Earth Observations and Machine Learning for Planted Area Estimation in Inaccessible Regions for Remote Food Security Assessments

Hannah Kerner

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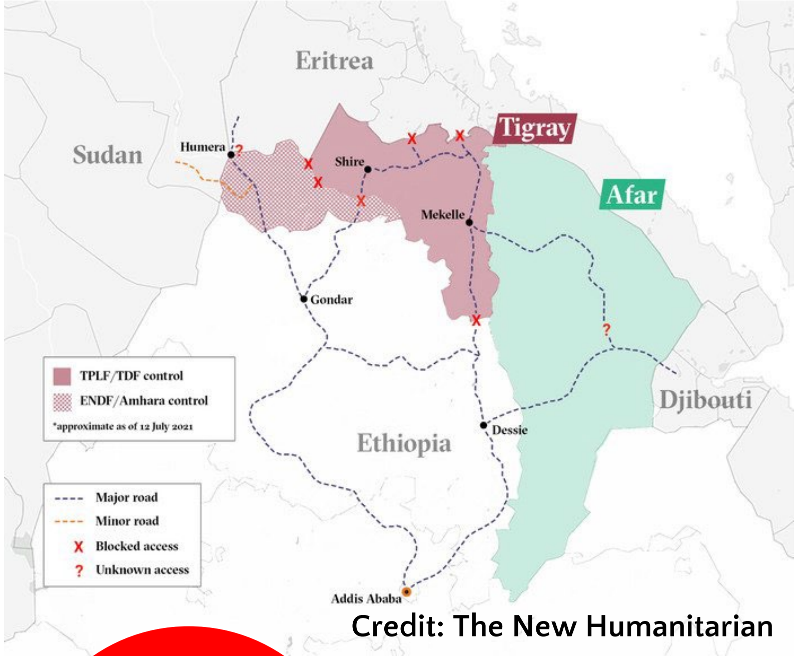
ML/AI Lead, NASA Harvest Program

Ivan Zvonkov[1], Gabriel Tseng[1], Eva Utzschneider[1], Amanda Lopez[1], Catherine Nakalembe[1], Amy McNally[2], Inbal Becker-Reshef[1]

[1] University of Maryland/NASA Harvest Program
[2] Famine Early Warning Systems Network (FEWS NET), USAID

Purple names indicate co-authors in attendance at LPS



The Lutheran World Federation

Aid agencies warn of looming famine in Tigray

(LWI) - Time is running out to prevent a looming famine in Ethiopia's Tigray region, where an estimated 5.2 million people are facing acute...

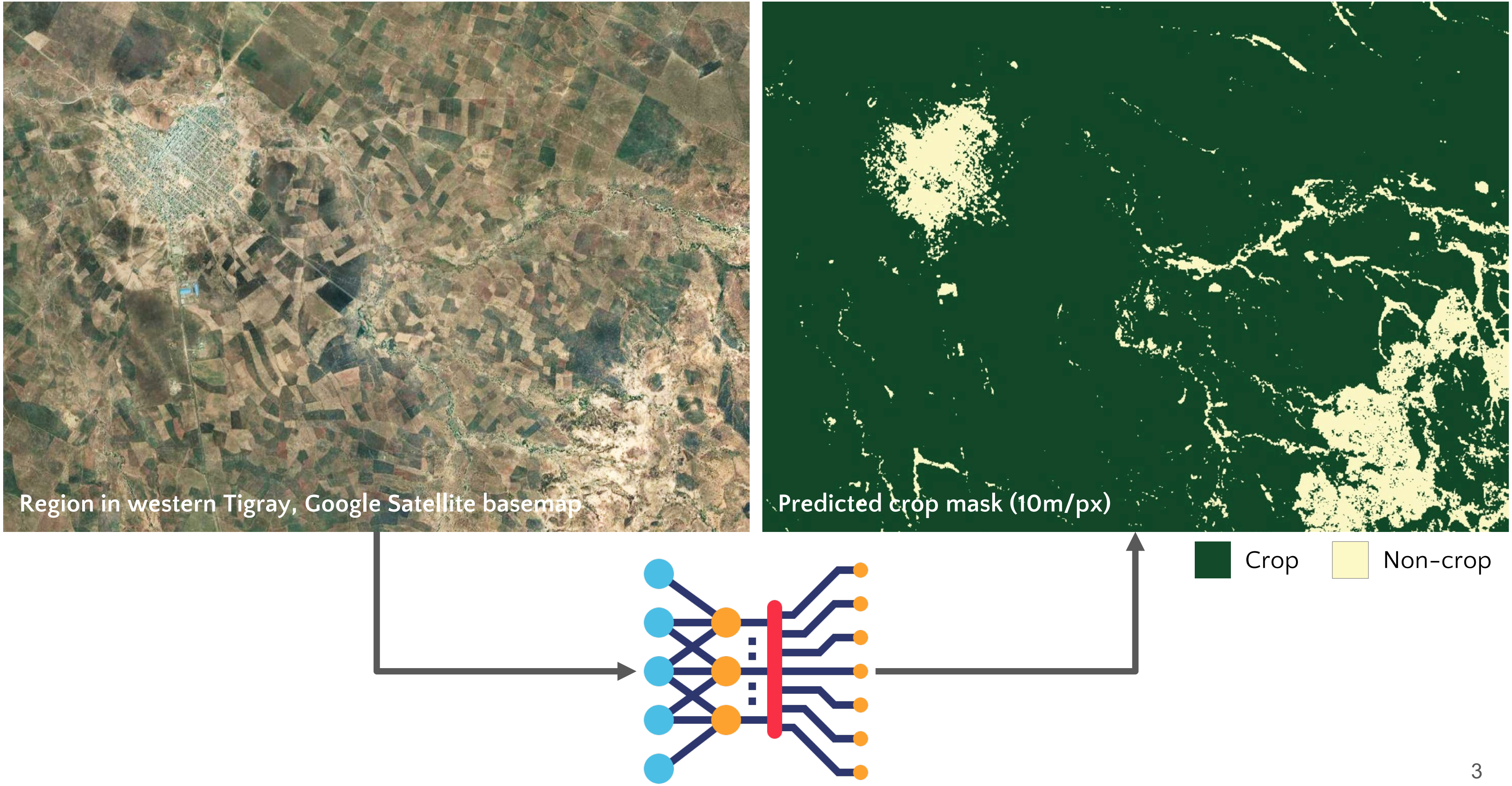
Jul 23, 2021

NPR

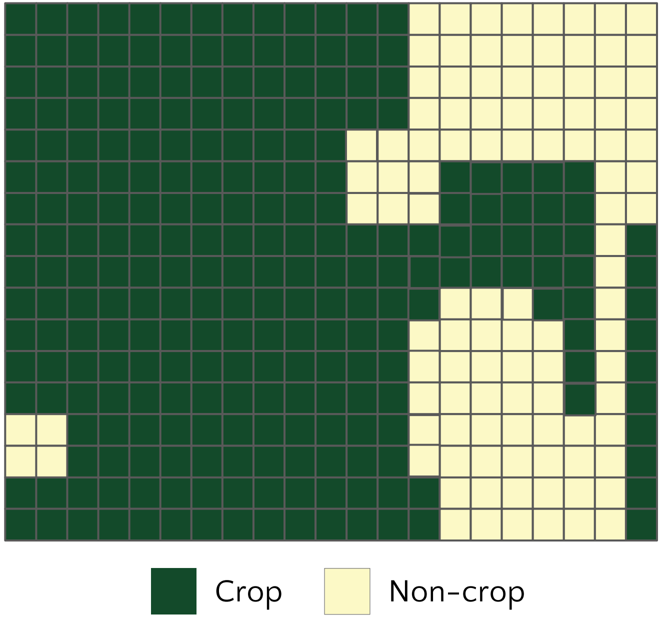
Famine Stalks Ethiopia's Embattled Tigray Region

For months, the United Nations has warned of famine in this embattled corner of northern Ethiopia, calling it the world's worst hunger crisis in...

Sep 20, 2021


Region in western Tigray, Google Satellite basemap
Predicted crop mask (10m/px)
Crop
Non-crop

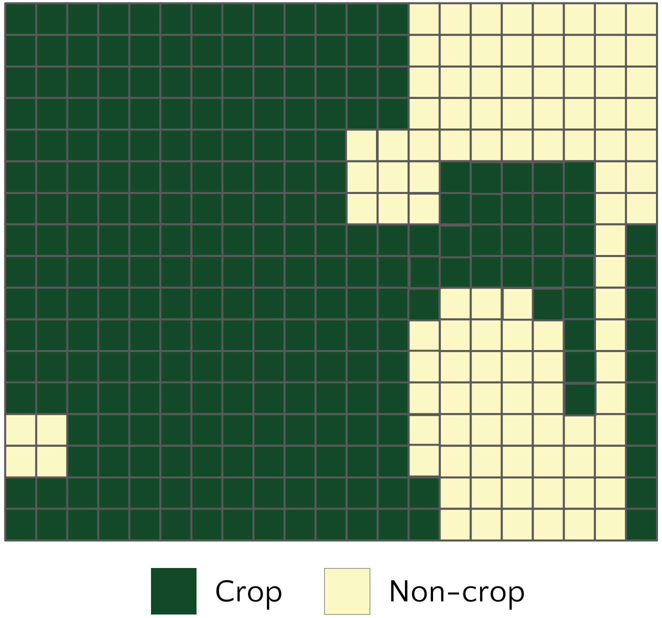
Planted area estimation approach



Crop mask for region and year of interest

Based on Kerner & Tseng et al., 2020, Rapid response crop maps in data sparse regions.

Planted area estimation approach



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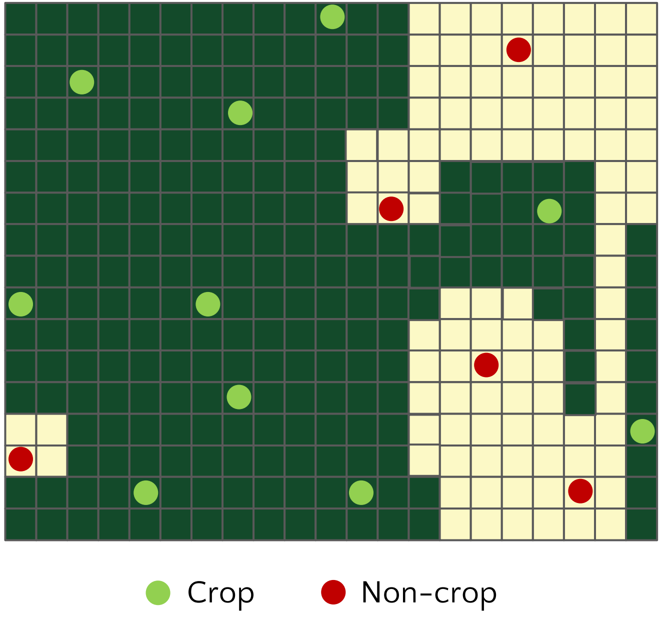
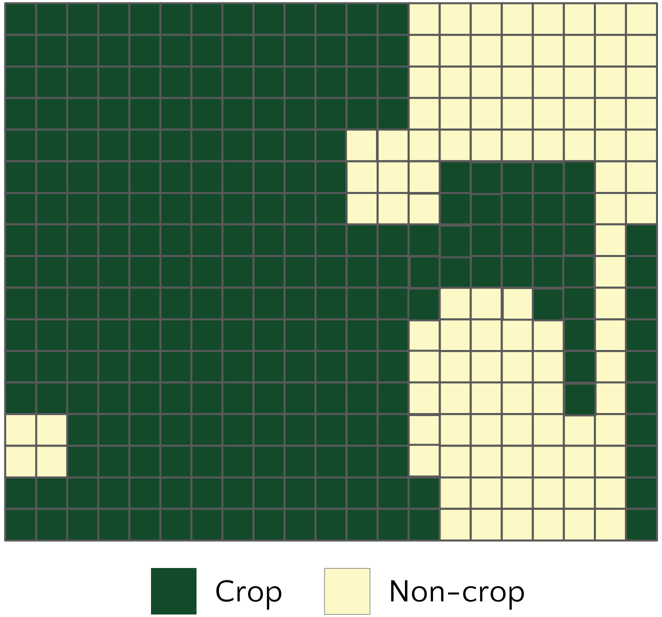


Stratified reference sample

Based on Olofsson et al., 2014, Good practices for estimating area and assessing accuracy of land change.

Planted area estimation approach



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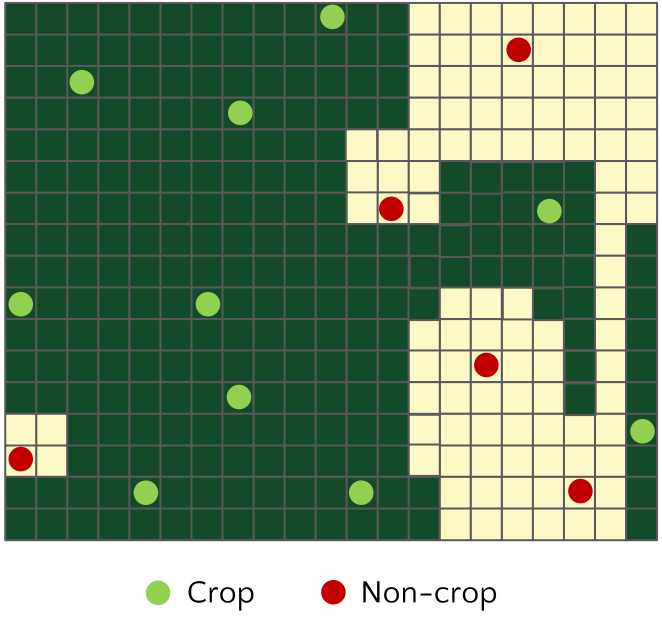

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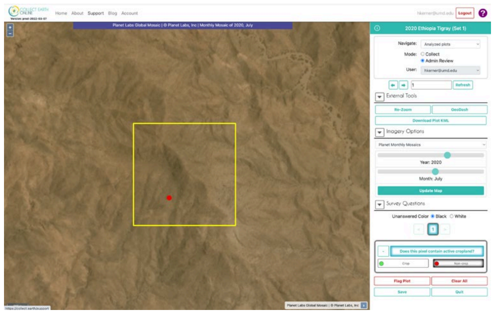

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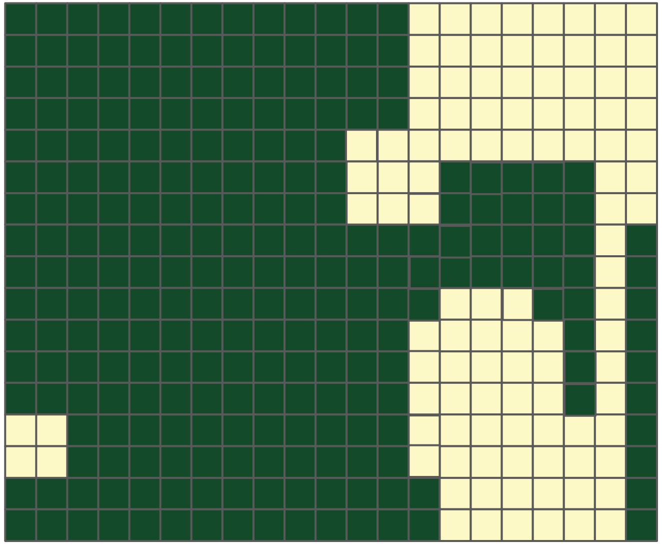

Crop Non-crop

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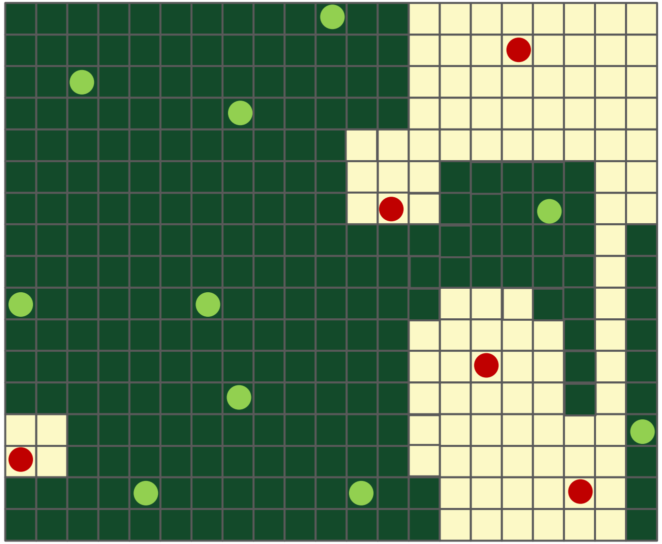

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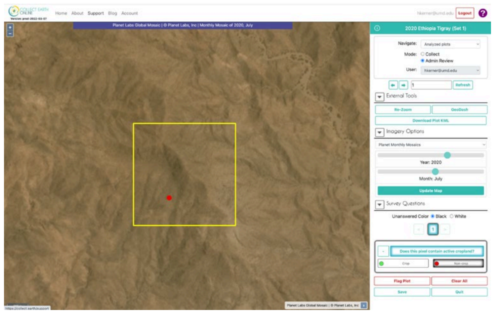

Labeled reference sample

Map	Reference: Planted	Reference: Not planted	Total
Planted	p_{11}	p_{12}	p_{1*}
Not planted	p_{21}	p_{22}	p_{2*}
Total	p_{*1}	p_{*2}	1

Confusion matrix

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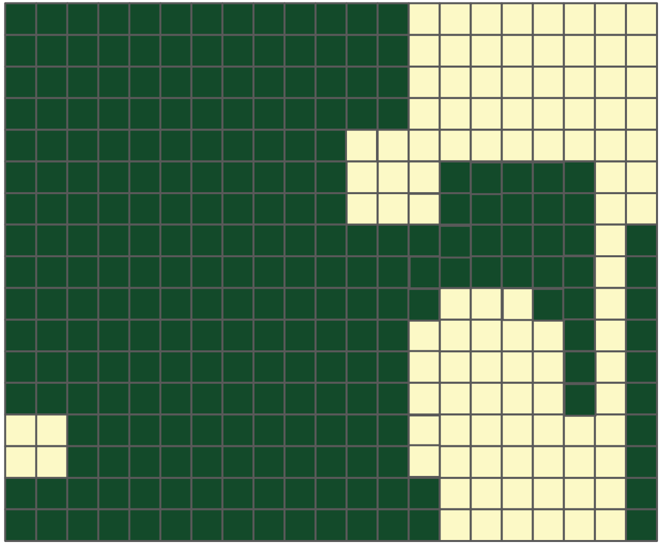
Planted area estimation approach



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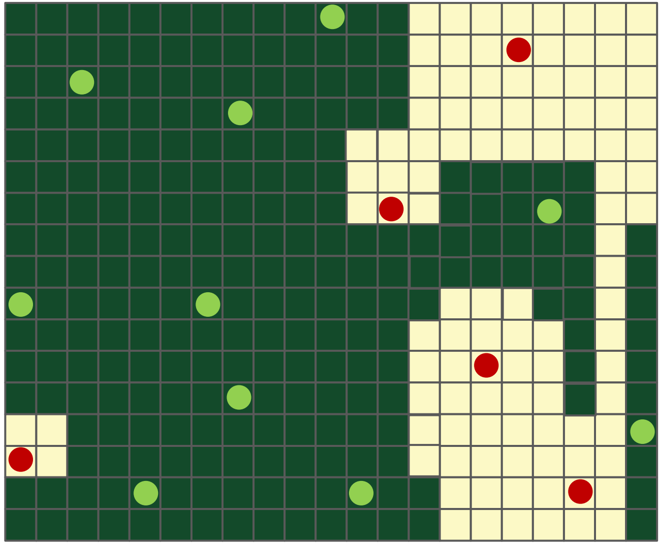

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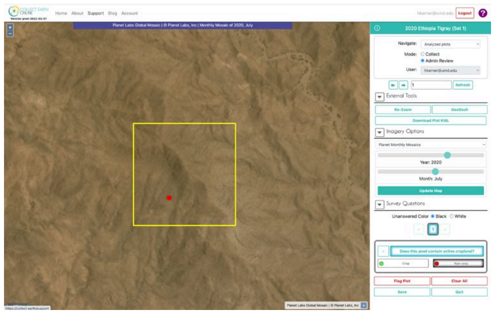

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Adjust map-based areas → $planted\ area \pm error\ at\ 95\%\ confidence\ interval$

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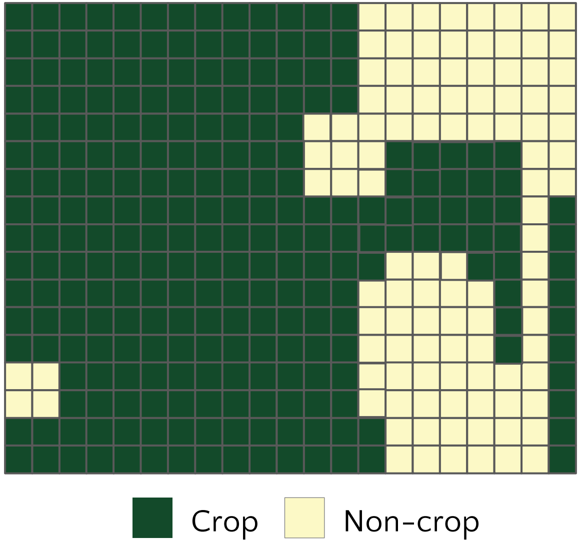
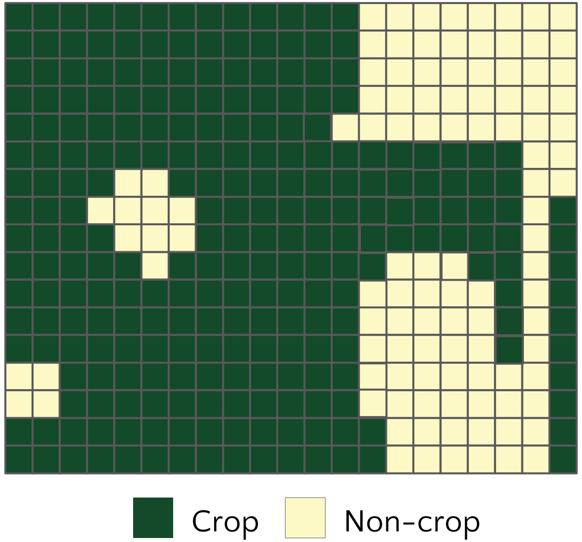
Planted area change estimation approach

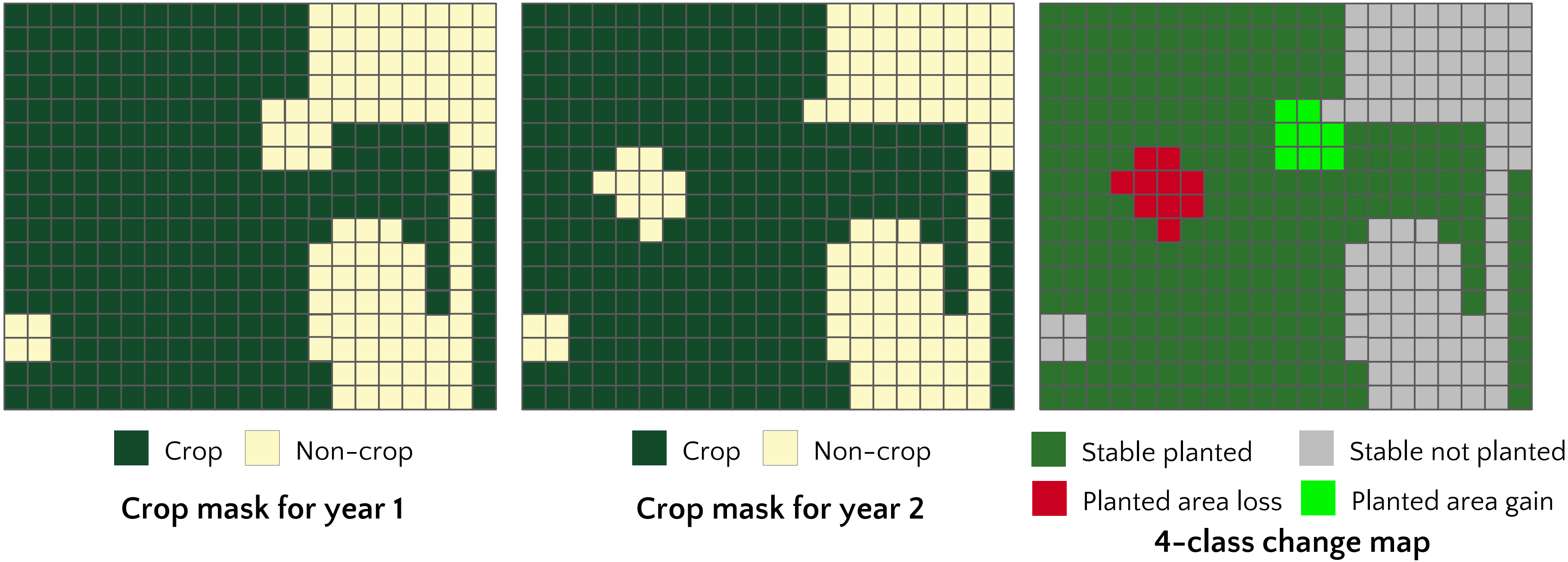


Crop mask for year 1

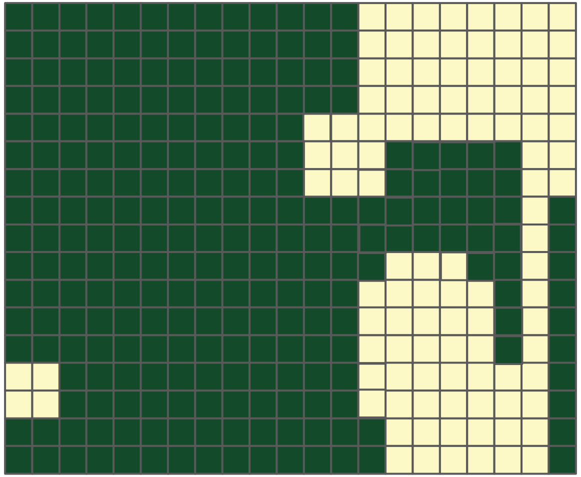


Crop mask for year 2

Planted area change estimation approach

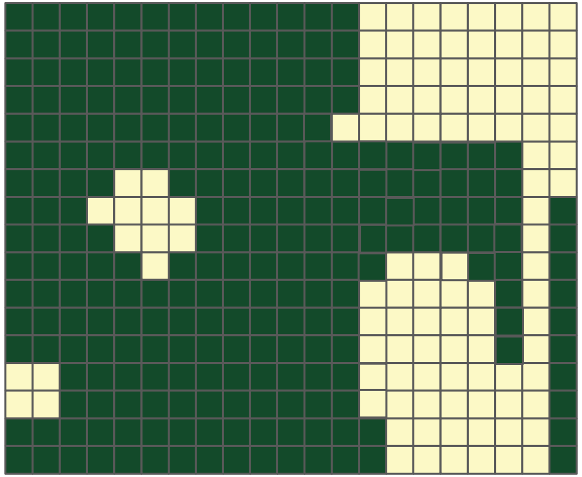


Planted area change estimation approach



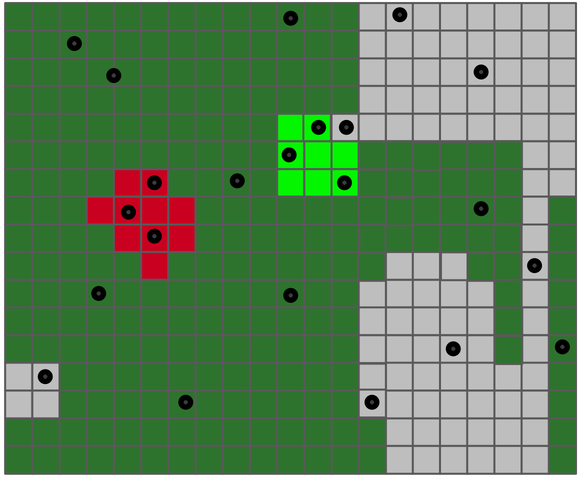
Crop · Non-crop

Crop mask for year 1



Crop · Non-crop

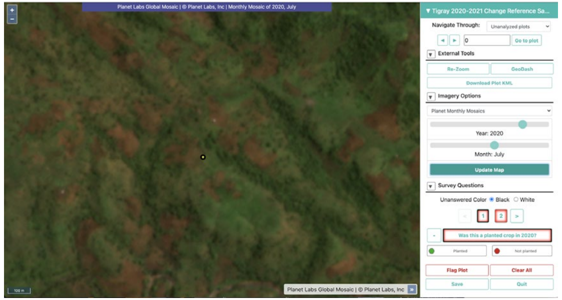
Crop mask for year 2



Stable planted · Stable not planted

Planted area loss · Planted area gain

4-class change map



Labeled reference sample

	NP -> NP	NP -> P	P -> NP	P -> P	Total
NP -> NP	p_{11}	p_{12}	p_{13}	p_{14}	p_{1*}
NP -> P	p_{21}	p_{22}	p_{23}	p_{24}	p_{2*}
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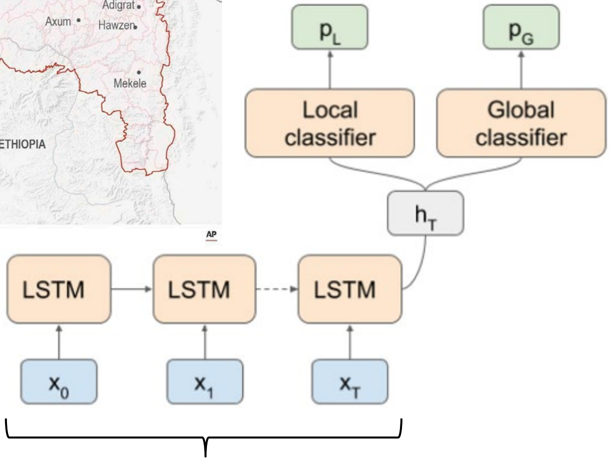
P -> P	p_{41}	p_{42}	p_{43}	p_{44}	p_{4*}
Total	p_{*1}	p_{*2}	p_{*3}	p_{*4}	1

Adjust map-based areas

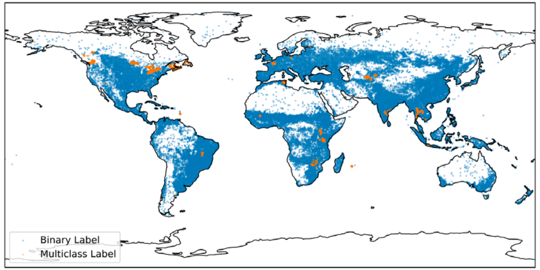
↓

$$class\ area\ \pm\ error$$

Crop mask generation approach



12-month time series of
Sentinel-2 multispectral
+ other satellite datasets

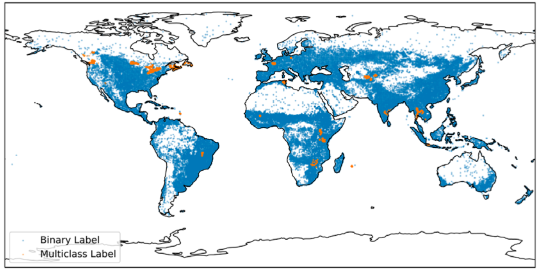


cropharvest 0.3.0

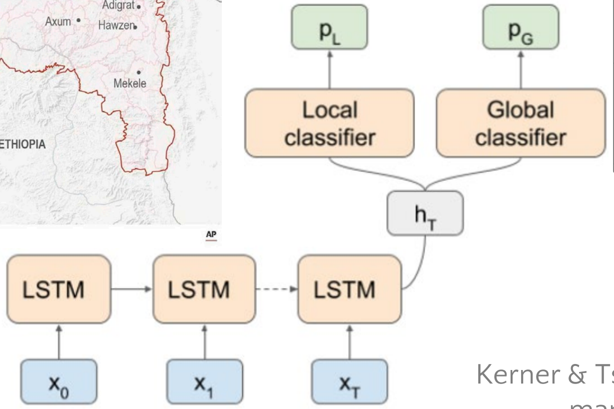
```
pip install cropharvest
```

Kerner & Tseng et al., 2020, Rapid response crop maps in data sparse regions. KDD.

Crop mask generation approach



In-season:
Auto-regressive LSTM used to forecast satellite observations



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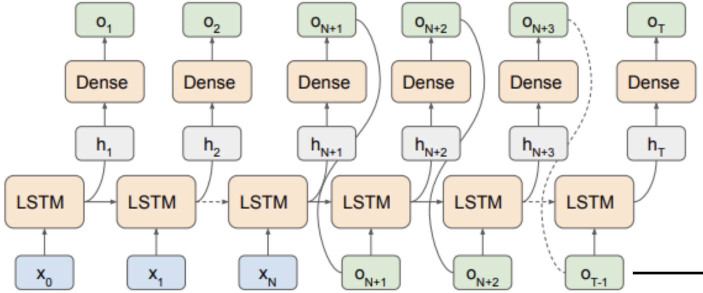

observed

forecasted

Tseng & Kerner et al., 2020. Annual and in-season mapping of cropland at field scale with sparse labels. NeurIPS.

Crop mask generation approach

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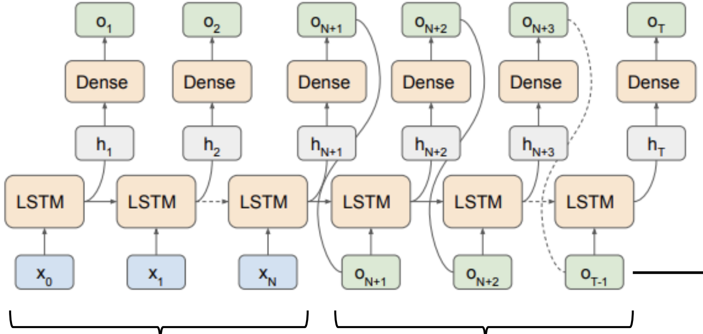

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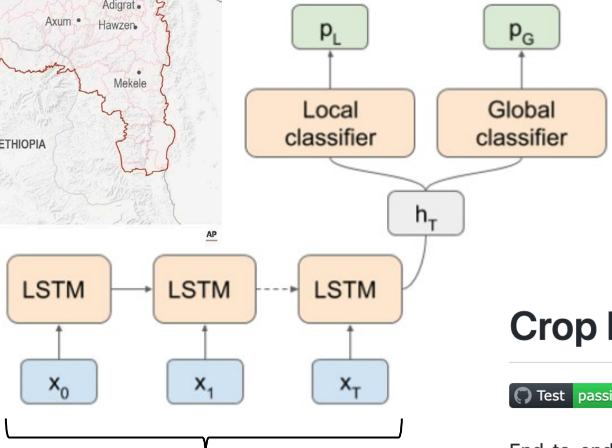

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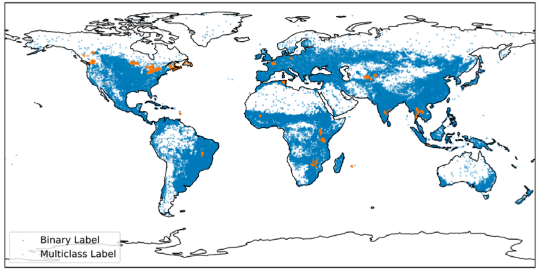

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Crop Map Generation

Test passing | Deploy passing

End-to-end workflow for generating high resolution cropland maps.

Contents

github.com/nasaharvest/crop-mask

- Creating a crop map
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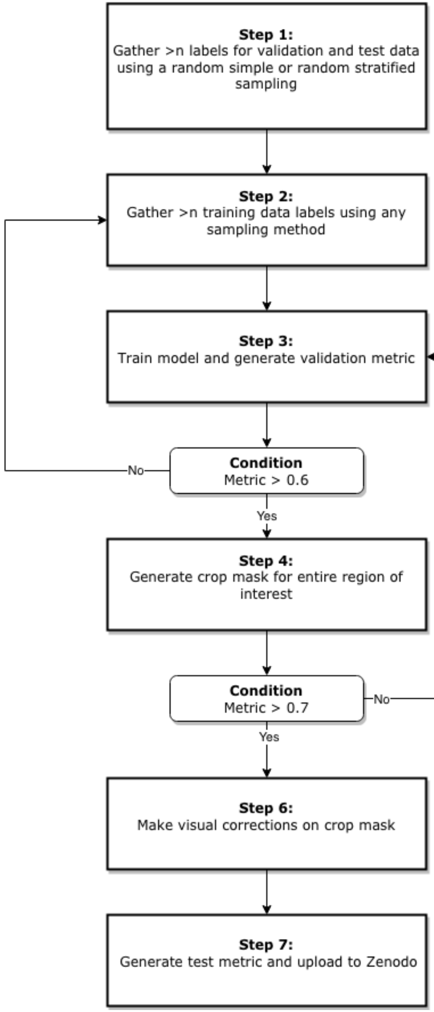

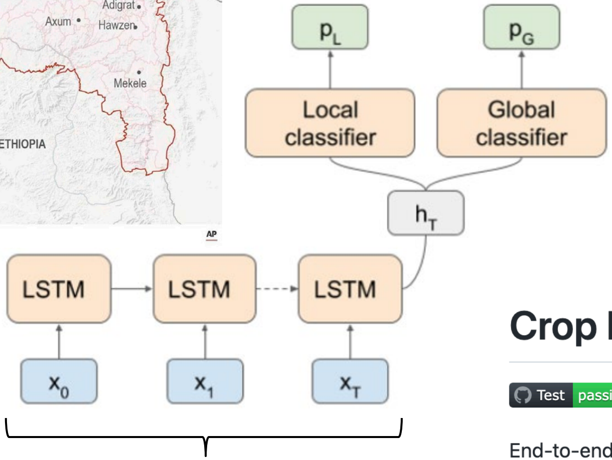

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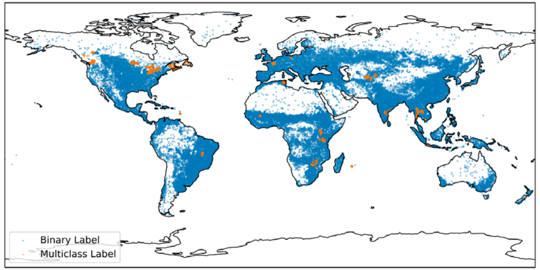

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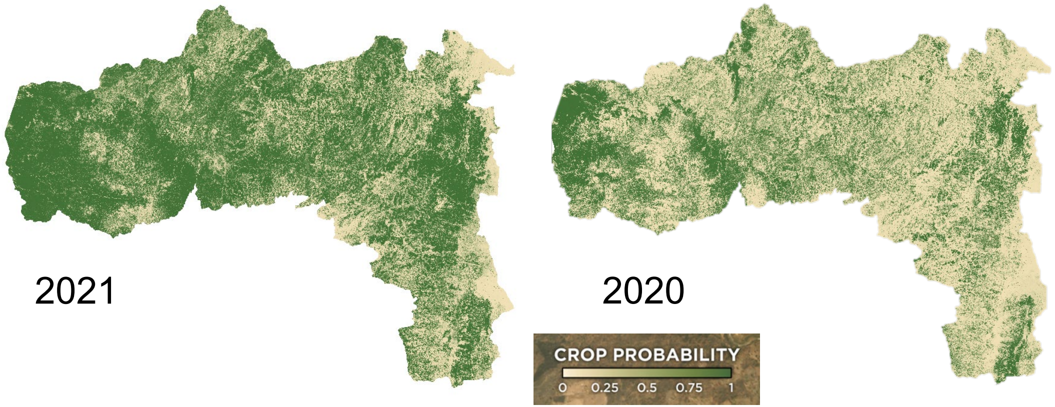
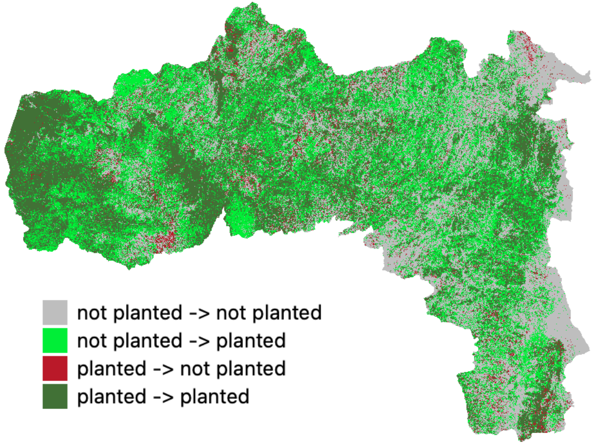
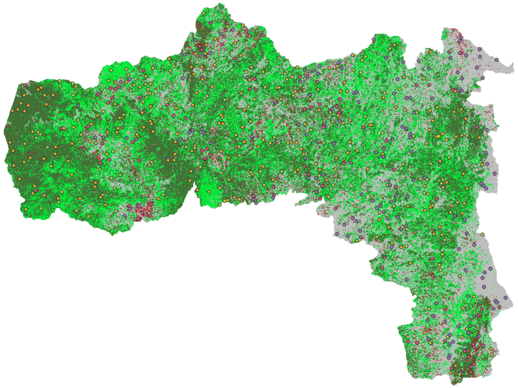
Tigray planted area change estimation

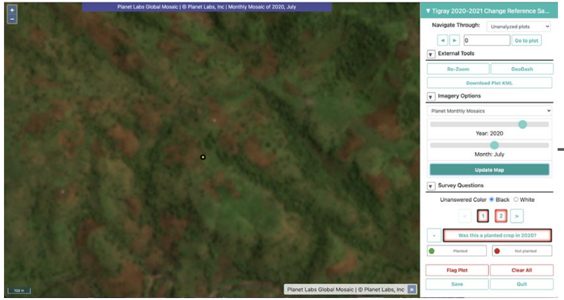
Classify predicted change map





Adjust mapped area based on errors in reference sample for each class





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$$class\ area\ \pm error$$

Tigray planted area change results (quantitative)

	P loss	P gain	Stable P	Stable NP
Estimated area [ha]	36,242	85,038	1,292,500	3,846,817
95% CI of area [ha]	±34,913	±55,872	±175,806	±177,235

Estimated area values as fraction of total area

	P loss	P gain	Stable P	Stable NP
Estimated area	0.01	0.02	0.25	0.72
95% CI of area	± 0.01	± 0.01	± 0.03	± 0.03

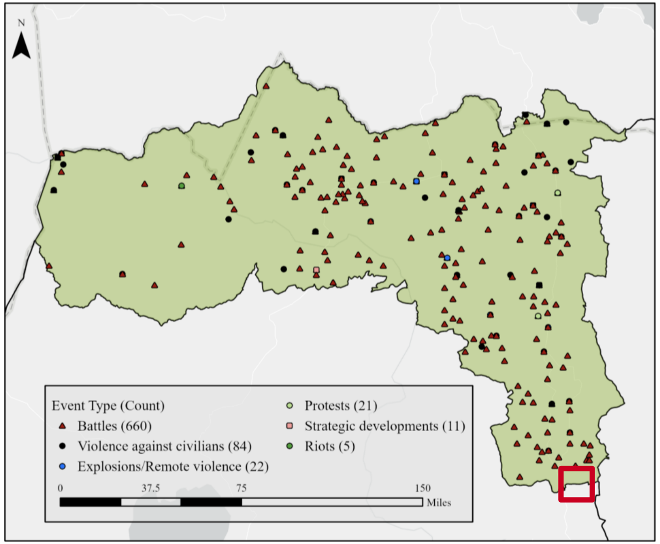
Summary

- Small fraction of area detected as planted area **loss (0–2%)** and **gain (1–3%)**
- Most of total area was stable **not planted (69–75%)**, **stable planted (22–28%)**

Tigray planted area change results (qualitative)

PlanetScope basemap Jul-Oct 2020

ACLED: Armed Conflict Location & Event Data



Reference label: **planted loss**

Mapped class: **planted loss**

Tigray planted area change results (qualitative)

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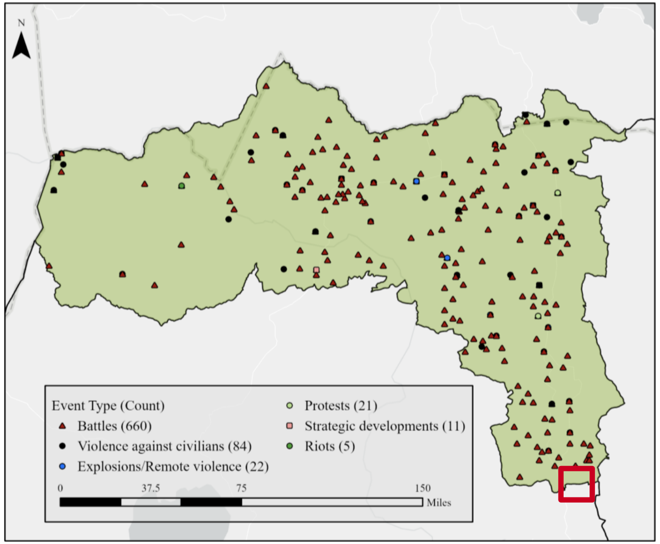

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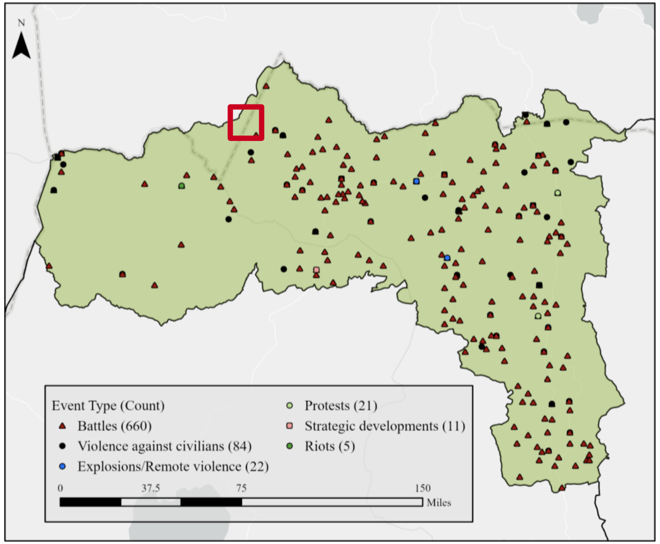

Reference label: planted loss

Mapped class: stable planted

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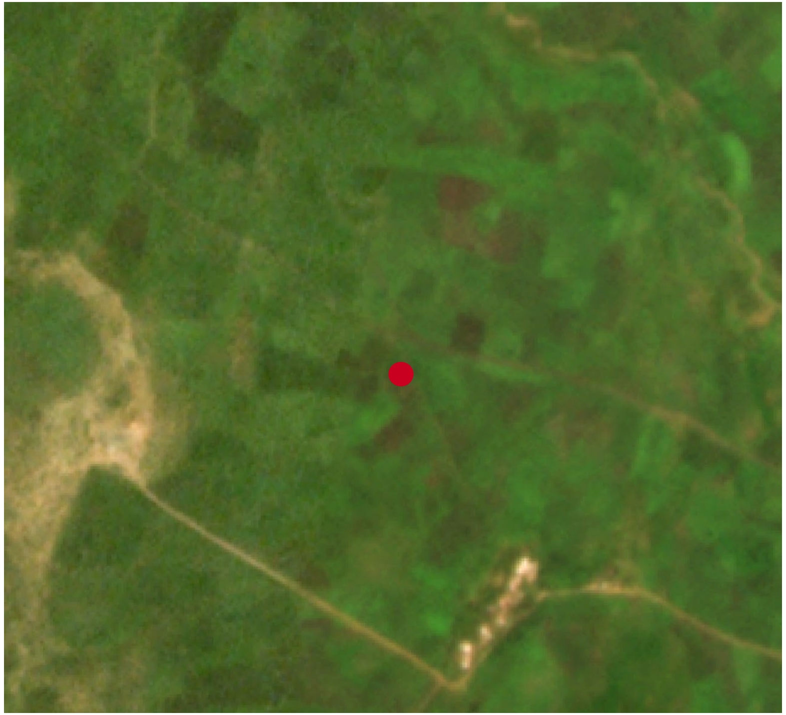

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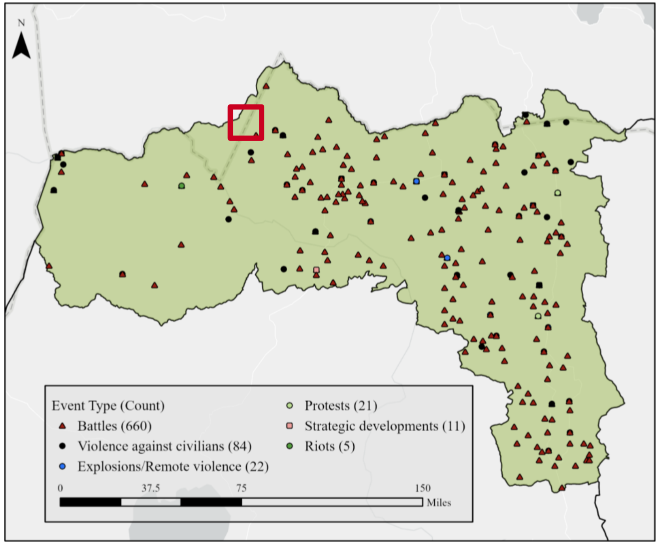

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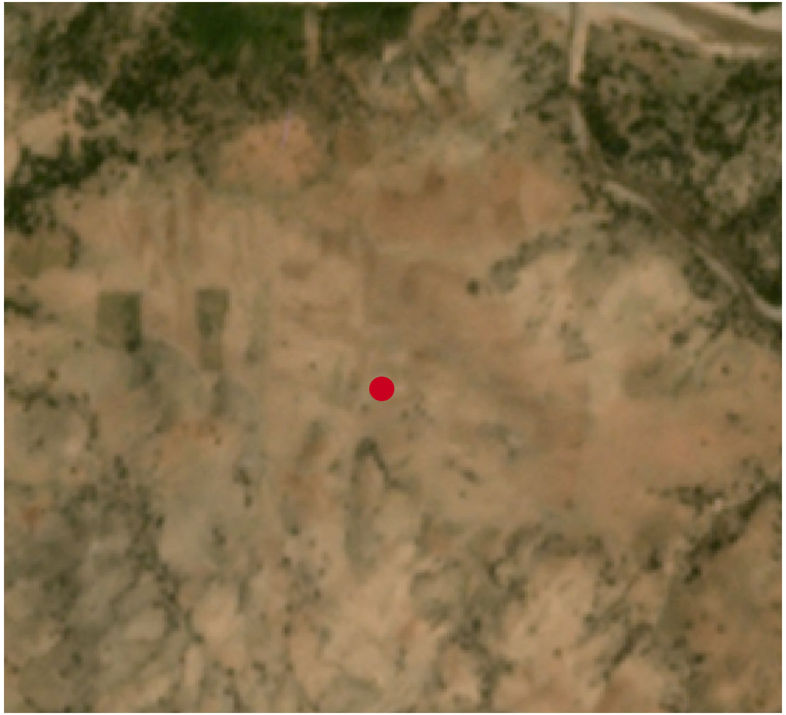

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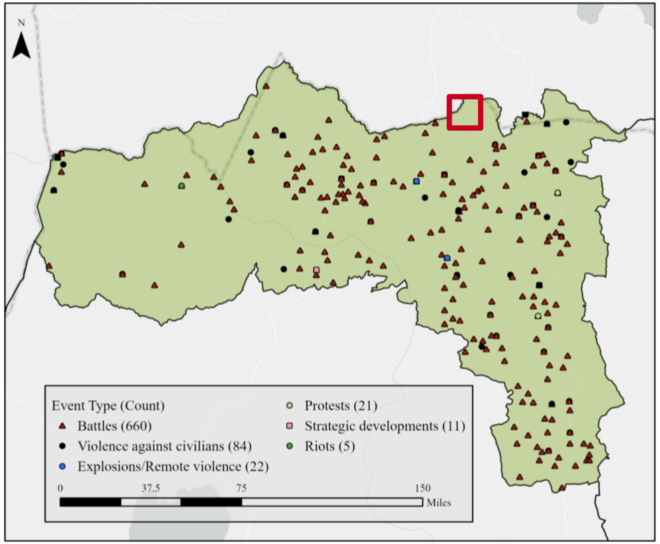

Reference label: planted gain

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Tigray planted area change results (qualitative)

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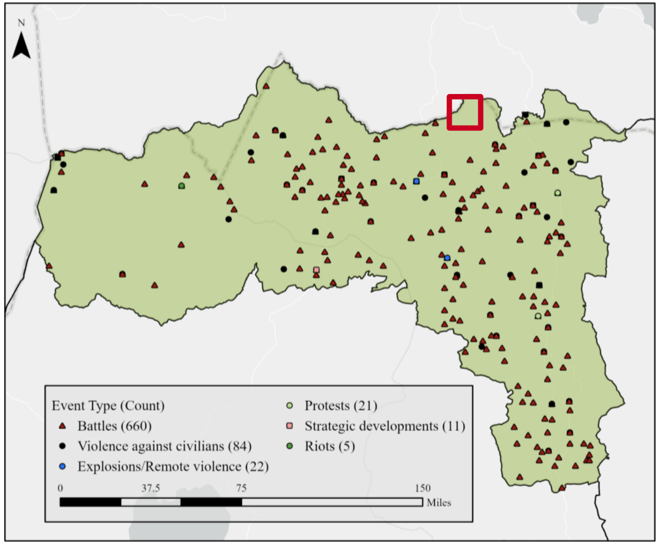

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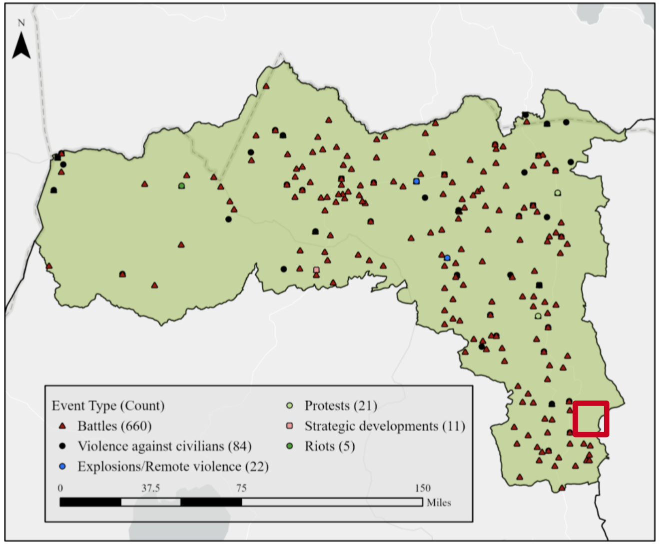

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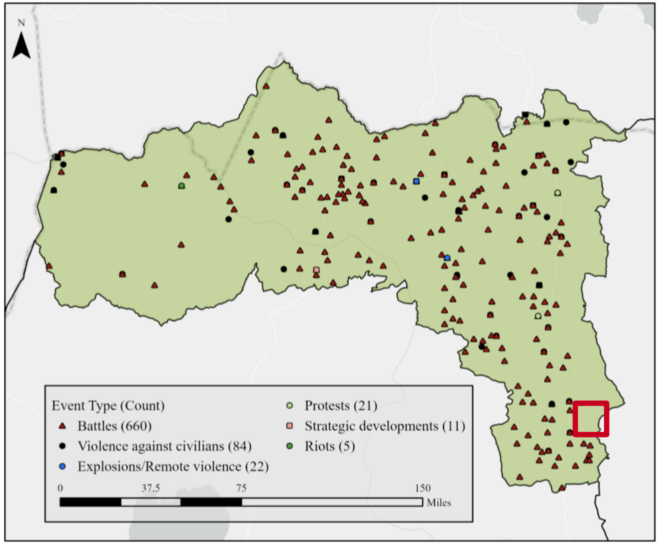


Reference label: planted gain

Mapped class: planted loss

Discussion and limitations

- Changes in planted area highly localized localized
- Method only detects total loss of a field
  - Delays in ploughing, planting or other variables
  - Blockades of supplies, lack of access to markets, blockage of food aid, different timelines or non-traditional crops, etc.
- Attribution of changes to conflict requires additional analysis
- Standard errors account for error in our estimate, but do not account for reference sample label errors / interpretations
  - Very hard to verify without ground-truthing

Ploughing activity visible in Google Earth image, April 2021

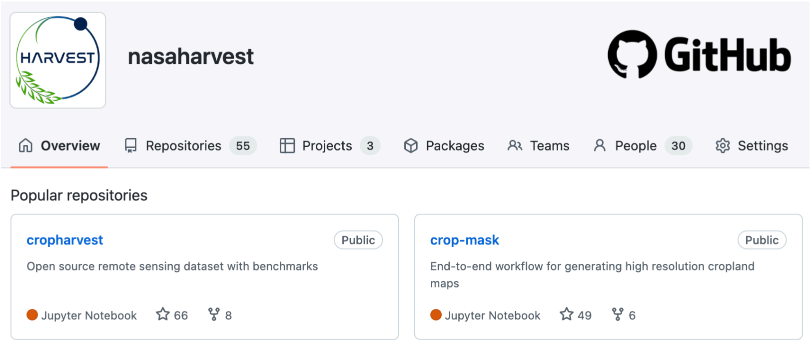
Lessons learned / takeaways for future work

- Labeling extremely difficult and time consuming
- Baseline of expected change
- Strategies for improving crop mask accuracies
  - More training data ≠ better map
  - Error analysis needed for informed decisions
- Pixel counting faster, but estimates not reliable
- More granular estimates (e.g., admin2)

PlanetScope basemap Jul–Oct 2021

Open source, open data

github.com/nasaharvest



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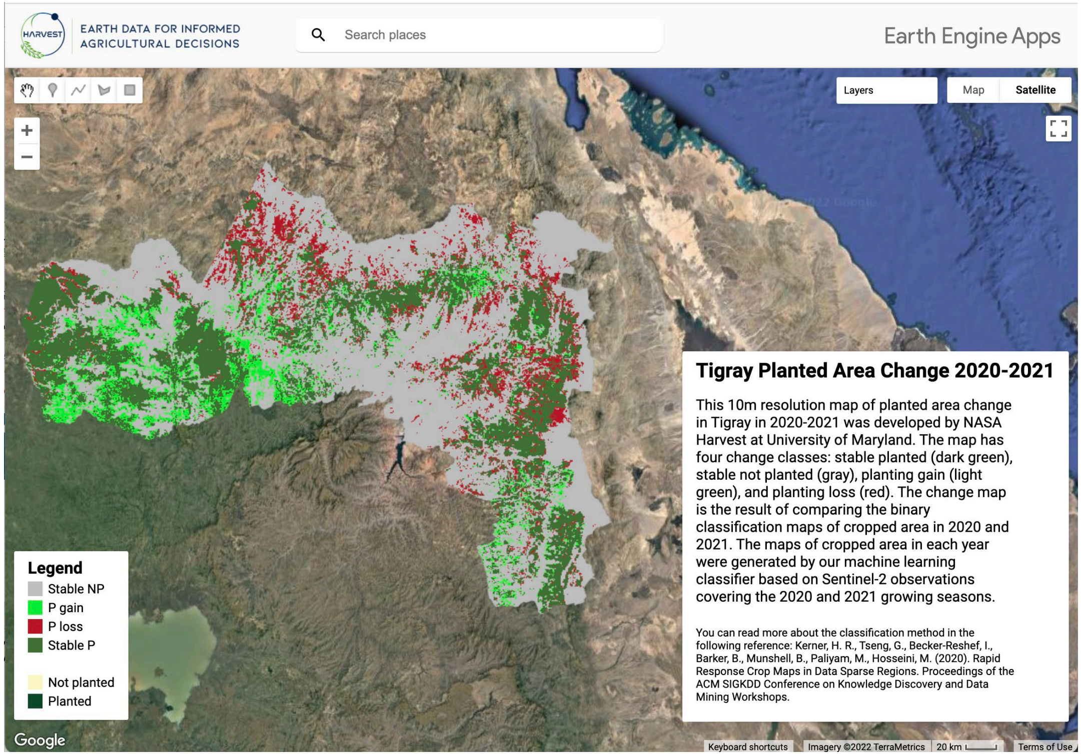

https://hkerner-umd.users.earthengine.app/view/tigraychange2020-2021

Conclusion

Workflow for estimating annual planted area and inter-annual change in support of Rapid Action for Policy Support (RAPS)

Hannah Kerner

Assistant Research Professor, University of Maryland
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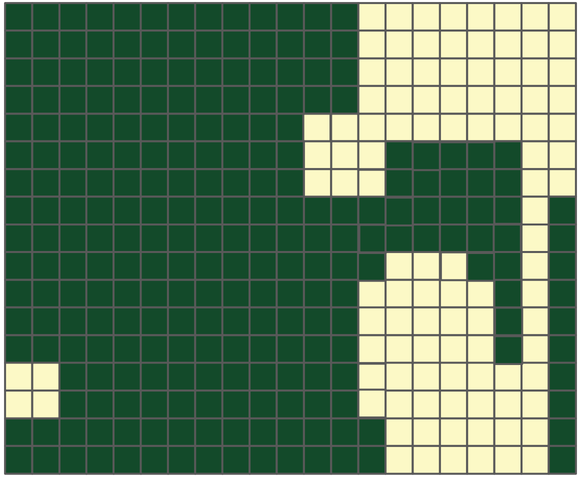
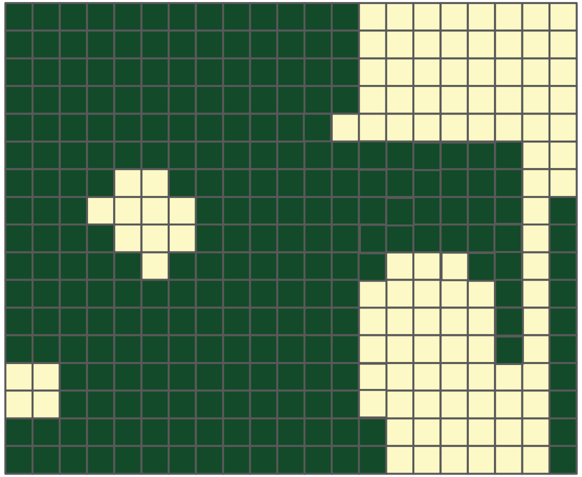


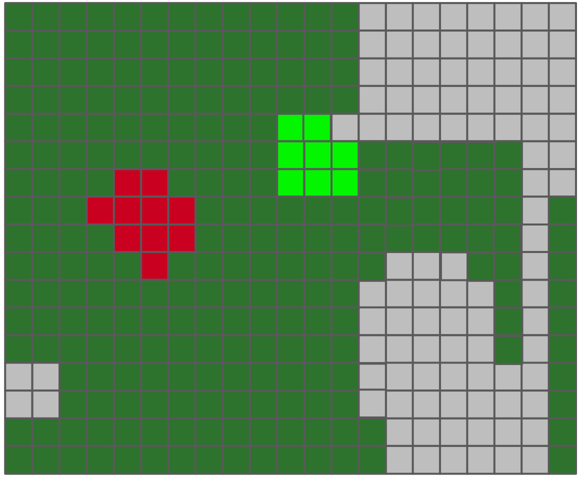
Crop Non-crop

Crop mask for year 1



Crop Non-crop

Crop mask for year 2



Stable planted Stable not planted
Planted area loss Planted area gain

4-class change map

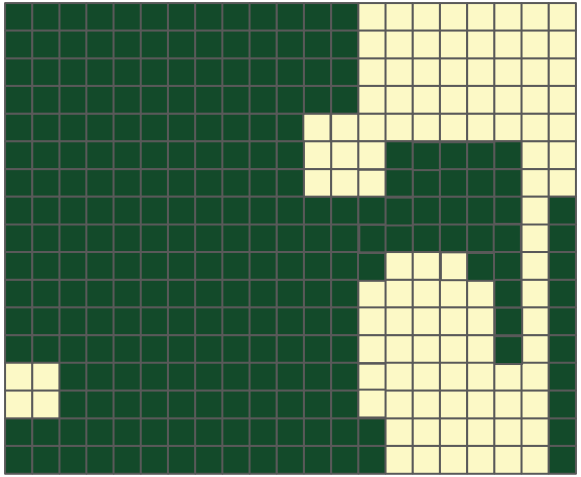
Why not estimate each year independently and compare?

Compounding standard errors

Suppose X ha planted in year 1 and Y ha planted in year 2:

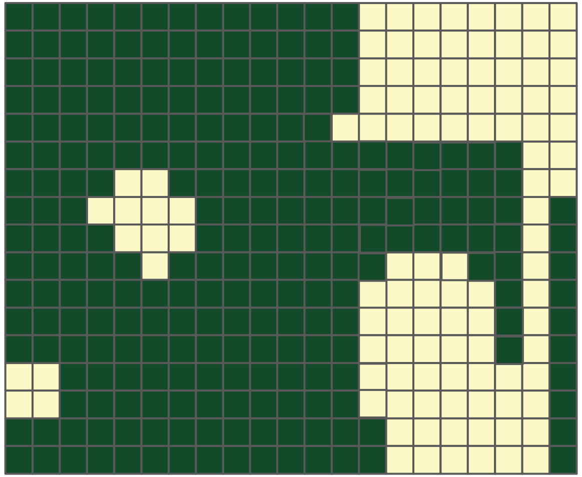
$$y_1 = X \pm \alpha$$
$$y_2 = Y \pm \beta$$
$$y_1 - y_2 = (X - Y) \pm (\alpha + \beta)$$

Planted area change estimation approach



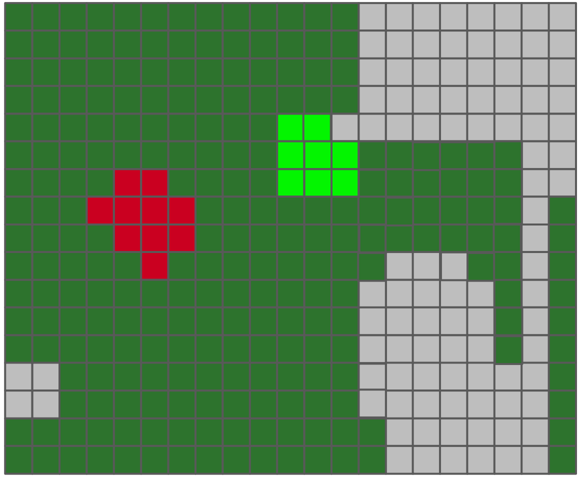
Crop Non-crop

Crop mask for year 1



Crop Non-crop

Crop mask for year 2



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Compounding classification error

Suppose map for each year has 80% accuracy:

$$acc_{change} \approx acc_{y1} * acc_{y2}$$
$$acc_{change} \approx 0.8 * 0.8 = 0.64$$