Google DeepMind

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Smallholder Agricultural Landscape Understanding (ALU)

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"Why" – The Global Challenge

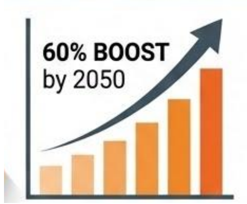
How do agricultural practices impact climate change?
How can we mitigate climate change by efficient agricultural practices?

1.

How is agriculture well poised to tackle climate change?

Climate Crisis

The global food system is a primary driver of the climate crisis[1,2], responsible for substantial greenhouse gas emissions from agricultural activities alone.



Need for food production increase

Projections indicate a required 60% boost in food production by 2050 to feed a growing global population[3]

Solution: Agriculture as a Carbon Sink

Agriculture as a carbon sink. This will be enabled by moving away from inefficient resource allocation to precise, data-driven land management. [4]

Such data driven management can be achieved by digitization of the agricultural sector.

How can we achieve digitization of agriculture?

Agricultural Field Segmentation
Prerequisite for field level analytics, monitoring farm health, crop yield etc.[2,5]

Tree and Agroforestry Delineation
Vital for quantifying carbon sequestration and promoting sustainability[5,1]

On farm: Water Source Identification
Essential for managing irrigation, protecting water quality and managing food security[6,7]

Challenges and Limitations of current ML Model

Smallholder Farm Limitations

Applying remote sensing and ML to smallholder farms is challenging due to the intricate nature of these systems, which feature very small fields (< 2 ha)[8], diverse land uses, and a mix of natural vegetation and water resources.

Lack of Panoptic Segmentation

Existing work has practical shortcomings, often focusing narrowly on field boundaries while neglecting interconnected features (like trees and water) and failing to utilize unified methods like panoptic segmentation.[9,10]

Lack of Real World Application

There is a major disconnect between academic work and real-world impact, as prior systems lack robust post-processing heuristics and have not been comprehensively evaluated or deployed at a large scale.

Our Contributions

We developed and evaluated a national-scale system for granular agricultural mapping, focusing on smallholder farms. The maps are publicly accessible via an API at http://agri.withgoogle.com.

Moving beyond traditional field delineation, we use a multi-class approach to segment fields, trees, and water bodies, providing a more holistic landscape understanding.

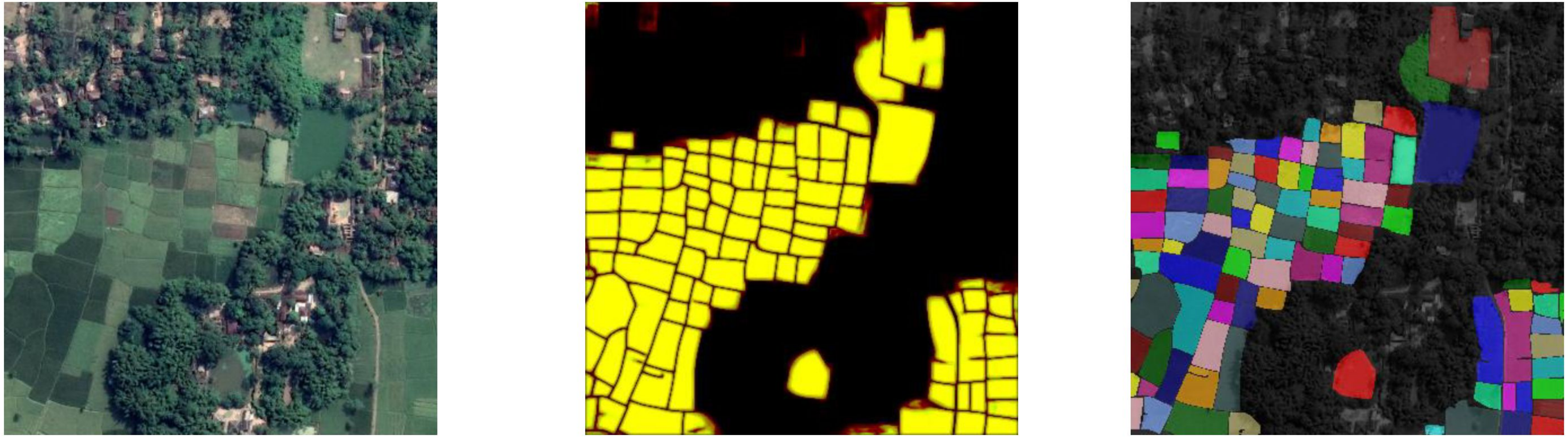
We introduce novel post-processing heuristics to refine model outputs into final maps, ensuring their accuracy, consistency, and usability for downstream applications.

We conduct rigorous, multi-faceted evaluation for real-world reliability, including benchmarking on public data, comparison with in-situ surveys, and on-ground validation with external partners

Methodology

2

Goal

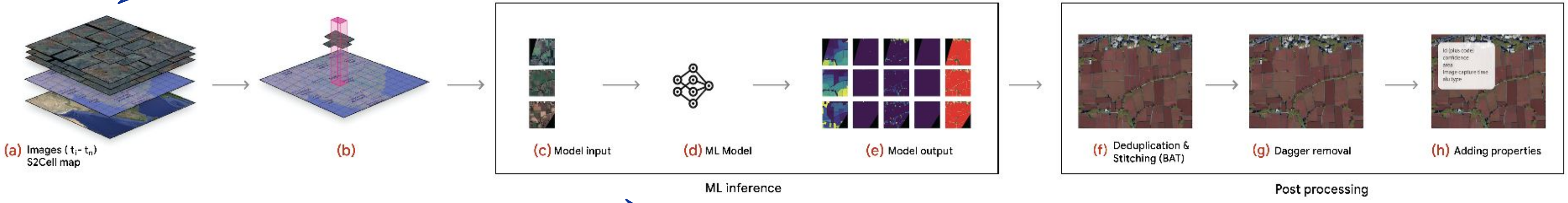


Given an input RGB satellite image (left), our goal is to generate both a semantic segmentation map (center) and an instance segmentation map (right) for each layer (shown here for Ground Layer only)

The ALU System

Stack of Satellite images available for a given S2 cell at different times

Novel Post Processing steps that to stitch and de-duplicate identical fragments of instances and remove undesirable artifacts



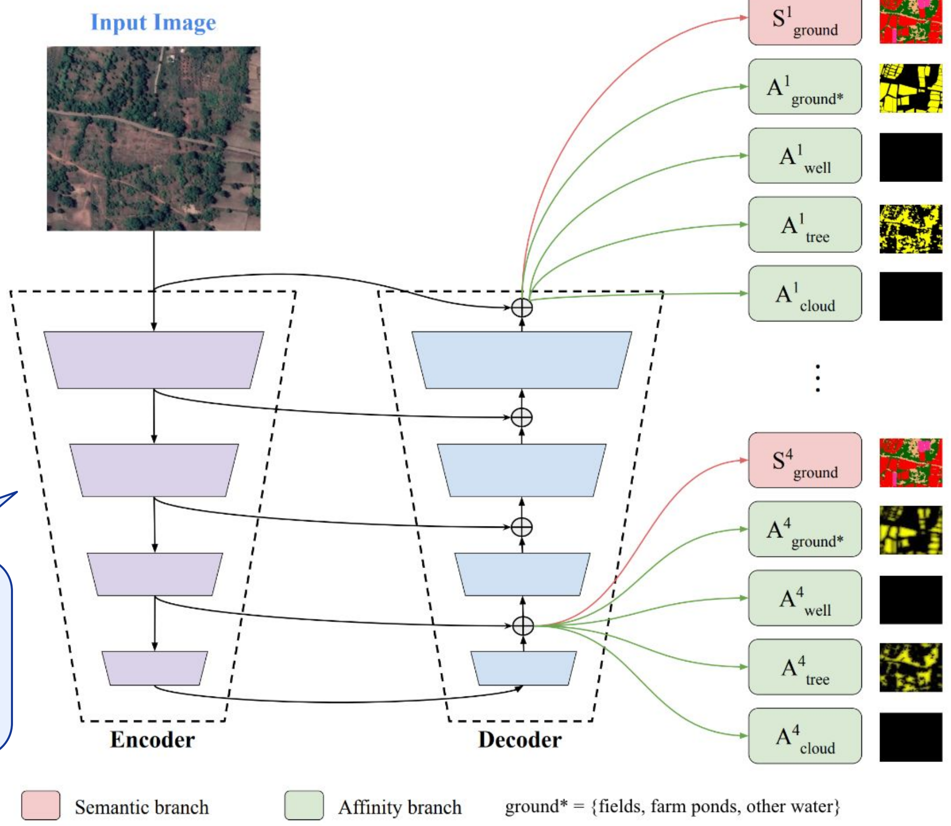
Using the ML model to predict instance and semantic segmentation for different features for a given image

ML Model

Adapted from Gao et. al [11]

The system utilizes a U-Net framework featuring a ResNet50 encoder that is pre-trained on ImageNet to extract features.

The decoder generates outputs at four distinct resolution scales (1x, 1/2x, 1/4x, 1/8x).



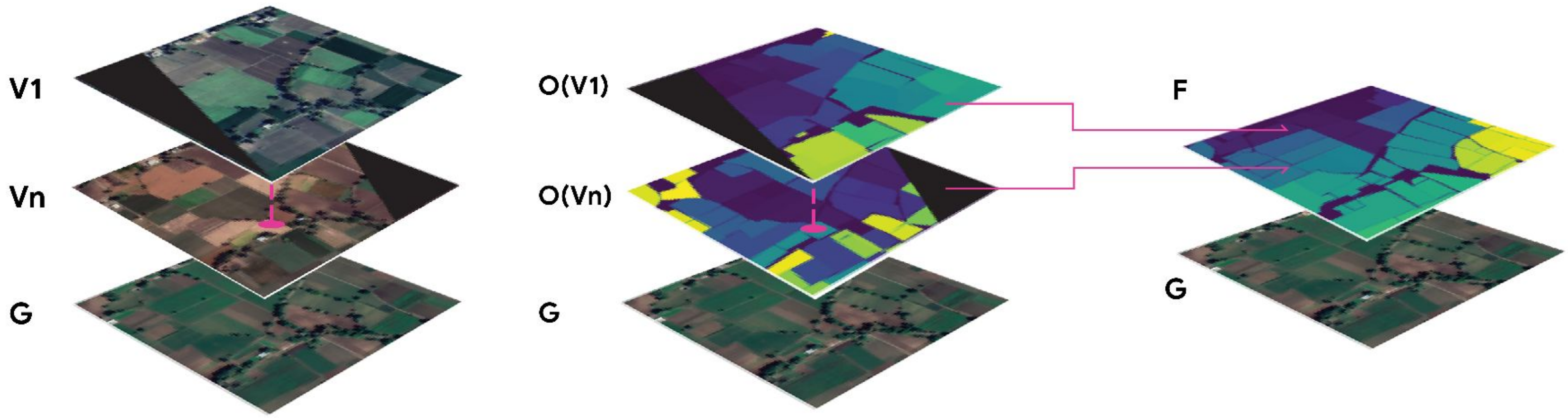
At each upsampling stage, the model employs five distinct output heads: one for the semantic segmentation map S and four for affinity masks (A) corresponding to specific layers (ground, well, tree, cloud).

Loss function:
- **Focal loss** (extended to multiple classes) for the semantic segmentation.
- An **average L2 loss** for the affinity predictions

Inference and Post Processing

3

BAT Deduplication



Left to right: Multiple input satellite images (V1, . . . , Vn) obtained for the ground location beneath (G), model inference outputs (O(V1), . . . , O(Vn)), BAT-based stitching and deduplication yields the final output (F).

BAT Deduplication Algorithm

Goal: isolate the single best shape for each physical object by resolving conflicts between overlapping detections.

Quality-Freshness Trade-off: The system addresses the challenge of balancing contour quality (derived from high-quality sensors) against data freshness (from recent imagery), as these attributes are often inversely correlated..

Part 1: Data Preparation and Bucketing

Input : A set of detections D, tiles T, and metadata M
Output : A final, deduplicated set of detections S_{final}

1. **Data Integrity and Preparation** Filter D, T, M to remove entries with broken data links;
$T_{\text{incomplete}} \leftarrow$ Identify and mark tiles in T with incomplete RGB or a maxed-out detection count;

2. **Geographic Bucketing** Partition D, T, M into geographic buckets with wide margins;

// The process in Part 2 is now run for each bucket in parallel.

Part 2: Parallel Processing per Bucket

forall *each bucket in parallel* **do**

3. Stitching Fragmented Detections $D_{\text{boundary}} \leftarrow$ Identify all boundary detections;
$D_{\text{stitched}} \leftarrow$ Cluster D_{boundary} and union their geometries;

4. Conflict Resolution $D_{\text{complete}} \leftarrow$ All non-boundary detections;
$S \leftarrow$ Resolve overlaps between D_{stitched} and D_{complete} ; // See Alg. 2

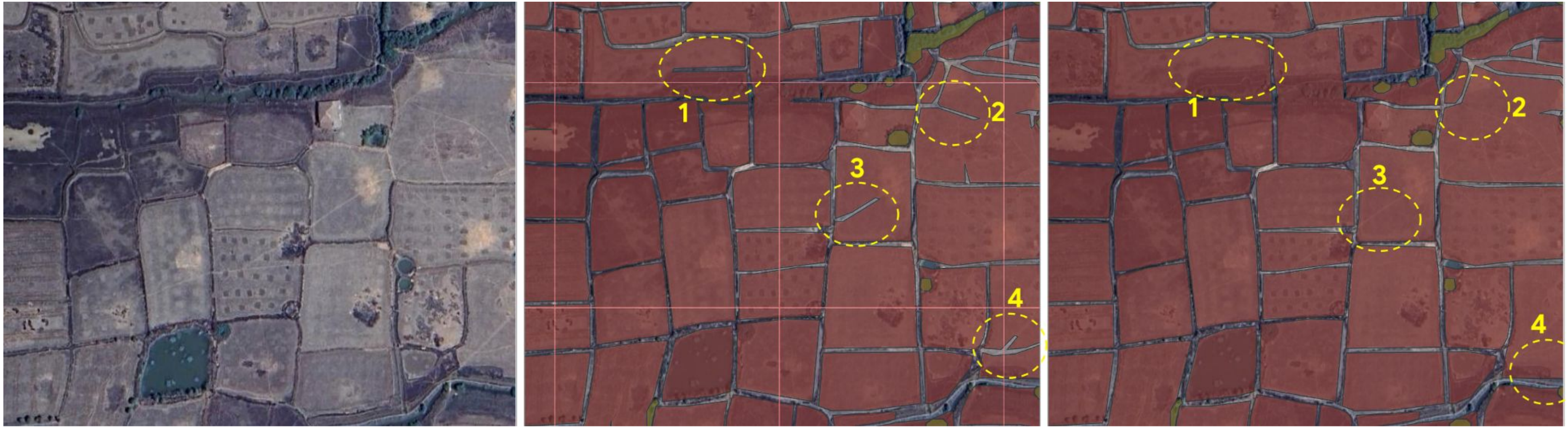
5. Chronological Validation Compute image quality scores ; // See Eq. 1
$M' \leftarrow$ Select top-n highest-scoring images;
$S' \leftarrow$ Create a candidate list from S from images in M';
Sort S' by quality, then by confidence;
$S_d \leftarrow$ Validate and merge S' into a non-overlapping set ; // See Alg. 3

6. Final Output Generation Filter S_d to remove detections outside the core area;

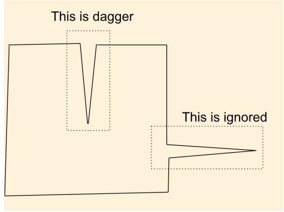
end

return *The combined and filtered S_d from all processes*;

Boundary Refinement



Left to right: Input satellite image, model output, model output post processed via Dagger removal (the sharp protrusions present in the field polygons are smoothed out



Boundary Refinement

Goal: remove unwanted dagger like artefacts from the model predictions

Input: A Polygon with vertex sequence $P = \{p_1, p_2, ..., p_n\}$
Output: Polygon without daggers with vertices $P' \in P$
$\mathcal{H}$: Convex Hull of P
$Q = \mathcal{H} \cup P$; `// Points in` P `which are on the hull`
`// Iterate in sequence`
for $q_i \in Q$ **do**
  R: sequence of points in P lying between q_i and q_{i+1}
  for *each pair* $(r_i, r_j) \in R \times R$ **do**
    if *isDagger*(r_i, r_j, P) **then**
      $P \leftarrow$ removeDagger(r_i, r_j, P);
    end
  end
end
return P

Experimental Results: System Evaluation

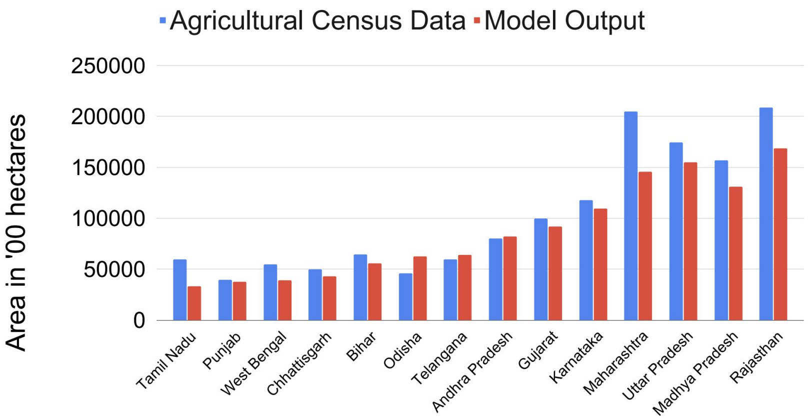
Data	**Kenya** [16]		**India** [36]		**Vietnam & Cambodia** [25]
Metric	mIoU (Border)	mIoU (Extent)	medIoU	IoU50	Polis
Previous	0.58	0.53	**0.85**	0.89	20.3
ALU (our)	**0.61**	**0.61**	0.84	**0.93**	**11.89**

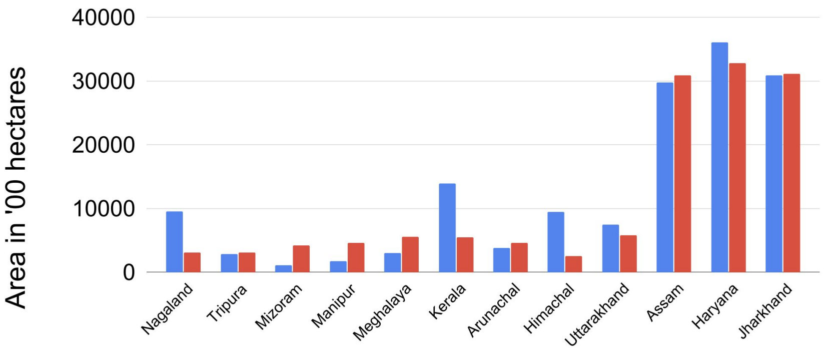
Experimental Results: ML Model Evaluation

Model	mIoU	medIoU	OS	FNR	US	FPR
ALU (our)	0.60	0.75	1.14	12.64	1.21	10.68
MaskRCNN [20]	0.51	0.67	1.11	26.47	1.13	17.89
DECODE [35]	0.25	0.07	1.09	0.005	1.47	18.94
ResUNet-a [34]	0.07	0.00	1.21	49.16	1.34	32.20

	ALU						DeepLab					
Class	mIoU	medIoU	OS	FNR	US	FPR	mIoU	medIoU	OS	FNR	US	FPR
Ground	0.60	0.75	1.14	12.64	1.21	10.68	0.55	0.63	1.39	3.87	1.39	13.63
Trees	0.40	0.47	1.14	32.56	1.08	42.30	0.11	0.03	1.36	40.94	1.14	50.78
Clouds	0.37	0.00	1.17	61.54	1.00	53.06	0.31	0.08	1.41	45.16	1.05	15.22
Wells	0.01	0.00	1.00	96.36	1.00	0.00	0.00	0.00	-	100.00	-	100.00

Post Launch Evaluation: Census Data Comparison





Comparison of aggregate statistics inferred from ALU outputs with Census Data which shows good alignment

Post Launch Evaluation: On-ground Validation in Telangana India

Sl. No.	Village	No. of Surveys	No. of Farm Fields	Over Segmentation	Under Segmentation	Boundary Error
1	SUNDARAGIRI	5	60	10	0	0
2	ARNAKONDA	2	29	2	0	0
3	YASWADA	9	61	0	7	0
4	KHASIMPET	19	128	0	4	14
5	PARVELLA	1	1	0	3	0
6	JANGAPALLE	10	105	11	2	5
7	KANDUGULA	25	343	18	0	18
8	IRUKULLA	29	239	6	4	18
9	DURSHED	6	13	4	6	2
10	MALKAPUR	9	53	10	2	0
11	REKURTHI	13	25	23	0	3
12	VELDI	1	9	0	0	3
13	GATTUDUDDENAPALLE	2	12	0	0	0
14	RAMADUGU	5	50	3	0	9
15	KACHAPUR	7	64	0	0	4
16	ALUGUNUR	2	10	0	0	0
17	NUSTULAPUR	5	50	13	2	1
18	SAIDAPUR	7	41	0	0	5
19	CHALLOOR	7	76	2	0	30
	Total	**164**	**1,369**	**102**	**30**	**112**
	Percentage (%)		**7.45**	**2.19**	**8.18**	

Conclusions

Holistic System Development
developed an end-to-end instance segmentation system that goes beyond traditional field boundary detection to map diverse agricultural features, such as trees and wells, using very-high-resolution RGB imagery.

Rigorous Validation
The system was verified through a multi-faceted evaluation process that combined public benchmarks with in-situ surveys and on-ground validation conducted alongside external partners.

National-Scale Impact
The project achieved the first comprehensive mapping of agricultural land use in India at a national scale, specifically focusing on smallholder farms to address critical social challenges regarding food security and climate change.

Video

Website and API

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