Microsoft | AI for Good Lab

Leveraging AI for Wildlife Conflict Resolution

Boma & Cattle Detection in the Masai Mara

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KENYA WILDLIFE TRUST

Smithsonian

Boma settlement
Malambo, Arusha Region, Tanzania

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.

KWT
KENYA WILDLIFE TRUST

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.*

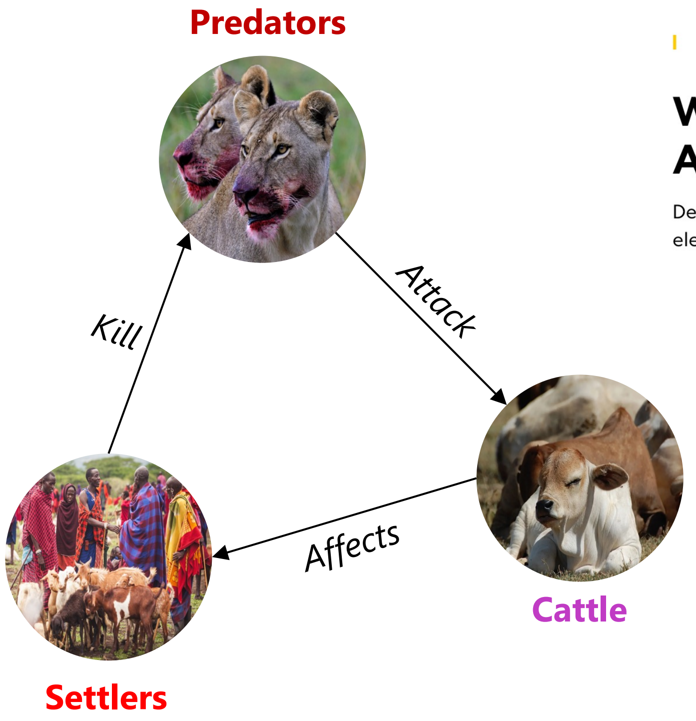
Problem: Human-Predator Conflict in the Maasai Mara

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 | NATIONAL GEOGRAPHIC

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.

INDEPENDENT

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 Chebet • 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.

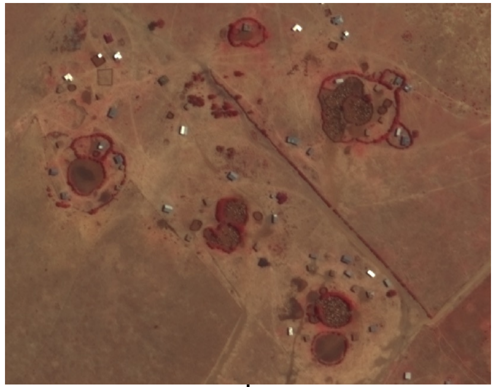
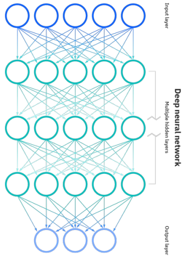


Image*: a high-resolution satellite image that contains multiple Bomas.*

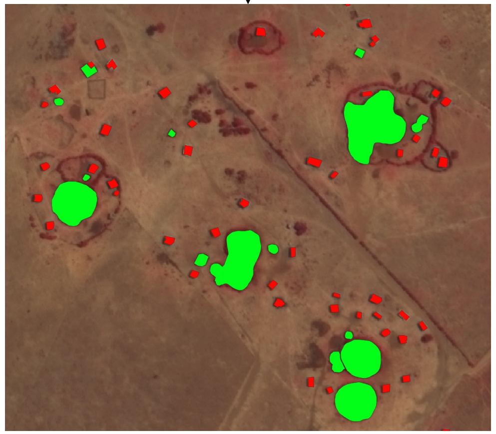
How can we find Bomas?

Automatic

Manual



Pros/Cons*:*
- *Some labeling.*
- *"Mostly" Accurate.*
- *Fast.*
- *Cheap.*
- *Scalable.*



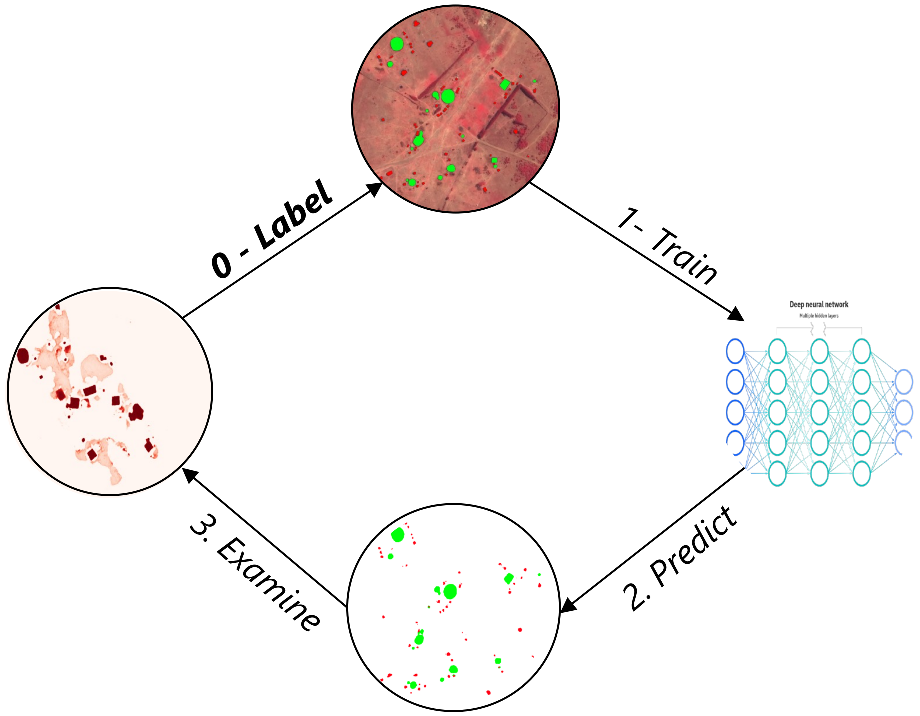
Labels*:*
- *Green: Bomas.*
- *Red: buildings.*

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
WV320230130081300P00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	1,001.04 MiB	Active
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
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WV320230130081306M00.zip	Hot (inferred)	01/06/2023, 01:43	Block Blob	application/x-zip-compressed	794.15 MiB	Active
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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-
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507514526050_01_P001.XML 23JAN30081259-M1BS-507514526050_01_P001_README.TXT
```
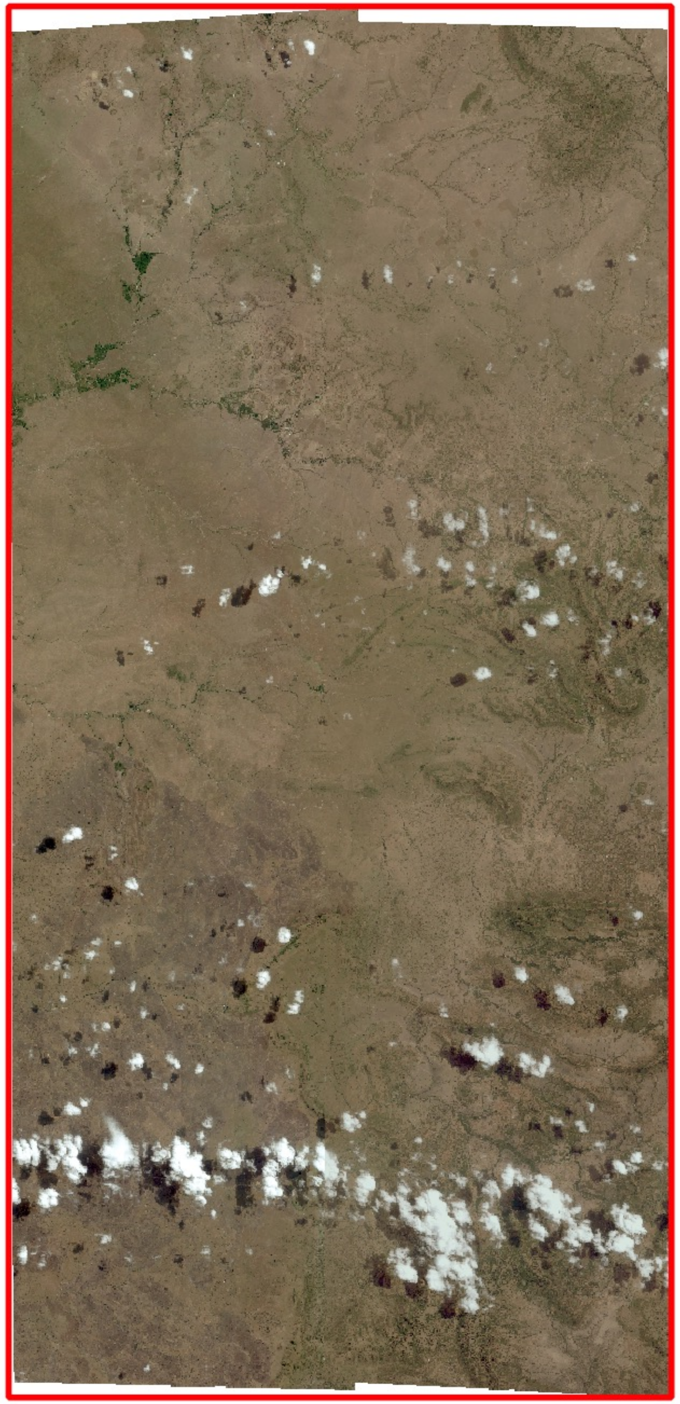

We use **Gdalwarp** for geo-referencing. Other processing steps:

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

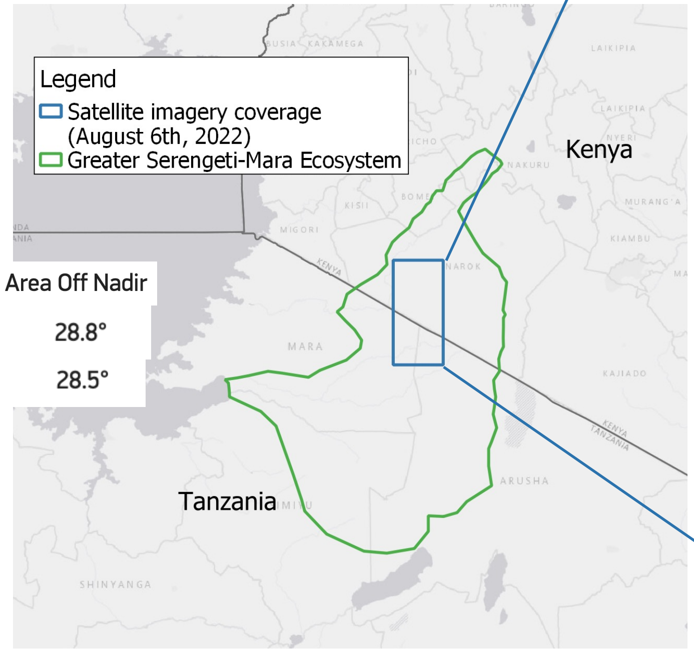
Data: Input Imagery

Inputs (imagery): WorldView-2

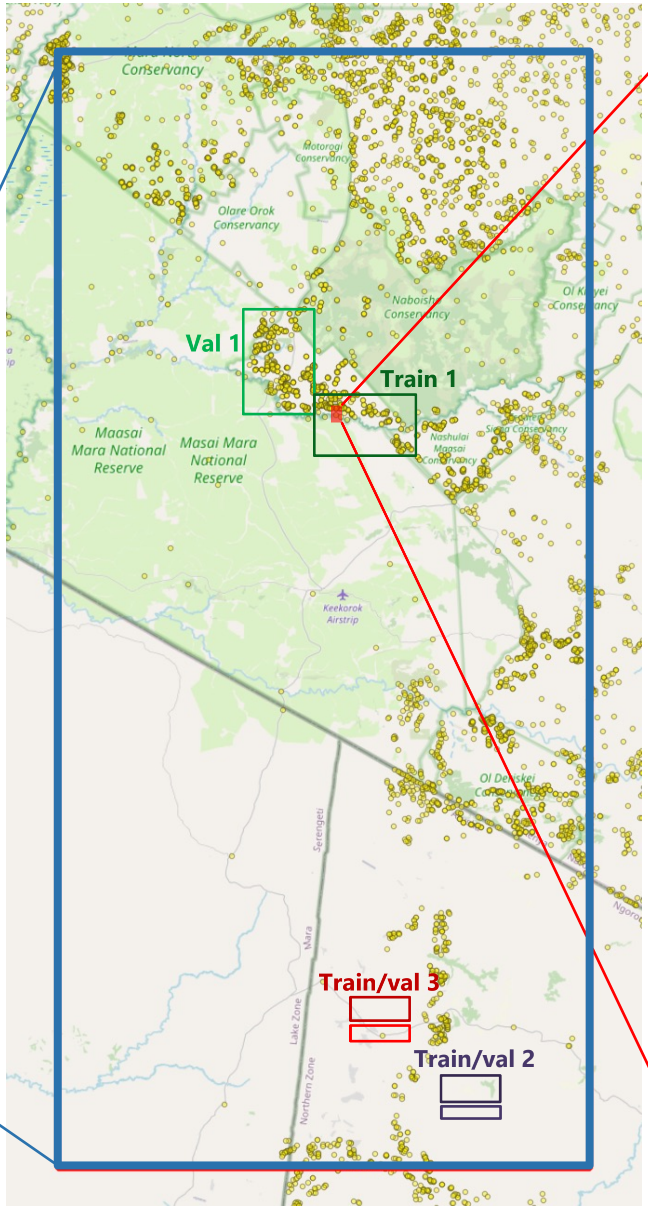
- Coverage: **~3,600 km2**
- Bands: **RGB-NIR-PAN**
- Spatial resolution: **50cm**
- Snapshot: **August 6, 2022 ~8AM**

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

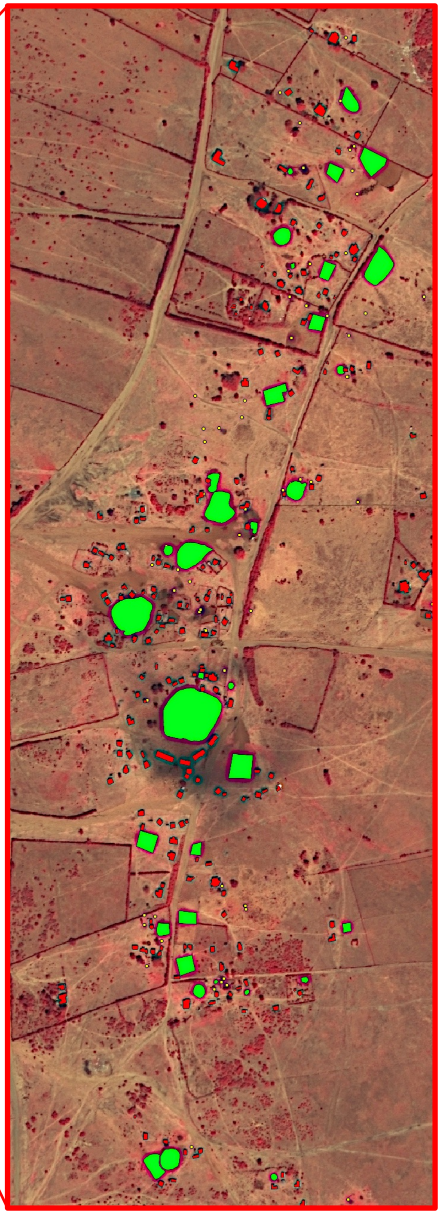
Scenes



Region of Interest (Blue).



3 Train/Validation splits.



Boma (Green); Structure (Red).

Data: Labels

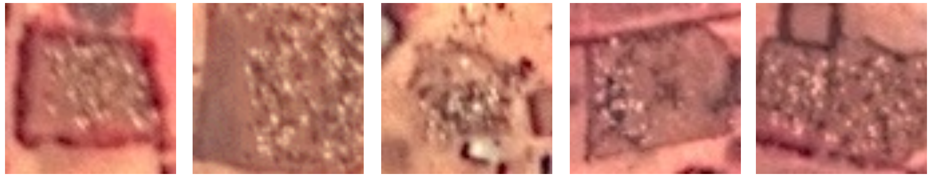
Targets

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

Bomas: **812**
Structures: **3,240**

0 or 1 (Cattle presence): 812 annotated Bomas

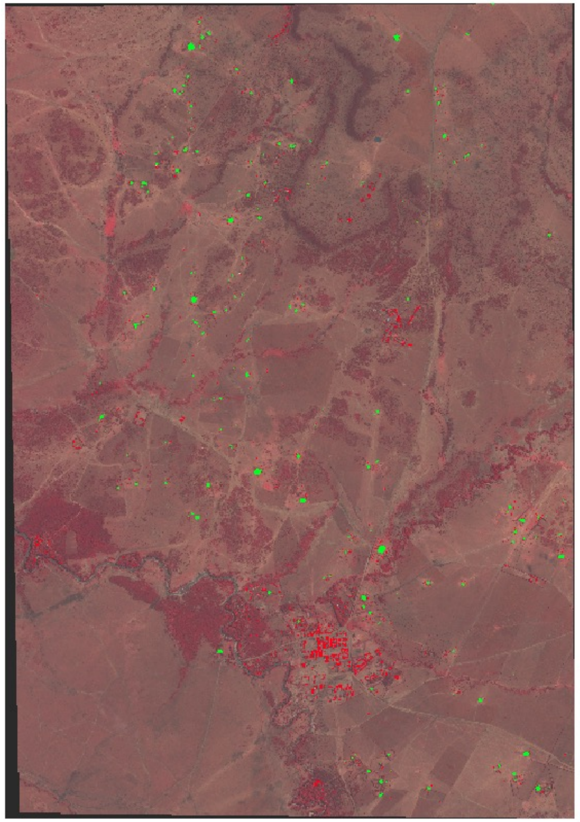
1



0

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

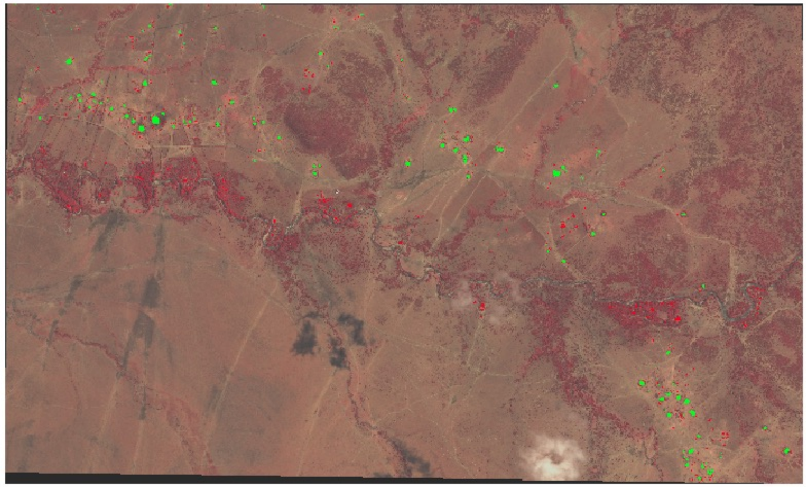
VAL 1



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

Spatial split

TRAIN 1



Methods

TorchGeo

ImageNet pre-trained encoders.

Class weighting.

Quantile normalization.

Data augmentation.

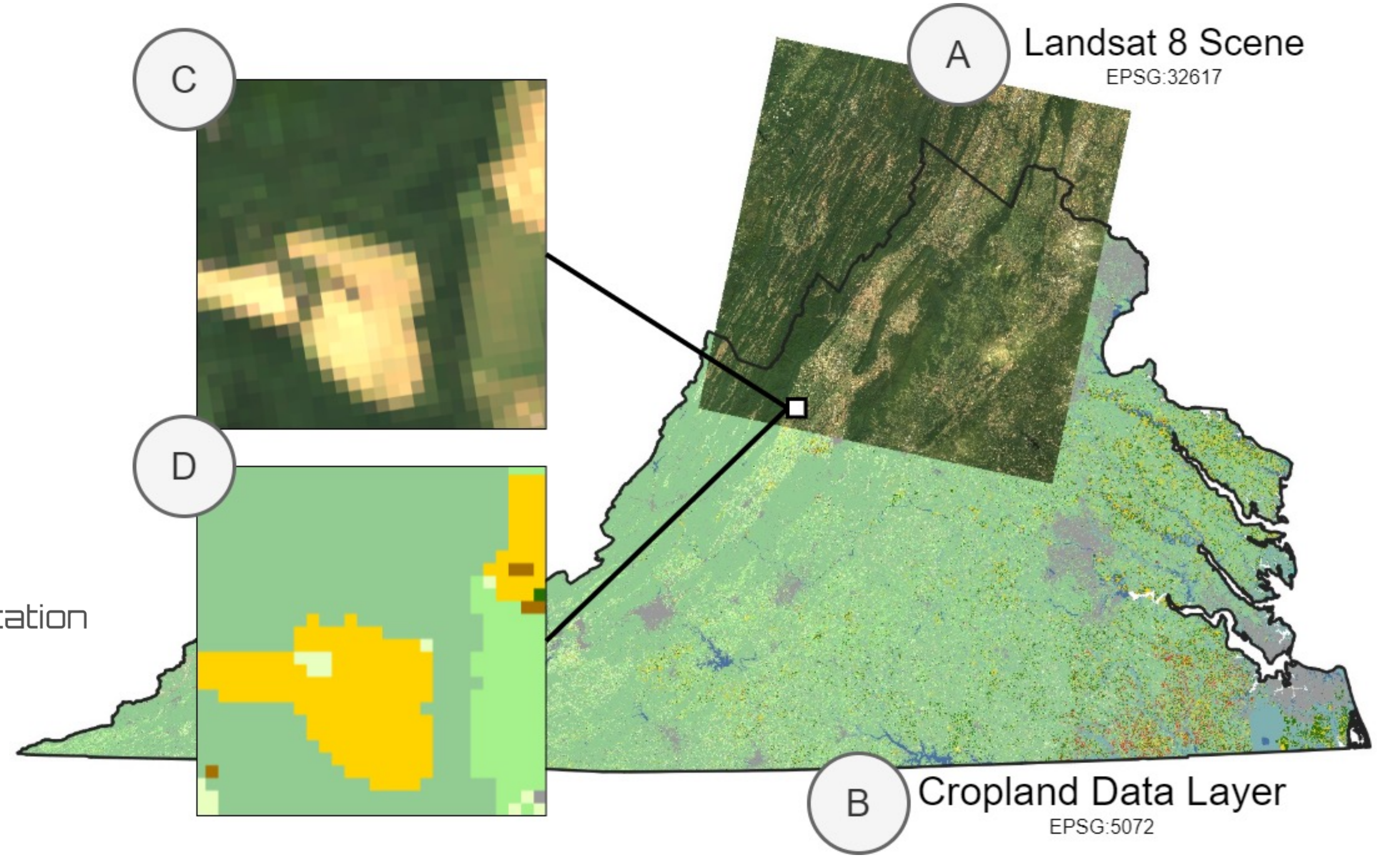
Architectures:

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

Segmentation Models

Backbones:

- ResNet
- ResNeXt
- DenseNet
- EfficientNet
- Vision Transformer

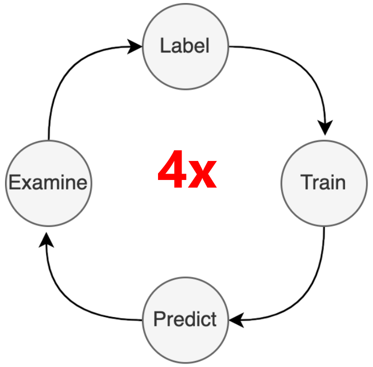


— TorchGeo for Patch Sampling—

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.

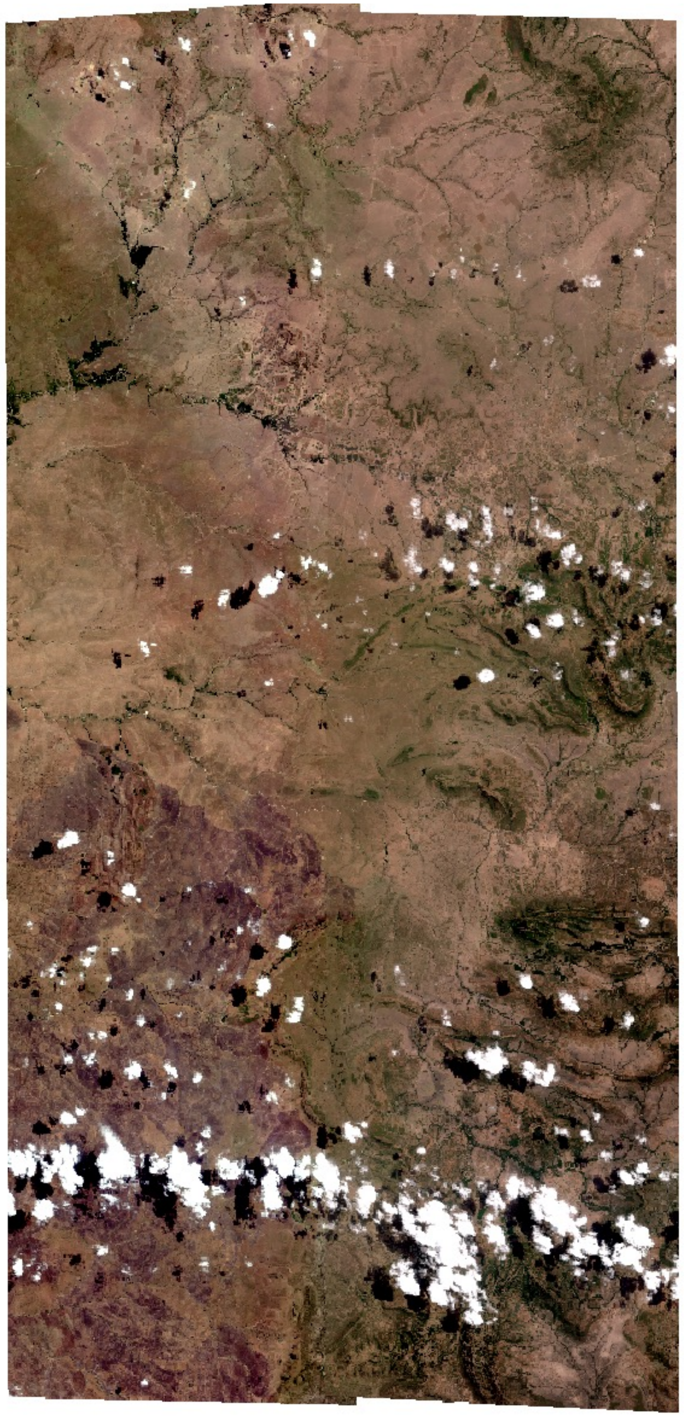
Preliminary Results

- **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 sparce regions with few positives.

Observation: artifacts are connected to uncertainty (or entropy)

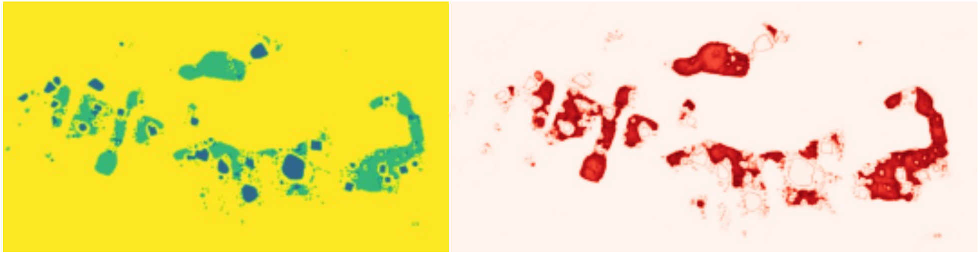
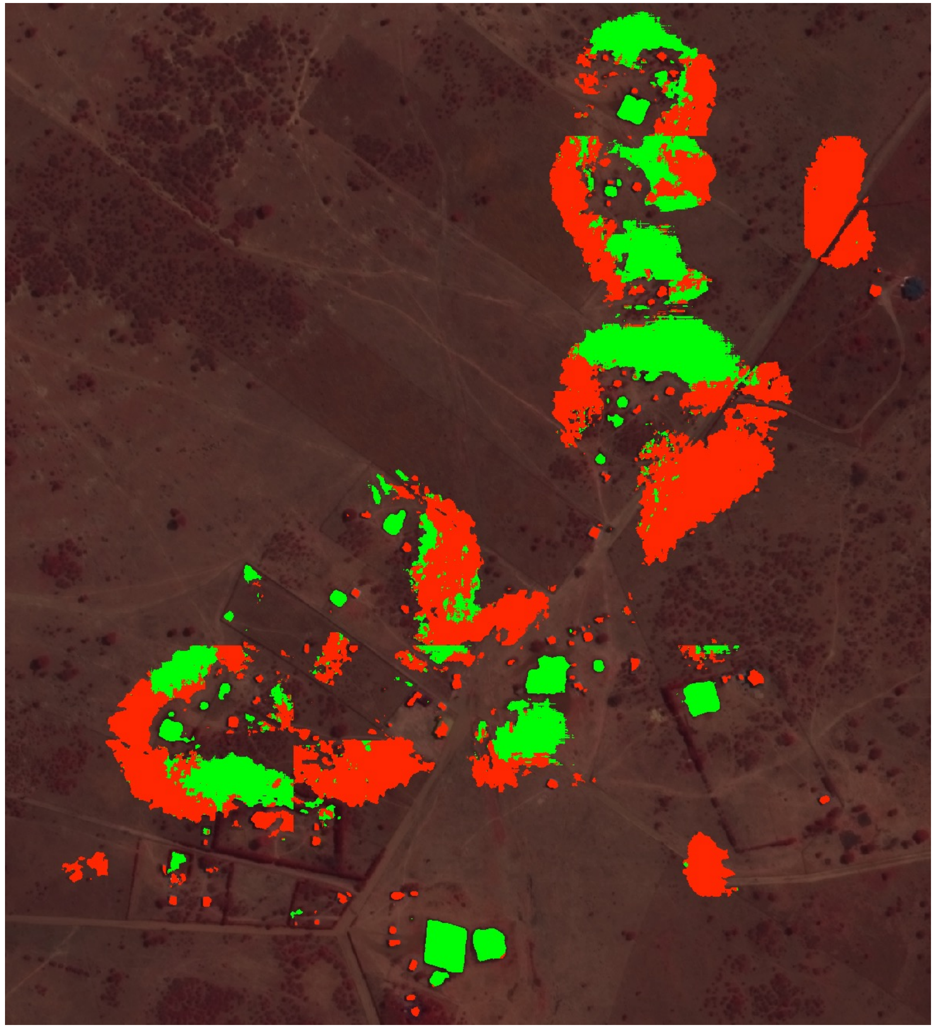


*Figure 6: **predicted probabilities** (left) | calculated **Entropy** (right).*

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

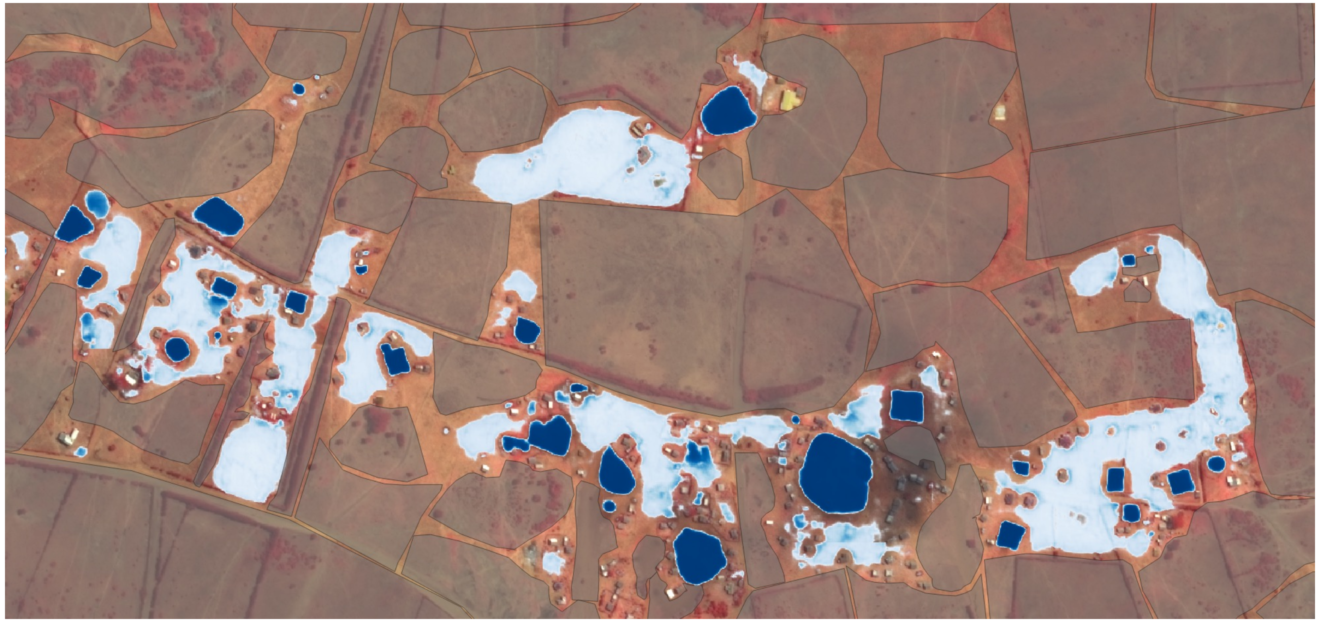


Figure of training region predictions: Artifact-producing models are uncertain in unlabeled pixels.

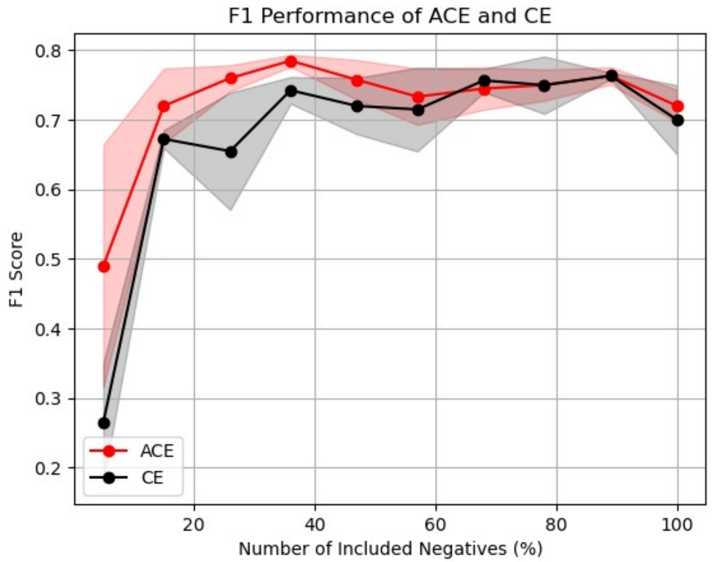
Low-Label Regularization

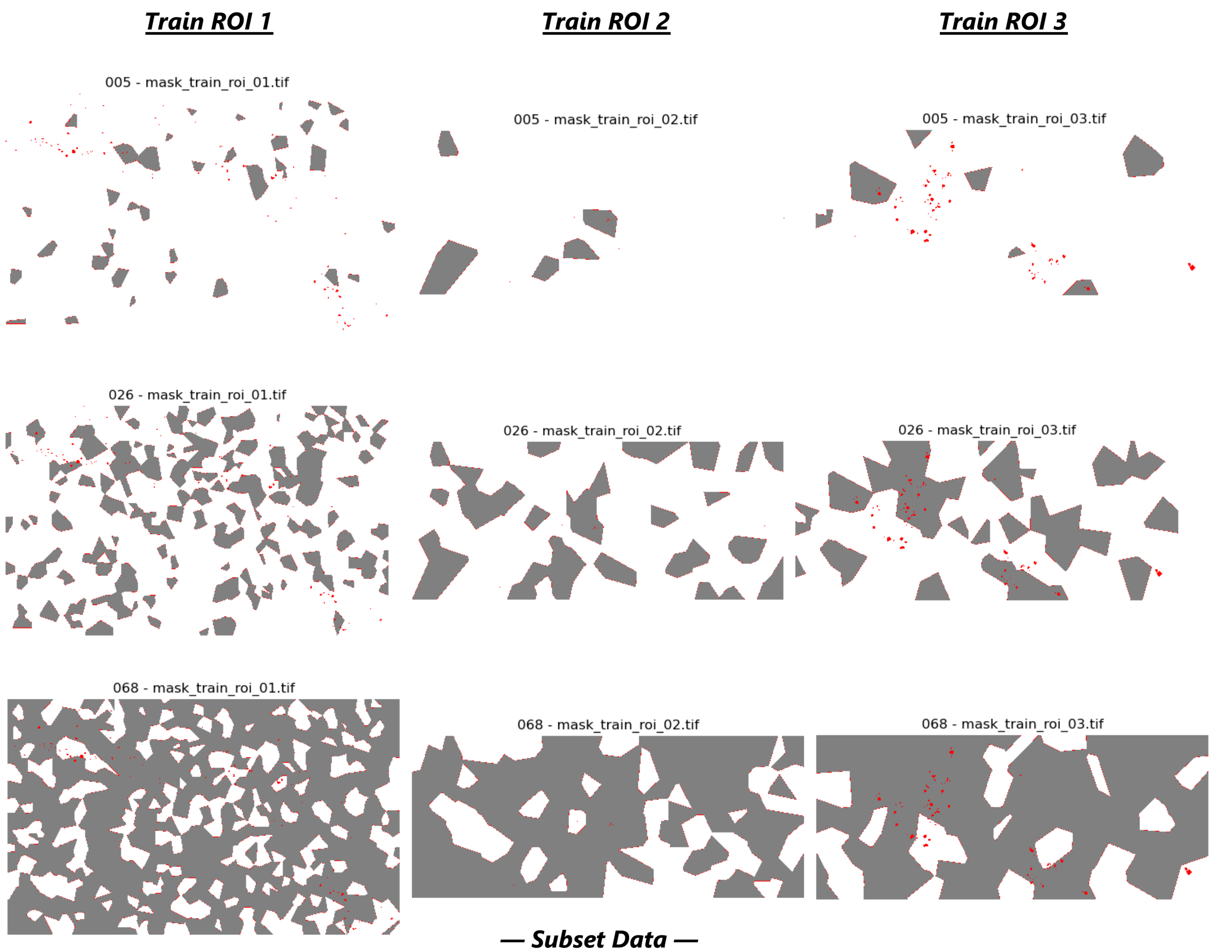
Approach: add an entropy regularization term to minimize model uncertainty during training.

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

Experimental setup:

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





— Subset Data —

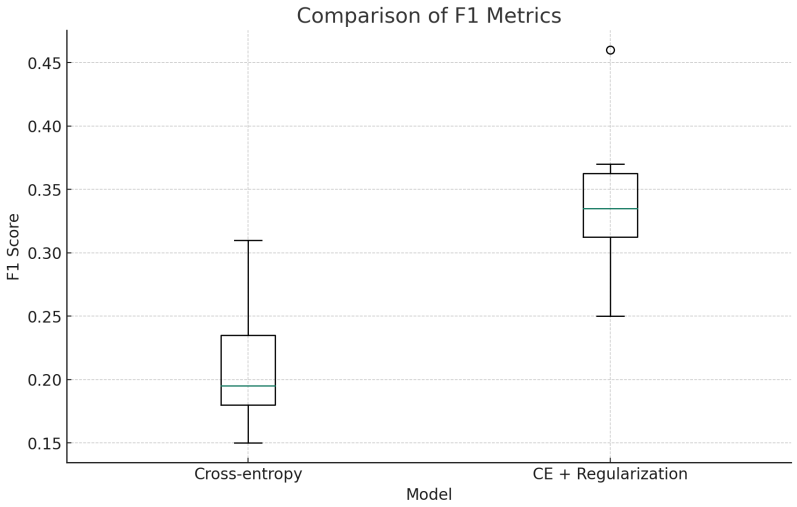
incremental data subsets (5% to 100%) to test our approach.

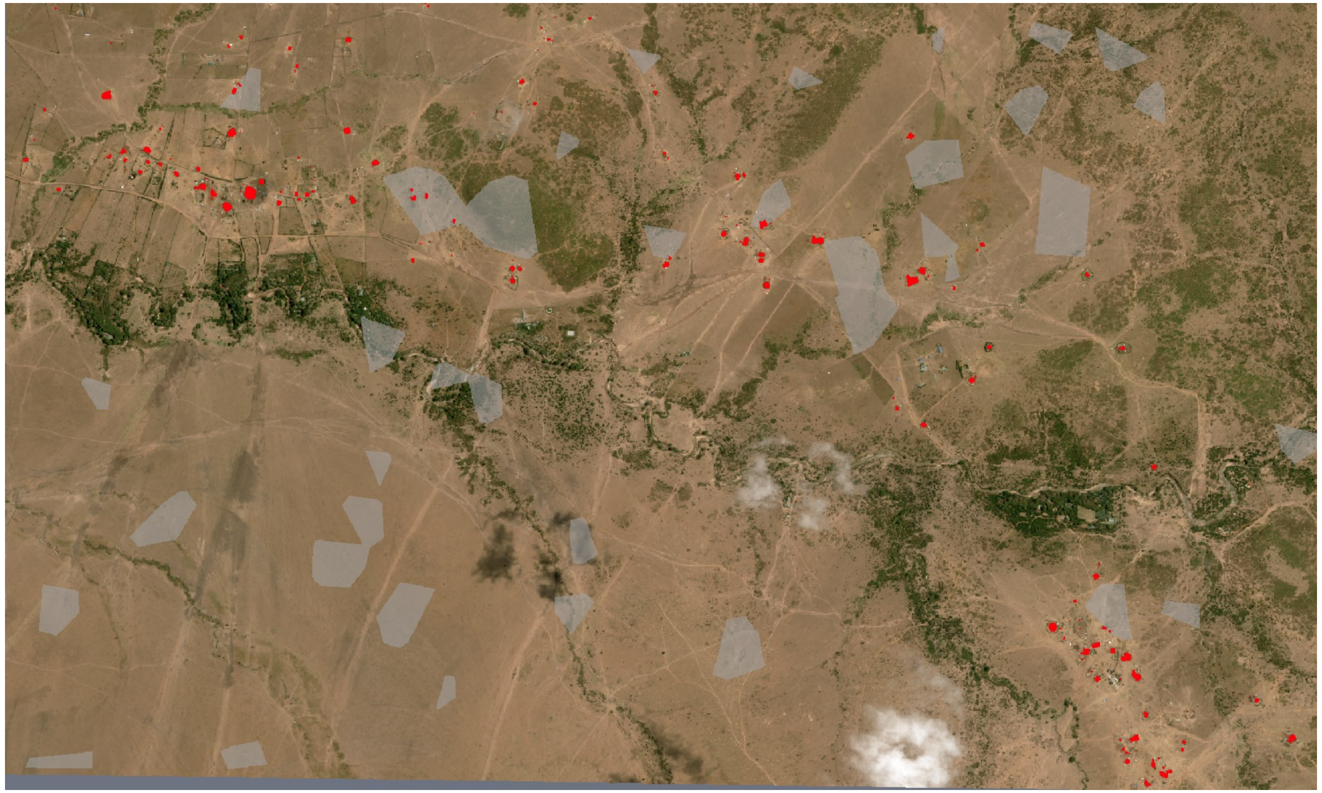
Example: Training on 10% Negatives

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:



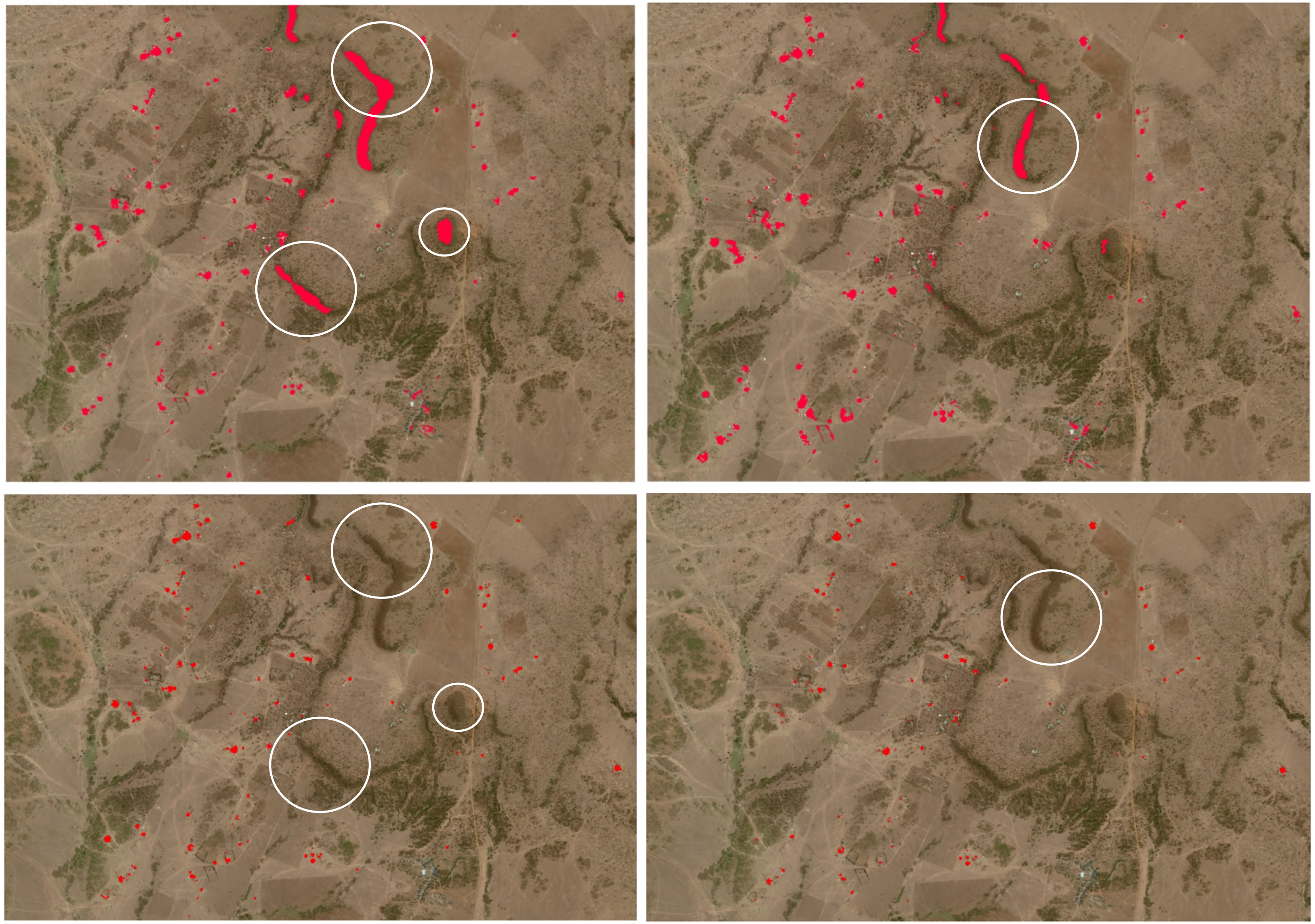


— Training Region 1—
Red: Boma
Gray: Negative
Transparent: Ignored

Example: Comparing Predictions

Cross-entropy ->

Cross-entropy + ER ->



Results: AI Dataset

Dataset details:

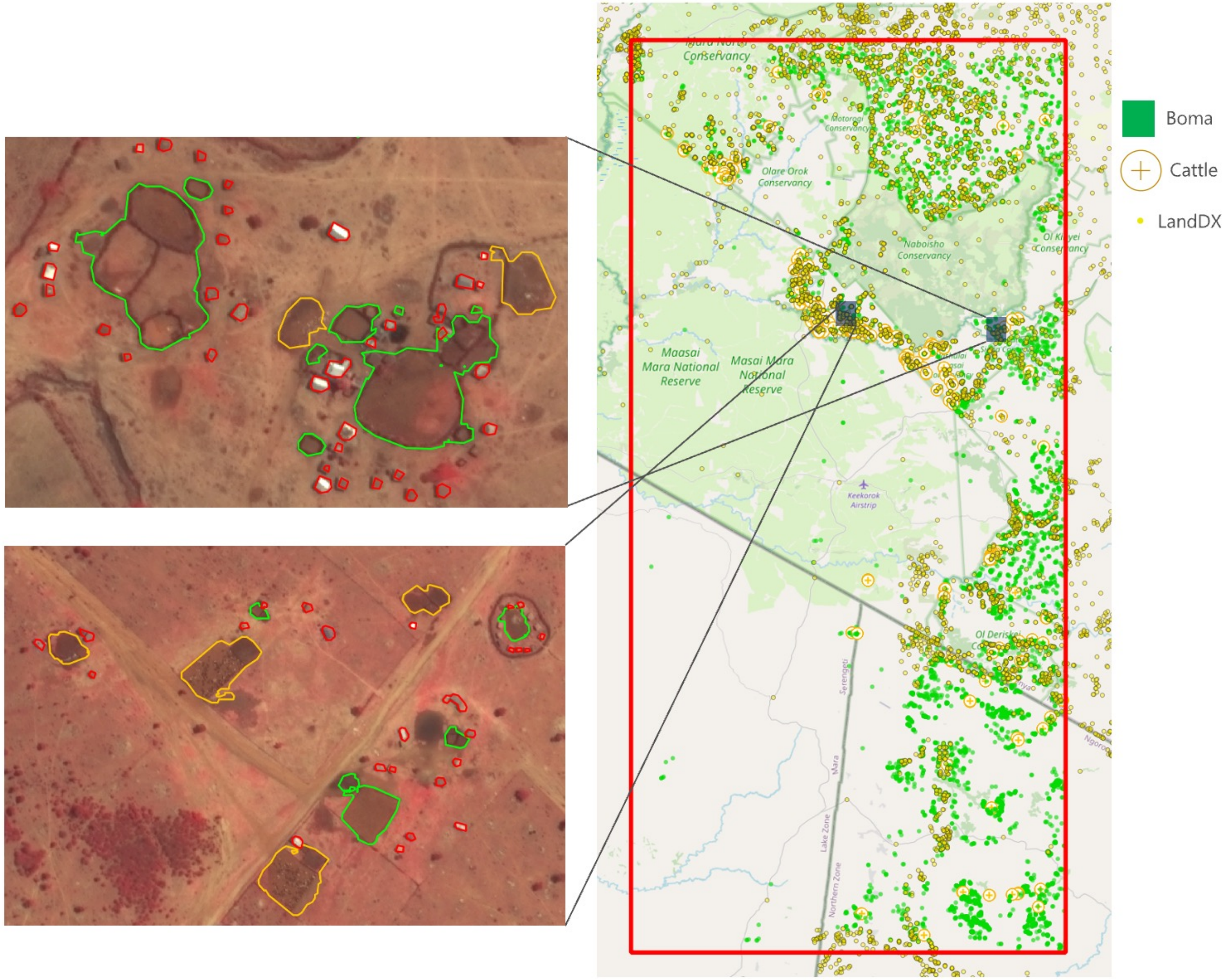
~5,100 empty Bomas
~160 populated Bomas.
~20,000 structures.

Post-processing:

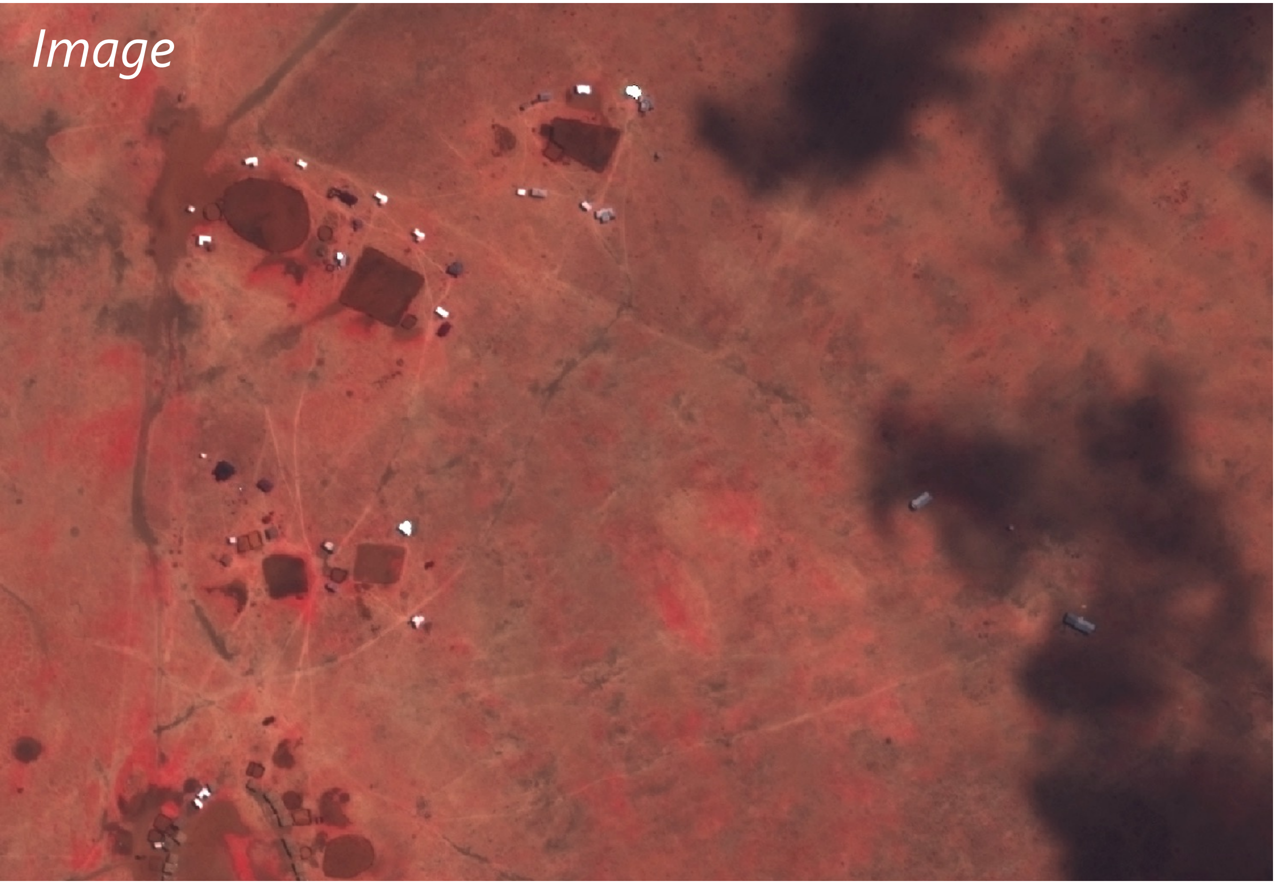
Geometry Simplification.
Remove outliers by area.
Filter by compactness & rectangularity.
Smoothing: dilation & erosion.

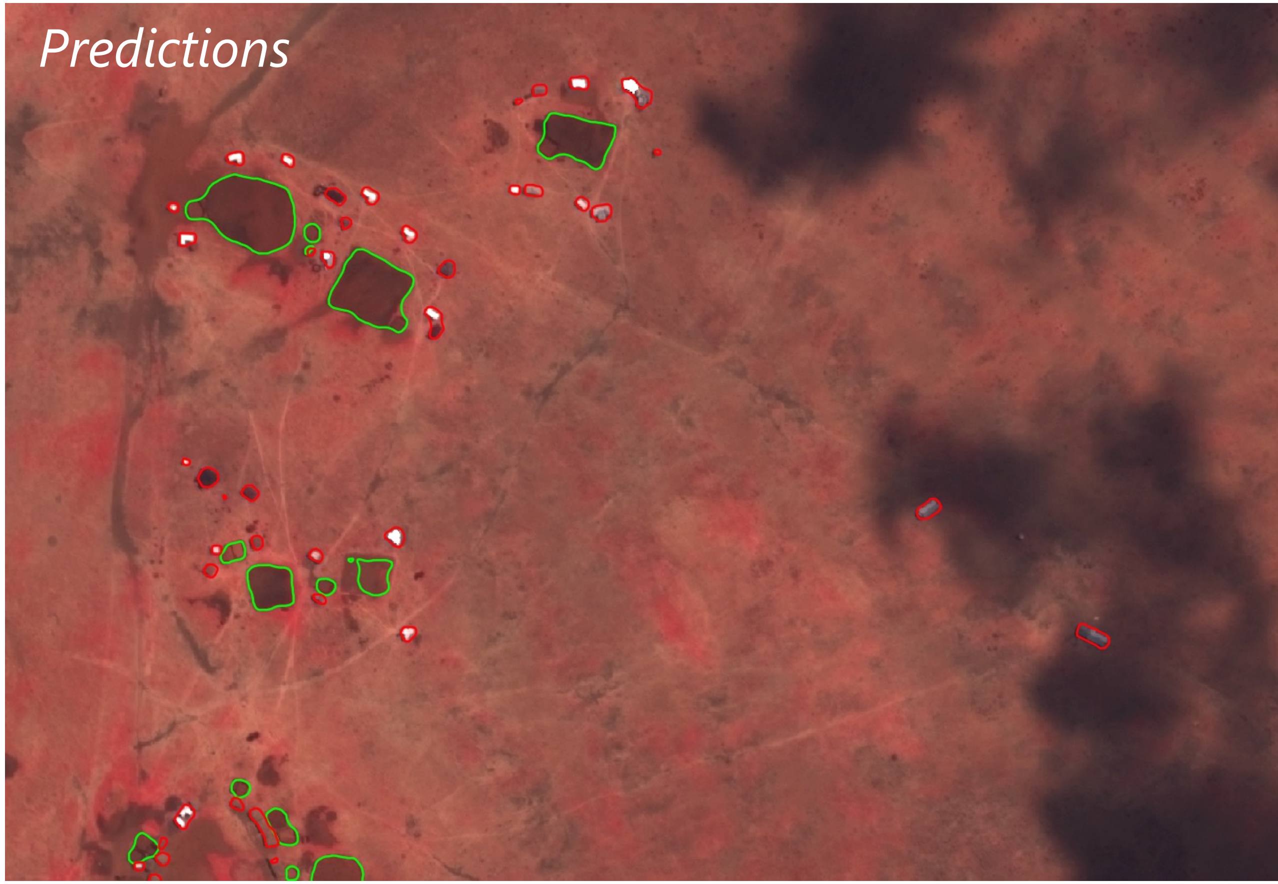
Data Enrichment:

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

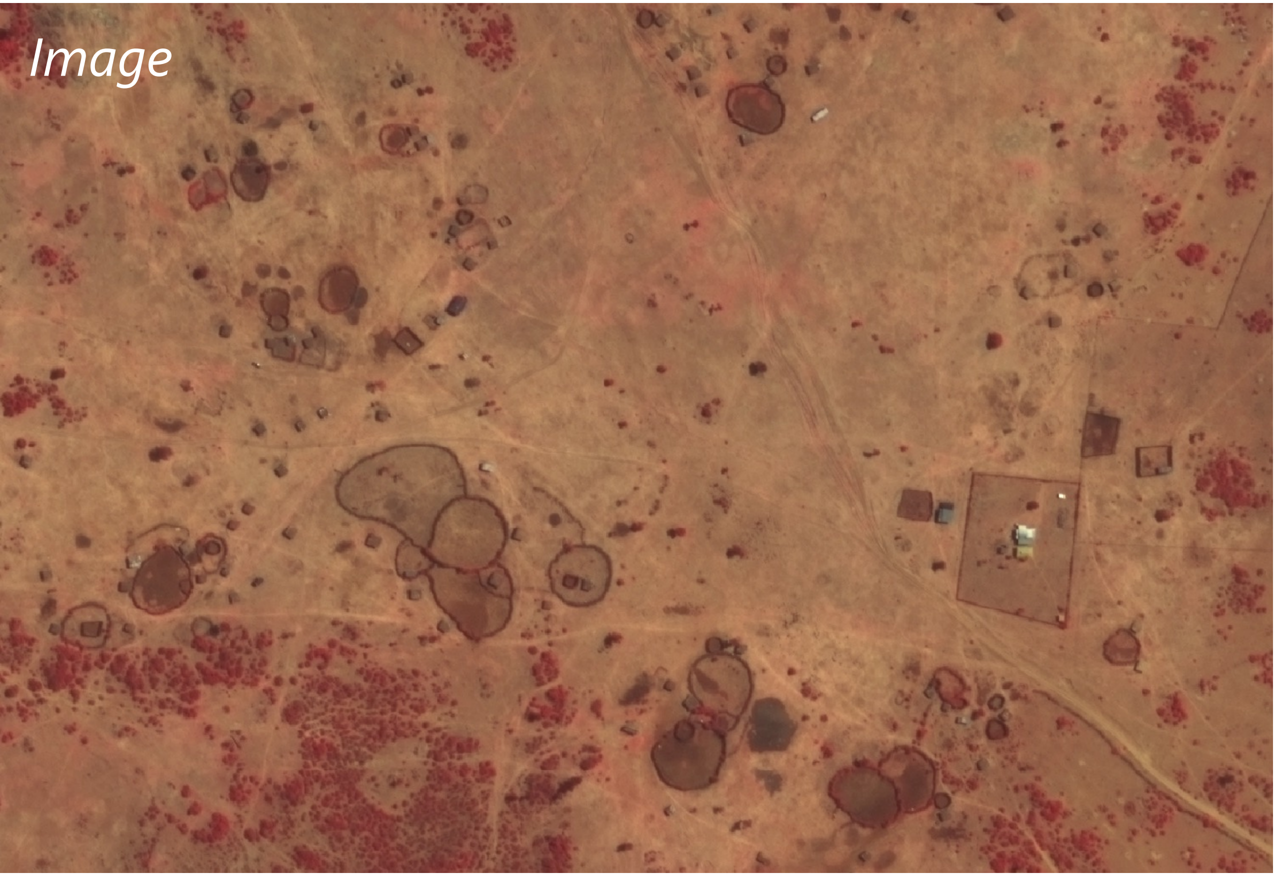


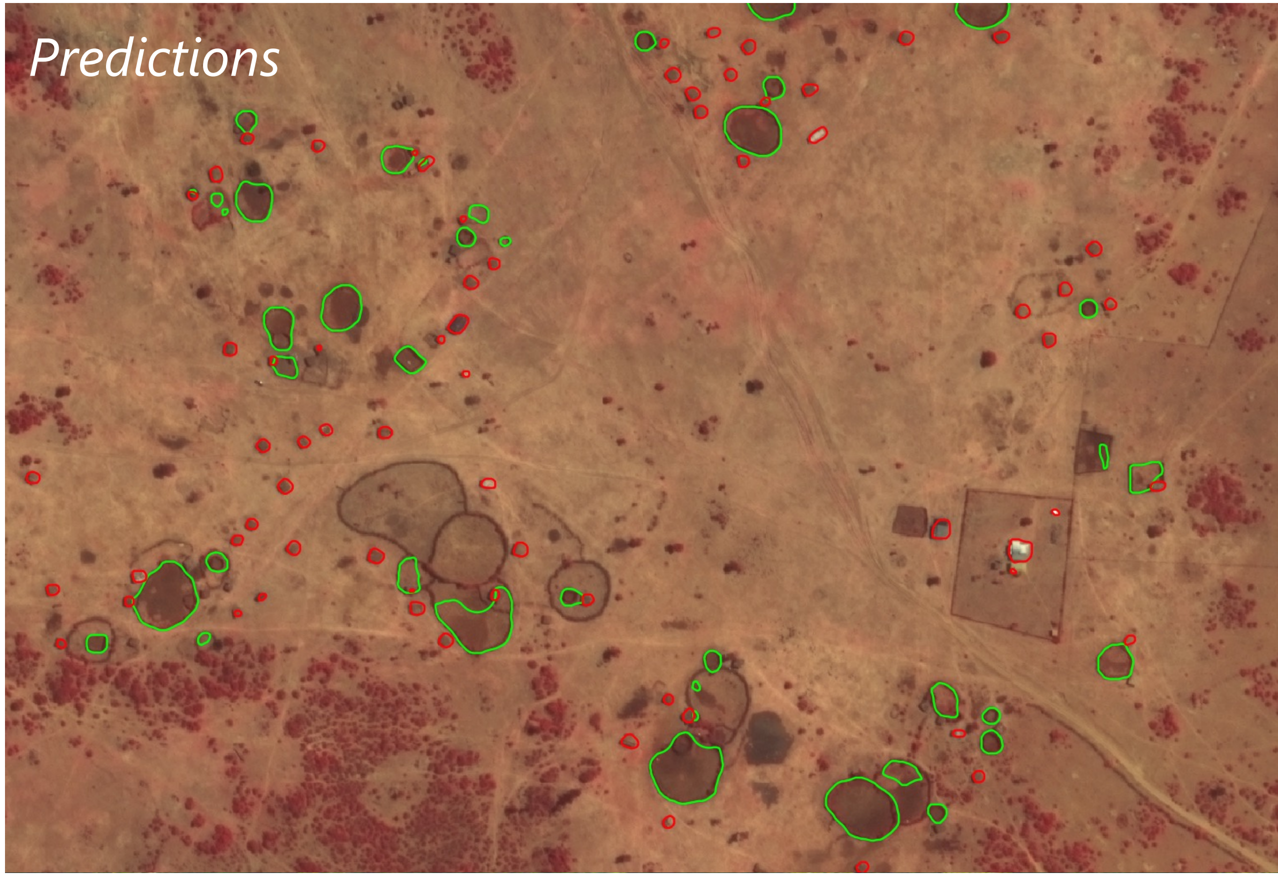
Example 1



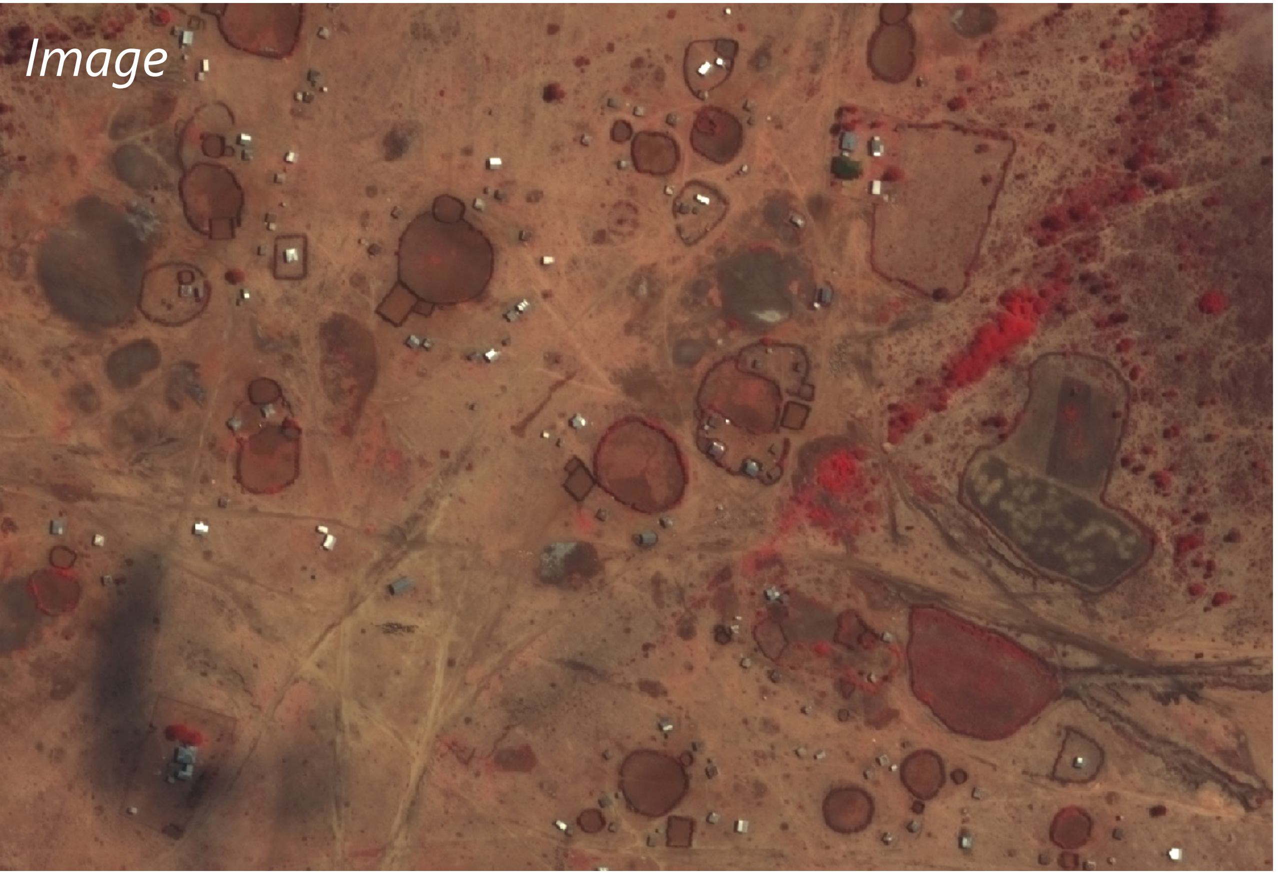


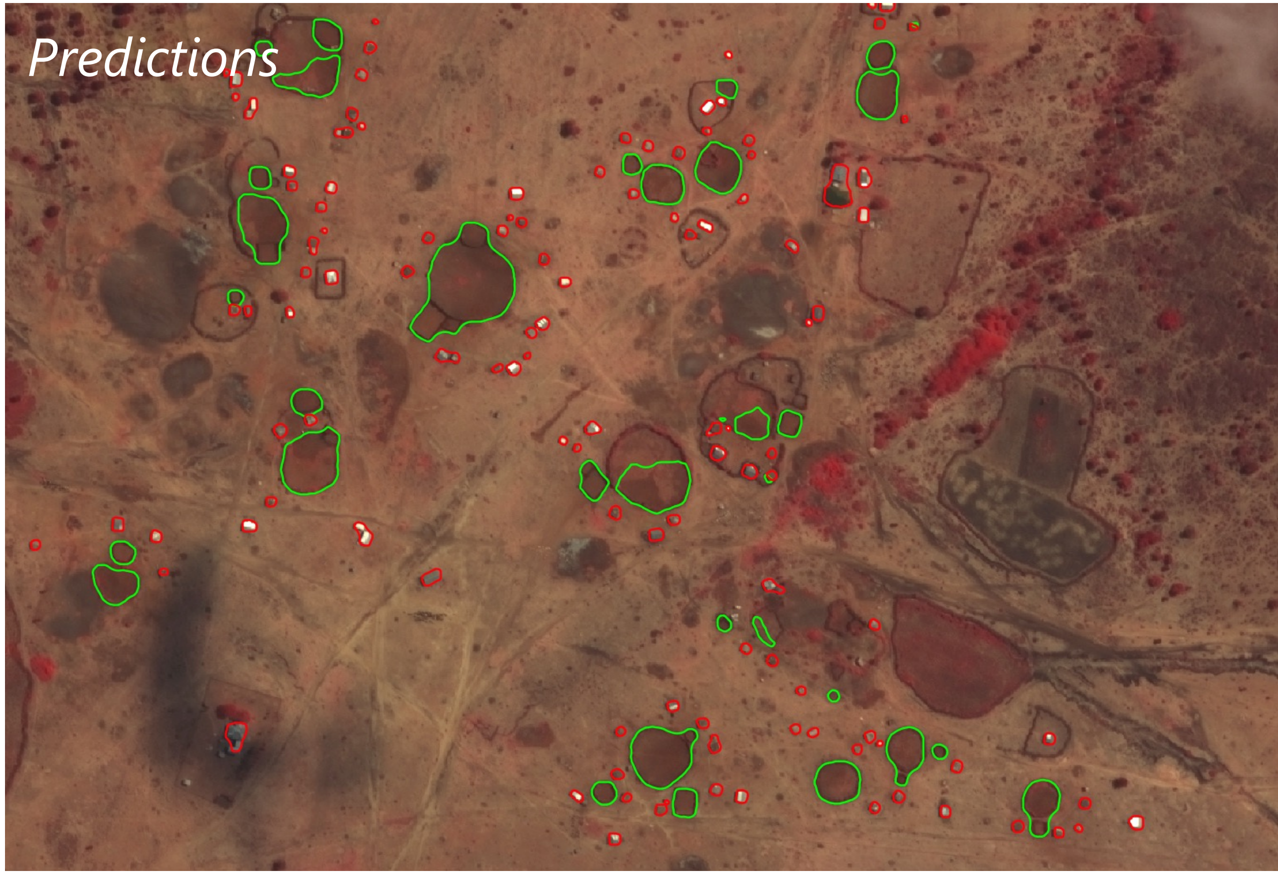
Example 2



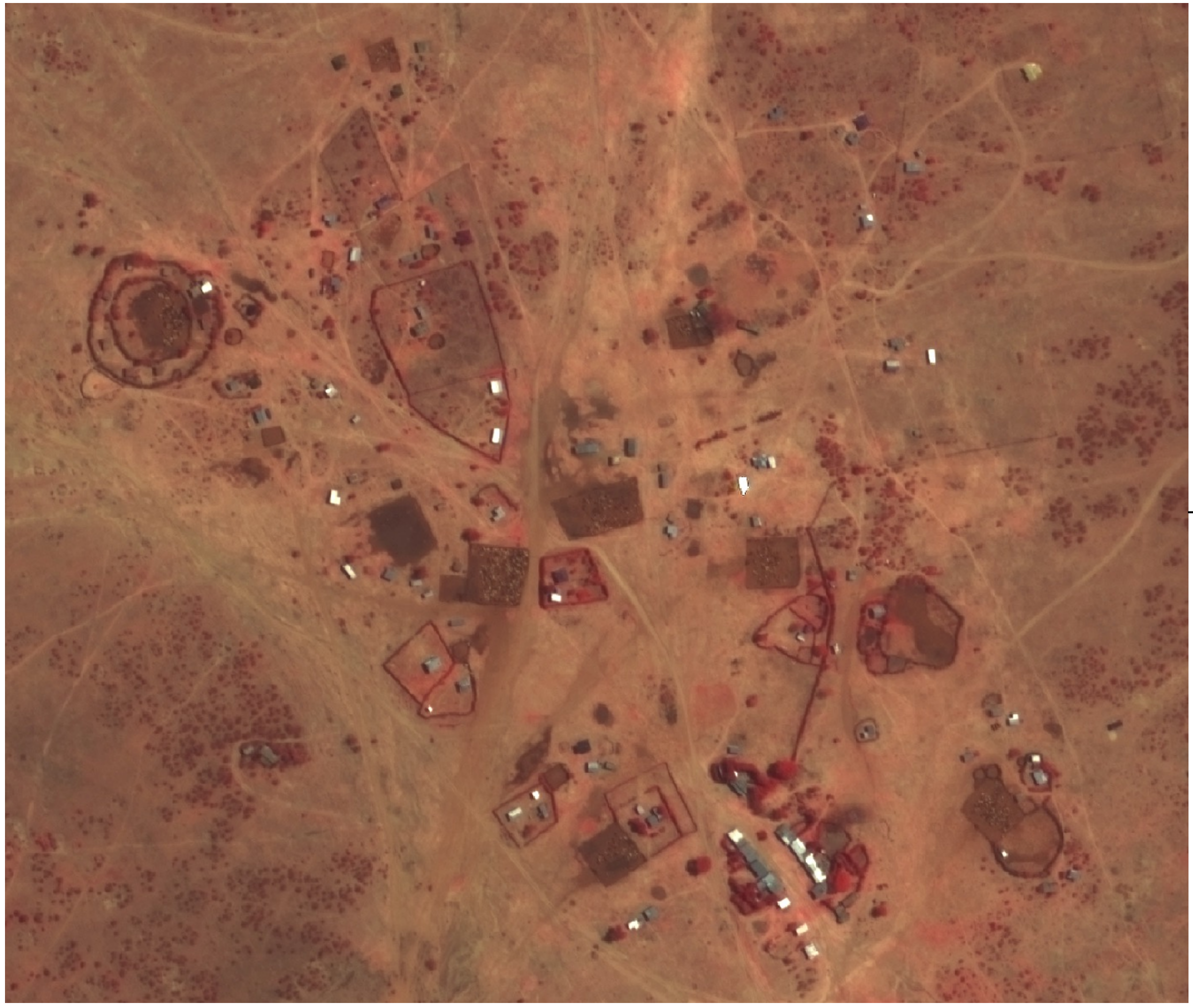


Example 3

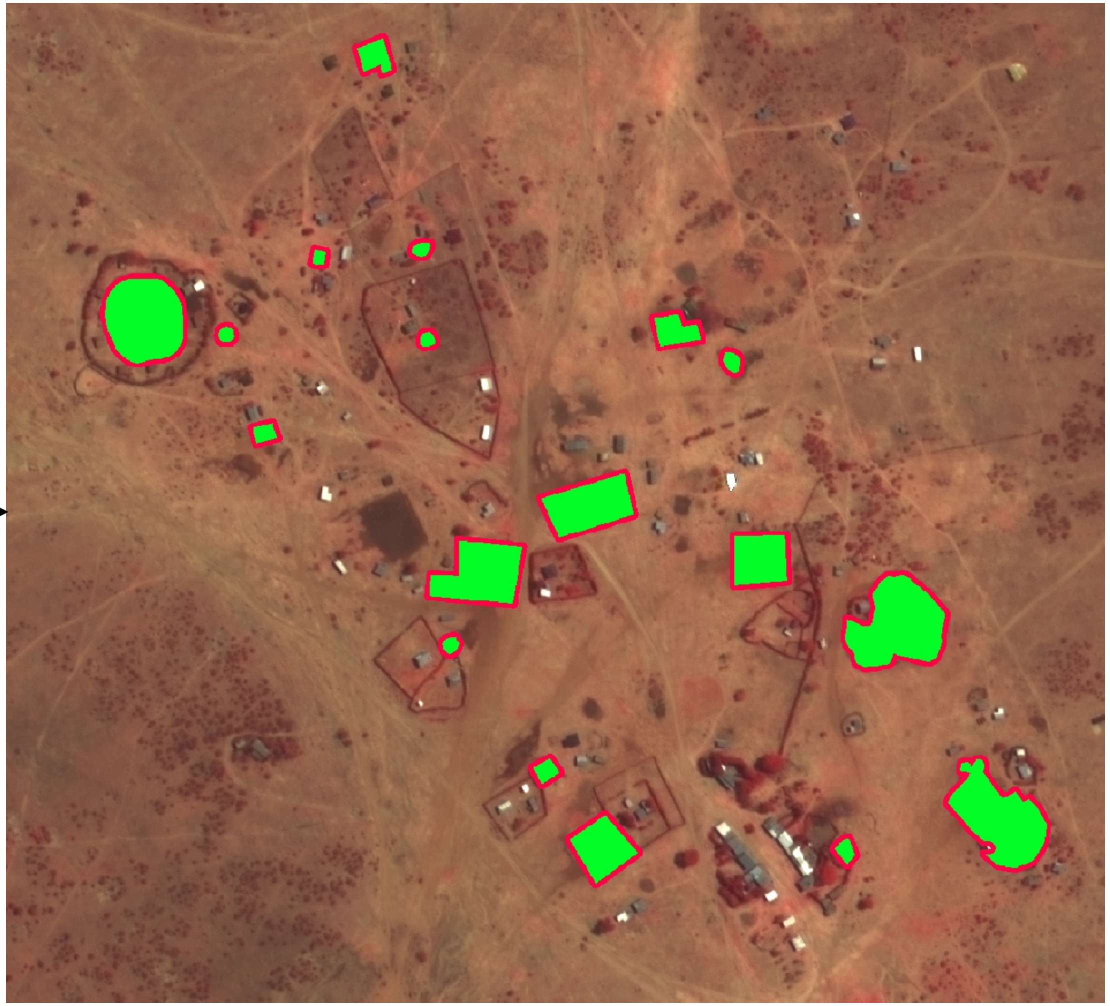




Lesson 1: **Negative Buffers** prohibit the "spilling" effect.



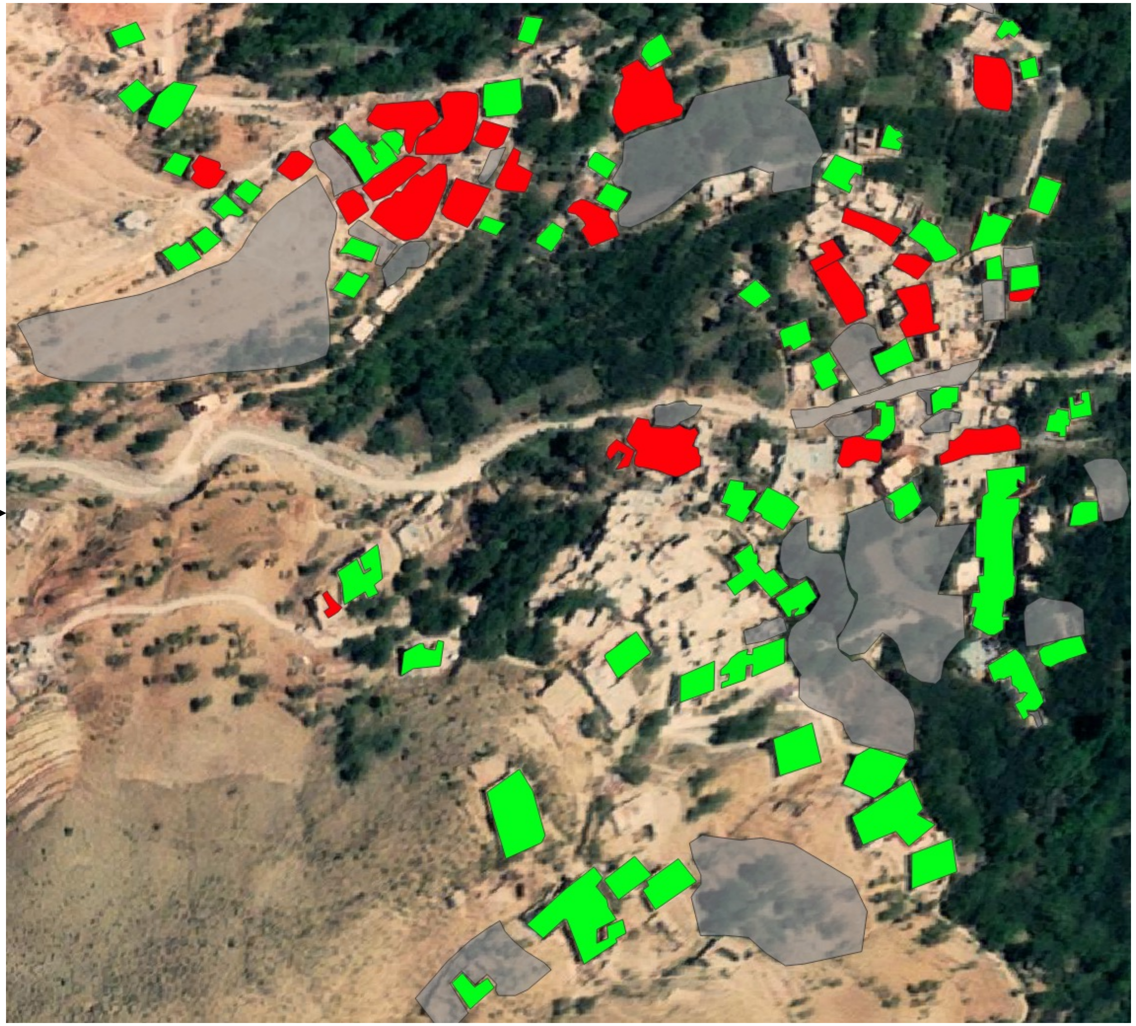
Label



Bomas in Green.
Negatives in Red.
Transparent pixels are ignored.

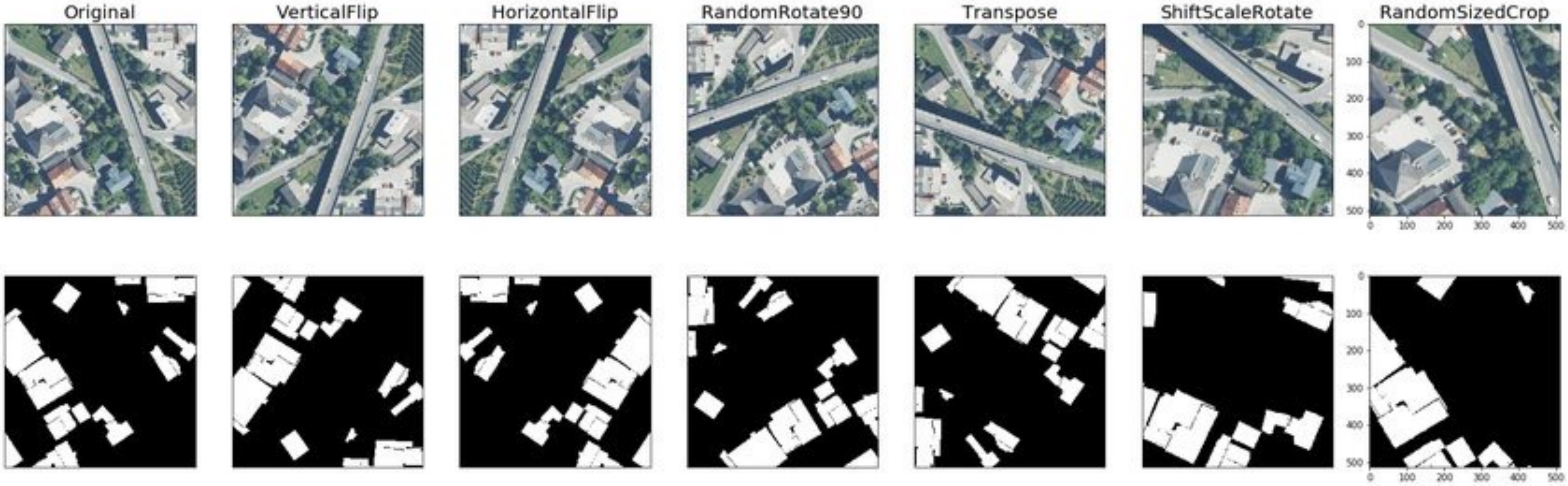
Lesson 2: **Label Quality**: Iteratively annotating a diverse & difficult set of patches.

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.

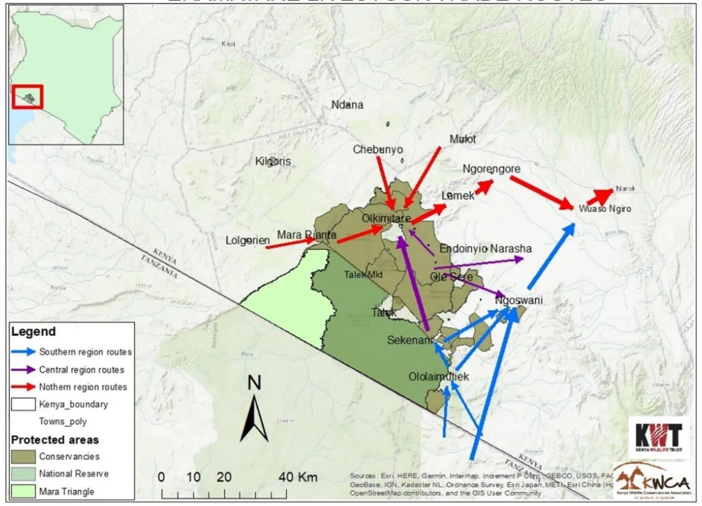
KWT can improve their **anti-poison campaigns** and provide more targeted education.

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 hotsopts are, KWT can help create community networks for trade .

ERAMATARE LIVESTOCK TRADE ROUTES



— Anti-poison campaigns —

— Predator-proof Bomas made of recycled plastic poles —

Credit: Kenya Wildlife Trust

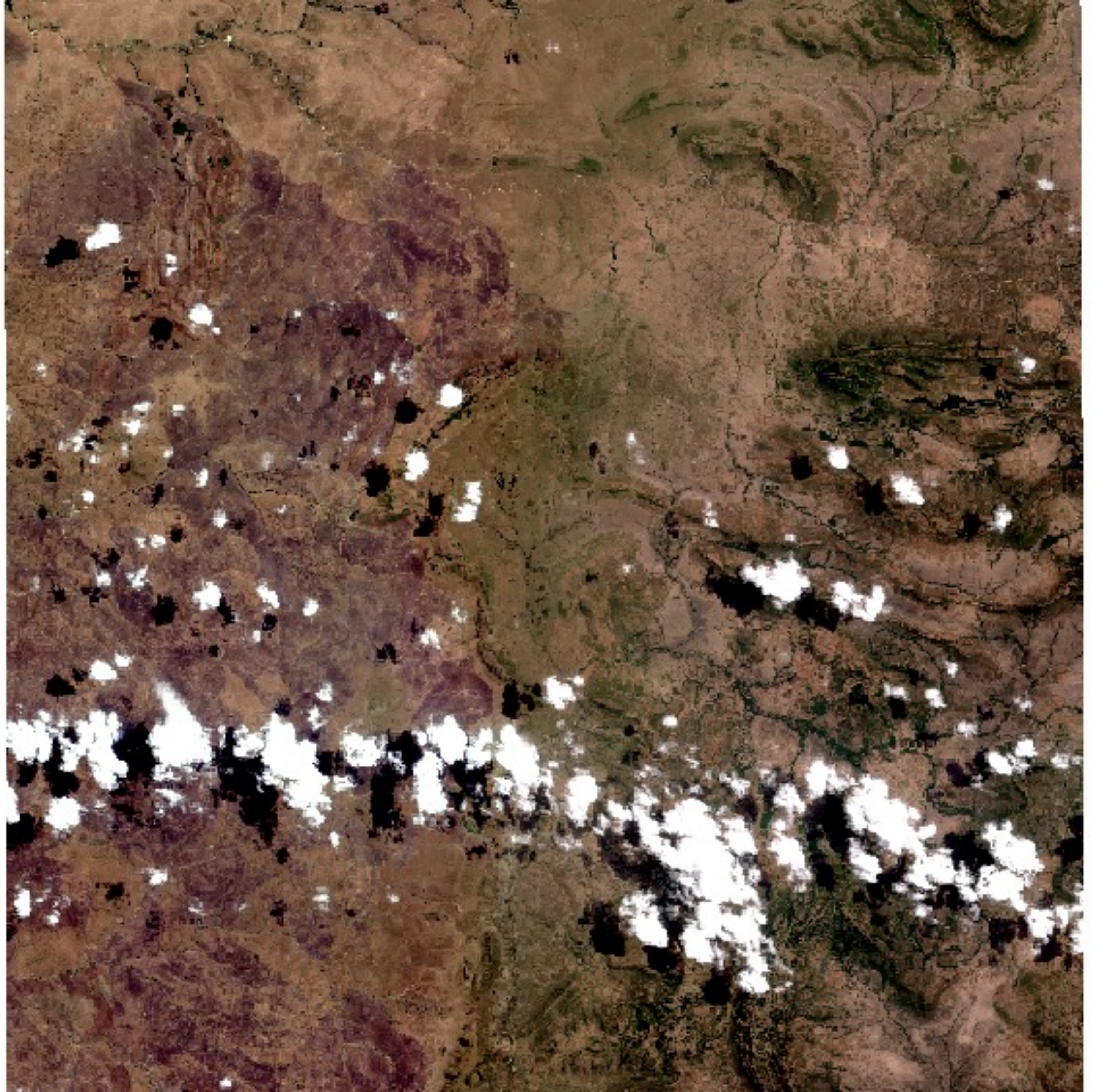
Next Steps

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.