Introduction to AI for Agriculture

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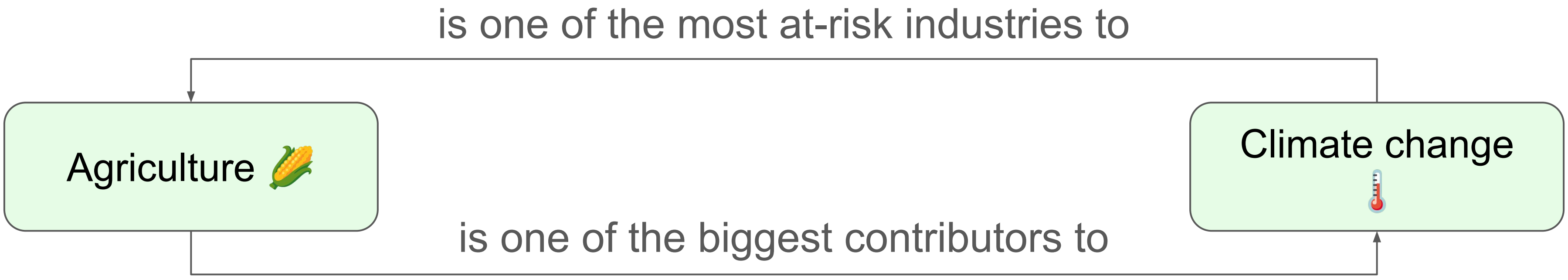
Agriculture, food security, and climate change

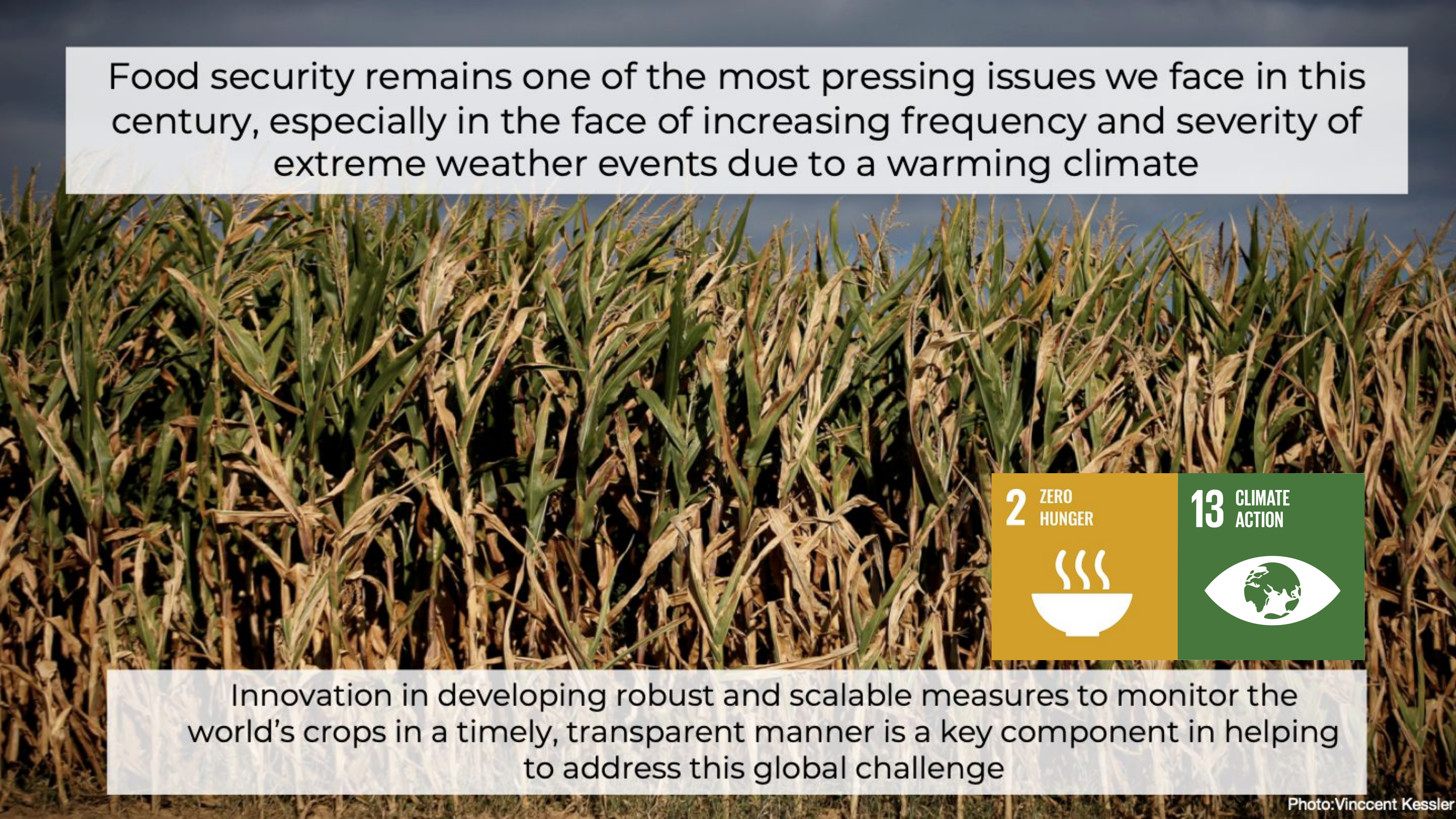


Effects of climate change **on agriculture**:

- 🌡️ Changing temperatures & precipitation patterns can reduce crop productivity
- 🌪️ Increased frequency of extreme weather events (droughts, floods) cause increased crop loss
- 🚰 Reduced water & increased competition for resources

Drivers of climate change **from agriculture**:

- 🐄 GHGs from methane emissions of livestock and rice production, emissions from fertilizers, etc.
- 🌳 Land use changes reduce carbon sinks (e.g., forests, grasslands) and biodiversity
- 🦠 Degraded soil health reduces carbon sequestration and ecosystem health


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
2 ZERO HUNGER
13 CLIMATE ACTION
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?

Who needs information about agriculture / food security?

Farmers

Policymakers

Aid organizations

Consumers

Economists

Agronomists

…

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)

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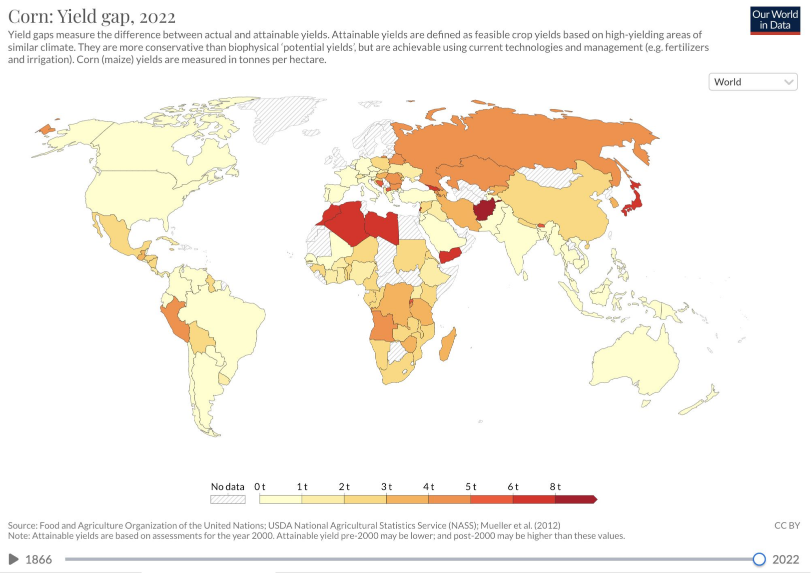

What do farmers want to know?

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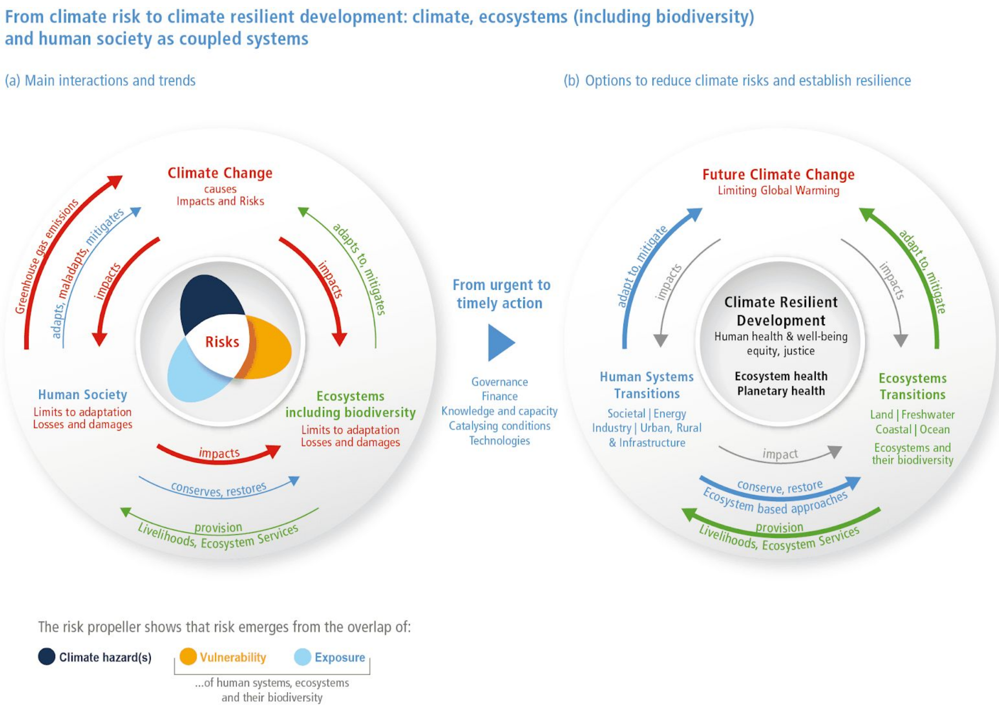
- Potential threats to production (e.g., climate change)
- Actual threats to production (e.g., nearby pest/disease outbreak or weather forecasts)
- Soil moisture, rainfall, temperature, etc.
- Productivity potential (yield gap)
- **Suitability of crops (would a different crop or variety grow better?)**

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


Harvest AI + Africa teams with Rwanda Space Agency leadership in Kigali


Acres AI team with local partners at Hawaii Taro Farm in Maui

NASA Harvest enables adoption of **satellite Earth observations** by public and private organizations to benefit **food security**, **agriculture**, and human and environmental **resilience** worldwide.

2017

HARVEST

EARTH DATA FOR INFORMED AGRICULTURAL DECISIONS

Acres

2023

NASA Acres focuses on applying **satellite Earth observation** (EO) information to the most pressing **agricultural** and **food security** challenges facing **U.S. farmers**, **ranchers**, and **agrifood system** stakeholders.

FEWS NET provides **evidence-based analysis** to help government **decision-makers** and relief agencies **plan for and respond to** humanitarian crises.

NASA Harvest enables adoption of **satellite Earth observations** by public and private organizations to benefit **food security**, **agriculture**, and human and environmental **resilience** worldwide.

FEWS NET
Famine Early Warning Systems Network

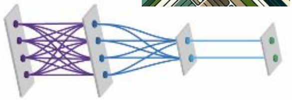
Request for analysis

HARVEST
EARTH DATA FOR INFORMED AGRICULTURAL DECISIONS

What is the **impact** of extreme **event X** on **cultivation** in **region Y**?

Event X in **region Y** corresponded to a **change of N (%, ha)** in crop cultivation.

KERNER LAB

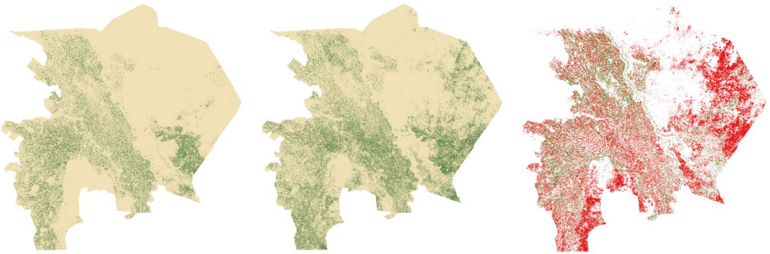


Forecast how shocks will affect households (e.g., needs for additional help)
→ **Early response**


World Food Program USA

WFP Warns That Hunger Catastrophe Looms in Conflict-Hit Sudan Without Urgent Food Assistance

PORT SUDAN – Parts of war-ravaged Sudan are at a high risk of slipping into catastrophic hunger conditions by next year's lean season if the...



FEWS NET
Famine Early Warning Systems Network

Request for analysis

HARVEST
EARTH DATA FOR INFORMED AGRICULTURAL DECISIONS

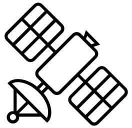
What is the **impact** of the **2023 war** on **cultivation** in **Sudan**?

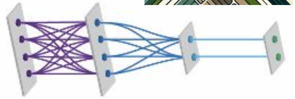
Cultivated area in Sudan ROIs is **20-30% lower** in 2023 compared to 2022.

September 2023

November 2023

KERNER LAB





Forecast how shocks will affect households (e.g., needs for additional help)
→ **Early response**

Maui United Way
Food Security Dashboard

About | Food Availability | Food Access | Food Utilization | Food Stability

About

The Food Security Dashboard synthesizes data sources related to food security.

The data in the dasboard is split into the four pillars of food security as defined by the FAO.[1]

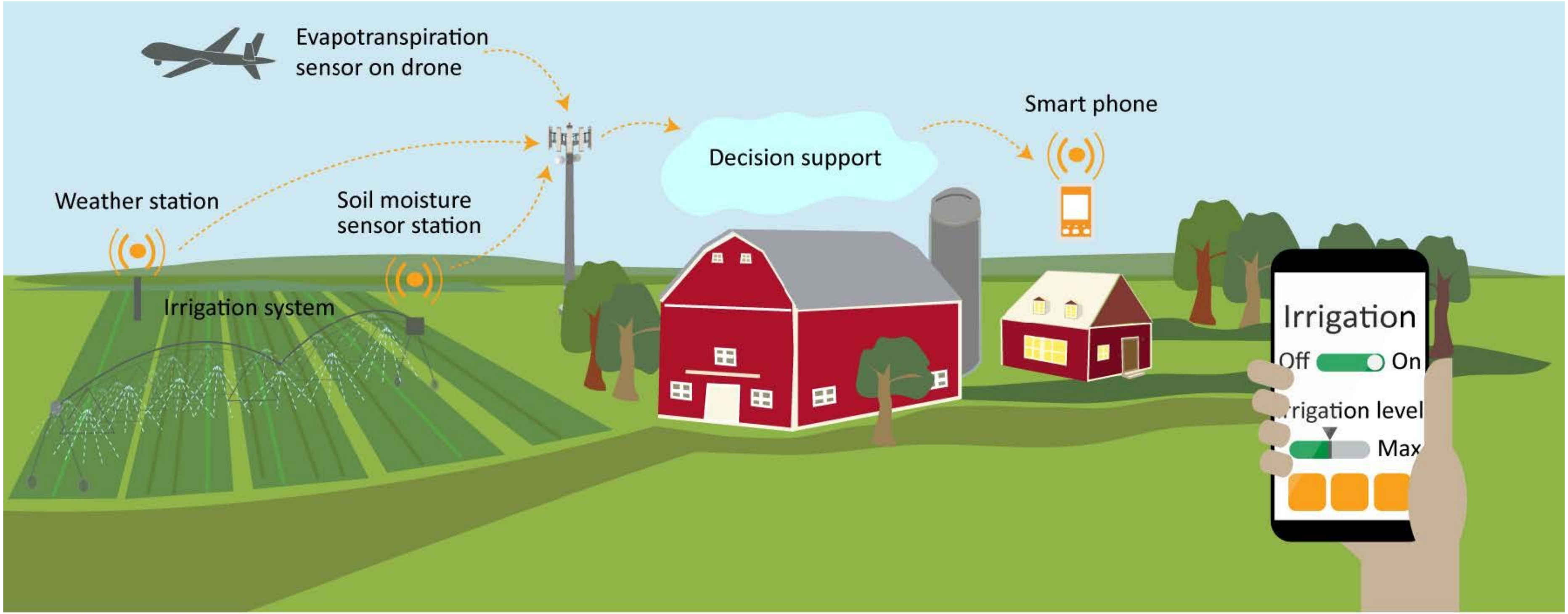
What is food security?
Access by all people at all times to enough food for an active, healthy life.[2]

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

- **Machine learning** models predict where crops growing based on satellite data
- Integrate crop maps with other relevant datasets (e.g., **socioeconomic** and price data) in a **public Food Security Dashboard**
- End users: Maui United Way, farmers, Dept of Ag, county council, community organizations

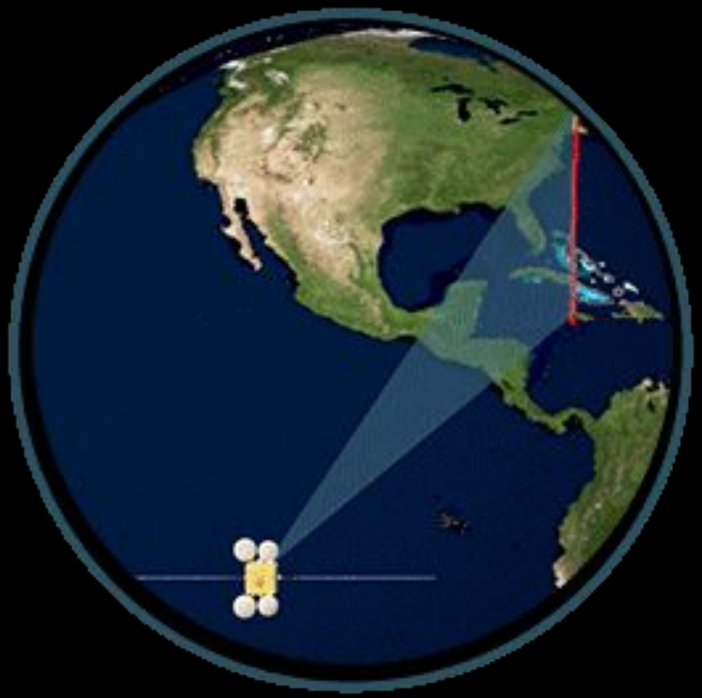
Acres

People usually think of precision ag on the ground…



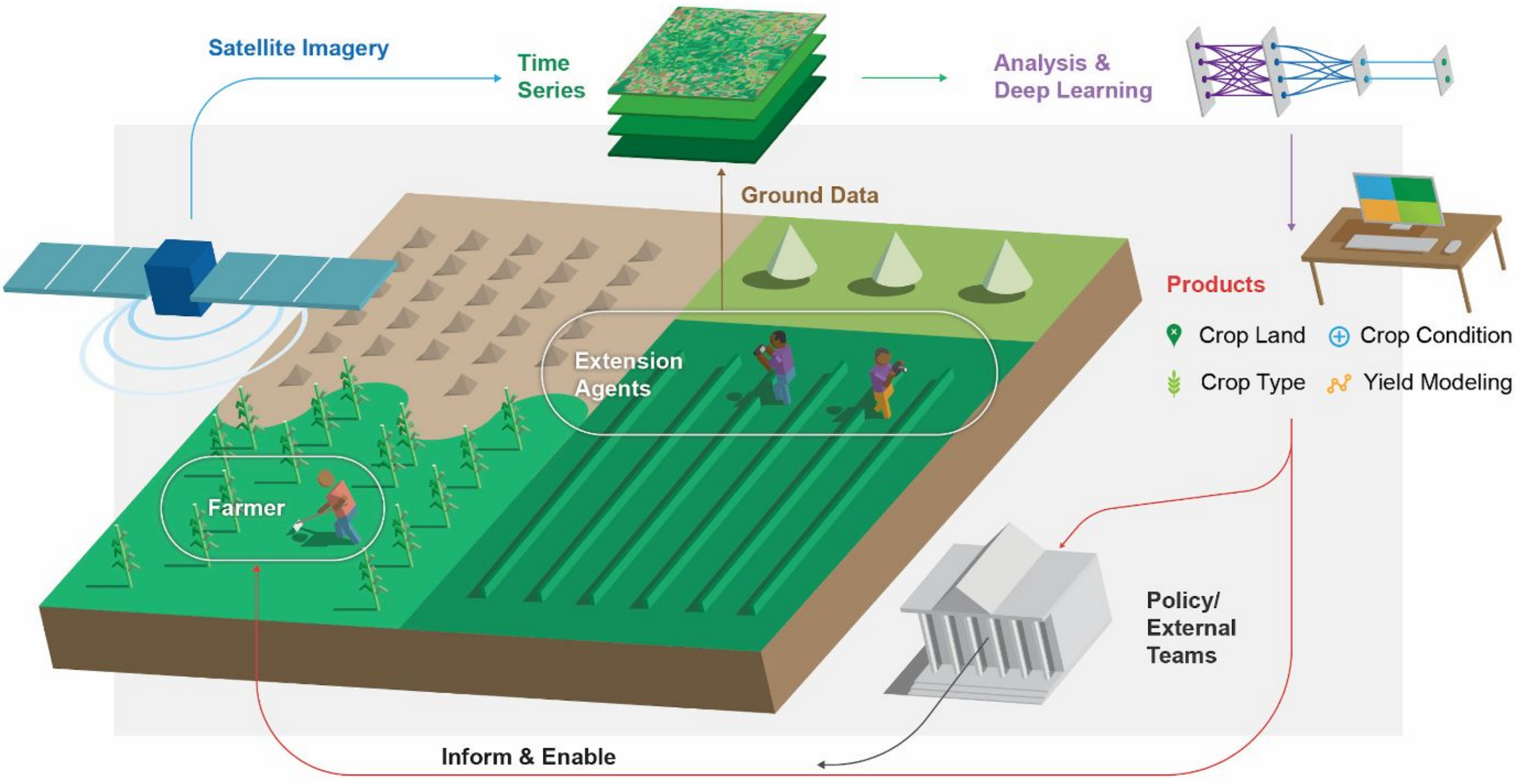
Source: GAO. | GAO-20-128SP

But we also have data from the sky



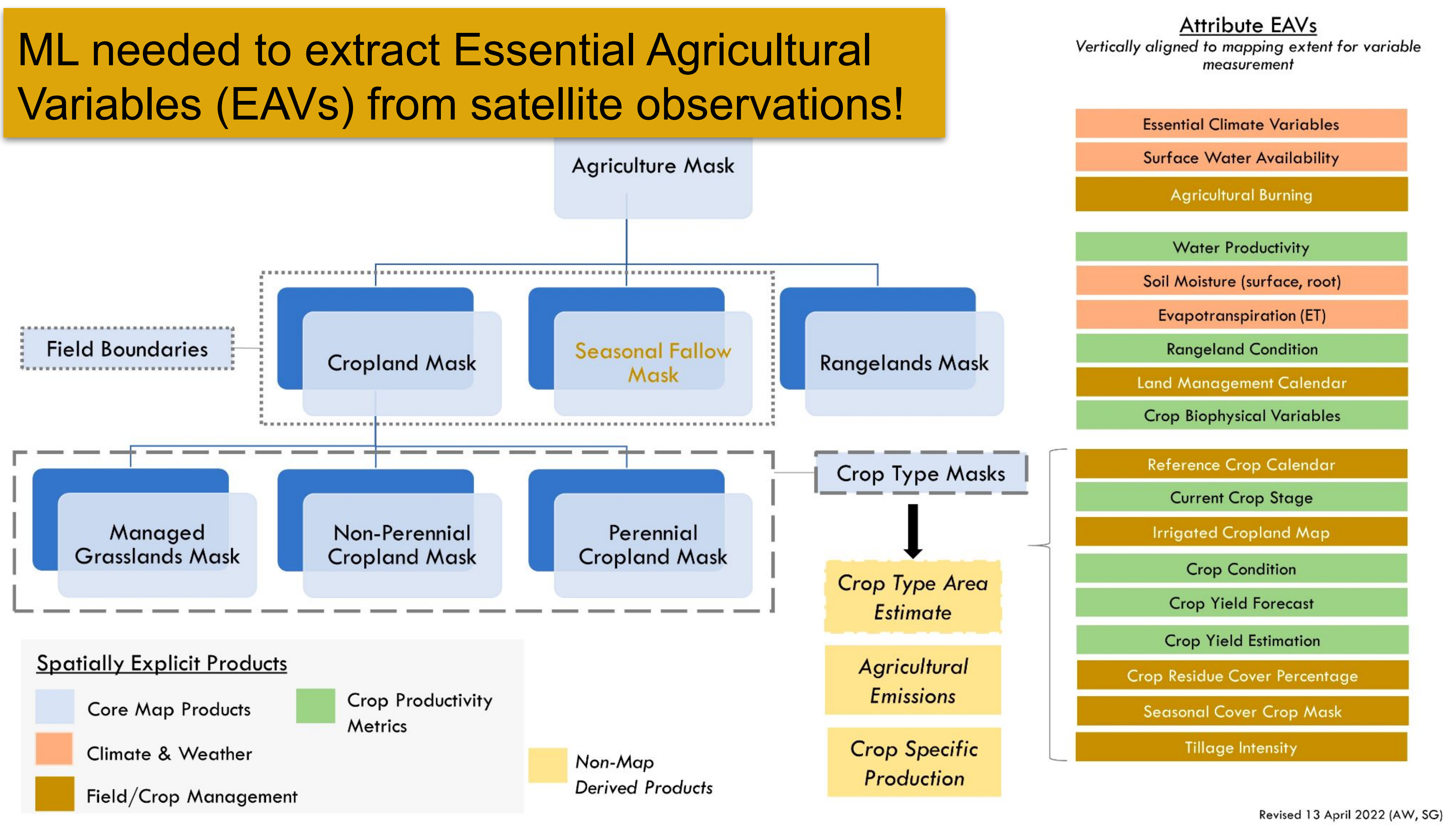
Since the 1970’s

Source: NASA

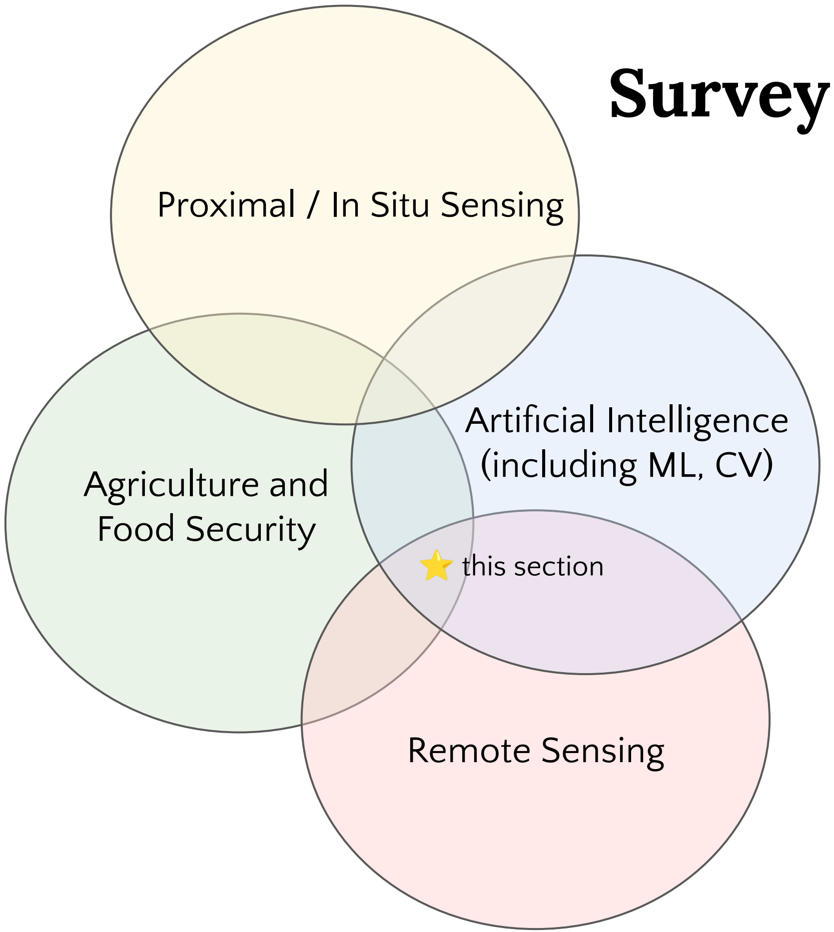


Satellite Imagery
Time Series
Analysis & Deep Learning
Ground Data
Products
Crop Land
Crop Condition
Crop Type
Yield Modeling
Extension Agents
Farmer
Policy/ External Teams
Inform & Enable

ML needed to extract Essential Agricultural Variables (EAVs) from satellite observations!



Survey of key topics



Crop mapping → Binary classification

Crop type mapping → Multi-class classification

Field boundary delineation → Segmentation

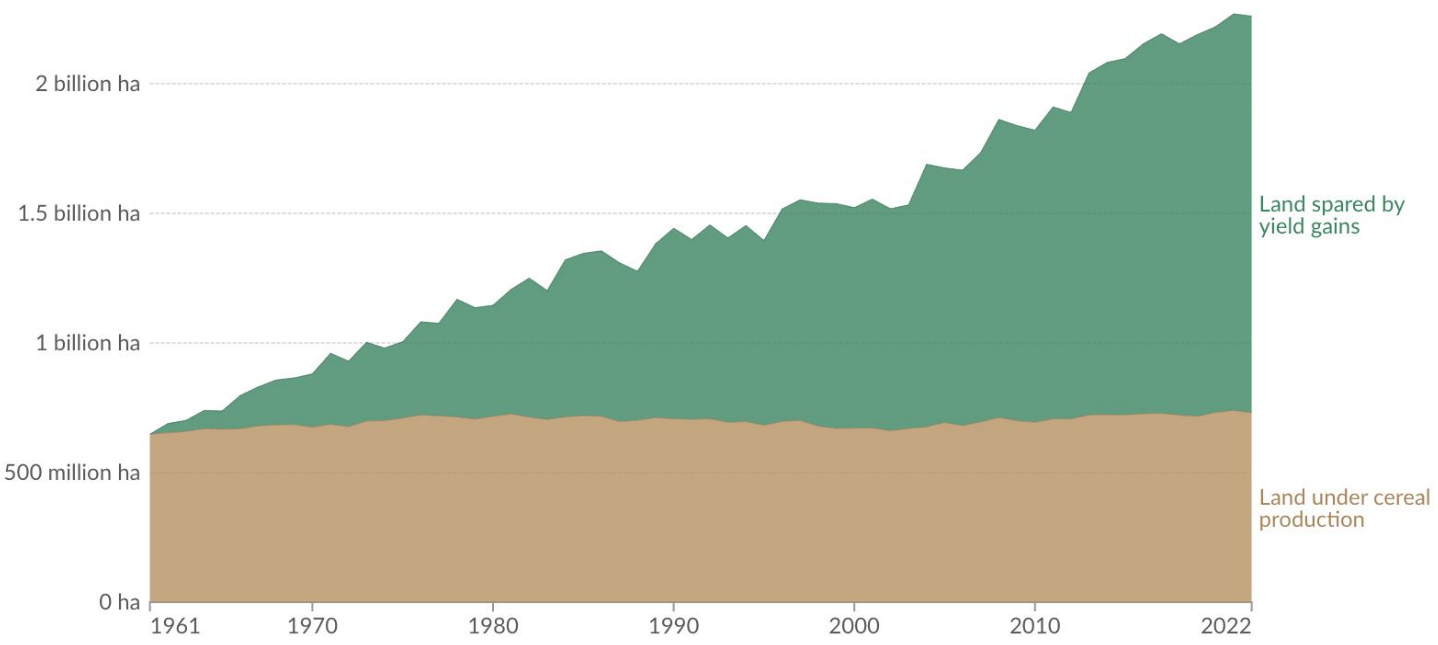
Yield estimation → Regression

Pest and disease detection → OOD detection

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

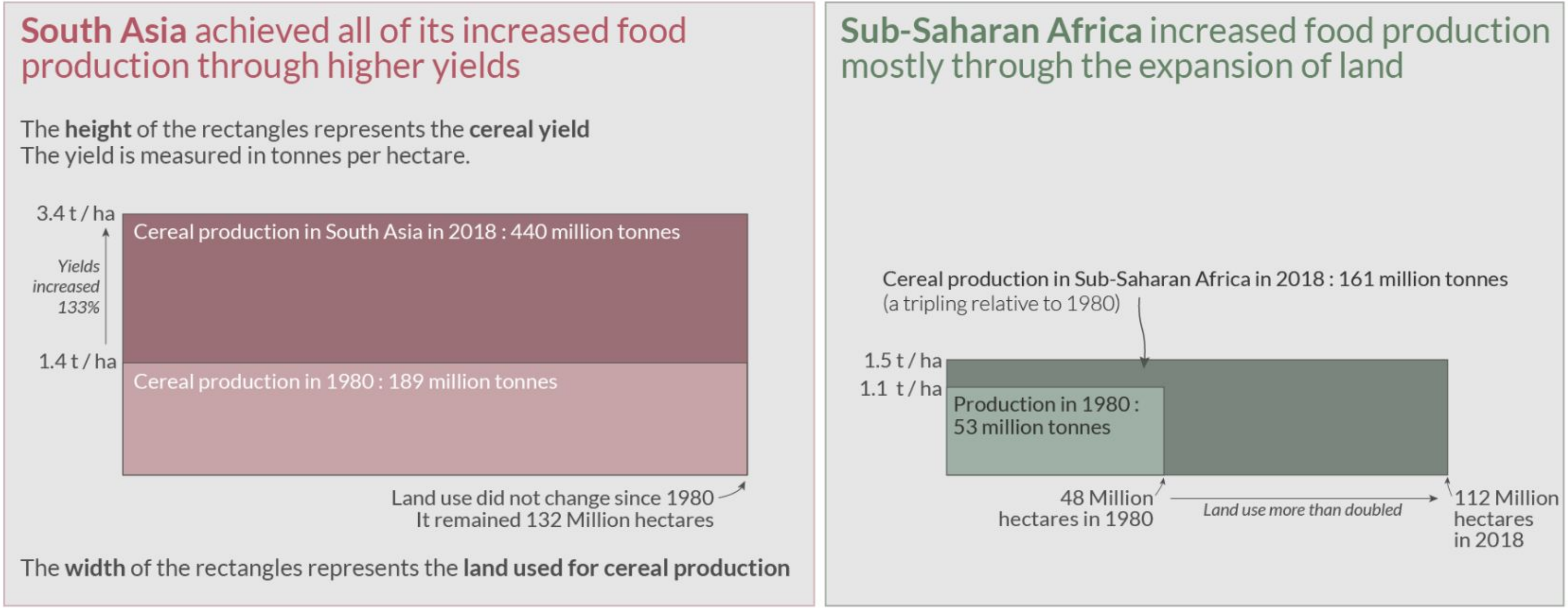
Global land spared as a result of cereal yield improvements

Land sparing is calculated as the amount of additional land that would have been needed to meet global cereal production if average crop yields had not increased since 1961.



Data source: Food and Agriculture Organization of the United Nations (2023) – Learn more about this data

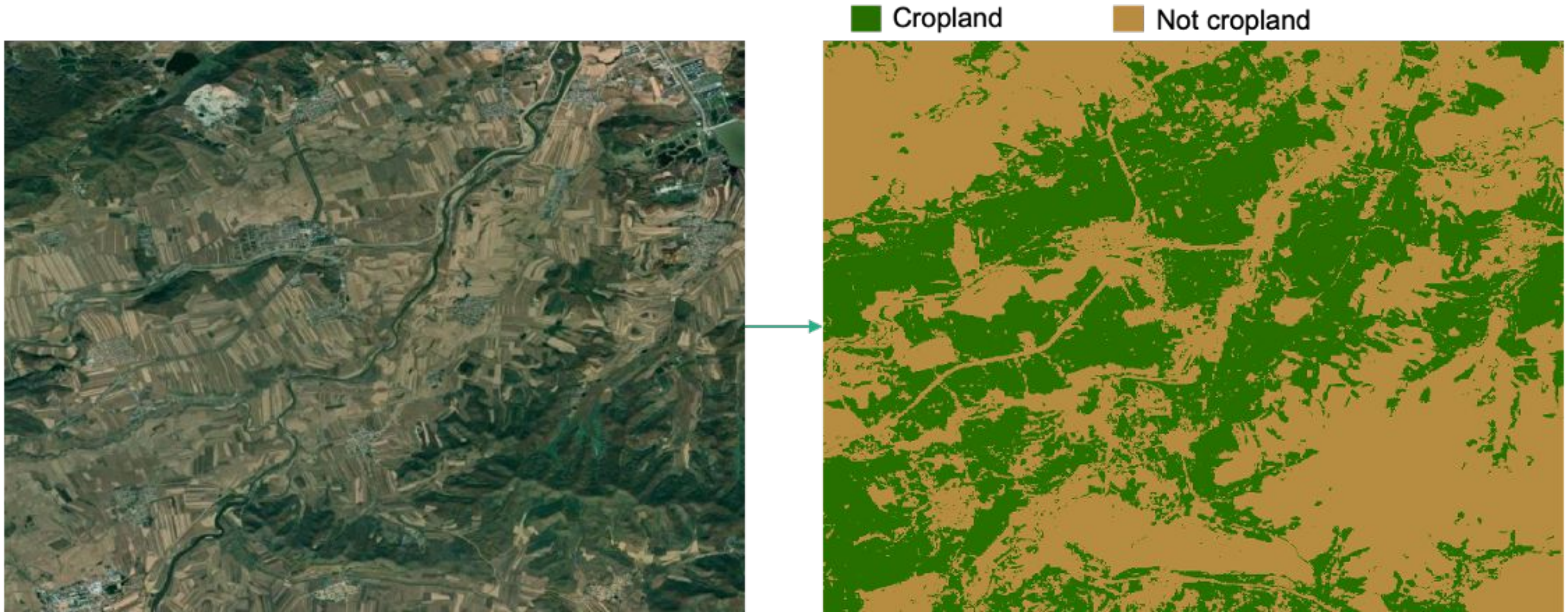
How do crop yields affect land use for food production?



Data source: Food and Agricuture Organization of the United Nations (UN FAO).
OurWorldinData.org – Research and data to make progress against the world's largest problems.

Crop mapping

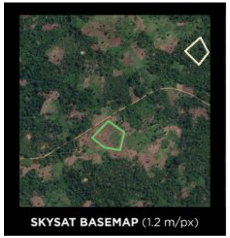
binary classification of pixels as crop or non-crop



Crop mapping

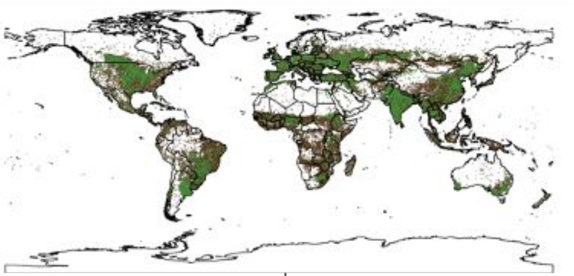
binary classification of pixels as crop or non-crop

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

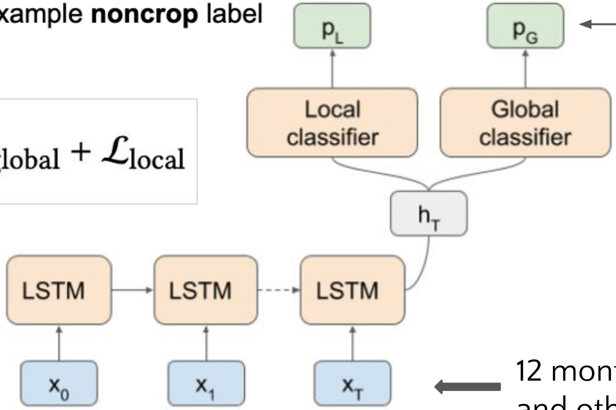


Example **crop** label

Example **noncrop** label



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

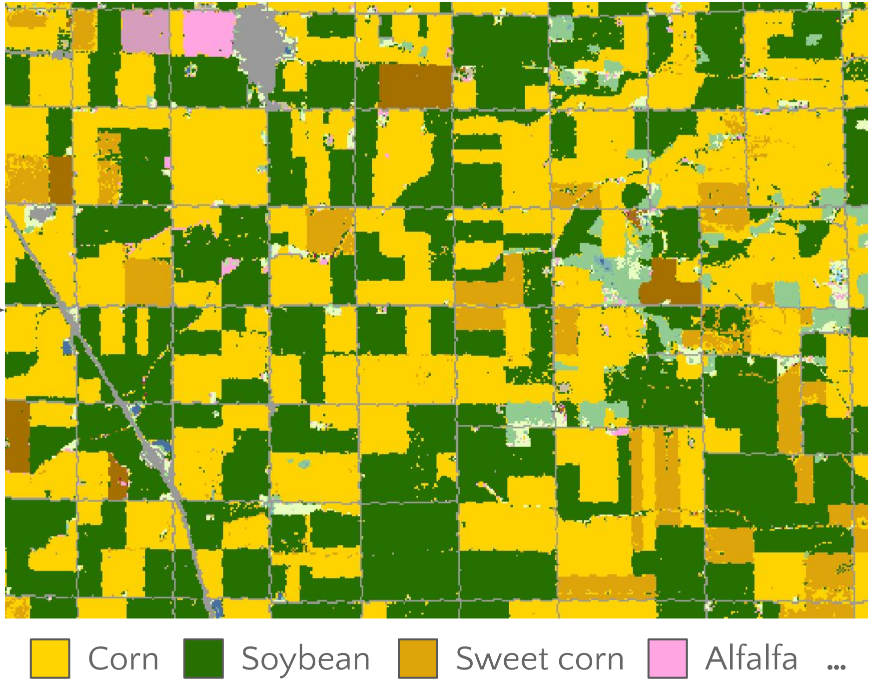


12 month time series of Sentinel-2 and other satellite observations

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

Time series vision transformer (TS-ViT) for crop type classification (Tarasiou et al., 2023)

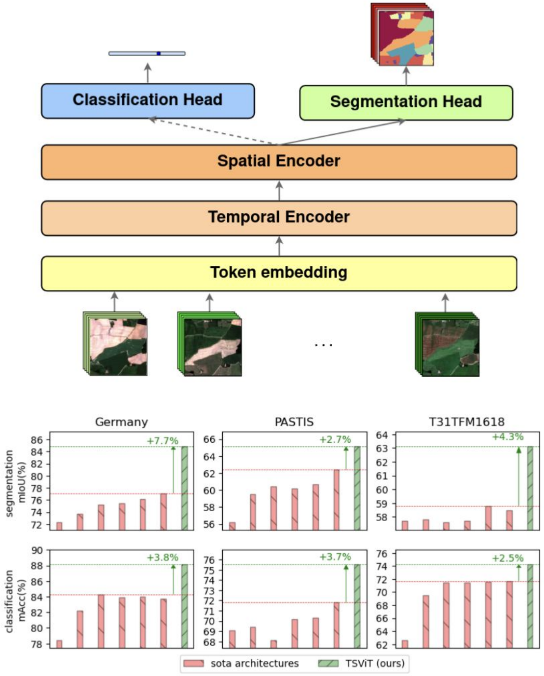


Figure 1. **Model and performance overview. (top)** TSViT architecture. A more detailed schematic is presented in Fig.4. **(bottom) TSViT performance** compared with previous arts (Table 2).

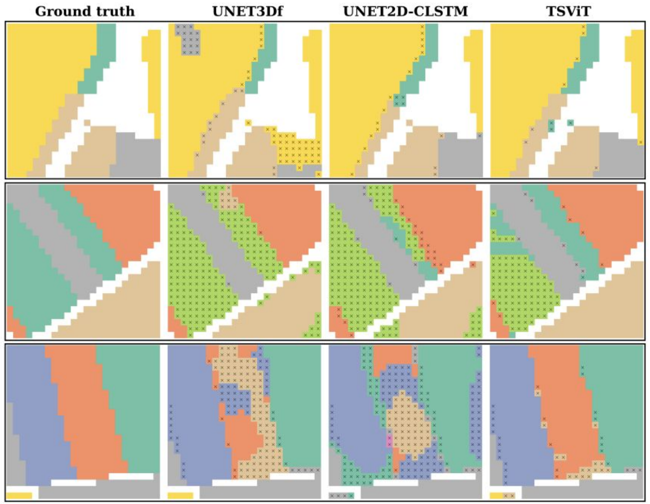
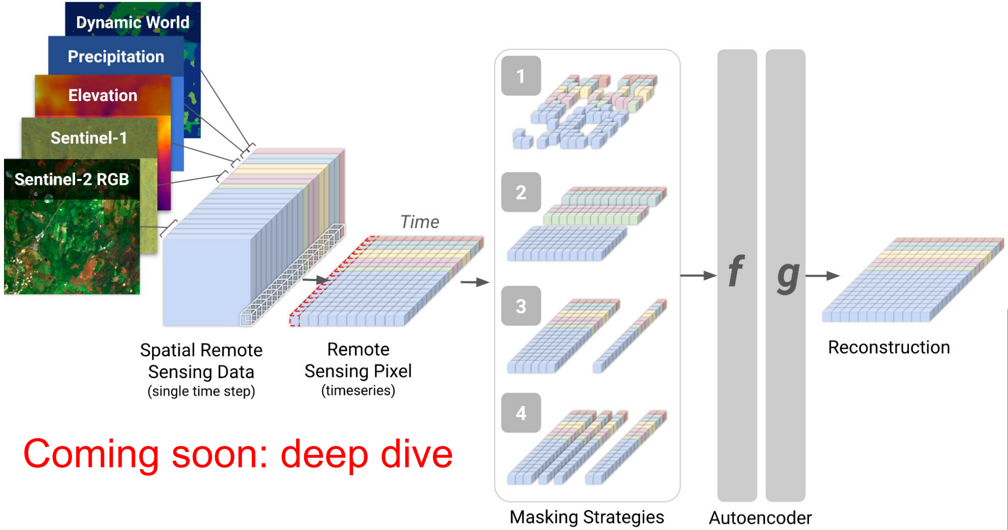


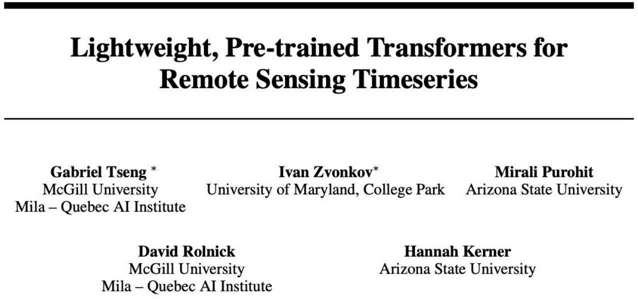
Figure 5. **Visualization of predictions** in Germany. The background class is shown in black, "x" indicates a false prediction.

Tarasiou, M., Chavez, E., & Zafeiriou, S. (2023). Vits for sits: Vision transformers for satellite image time series. CVPR.

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

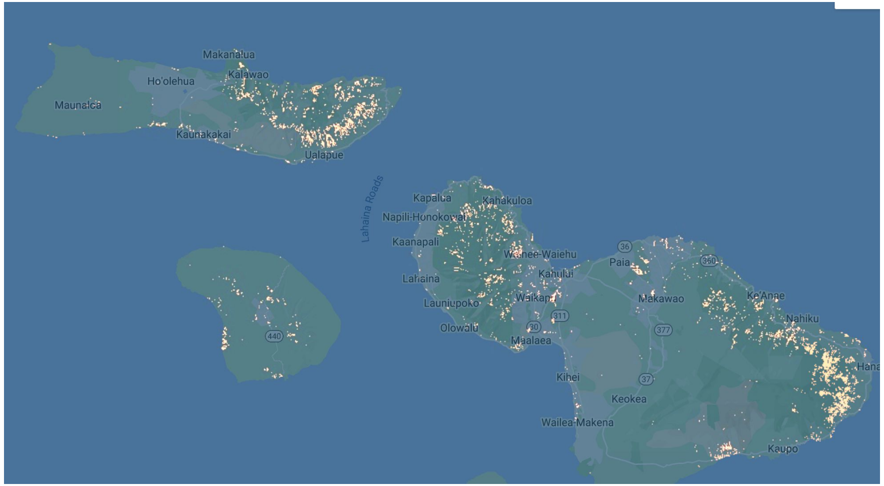
Ivan Zvonkov*
University of Maryland, College Park

Mirali Purohit
Arizona State University

David Rolnick
McGill University
Mila – Quebec AI Institute

Hannah Kerner
Arizona State University

Coming soon: deep dive

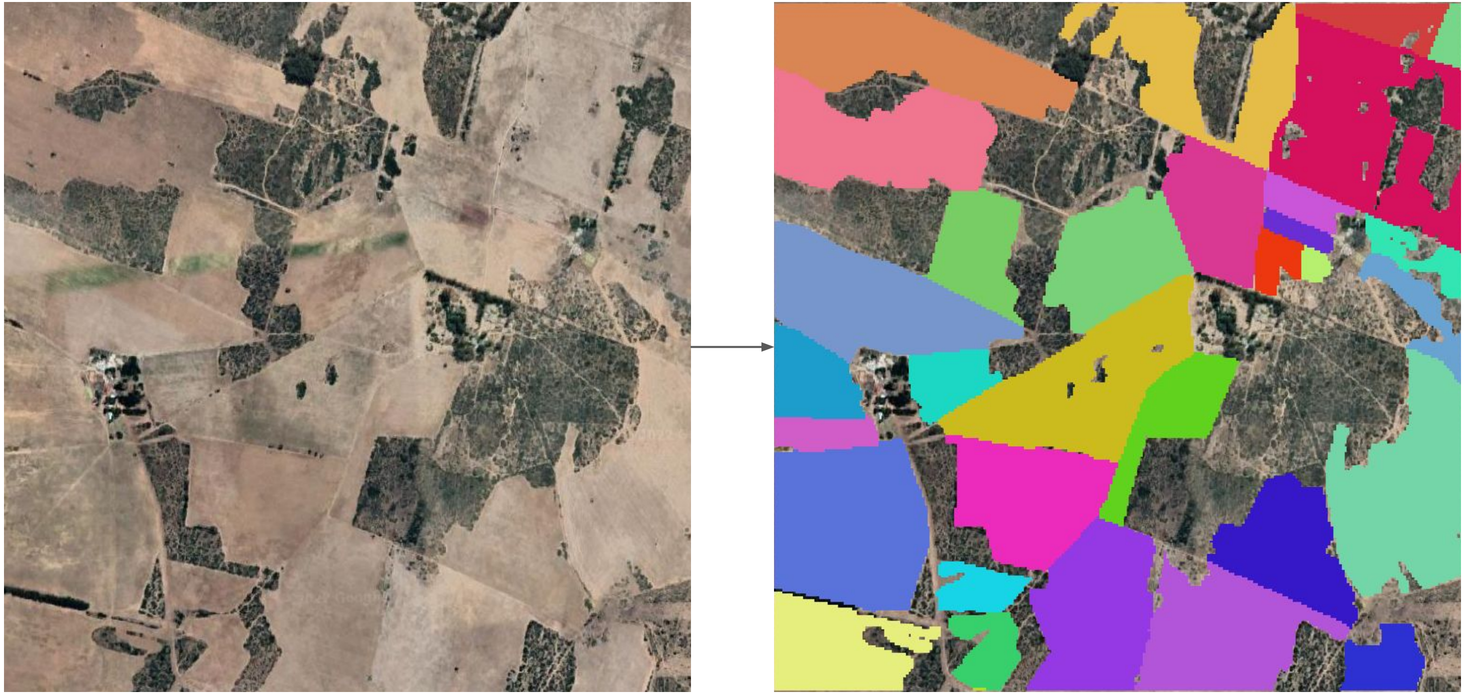


Predicted map of **taro in Maui county** using fine-tuned Presto (pre-trained remote sensing transformer)

Field boundary delineation

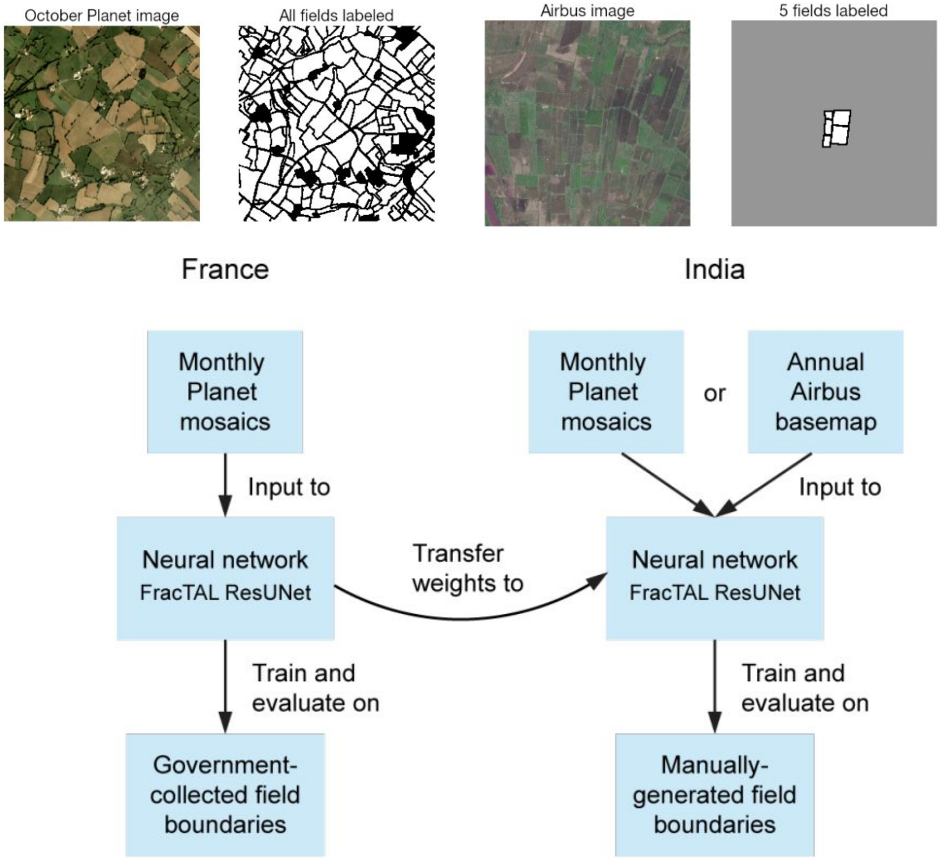
segmentation of individual field/parcel boundaries

Radiant Earth South Africa Field Boundaries



Field boundary delineation

segmentation of individual field/parcel boundaries

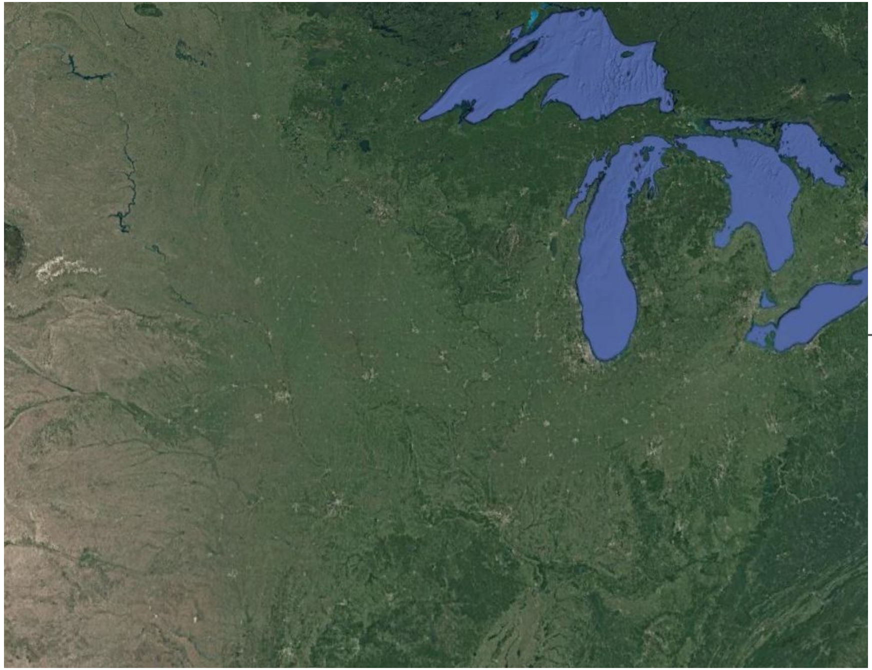


Field boundary delineation using deep transfer learning and weak supervision
(Wang et al., 2022)

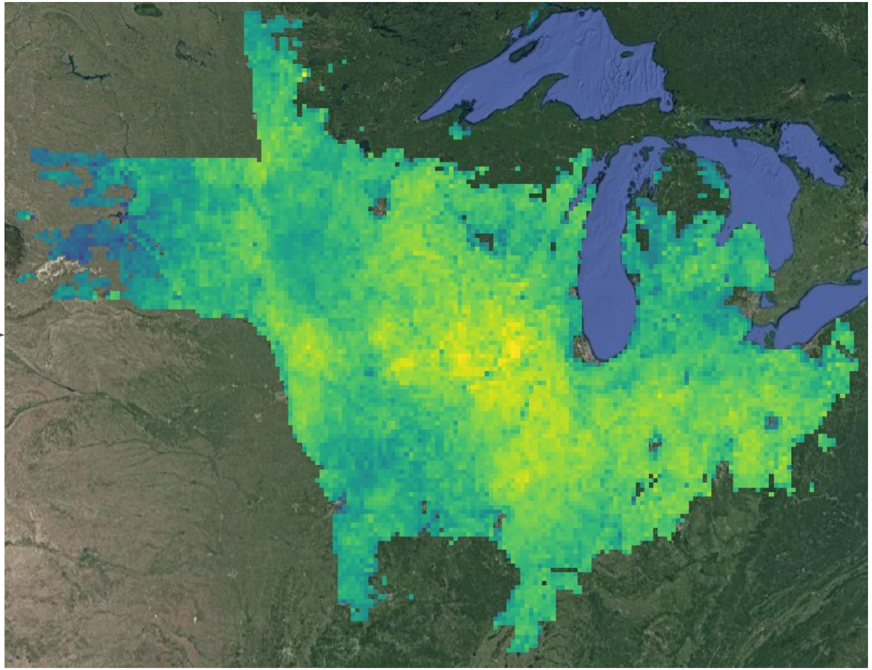
- Trained model using label-rich dataset from France and fine-tuned using sparse dataset from India
- Weak supervision: loss masked to ignore pixels without labels (India)
- FracTAL-ResUNet
  - self-attention layer: FracTAL unit
  - skip-connections (ResNet)
  - encoder-decoder architecture (U-Net)

Yield estimation

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



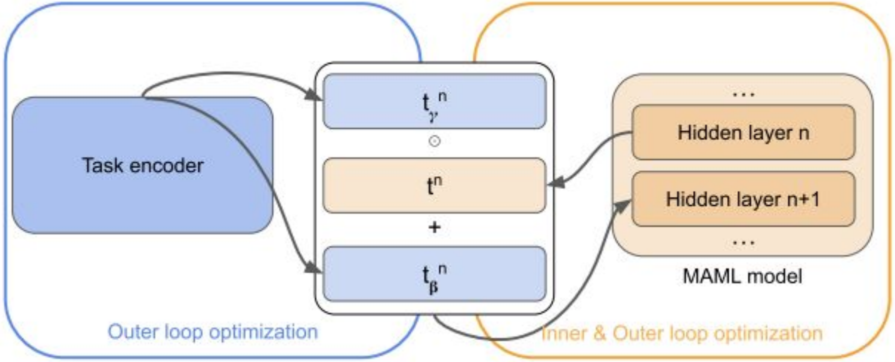
Maize yields in US 2018 (Deines et al., 2020)



4 tonnes/ha 17 tonnes/ha

Yield estimation

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



Model	2011	2012	2013	2014	2015	Mean
LSTM	5.62 ± 0.10	6.60 ± 0.29	5.57 ± 0.21	6.63 ± 0.13	6.69 ± 0.31	6.22
+ GP	5.32 ± 0.10	$\mathbf{5.83 \pm 0.18}$	5.70 ± 0.19	5.61 ± 0.12	$\mathbf{5.24 \pm 0.14}$	**5.54**
+ MAML	26.90 ± 0.01	30.97 ± 0.01	29.57 ± 0.01	30.84 ± 0.01	32.02 ± 0.01	30.06
+ TIML	$\mathbf{5.16 \pm 0.03}$	$\mathbf{5.77 \pm 0.05}$	$\mathbf{5.39 \pm 0.02}$	5.24 ± 0.04	$\mathbf{4.89 \pm 0.04}$	**5.29**
CNN	6.08 ± 0.77	6.94 ± 1.83	6.42 ± 1.23	$\mathbf{4.80 \pm 0.83}$	5.57 ± 0.38	5.96
+ GP	5.55 ± 0.14	6.18 ± 0.49	6.44 ± 0.67	$\mathbf{4.87 \pm 0.31}$	6.02 ± 0.26	5.81
+ MAML	12.93 ± 0.05	8.28 ± 0.07	7.98 ± 0.04	12.05 ± 0.05	7.69 ± 0.06	9.79
+ TIML	$\mathbf{5.23 \pm 0.02}$	6.59 ± 0.02	$\mathbf{5.34 \pm 0.01}$	4.93 ± 0.02	6.35 ± 0.01	5.69
(You et al., 2017)						
LSTM + GP	5.77	6.23	5.96	5.70	5.49	5.83
CNN + GP	5.70	5.68	5.83	4.89	5.67	5.55

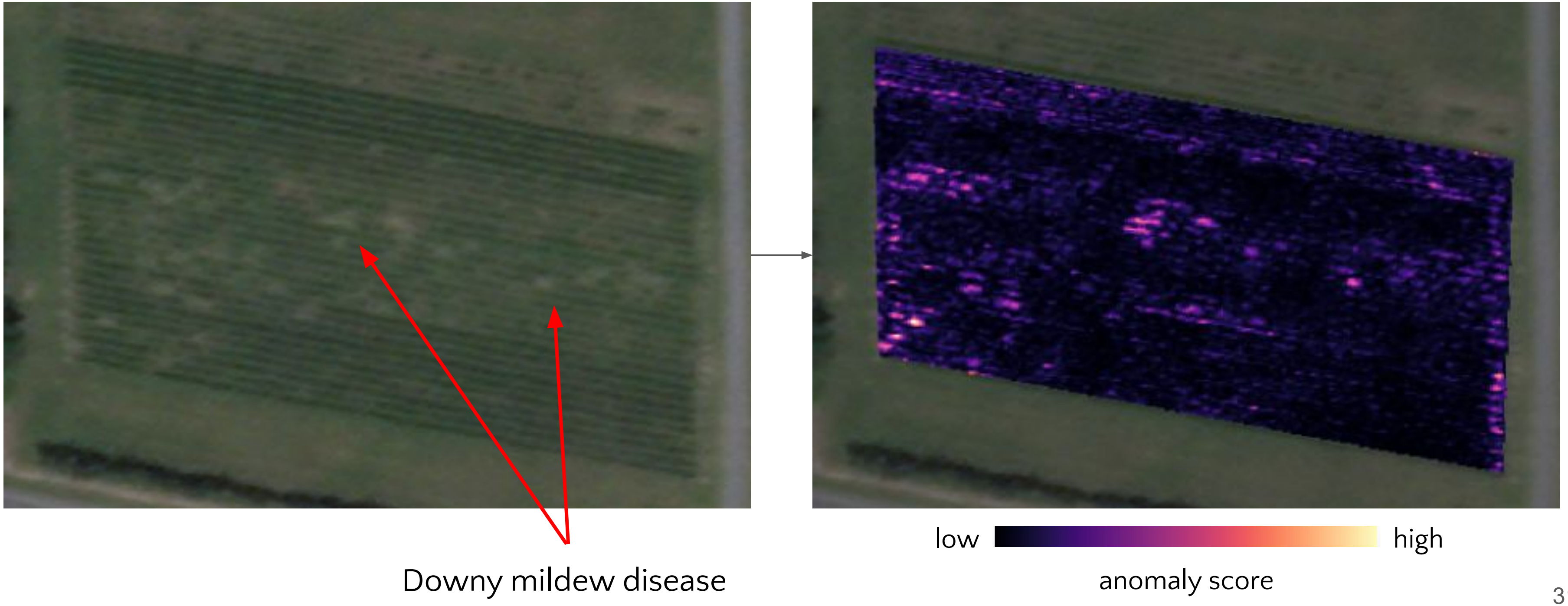
Tseng, G., Kerner, H., Rolnick, D. (2022). TIML: Task-Informed Meta-Learning for crop type mapping. Association for the Advancement of Artificial Intelligence (AAAI) Workshops, AI for Agriculture and Food Systems (AIAFS).

TIML: Task-Informed Meta-Learning
(Tseng et al., 2022)

- Task: predict county-scale yield in US using satellite time series
- All pixels in entire county too large to use as model input
  → 3D histograms (band, time, bin)
- TIML algorithm uses task metadata (lat/lon, state) to move starting weights closer to optimum for transfer learning

Pest, disease, and hotspot detection

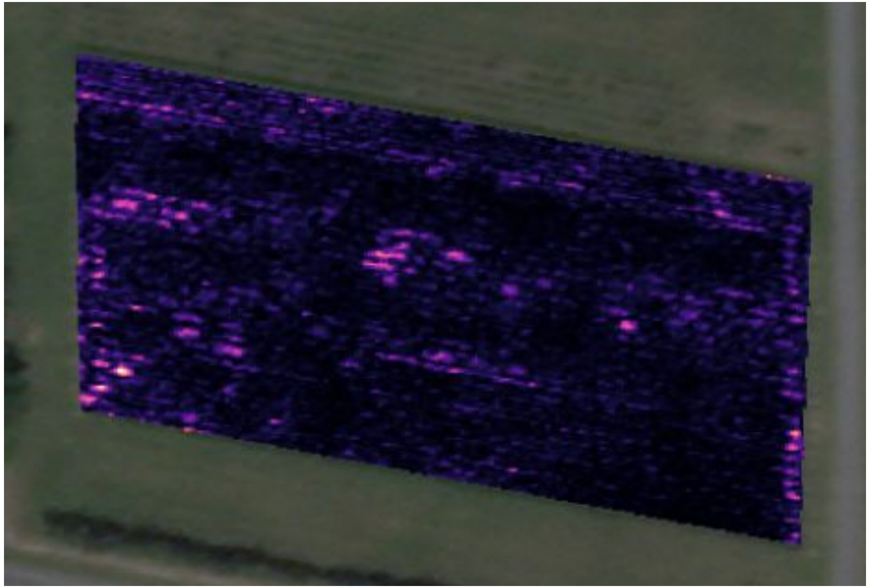
detection of in-field anomalies that represent unfavorable growing conditions



Pest, disease, and hotspot detection

detection of in-field anomalies that represent unfavorable growing conditions

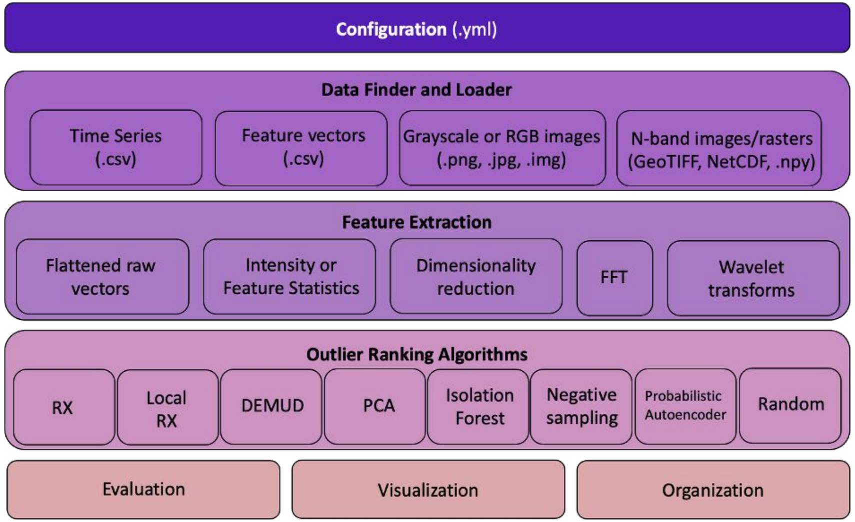
Despite great promise, few recent studies using AI for detection in remote sensing images



low high

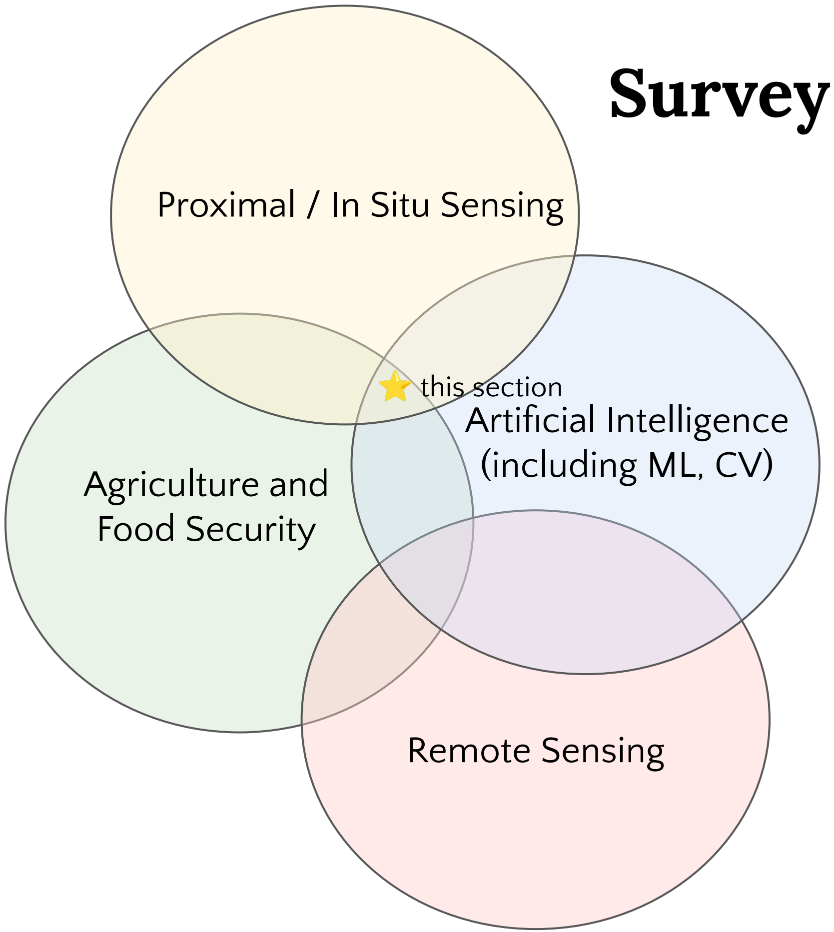
anomaly score

Domain-agnostic Outlier Ranking Algorithms (DORA)



Kerner et al., 2022

Survey of key topics



Precision agriculture (resource optimization)

Robotic farming

Yield estimation and optimization

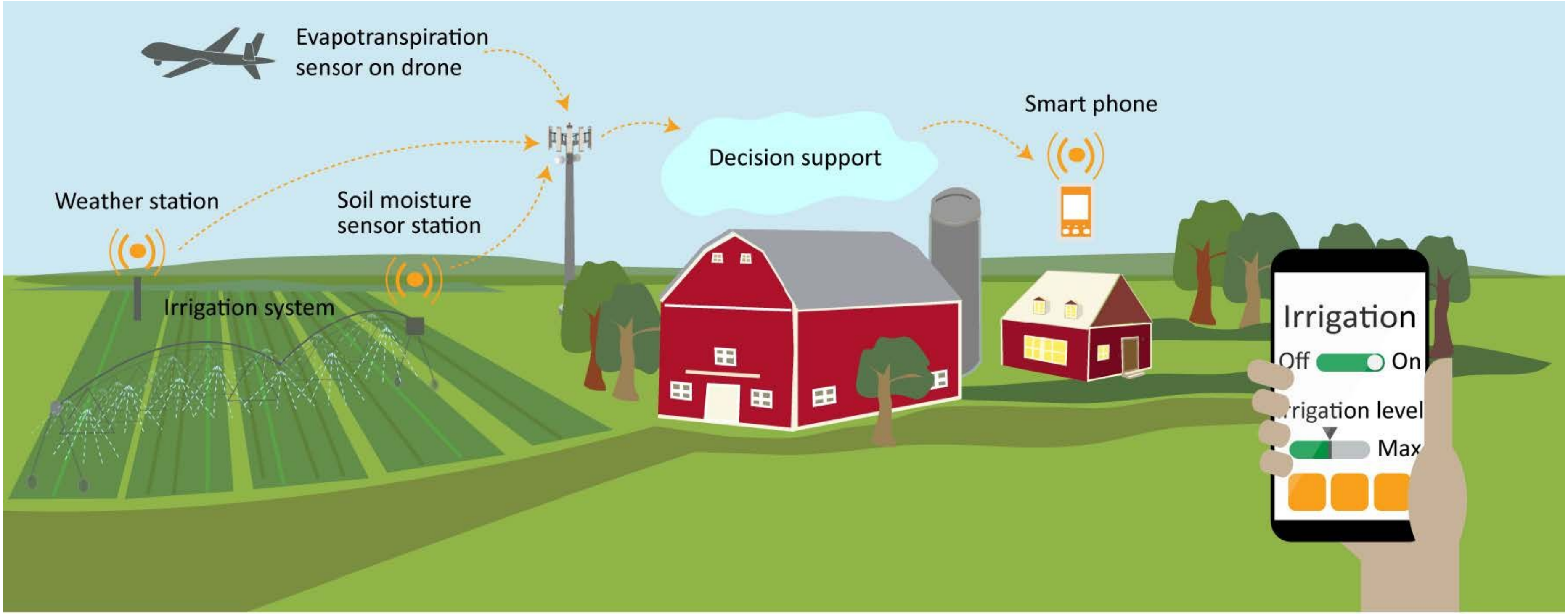
Pest and disease identification

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.)

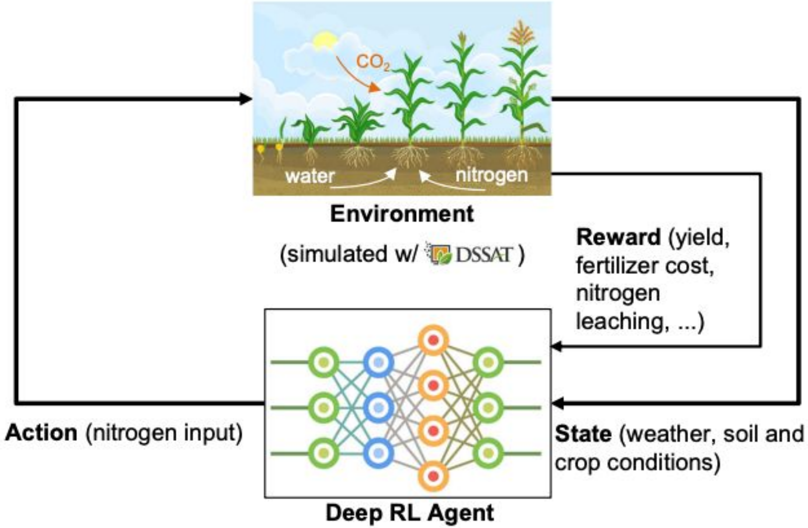


Figure 1. A framework for optimizing N management with deep RL and DSSAT-based crop simulations

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

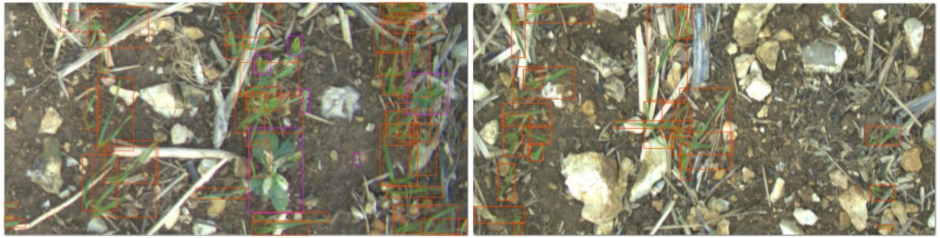
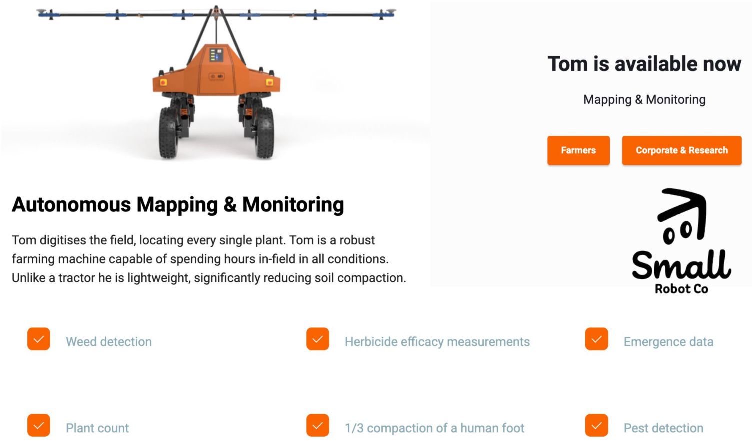


Figure 1: Sample annotated images. Orange boxes represent wheat & purple boxes represent weeds.



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.

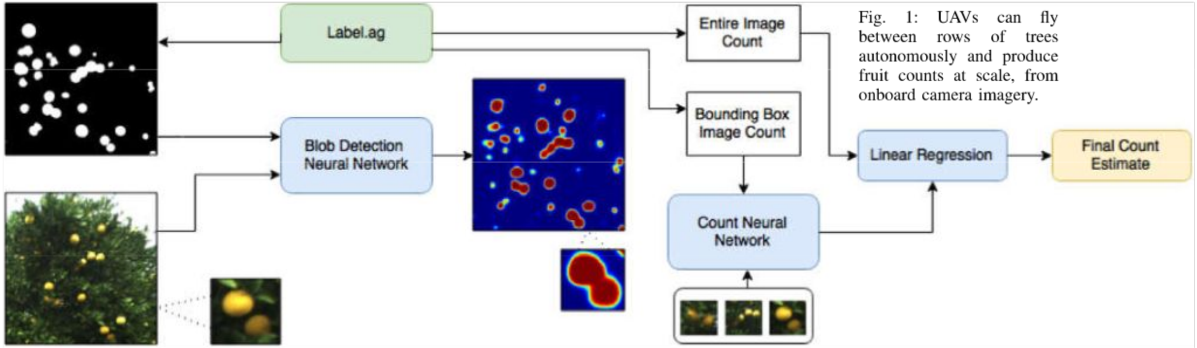


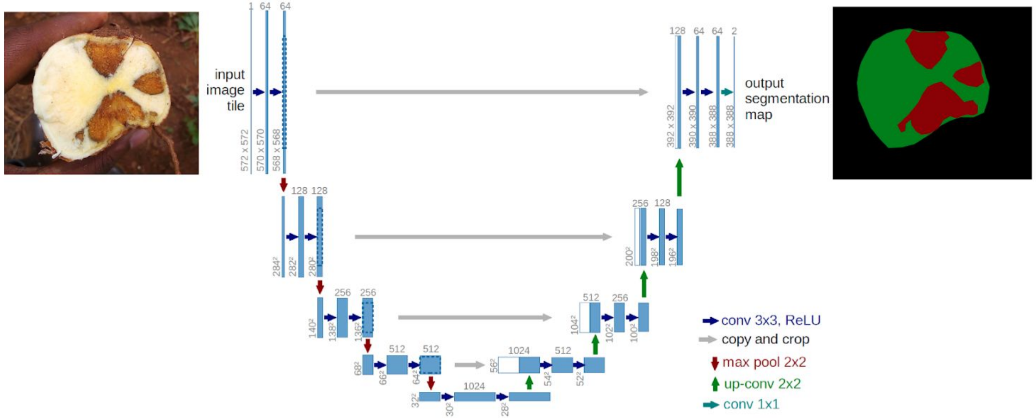
Fig. 4: The training pipeline starts with a given image. Label.ag then produces the corresponding ground truth *label map*, and these two inputs are used to train the **blob detection neural network**. This neural network outputs a segmented image, and the pipeline extracts the coordinates of the bounding 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

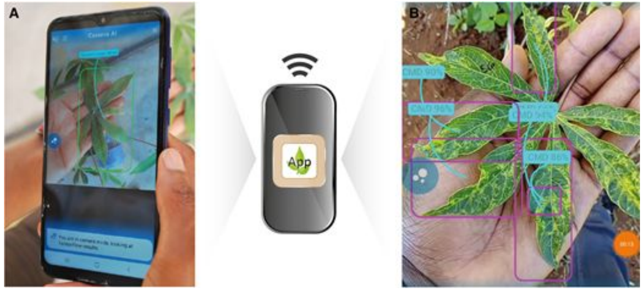
Pest, disease, and hotspot detection

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

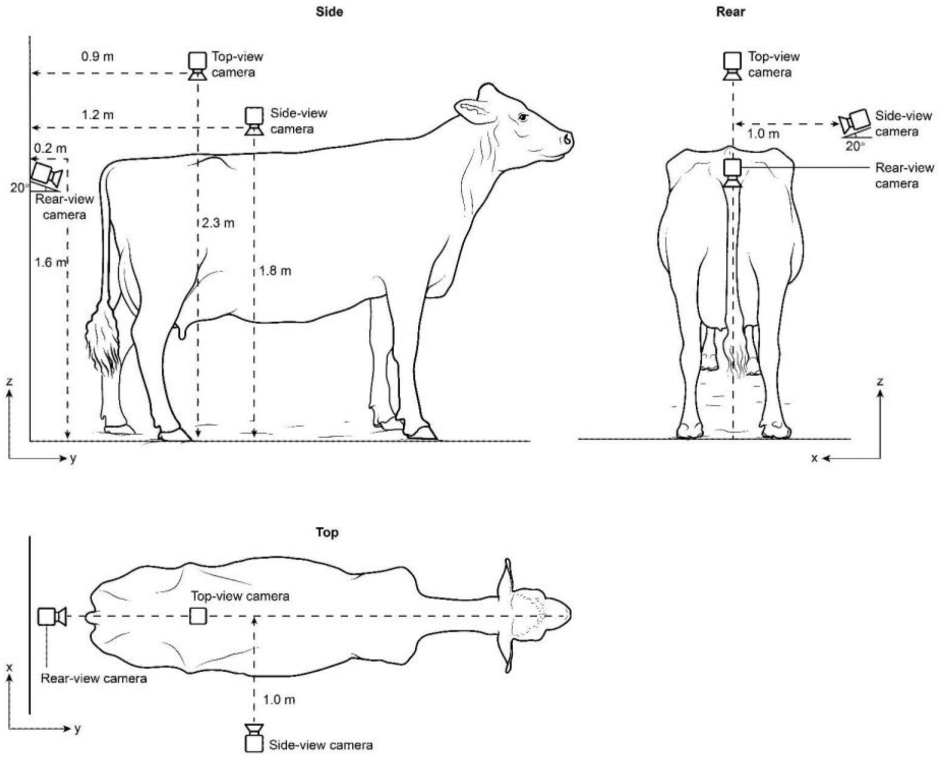
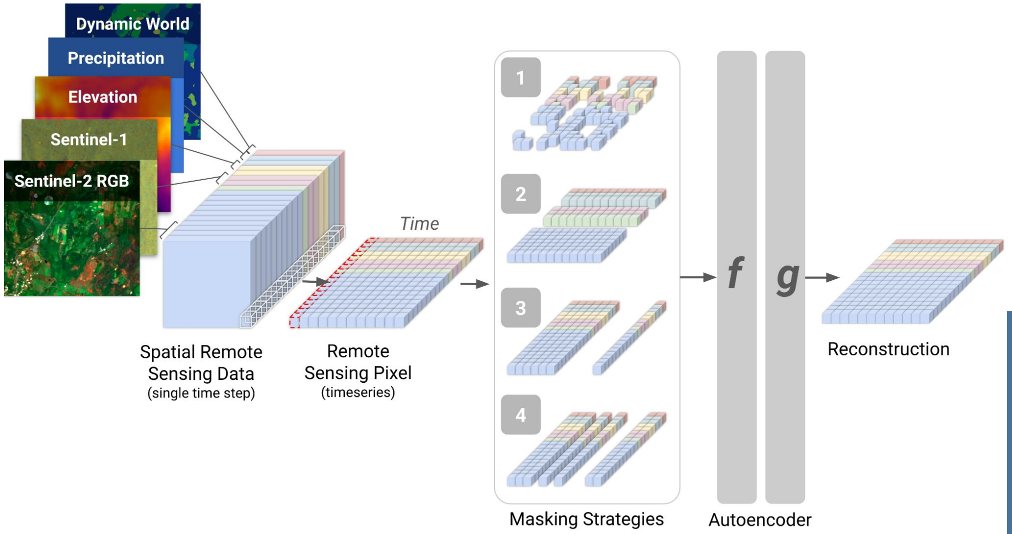


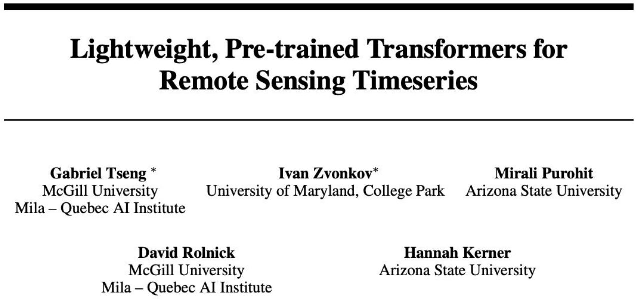
Figure 3-2. Image recording setup with the mounting positions and angles of the 3 cameras.

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

Deep dive: how Presto works and how it is used for crop type mapping (and other agriculture use cases)





Lightweight, Pre-trained Transformers for Remote Sensing Timeseries

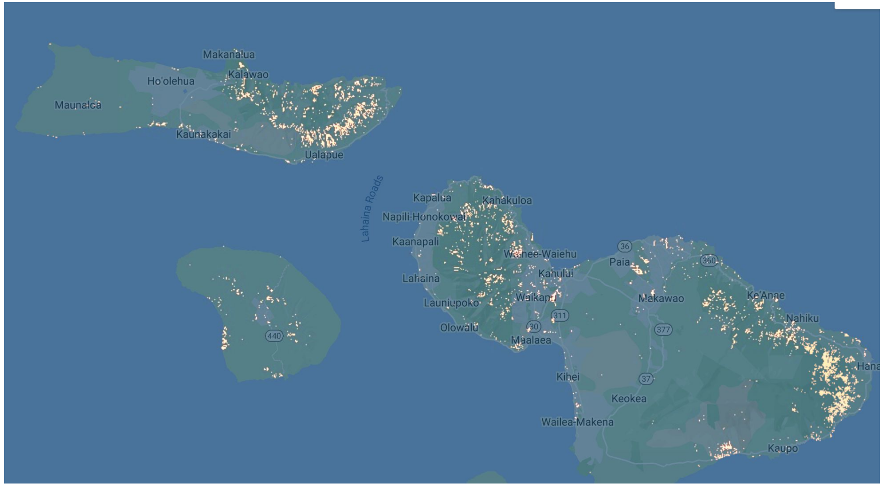
Gabriel Tseng *
McGill University
Mila – Quebec AI Institute

Ivan Zvonkov*
University of Maryland, College Park

Mirali Purohit
Arizona State University

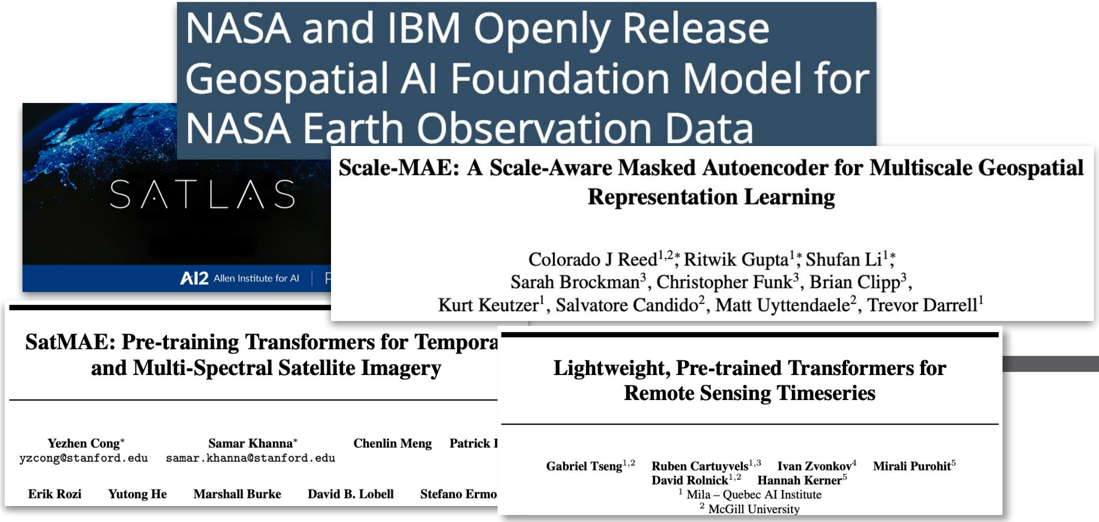
David Rolnick
McGill University
Mila – Quebec AI Institute

Hannah Kerner
Arizona State University



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

Self-supervised "foundation" models for remote sensing



NASA and IBM Openly Release Geospatial AI Foundation Model for NASA Earth Observation Data

SATLAS

AI2 Allen Institute for AI

Scale-MAE: A Scale-Aware Masked Autoencoder for Multiscale Geospatial Representation Learning

Colorado J Reed[1,2]*, Ritwik Gupta[1]*, Shufan Li[1]*,
Sarah Brockman[3], Christopher Funk[3], Brian Clipp[3],
Kurt Keutzer[1], Salvatore Candido[2], Matt Uyttendaele[2], Trevor Darrell[1]

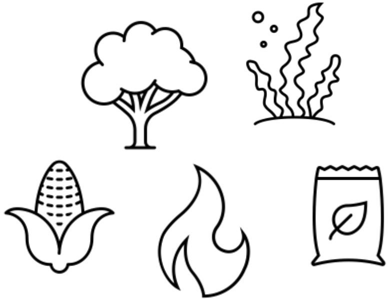
SatMAE: Pre-training Transformers for Tempora and Multi-Spectral Satellite Imagery

Yezhen Cong* yzcong@stanford.edu Samar Khanna* samar.khanna@stanford.edu Chenlin Meng Patrick I
Erik Rozi Yutong He Marshall Burke David B. Lobell Stefano Ermo

Lightweight, Pre-trained Transformers for Remote Sensing Timeseries

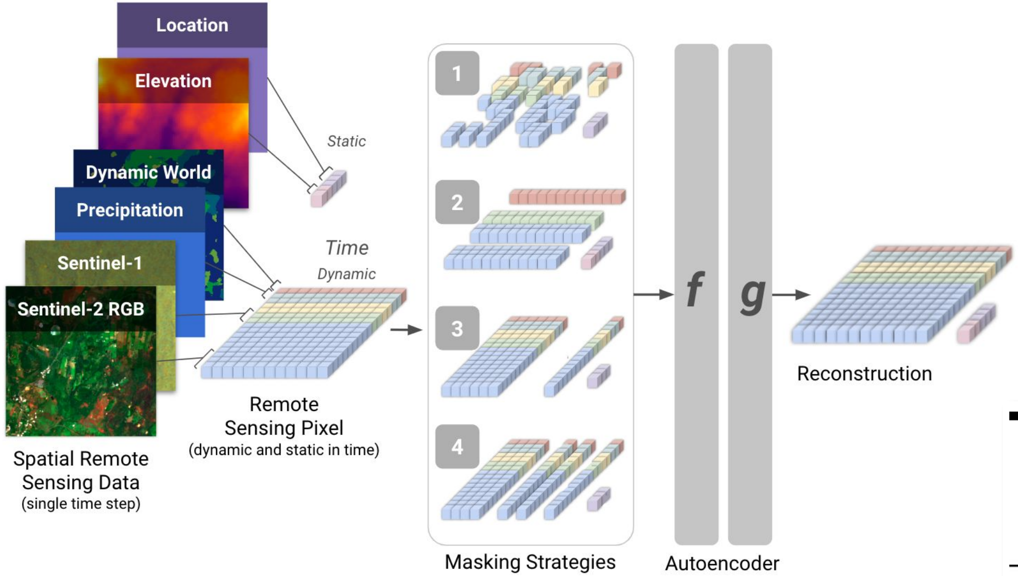
Gabriel Tseng[1,2] Ruben Cartuyvels[1,3] Ivan Zvonkov[4] Mirali Purohit[5]
David Rolnick[1,2] Hannah Kerner[5]
[1] Mila – Quebec AI Institute
[2] McGill University

Self-supervised pre-training
leveraging massive archive of
unlabeled remote sensing data



Supervised fine-tuning
using small[er] labeled datasets
for specific regions and/or
application tasks

Presto's design is inspired by agriculture use cases and the unique character of satellite data



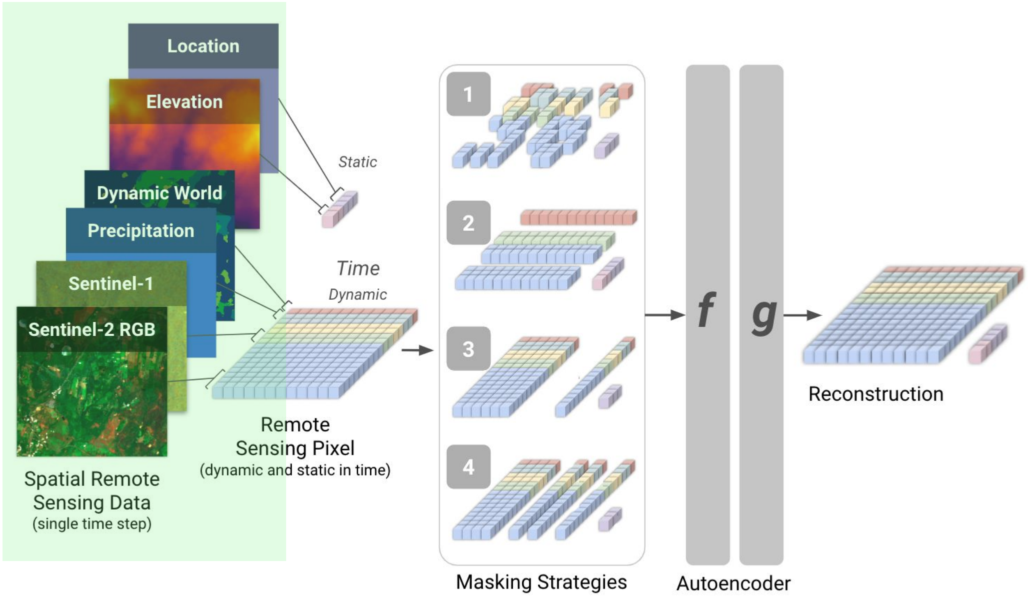
Presto

(Pretrained remote sensing transformer)

Lightweight, Pre-trained Transformers for Remote Sensing Timeseries

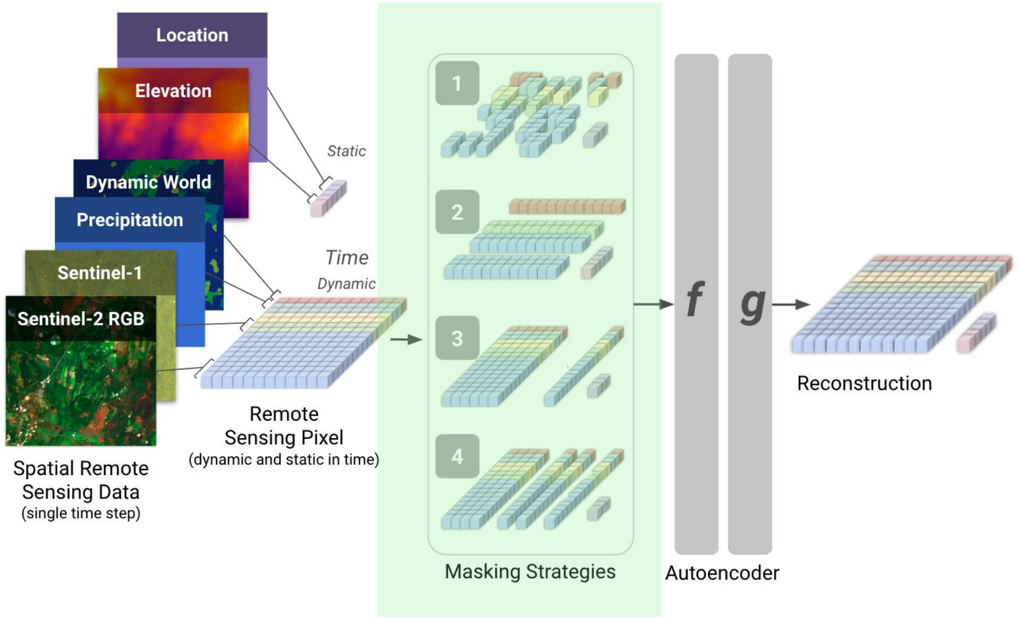
Gabriel Tseng[1,2] **Ruben Cartuyvels**[1,3] **Ivan Zvonkov**[4] **Mirali Purohit**[5]
David Rolnick[1,2] **Hannah Kerner**[5]
[1] Mila – Quebec AI Institute
[2] McGill University
[3] KU Leuven
[4] University of Maryland, College Park
[5] Arizona State University

Presto's design is inspired by agriculture use cases and the unique character of satellite data



1. Use a wide diversity of input sensors at pre-training time

Presto's design is inspired by agriculture use cases and the unique character of satellite data

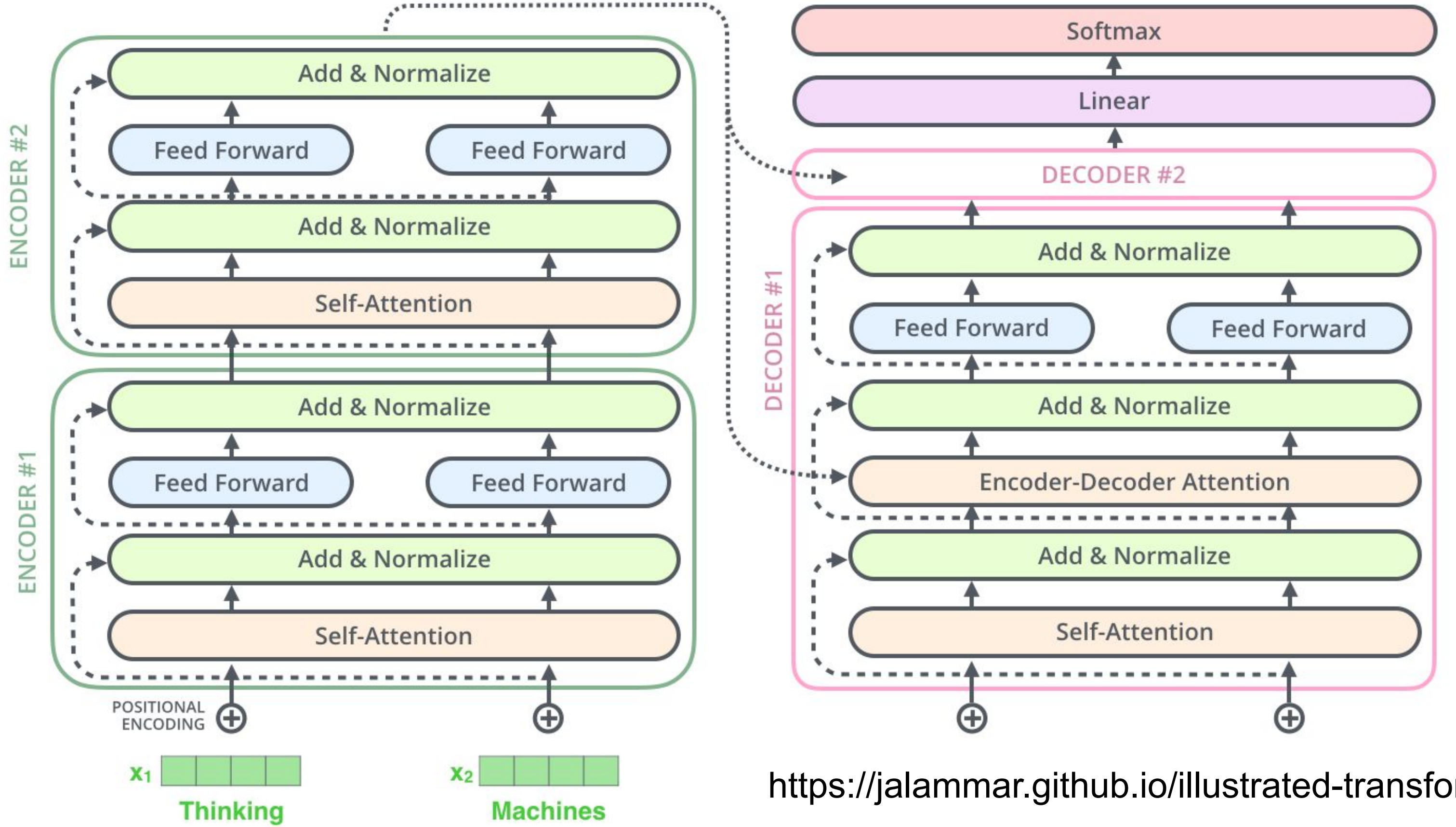


Masked autoencoder

1. Use a wide diversity of input sensors at pre-training time

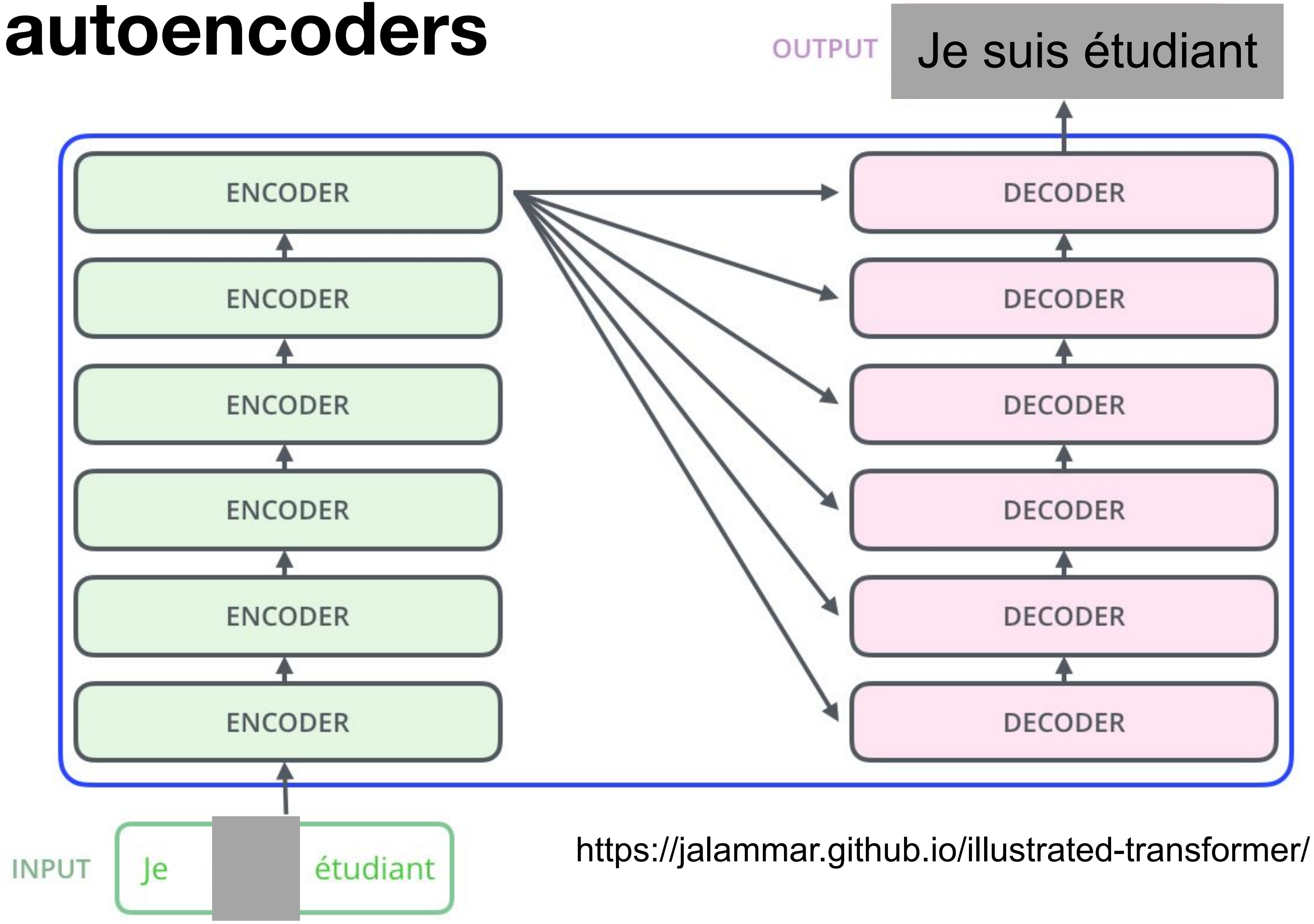
2. Apply **structured** masking strategies so that the model can handle missing **channels** or **timesteps**

Refresher: what are Transformers?



https://jalammar.github.io/illustrated-transformer/

Masked autoencoders



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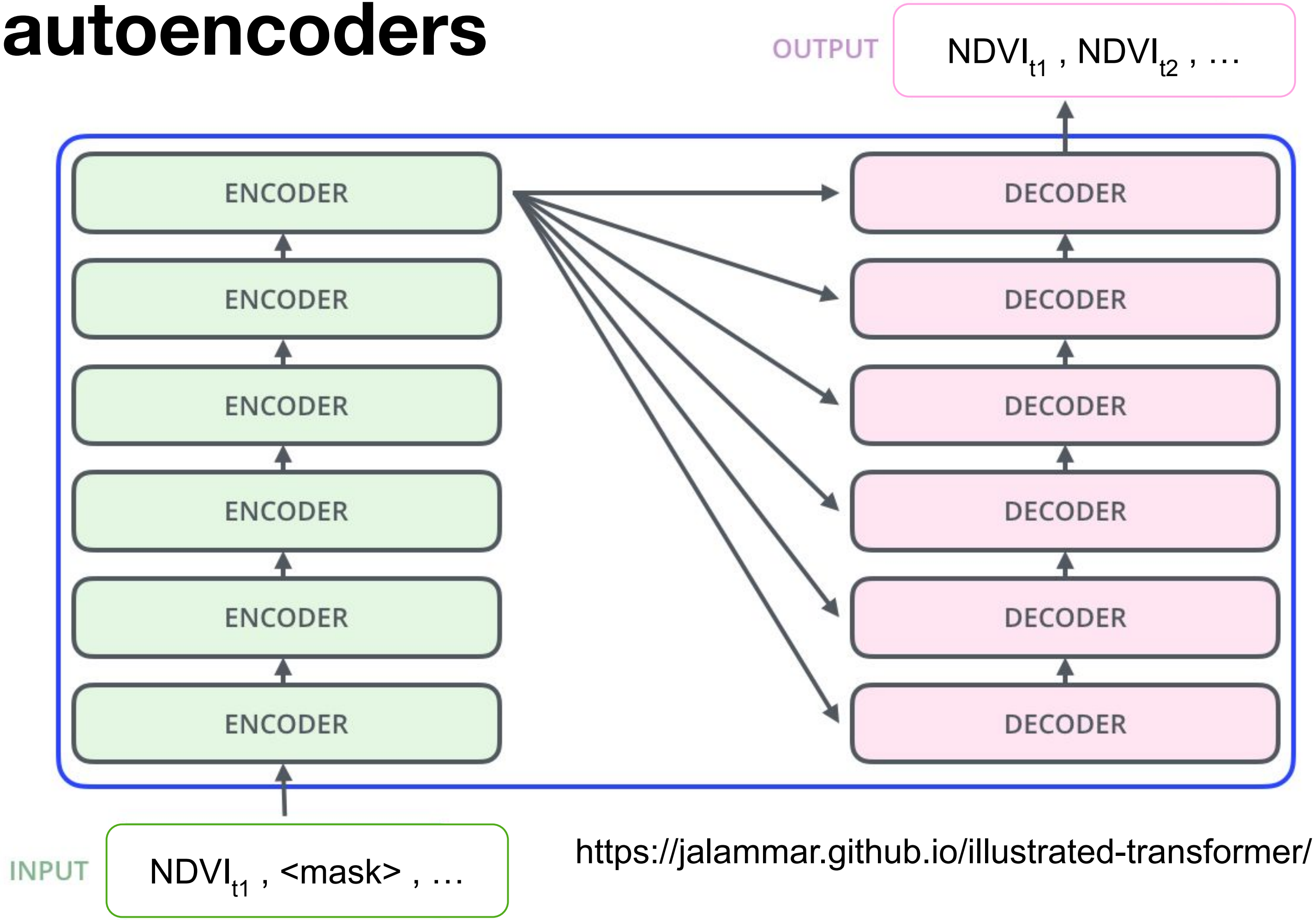
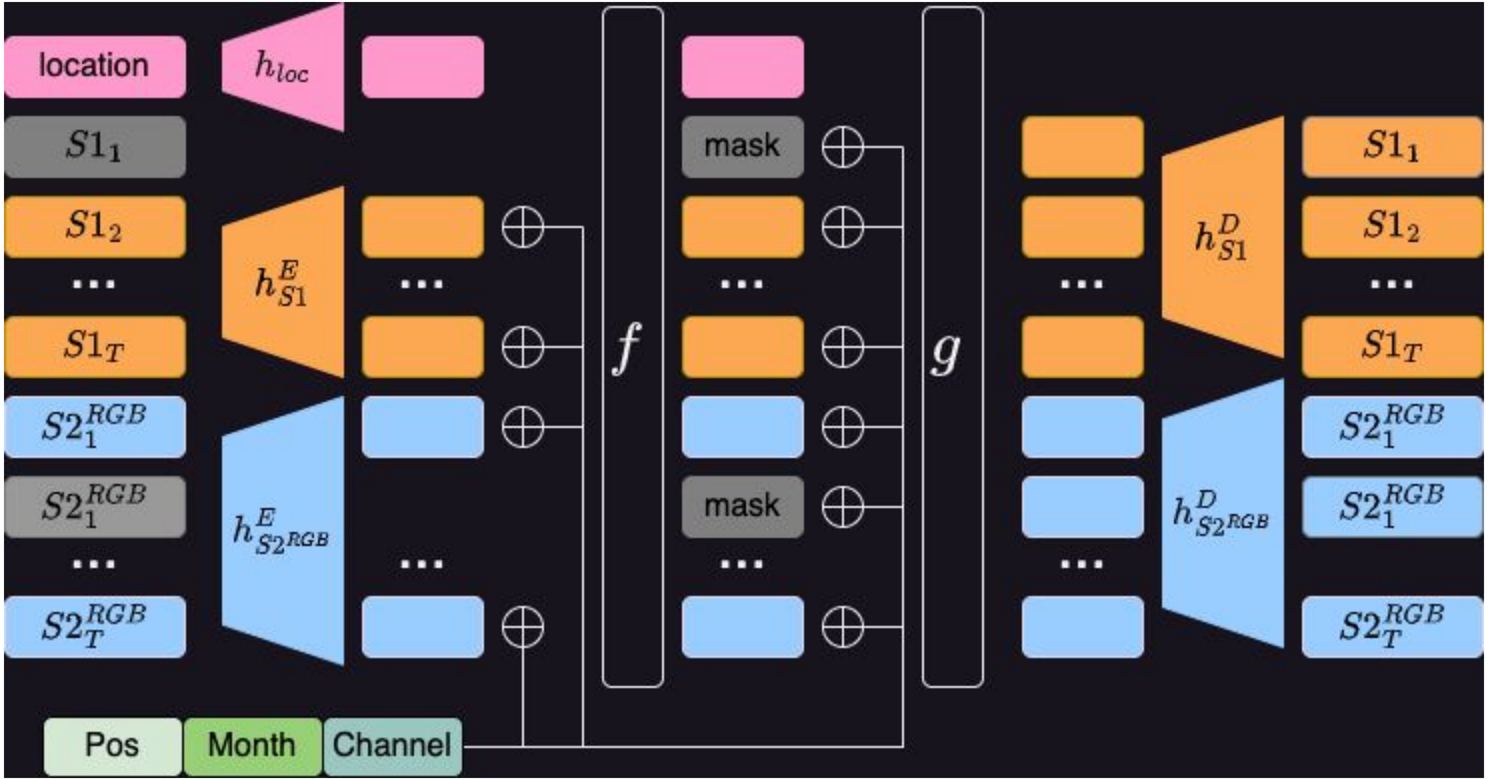
Masked autoencoders

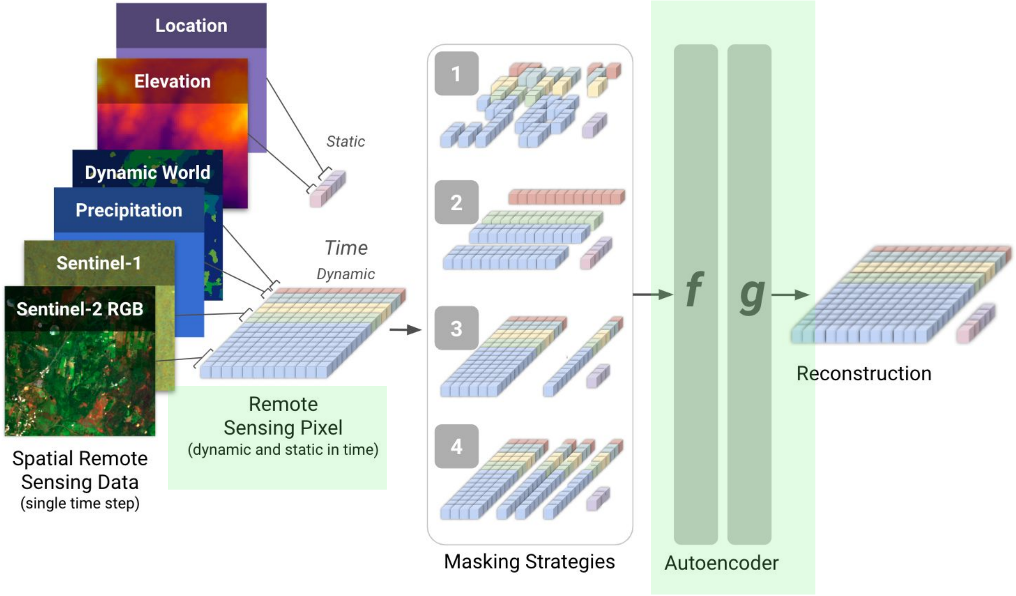


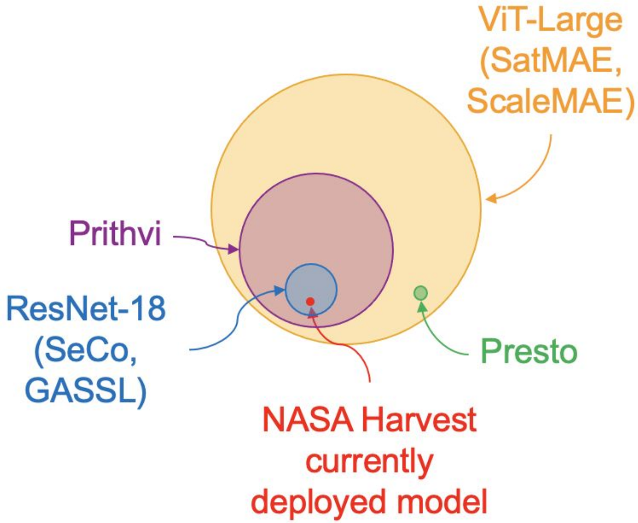
https://jalammar.github.io/illustrated-transformer/

Presto’s masked autoencoder



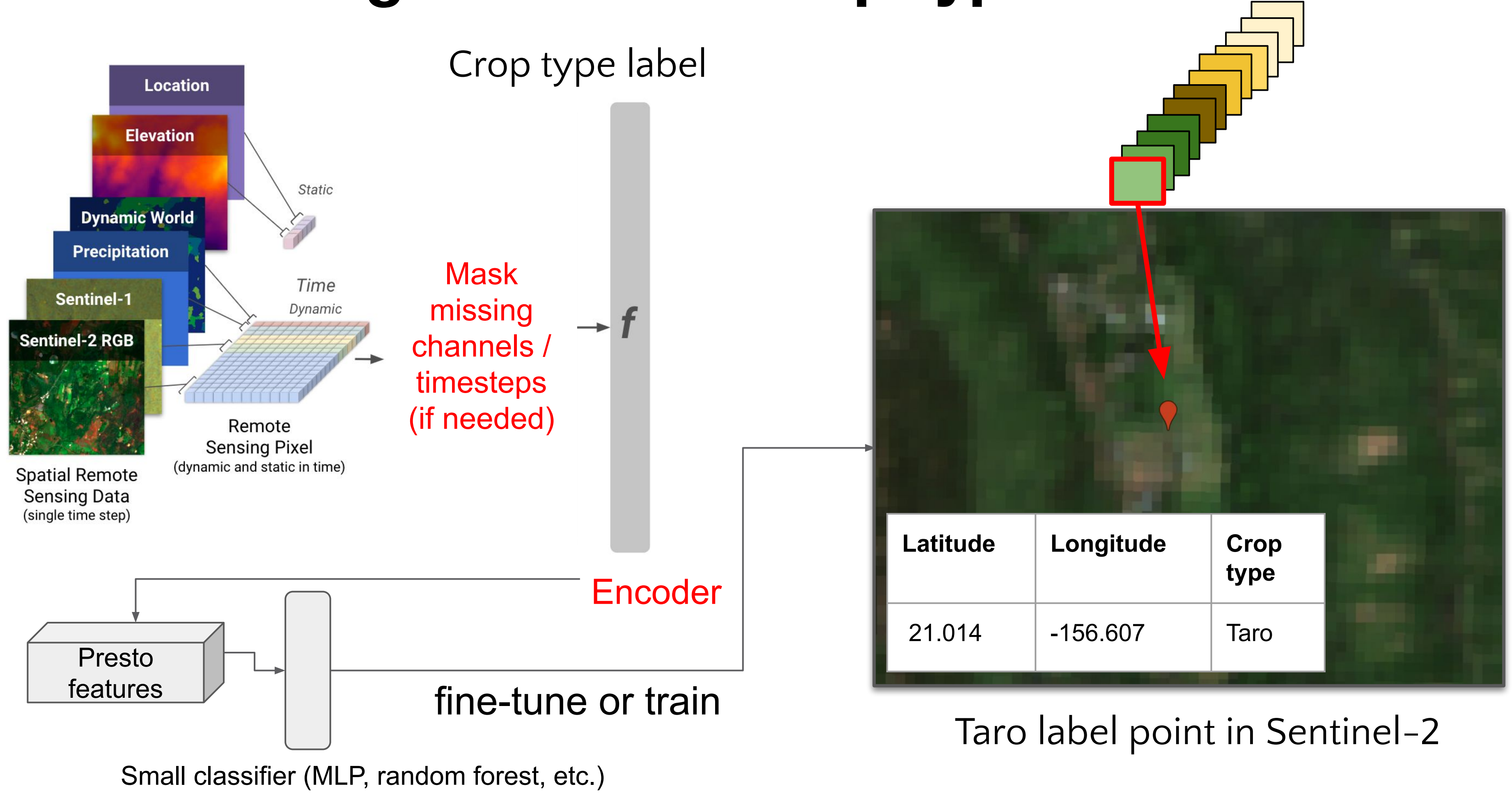
Presto's design is inspired by agriculture use cases and the unique character of satellite data



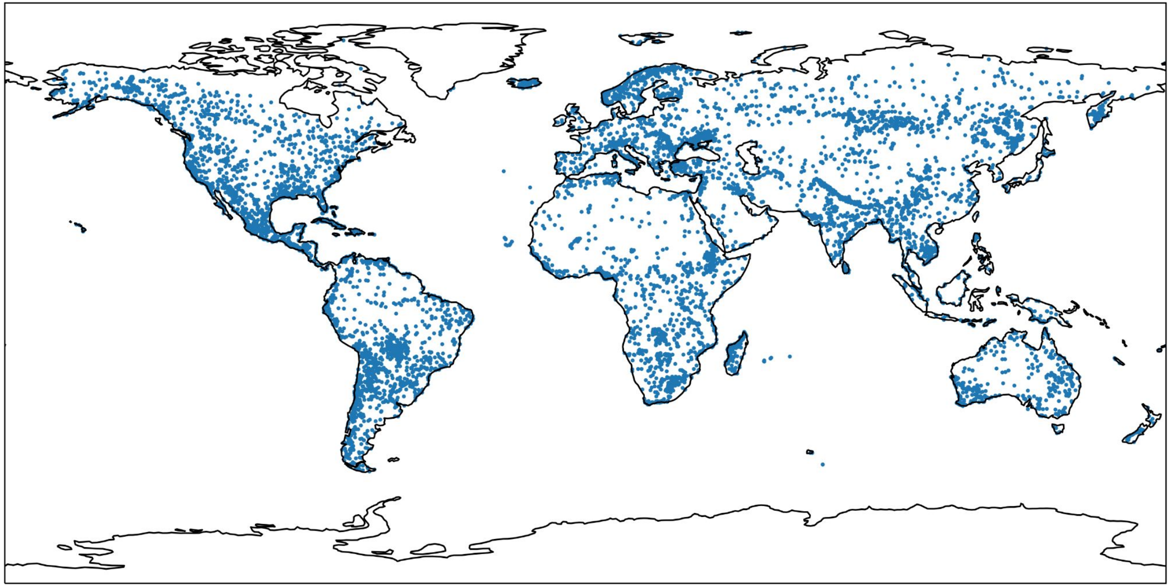


3. Use time-series inputs, which are much smaller than images. Smaller inputs → smaller model

Fine-tuning Presto for crop type classification



Presto's design is inspired by agriculture use cases and the unique character of satellite data



1. Use a wide diversity of input sensors at pre-training time
2. Apply **structured** masking strategies so that the model can handle missing channels or timesteps
3. Use time-series inputs, which are much smaller than images. Smaller inputs → smaller model
4. Global representation and diversity in pre-training data

Fine-tuning Presto for downstream tasks is computationally efficient

Model	Number of parameters: Total	Number of parameters: Finetuned	F1 score: Kenya	F1 score: Brazil	F1 score: Togo	F1 score: Mean
Random Forest			0.559	0.000	0.756	0.441
MOSAIKS-1D$_R$	418K	8193	0.790	0.746	0.679	0.738
TIML	91K	91K	0.838	0.835	0.732	0.802
Presto$_R$	401K	129	0.816	**0.891**	**0.798**	0.835
no DW			**0.861**	0.888	0.760	**0.836**

Presto embeddings + logistic regression

🌽 CropHarvest benchmark

Presto is lightweight and accessible

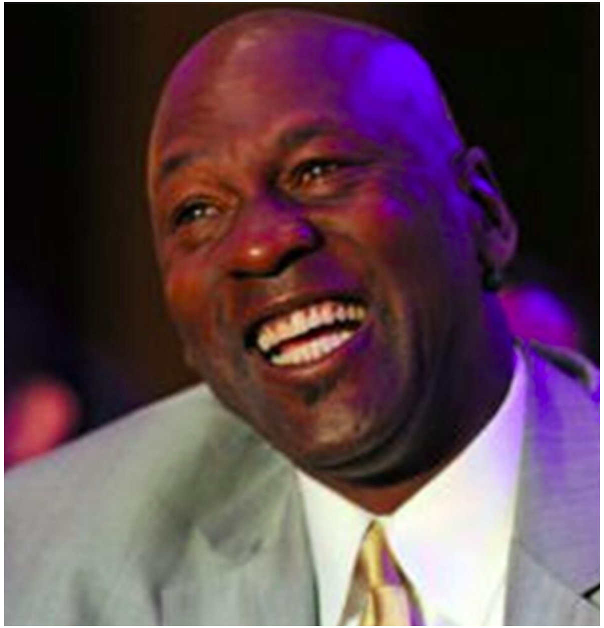
```python
# either import works. The single_file_presto has no load_pretrained function, since this
# requires knowing where the pretrained file is. The state dict can be loaded directly
# from data/default_models.pt
from single_file_presto import Presto
from presto import Presto

# to make a randomly initialized encoder-decoder model
encoder_decoder = Presto.construct()
# alternatively, the pre-trained model can also be loaded
encoder_decoder = Presto.load_pretrained()

# to isolate the encoder
encoder_only = encoder_decoder.encoder
# to add a linear transformation to the encoder's output for finetuning
finetuning_model = encoder_decoder.construct_finetuning_model(num_outputs=1, regression=True)
```

1. Easy loading from a python package
2. Single-file version for integration into other applications
3. Model weights stored on git (3.17Mb)
4. Finetuning possible in **minutes on a 2017 Macbook Pro**

What are the challenges?

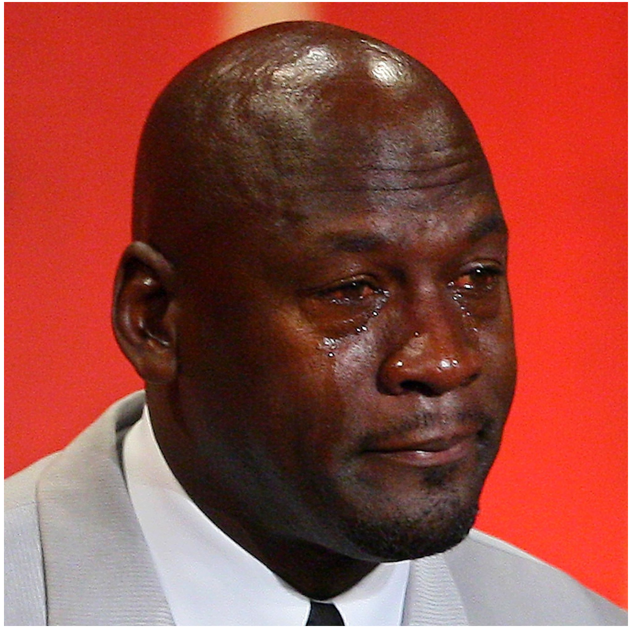
What do you think?

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

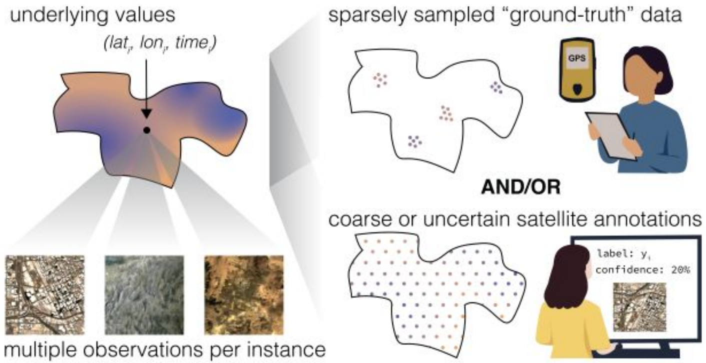
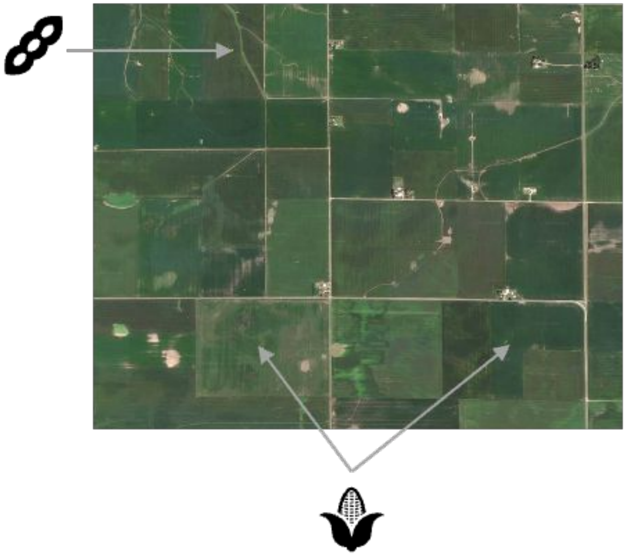


Figure 2. **In SatML, multiple observations and multiple (or no) labels may correspond to a given (lat, lon, time) index**, whereas in many ML settings, labels are defined directly from images.

Rolf, E., Klemmer, K., Robinson, C., and Kerner, H. (2024). Mission Critical–Satellite Data is a Distinct Modality in Machine Learning. ICML.



Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Benchmark datasets over-idealized and not representative of real world

Maize intercropped with beans in Kenya
Muoni et al., 2019

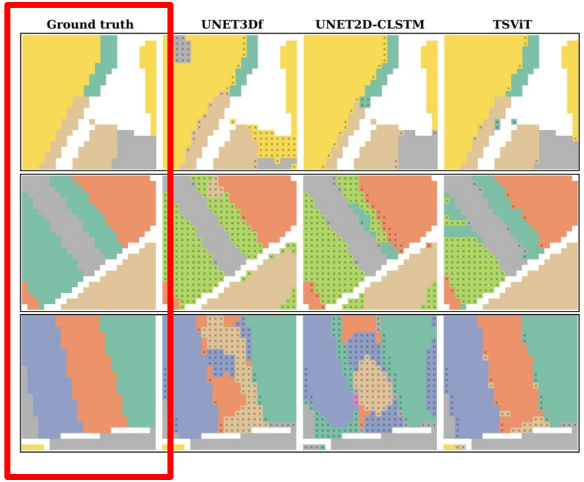
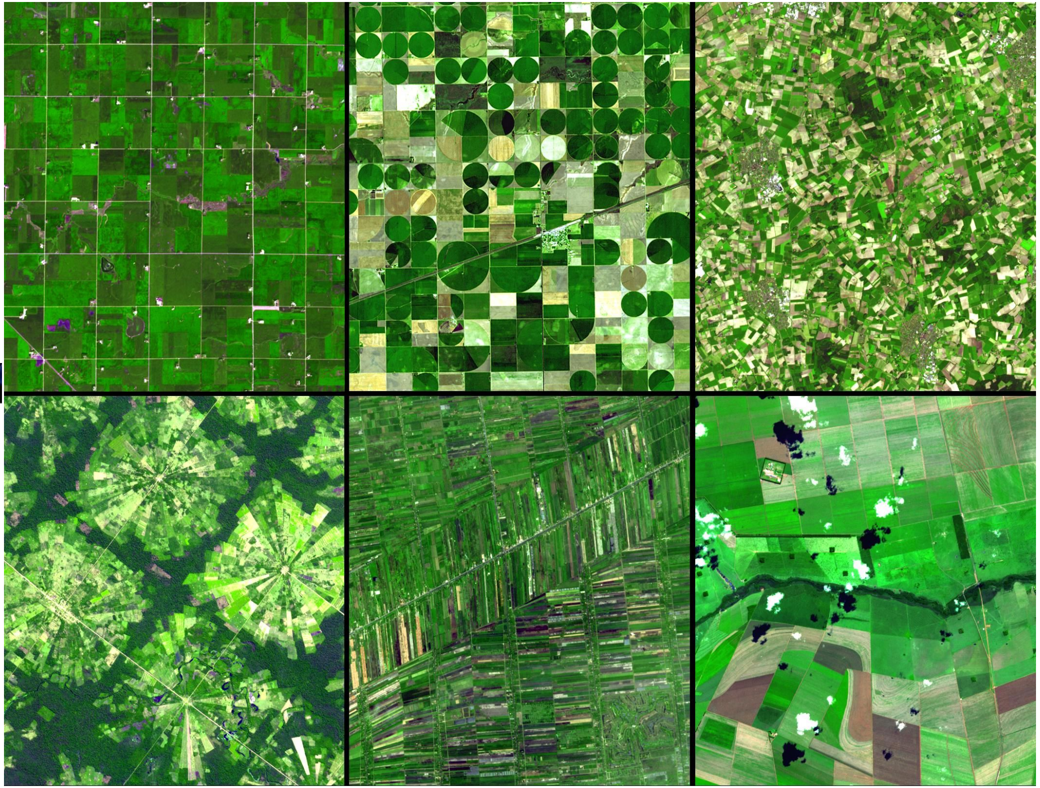


Figure 5. **Visualization of predictions** in Germany. The background class is shown in black, "x" indicates a false prediction.

Tarasiou, M., Chavez, E., & Zafeiriou, S. (2023). ViTS for SITS: Vision transformers for satellite image time series. CVPR.

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Benchmark datasets over-idealized and not representative of real world
- Spatial and temporal generalization difficult



Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Benchmark datasets over-idealized and not representative of real world
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking

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*.

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

Challenges for AI + agriculture

- Labeled/ground-truth data sparse and difficult/expensive to acquire
- Benchmark datasets over-idealized and not representative of real world
- Spatial and temporal generalization difficult
- Lack of open data and code for reproducibility, re-use, and benchmarking
- End-user uptake, communication, deployment, and sustainability takes significant time, effort, and $$

Challenges for AI + agriculture

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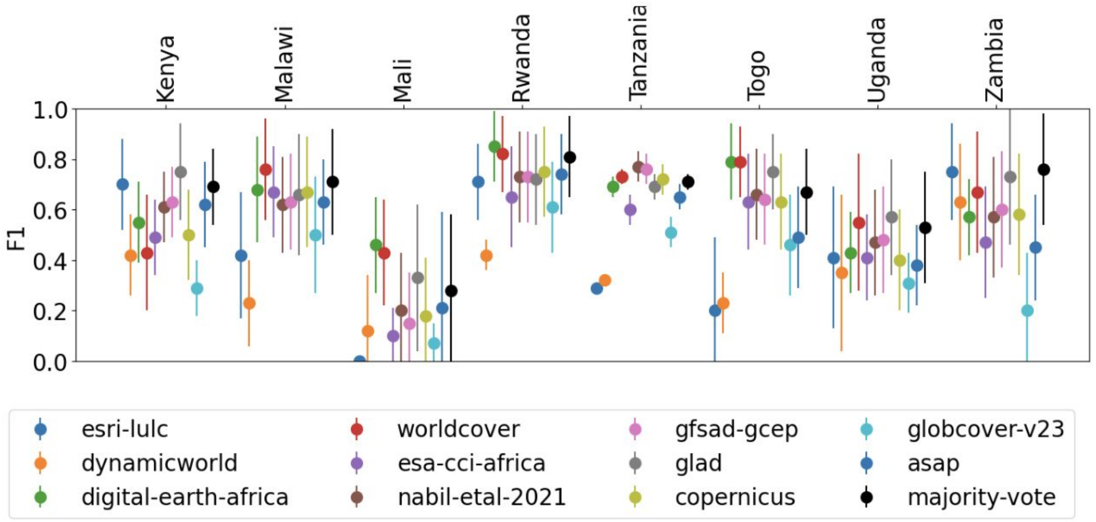
- End-user uptake, communication, deployment, and sustainability takes significant time, effort, and $$
- Lower performance and investment in data-sparse regions (e.g., sub-saharan africa)



Kerner et al. (2024). How accurate are existing land cover maps for agriculture in Sub-Saharan Africa? *Nature Scientific Data.*

Ready to get started?

🌽 CropHarvest dataset

https://github.com/nasaharvest/cropharvest

🧠 CVPR 2022 tutorial

https://nasaharvest.github.io/cvpr2022.html

🛰️ CVPR 2022 tutorial

https://appliedsciences.nasa.gov/what-we-do/capacity-building/arset/arset-agriculture-trainings