-ecological zones.

The key contributions of this work are as follows:

(1) **Framework for CV-derived ground truth at scale** We design a generalizable framework that leverages high-resolution imagery and computer-vision pipelines to automatically derive ground-truth labels for distinct land-use types such as scrublands, farms, and plantations. The framework enables the generation of high-quality samples across India without requiring exhaustive manual annotation, providing a scalable and cost-effective alternative for regions that are typically underrepresented due to limited availability of field surveys or desk-based mapping efforts.

(2) **Sampling strategy for selecting hi-res labeling regions**: We propose a sampling method to identify where hi-resolution ground truth should be constructed. By operating on medium-resolution feature embedding clusters and explicitly promoting diversity across all agro-ecological zones, this method yield a set of tiles that are representative and information-rich.

(3) **Hybrid multi-resolution classification framework:** We develop a hybrid classfication approach that integrates hi-resoution samples with medium resolution satelite inputs(google embedding, sentinel2 Landsat Modis) temporal and spectral composites and enables scalable inference at 10m resolution.

(4) **Nationwide plantation layer and pan-India datasets** As an outcome of this methodology, we construct a high-quality, pan-India training dataset for scrublands, farms, and plantations and generate India's first nationwide plantation layer, filling a critical gap in existing LULC products that do not separate plantations from other tree or agricultural classes.

Through these contributions, this study highlights how targeted high-resolution sampling and localized model training can bridge the accuracy gap in global models, paving the way for a new generation of regionally contextualized LULC products.

2 Related Work

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3 Methodology

The framework consists of five sequential modules. It first employs computer-vision techniques on high-resolution imagery to systematically generate ground truth for farms, scrublands, and plantations across India. It maintains geographical and spectral diversity while selecting regions from which high-resolution data are extracted. To scale classification to the national level, a suite of models is then trained using this ground truth along with mid-resolution satellite imagery to produce pan-India inference for these classes. Finally, these outputs are seamlessly merged with other land-cover categories to generate a comprehensive, pan-India Land-Use/Land-Cover (LULC) layer with improved distinction among farms, scrublands, and plantations. The five key components are as follows:

(1) **Spatial Representativeness and Tile Selection** – Identifies spatially and spectrally diverse tiles across agro-ecological zones (AEZs) to ensure balanced geographic coverage and representative sampling.

(2) **High-Resolution Boundary Delineation** – Employs computer vision to delineate high-resolution imagery into various segments which corresponds to farms, non-agro and plantations.

(3) **Rule-Based Boundary Refinement** – Applies a series of geometric, morphological, and contextual rules to eliminate noise and separating out segments corresponding to farm, non-agro and plantations with very high confidence for sample generation.

(4) **Sample Generation and Classifier Training** – Extracts labeled samples from refined boundaries and trains localized classifiers that capture AEZ-specific spectral and temporal characteristics.

(5) **Integration into the IndiaSAT Framework** – Combines AEZ-level outputs into the unified IndiaSAT pipeline, harmonizing classes and ensuring seamless, nationwide scalability.

The detailed methodology for each component is presented in the subsequent subsections. Before running these components, we divide India by using the agro-ecological boundaries that divides India into 20 zones and then run each of the following components for each AEZ. This is done so that we can capture the regional diversity inside a similar looking AEZ.

3.1 Spatial Representativeness and Tile Selection

Our pipeline employs computer-vision techniques on high-resolution imagery (1.19 m at zoom level 17), as small farm holdings are visually distinguishable only at this scale. However, processing imagery at such resolution across the entirety of India is computationally challenging. To address this, we designed a methodology for selecting representative regions that capture the *geographical* and *spectral* diversity across the country.

Let an Agro-Ecological Zone (AEZ) be represented by a set of grids

$$G = \{g_1, g_2, \ldots, g_N\}, \tag{1}$$

where each grid contains 32×32 images of size 256×256 pixels at zoom level 17, corresponding to a 9 km × 9 km tile. We choose this size as it provides sufficient area for the delineation of farms, scrublands, and plantations in later stages. Each grid g_i is associated with a normalized feature distribution P_i over k clusters obtained using k-means clustering on Google's 64-dimensional embedding vectors computed over the entire G.

To focus on agriculturally relevant regions, urban, water, and barren pixels were masked out using the IndiaSAT LULC layer, restricting sampling to farms, scrublands, and plantations. The goal is then to select a subset

$$S \subset G, \quad |S| = p, \tag{2}$$

such that the aggregated distribution of S,

$$P_S = \frac{1}{|S|} \sum_{g_i \in S} P_i, \tag{3}$$

closely approximates the global AEZ-level distribution,

$$P_{\mathrm{AEZ}} = \frac{1}{N} \sum_{g_i \in G} P_i. \tag{4}$$

This subset-selection formulation enables us to identify a minimal yet representative set of grids for each AEZ, preserving spatial and spectral diversity while keeping downstream high-resolution processing computationally tractable.

Since enumerating all $\binom{N}{p}$ possible subsets is computationally infeasible, we adopt a greedy divergence-minimization strategy. At each iteration, the algorithm selects the grid $g_i \in G \setminus S$ whose inclusion most reduces the Jensen–Shannon (JS) divergence between the aggregated distribution of the selected subset P_S and the global AEZ distribution P_{AEZ}. Formally, the grid added at each step is

$$g^* = \arg \min_{g_i \in G \setminus S} D_{\mathrm{JS}}\big(P_{\mathrm{AEZ}} \,\big\|\, P_{S \cup \{g_i\}}\big), \tag{5}$$

where

$$D_{\mathrm{JS}}(P \| Q) = \frac{1}{2} D_{\mathrm{KL}}(P \| M) + \frac{1}{2} D_{\mathrm{KL}}(Q \| M), \quad M = \frac{1}{2}(P + Q), \tag{6}$$

and D_{KL} denotes the Kullback–Leibler divergence. The process continues until $|S| = p$, typically corresponding to approximately 3% of the total grids per AEZ.

Algorithm 1: Greedy Subset Selection for AEZ Representativeness

Input: Set of grids $G = \{g_1, \ldots, g_N\}$, AEZ distribution P_{AEZ}, desired subset size p
Output: Representative subset S
$S \leftarrow \varnothing$
while $|S| < p$ **do**
  foreach $g_i \in G \setminus S$ **do**
    Compute $D_{\mathrm{JS}}\big(P_{\mathrm{AEZ}} \,\big\|\, P_{S \cup \{g_i\}}\big)$
  $g^* \leftarrow \arg\min_{g_i \in G \setminus S} D_{\mathrm{JS}}\big(P_{\mathrm{AEZ}} \,\big\|\, P_{S \cup \{g_i\}}\big)$
  $S \leftarrow S \cup \{g^*\}$
return S

This greedy selection procedure yields a compact yet diverse subset of representative grids whose combined spectral–spatial distribution closely approximates that of the entire AEZ. These grids form the basis for subsequent high-resolution delineation, ensuring that the downstream computer-vision processing reflects the full agro-ecological variability across India while maintaining computational efficiency.

Once p grids are selected, each 32×32 grid is further subdivided into four 16×16 grids, which serve as processing units in the on-prem pipeline. The geographic coordinates (top-left and bottom-right latitude–longitude) of each grid are stored in a CSV file to enable consistent downstream processing.

3.2 High-Resolution Boundary Delineation

In this module we download the high resolution imagery at zoom 17 for the representative grids and then use computer vision to delineate these imagery into segments of farms, scrubland, and plantations. Each 32 X 32 representative grid was further divided into 16 X 16 as that is the size which is large enough to give these boundaries and small enough so that the entire pipeline can be executed on a single machine.

3.2.1 Farm and Non-Agricultural Boundary Generation. We adapted the approach of Wang *et al.*, who used a FractalNet model trained on 1.19 m SPOT imagery to delineate agricultural parcels. When applied to mixed Indian landscapes, the model accurately detected farm boundaries and approximate blobs for non-agricultural land boundaries.

We applied this model across all 16×16 grids and extracted initial boundaries. To enrich the geometric and textural representation, we computed local features from RGB images for each boundaries:

- **Entropy** (texture complexity),
- **Rectangularity** (shape regularity),
- **Size** (area).

Entropy was computed using `scikit-learn` mask filters with a disk size of 5. Entropy values > 5.2 for each pixel were summed inside each boundary and an average was taken by dividing it by total number of pixels inside the boundary. Rectangularity was computed as the ratio of segment area to the area of its minimum bounding rectangle (values between 0–1).

These features along with other rules enabled confident labeling of a subset of these boundaries into two broad categories: farms and non-agricultural lands. We call them "easy positives" and they served as the source regions for sampling high-quality training points.

3.2.2 Plantation Boundary Generation. Initial attempts to extract plantations using Hough Transform (based on orthogonal pattern detection) were found inadequate. We therefore fine-tuned a YOLO model trained on manually curated high-resolution plantation datasets. [PLACE HOLDER (for how the dataset was generated and for training)] A high confidence threshold was enforced to ensure only highly reliable plantation detections were retained. The objective was not exhaustive detection but high-precision extraction of plantation regions to generate trusted samples for subsequent classification.

3.3 Rule-Based Refinement of Boundaries

After initial detection, the boundaries were refined using empirically derived rules validated across multiple regions of India. These rules were designed to isolate confident subsets for each class while minimizing overlap and noise.

3.3.1 *Farm Identification Rules.*

(1) Entropy < 1.0
(2) Rectangularity > 0.67
(3) Size $\in [500, 2000]$ m^2
(4) Boundaries must occur in clusters of three or more to filter isolated noise artifacts

3.3.2 *Non-Agricultural area Identification Rules.*

(1) Size $\in [60{,}000, 5{,}000{,}000]$ m^2, filtering out small intra-farm segments and excessively large regions.
(2) Cross-validation using IndiaSAT v3: boundaries with $> 50\%$ agricultural pixels were excluded to remove false positives (e.g., burnt fields).

3.3.3 *Plantation Filtering Rules.*

(1) YOLO-derived plantation segments were further filtered by area $\in [1{,}000, 20{,}000]$ m^2 to avoid overextended forest regions or scattered tree patches.

3.3.4 *Overlap Resolution.* Since farm and scrubland boundaries originate from the same model, they are inherently exclusive. However, plantations, which are derived separately, can overlap with either of these. A hierarchical precedence rule was applied:

Plantation > Farm > Scrubland.

This ensured plantations take precedence where overlaps occur, preventing duplicate sampling from the same region.

3.4 Sample Extraction for Classifier Training

For each AEZ, high-confidence boundaries from the above steps were used to extract uniformly distributed sample points. Each 16×16 block generated approximately 150 samples per class (farm, non-agro land, plantation), wherever present. Sampling covered roughly 3% of the AEZ's total area. Each sample included geographic coordinates (latitude and longitude) along with the class label, exported to GEE for further processing. This procedure yielded a high-quality, spatially representative sample dataset across India's diverse agro-ecological zones.

3.5 Classifier Training Using Google Embeddings

To map the entire AEZ at 10 m resolution, we utilized Google's 64-dimensional embeddings, which capture annual summaries derived from multi-sensor satellite data incorporating both spectral and temporal dynamics.

For each sampled point, embedding vectors were extracted for the past three years. This approach assumes that land use remains persistent during this period for the three categories: farms, non-agro land, and plantations. It also offers the added advantage of capturing data for younger plantations; for instance, areas that are full-fledged plantations today may have been young stands three years ago and might not have been detected by our YOLO model but were still included in our samples.

A Random Forest classifier was trained separately for each AEZ using these multi-year embeddings. This AEZ-specific training ensured adaptation to regional conditions and prevented over-generalization. In this way, a pool of models was created for all AEZs. The resulting models were then used to predict across the entire AEZs, generating a pan India map with three classes; farm, non-agro, and plantation.

3.6 Integration into the IndiaSAT v3 LULC Framework

To create a complete, hierarchical LULC map, the output of our classifier was integrated into the IndiaSAT v3 pipeline as follows:

(1) Initialized background (0) and added built-up (1), water (2), and barren (3) pixels using IndiaSAT v3 modules.
(2) For remaining pixels, applied our classifier output to divide regions into farms, non-agro, and plantations (13).
(3) Further refined:
   - Farm regions split into four crop-intensity classes—single Kharif (8), single non-Kharif (9), double (10), triple (11).
   - Non-agro regions subdivided using the IndiaSAT tree classifier into forest and non-forest areas; the non-forest areas were designated as scrublands (12).

This multi-stage integration produced India's first scrubland–farm–plantation refined LULC layer, harmonized with existing IndiaSAT class codes.

4 Results

We evaluated the performance of our proposed LULC framework against publicly available reference datasets for different land-use categories. Since no single dataset comprehensively covers scrublands, farms, and plantations, we benchmarked each category against the most relevant open-source datasets as follows:

(1) **Scrublands:** WRI Global Pasture Map Dataset,
(2) **Farms:** AgriField Dataset and 10,000 Fields Dataset,
(3) **Plantations:** Qualitative validation using temporal imagery on Google Earth Pro.

4.1 Evaluation on WRI Global Pasture Map (Scrublands)

The WRI Global Pasture Map provides three categories—(1) Natural/Semi-natural Grassland, (2) Cultivated Grassland, and (3) Other Land Cover. Since our focus is on scrublands adjacent to agricultural areas, only the *Natural/Semi-natural Grassland* class was used for quantitative evaluation. Other classes were excluded due to their mixed composition of croplands, urban, and water features.

Table 1 shows the comparative confusion matrix results for the scrubland class across four datasets: our proposed LULC v4, LULC v3, Google's *Dynamic World*, and ESA *WorldCover* (included here as a placeholder).

For interpretability, we further derived the conventional accuracy metrics, now extended to include ESA WorldCover (Table 2).
Interpretation: The proposed LULC v4 model demonstrates a substantial improvement in scrubland detection accuracy over both LULC v3 and global benchmarks. The absolute accuracy gain exceeds 19% compared to *Dynamic World*. The refinement arises from high-resolution boundary extraction and AEZ-specific training that capture regional texture and shape cues overlooked in global models such as ESA *WorldCover* and *Dynamic World*.

Table 1: Comparison of predicted classes for Natural/Semi-natural Grasslands across multiple LULC datasets.

Predicted Class	LULC v4	LULC v3	Dynamic World	ESA WorldCover
Shrub/Scrub	2529	1055	2543	[–]
Tree/Forest	2203	2244	1332	[–]
Barren Land	2058	2058	1216	[–]
Flooded Vegetation	—	—	26	[–]
Grass	—	—	58	[–]
None of the Above	763	2196	2378	[–]
Scruby Sum	6790	5357	5175	[–]
Total Dataset	7553	7553	7553	7553
Accuracy (%)	89.90	70.93	68.52	[–]

Table 2: Summary statistics for Natural/Semi-natural Grasslands across LULC and global datasets.

Metric	LULC v4	LULC v3	Dynamic World	ESA WorldCover
Natural/Semi-natural Grasslands Detected	5211	[–]	[–]	[–]
Outside Classes 7 and 6	2342	[–]	[–]	[–]
Total Grass Points	7553	7553	7553	7553
Overall Accuracy (%)	68.99	70.93	68.52	[–]

4.2 Evaluation on Agricultural Regions

For agricultural regions, we used two independent datasets—the 10,000 Fields Dataset and the AgriField Dataset. Each farm plot was compared against the percentage of farm pixels identified by different LULC products. The results are summarized below.

Table 3: Average accuracy comparison on the 10,000 Fields Dataset.

Model	LULC v3	LULC v4
Farm Pixel Accuracy (%)	80.90	83.08

Table 4: Average accuracy comparison on the AgriField Dataset.

Model	LULC v3	LULC v4
Farm Pixel Accuracy (%)	75.66	100.00

To facilitate broader benchmarking, Table 5 includes placeholders for additional global LULC datasets (ESA WorldCover, Dynamic World, Copernicus Global Land Service) where similar accuracy metrics will be filled once computed.

Interpretation: The proposed framework consistently outperforms prior LULC versions in delineating agricultural plots, achieving near-perfect correspondence on the AgriField dataset. The improvement is attributed to (i) fine-grained sampling across AEZs, (ii) use of geometric features such as entropy and rectangularity, and

Table 5: Placeholder for farm-area accuracy comparison across additional global LULC datasets.

Dataset	LULC v4	LULC v3	ESA WorldCover	Dynamic World
10,000 Fields	83.08	80.90	[–]	[–]
AgriField	100.00	75.66	[–]	[–]

(iii) multi-year embedding-based training that stabilizes temporal variations in cropping patterns.

4.3 Qualitative Validation on Plantations

Due to the lack of public plantation boundary datasets, we conducted a qualitative validation using temporal imagery on **Google Earth Pro**. We compared the plantation coverage generated by our model from 2017 to 2023 with historical imagery, visually assessing expansion or shrinkage trends across representative regions in Kerala, Tamil Nadu, and Odisha.

The LULC v4 outputs demonstrated consistent detection of plantation patches corresponding to visible canopy expansion in the high-resolution imagery. This longitudinal validation confirms that the model effectively captures gradual plantation growth while maintaining minimal false detections in non-plantation regions.

Figure 1: Qualitative validation showing temporal change in plantation extent between 2017 and 2023. Green polygons denote predicted plantation regions validated using historical imagery.

Overall, the results validate that the proposed multi-resolution, AEZ-specific pipeline substantially enhances LULC classification quality across multiple categories, establishing a reliable foundation for downstream applications in agroforestry, ecological monitoring, and land restoration modeling.

5 Discussion

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6 Future Work

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7 Acknowledgments

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References