

## Earth Observations for Humanitarian Applications

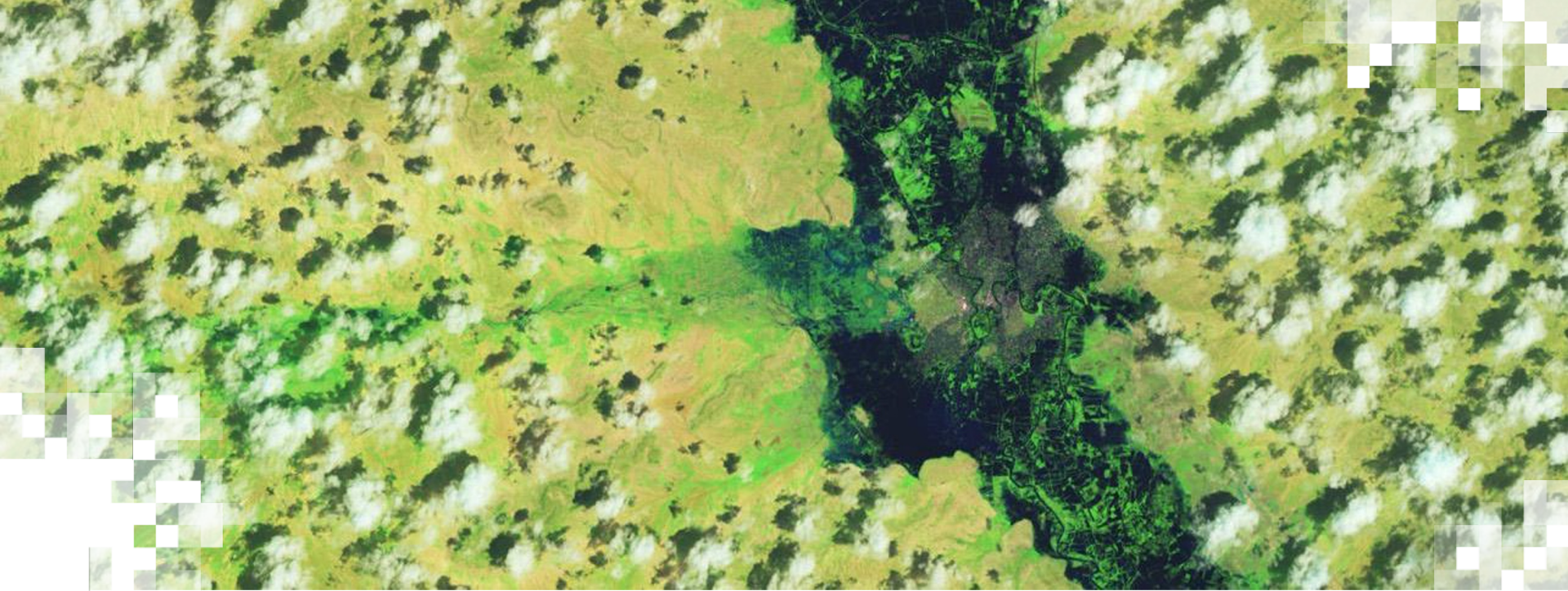
### Part 3: Tracking Drought Effects on Agricultural Landscapes in Refugee Settings

Sitian Xiong (Clark University), Jamon Van Den Hoek (Oregon State University), & Lyndon Estes (Clark University)

June 20, 2024







# Earth Observations for Humanitarian Applications

## **Overview**

## Motivation for Training

- More than 114 million individuals have been forcibly displaced worldwide as a result of persecution, conflict, violence or human rights violations ([UNHCR](#)).
- Refugees, internally displaced people (IDPs), and other displaced populations are made more vulnerable to climate change impacts due to their socio-political marginalization.
- Recent Earth observation (EO)-driven research that recognizes this has made progress towards characterizing the manner and magnitude of climate-related risks in humanitarian (refugee and IDP) settings.



In the outskirts of Thata in Pakistan, women displaced by the 2010 flooding line up to fetch water.  
Credit: [Asian Development Bank](#)



# Training Learning Objectives

By the end of this training, participants will be able to:

- Recognize the importance of measuring flood risk, long-term heat stress, and drought effects in refugee and IDP communities around the world.
- Apply workflows incorporating Earth observations, geospatial, and demographic data to identify localized climate risk in refugee and IDP settings.
- Discuss decision making strategies for mapping and managing climate conditions with risks faced by refugee and IDP communities.
- Summarize opportunities and shortcomings of specific Earth observations and geospatial datasets for climate risk and development indicators in humanitarian settings.





# Prerequisites

- [Monitoring and Modeling Floods using Earth Observations](#)
- [Satellite Remote Sensing for Measuring Urban Heat Islands and Constructing Heat Vulnerability Indices](#)
- [Satellite Remote Sensing for Agricultural Applications](#)
- [Humanitarian Applications Using NASA Earth Observations](#)



## Part 3 Prerequisites

**Google Earth Engine (GEE):** Understand account management, authentication, using the code editor (JavaScript and Python API), recognizing computation and memory limits, and have some experience in using GEE. [GEE Authentication](#) [GEE Python API Doc](#)

**Colab Environment:** Understand file management (e.g., upload a file) and how to mount and access Google Drive if necessary.

**Python:** Basic Python knowledge, familiarity with popular scientific computing and visualization libraries (e.g., NumPy, Pandas, Scikit-learn, Matplotlib), and troubleshooting skills.

**Remote Sensing:** Understand biophysical remote sensing basics (e.g., Vegetation Index) and commonly used sensors along with their characteristics.

**GIS and Statistics:** Understand commonly used vector and raster data formats, descriptive Statistics, linear regression and scatter plots.



# Training Outline

## Part 1

Assessing Flood  
Risk in Refugee  
Camp Settings

June 6, 2024

## Part 2

Gauging Long-  
Term Heat Stress  
in Refugee  
Settings

June 13, 2024

## Part 3

Tracking Drought  
Effects on  
Agricultural  
Landscapes in  
Refugee Settings

June 20, 2024

## Homework

Opens June 20 – **Due July 5** – Posted on Training Webpage

A certificate of completion will be awarded to those who attend all live sessions and complete the homework assignment(s) before the given due date.



# How to Ask Questions

- Please put your questions in the Questions box and we will address them at the end of the webinar.
- Feel free to enter your questions as we go. We will try to get through all the questions during the Q&A session after the webinar.
- The remainder of the questions will be answered in the Q&A document, which will be posted to the training website about a week after the training.





## Part 3 – Trainers

**Sitian Xiong**

PhD Candidate  
Clark University



**Lyndon Estes**

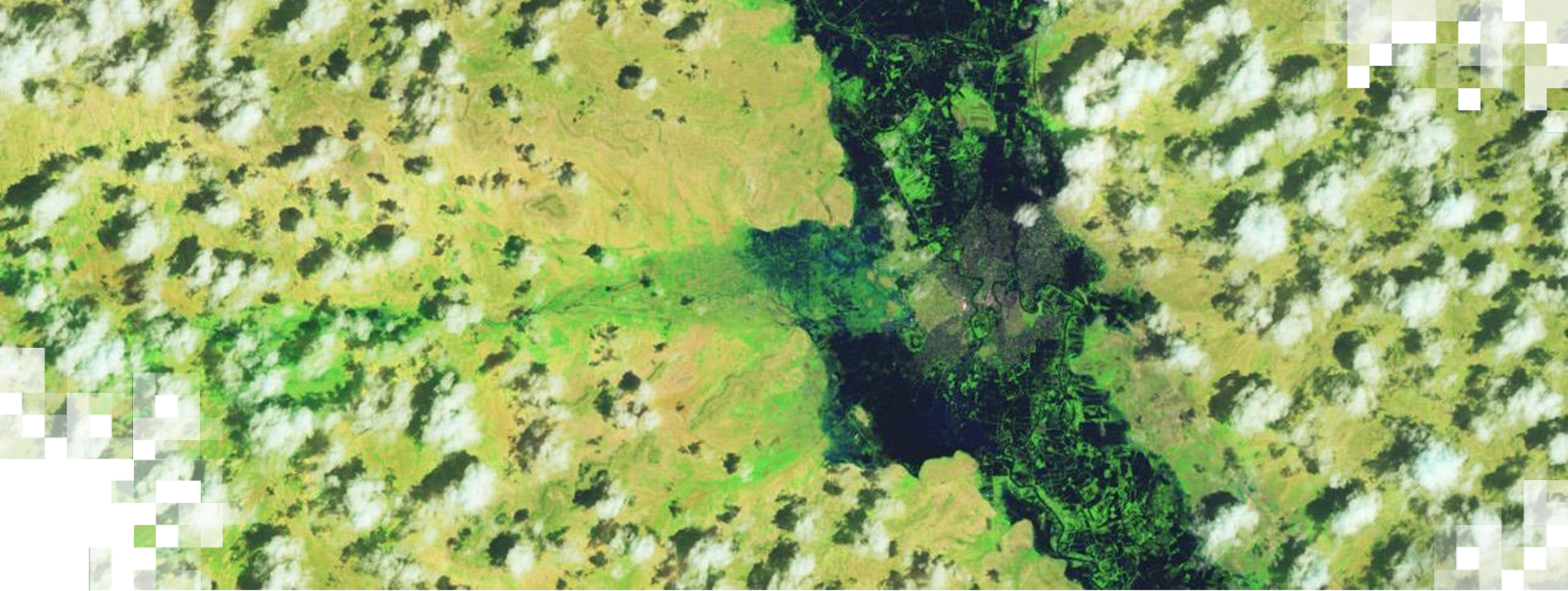
Associate Professor  
Clark University



**Jamon Van Den Hoek**

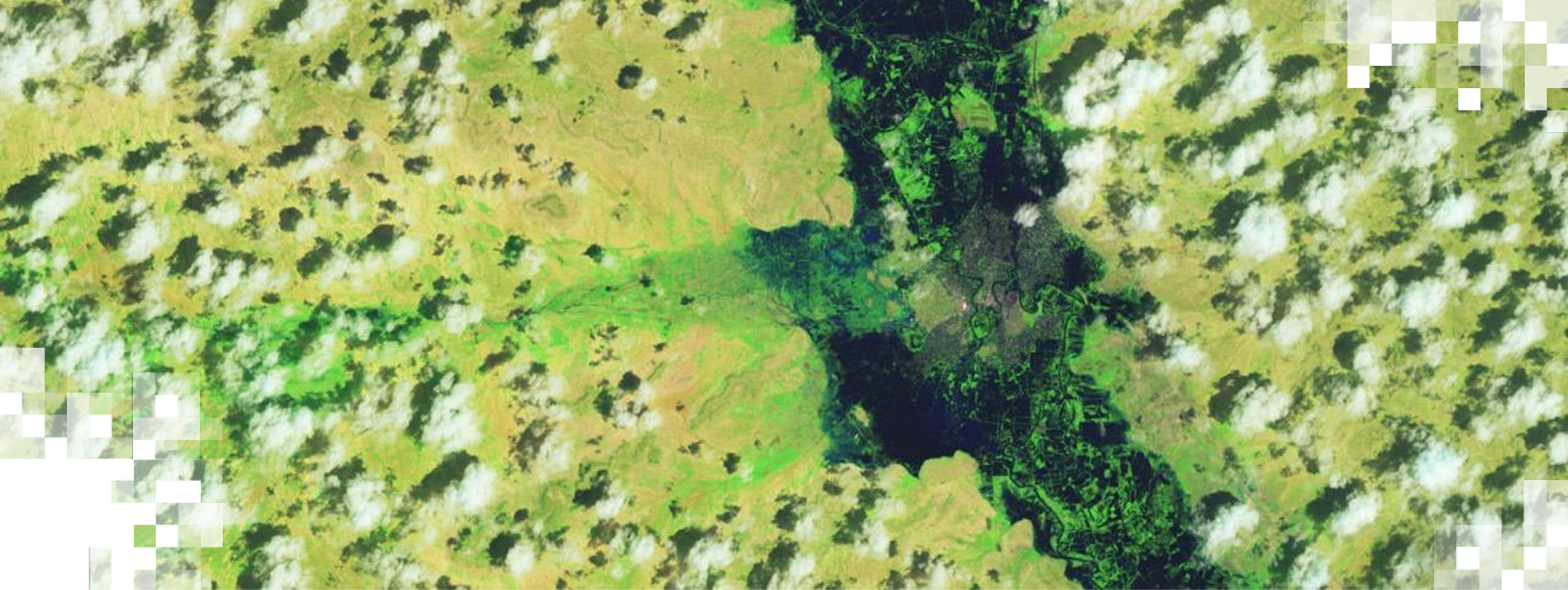
Associate Professor  
Oregon State University





Earth Observations for Humanitarian Applications  
**Part 3: Tracking Drought Effects on Agricultural  
Landscapes in Refugee Settings**

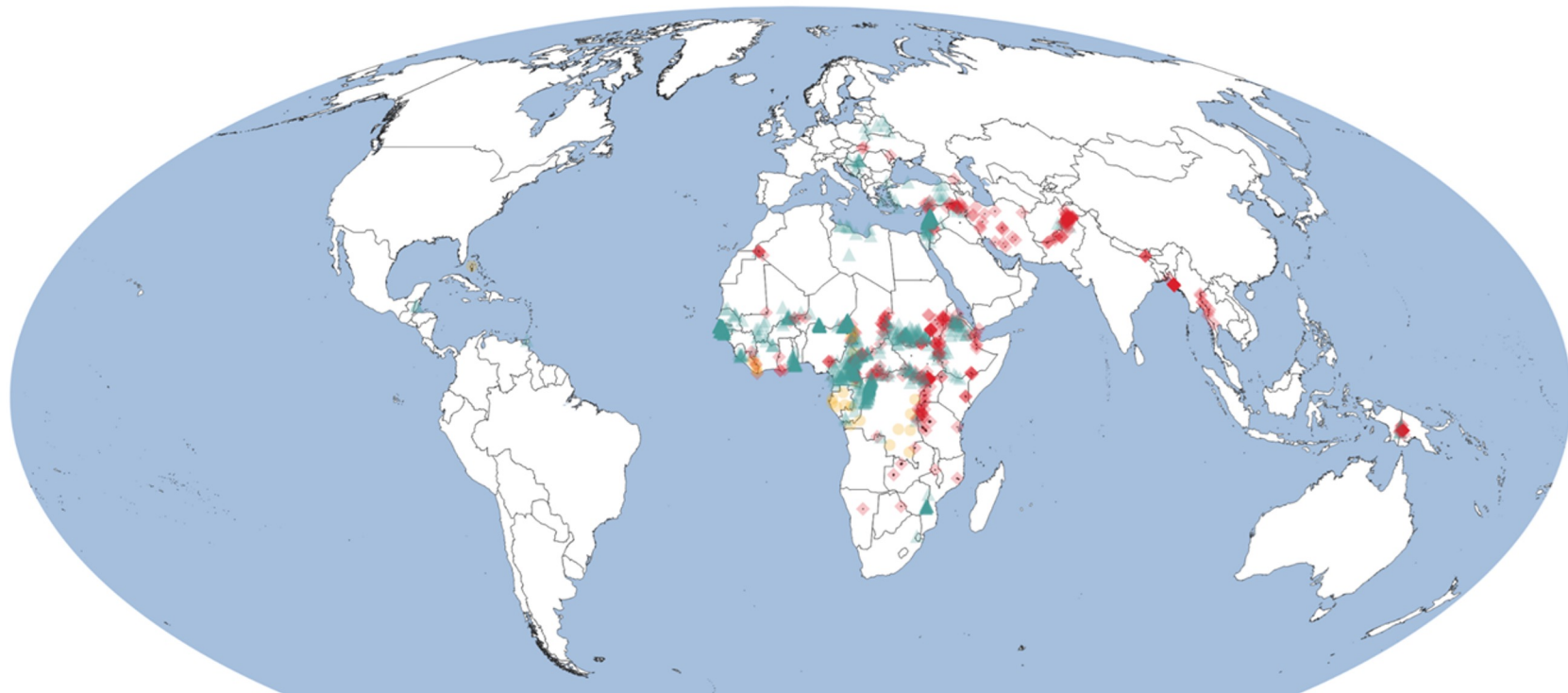




Part 3:  
**Material**

# There are 36.4 million refugees across 132 of the world's 195 countries who have been displaced by violence or persecution.

◆ Planned Settlement (379)    ▲ Spontaneous or Unplanned Settlement (7149)    ● Dispersed Location (27)

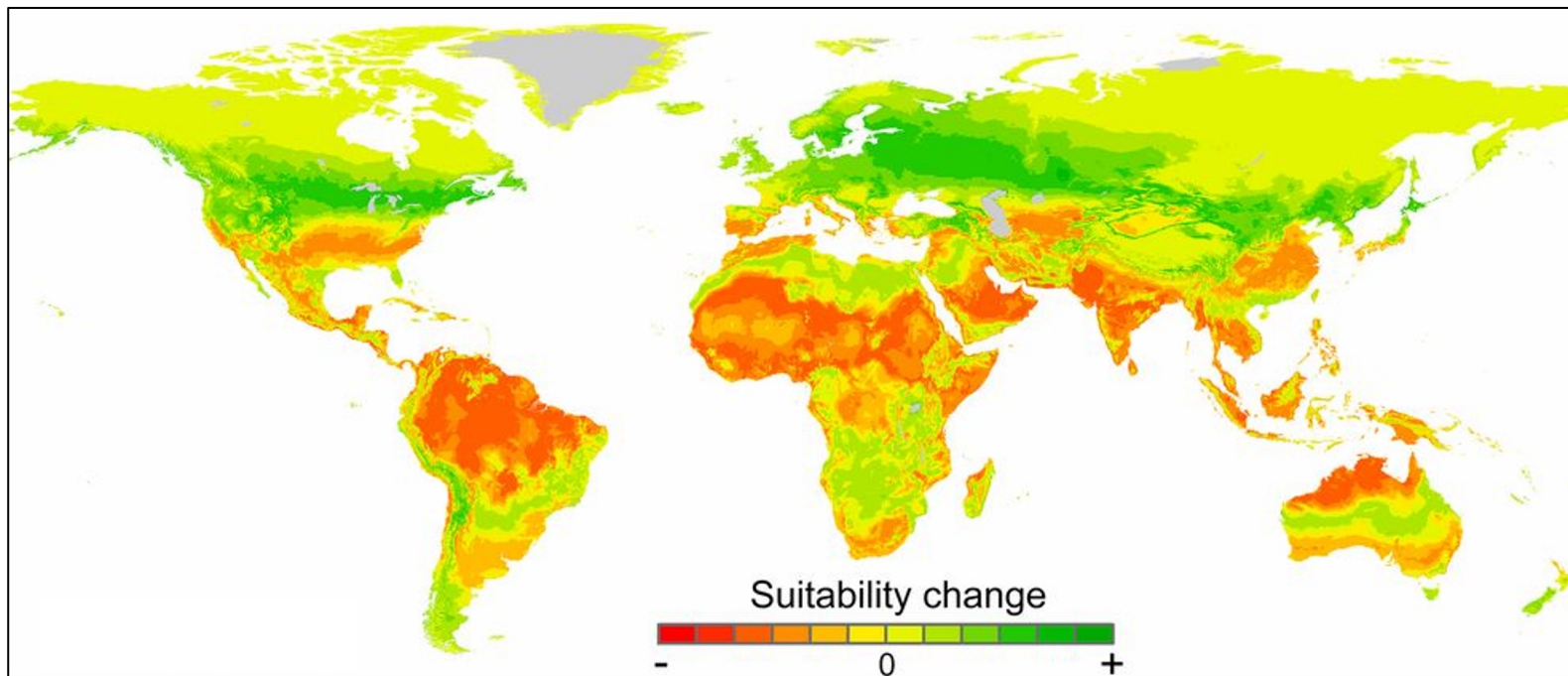


Credit: Van Den Hoek based on [UNHCR data](#)





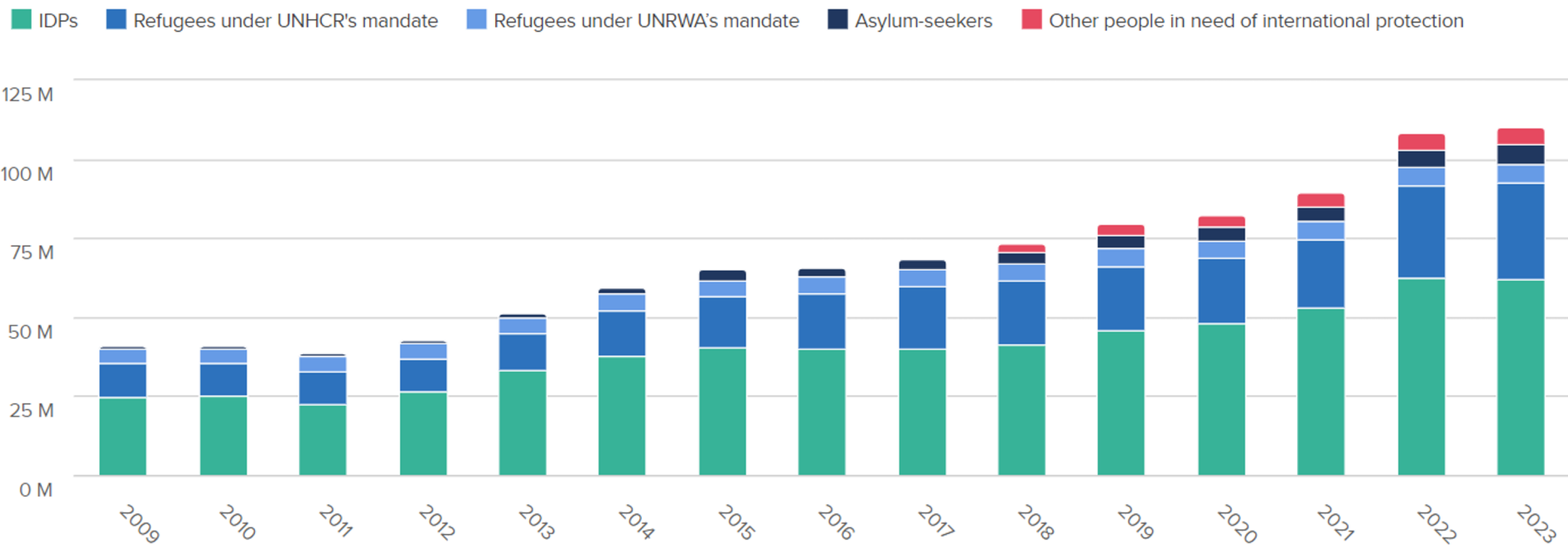
Climate change is expected to broadly make conditions unsuitable (and potentially uninhabitable) for many regions currently hosting refugees.



[Future of the human climate niche](#)



# Refugees made up about one-third of the 108 million people worldwide who were forcibly displaced by mid-2023.



Refugees are international migrants who have been forcibly displaced from their home countries due to violence or persecution and have been granted protection under international law.

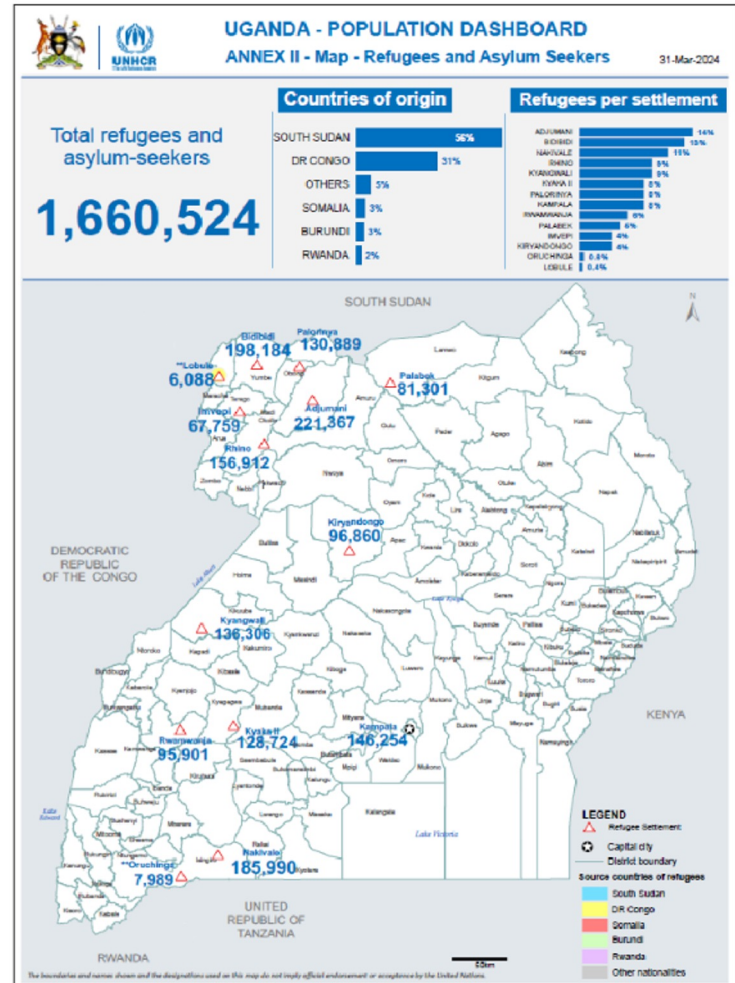
## UNHCR Mid-Year Trends



# Refugee Settlements in Uganda

- Africa's largest refugee host country
  - Supports over 1.5 million people
  - 57% - South Sudan
  - 32% - Democratic Republic of the Congo
- Rural settlements (not “camps”) in the north and west in close proximity to non-refugee host communities
- Refugee Population
  - 51% women and girls
  - 57% children
  - 3% over 60 years old
- Policies promote self-sufficiency and food security
- Droughts reduce access to clean, safe water and increase malnutrition and hunger.

## [UNHCR Uganda Operational Update - March 2024](#)



Uganda has 13 refugee-hosting districts (Adjumani, Isingiro, Kampala, Kamwenge, Kikuube, Kiryandongo, Kyegegwa, Koboko, Lamwo, Madi-Okollo, Obongi, Terego and Yumbe). Refugees are hosted in 13 settlements (Adjumani, Bidiidi, Imvepi, Kiryandongo, Kyaka II, Kyangwali, Lobule, Nakivale, Oruchinga, Palabek, Palorinya, Rhino Camp and Rwamwanja), in addition to the urban refugees in Kampala.

# Refugee farming is central to Uganda's "self-reliance" approach to supporting food security and livelihoods.

- Across Uganda, agriculture is predominantly smallholder and for subsistence farming.
- Nearly 60% of Western and 70% Northern refugee households consume their entire production.
- However, 35% of refugee households primarily rely on food aid to meet basic needs.
- Long term changes in precipitation and temperature are reducing crop yield.
- Future projected climate changes are expected to lead to more extreme events like droughts and floods, which will likely impact crop productivity.

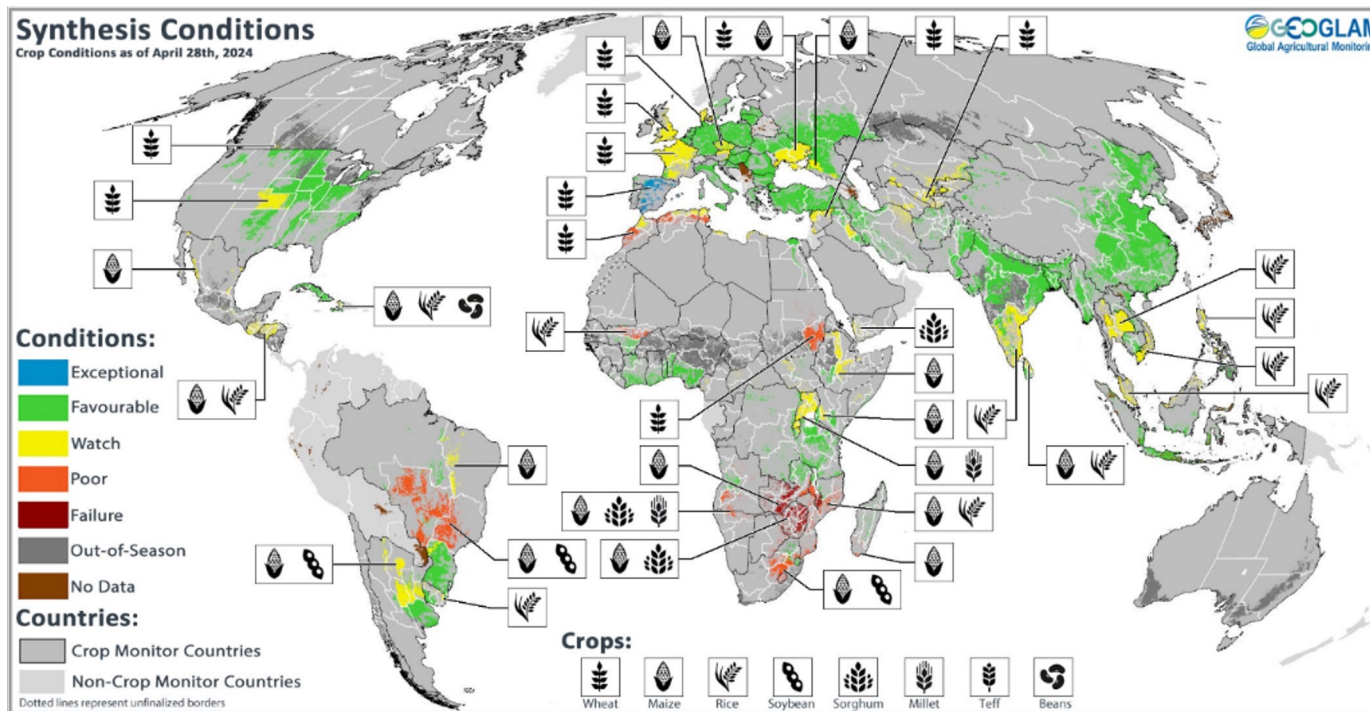


World Potato Congress





# Global Crop Conditions



Source: [GeoGLAM](https://www.geo-glam.org/)

\*GEOGLAM is a collaborative partnership involving governments, international organizations, and NASA, to enhance agricultural information.



# Crop Productivity Monitoring – The Scientific Foundations

Biomass, Leaf Area Index (LAI),  
and Crop Yield

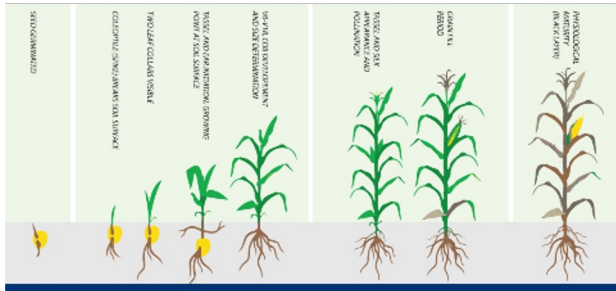
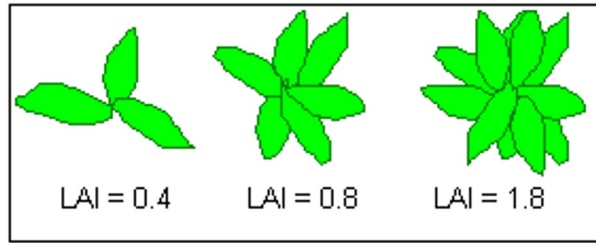


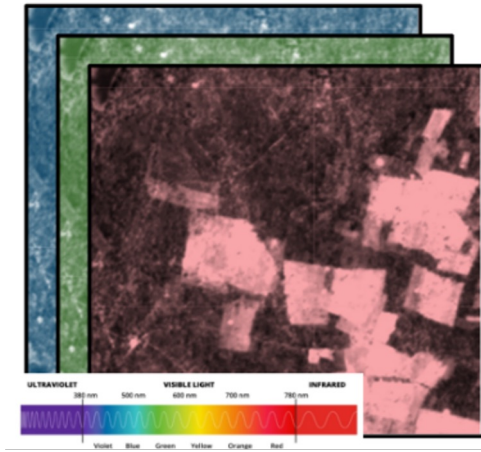
Photo: Michael Cecil

[Image Source for Maize Growing Stages.](#)



# Crop Productivity Monitoring – The Scientific Foundations

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$



Other VIs: [SAVI](#) [EVI](#)

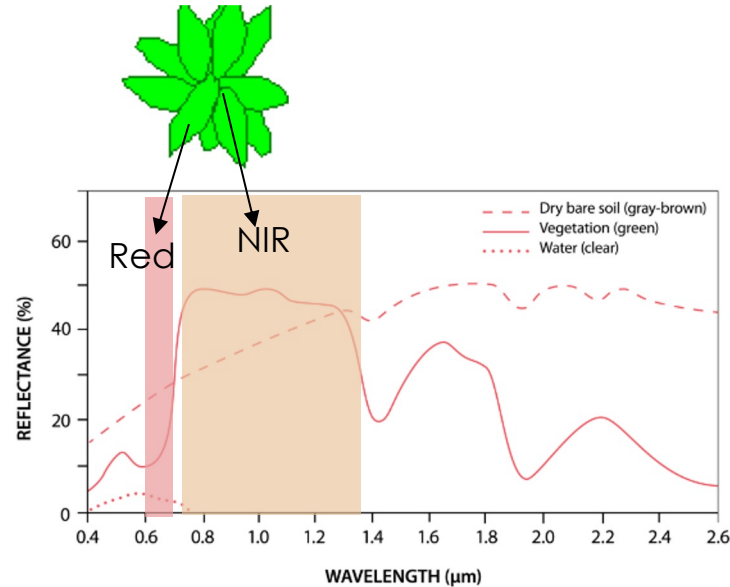
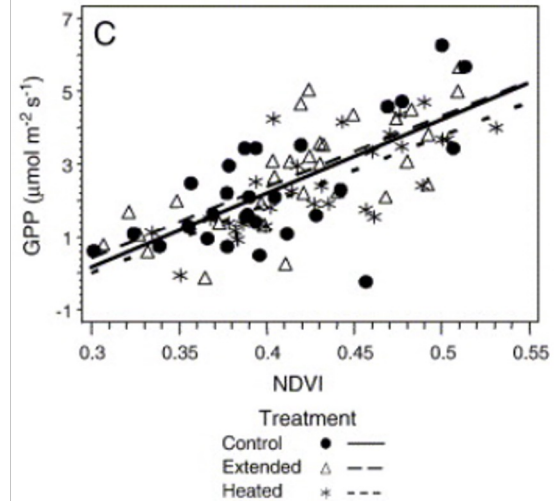


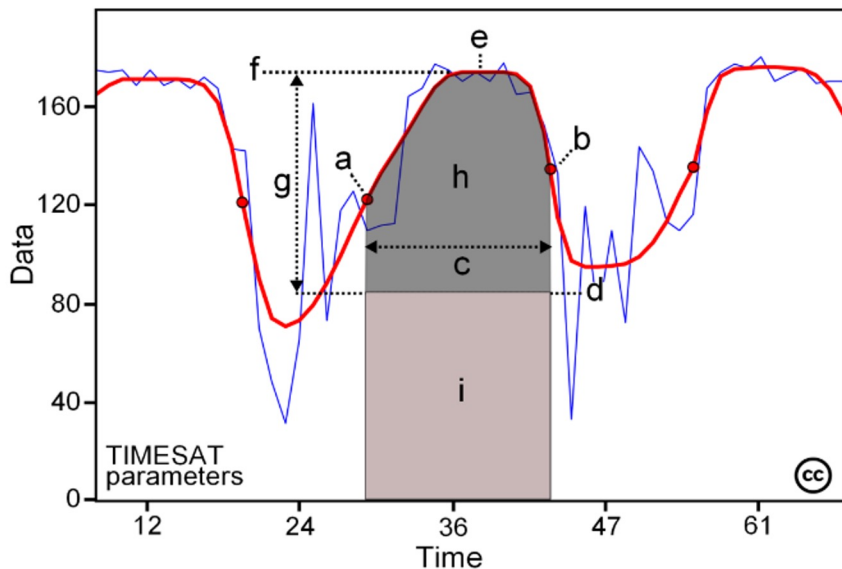
Figure was adapted from TerrSet Manual



La Puma et al. (2007)



# Crop Productivity Monitoring – Seasonality and Productivity Metrics



Parameter	Explanation
Time for the start of the season (a)	Time for which the left edge has increased to a user-defined level (often a certain fraction of the seasonal amplitude) measured from the left minimum level.
Time for the end of the season (b)	Time for which the right edge has decreased to a user-defined level measured from the right minimum level.
Length of the season (c)	Time from the start in the end of the season.
Base level (d)	The average of the left and right minimum values.
Time for the middle of the season (e)	Computed as the mean value of the times for which respectively, the left edge has increased to the 80% level and the right edge has decreased to the 80% level.
Seasonal max value (f)	Maximum value of the season.
Seasonal amplitude (g)	Difference between the maximum value and the base level.
Large seasonal integral (h+i)	The integral of the function describes the season from the season start to the season end.
Small season integral (h)	The integral of the difference between the function describing the season and the base level from season start to season end.

Figure and table were adapted from: [TIMESAT Software Documentation](#)

See [Paruelo et al \(1998\)](#) and [Sakamoto et al \(2013\)](#) for analyses of interannual vegetation productivity and environmental factors using NDVI, focused on either crop or non-crop vegetation.

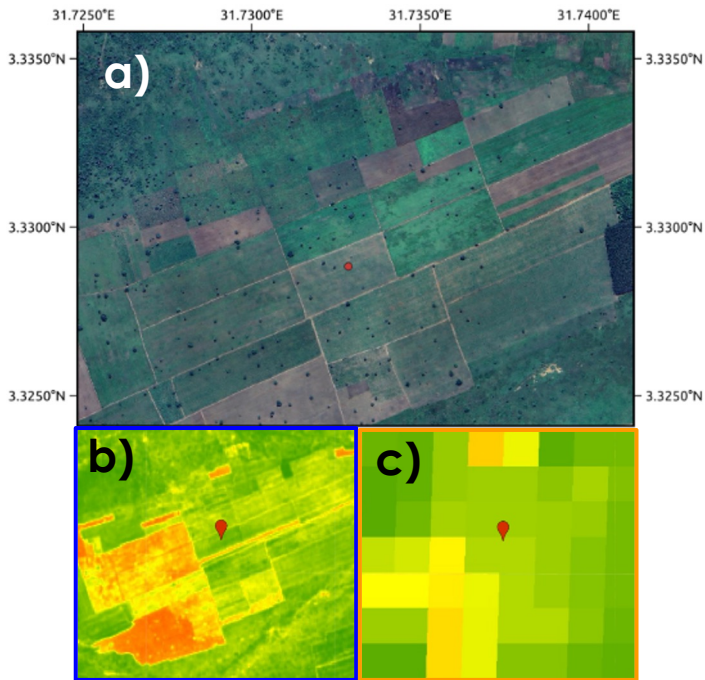




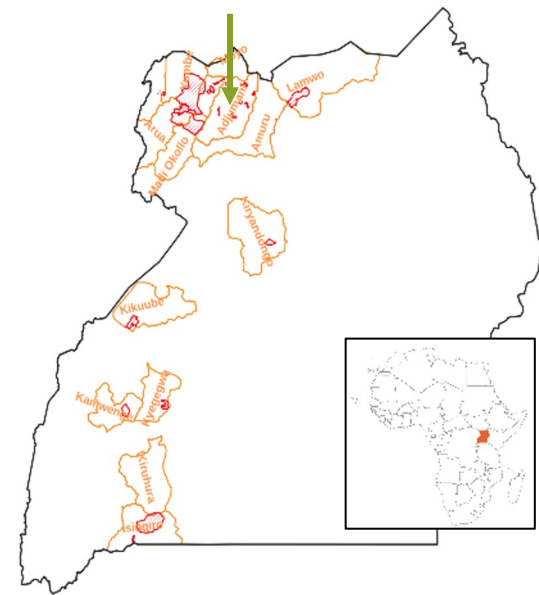
# Considerations in EO Data (Sensor Characteristics I)

- Spatial Coverage
- Spatial Resolution
- Temporal Resolution
- Common examples
  - MODIS
  - Landsat
  - Sentinel-2

Spatial resolutions and remote sensing models: [Strahler et al \(1986\)](#)



a) An example region in Google Images. b) Sentinel-2 30m NDVI around August 2022. c) MODIS 250m NDVI around a similar time. NDVI: green indicates higher values, and red indicates lower values.



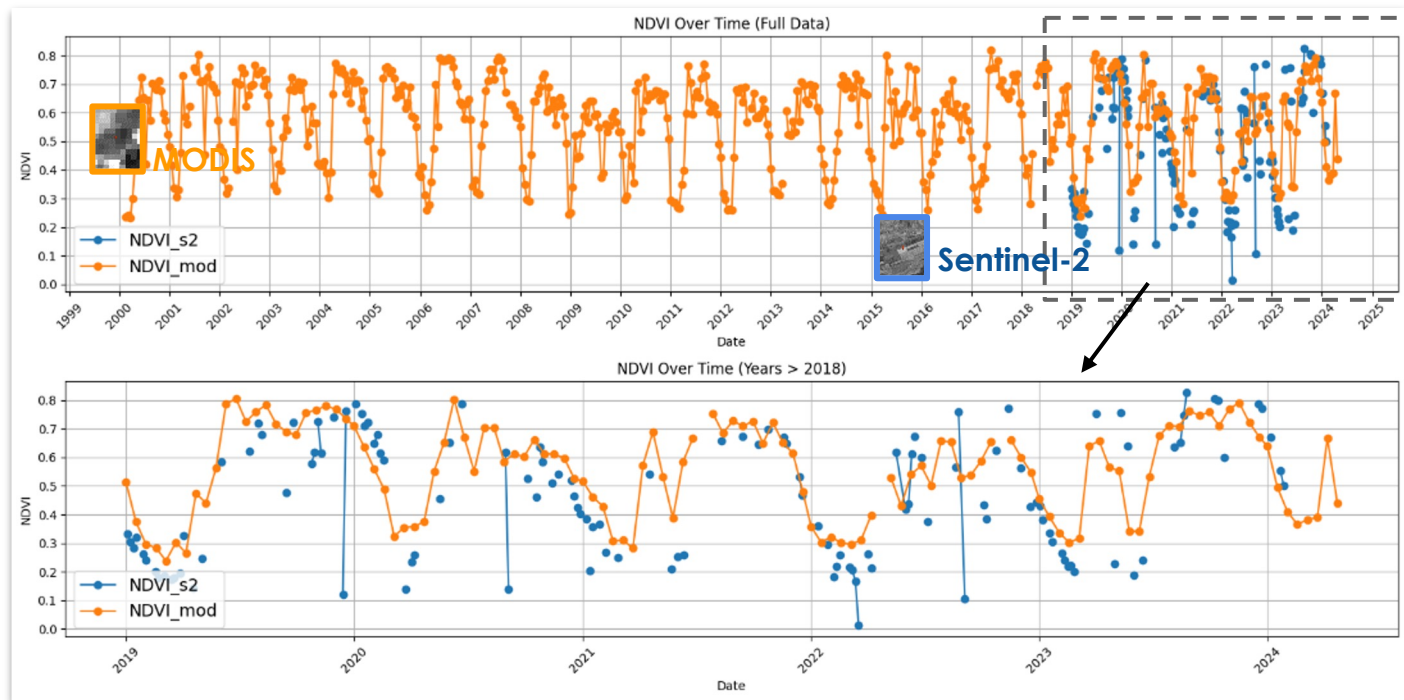
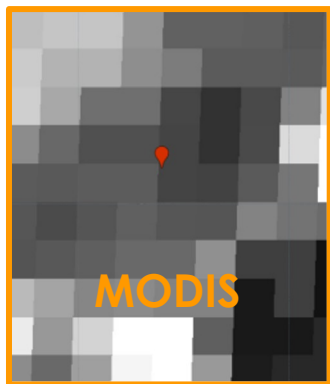
## Adjumani District, Uganda

Lat: 3.328829

Lon: 31.7328667



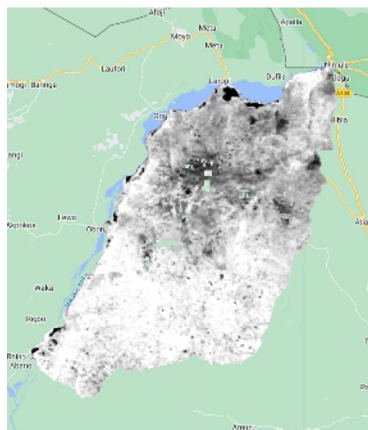
# Considerations in EO Data (Sensor Characteristics II)



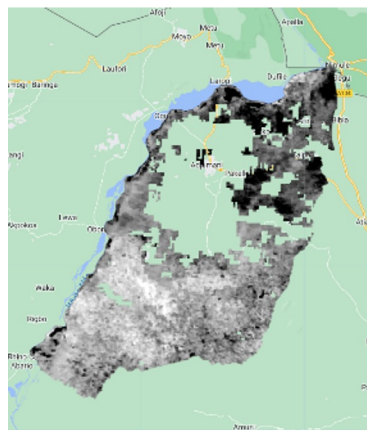
\* MODIS data came from MOD13Q1 product, a 16-day composite from near daily observation, and appears to have more coherent observations at this 16-day interval. Sentinel-2 (blue dots) came from Sentinel 2 Harmonized product, available at 2-3 days interval. Sentinel-2 (blue dots) were mostly not connected as broken by nan values (cloud masked) in dates between.



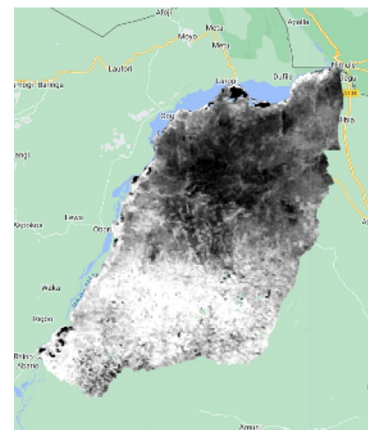
# Considerations in EO Data (Sensor Characteristics III)



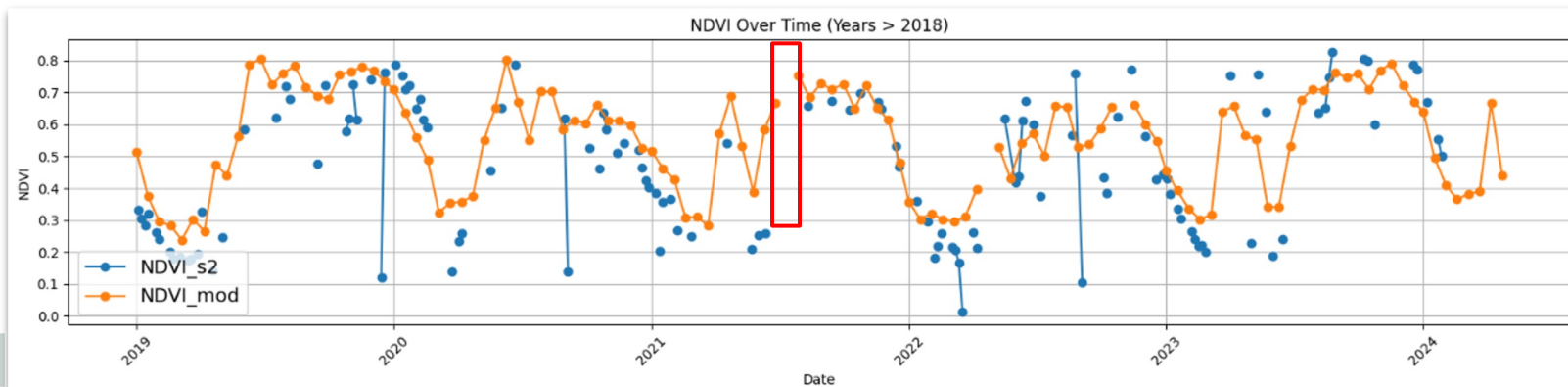
Day Before: Clear Observation



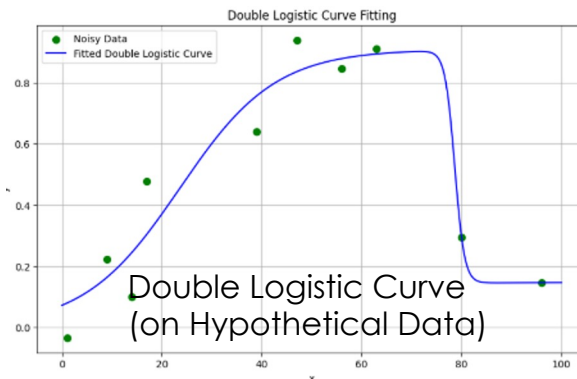
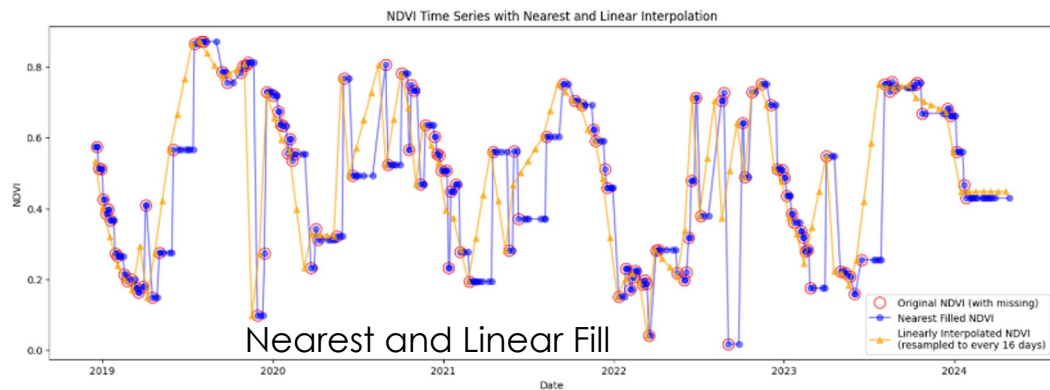
Cloudy Day (masked)



Day After: Clear Observation



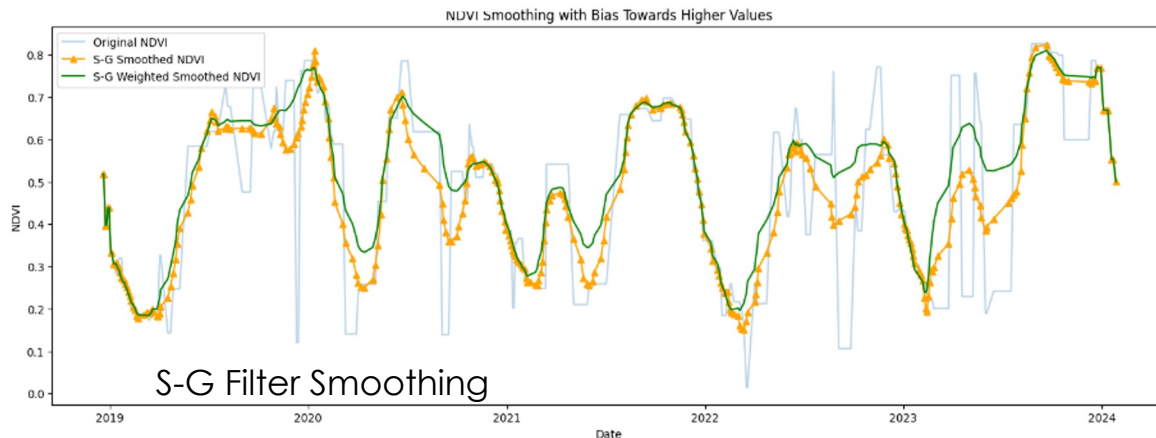
# Considerations in EO Data (Noise and Noise Reducing Techniques)



Gap-filling: linear interpolation, nearest available data etc.

Curve-smoothing: Savitzky-Golay filter

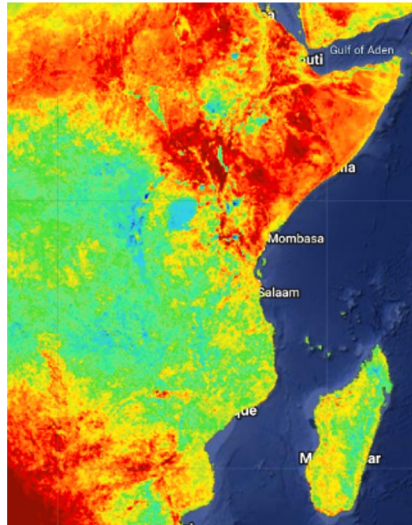
Also see some tools such as [phenofit](#) for more curve-fitting choices.



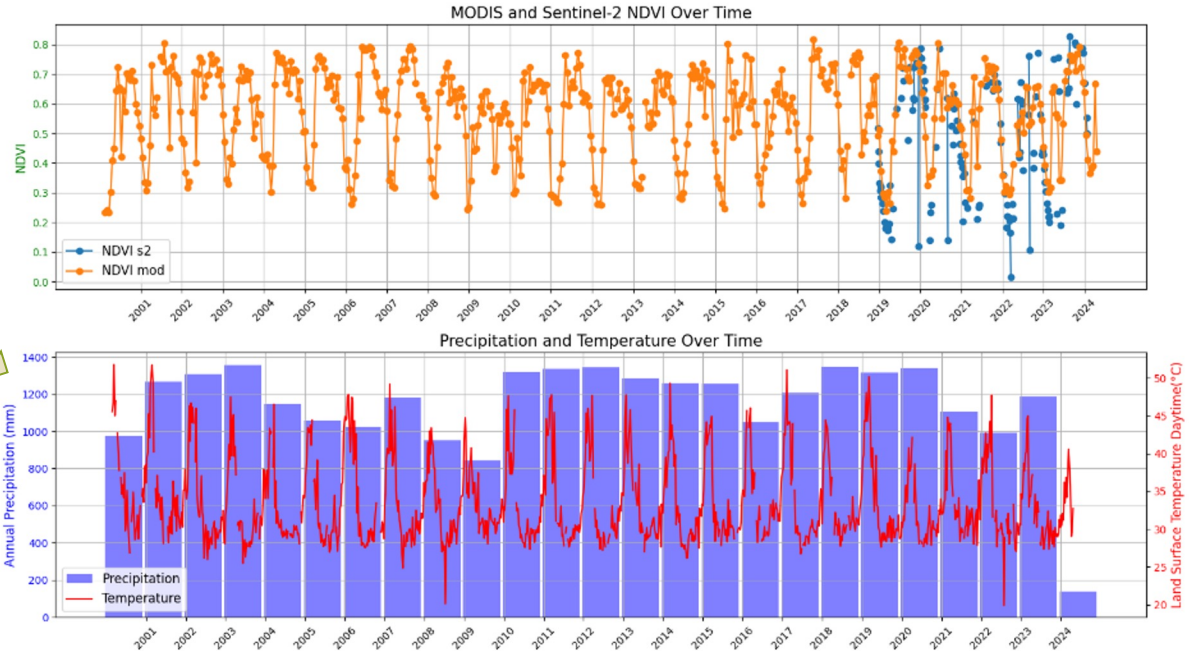


# Correlating Environmental Factors (Weather)

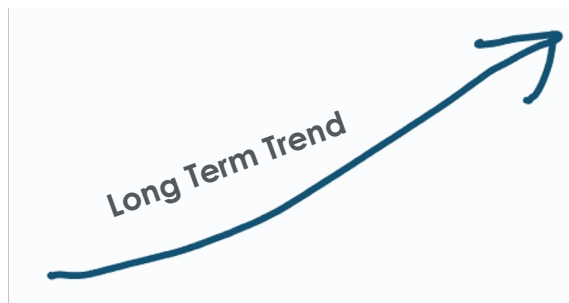
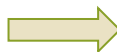
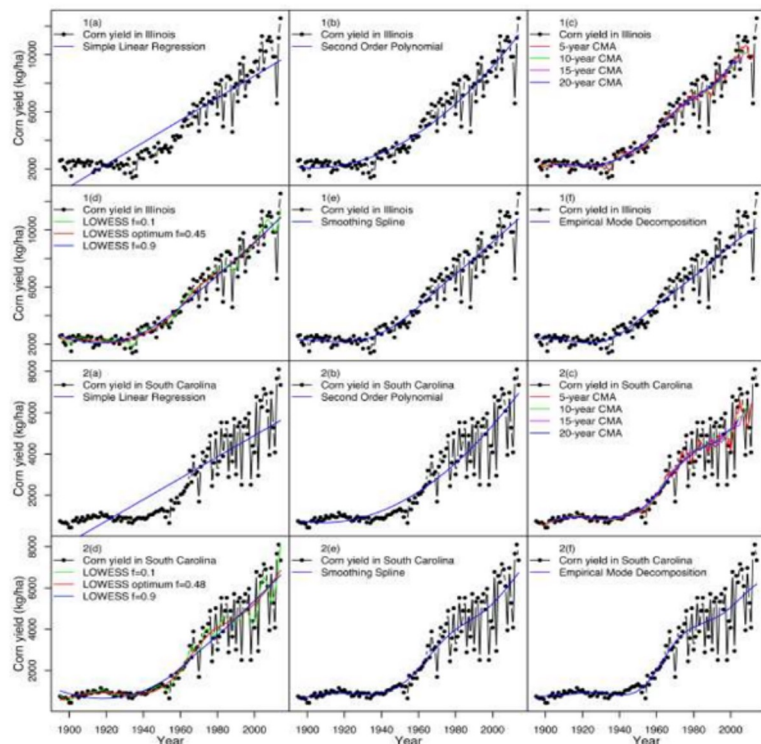
Gridded temperature and precipitation: MODIS Land Surface Temperature (2000-), CHIRPS (1981-)



MOD11A2.061 Terra Land Surface Temperature and Emissivity 8-Day Global 1km



# Evaluating Trend and Anomalies (Detrending Analysis)

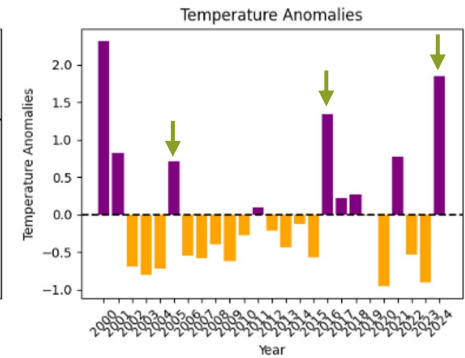
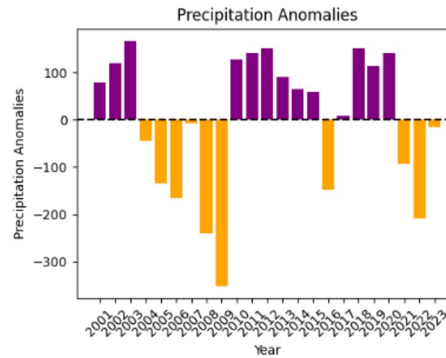
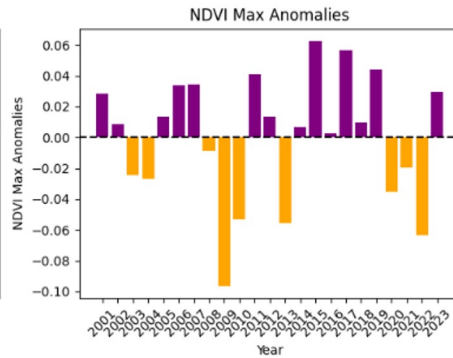
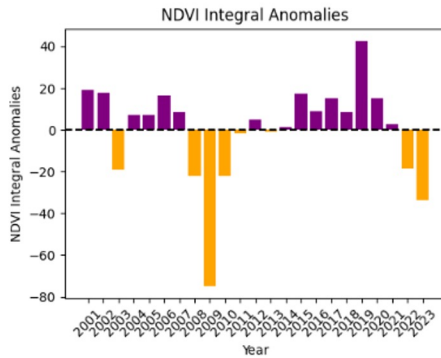
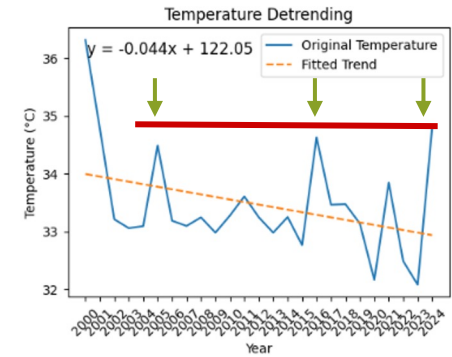
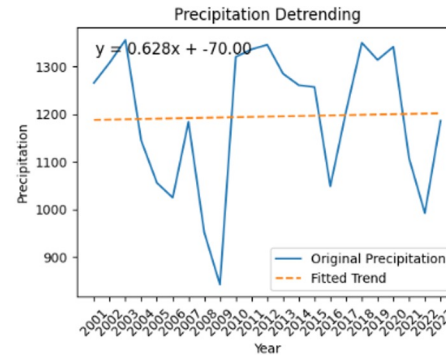
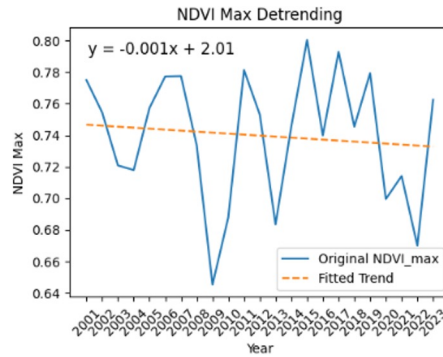
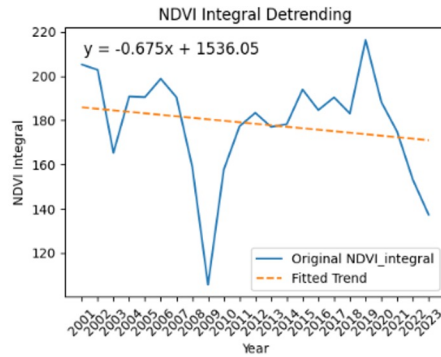


Short Term Variation from Trend

Lu et al (2017)



# Evaluating Rainfall and Temperature Trends and Anomalies

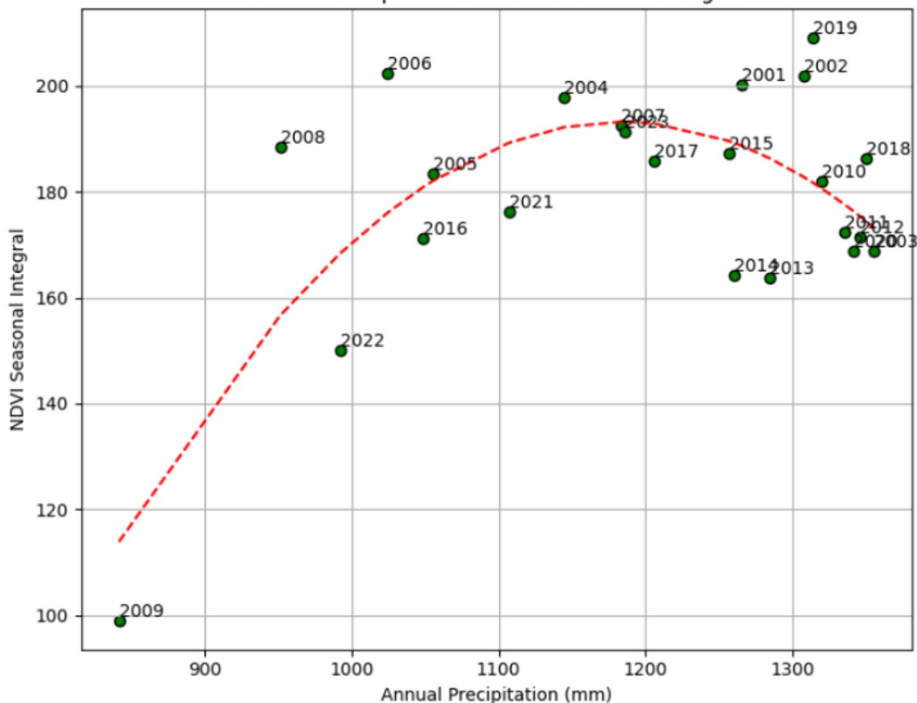




# Evaluating Rainfall and Temperature Effects on Crop Productivity Anomalies (Regression Analysis)



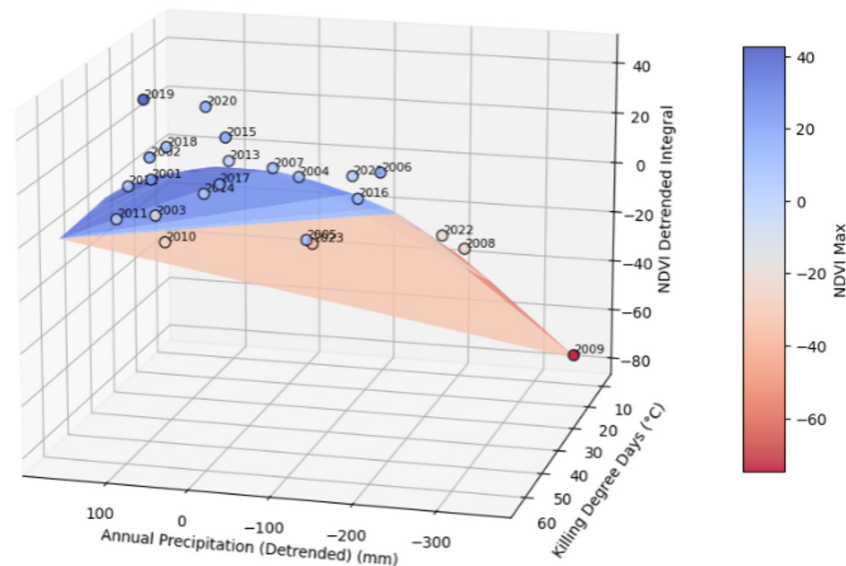
Annual Precipitation vs NDVI Seasonal Integral



Detrended Precipitation & KDD vs Detrended NDVI Seasonal Integral (Polynomial Surface)

$R^2 = 0.65$

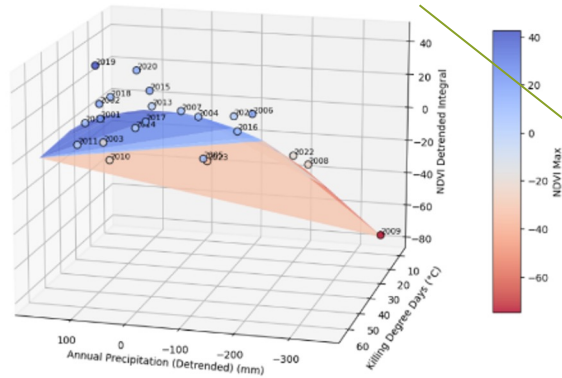
$$z = -2.78e-04x^2 + -1.15e-02y^2 + -2.38e-03xy + 1.02e-01x + 1.40e+00y + -25.01$$



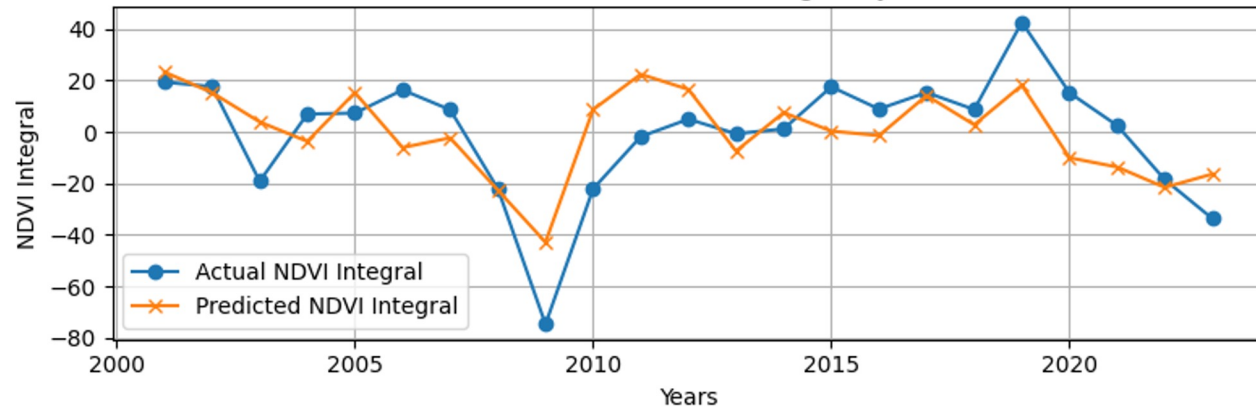
# Predictive Models for Crop Productivity (Multivariate Regression)

$R^2 = 0.65$

$$z = -2.78e - 04x^2 + -1.15e - 02y^2 + -2.38e - 03xy + 1.02e - 01x + 1.40e + 00y + -25.01$$

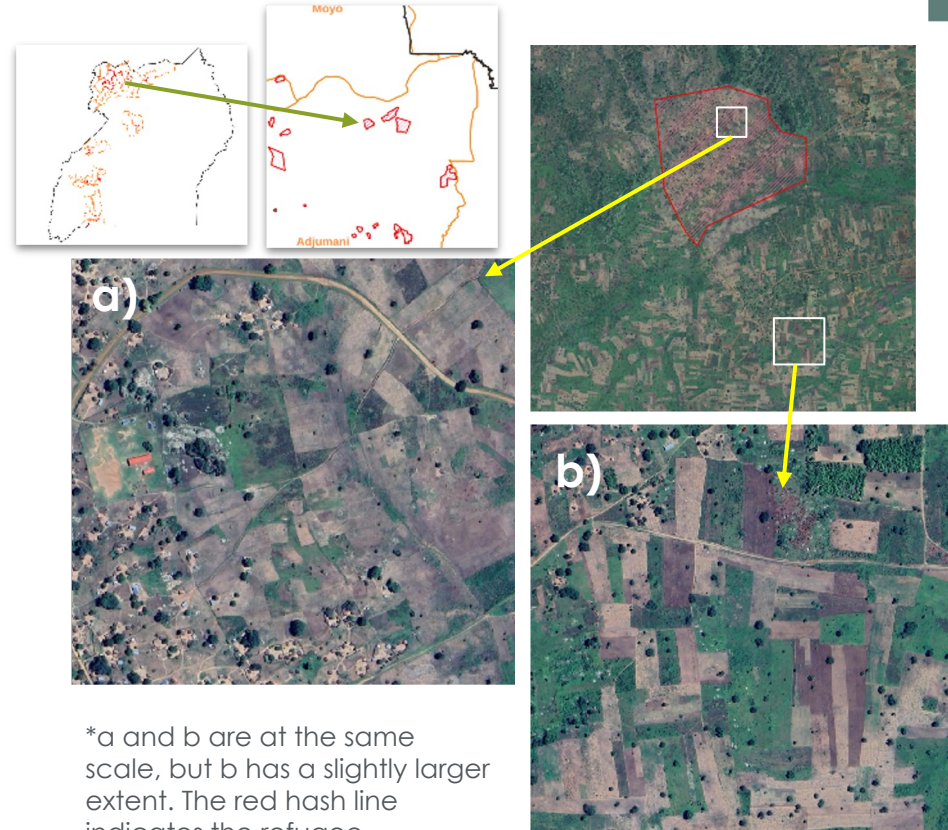


## Actual vs Predicted NDVI Integral by Years



# Considerations in Ancillary Data

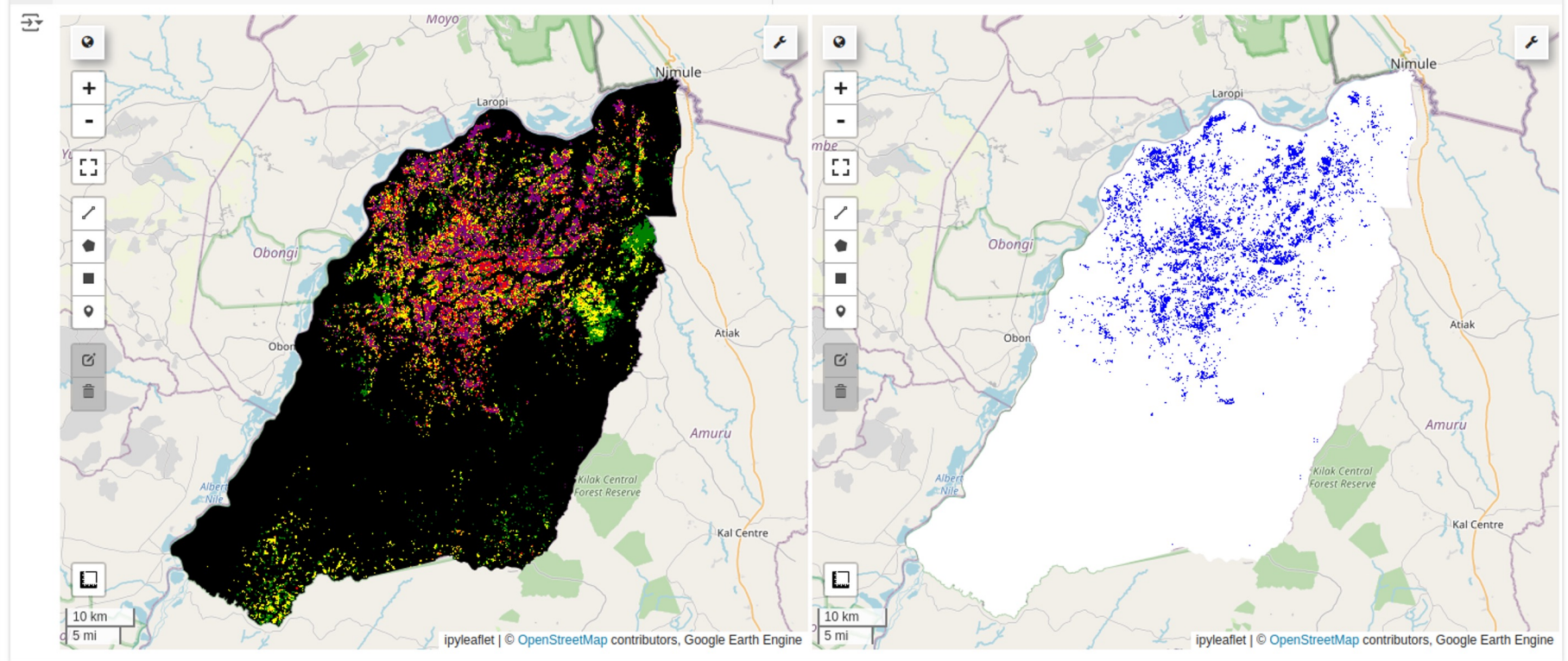
- Understand the context of the refugee hosting region
  - Which crop field(s) is cultivated by the refugee populations?
- How many growing season(s) in a year? What is the typical crop calendar?
  - This help us to interpret and guide use to process the NDVI time-series.



\*a and b are at the same scale, but b has a slightly larger extent. The red hash line indicates the refugee settlement area.



# Two Types of Analyses – Point-based vs. Region-wise

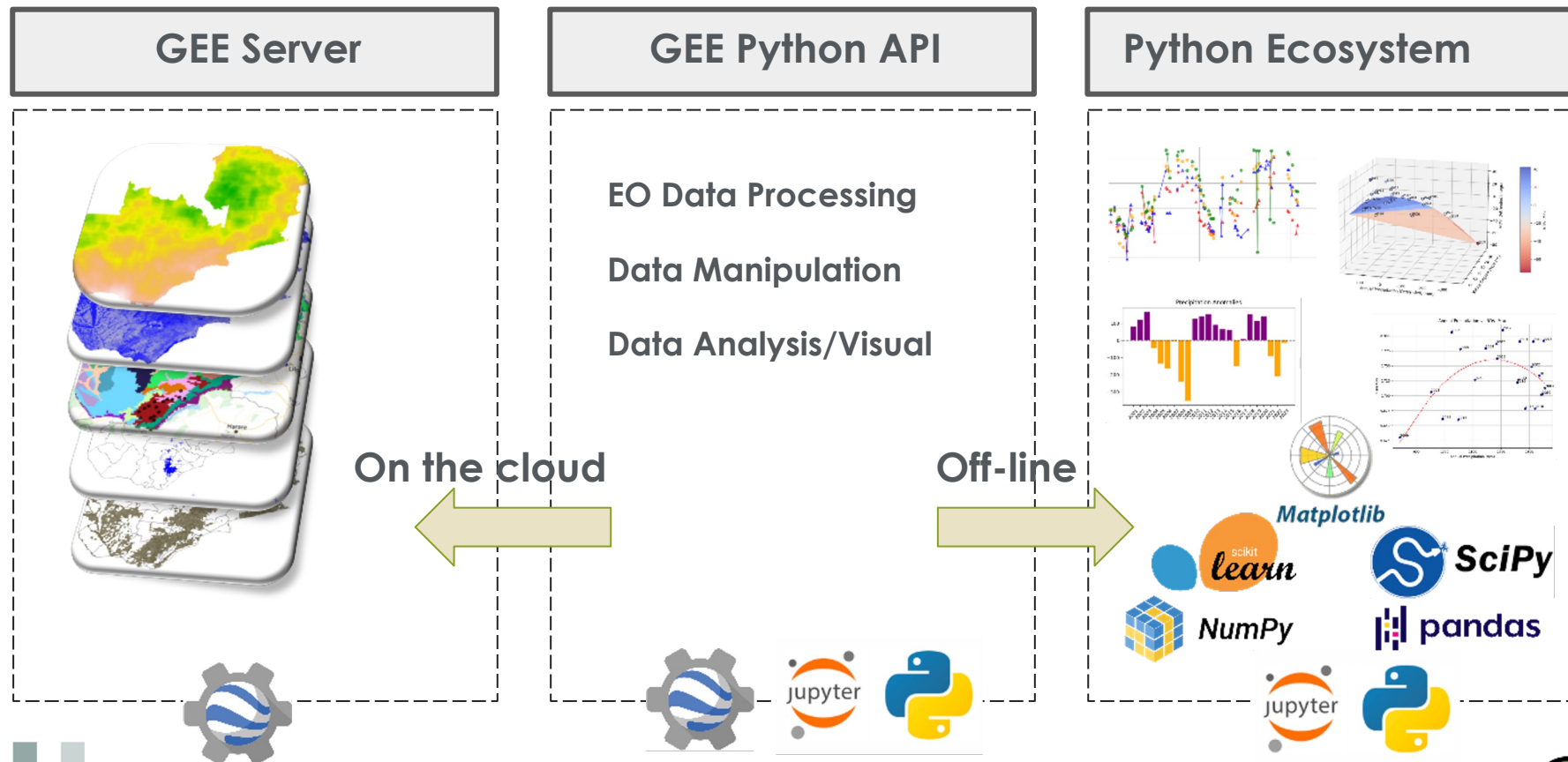


Cropland Expansion (left) and Stable Cropland (right)  
2003 – 2019





# Platforms Choice and Workflow Design



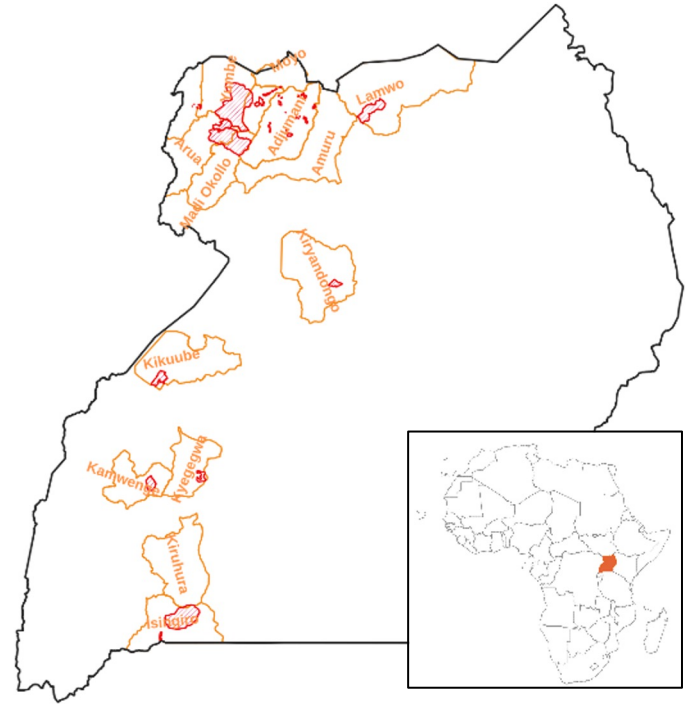
# Making Your Own EO Analysis to Help Decision Making (Demo)

## Goal:

Investigate cropland productivity in Uganda's refugee hosting region.

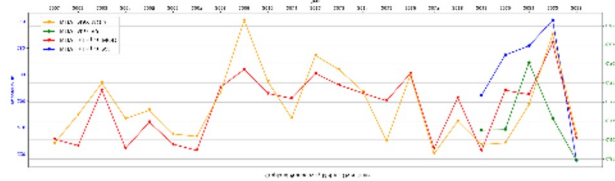
## Objectives:

- Retrieve and process satellite imagery for NDVI and weather variables.
- Process the NDVI time series and extract crop productivity metrics.
- Conduct anomaly and correlation analysis with weather factors.

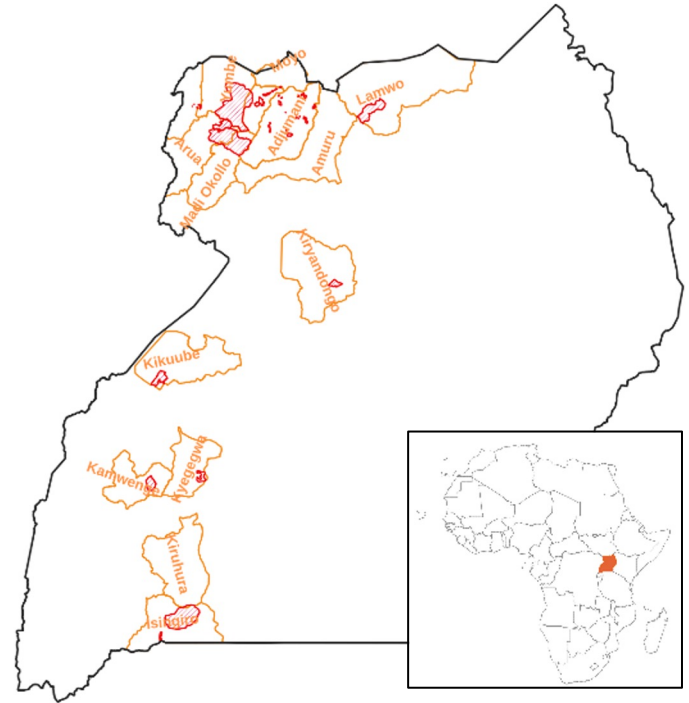
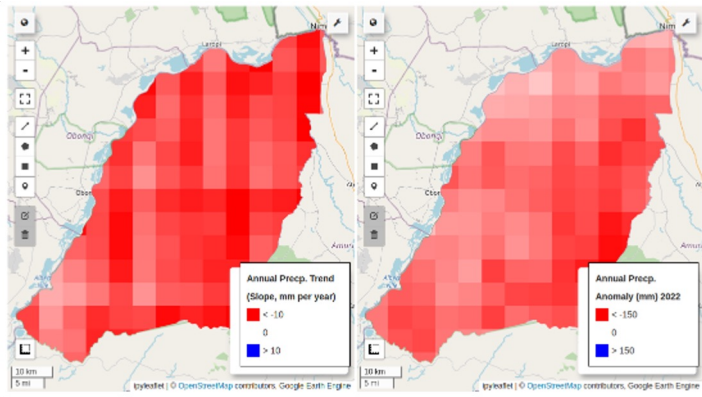


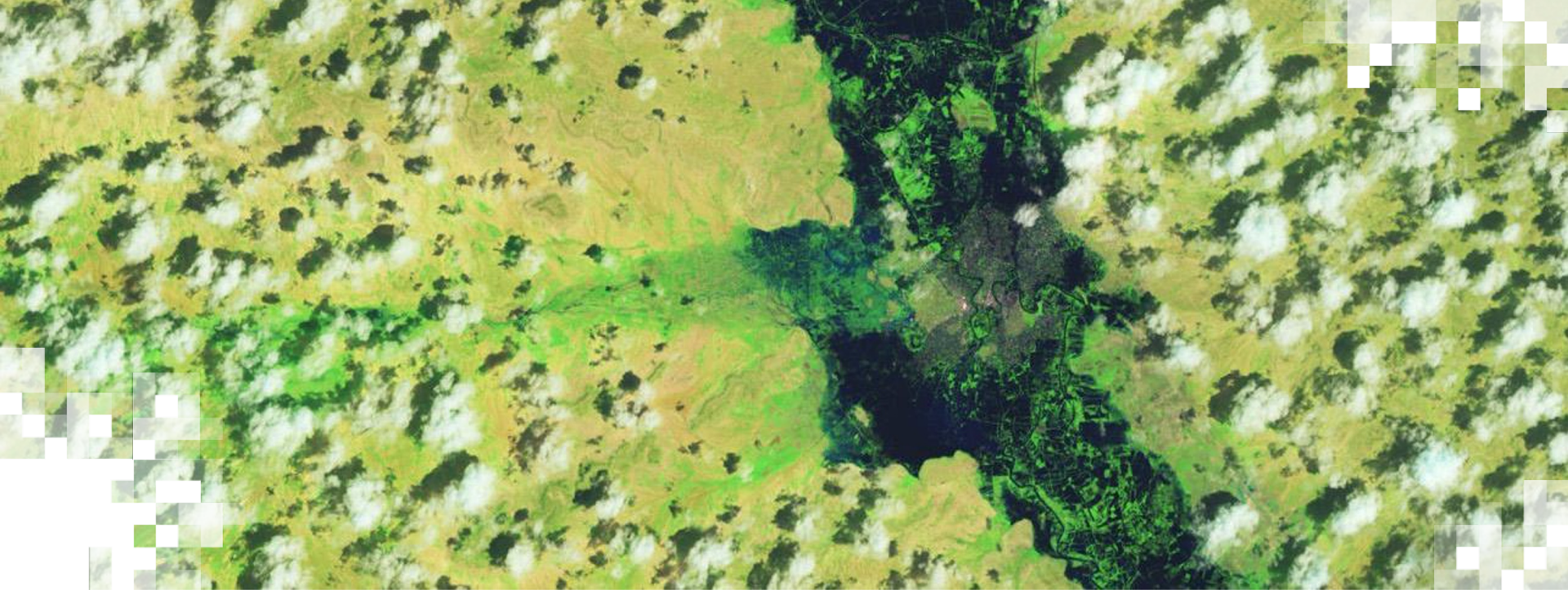
# Making Your Own EO Analysis to Help Decision Making

## Notebook 1: Point-based Area of Interest (AOI)



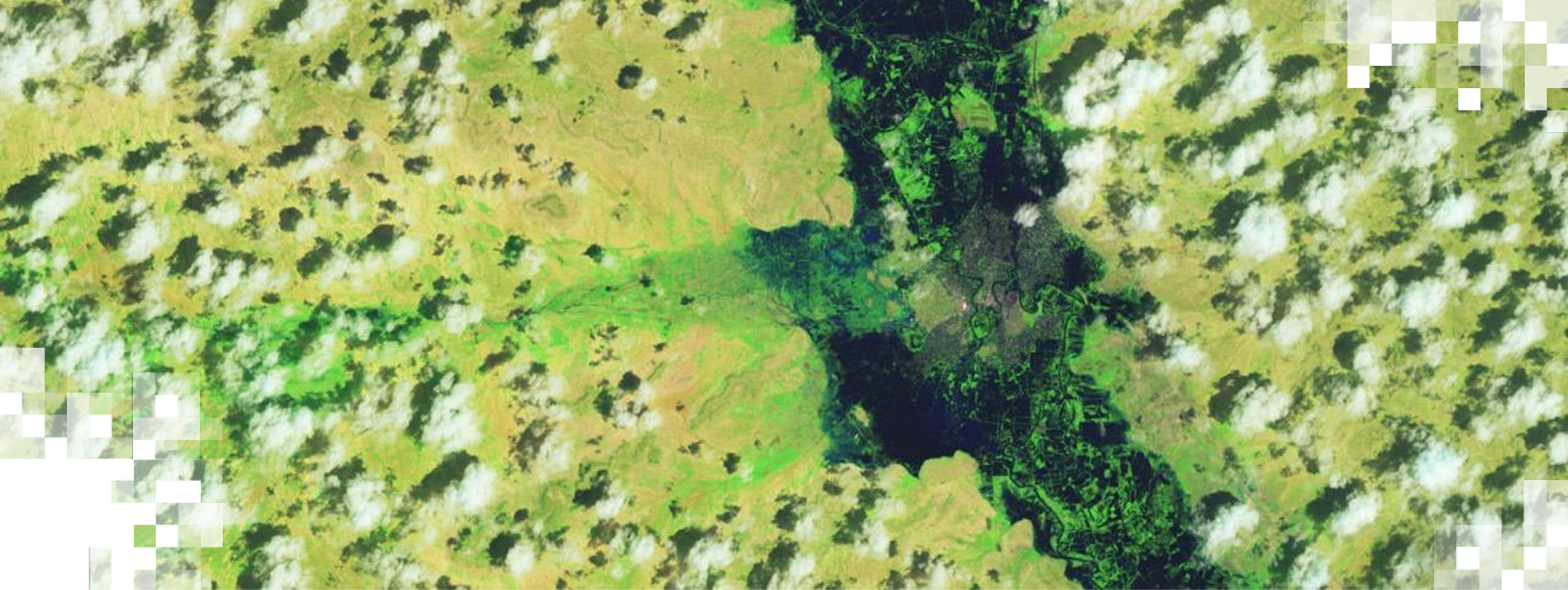
## Option 2: Region-wise AOI





Part 3:  
**Demonstration**





Part 3:  
**Summary**

# Post-coding Reflection

1. Understand the workflow and results:
  1. Point-base workflow and scale
  2. Crop productivity and VI
  3. Scale
  4. Refugee agriculture context
  5. Crop type and locations
  
1. Understand the limitations:
  1. Data availability
  2. Cloud issue
  3. Is VI a good proxy of productivity?
  4. What weather metrics are good for capturing drought and/or flood.
  5. Gap-filling and curve smoothing.



## Summary

- Fundamental Concepts
  - Crop productivity, LAI, and NDVI
  - NDVI based crop productivity metrics
  - Anomaly and correlation analysis
- Considerations in EO data and methods:
  - Spatial, temporal resolution of sensor
  - Weather data
  - Ancillary data and contextual knowledge
  - Point-based and region-wise analysis
- Technological considerations:
  - Platforms and workflows
  - Time-series processing related, e.g., gap-filling and curve smoothing



# Future Outlook

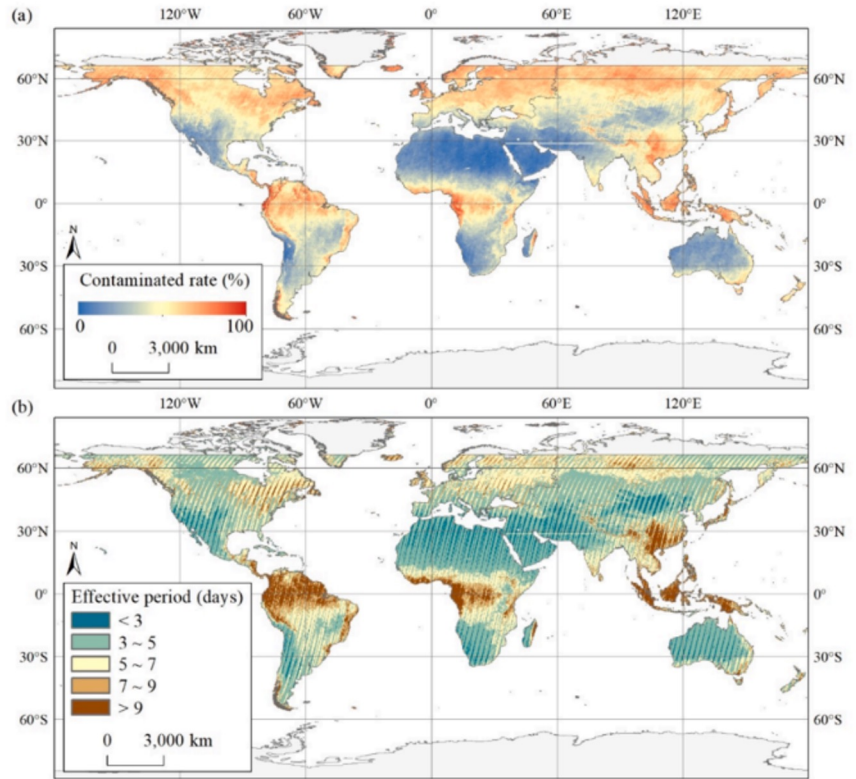
Advances in sensors and algorithms:

- Planet, drone, active sensors (radar, lidar)
- AI (gap-filling algorithm, )

New data product and applications for easier analysis:

- [Harmonized Landsat Sentinel-2 Data](#)
- [Digital Africa Platform](#)
- [Library for Javascript GEE \(OEEL\)](#)

Better in-situ data and ancillary data (high resolution observation, annual crop mask, soil moisture data, ground truth)



**Fig. 7.** Spatial distribution of contaminated rate (a) and effective period (b). The Polar regions were excluded. Observation frequency with Landsat 8/9 and Sentinel A/B combined.

[Jia et al. \(2024\)](#)





## How can we go forward with this analysis?

- Refugee settlement-level data on crop productivity and drought impacts provide localized insights with more specificity and relevance than nationwide assessments
  - Further integration of EO-derived data with food security assessments typically measured at the refugee household-level would better link landscape and household conditions
- Refugee populations may or may not have similar food security conditions compared to nearby non-refugee (host) populations
  - Better understanding refugee-host similarities and differences will help inform the timing and type of potential aid for refugees and hosts
- Needs and solutions for supporting refugee food security are not uniform across refugee settings
  - Access to arable land for refugees in Uganda should provide a greater degree of resilience to climate impacts on food security than in other refugee-hosting countries where access to land is restricted, but we don't have the data to show this yet
  - Country by country, we need further research to understand how climate impacts, land access, and aid delivery come together to influence food security outcomes in refugee settings



# References

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# Acknowledgements

- Junren Wang, PhD Candidate, UIUC for thoughts in time series processing.
- Rahebe Abedi, PhD Student, Clark University for suggestions in data analysis and testing code.
- Dr. John Rogan, Clark University for pictures used in this presentation.
- Dr. Michael Cecil, Post Doc. at NASA Harvest, University of Maryland, for pictures used in this presentation and data about satellite and ground sensor NDVI comparison.
- Dr. Ximin Piao, UIUC, for review of crop growth-related content.
- Funding support for methodology development from NSF.
- ChatGPT 4o for assistance in design and improving code.



# Homework and Certificates

- **Homework:**

- One homework assignment
- Opens on 20 June 2024
- Access from the [training webpage](#)
- Answers must be submitted via Google Forms
- **Due by 05 July 2024**

- **Certificate of Completion:**

- Attend all three live webinars (attendance is recorded automatically)
- Complete the homework assignment by the deadline
- You will receive a certificate via email approximately two months after completion of the course.





# Contact Information

## Trainers:

- Sitian Xiong
  - [SXiong@clarku.edu](mailto: SXiong@clarku.edu)
- Jamon Van Den Hoek
  - [jamon.vandenhoeck@oregonstate.edu](mailto: jamon.vandenhoeck@oregonstate.edu)
- Lyndon Estes
  - [LEstes@clarku.edu](mailto: LEstes@clarku.edu)
- Sean McCartney
  - [sean.mccartney@nasa.gov](mailto: sean.mccartney@nasa.gov)

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**Thank You!**

