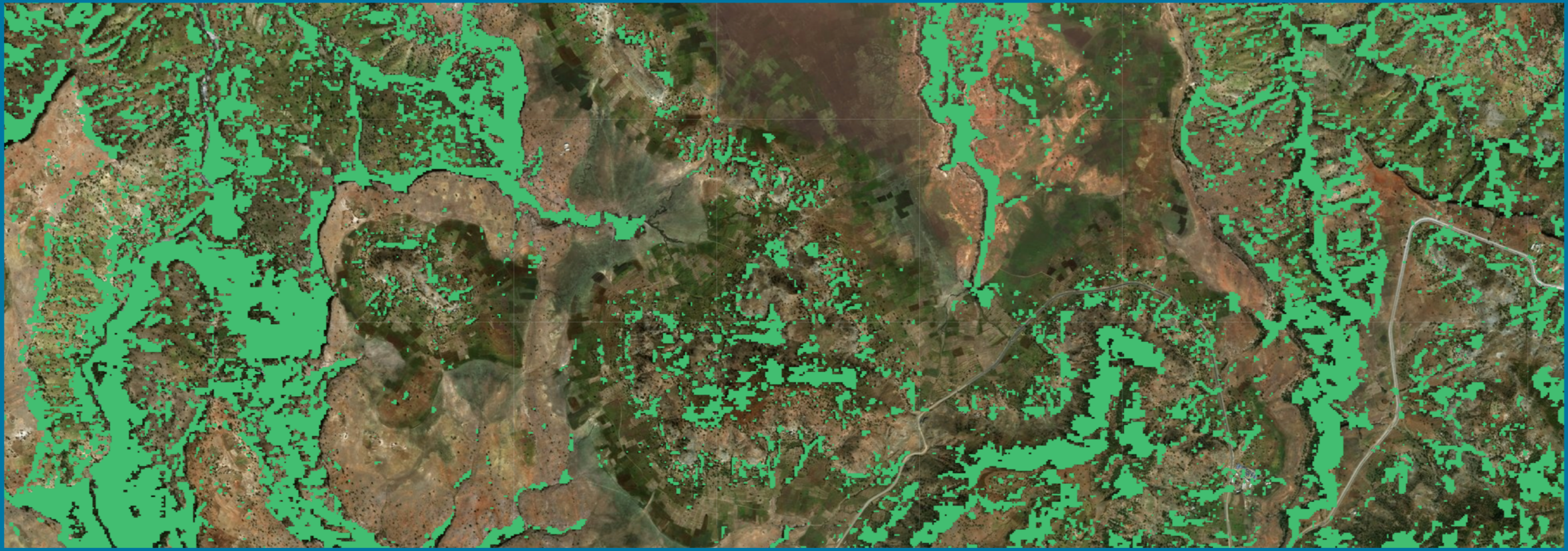
WORLD RESOURCES INSTITUTE

MONITORING TREES OUTSIDE THE FOREST



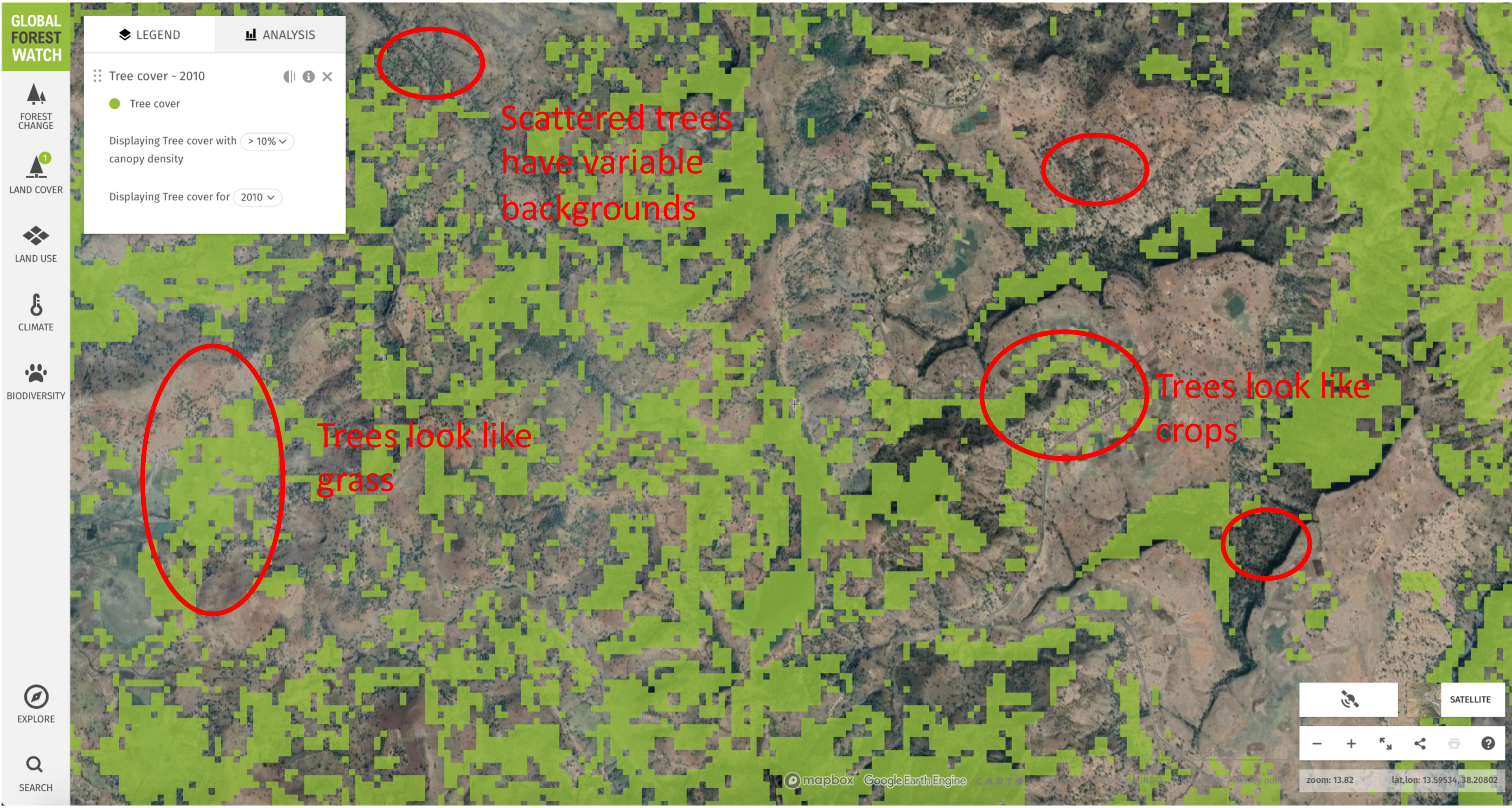
John Brandt

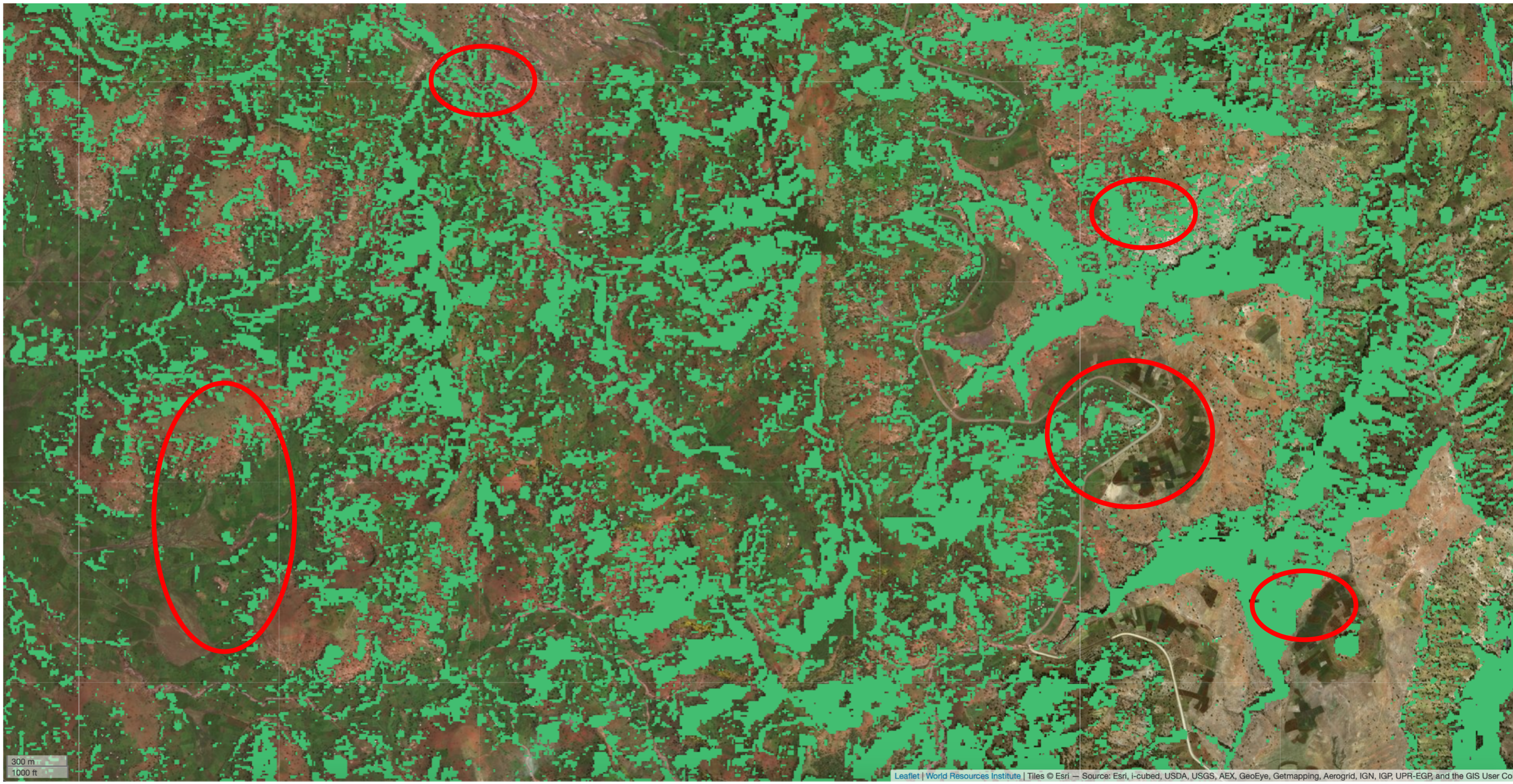
ISSUES IN MONITORING TREES OUTSIDE FOREST

- Low resolution of imagery
- High background variability and noise
- Small object size
- Sub 10m shifts in georeferencing
- Hill shade and terrain
- Traditional ML approaches on GEE are not expressive enough (RF)
- Out of box computer vision approaches do not work because of small image size, variability of data, and variability of segmentation maps

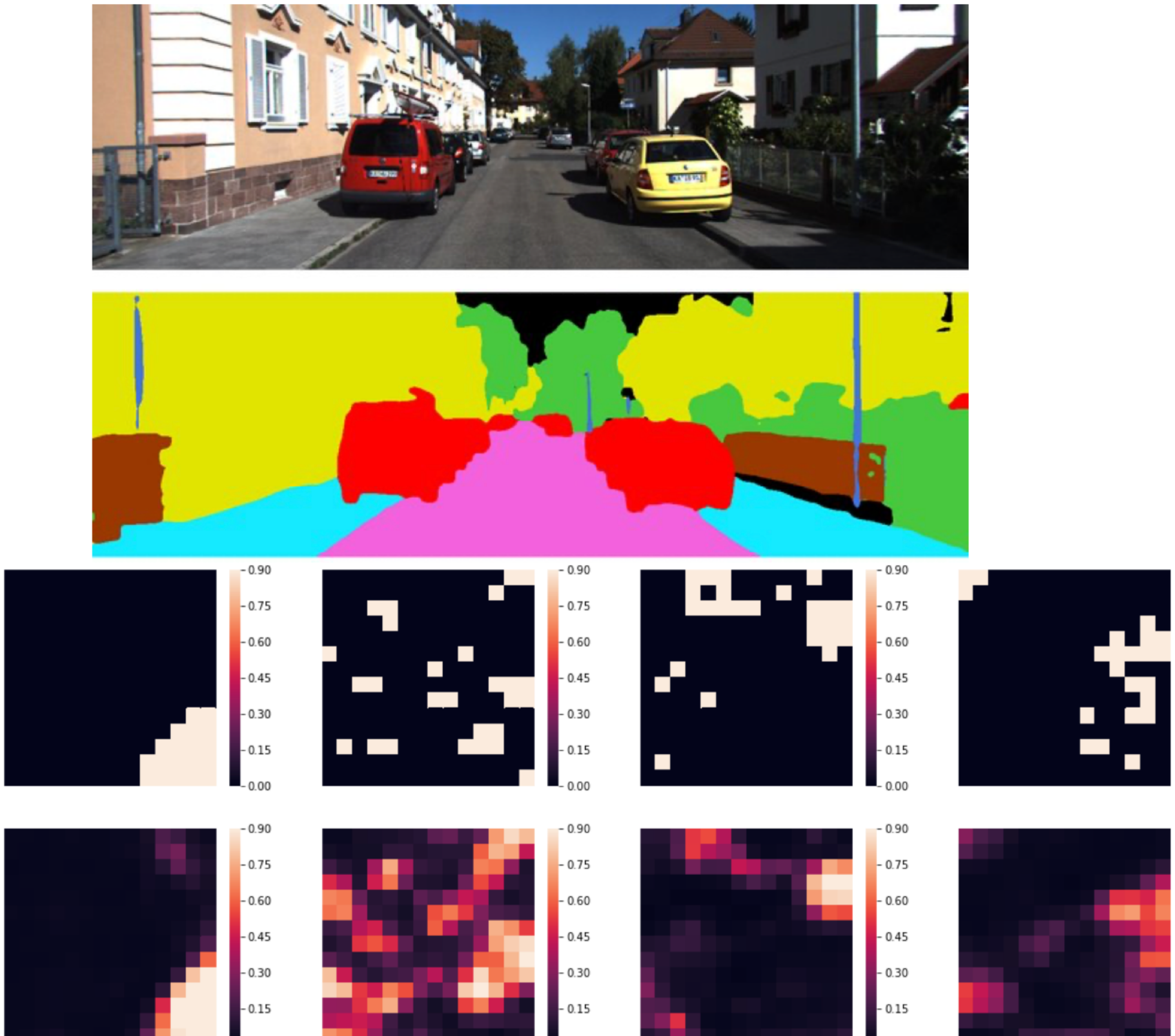
GOING OUT OF THE FORESTS

- While current forest monitoring data is great at *forest monitoring,* it is not tailored to monitoring restoration *outside the forest*
  - False positives in grasslands and crops
  - False negatives in mosaic landscapes
- Wall-to-wall restoration monitoring must prioritize accuracy on heterogenous landscapes, rather than homogenous landscapes
- Proposing complimentary data to monitor trees outside the forest


GLOBAL FOREST WATCH
LEGEND
ANALYSIS
Tree cover - 2010
Tree cover
Displaying Tree cover with > 10% canopy density
Displaying Tree cover for 2010
FOREST CHANGE
LAND COVER
LAND USE
CLIMATE
BIODIVERSITY
EXPLORE
SEARCH
Scattered trees have variable backgrounds
Trees look like grass
Trees look like crops
SATELLITE
mapbox
Google Earth Engine
zoom: 13.82
lat,lon: 13.59534, 38.20802


300 m
1000 ft
Leaflet | World Resources Institute | Tiles © Esri — Source: Esri, i-cubed, USDA, USGS, AEX, GeoEye, Getmapping, Aerogrid, IGN, IGP, UPR-EGP, and the GIS User Co

WHY OUT-OF-BOX ALGORITHMS FAIL

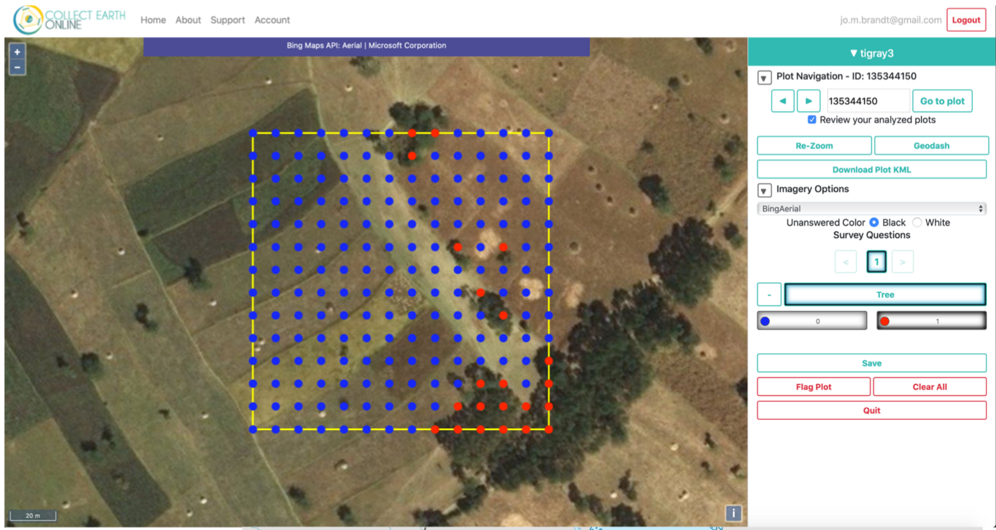


- 1 million + pixels
- Shapes consistent
- Regions consistent
- Colors consistent

- 196 pixels
- No shape, region, or color consistency
- Each output is distinct

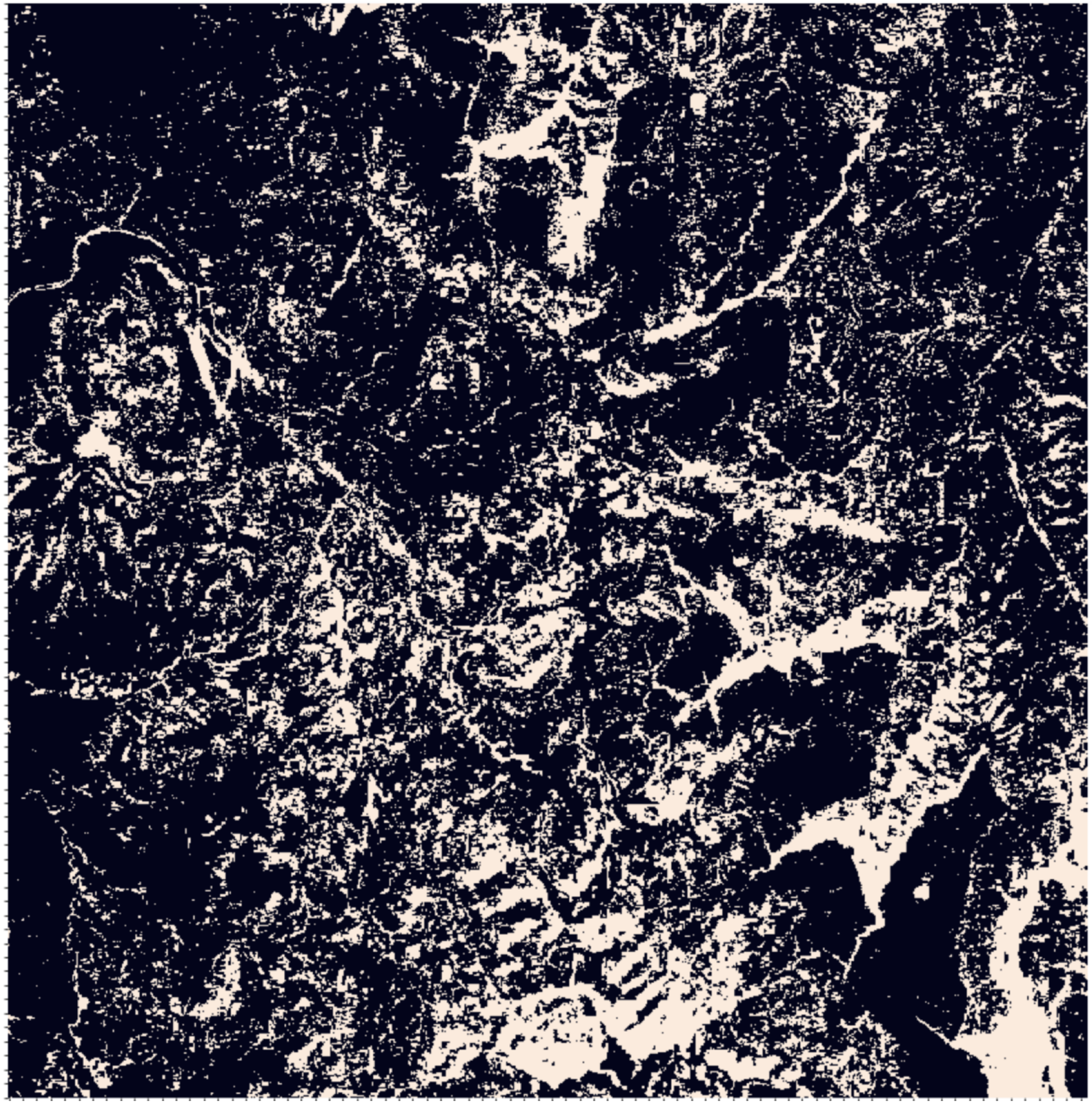
DATA

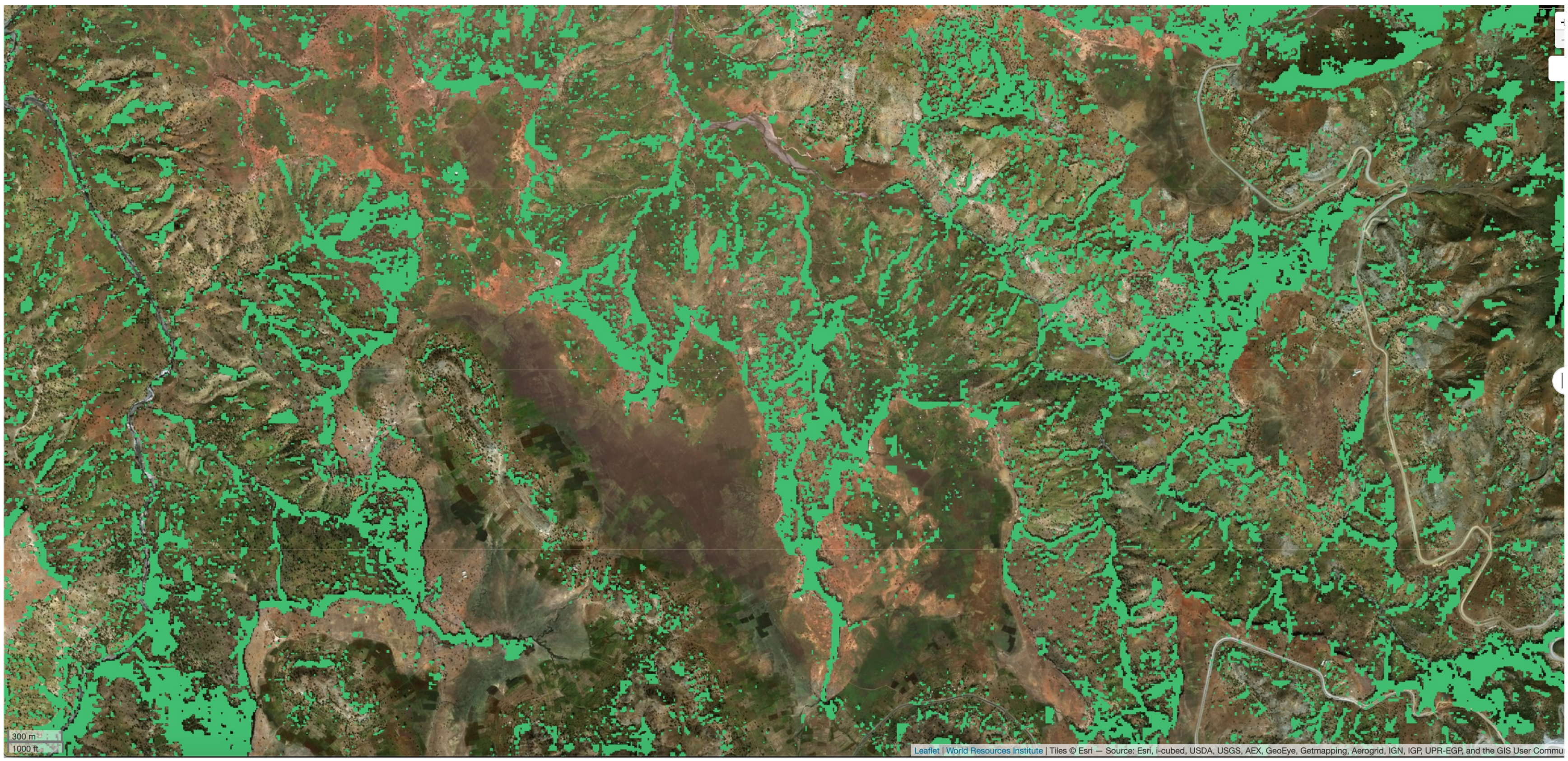
- 700 2 hectare plots
- Randomly sampled across Tigray, Ethiopia



QUICK DEMO

- Link

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METHODS - PREPROCESSING

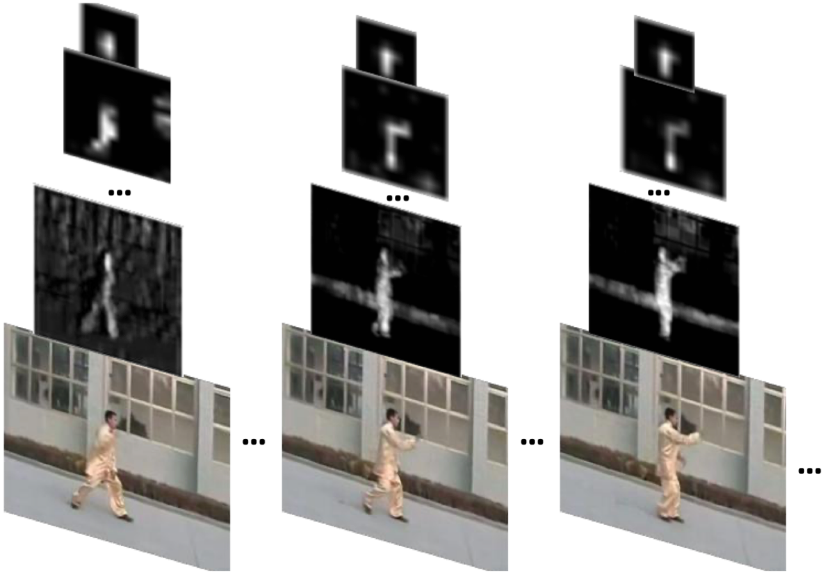
- Data selection
  - Biweekly mean composites of 10 and 20m bands
  - 2 images / month with lowest cloud cover, capped at 20%
  - Bilinearly interpolate missing imagery
  - Normalize data to [0, 1] range
  - Fuse slope calculated from DEM to S2
- Georeference correction
  - Expectation maximization

METHODS - MODELING

- Fully convolutional network with:
- Convolutional LSTM encoder with layer normalization and zone out
- Feature pyramid attention between encoder and decoder with DropBlock
- Concurrent spatial and channel squeeze excitation decoder
- AdaBound optimizer
- Focal loss for a warm-up, fine tuned with Lovasz softmax. Focal loss is tuned (gamma and alpha) for each image.
- Equibatch sampling, visiting every C clusters each N samples

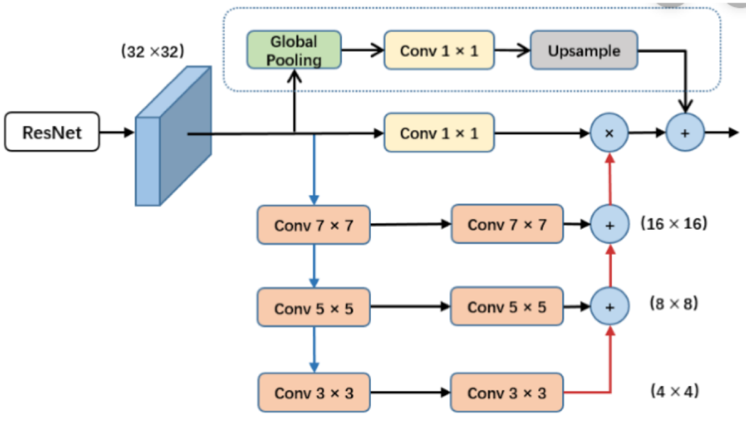
MODELING SPATIOTEMPORAL RELATIONSHIPS

- Generate 24 different “feature maps” that represent how 30x30m grids of the plot change over the year
- Weight the 24 different feature maps by how relevant they are to disambiguating trees from background
- Convolutional LSTMs allow for the representation of temporal *and* temporal relationships *concurrently*



INCORPORATING LONG-DISTANCE CONTEXT

- To optimize single pixel accuracy while modeling long distance relationships:
  - Feature pyramid attention (+4%)
  - Adabound optimizer (+3%)
  - Hypercolumn decoder (+2%)
  - cSSE blocks (+1%)



(b) Feature Pyramid Attention

SAMPLING METHODS, REGULARIZATION

- Stratified sampling
- Equibatch (+5%)
- Layer norm, batch re-norm (+1%)
- L2 loss (+0.5%)
- Zone out (+3%)
- Data augmentation (+3%)
- Heavy gradient clipping

METRICS

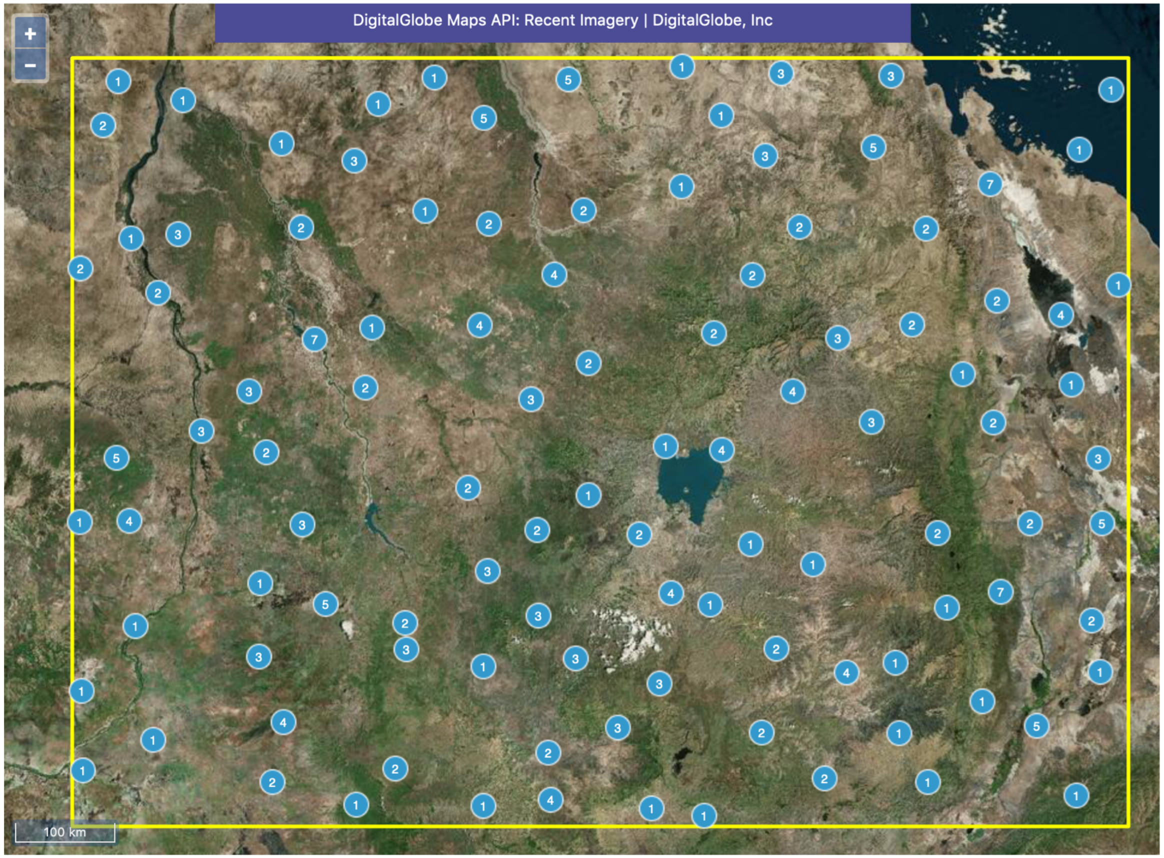
- Prediction speed: 312,000 ha/hour/core
- Model parameter size: 90,000 (vs. 60M-130M+ in out of box algorithms) – 600-1400x faster
- Map of Ethiopia, 16 core VM / K80 GPU @ $0.48 / hour (above fixed cost of data IO)
  - *This approach: 20 hours / $9*
  - *DeepLab V3: 36 months / $12,441*
  - *PSPNet: 13 months / $4,416*

Tree cover %	Precision @ 10 m	Recall @ 10 m	Percent error @ 2 ha
50+	90%	88%	2%
20-50	68%	70%	2%
<20	45%	68%	2%
Overall	65%	72%	1.60%

- *Suggests ability to detect 2% tree cover difference at 2 ha scale outside of forests*

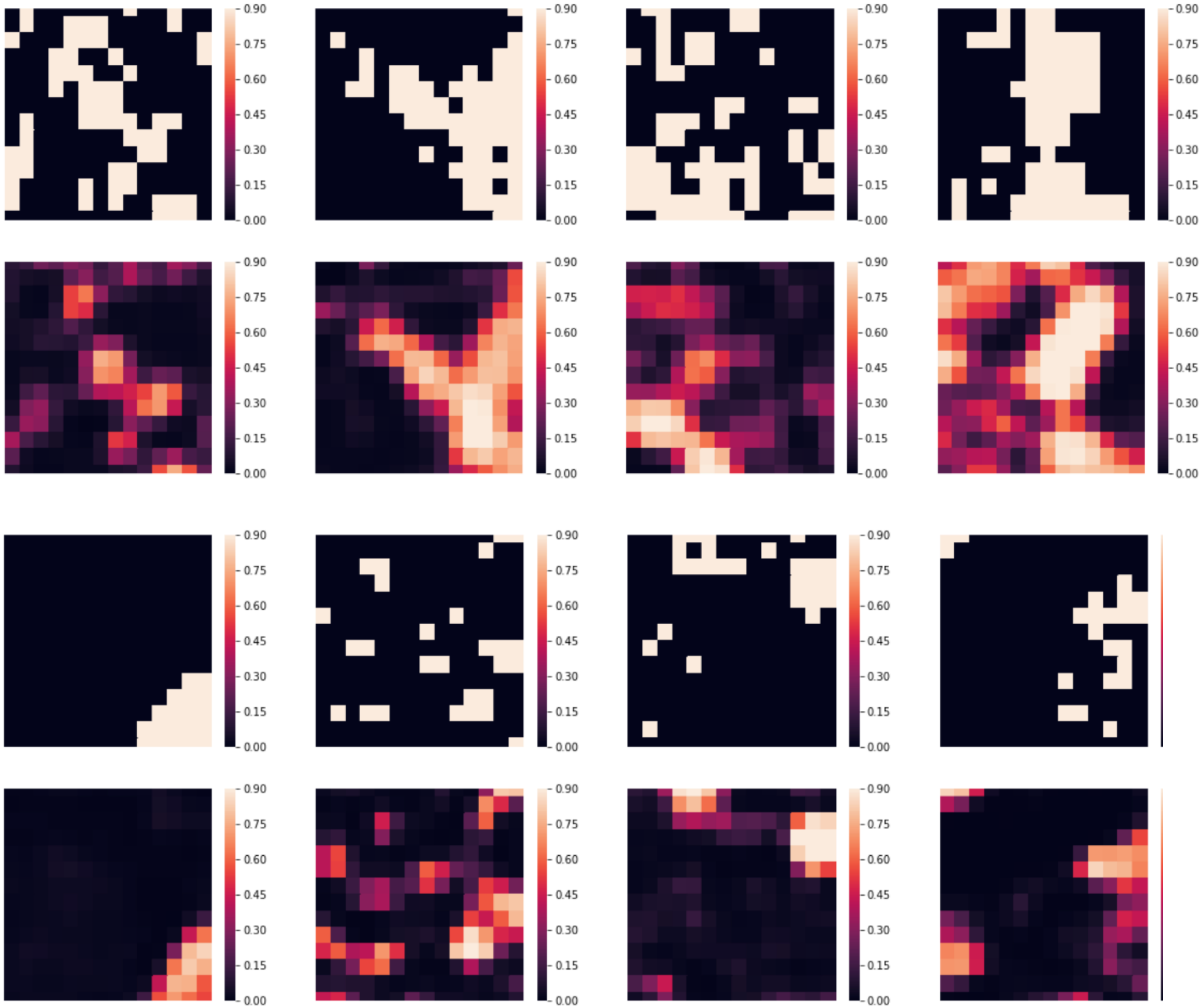
TEST PLOTS

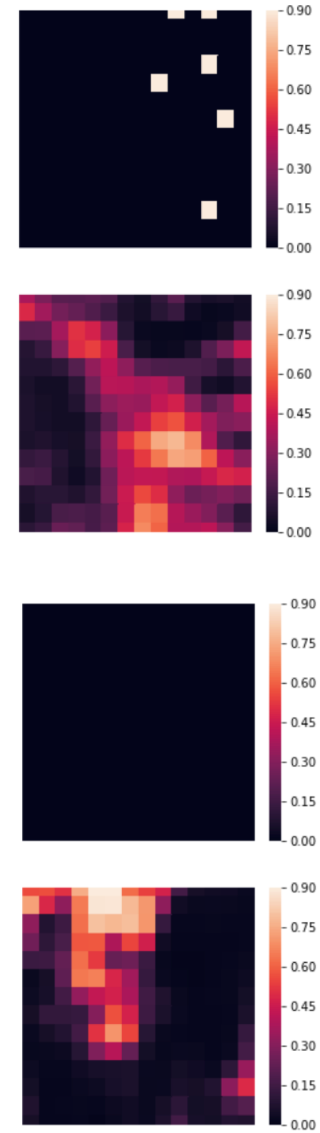
- 200 2 ha plots across 8 million km^2 in
  - Ethiopia
  - Sudan
  - South Sudan
  - Djibouti
  - Somalia



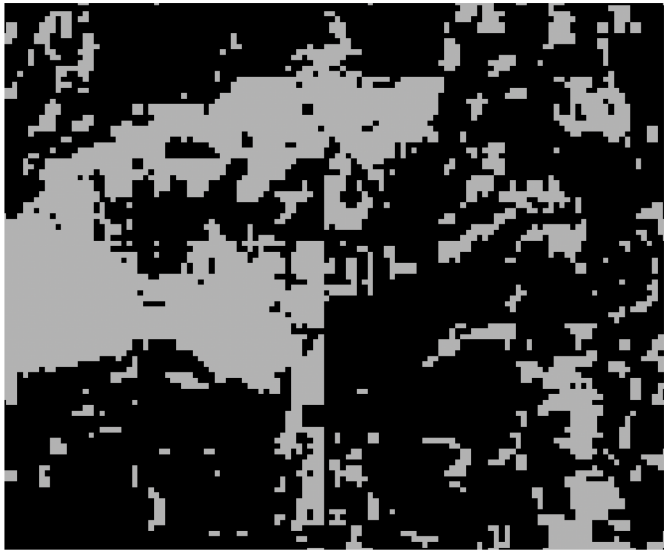
SUCCESS CASES

FAILURES





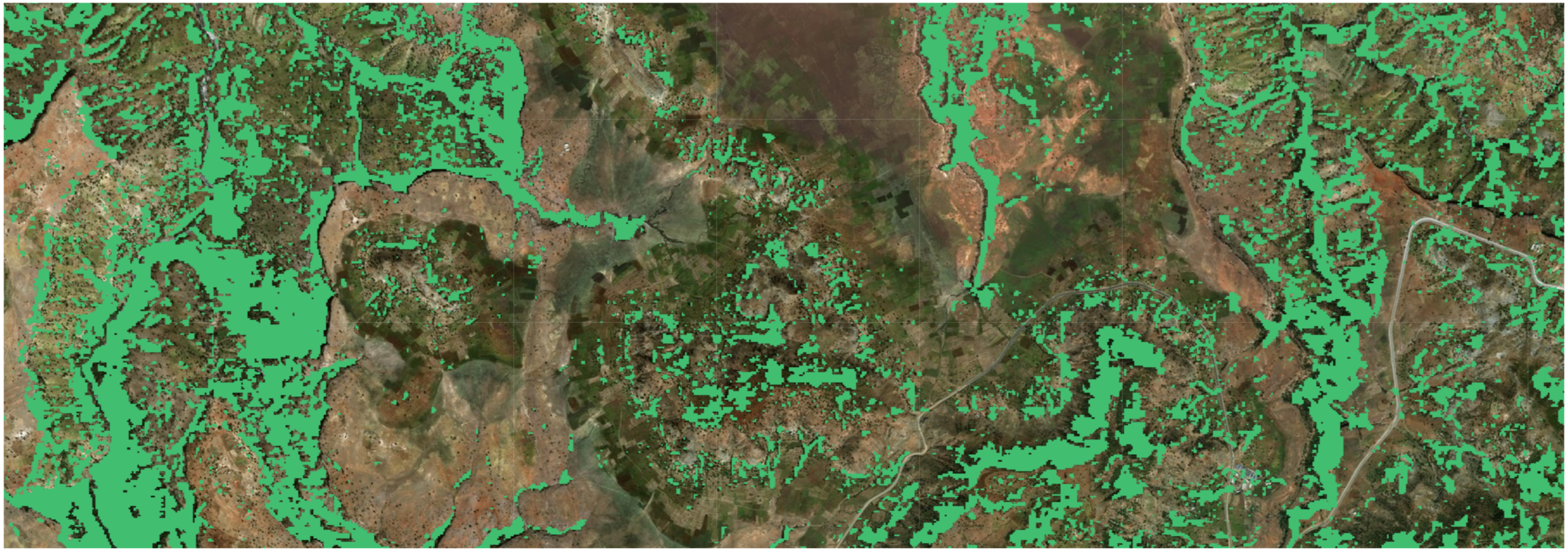
FUTURE RESEARCH DIRECTIONS - METHODS



- S1 S2 fusion
- Atruous convolutions
- Better data augmentation
- Hyperparameter search
- Regularization search
- Self training
- Stratified K-fold training and ensembling
- Temporal squeeze and excitation
- Post processing – smoothing and conditional random fields

FUTURE RESEARCH DIRECTIONS - APPLICATIONS

- Short term: 50,000 hectare -> 500,000 hectare maps (regional)
- Medium term: Multi-year imagery and tree cover change
- Long term: Other biomes and geographic regions



CONCLUSIONS AND QUESTIONS

- Complimentary research product to existing forest monitoring data and methodologies, focusing on trees outside the forest by using artificial intelligence to focus attention on disambiguating trees from crops and grassland with a methodology that is computationally scalable to global levels
- Still in research stage but performs well on 30-50,000 ha mosaic landscapes with only 1,000 ha of labeled data
- Issues of hill shade, georeferencing shifts, data quality are actively being mitigated
  - Azimuth correction
  - Expectation maximization
  - Label smoothing, teacher networks
  - Post-processing
- Expect regional 500,000 to 1,000,000 ha maps across priority drylands area within next year