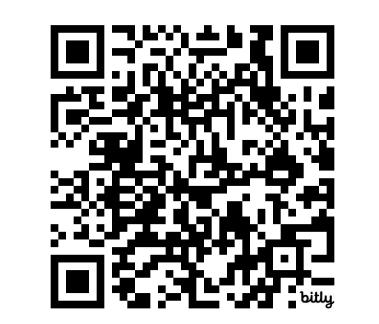


# Microsoft Wherobots Agricultural Monitoring with Fields of The World (FTW)

Hannah Kerner<sup>1</sup>, Caleb Robinson<sup>2</sup>, Isaac Corley<sup>3</sup>, Matthias Mohr<sup>4</sup>, Gedeon Muhawenayo<sup>1</sup>, Ivan Zvonkov<sup>5</sup>, Tristan Grupp<sup>6</sup>, Nathan Jacobs<sup>7</sup> <sup>1</sup> Arizona State University, <sup>2</sup> Microsoft AI for Good Research Lab, <sup>3</sup> Wherobots, <sup>4</sup> Taylor Geospatial Engine, <sup>4</sup> University of Maryland, <sup>4</sup> World Resources Institute, <sup>6</sup> Washington University in St. Louis | **E** hkerner@asu.edu





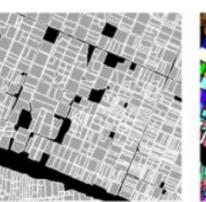
#### Overview

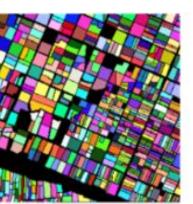
### Fields of The World (FTW)<sup>1</sup>

- Al ecosystem for automated field boundary segmentation and postprocessing
- Includes benchmark dataset, pretrained models, command line interface (CLI), and other tools











FTW dataset example. Left to right: Sentinel-2 images from

#### planting and harvest season, 3-class semantic segmentation mask (background, interior, and boundary), and instance mask

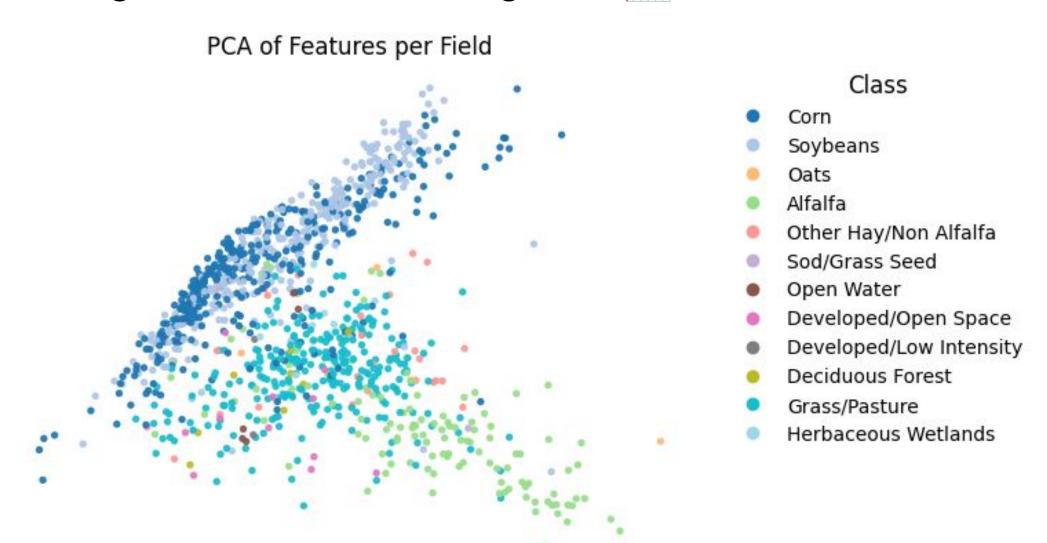
#### Tutorial objectives

Use FTW to extract field boundaries for an ROI Use field boundaries for perform field-scale crop type classification (in Iowa, USA)

Use field boundaries to identify forest loss in agricultural landscapes (in Mato Grosso, Brazil)

## Use Case: Crop Type Classification

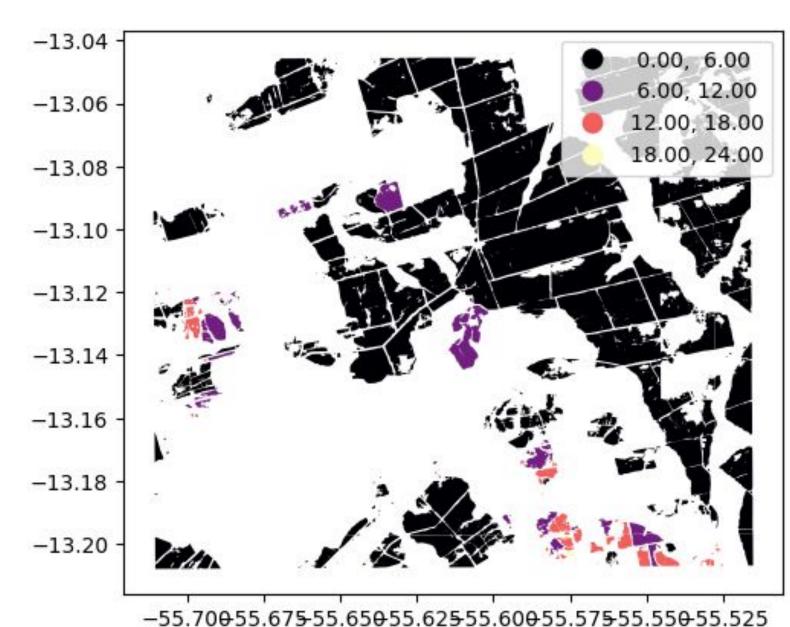
- Predict boundaries for crops in Iowa, 2023
- Generate embeddings 🧠 for each field with MOSAIKS<sup>2</sup>
- Extract crop type labels \(^\infty\) to fields using majority class from USDA Cropland Data Layer<sup>3</sup>
- Train logistic regression model to predict crop type using 1-50% of the training data



MOSAIKS embeddings visualized using PCA. Corn and soybeans have similar spectral signatures, making them hard to differentiate. Alfalfa and Grass/Pasture are also similar to each other, but different from corn/soy.

## Use Case: Forest Loss Monitoring

- Predict boundaries for crops in Mato Grosso, 2022
- 2. Extract "loss year" (year of deforestation) 🦇 using mean value from Hansen Forest Change dataset<sup>4</sup>
- 3. Visualize the deforestation year for each field



Black: fields cleared before

Purple: Forest loss between 2006-2012.

Red: Forest loss between 2012-2018.

Yellow: recent loss

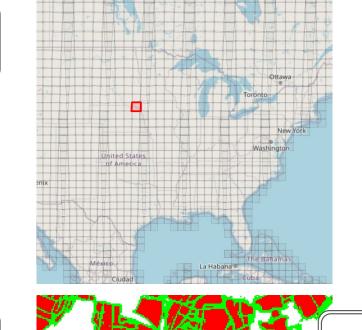
Visualization of average forest loss year in each field. Most fields in this area of Mato Grosso, Brazil were cleared before 2006. However, there are clusters of expansion from 2006-2023 (purple) and 2012-2018 (red).

## Climate Change Relevance

- Agricultural expansion and management contribute to deforestation, biodiversity loss, and greenhouse gas emissions
- Climate change threatens crop yields, food security, and rural livelihoods
- Accurate, up-to-date data about field location and management is essential for building sustainable and resilient food systems
- This information is unavailable, outdated, or fragmented in most parts of the world

## Steps for Generating Field Boundaries with FTW

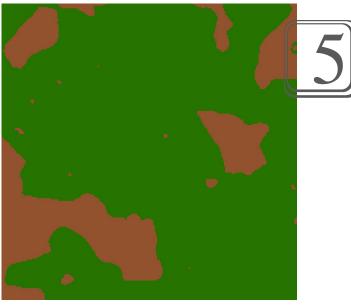
- 1. Specify your region of interest (ROI) 📍 and time of interest (TOI)
- 2. Download Sentinel-2 mages from two time
- 3. Use pretrained FTW model to predict field boundaries (segmentation mask)
- 4. [Optional] Filter predictions by land cover/land use mask (removes false positives) 🏡
- 5. Polygonize boundaries: convert the segmentation mask to vector-format polygons













Acknowledgements: This project was supported by funding from the Taylor Geospatial Engir References: <sup>1</sup>Kerner et al. (2024) AAAI. <sup>2</sup>Rolf et al. (2024) Nature Comms. <sup>3</sup>USDA NASS, Cropland Data Layer (CropScape). <sup>4</sup>Hansen et al. (2013) Science.