Introduction to AI for Agriculture

Hannah Kerner

Assistant Professor, Arizona State University
Adjunct Assistant Professor, University of Maryland
AI/ML Lead, NASA Harvest

Food security remains one of the most pressing issues we face in this century, especially in the face of increasing frequency and severity of extreme weather events due to a warming climate

Innovation in developing robust and scalable measures to monitor the world's crops in a timely, transparent manner is a key component in helping to address this global challenge

Photo:Vinccent Kessler

Who needs information about agriculture / food security?

Who are the end-users / decision makers?

What do farmers want to know?

What do you think?

What do farmers want to know?

- **When to plant?**
- Crop performance
- Potential threats to production (e.g., climate change)
- Actual threats to production (e.g., nearby pest/disease outbreak or weather forecasts)
- Soil moisture, rainfall, temperature, etc.
- Productivity potential (yield gap)


Kenya - Key Message Update: Thu, 2022-03-31 31/03/22 21:46

Famine Early Warning Systems Network

East Africa

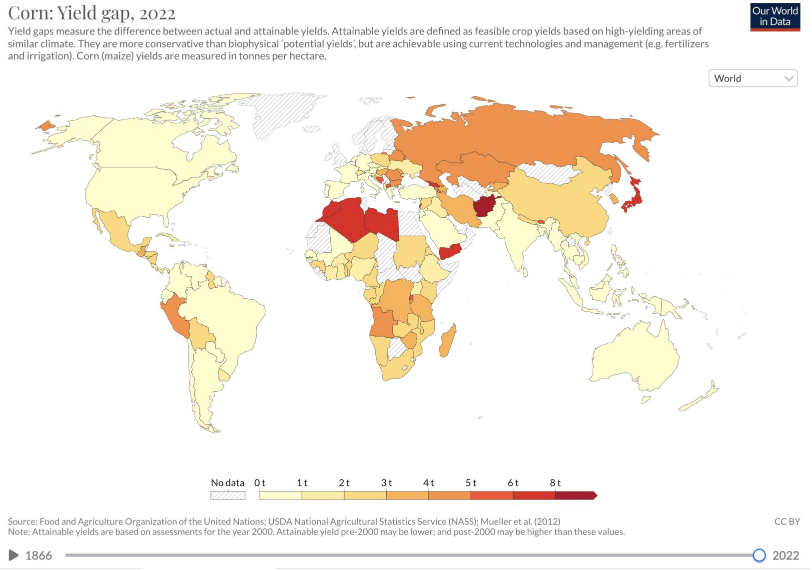
Kenya

Key Message Update

A delayed start to the March-to-May long rains expected to further intensify food insecurity

What do farmers want to know?

- When to plant?
- Crop performance
- Potential threats to production (e.g., climate change)
- Actual threats to production (e.g., nearby pest/disease outbreak or weather forecasts)
- Soil moisture, rainfall, temperature, etc.
- **Productivity potential (yield gap)**

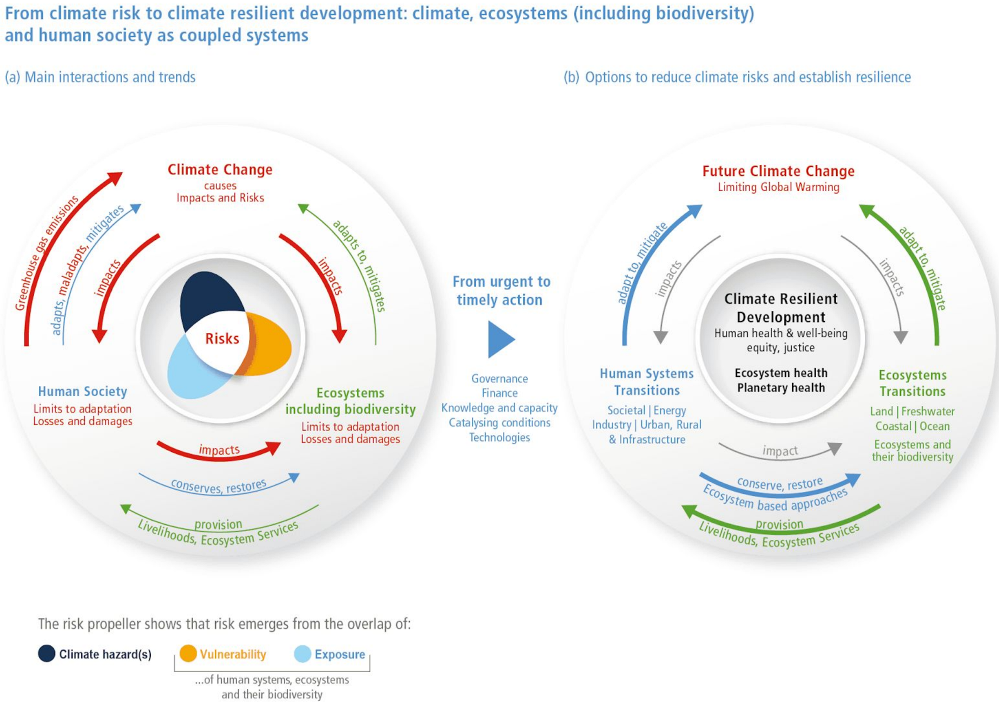


What do farmers want to know?

- When to plant?
- Crop performance
- Potential threats to production (e.g., climate change)
- Actual threats to production (e.g., nearby pest/disease outbreak or weather forecasts)
- Soil moisture, rainfall, temperature, etc.
- Productivity potential (yield gap)
- **Suitability of crops (would a different crop or variety grow better?)**

What do policymakers want to know?

- Crop performance
- Potential threats to production
- Actual threats to production
- When to intervene
- How to intervene
- Productivity potential
- Suitability of crops
- How suitability will change
- Measure impacts of policies



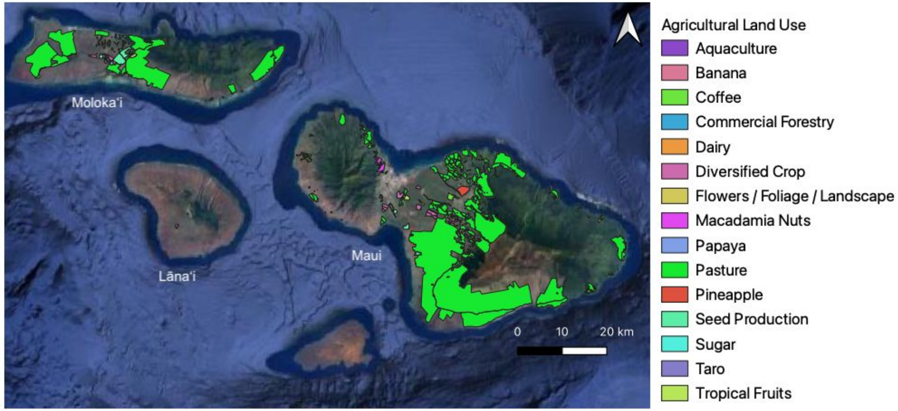
Source: IPCC Sixth Assessment Report

Example: Satellite-Enabled Food Security Dashboard for Maui County

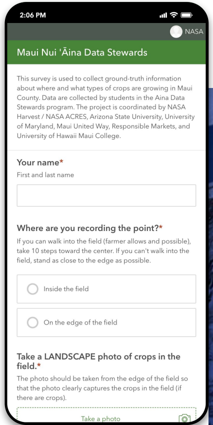
Goal: create baseline geospatial datasets for **measuring and monitoring agricultural production in Maui County** to support policy & efforts to improve food security

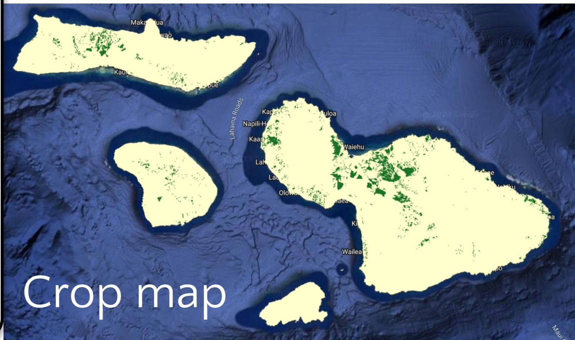
How?

- Train **machine learning** models to predict where crops growing based on **Earth observation**/satellite data
- Integrate crop maps with other relevant datasets (e.g., **socioeconomic** and price data)
- Make data available in a **public Food Security Dashboard**
- Collaborate with stakeholders to ensure products & Dashboard serve **community decisions and actions**
    - End users: Maui United Way, farmers, Dept of Ag, county council, community organizations, etc.
    - Develop of policies and practices that result in more equitable access to food for Hawaii residents
    - Boost agricultural production for food crops, including native Hawaiian crops

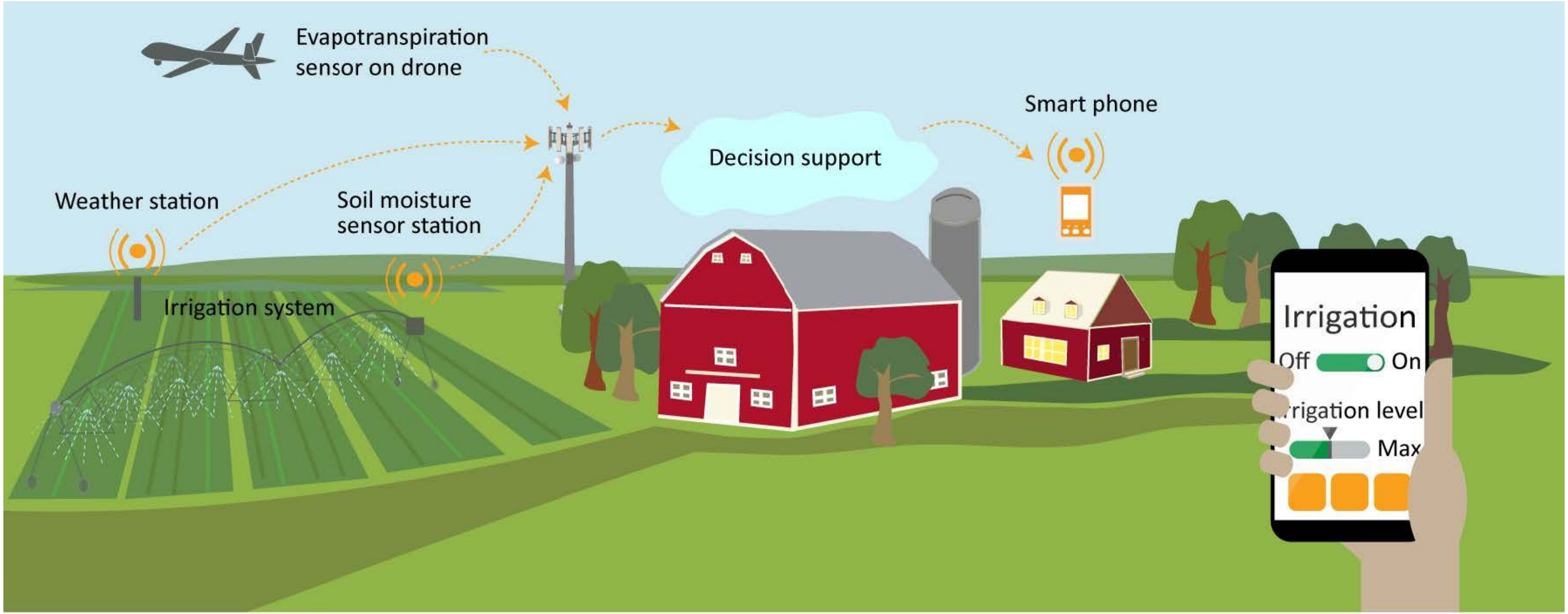


Hawaii Ag Land Use Baseline, 2020





People usually think of precision ag on the ground…

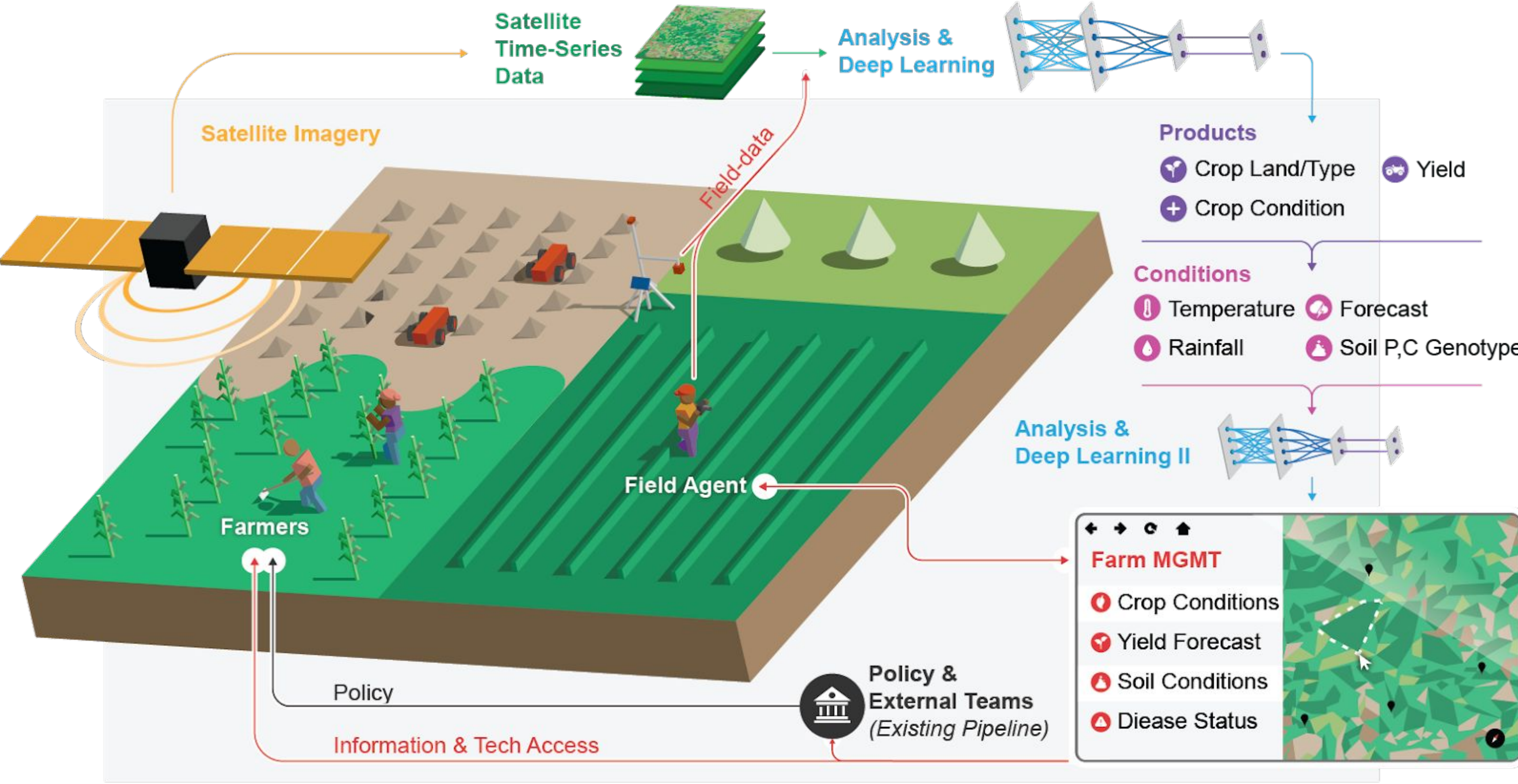


Source: GAO. | GAO-20-128SP

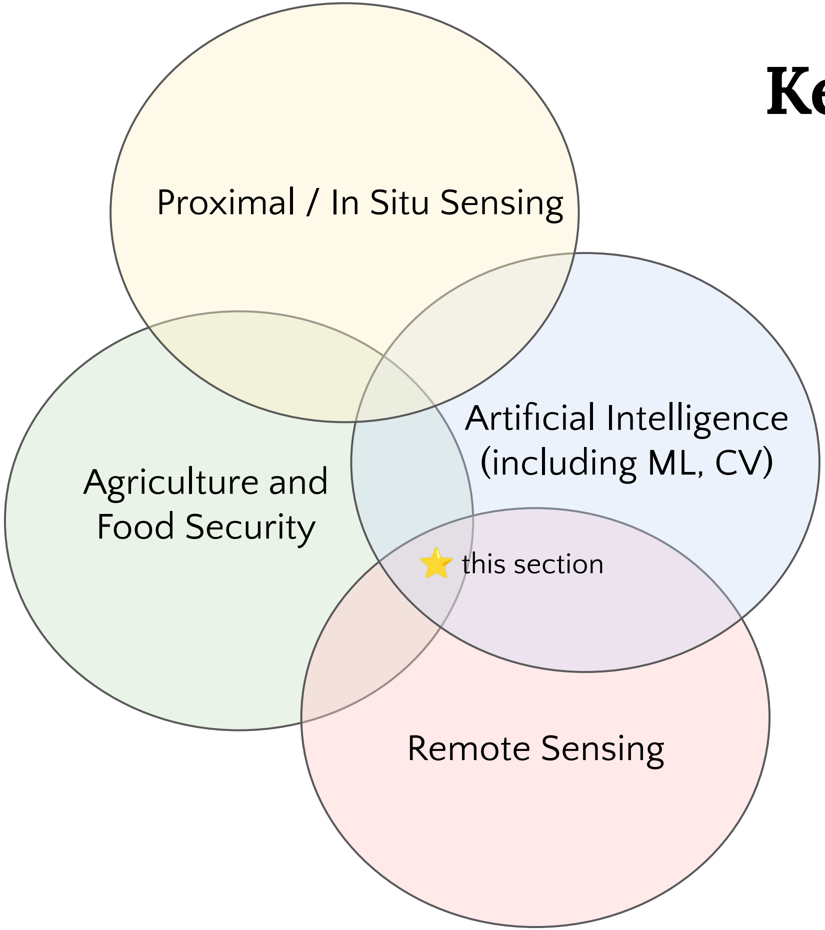
But we also have data from the sky

Since the 1970's

Source: NASA


Satellite
Time-Series
Data
Analysis &
Deep Learning
Satellite Imagery
Field-data
Products
Crop Land/Type
Yield
Crop Condition
Conditions
Temperature
Forecast
Rainfall
Soil P,C Genotype
Analysis &
Deep Learning II
Field Agent
Farmers
Farm MGMT
Crop Conditions
Yield Forecast
Soil Conditions
Diease Status
Policy &
External Teams
(Existing Pipeline)
Policy
Information & Tech Access

Key topics



Crop mapping → Binary classification

Crop type mapping → Multi-class classification

Field boundary delineation → Segmentation

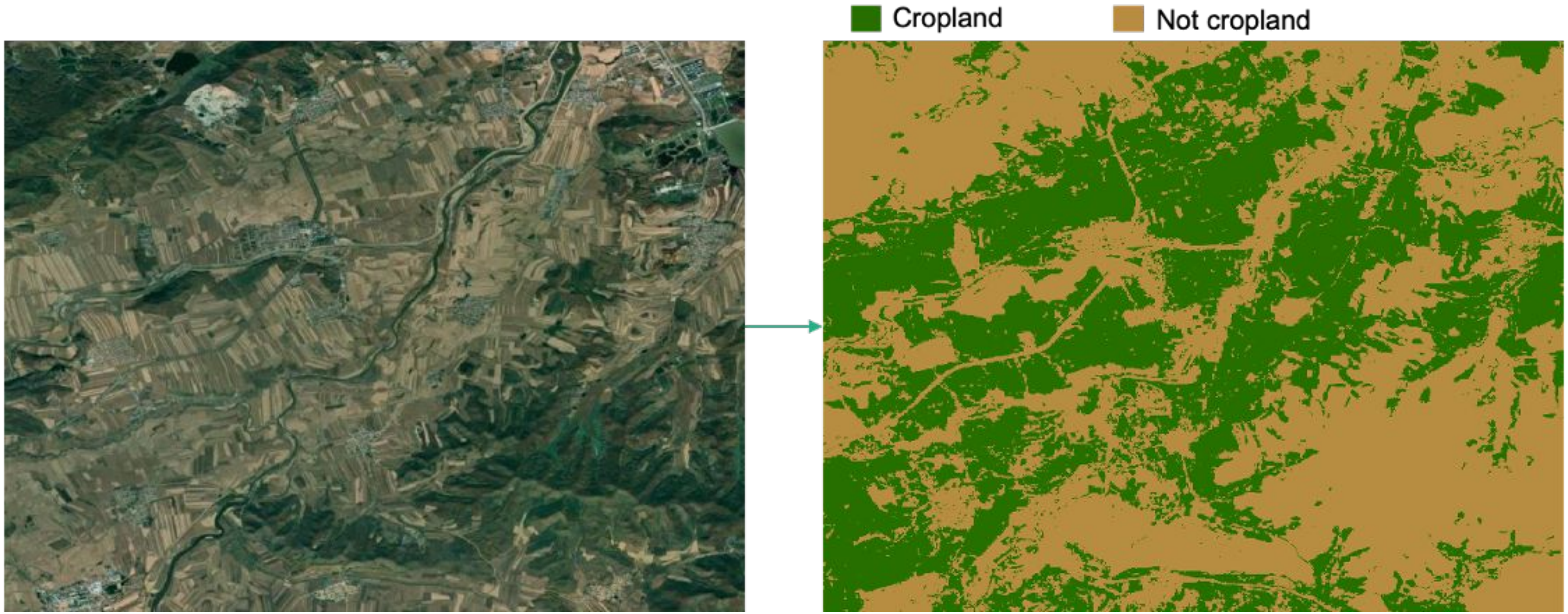
Yield estimation → Regression

Pest and disease detection → OOD detection

Domain adaptation, distribution shift, multi-fidelity data fusion, learning from limited labeled data, etc.

Crop mapping

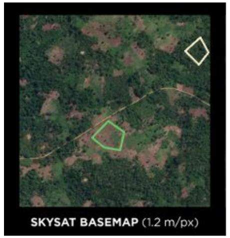
binary classification of pixels as crop or non-crop



Crop mapping

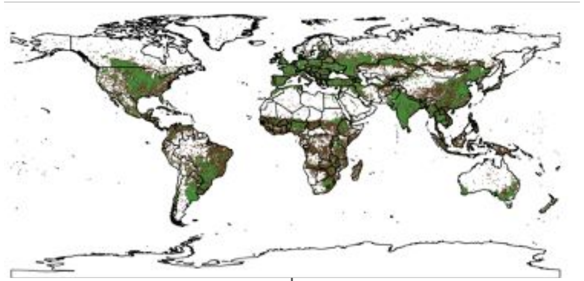
binary classification of pixels as crop or non-crop

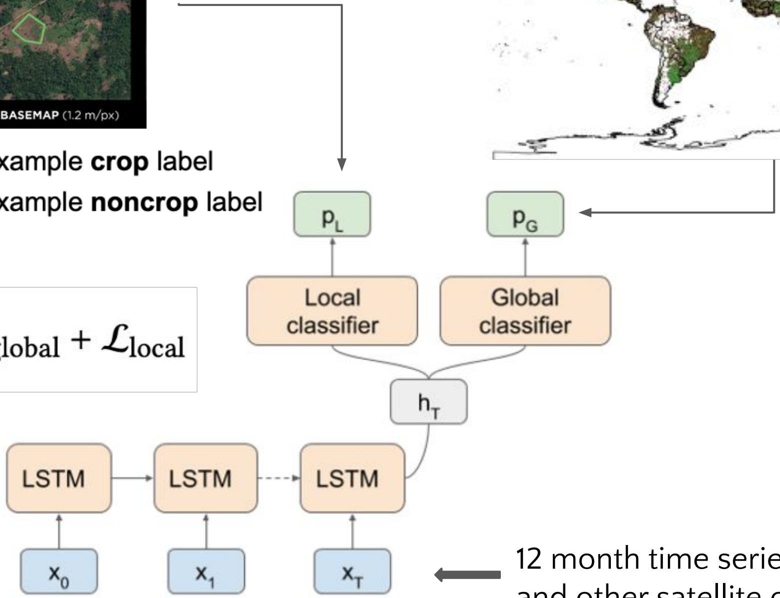
Classifying cropland in Togo (Kerner & Tseng et al., 2020)



Example **crop** label

Example **noncrop** label





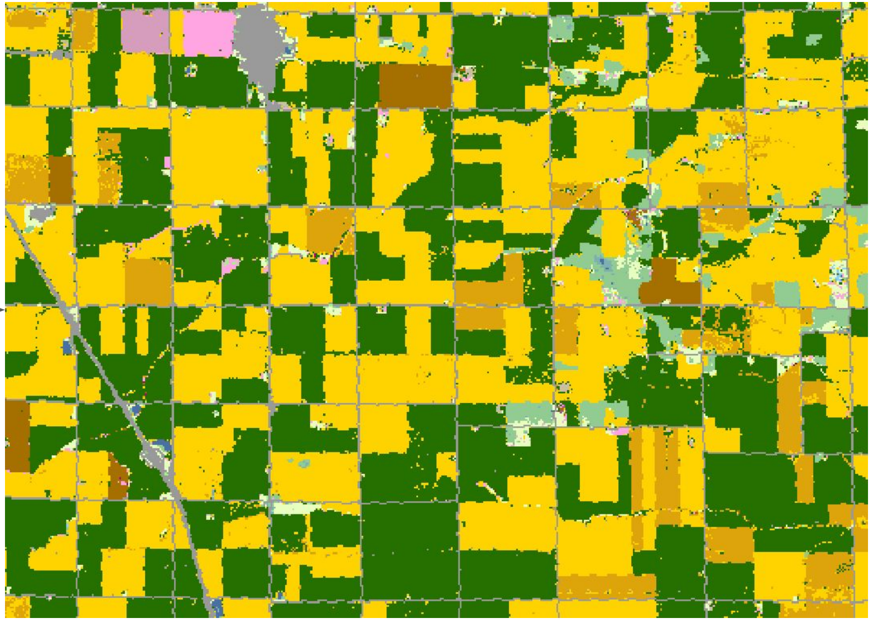
$$\mathcal{L} = \frac{W}{\alpha}\mathcal{L}_{\text{global}} + \mathcal{L}_{\text{local}}$$

12 month time series of Sentinel-2 and other satellite observations

Crop type mapping

multi-class classification of pixels into N crop types

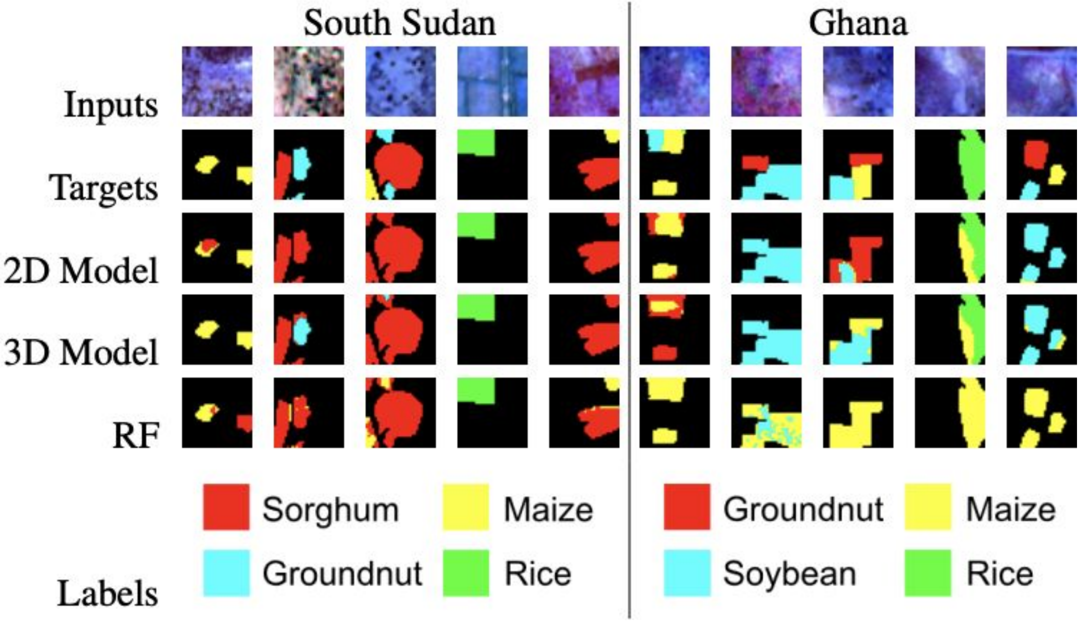
USDA Cropland Data Layer



Crop type mapping

multi-class classification of pixels into N crop types

Multi-crop classification in Ghana and South Sudan (Rustowicz et al., 2019)



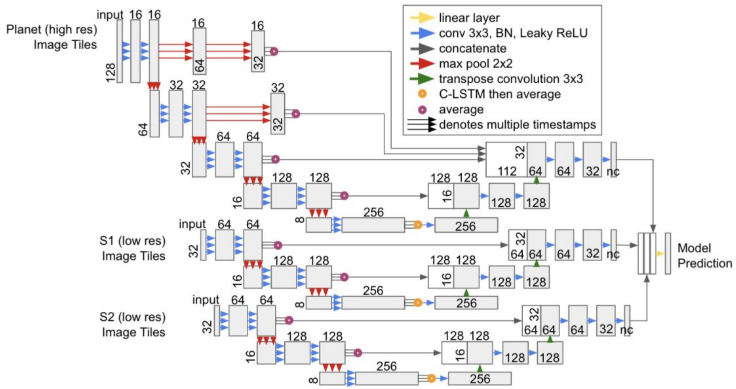
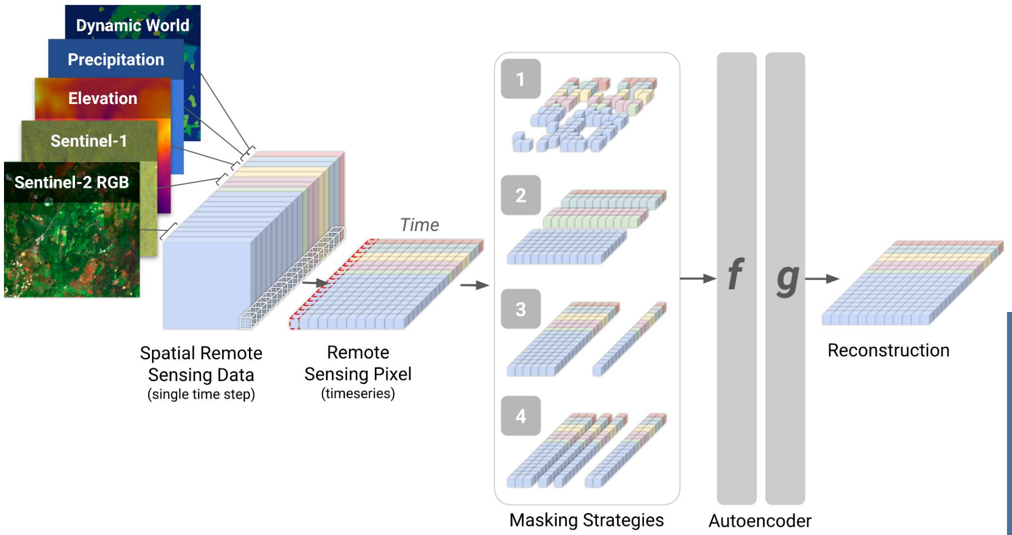


Figure 2. The 2D U-Net + CLSTM model architecture used in this study; "nc" denotes number of output classes

Crop type mapping

binary classification of one vs. rest crop types



Lightweight, Pre-trained Transformers for Remote Sensing Timeseries

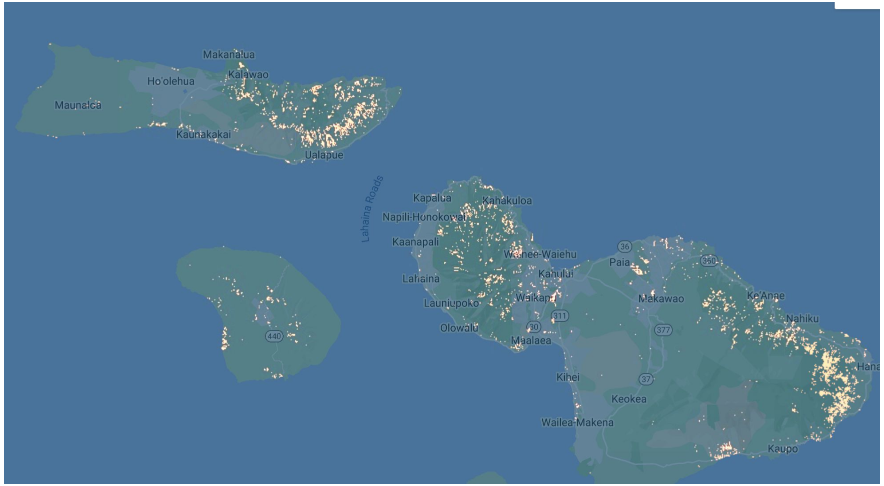
Gabriel Tseng *
McGill University
Mila – Quebec AI Institute

Ivan Zvonkov*
University of Maryland, College Park

Mirali Purohit
Arizona State University

David Rolnick
McGill University
Mila – Quebec AI Institute

Hannah Kerner
Arizona State University

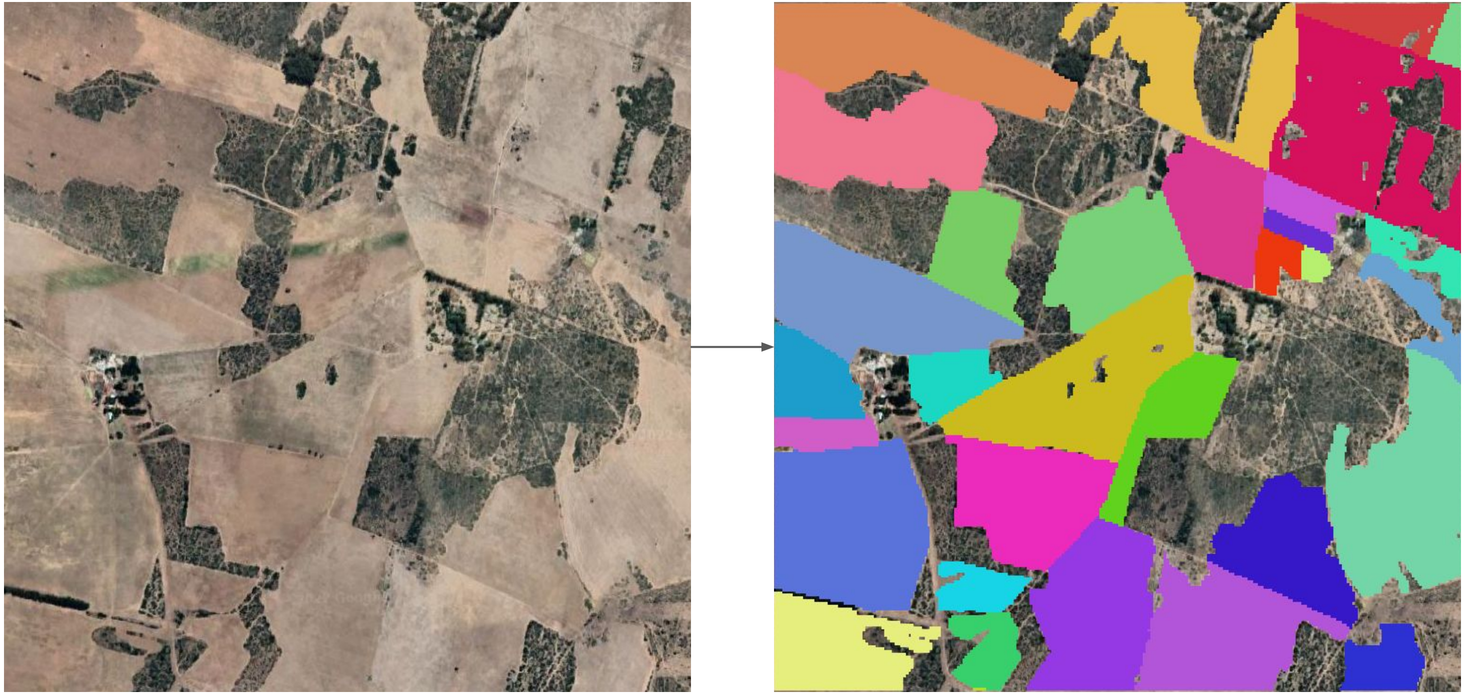


Predicted map of **taro in Maui county** using fine-tuned Presto (pre-trained remote sensing transformer)

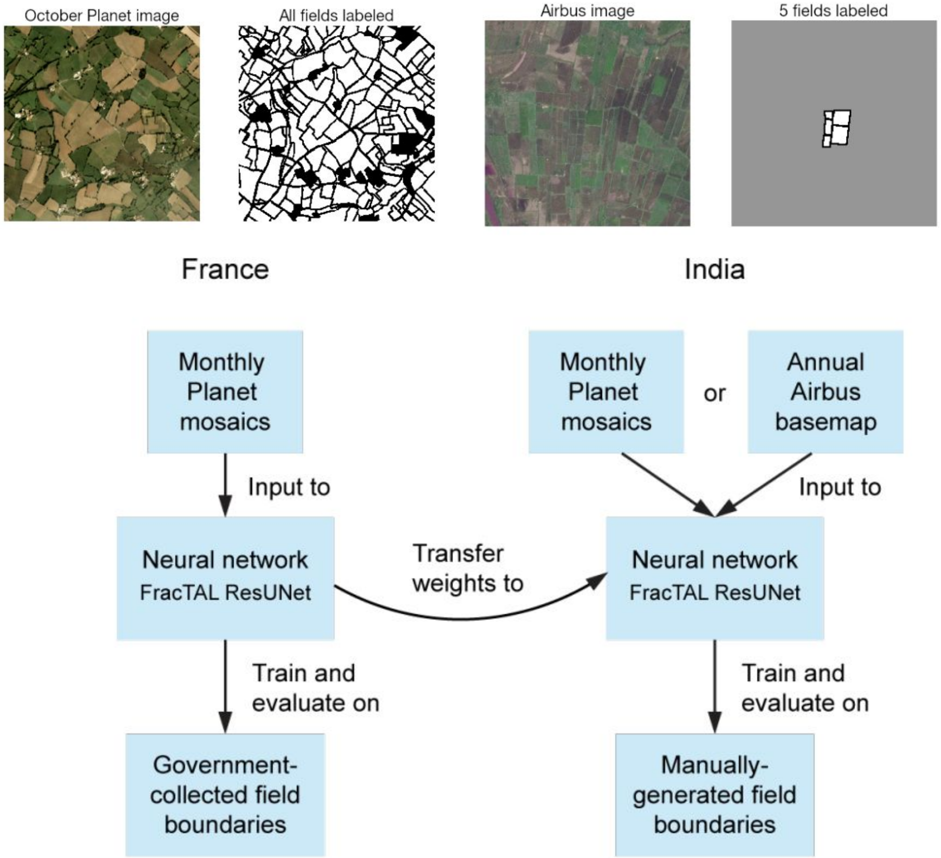
Field boundary delineation

segmentation of individual field/parcel boundaries

Radiant Earth South Africa Field Boundaries



Field boundary delineation
segmentation of individual field/parcel boundaries



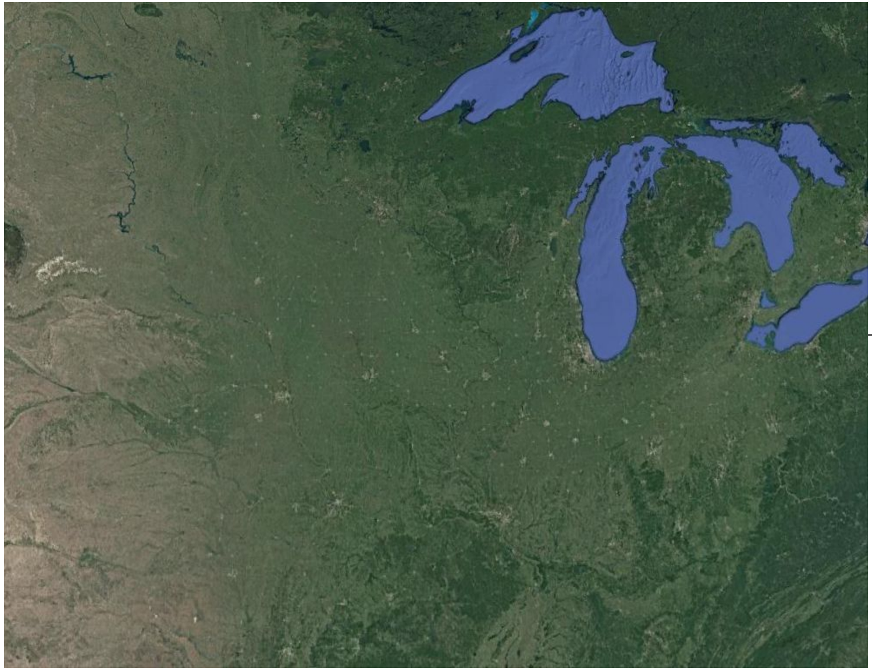
Field boundary delineation using deep transfer learning and weak supervision (Wang et al., 2022)

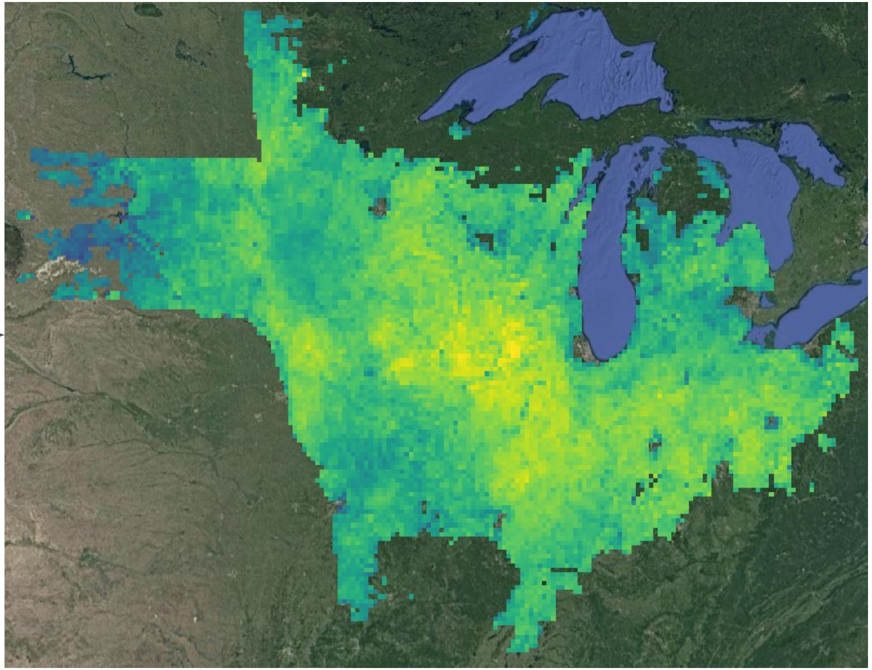
- Trained model using label-rich dataset from France and fine-tuned using sparse dataset from India
- Weak supervision: loss masked to ignore pixels without labels (India)
- FracTAL-ResUNet
  - self-attention layer: FracTAL unit
  - skip-connections (ResNet)
  - encoder-decoder architecture (U-Net)

Yield estimation

estimation of crop harvested per unit area, e.g., kg/ha

Maize yields in US 2018 (Deines et al., 2020)

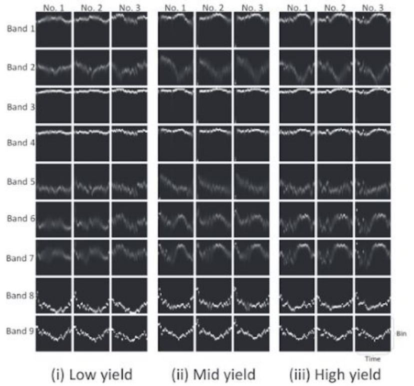




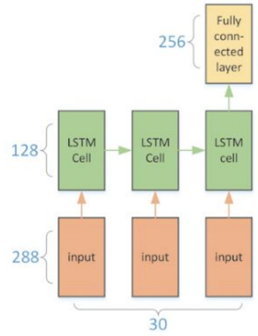
4 tonnes/ha 17 tonnes/ha

Yield estimation

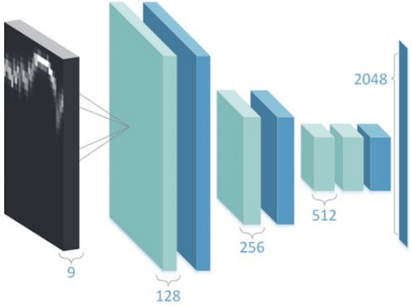
estimation of crop harvested per unit area, e.g., kg/ha



(a) 3-D histogram visualization



(b) The LSTM structure



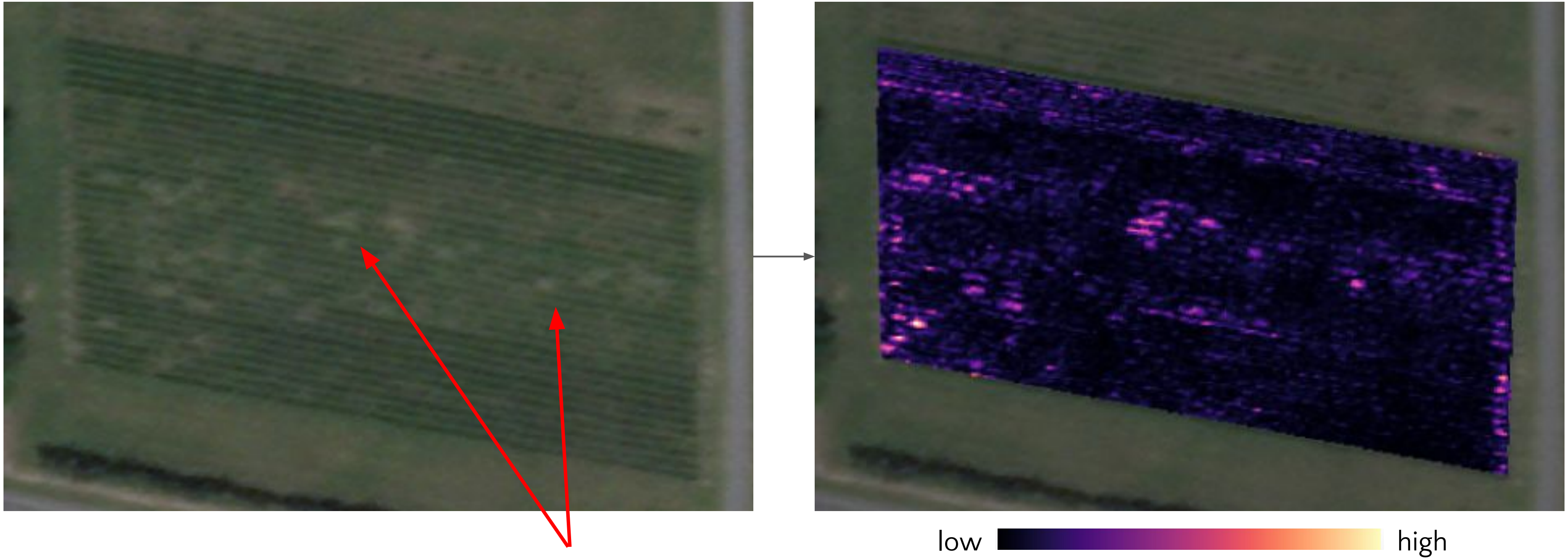
(c) The CNN structure

Deep Gaussian Process for Crop Yield Prediction Based on Remote Sensing Data
(You et al., 2017, AAAI)

- Goal: predict county-scale yield in US using remote sensing observations
- All pixels in entire county way too large to use as model input
  → 3D histograms (band, time, bin)
- Implemented Deep Gaussian Process using (b) LSTM and (c) CNN architectures

Pest, disease, and hotspot detection

detection of in-field anomalies that represent unfavorable growing conditions



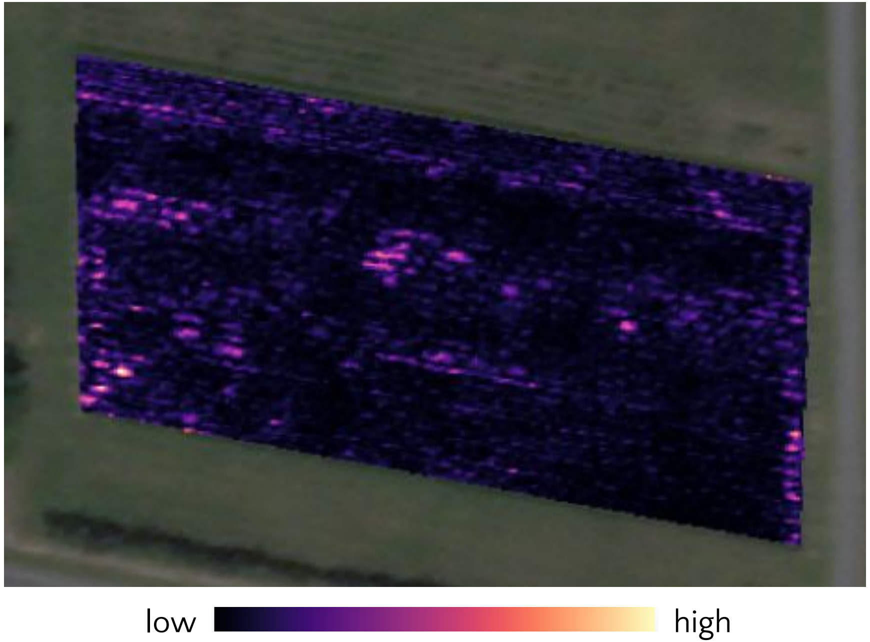
Downy mildew disease

anomaly score

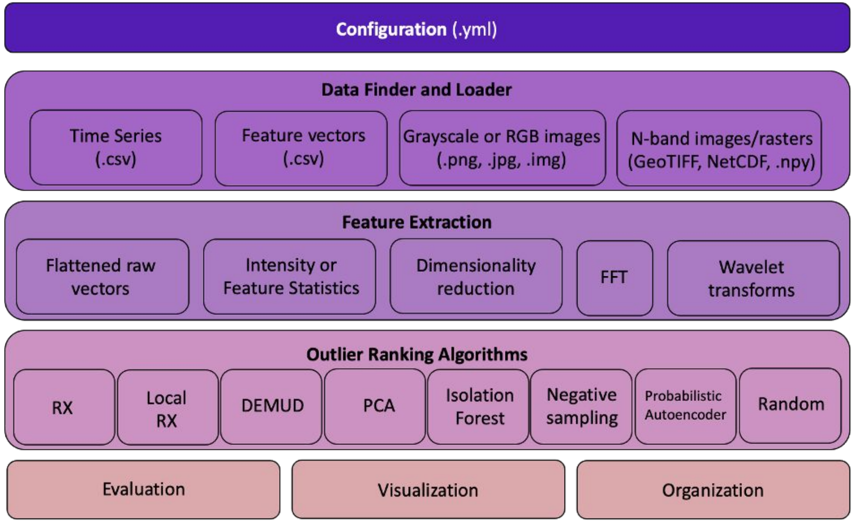
Pest, disease, and hotspot detection

detection of in-field anomalies that represent unfavorable growing conditions

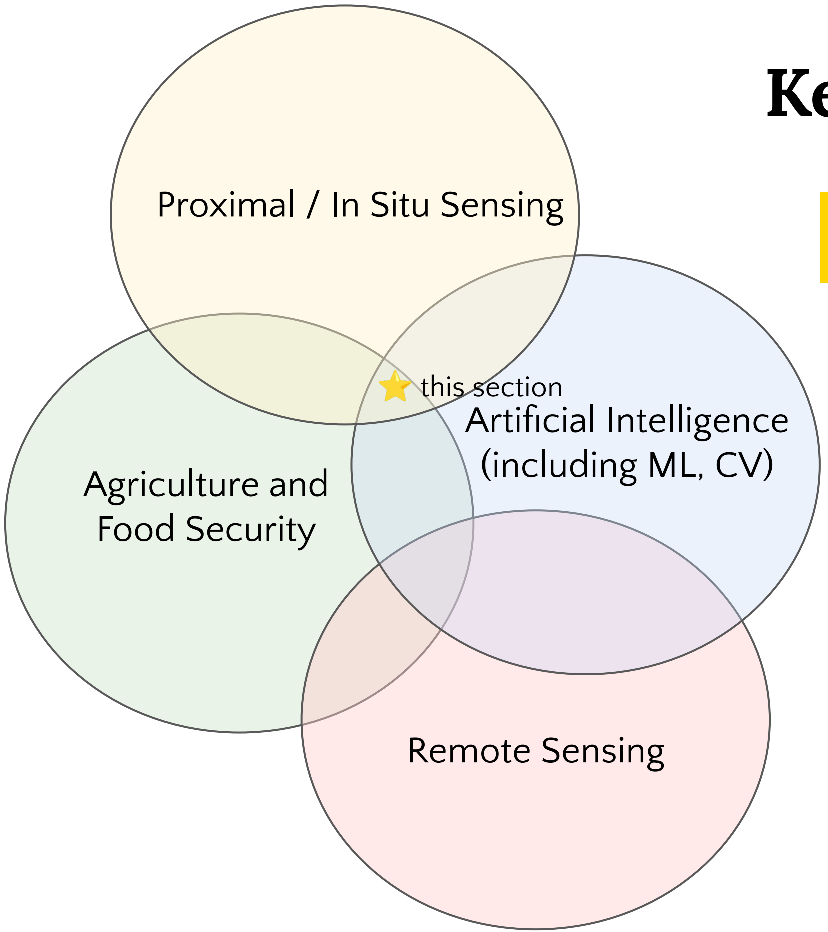
Despite great promise, few recent studies using AI for detection in remote sensing images



Domain-agnostic Outlier Ranking Algorithms (DORA)



Kerner et al., 2022



Key topics

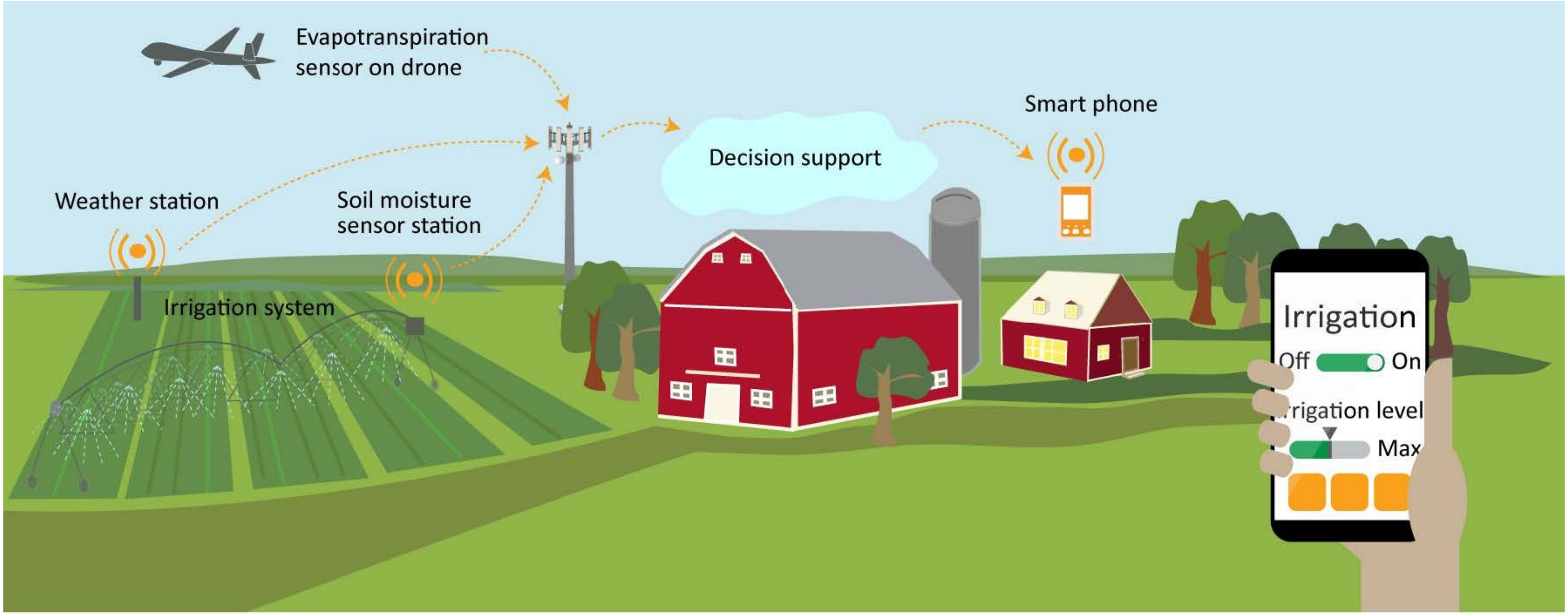
What are some specific tasks involved in these?

- Precision agriculture (resource optimization)
- Robotic farming
- Yield estimation and optimization
- Pest and disease identification
- Livestock and rangeland management

Domain adaptation, distribution shift, multi-fidelity data fusion, learning from limited labeled data, etc.

Precision agriculture

data-driven management of on-farm resources (water, nutrients, equipment, etc.)



Source: GAO. | GAO-20-128SP

Precision agriculture

data-driven management of on-farm resources (water, nutrients, equipment, etc.)

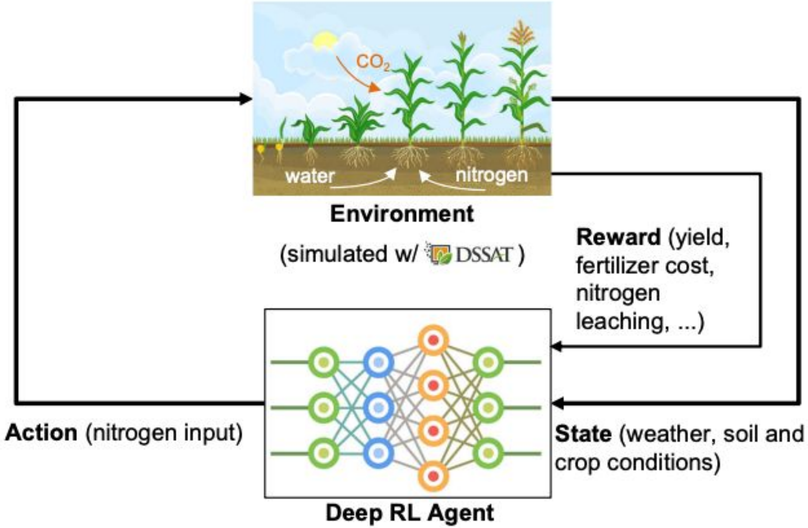


Figure 1. A framework for optimizing N management with deep RL and DSSAT-based crop simulations

Table 3. Performance comparison between DQN and baseline policies for Florida. Baseline (X) indicates that X kg/ha of nitrogen is applied at stage v5.

Methods	Nitrogen input (kg/ha)	Nitrate leaching (kg/ha)	Nitrogen uptake (kg/ha)	Top weight at maturity (kg/ha)	Cumulative reward
Baseline (40)	40	46	55	4393.3	430.7
Baseline (80)	80	65	66	4673.1	452.8
Baseline (160)	160	97	86	5190.4	493.3
DQN	80	33	105	**6310.8**	**619.7**

Optimizing Nitrogen Management with Deep Reinforcement Learning and Crop Simulations
(Wu et al., 2022, AAAI Workshops)

- Goal: learn policy for N application that minimizes input and leaching without jeopardizing yield
- Train management policies with deep Q-network and soft actor-critic algorithms
- Gym-DSSAT interface models daily interactions between the simulated crop environment and RL agents
- RL policies achieve higher or similar yield while using less fertilizer for maize in Iowa and Florida experiments

Robotic farming

automating farming operations such as seeding, harvesting, sorting, or spraying

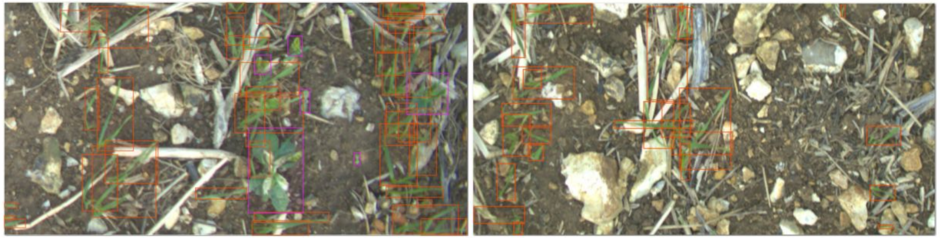
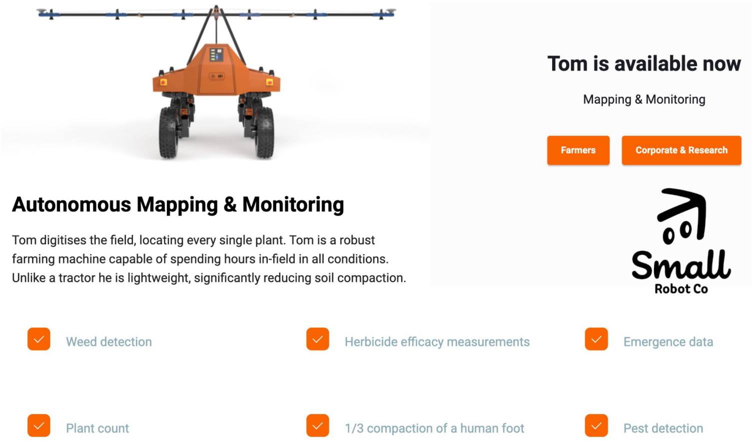


Figure 1: Sample annotated images. Orange boxes represent wheat & purple boxes represent weeds.



Semi-Supervised Object Detection for Agriculture

(Tseng et al., 2023, AAAI Workshops)

- Goal: detect identify locations of weeds vs. crops (wheat) in field robot images for precision spraying
- Train student-teacher models for semi-supervised object detection for two classes: wheat and weeds
- Autonomous robots can then spray individual weed plants while avoiding crops

Yield estimation and optimization

data-driven management of on-farm resources (water, nutrients, equipment, etc.)

Fig. 1: UAVs can fly between rows of trees autonomously and produce fruit counts at scale, from onboard camera imagery.

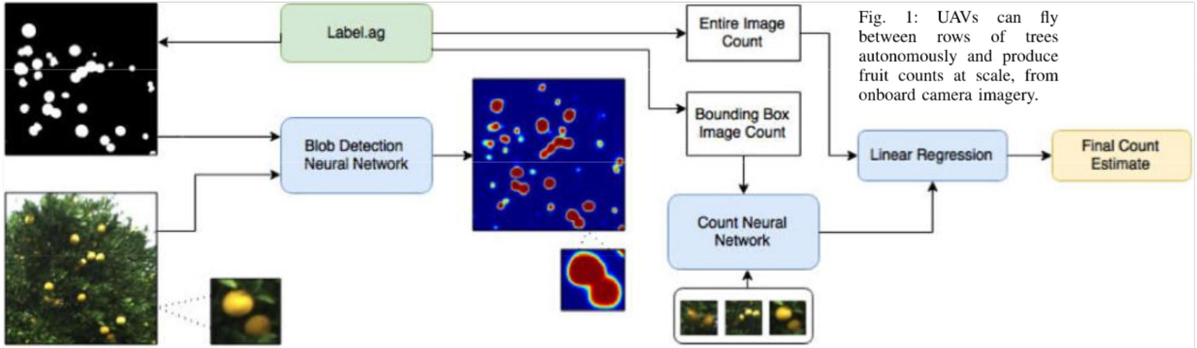


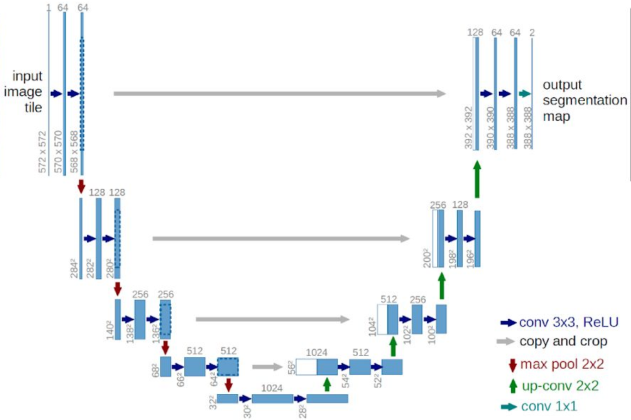
Fig. 4: The training pipeline starts with a given image. Label.ag then produces the corresponding ground truth *label map*, and these two inputs are used to train the **blob detection neural network**. This neural network outputs a segmented image, and the pipeline extracts the coordinates of the bounding boxes around each blob. These coordinates are then used to extract the corresponding window in the original image. Label.ag produces the corresponding ground truth *counts* for each bounding box, and these are used as inputs to train the **count neural network**. The count neural network then estimates and sums up the count for each blob in the segmented image to produce an intermediate count estimate. The intermediate count estimate is **regressed** on the entire image ground truth count provided by label.ag to produce the final count estimate.

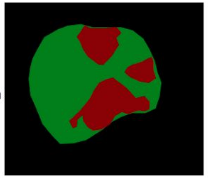
Counting Apples and Oranges with Deep Learning: a Data Driven Approach
(Chen et al., 2016, IEEE Robotics and Automation Letters)

- Goal: estimate fruit yield in orchards using AI + drones
- Train model to detect fruit instances and regress counts using real-time drone images

Pest, disease, and hotspot detection

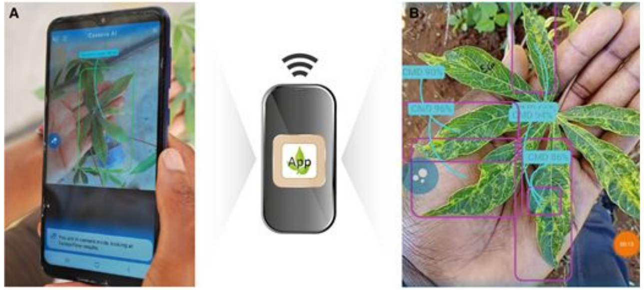
detection and identification of crop diseases





Example: Scoring root necrosis in cassava using semantic segmentation
Tusubira et. al, 2020, CVPR AgVision Workshop

- Goal: calculate area of root necrosis caused by Cassava Brown Streak Disease (CBSD)
- Necrosis score: percentage of area predicted as necrotized
- Labels by specialists at National Crop Resources Research Institute (NaCRRI)



PlantVillage Nuru app (Silva et al., 2021)

Livestock and rangeland management

monitoring & optimizing animal behavior, health conditions, and feeding patterns

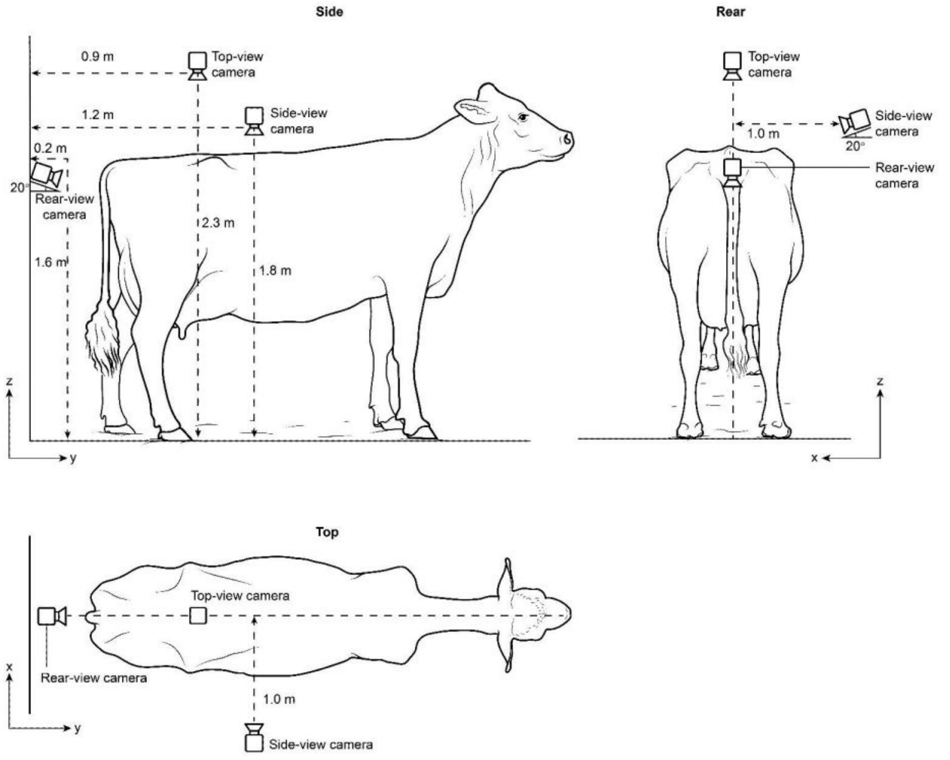
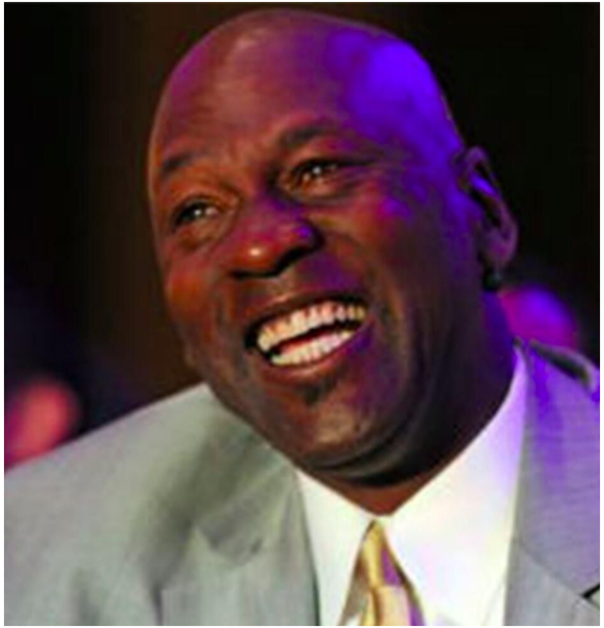


Figure 3-2. Image recording setup with the mounting positions and angles of the 3 cameras.

Example: Automated Body Condition Scoring of Dairy Cows using 3-Dimensional Feature Extraction from Multiple Body Regions
Song et. al, 2019, Journal of Dairy Science

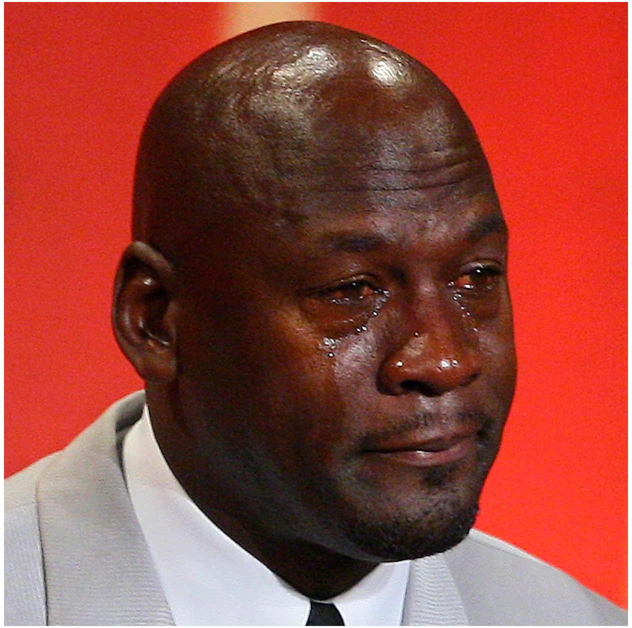
- Goal: automatically assess body condition of dairy cows for livestock
- Manually computed body condition score (BCS) for dairy cows in real conditions
- Extract vision-based features related to body condition from camera images
- Compute BCS of new images using 1-nearest neighbor in training set

What are the challenges?



Learning about the real world impact we can have with AI

Getting initial promising results on clean data



Trying to make your models work for real data and deployment

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire

Crops in StreetView images, June 2018

Crops in GoPro images, Dec 2020

Smartphone Image (US)

Street View Image (US)

Car-Mounted GoPro Image (Kenya)

Lacuna Fund
Our voice on data

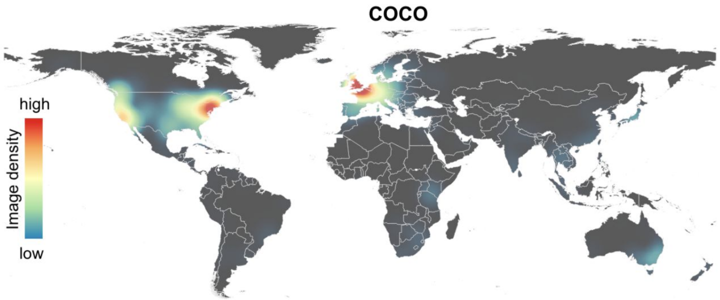
PI: C. Nakalembe

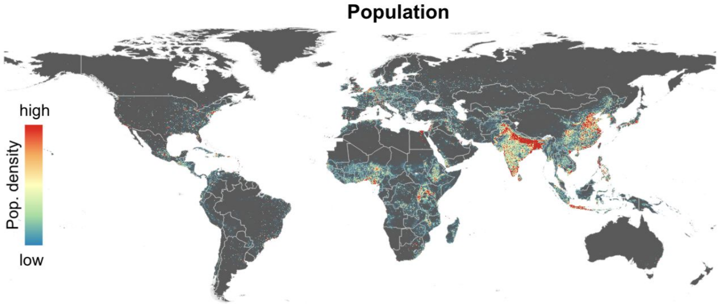
1. Metadata extraction
2. Crop identification
3. Distance estimation
4. Geo-referenced points with crop type+

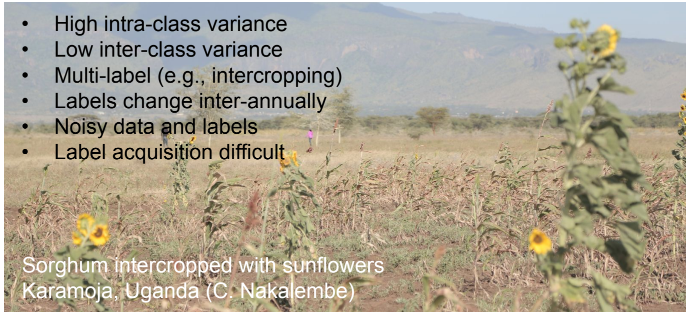
HARVEST

Challenges for AI + agriculture

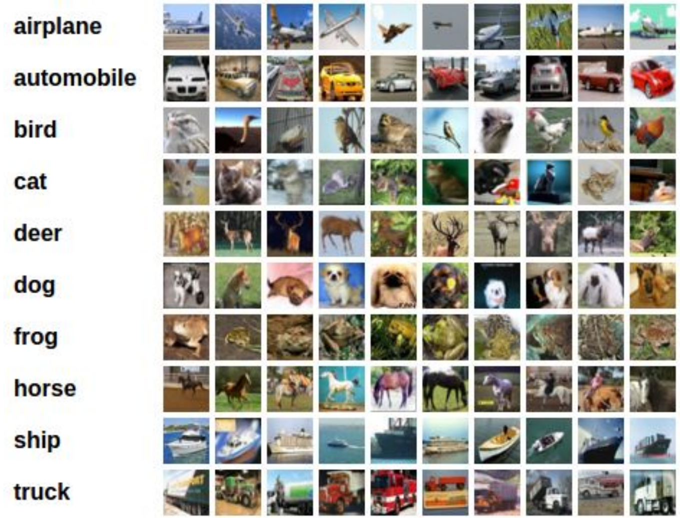
- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?







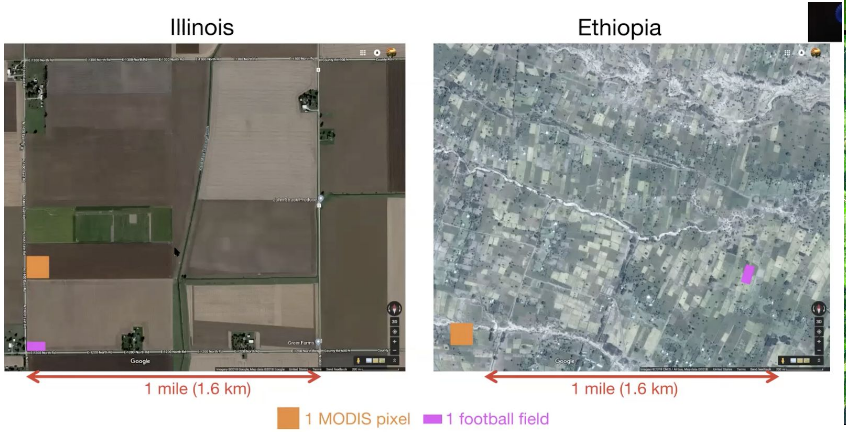
Sorghum intercropped with sunflowers
Karamoja, Uganda (C. Nakalembe)

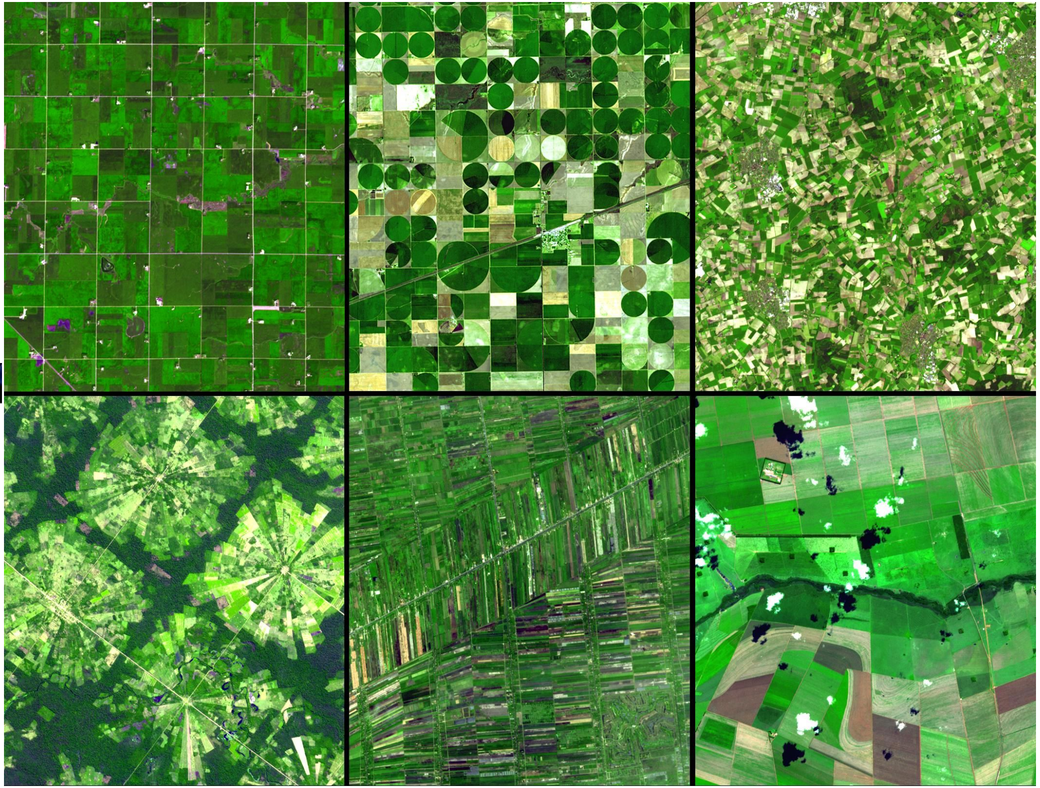


CIFAR-10 classes

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?
- Spatial and temporal generalization difficult





Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking

Lacuna Fund
Our voice on data

Announcing Our Inaugural Round of Funding for Agricultural Datasets for AI

We are thrilled to share Lacuna Fund's first cohort of supported projects in the agricultural AI for social good domain. With over 100 applications from, or in partnership with, organizations across Africa, we were deeply encouraged by the depth and breadth of the proposals.

The recipients of this first round of funding are unlocking the power of machine learning to alleviate food security challenges, spur economic opportunities, and give researchers, farmers, communities, and policymakers access to superior agricultural datasets. We are proud to support their work.

Radiant Earth Foundation
EARTH IMAGERY FOR IMPACT

Radiant MLHub

Radiant MLHub is the world's first cloud-based open library dedicated to Earth observation training data for use with machine learning algorithms. Designed to encourage widespread data collaboration, Radiant MLHub allows anyone to access, store, register, and share open training datasets for high-quality Earth observations.

LEARN MORE

CropHarvest: a global satellite dataset for crop type classification

Tseng, G., Zvonkov, I., Nakalembe, C., Kerner, H. (2021). CropHarvest: a global satellite dataset for crop type classification. To appear in *Neural Information Processing Systems (NeurIPS) Datasets and Benchmarks*.

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking
- Deploying ML models is hard

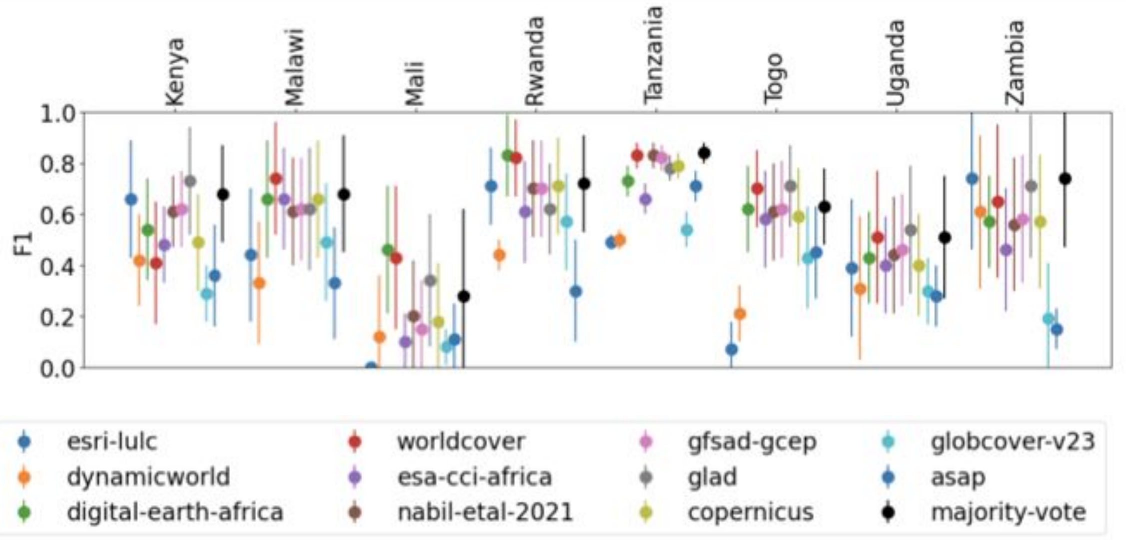
> *"…only 22 percent of companies using machine learning have successfully deployed a model."*
>
> deeplearning.ai

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking
- Deploying ML models is hard
- End-user uptake, communication, and sustainability not easy

Challenges for AI + agriculture

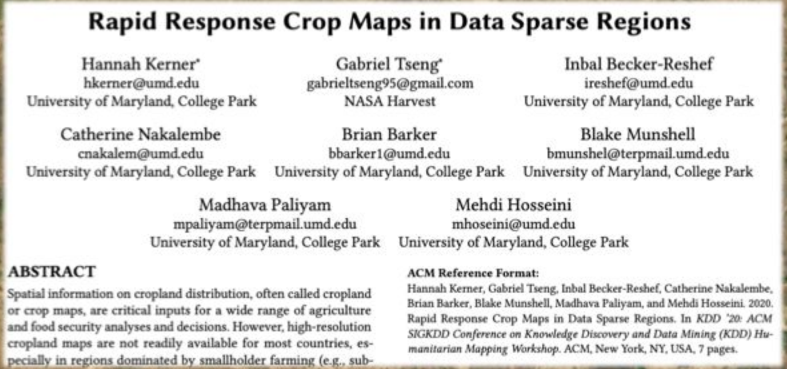
- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Real world != ImageNet
  … should we try to make it so?
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking
- Deploying ML models is hard
- End-user uptake, communication, and sustainability not easy
- Geographic distribution shift / disparate performance



Kerner, H. et al (2023). How accurate are existing land cover maps for agriculture in Sub-Saharan Africa? Under review.

Cina Lawson
Togolese Minister of Post, Digital Economy and Technological Innovation

"This map provides unmatched clarity into the nature and distribution of agricultural land nationwide [and helps] provide decisive knowledge being used to design social protection policies aimed at improving the livelihoods of agrarian rural communities."



Rapid Response Crop Maps in Data Sparse Regions

Hannah Kerner* hkerner@umd.edu University of Maryland, College Park
Gabriel Tseng* gabrieltseng95@gmail.com NASA Harvest
Inbal Becker-Reshef ireshef@umd.edu University of Maryland, College Park
Catherine Nakalembe cnakalem@umd.edu University of Maryland, College Park
Brian Barker bbarker1@umd.edu University of Maryland, College Park
Blake Munshell bmunshel@terpmail.umd.edu University of Maryland, College Park
Madhava Paliyam mpaliyam@terpmail.umd.edu University of Maryland, College Park
Mehdi Hosseini mhoseini@umd.edu University of Maryland, College Park

ABSTRACT

Spatial information on cropland distribution, often called cropland or crop maps, are critical inputs for a wide range of agriculture and food security analyses and decisions. However, high-resolution cropland maps are not readily available for most countries, especially in regions dominated by smallholder farming (e.g., sub-

ACM Reference Format:

Hannah Kerner, Gabriel Tseng, Inbal Becker-Reshef, Catherine Nakalembe, Brian Barker, Blake Munshell, Madhava Paliyam, and Mehdi Hosseini. 2020. Rapid Response Crop Maps in Data Sparse Regions. In *KDD '20: ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD) Humanitarian Mapping Workshop*. ACM, New York, NY, USA, 7 pages.

Kerner et al. (2020), *KDD*