

# Leveraging AI for Wildlife Conflict Resolution

Boma & Cattle Detection in the Masai Mara

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# Our Partners

- **The Kenya Wildlife Trust:** ground-work in helping the Masai people, boma fencing, spatial planning, market formation, to protect Lions, Cheetahs, and Wild Dogs.
- **The Smithsonian Conservation Biology Institute:** expertise in spatial ecology and endangered species management, focused on mitigating human-wildlife conflict. Provided 50cm resolution imagery for the study.



***Role:** domain expertise and ground truth data on wildlife conflict in Kenya. Their input will help validate our machine learning models.*



**Smithsonian  
Institution**

***Role:** Provided high-quality satellite imagery crucial for our machine learning models.*

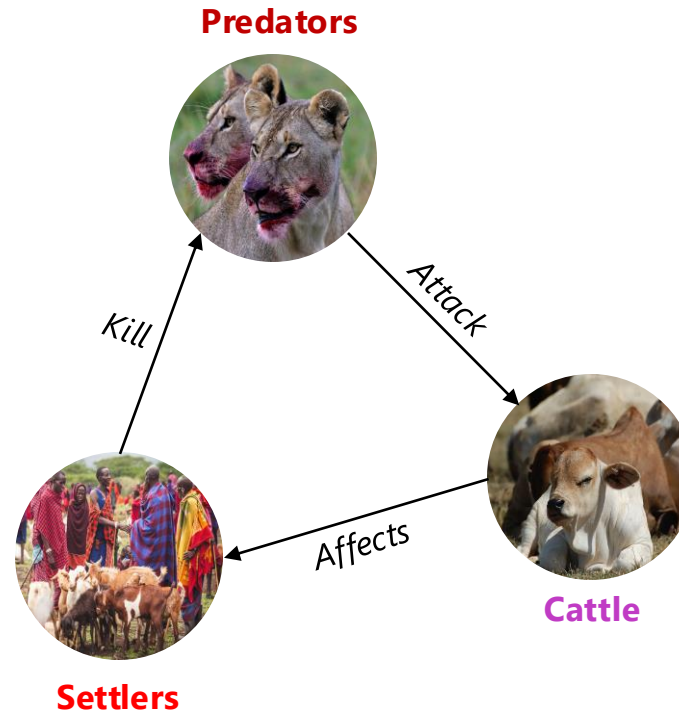
# Problem: Human-Predator Conflict in the Maasai Mara

**The Maasai Mara people** coexist with an array of predatory species, as their population expands, they clash with predators more frequently.

**Livestock Depredation:** Predators attack livestock housed in poorly protected bomas.

**Retaliatory Attacks:** Communities, fearing for their livelihoods, resort to predator killings.

**Our Contribution:** We use AI and satellite imagery to automatically identify hotspots of human-predator conflict (models are cost-effective, scalable, consistent).



**Goal:** We aim to break this cycle by supporting settlers & protecting wildlife animals.

| MAGAZINE |



## Why Poison Is a Growing Threat to Africa's Wildlife

Deadly chemicals are now a weapon of choice for those who see lions, elephants, and other wild animals as threats to livestock and property.



## Could painting eyes on cows' rumps cut human wildlife conflict?

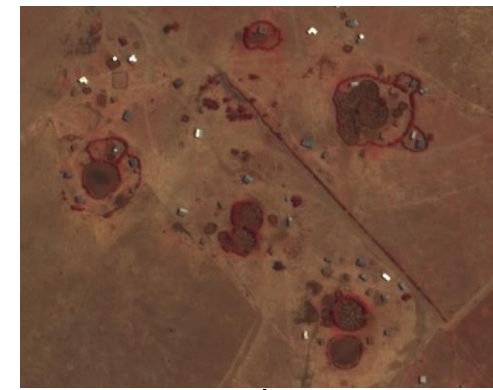
Herders retaliating for predator attacks on their livestock is a leading cause of wildlife deaths

Caroline Chubb • Tuesday 30 August 2022 15:10 • Comments

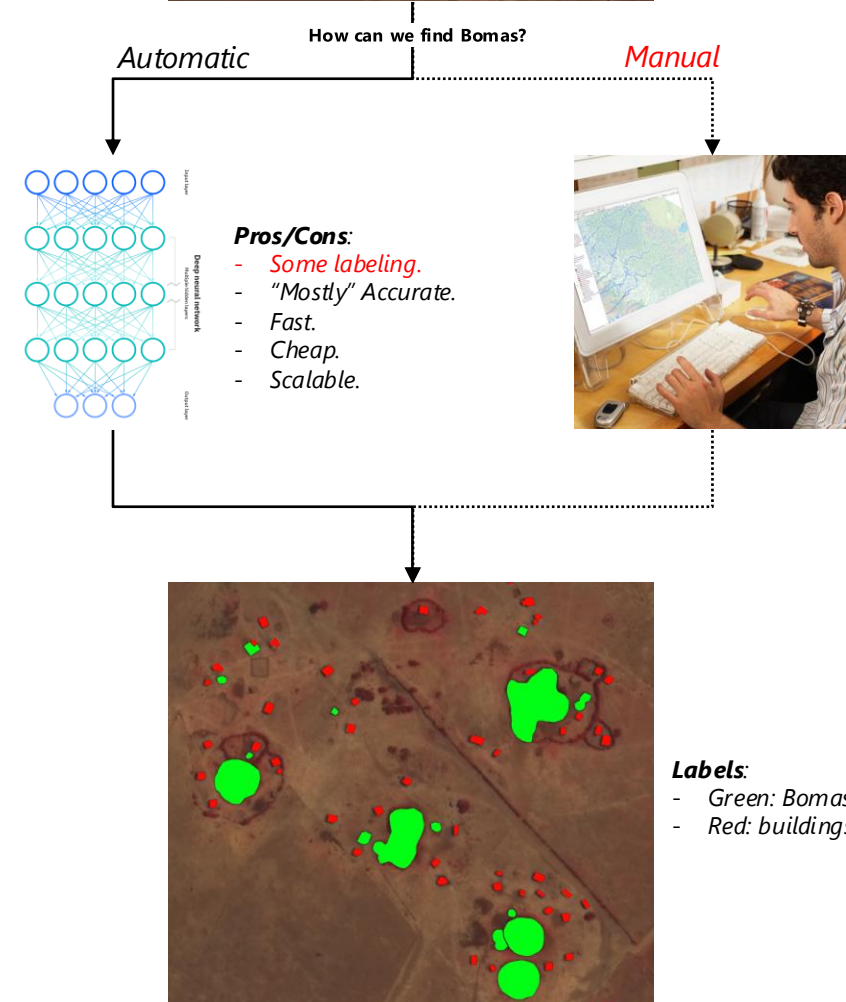


# How can AI help?

- **Cost-effective:** AI automates the mapping process, significantly reducing the time and manpower costs compared to manual methods.
- **Scalable:** AI can (potentially) predict on adjacent domains (in space & time).
- **Consistent:** AI algorithms ensure standardized mapping with consistent quality, eliminating human errors and biases.



*Image: a high-resolution satellite image that contains multiple Bomas.*



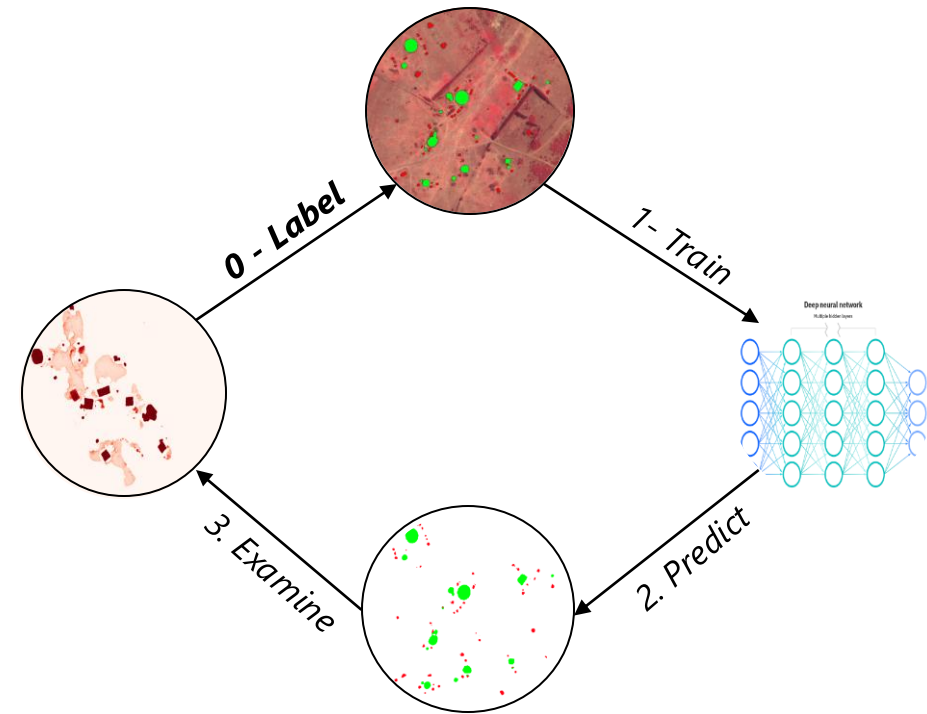


# Approach

**Task 1: Find the Bomas:** we train a model to segment settlements in the Masai Mara region.

**Task 2: Is the Boma Populated?:** we then use a classifier to tell the difference between a populated Boma and an empty one.

**ML Pipeline:** we construct an ML workflow that makes use of the two models to map the spatial distribution of Bomas, cattle, and buildings.



*An Iterative weak labelling approach for task 1.*

# Data Acquisition & Processing

We acquire the **WV2** images from Maxar's catalog:

📄 WV320230130081259M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	749.18 MiB	Active
📄 WV320230130081259P00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	933.81 MiB	Active
📄 WV320230130081300M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	803.76 MiB	Active
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📄 WV320230130081302P00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	1,001.00 MiB	Active
📄 WV320230130081304M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	763.25 MiB	Active
📄 WV320230130081304P00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	1,001.45 MiB	Active
📄 WV320230130081306M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	794.15 MiB	Active
📄 WV320230130081306P00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	1,001.41 MiB	Active
📄 WV320230130081308M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	255.74 MiB	Active

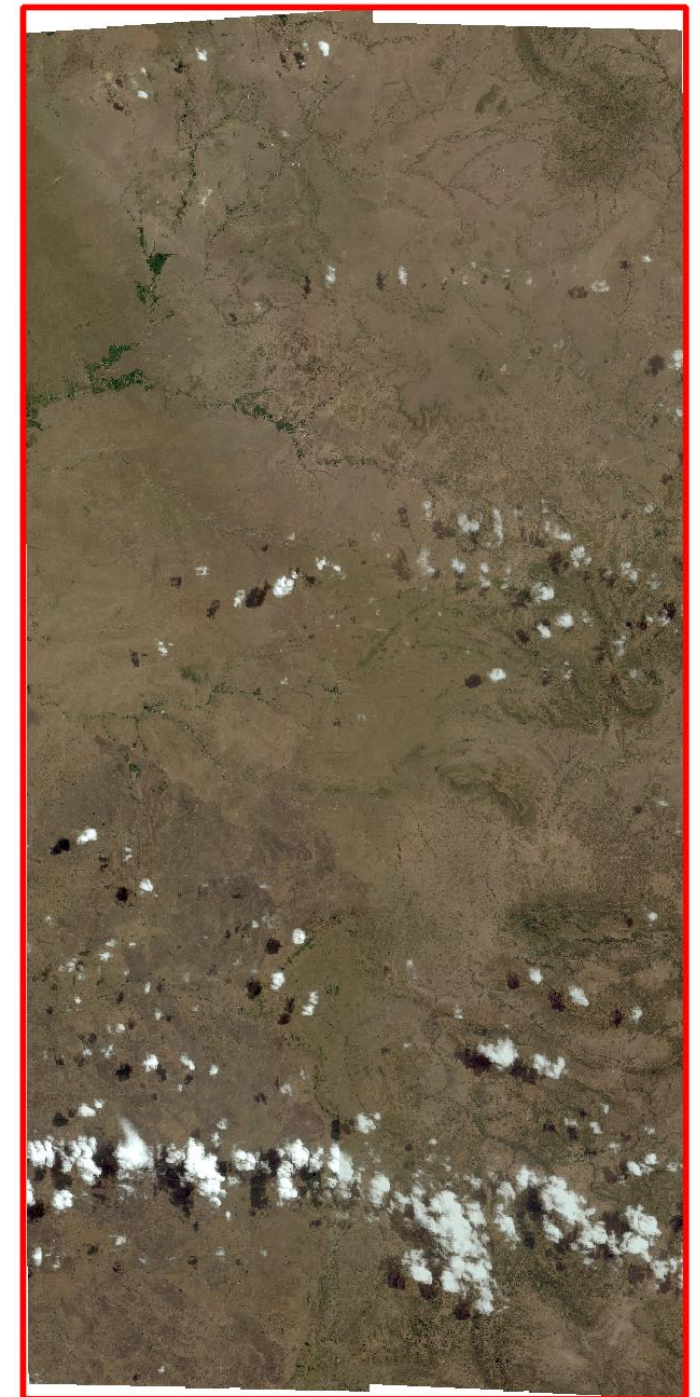
23JAN30081259-M1BS-507514526050\_01\_P001-BROWSE.JPG 23JAN30081259-M1BS-507514526050\_01\_P001.ATT 23JAN30081259-M1BS-507514526050\_01\_P001.EPH 23JAN30081259-M1BS-507514526050\_01\_P001.GEO 23JAN30081259-M1BS-507514526050\_01\_P001.IMD 23JAN30081259-M1BS-507514526050\_01\_P001.NTF 23JAN30081259-M1BS-507514526050\_01\_P001.RPB 23JAN30081259-M1BS-507514526050\_01\_P001.TIL 23JAN30081259-M1BS-507514526050\_01\_P001.XML 23JAN30081259-M1BS-507514526050\_01\_P001\_README.TXT

We use **Gdalwarp** for geo-referencing. Other processing steps:

1. Create mosaics from the RGB-NIR & PAN imagery.
2. Standardize MULT & PAN using band-wise mean/std.
3. Up-sample (bilinear) RGB-NIR to match PAN.
4. Stack and save the RGB-NIR-PAN file.

— **A Single Image** —  
RGB-NIR-PAN (5 bands).  
Standardized for DL

Source: Worldview-2





# Data: Input Imagery

Inputs (imagery): WorldView-2

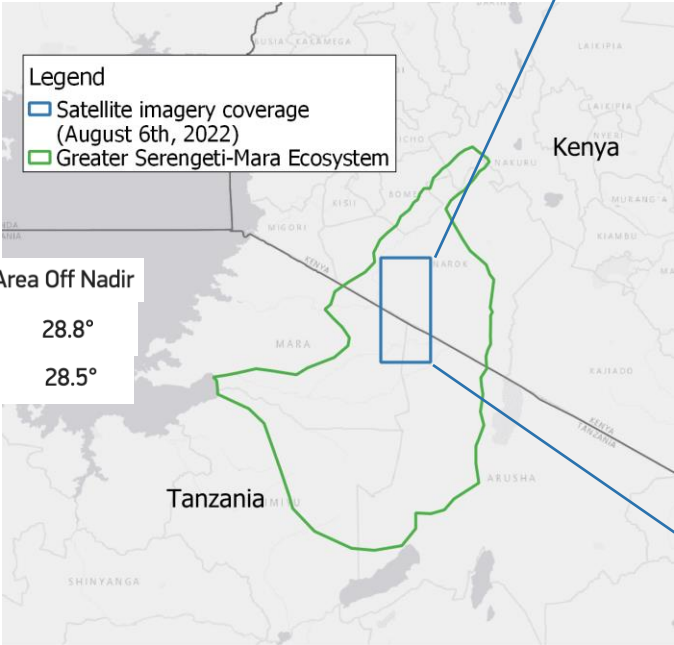
Coverage: ~3,600 km2

Bands: **RGB-NIR-PAN**

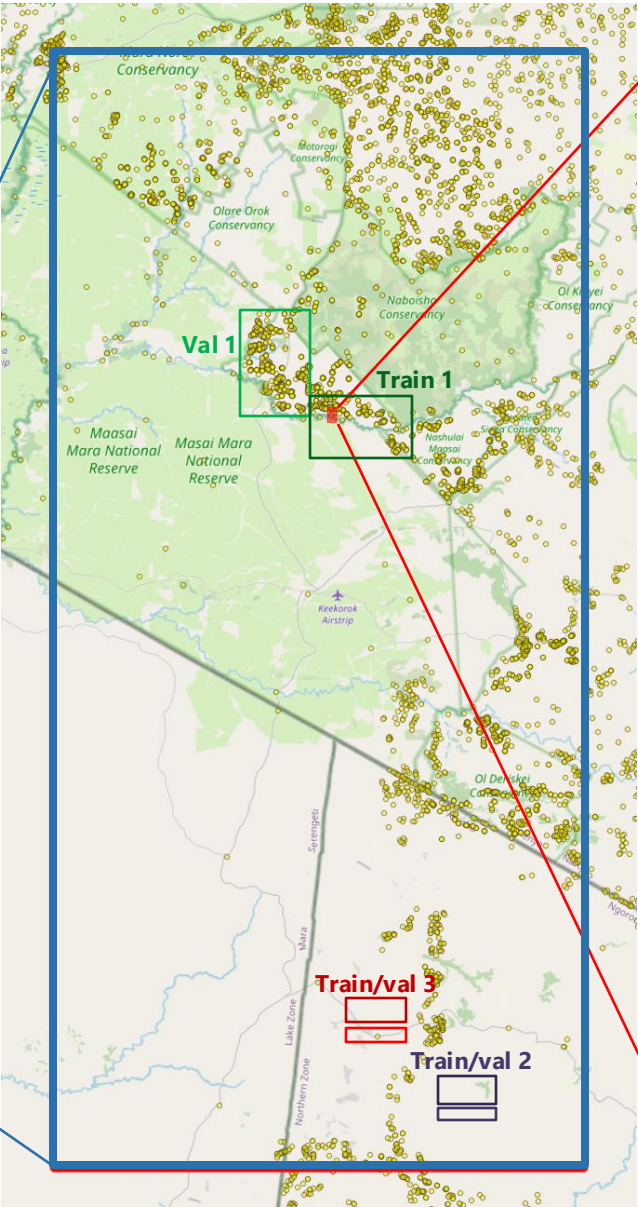
Spatial resolution: **50cm**

Snapshot: **August 6, 2022 ~8AM**

Source	Collected	Area Clouds	Area Off Nadir
WV02	2022/08/06	3.0%	28.8°
WV02	2022/08/06	5.0%	28.5°
<u>Scenes</u>			



Region of Interest (Blue).



3 Train/Validation splits.



Boma (Green);  
Structure (Red).

# Data: Labels

## Targets

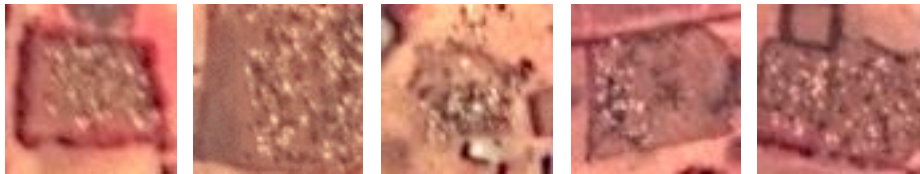
Geometries (bomas + buildings): **4,052**

Bomas: **812**

Structures: **3,240**

0 or 1 (Cattle presence): 812 annotated Bomas

1

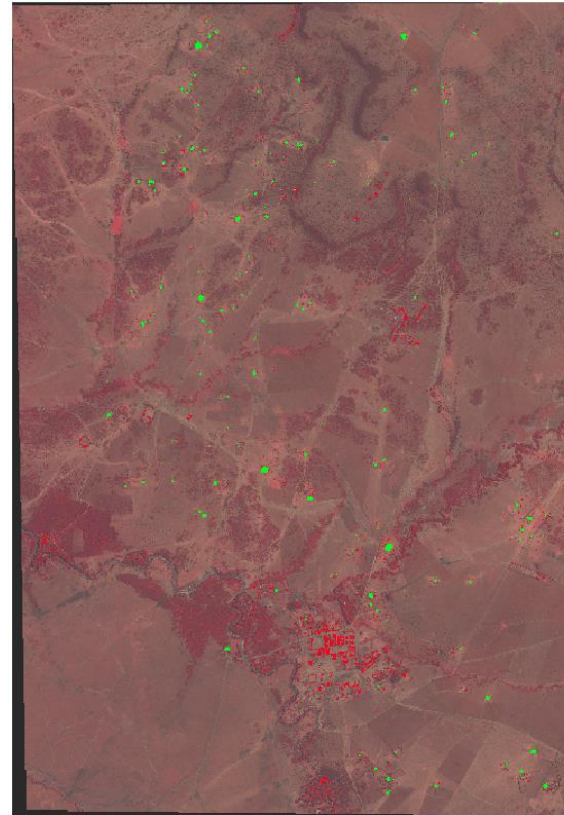


0



— **Task 2: Classification** —  
*Input: image square patches*  
*Outputs: 0 or 1*

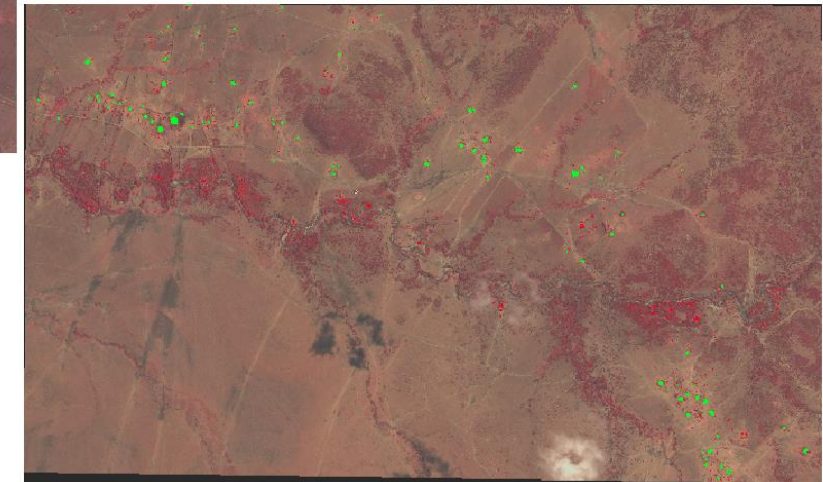
**VAL 1**



— **Task 1: Segmentation** —  
*Input: RGB-NIR-PAN 50cm*  
*Outputs: Masks (vals: 0,1,2,3)*

Spatial split

**TRAIN 1**





# Methods

ImageNet pre-trained encoders.

Class weighting.

Quantile normalization.

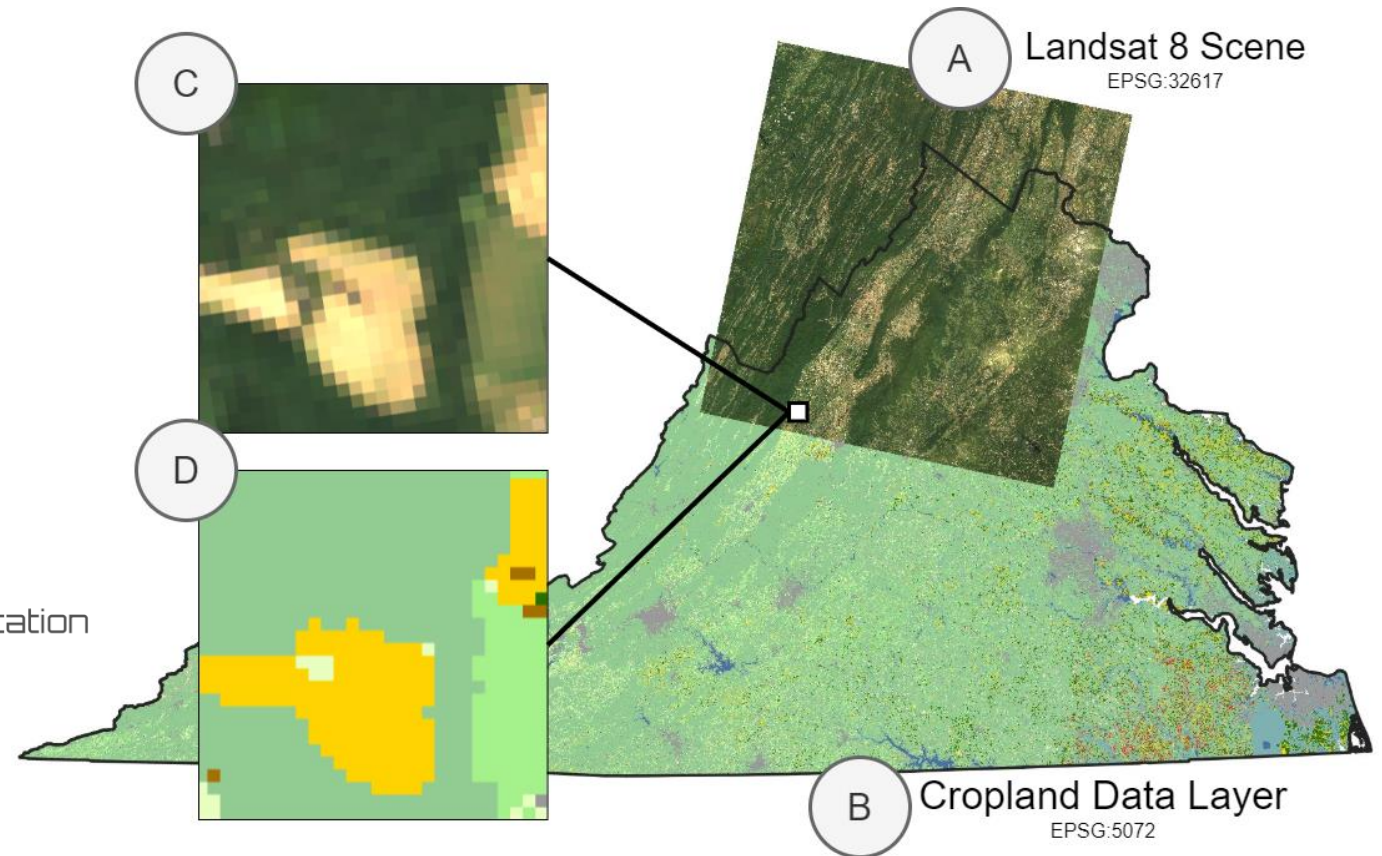
Data augmentation.

Architectures:

- UNet
- Deeplabv3+
- UNet++
- MANet
- LinkNet
- FPN
- PSPNet
- PAN
- Deeplabv3

Backbones:

- ResNet
- ResNeXt
- DenseNet
- EfficientNet
- Vision Transformer

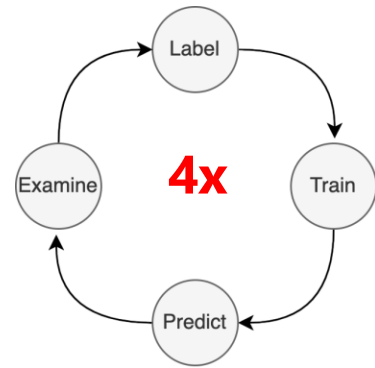


## — TorchGeo for Patch Sampling —

A) a scene from [Landsat 8](#) and B) [Cropland Data Layer](#) labels, even though these files are in different EPSG projections. We want to sample patches C) and D) from these datasets using a geospatial bounding box as an index.

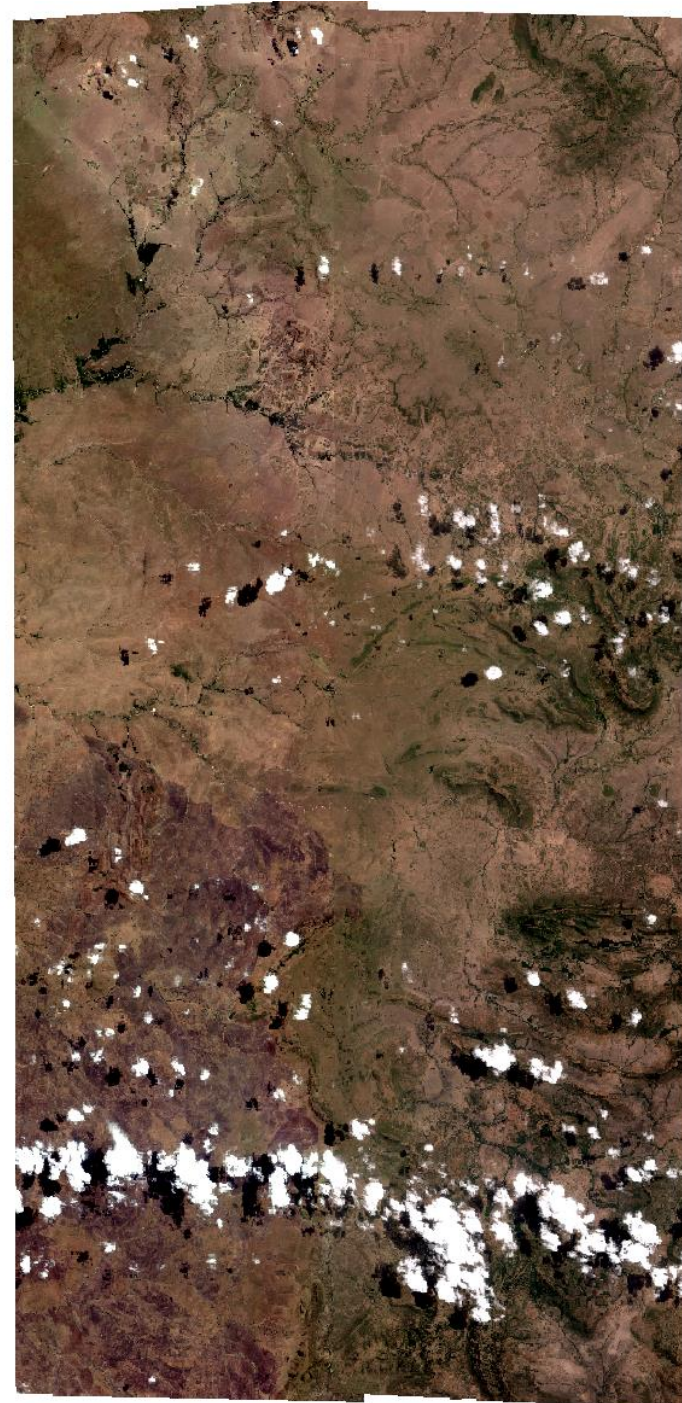
# Preliminary Results

- **Segmentation:** F1 scores:
  - Bomas: **0.85**
  - Structures: **0.79**
- **Classification:** F1 scores:
  - Cattle presence: **0.97**



## Challenge

**Limited Labels:** AI struggles to scale to other regions, necessitating more labels.



— **Low-label Challenges** —  
Sparse imagery comes with variabilities across subregions, land covers, processing conditions, etc.

*Source: Worldview-2*



# Challenge: Scarce Labels

**Problem:** we can't label sparse regions with few positives.

**Observation:** artifacts are connected to uncertainty (or entropy)

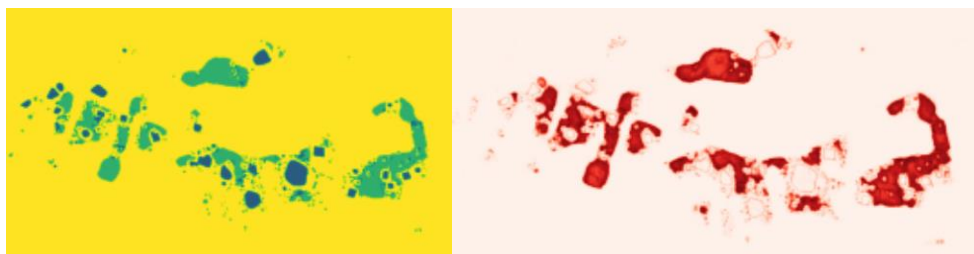
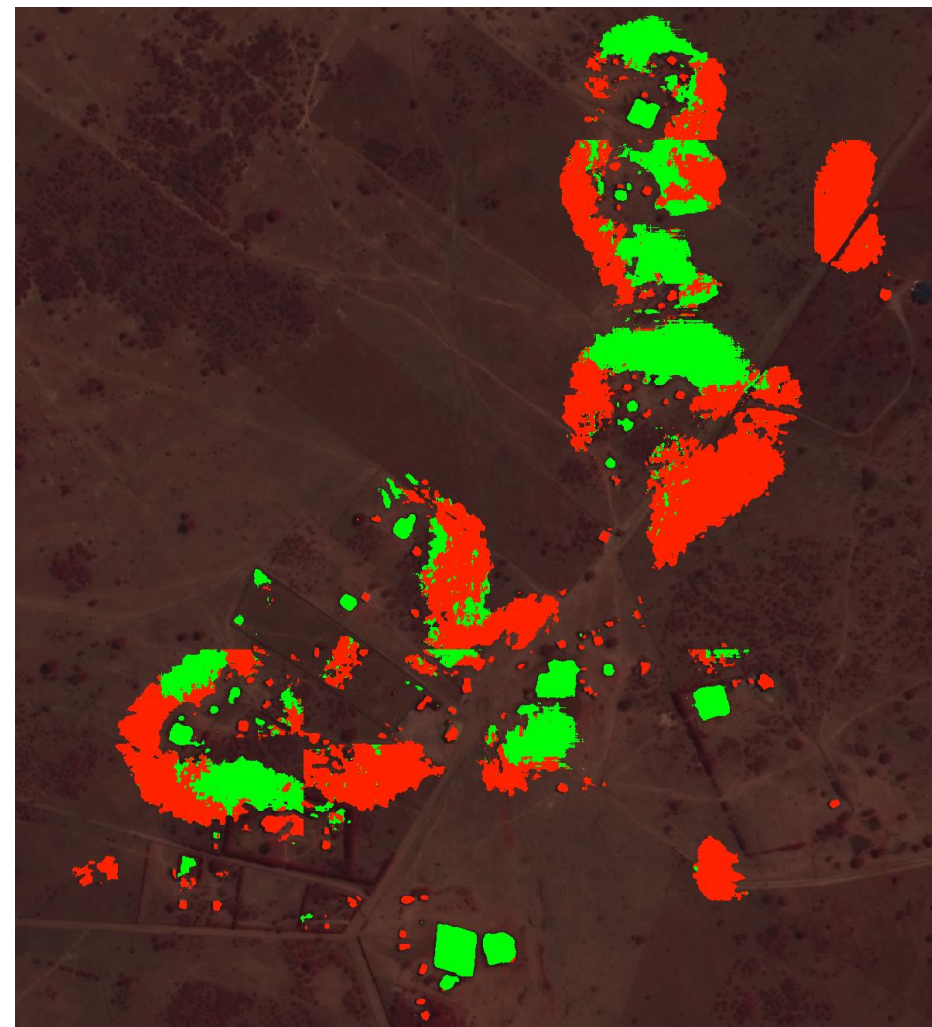


Figure 6: **predicted probabilities** (left) | **calculated Entropy** (right).

## Solutions

- Solution 1: label as much as possible and set the remaining pixels to "negative".
- Solution 2: mark a few regions as negative, penalize the model for uncertainty.



— **Artifacts** —  
Example artifacts produced  
in an "unlabeled" region in  
the validation set.

Source: Worldview-2

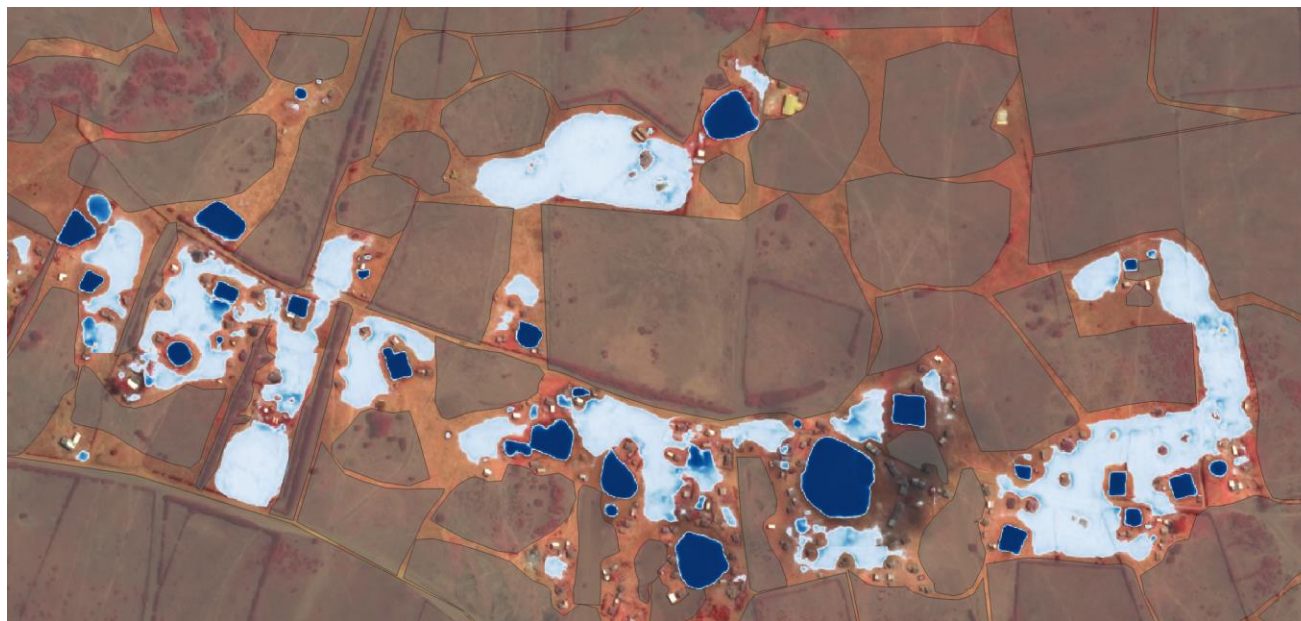


# Low-Label Regularization

**Cross Entropy**: operates on **labeled** pixels:  $L(y, \hat{y}) = - \sum_i^C y_i \log(\hat{y}_i)$

**Entropy**: operates on **unlabeled** pixels:  $H(\hat{y}) = - \sum_i^C \hat{y}_i \log(\hat{y}_i)$

**Loss: Correct & Confident** models:  $J(y, \hat{y}) = \rho(L(y, \hat{y}) \odot M_{labeled}) + (1 - \rho)(H(\hat{y}) \odot M_{unlabeled})$



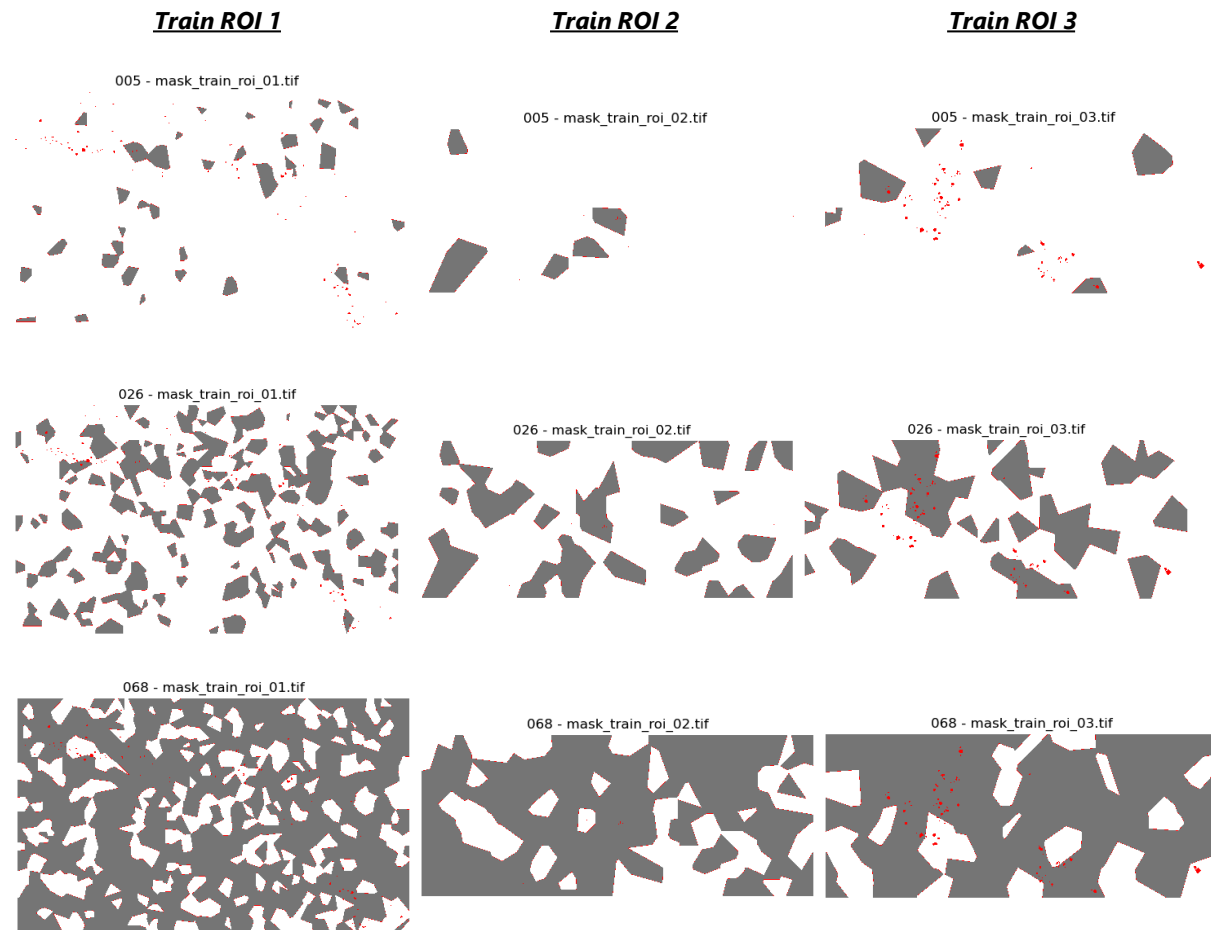
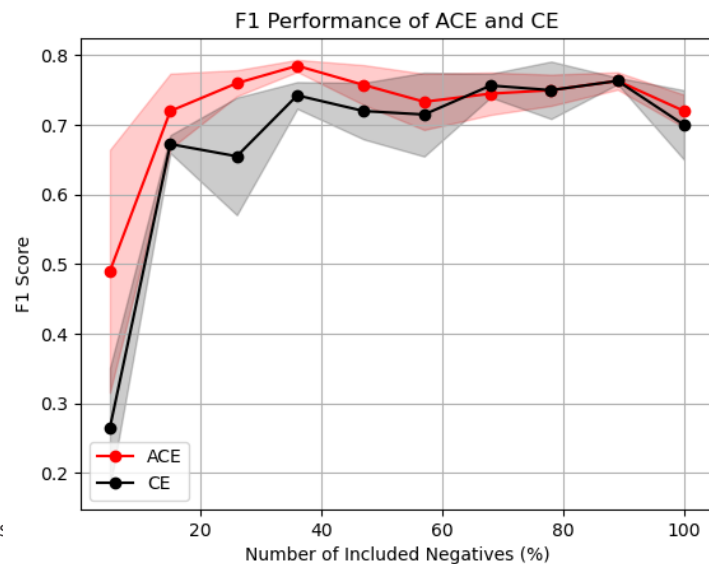
# Low-Label Regularization

**Approach:** add an entropy regularization term to minimize model uncertainty during training.

$$J(y, \hat{y}) = \rho(L(y, \hat{y}) \odot M_{labeled}) + (1 - \rho)(H(\hat{y}) \odot M_{unlabeled})$$

## Experimental setup:

- Train the model on different percentages of negatives with & without the entropy regularizer.



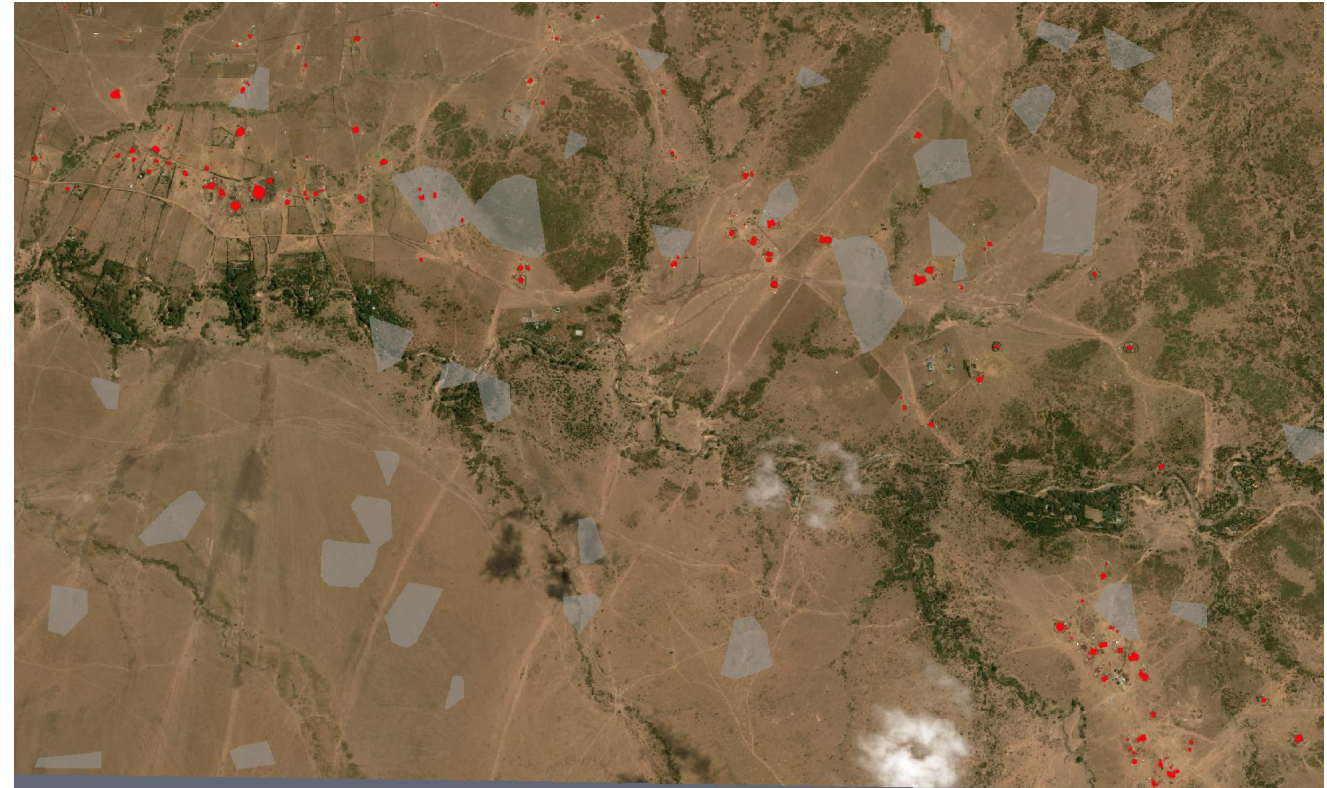
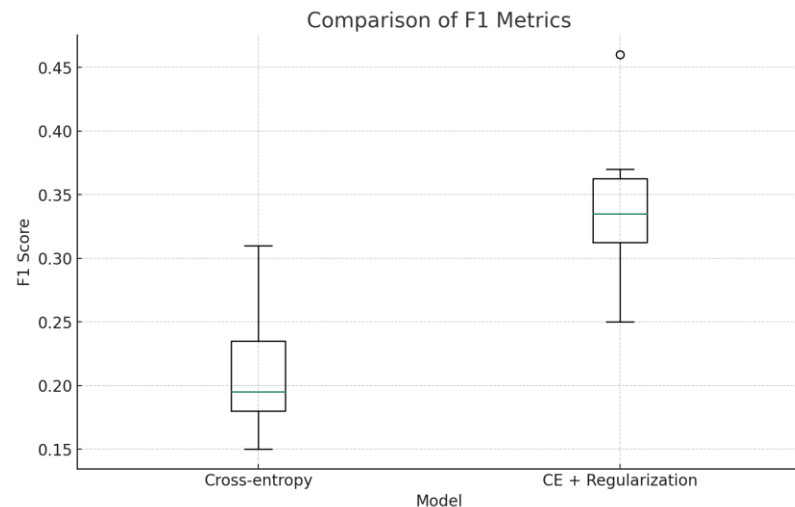
— **Subset Data** —  
incremental data subsets (5% to 100%) to test our approach.

# Example: Training on 10% Negatives

We use all positives and...

- We limit the negatives to **10%**.
- The resulting mask ->
- Hyperparameters stay the same. We change the loss function from Cross-Entropy to CE + regularization.

## Results:



— **Training Region 1** —  
Red: Boma  
Gray: Negative  
Transparent: Ignored

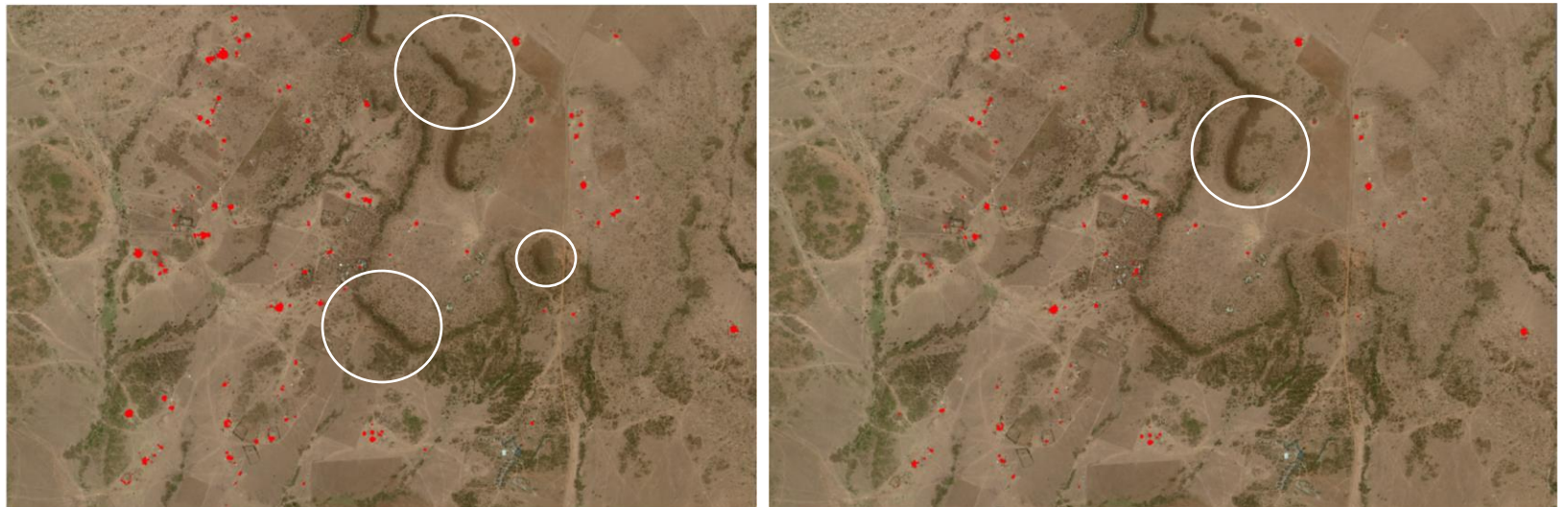


# Example: Comparing Predictions

**Cross-entropy ->**



**Cross-entropy + ER ->**





# Results: AI Dataset

## Dataset details:

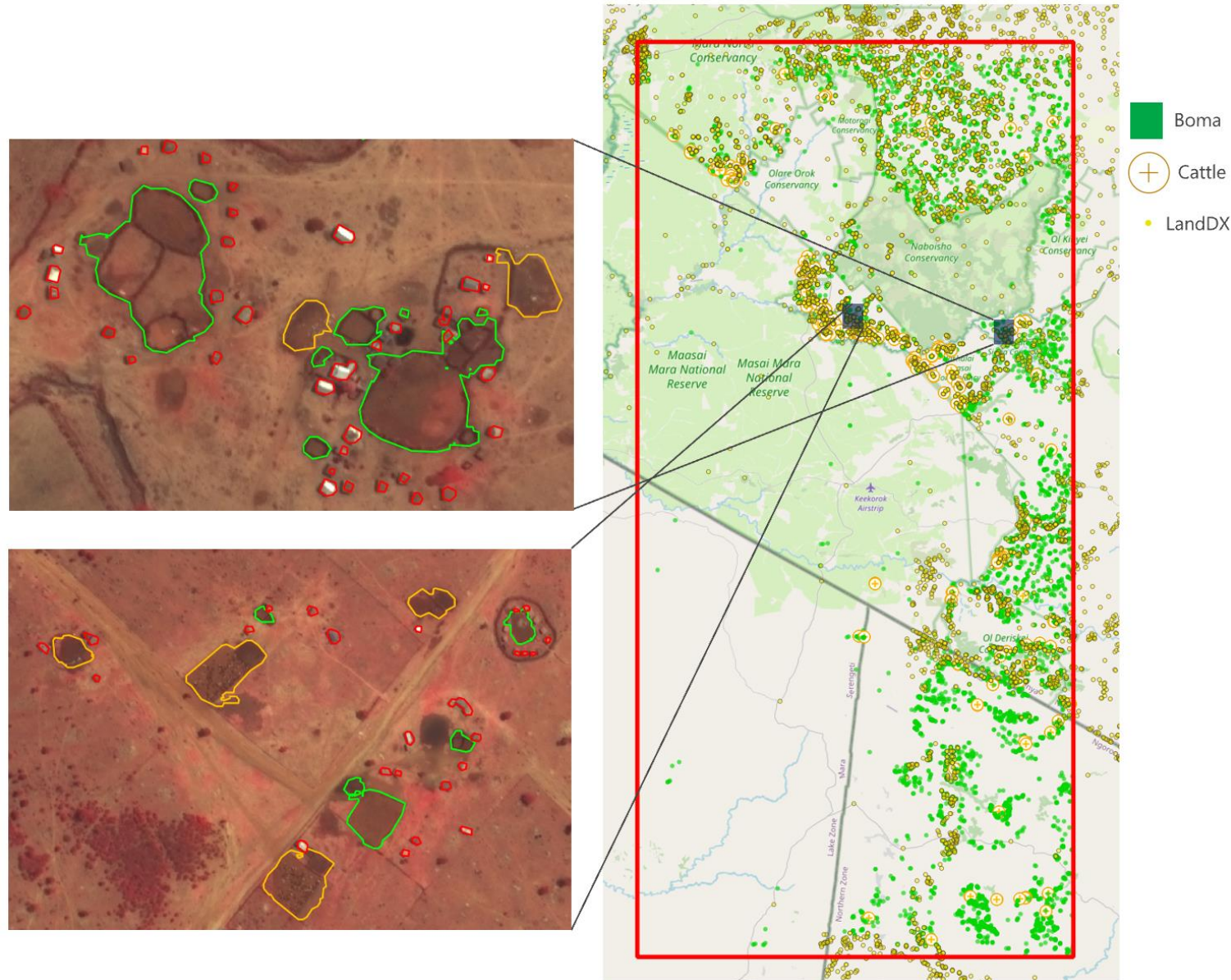
- ~5,100 empty Bomas
- ~160 populated Bomas.
- ~20,000 structures.

## Post-processing:

- Geometry Simplification.
- Remove outliers by area.
- Filter by compactness & rectangularity.
- Smoothing: dilation & erosion.

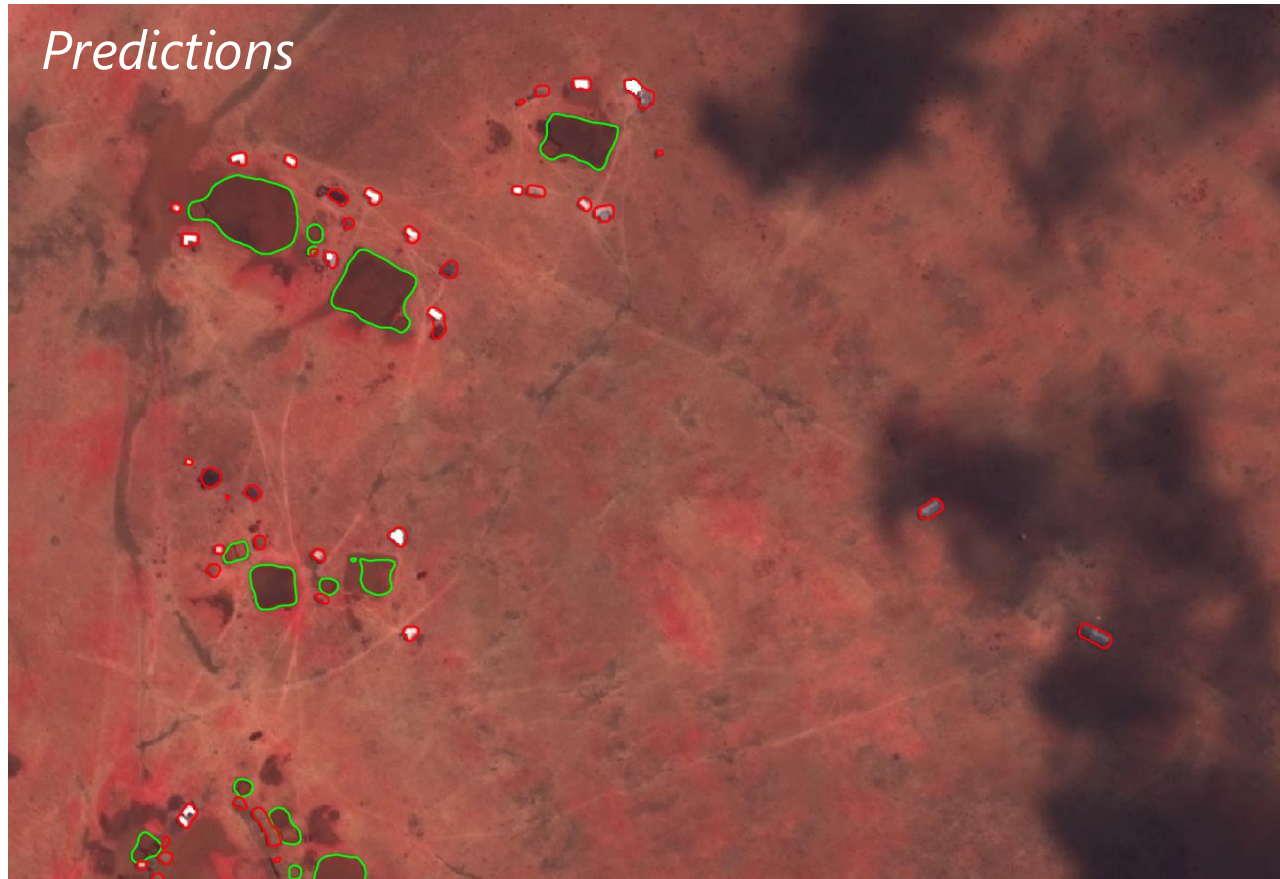
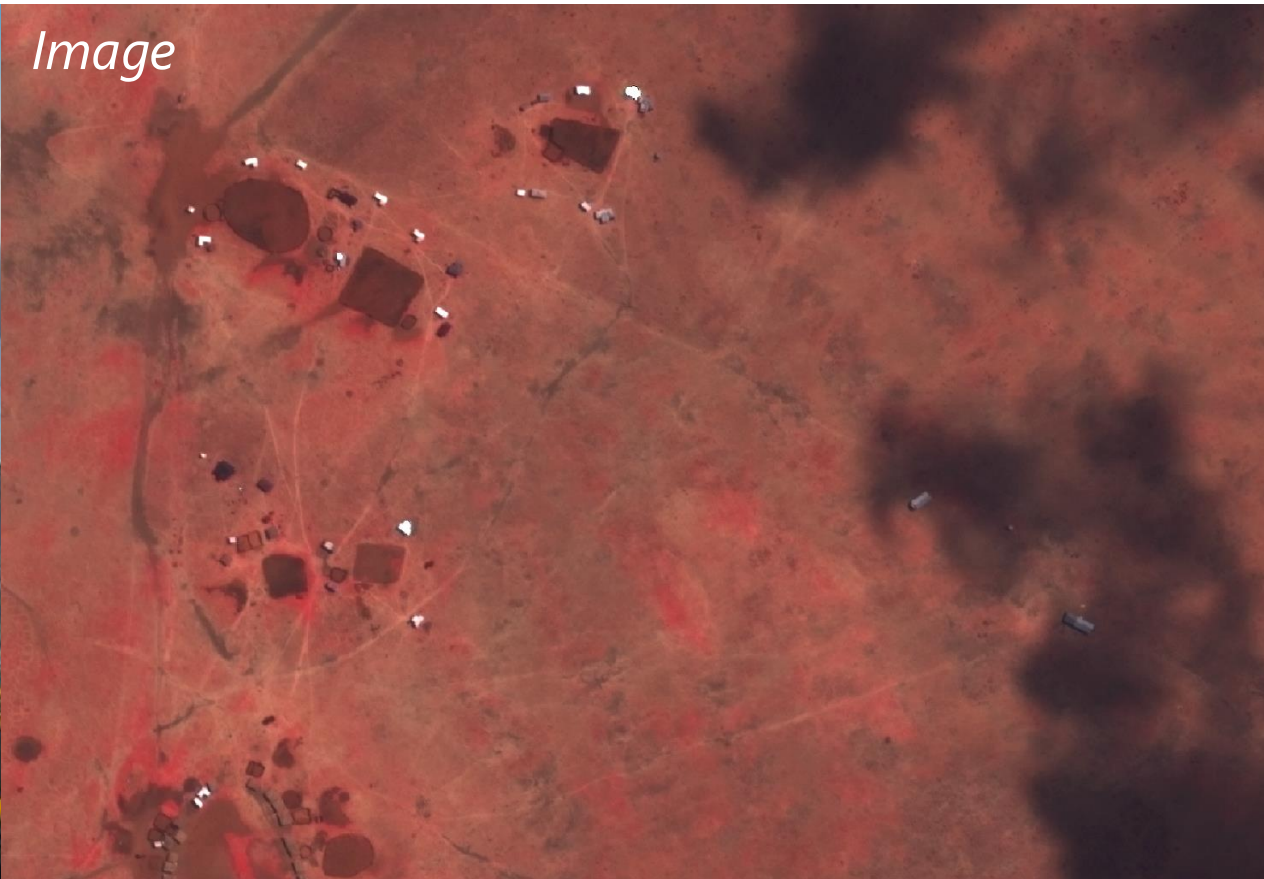
## Data Enrichment:

We aim to enhance data availability in label-limited regions.



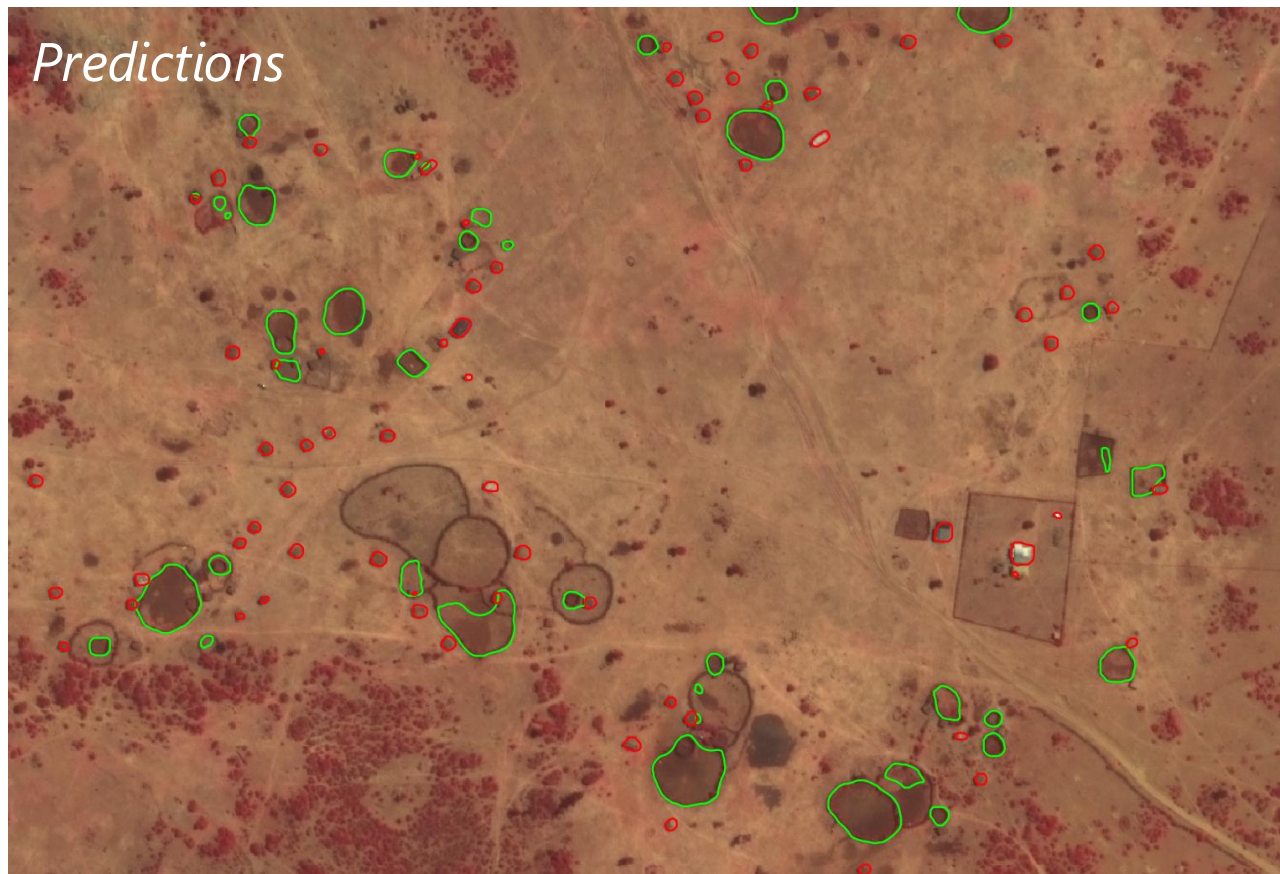
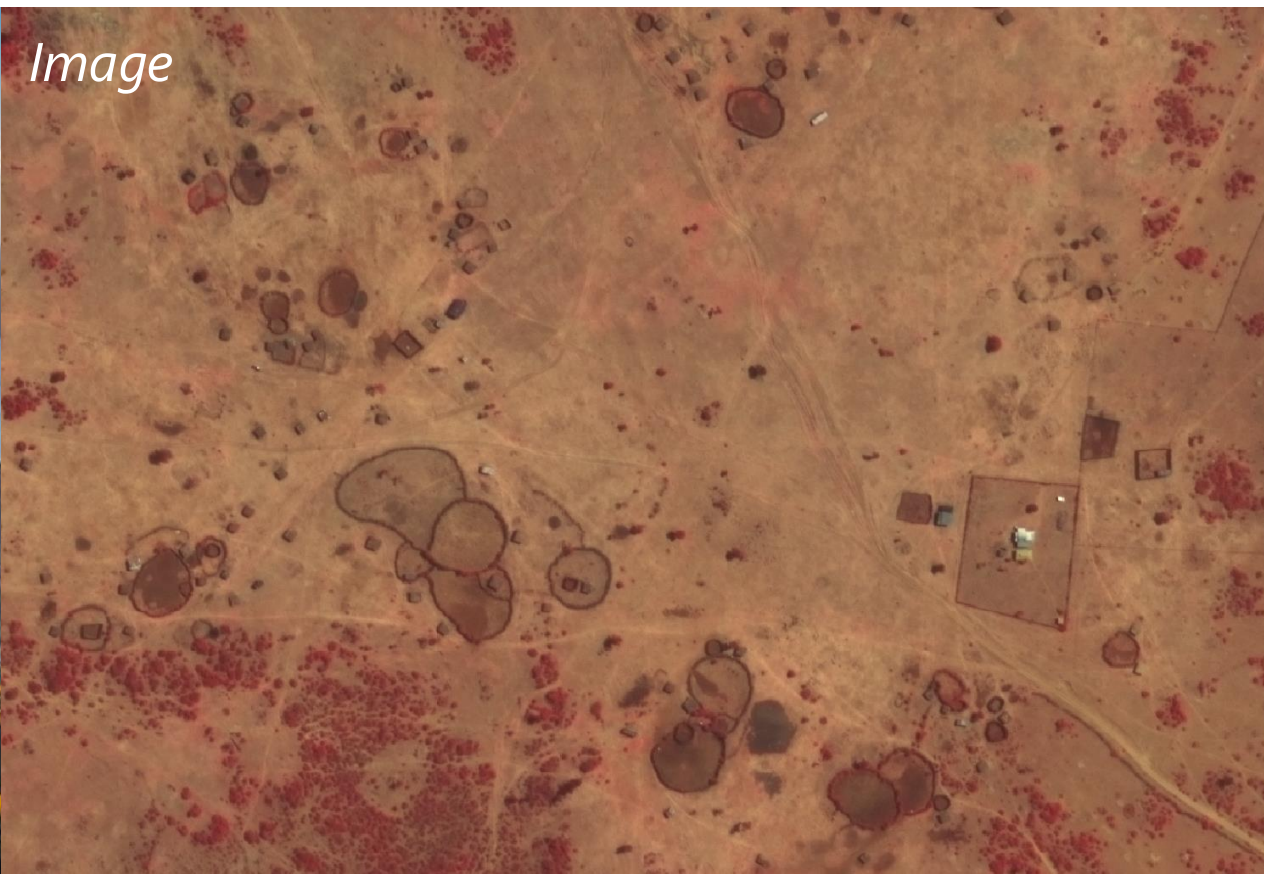


# Example 1



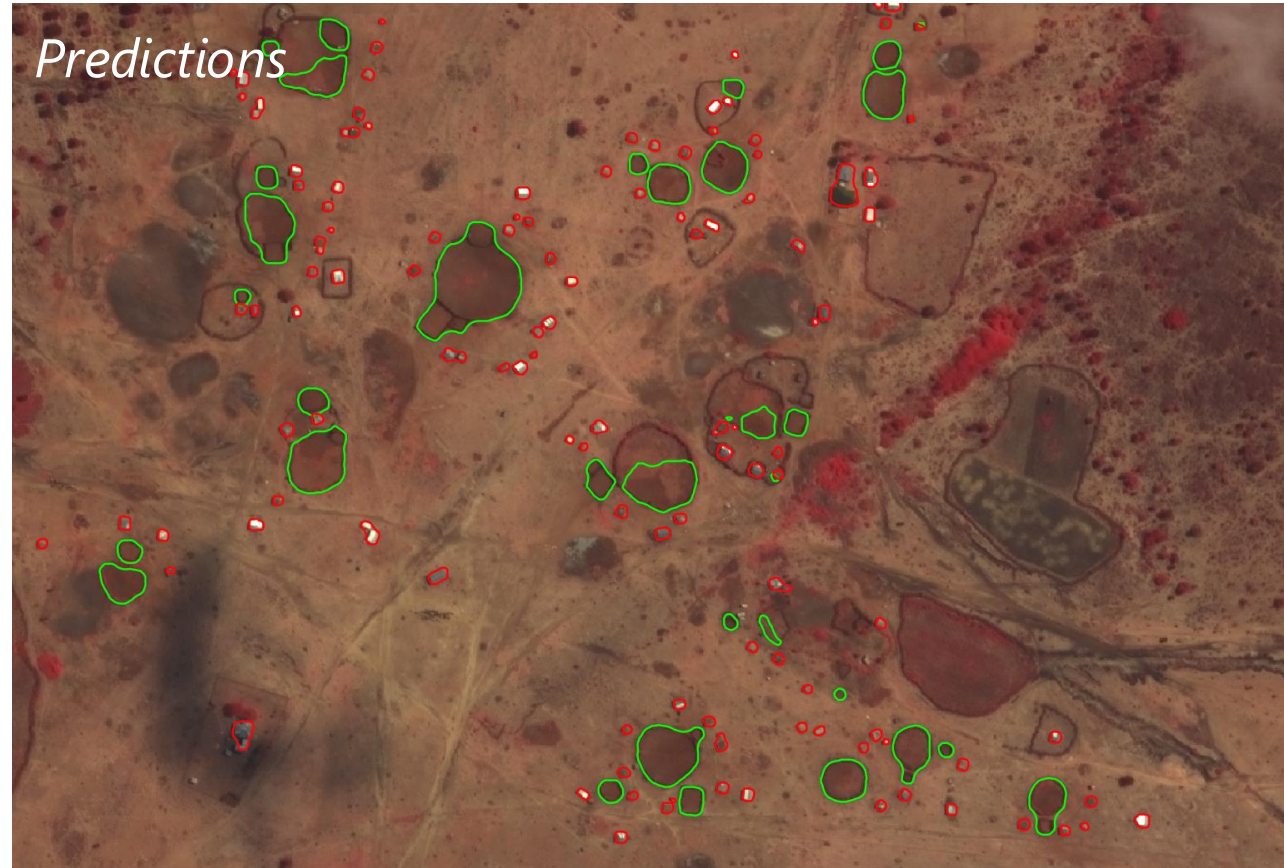
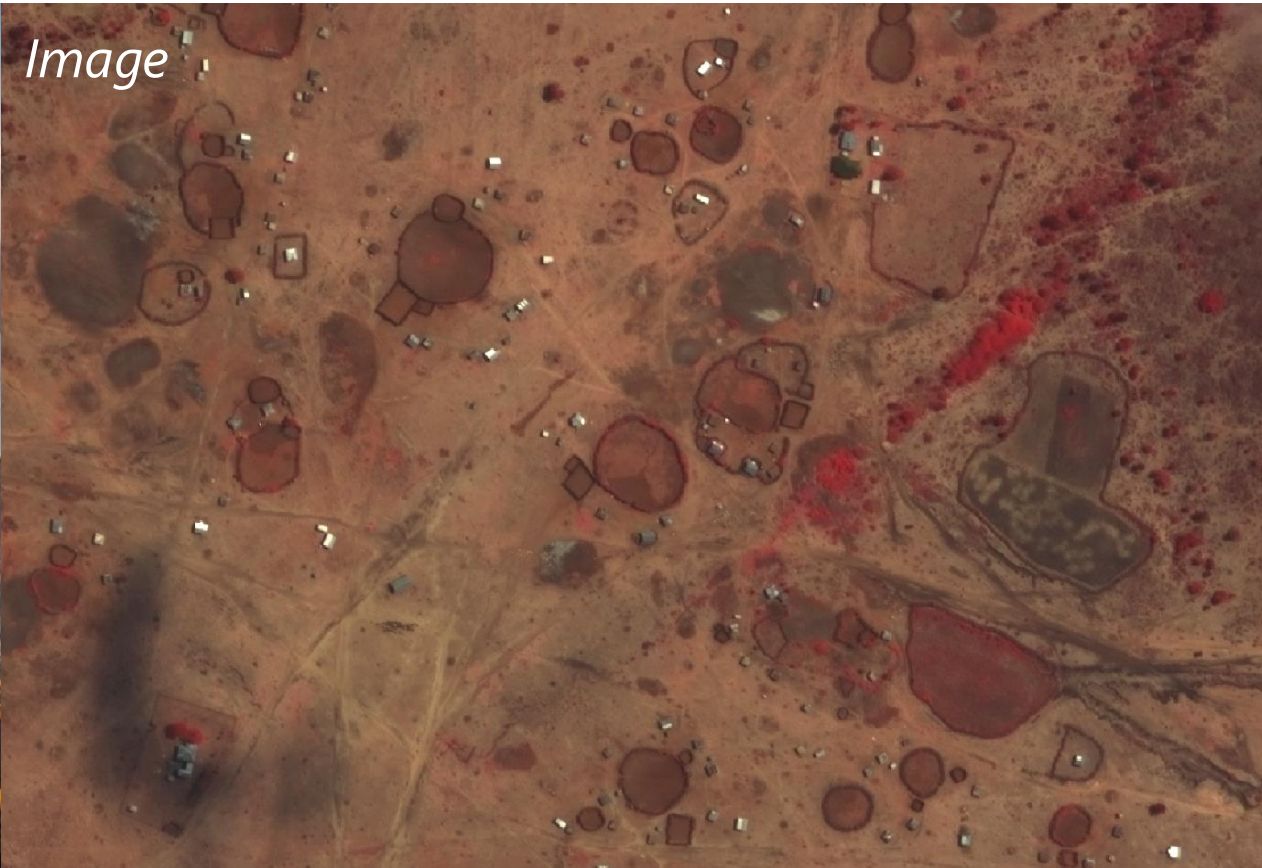


## Example 2



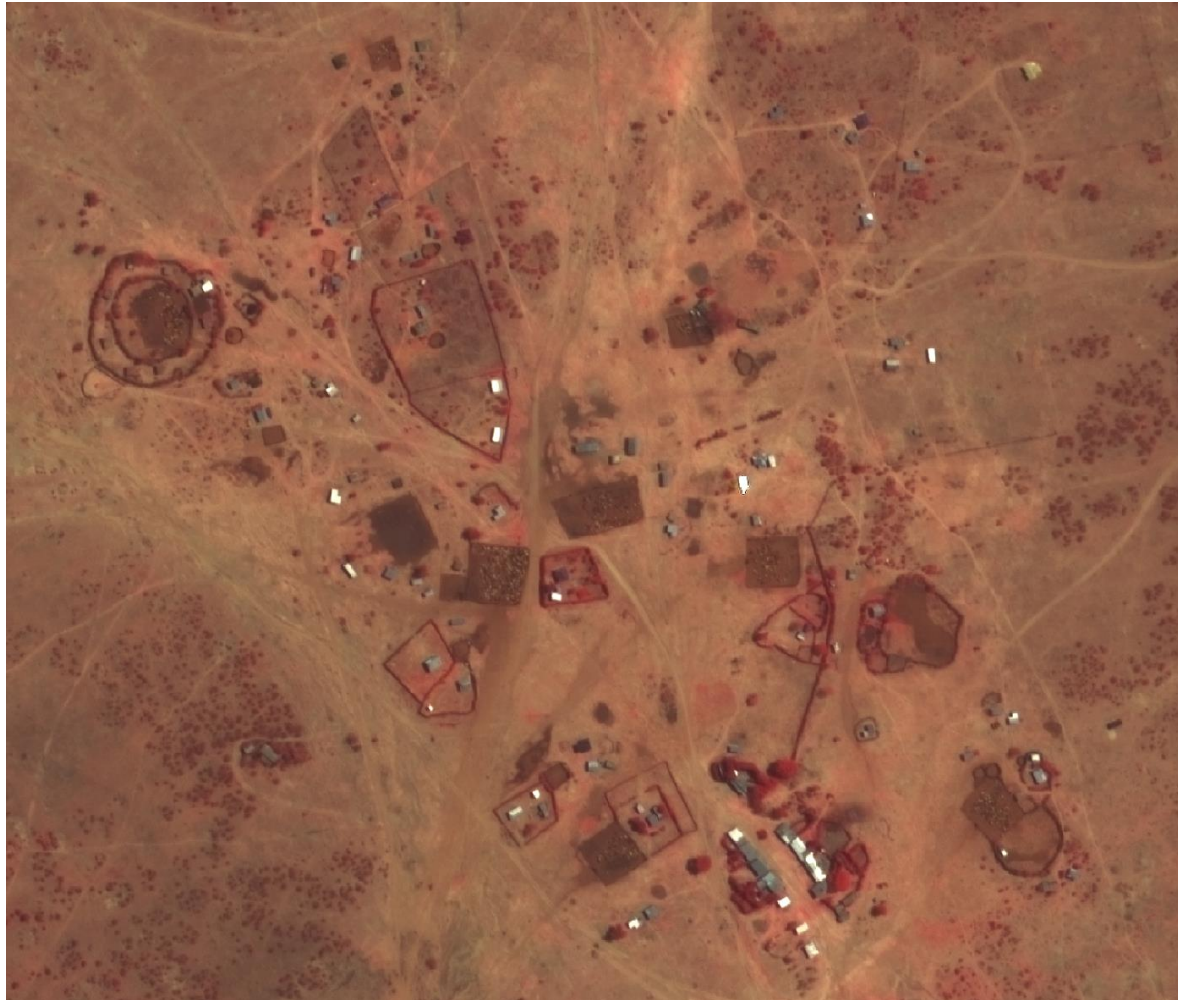


## Example 3





# Lesson 1: Negative Buffers prohibit the “spilling” effect.



*Label*



*Bomas in Green.*

*Negatives in Red.*

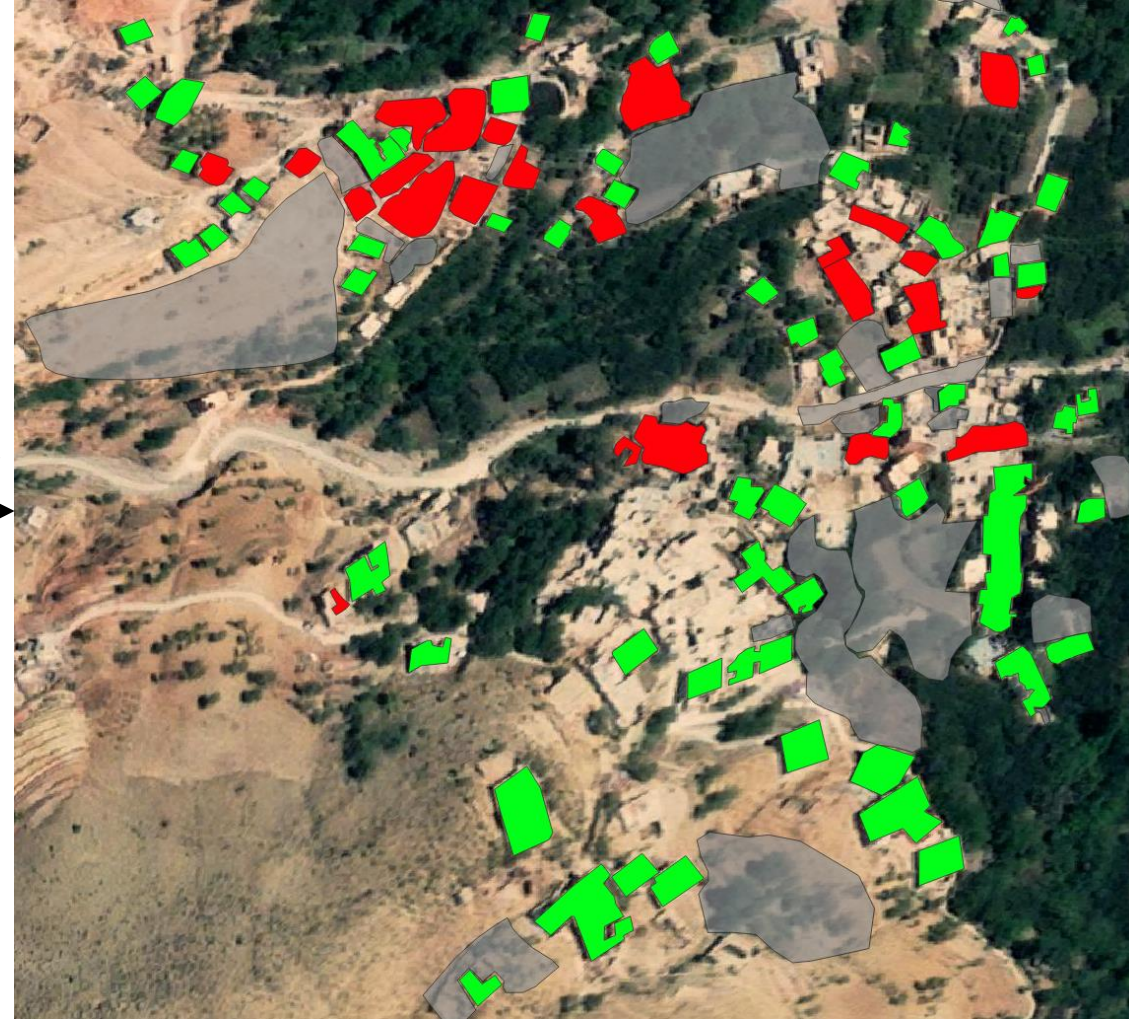
*Transparent pixels are ignored.*



## Lesson 2: Label Quality: Iteratively annotating a diverse & difficult set of patches.



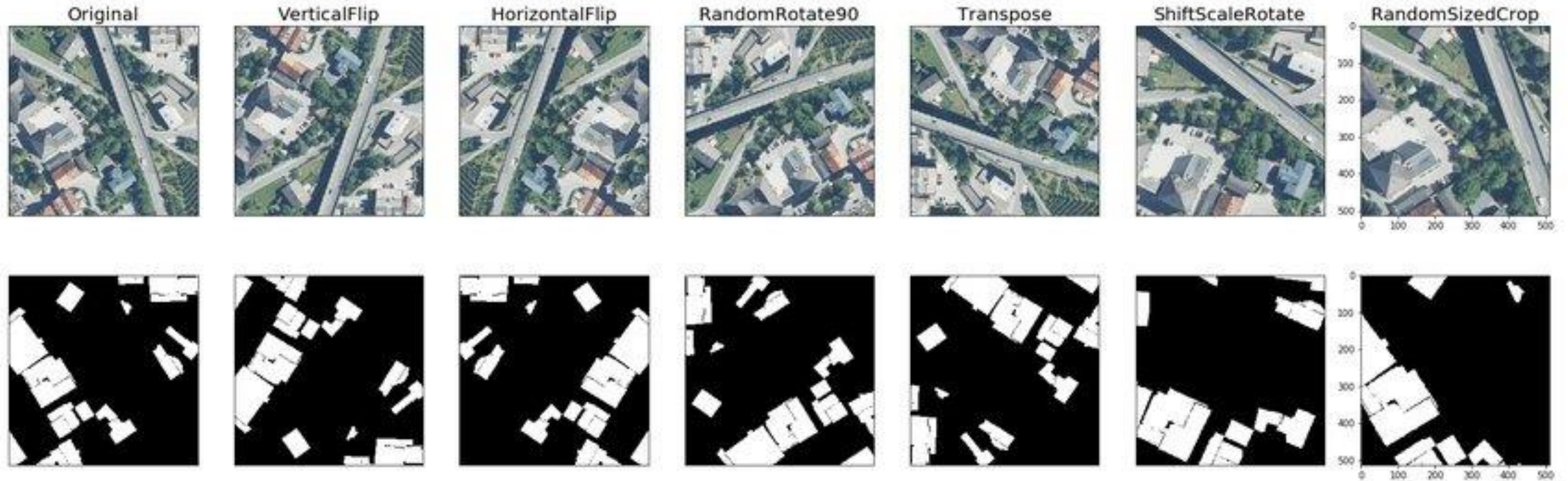
*Label* →



*Building in Green.  
Destroyed buildings in Red.  
Transparent pixels are ignored.*



# Lesson 3: Patch augmentation: horizontal/vertical flipping, rotation, cropping, Color Jitter,...





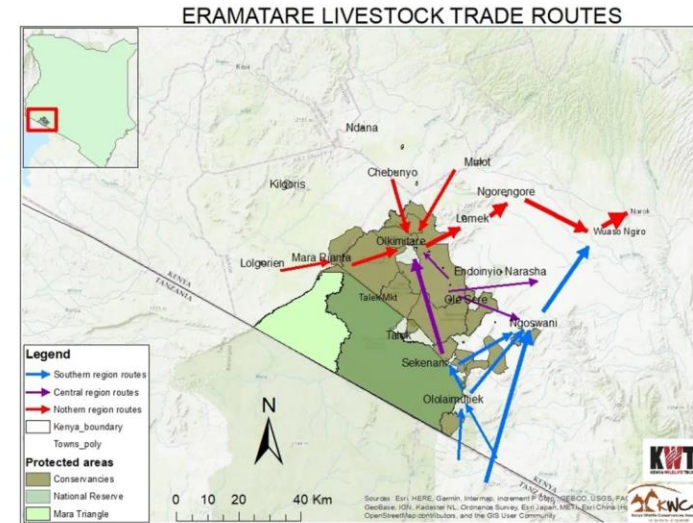
# Impact

KWT can prioritize where to build **predator-proof** bomas made of recycled plastic poles, thus protecting communities' livestock from predator attacks.

KWT can improve their **anti-poison campaigns** and provide more targeted education.

The data can aid in the planning of programs like the Livelihoods Program **"Ufugaji Hifadhi"** that connects farmers to each other.

— **Supporting Markets** —  
By knowing where conflict hotspots are, KWT can help create community networks for trade .



— **Anti-poison campaigns** —



— **Predator-proof Bomas made of recycled plastic poles** —

Credit: Kenya Wildlife Trust



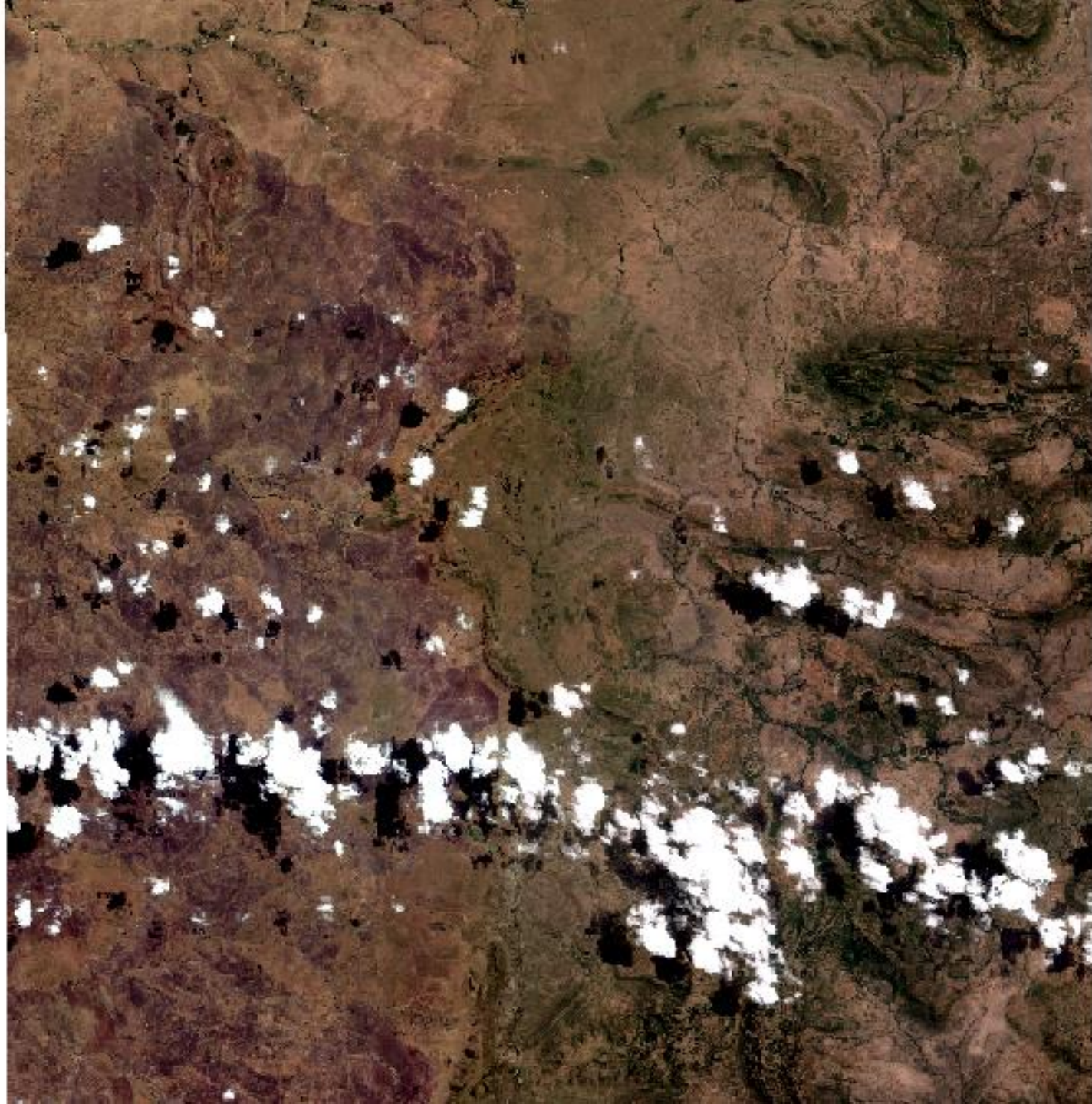
# Next Steps

In-ground validation.

Scaling to other regions & times.

Overlay maps with protected regions,  
georeferenced historical incidents, ..

Analyze the change in the distribution  
of Bomas, their areas, growth/churn, ...





# Conclusion

**Summary:** we used AI to map bomas & structures in the Masai-Mara, including 5K empty bomas, 160 populated bomas, and 20K structures.

**Impact:** The data aims to aid organizations like Kenya Wildlife Trust in predator conservation and mitigating human-wildlife conflict.

**Collaboration with KWT:** We will work with KWT to ensure the data's accuracy & usability in conservation.

**Support Open Data & AI:** Contribute to open data initiatives for accelerating research and collaboration in conservation.

