# Earth Observations and Machine Learning for Agriculture Monitoring for Food Security in Africa

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Innovate UK
KTN

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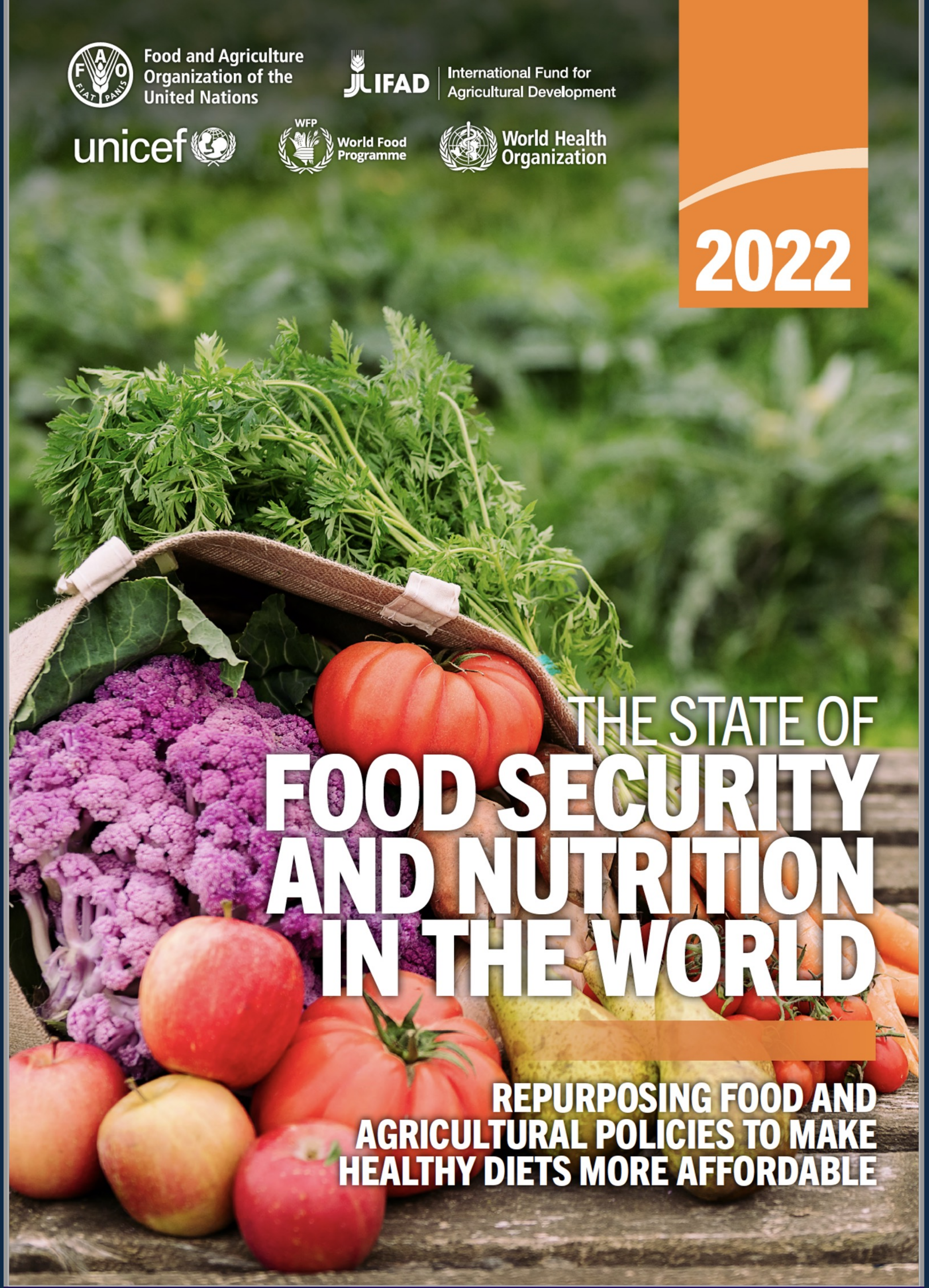
GEOGLAM Global Agricultural Monitoring


AVAILABILITY
ACCESS
UTILISATION
STABILITY
FOOD SECURITY
"Exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life"

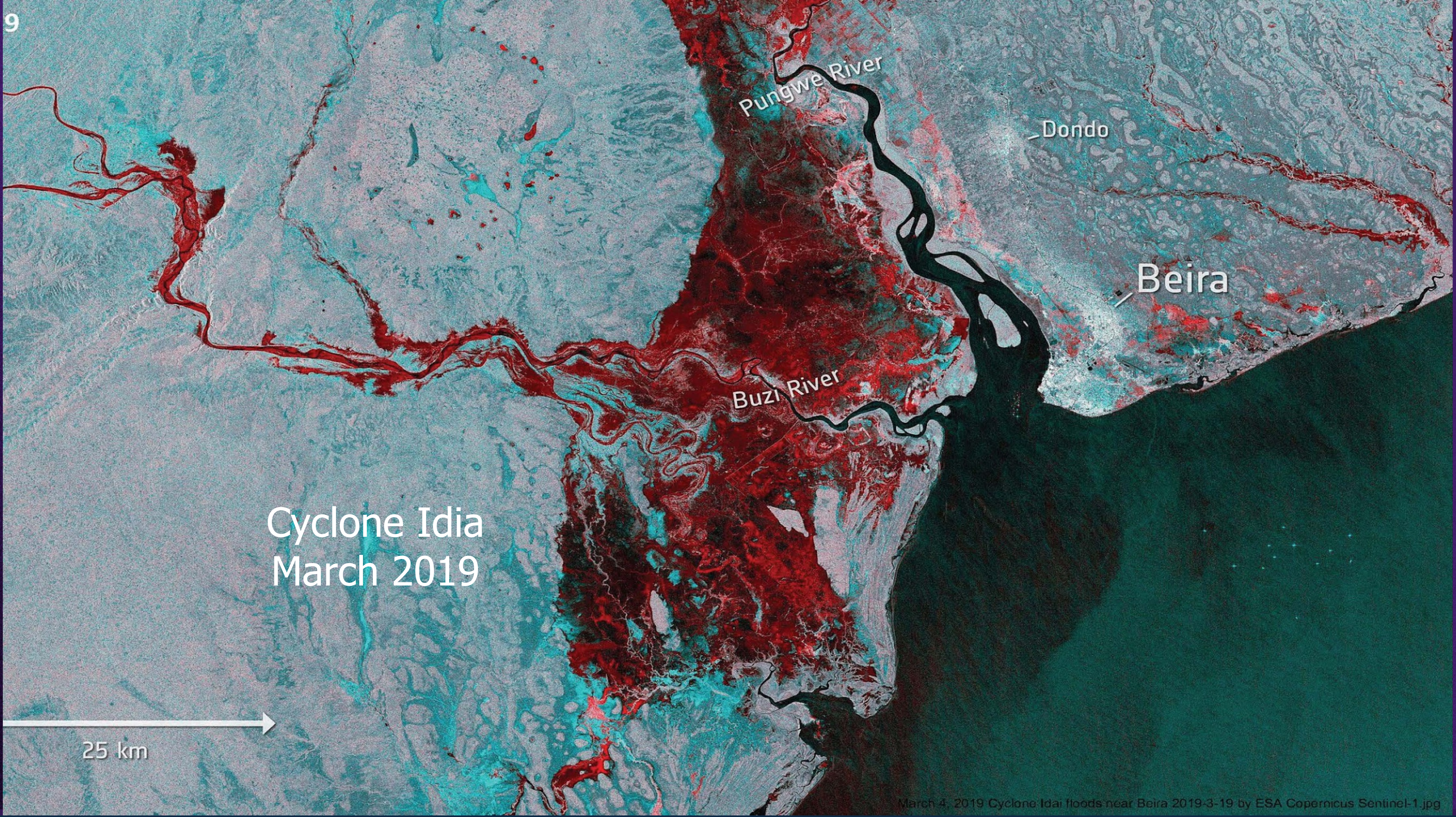


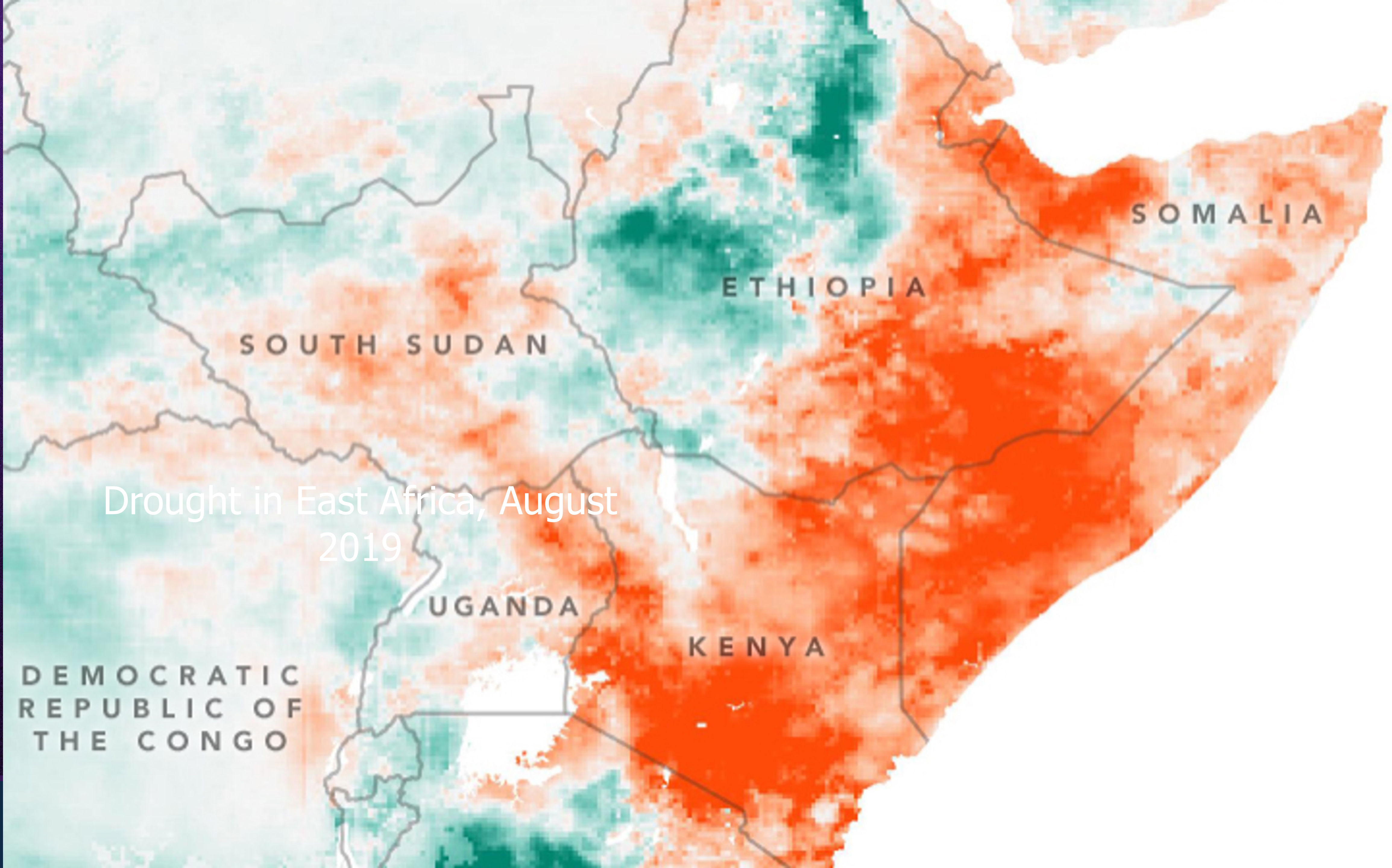

# 702 and 828 million people were affected by hunger in 2021

Projections are that nearly 670 million people will still be facing hunger in 2030 – 8 percent of the world population, which is the same as in 2015 when the 2030 Agenda was launched

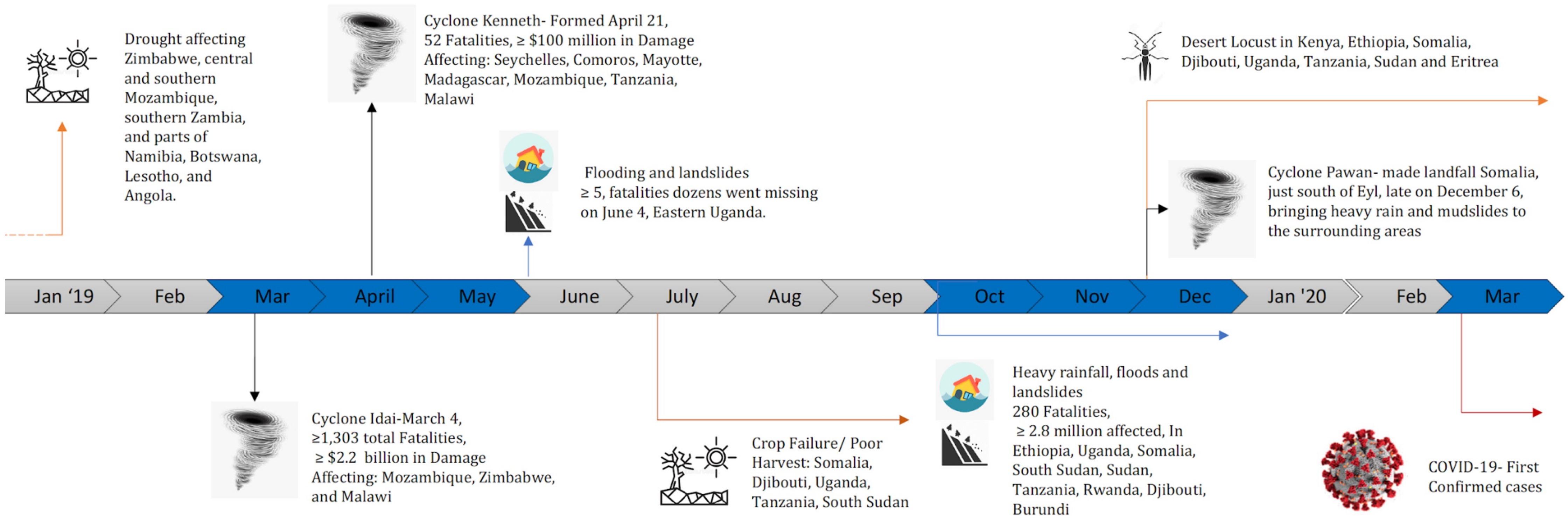
# SDG-2 (Zero Hunger)- further away

- With Covid-19
- More conflict
- More refugees
- More disasters


Pungwe River
Dondo
Beira
Buzi River
Cyclone Idia
March 2019
25 km
March 4, 2019 Cyclone Idai floods near Beira 2019-3-19 by ESA Copernicus Sentinel-1.jpg




Drought in East Africa, August 2019


Drought affecting Zimbabwe, central and southern Mozambique, southern Zambia, and parts of Namibia, Botswana, Lesotho, and Angola.
Cyclone Kenneth- Formed April 21, 52 Fatalities, ≥ $100 million in Damage Affecting: Seychelles, Comoros, Mayotte, Madagascar, Mozambique, Tanzania, Malawi
Flooding and landslides ≥ 5, fatalities dozens went missing on June 4, Eastern Uganda.
Desert Locust in Kenya, Ethiopia, Somalia, Djibouti, Uganda, Tanzania, Sudan and Eritrea
Cyclone Pawan- made landfall Somalia, just south of Eyl, late on December 6, bringing heavy rain and mudslides to the surrounding areas
Jan '19
Feb
Mar
April
May
June
July
Aug
Sep
Oct
Nov
Dec
Jan '20
Feb
Mar
Cyclone Idai-March 4, ≥1,303 total Fatalities, ≥ $2.2 billion in Damage Affecting: Mozambique, Zimbabwe, and Malawi
Crop Failure/ Poor Harvest: Somalia, Djibouti, Uganda, Tanzania, South Sudan
Heavy rainfall, floods and landslides 280 Fatalities, ≥ 2.8 million affected, In Ethiopia, Uganda, Somalia, South Sudan, Sudan, Tanzania, Rwanda, Djibouti, Burundi
COVID-19- First Confirmed cases

# There are thousands of satellites observing our Earth

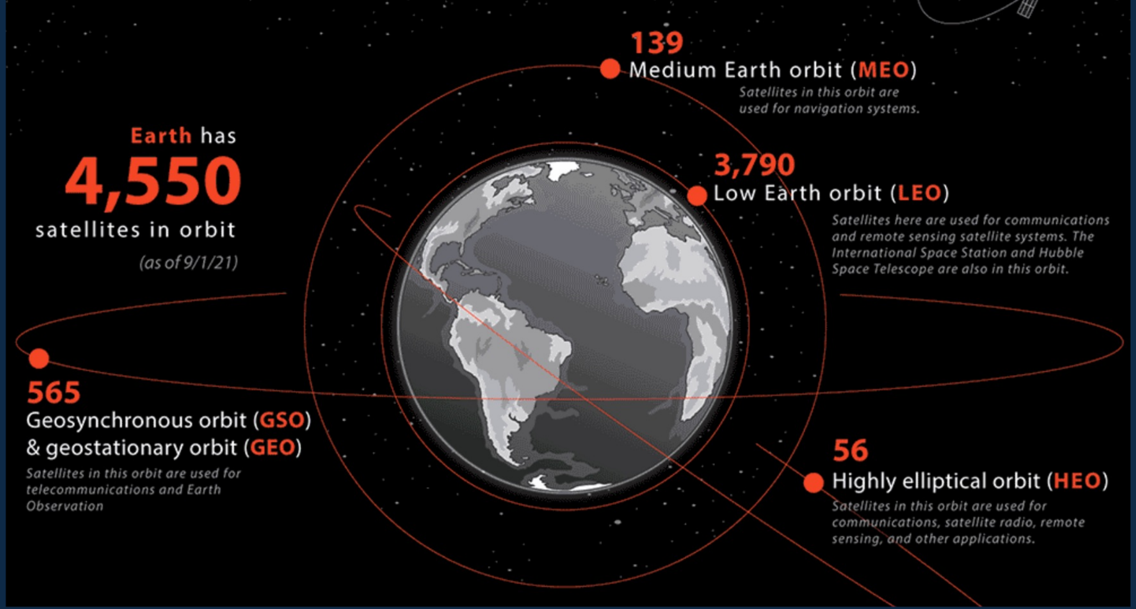
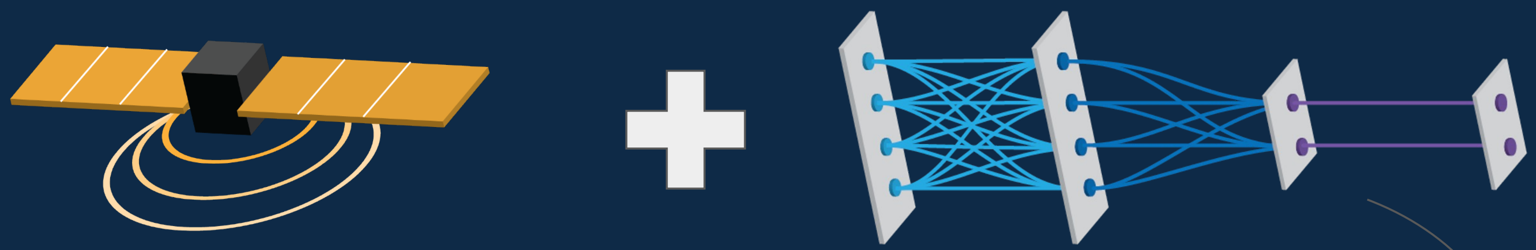



Image Credit: dewesoft.com & European Space Agency/SPL

# A New Era



# Data…models………………………………. Impact

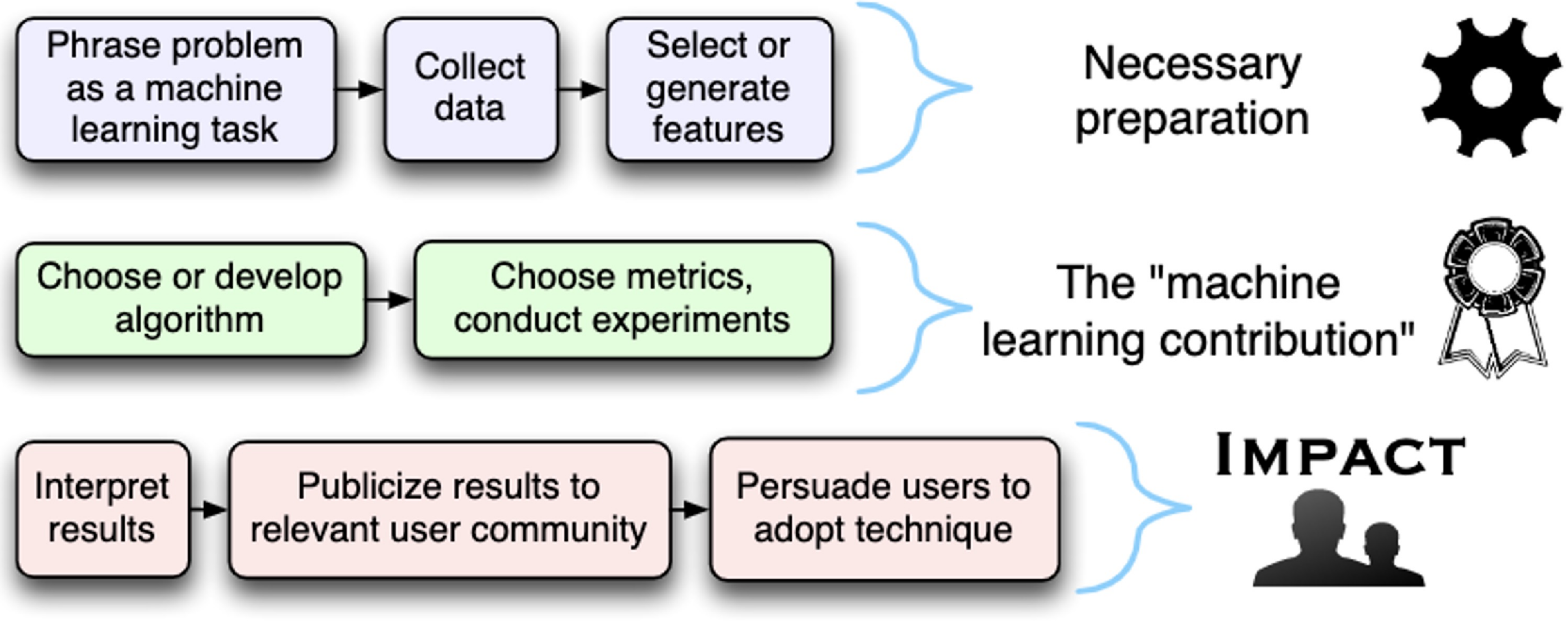


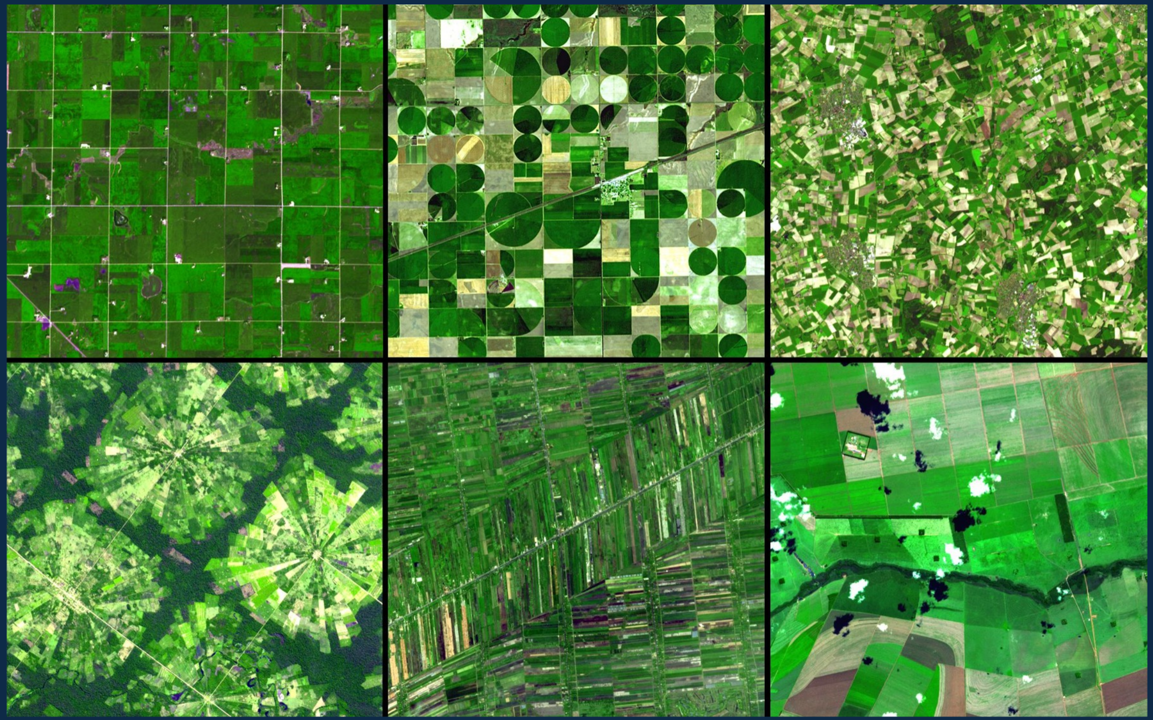

Fig. Stages of a machine learning research program

Wagstaff, K., 2012. Machine learning that matters. arXiv preprint arXiv:1206.4656.

NASA Harvest

NASA's Food Security and Agriculture Program, led by University of Maryland

Goal: enable and advance the adoption of satellite Earth observations to benefit food security, agriculture, and human and environmental resiliency

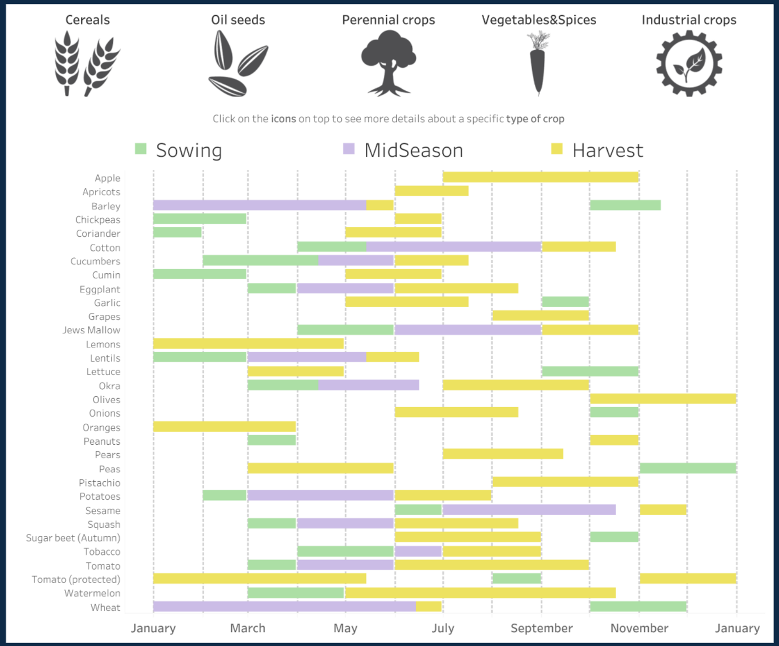


**NASA's Contribution to** GEOGLAM Global Agricultural Monitoring

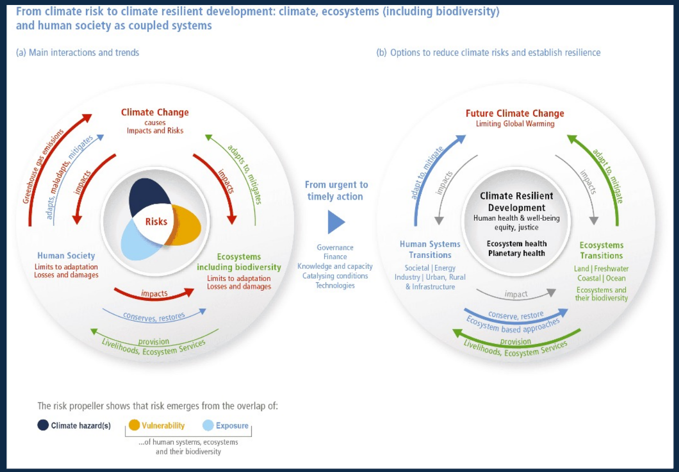
https://www.nasaharvest.org/

# Some things **farmers** and **policy makers** need 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




Syria crop calendar by type of crop. Source FAO

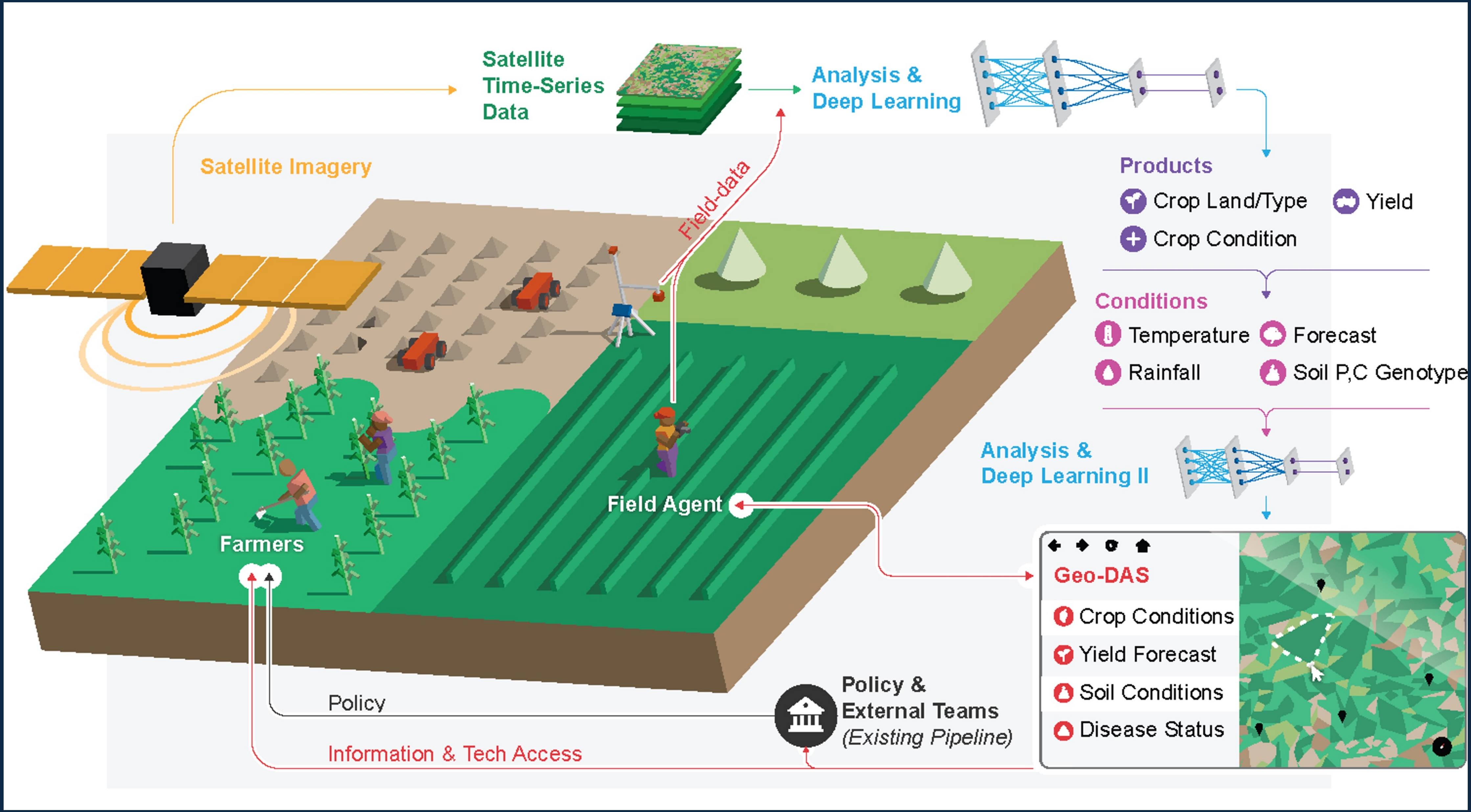



Source: IPCC Sixth Assessment Report

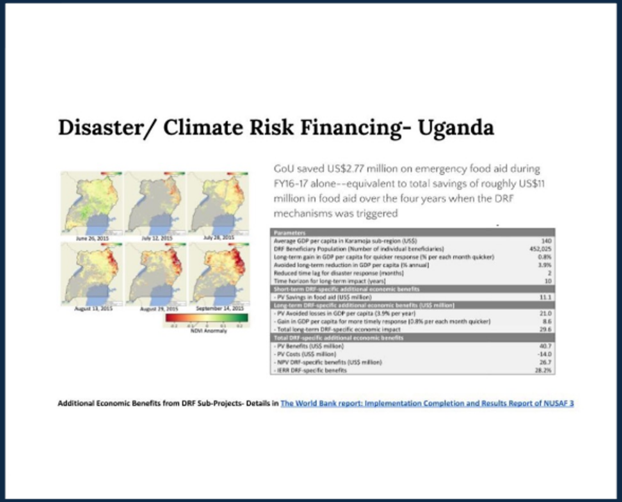
# NASA Harvest Africa Program Priorities

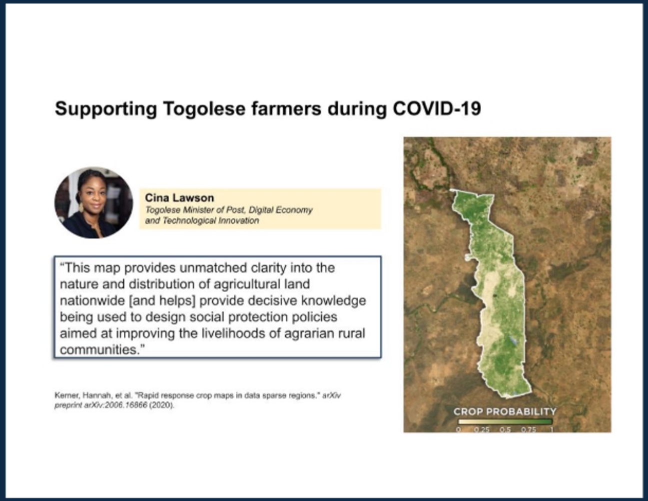
1. Improve and leverage monitoring and early warning **systems** that provide actionable data and information on agricultural productivity and food security at multiple scales,
2. Advancing **EO-AI methods** that underpin the data and systems,
3. Developing and transferring **capacity** to national and local users that influence decision making, and
4. Developing strong long-term **partnerships**.

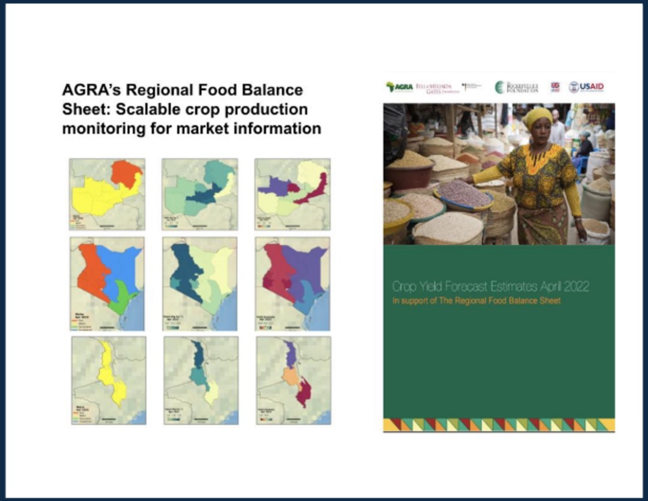
Nakalembe C., Justice, C.J., Kerner, H., Justice, C.O., & Inbal Becker-Reshef. Sowing Seeds Food Security in Africa From Space. EOS Science News by AGU, 21 February 2021

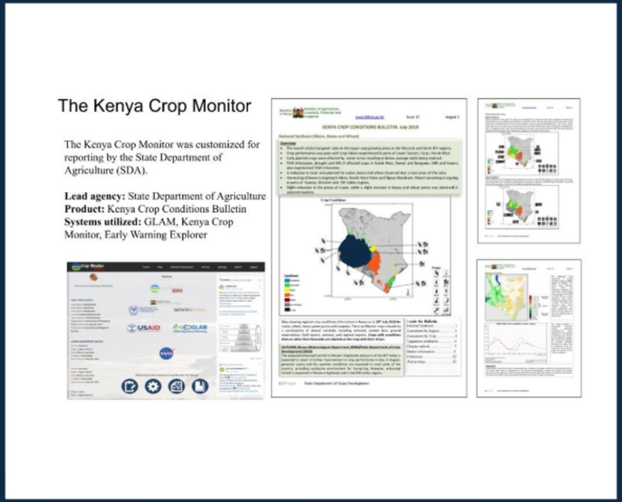


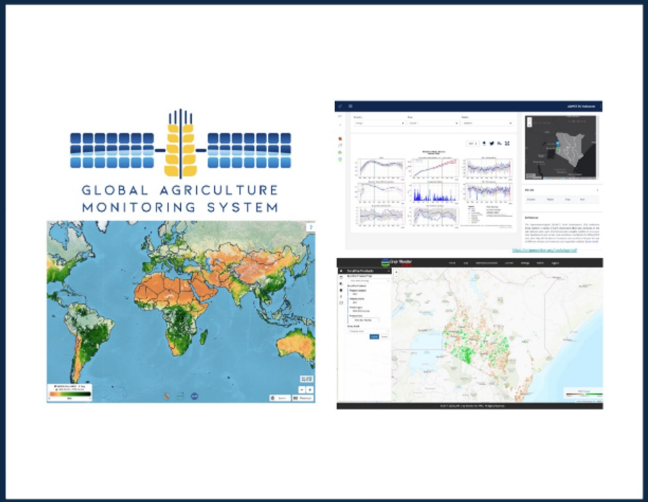
Satellite Time-Series Data
Analysis & Deep Learning
Satellite Imagery
Field-data
Products
Crop Land/Type
Yield
Crop Condition
Conditions
Temperature
Forecast
Rainfall
Soil P,C Genotype
Analysis & Deep Learning II
Field Agent
Farmers
Geo-DAS
Crop Conditions
Yield Forecast
Soil Conditions
Disease Status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

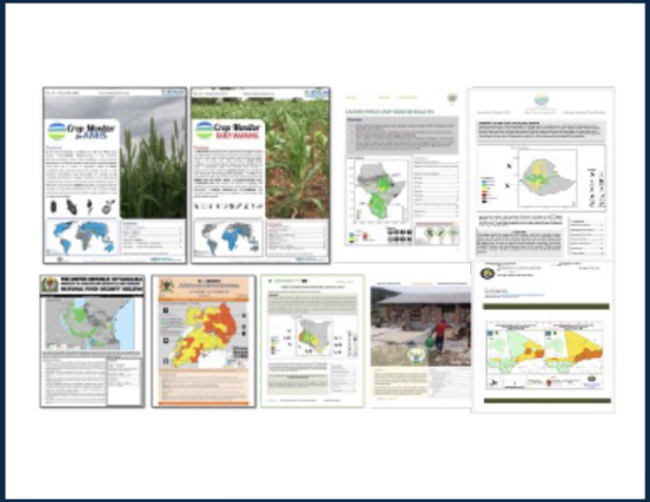

Disaster/ Climate Risk Financing- Uganda
June 26, 2015
July 12, 2015
July 28, 2015
August 13, 2015
August 29, 2015
September 14, 2015
NDVI Anomaly
GoU saved US$2.77 million on emergency food aid during FY16-17 alone--equivalent to total savings of roughly US$11 million in food aid over the four years when the DRF mechanisms was triggered
Parameters
Average GDP per capita in Karamoja sub-region (US$) 140
DRF Beneficiary Population (Number of individual beneficiaries) 452,025
Long-term gain in GDP per capita for quicker response (% per each month quicker) 0.8%
Avoided long-term reduction in GDP per capita (% annual) 3.9%
Reduced time lag for disaster response (months) 2
Time horizon for long-term impact (years) 10
Short-term DRF-specific additional economic benefits
- PV Savings in food aid (US$ million) 11.1
Long-term DRF-specific additional economic benefits (US$ million)
- PV Avoided losses in GDP per capita (3.9% per year) 21.0
- Gain in GDP per capita for more timely response (0.8% per each month quicker) 8.6
- Total long-term DRF-specific economic impact 29.6
Total DRF-specific additional economic benefits
- PV Benefits (US$ million) 40.7
- PV Costs (US$ million) -14.0
- NPV DRF-specific benefits (US$ million) 26.7
- IERR DRF-specific benefits 28.2%
Additional Economic Benefits from DRF Sub-Projects- Details in The World Bank report: Implementation Completion and Results Report of NUSAF 3


Supporting Togolese farmers during COVID-19
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."
Kerner, Hannah, et al. "Rapid response crop maps in data sparse regions." arXiv preprint arXiv:2006.16866 (2020).
CROP PROBABILITY

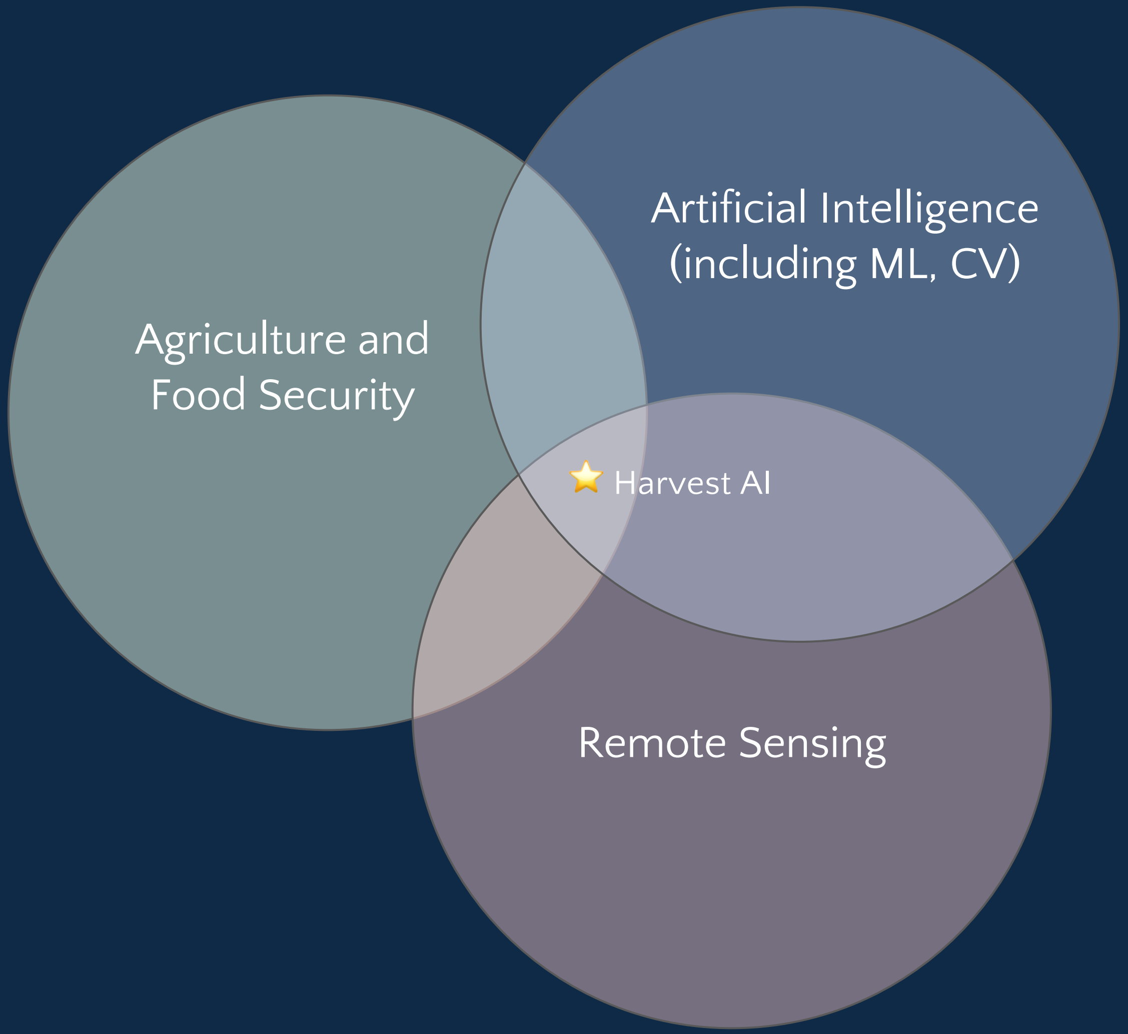

AGRA's Regional Food Balance Sheet: Scalable crop production monitoring for market information
USAID
Crop Yield Forecast Estimates April 2022
In support of The Regional Food Balance Sheet


The Kenya Crop Monitor
The Kenya Crop Monitor was customized for reporting by the State Department of Agriculture (SDA).
Lead agency: State Department of Agriculture
Product: Kenya Crop Conditions Bulletin
Systems utilized: GLAM, Kenya Crop Monitor, Early Warning Explorer
KENYA CROP CONDITIONS BULLETIN: July 2018
USAID


GLOBAL AGRICULTURE MONITORING SYSTEM



# AI for Remote Sensing & Agriculture




Crop mapping → Binary classification

Crop type mapping → Multi-class classification

Field boundary delineation → Segmentation

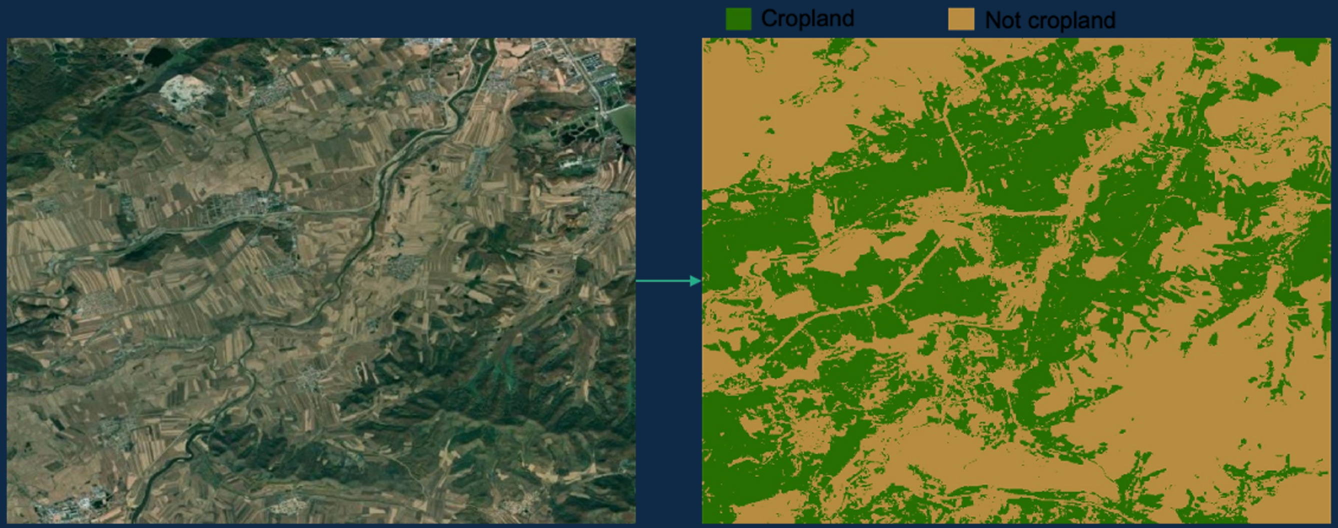
Yield estimation → Regression

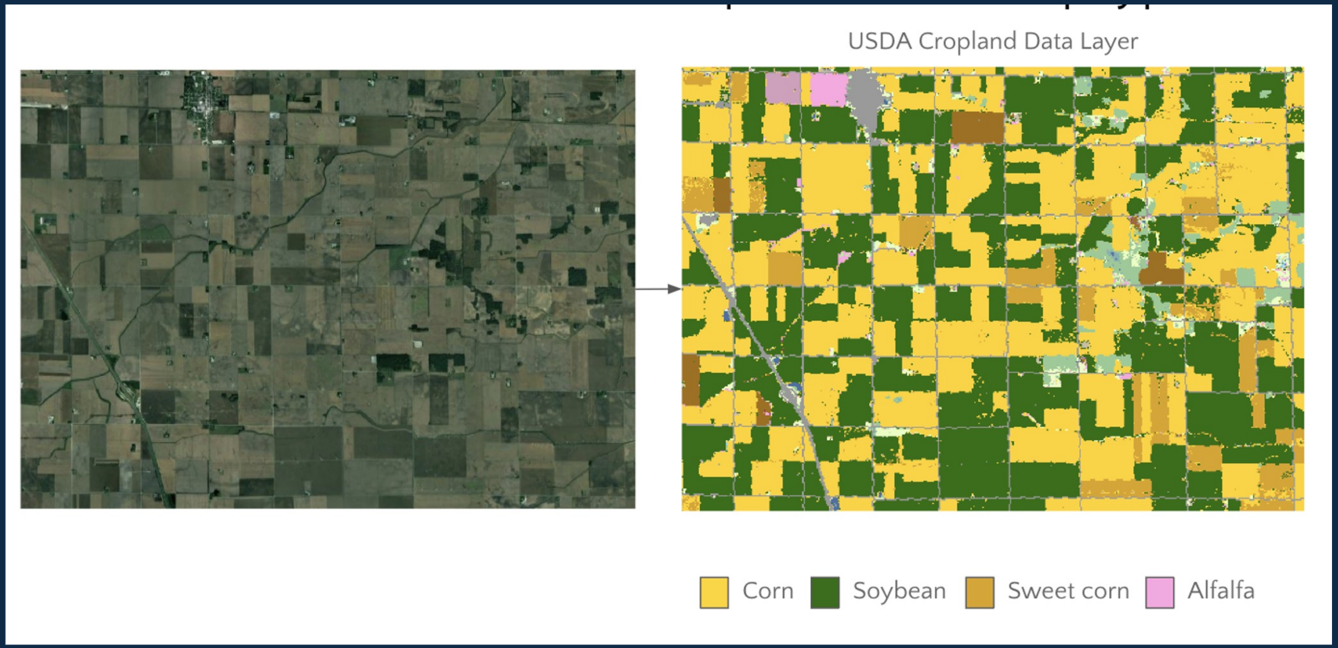
Pest and disease detection → OOD detection

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

Credit- @Kerner, ML Lead NASA Harvest

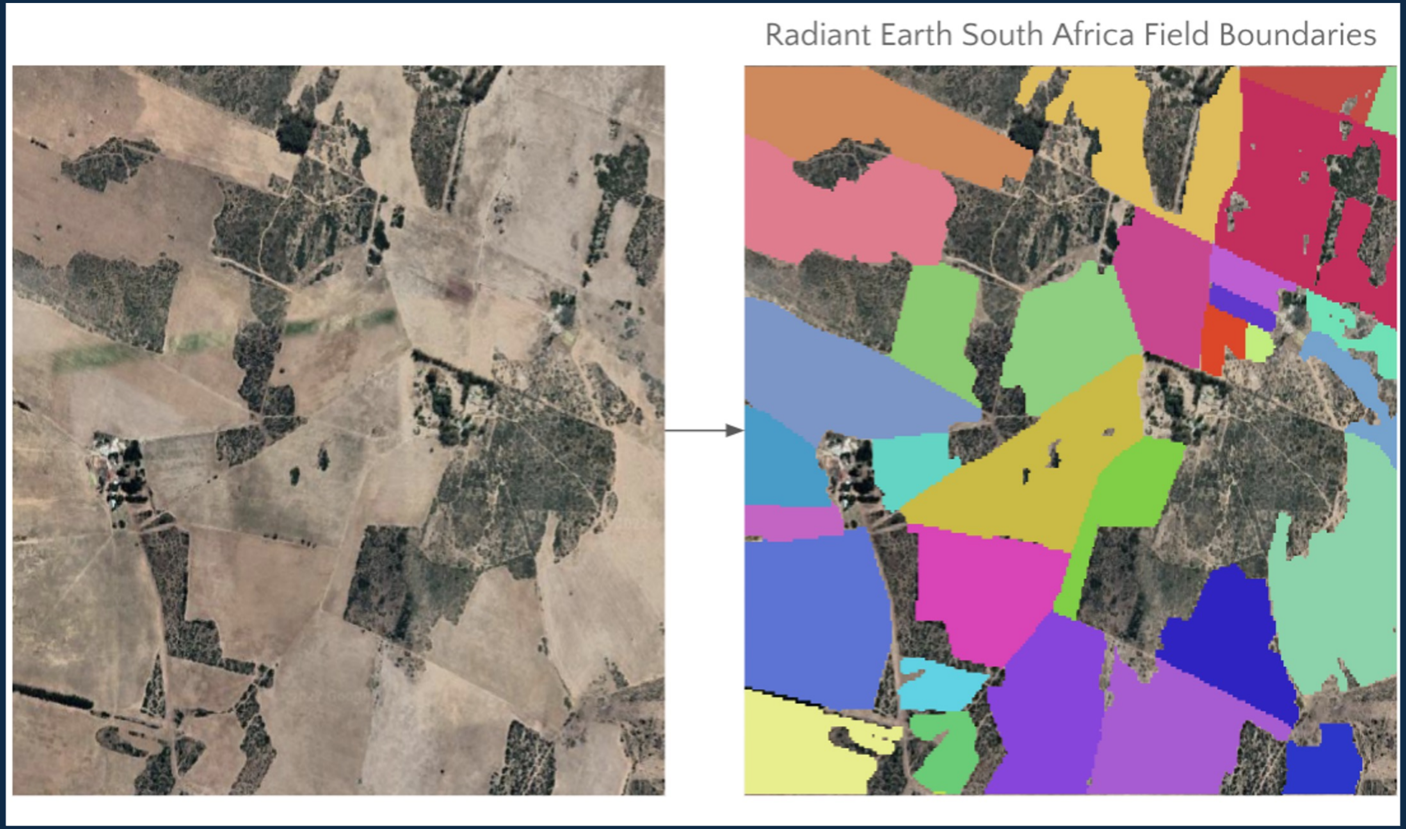
# **Cropland and** Crop-type **mapping**




**Use example:** Agricultural statistics, input to yield forecasting, conditions monitoring, risk financing

**Field boundary delineation** /Segmentation of individual field/parcel boundaries

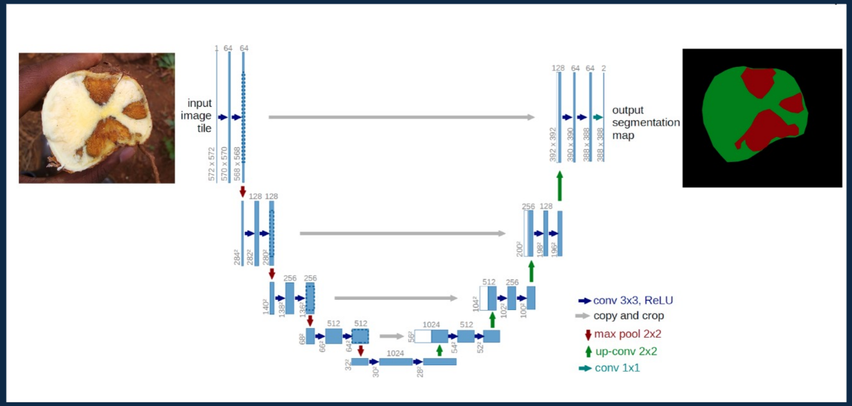


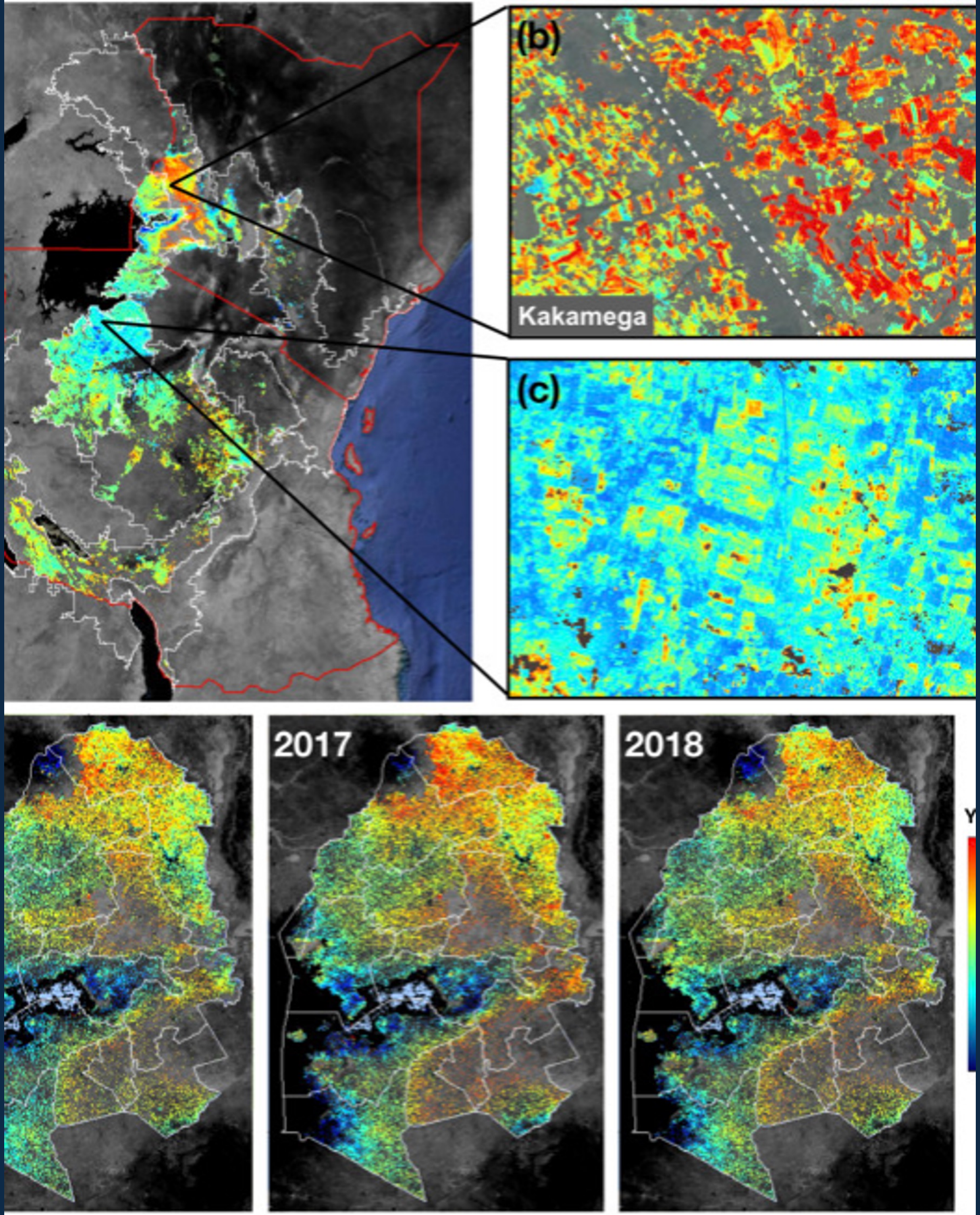

**Use example:** Area estimation, monitoring cropping practices, crop insurance

# Pest, disease, and hotspot detection

**Use example:** Early detection, effective control

**Example**
**Top: Scoring root necrosis in cassava using semantic segmentation (**Tusubira et. al, 2020), **Bottom:** Deep learning models for plant disease detection and diagnosis→ Banana with Black sigatoka (Ferentinos, 2018)



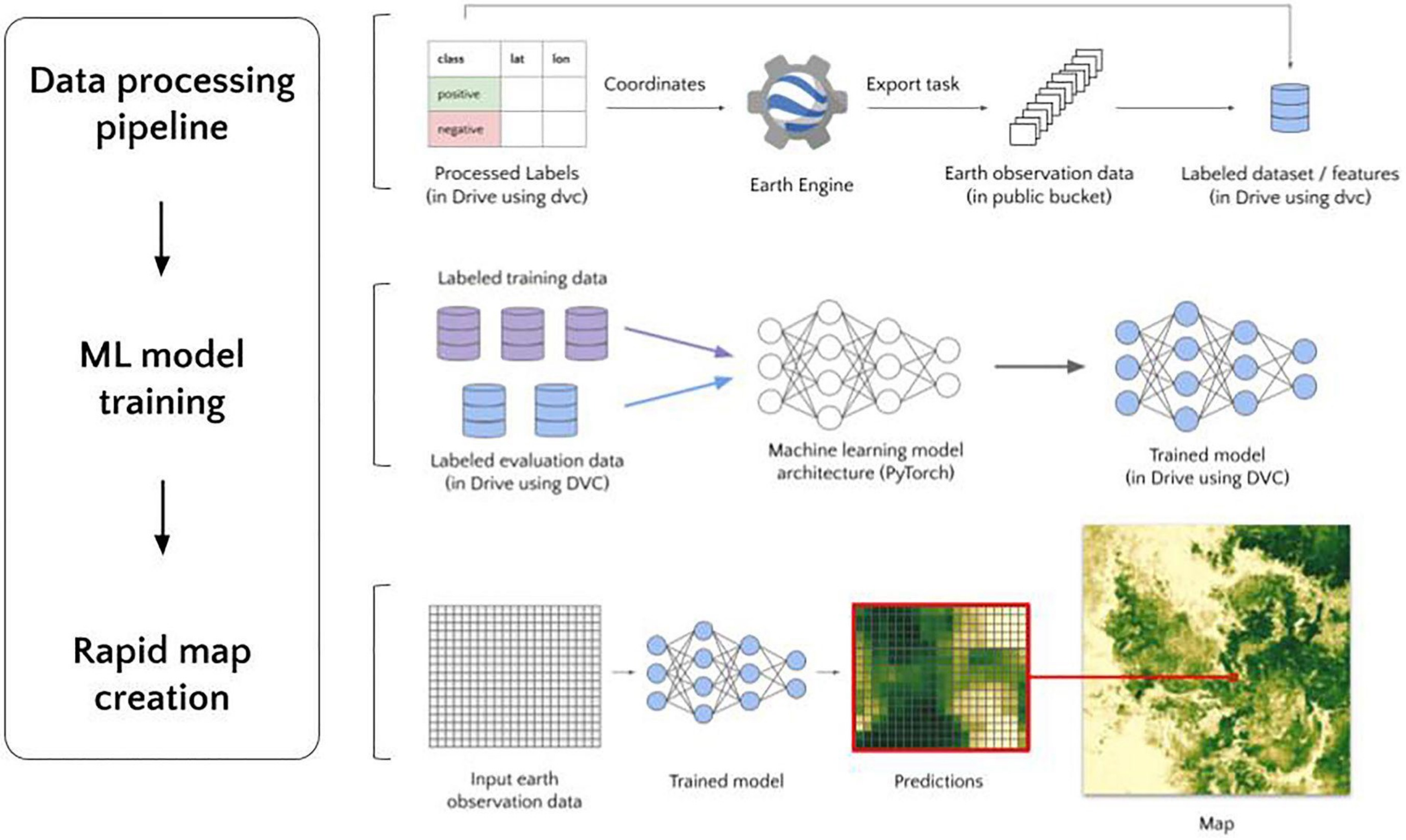




# Yield estimation

Example: maize yield estimation for smallholder fields in Kenya and Tanzania using crop simulation + statistical regression model (Jin et al., 2019)

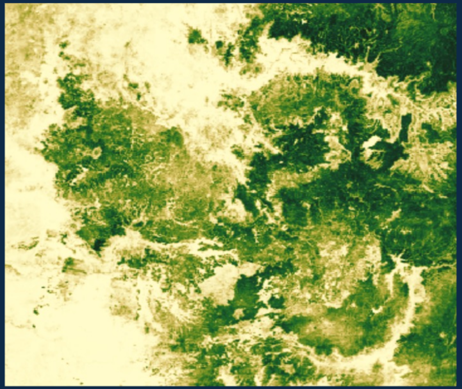
**Use example:** Market monitoring, early warning, crop insurance, policy

# OpenMapFlow 🌍

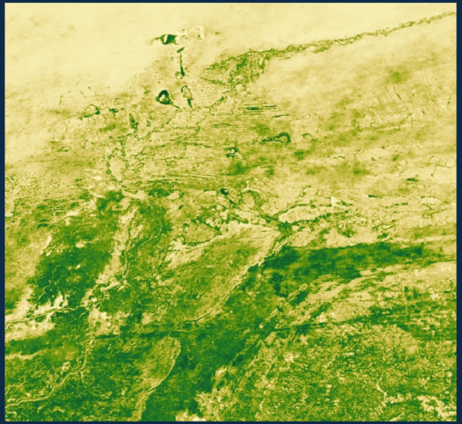



Training + getting started https://nasaharvest.github.io/rcmrd2022
GitHub-nasaharvest/openmapflow https://github.com/nasaharvest/openmapflow

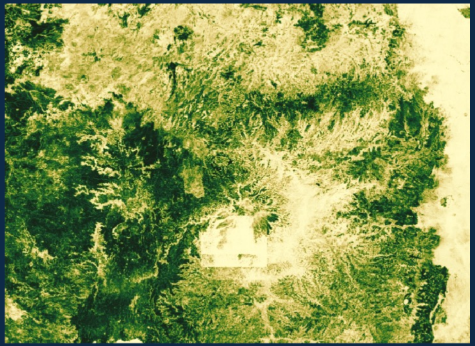
# Results



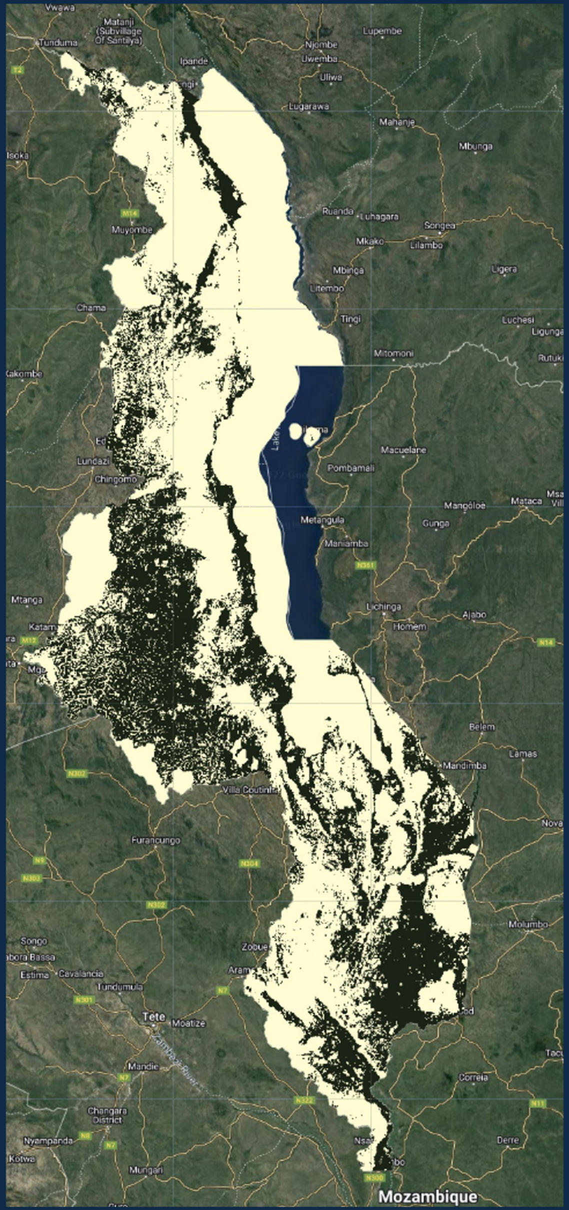
Ethiopia
Bure Jimma
2020



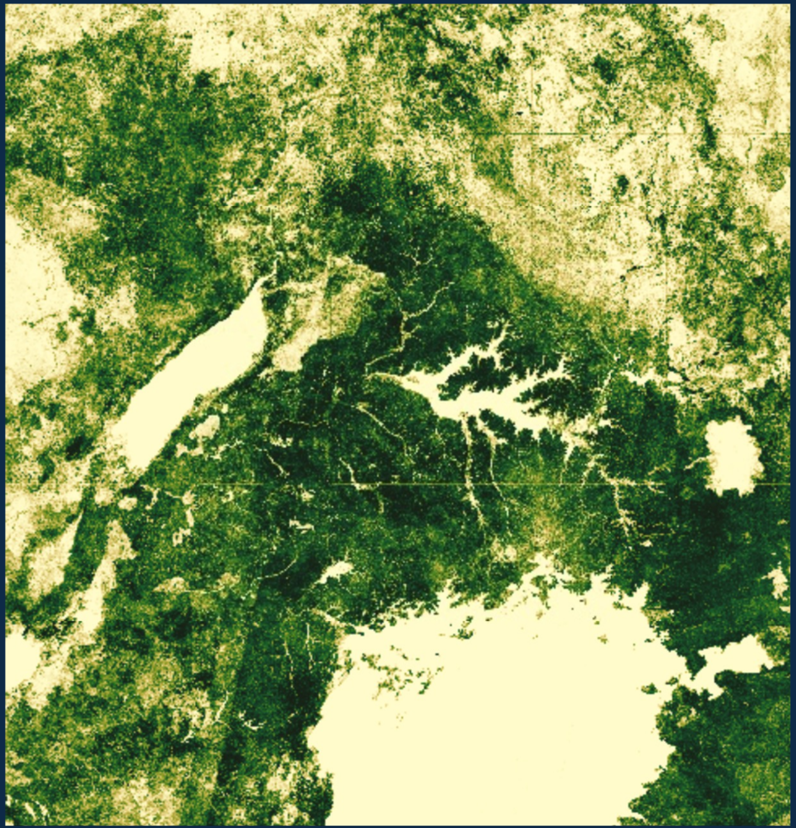
North
Mali
2019



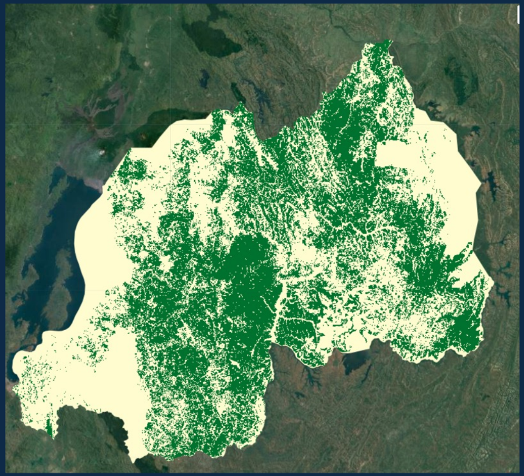
Ethiopia
Tigray
2021




Malawi 2021



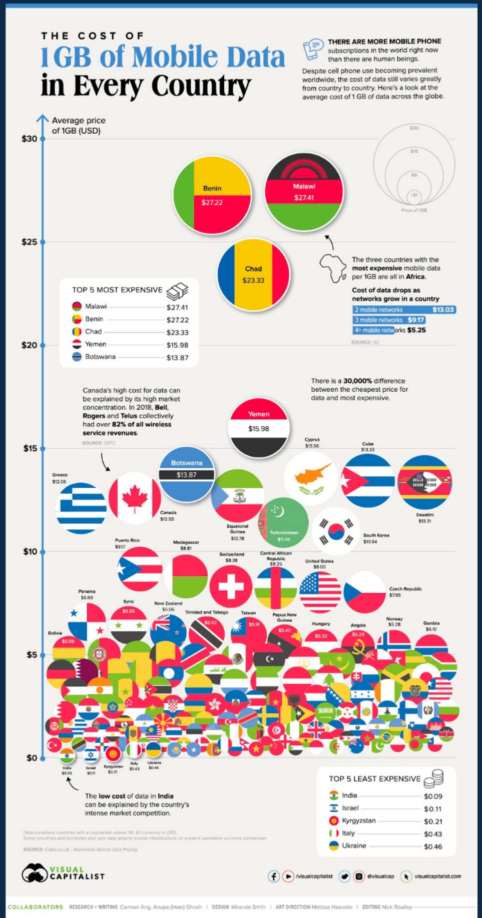
Uganda 2019



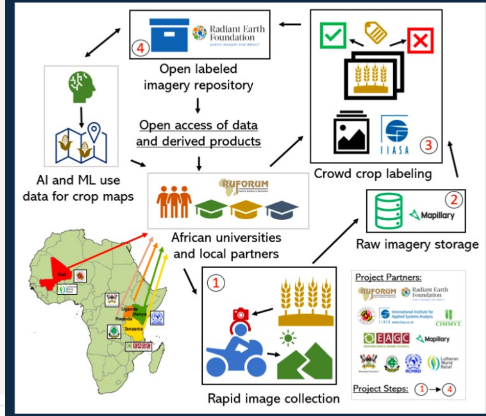
Rwanda
2019

# Considerations AI-EO 4 Ag

1. Interdisciplinary teams are a requirement
2. Consider the resource context of stakeholders
3. Work with stakeholders from the beginning
4. Limited labeled/ training data
5. Technified ≠ better
6. Decolonize research methods and practices
7. Meaningful partnerships with local institutions
8. Institutionalized investments → sustainable solutions
9. High-resolution imagery needs to be accessible
10. Assess and communicate limitations of AI-EO solutions








Nakalembe, Catherine, and Hannah Kerner. "Considerations for AI-EO for agriculture in Sub-Saharan Africa." Environmental Research Letters 18.4 (2023): 041002.

# Thank you!

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