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

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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) is further away:

- With Covid-19
- More conflict
- More refugees
- More disasters
Cyclone Idia
March 2019
Drought in East Africa, August 2019
There are thousands of satellites observing our Earth.

Image Credit: dewesoft.com & European Space Agency/SPL
Fig. Stages of a machine learning research program

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

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.
AI for Remote Sensing & Agriculture

Agriculture and Food Security

Artificial Intelligence (including ML, CV)

Remote Sensing

⭐ Harvest AI

**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

Data processing pipeline

ML model training

Rapid map creation

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

Thank you!

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