Remote Sensing of Severe Weather Impacts to Regional and Global Agriculture

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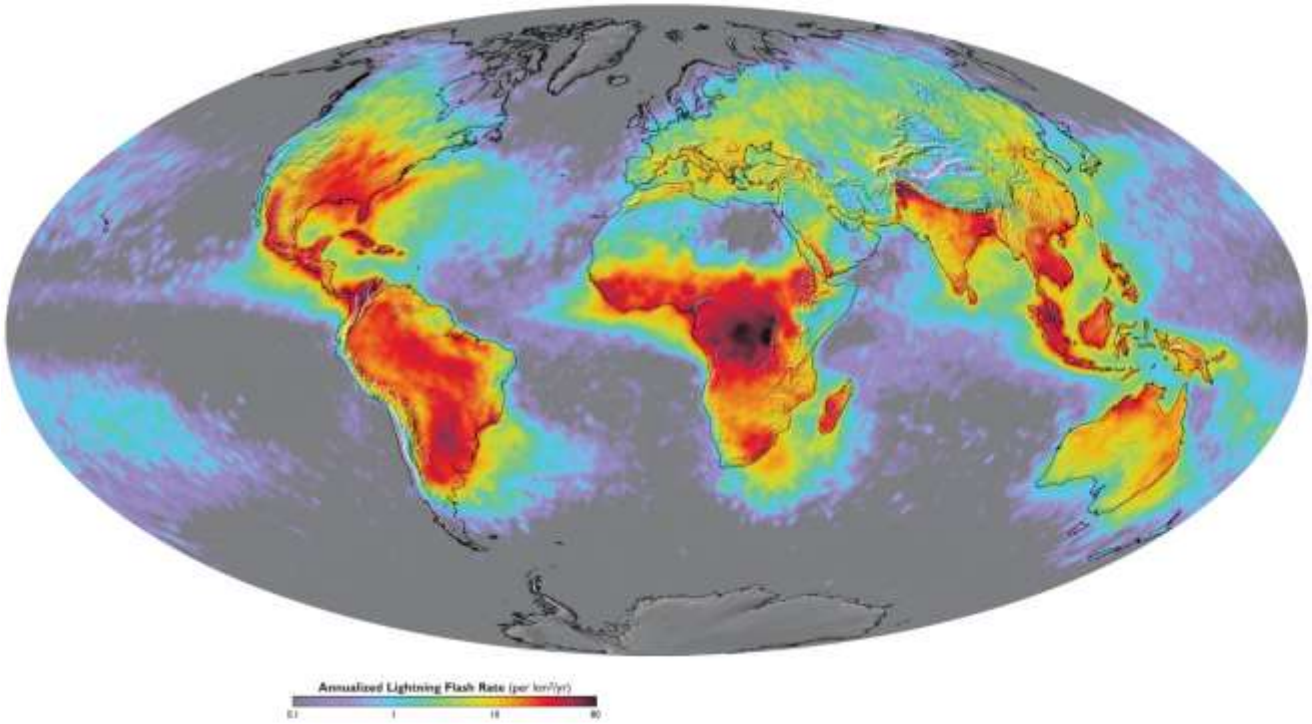
Mapping the Future of Agriculture: The Human Dimension of International Crop Monitoring

Why severe weather impacts?

- In addition to drought and flooding, intense thunderstorms can bring additional risks from damaging winds, large hail, and tornadoes.
  - Intense thunderstorms are not just limited to North America. There are several thunderstorm hot-zones across the world.
  - These hot zones coincide with many of agricultural zones

How is remote sensing being used?

- A combination of domestic, international and commercial Earth observing satellite are being used to monitor risk and impacts to agricultural regions

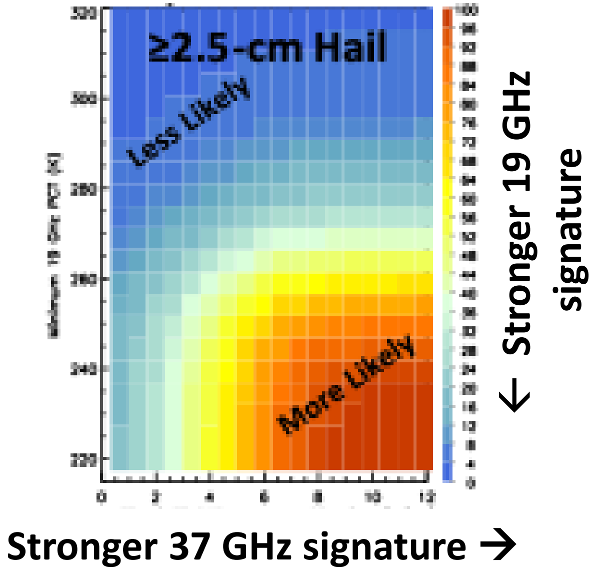


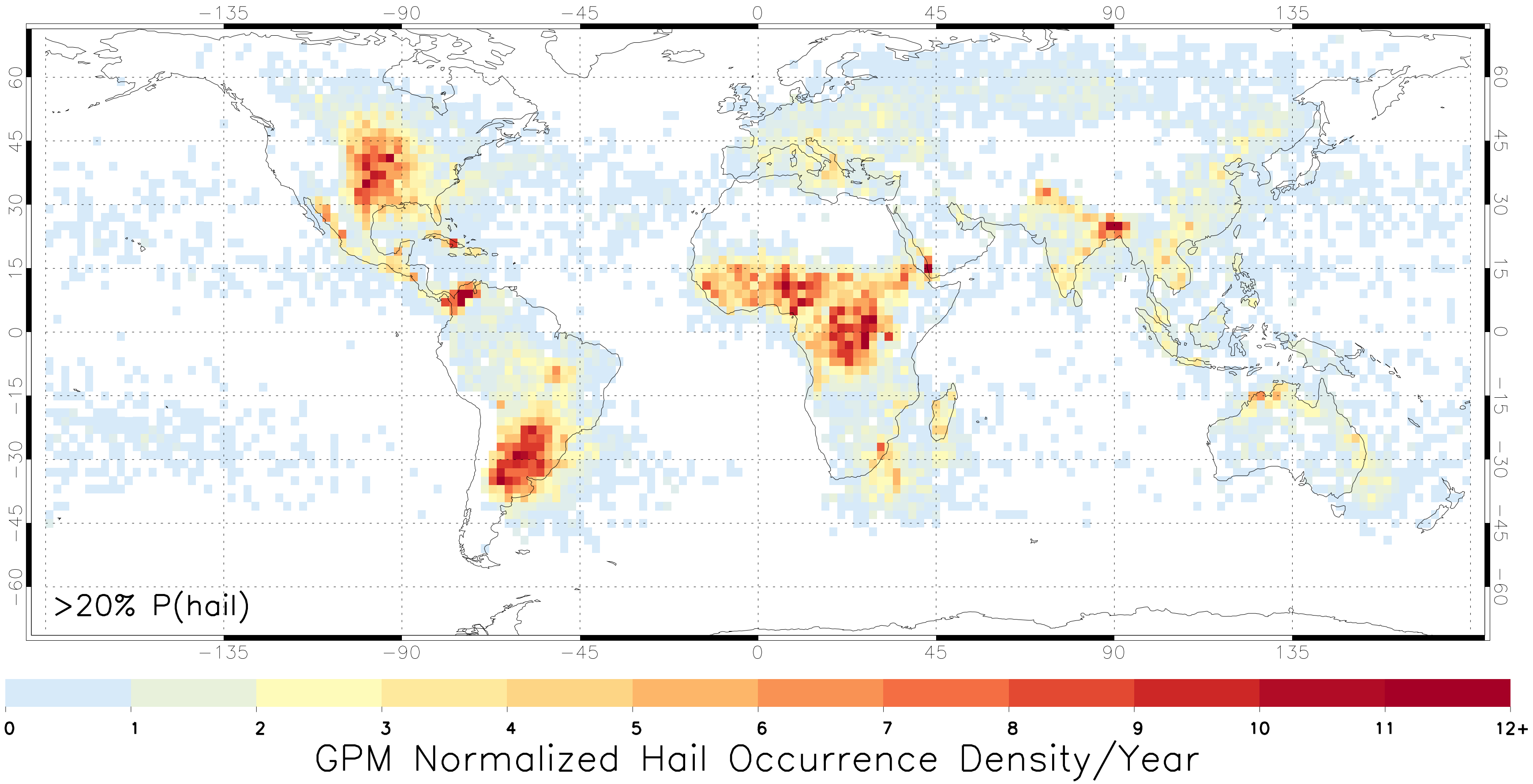
Goodman et al., 2007. Glimpses of a Changing Planet, M. King, ed., Cambridge University Press

Using Passive Microwave to Construct a Hail Retrieval and Climatology

Sarah Bang (NPP) and Dan Cecil, NASA MSFC

- Probability of hail occurrence increases rapidly with decreasing microwave brightness temperature.
- Long microwave wavelengths penetrate clouds, detect large ice
- Probabilities are computed using matchups with 1”+ diameter hail reports in USA





- For precipitating features within any GPM orbit, we can estimate the likelihood of severe hail
- This approach can be then applied to other satellite-borne platforms with the same (or similar) passive microwave frequencies
  - *TRMM (1998-2014)*
  - *AMSR-E and AMSR-2 (2002-present)*
  - *SSMI and SSMIS (1987-present)*

from Bang and Cecil, 2019 JAMC

Anvil and Overshooting Top Climatology

Kris Bedka (LaRC)

A 14-year database of infrared-based storm detections at 3 km spatial and 15 km temporal resolution was derived over South Africa with Meteosat 8-11 geostationary imagery and MERRA-2 reanalysis.

Data is aggregated into hourly timesteps at daily and monthly timescales, accounting for parallax. See Reference Material slides for a product list

We'v developed the capability to analyze data in terms of average number of days per year with a satellite-detected overshooting top updraft region (A)

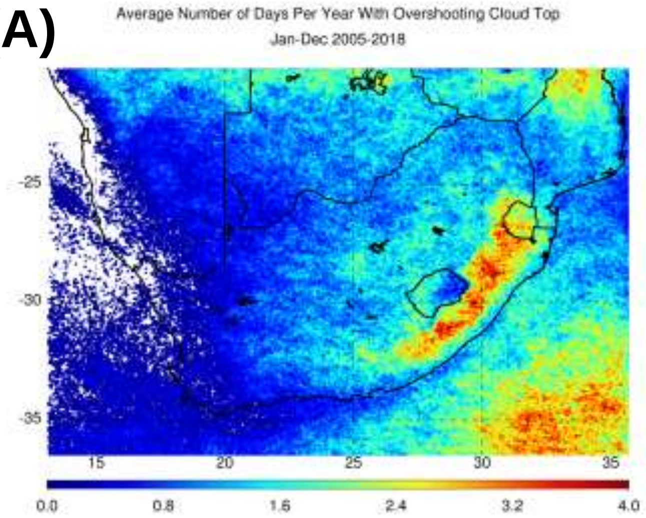
We've also derived a preliminary severe storm risk analysis based on storm frequency and population density from the SEDAC Gridded Population of the World (GPW) dataset (B)

Risk= Mean number of overshooting top events per year multiplied by log(population density) (C)

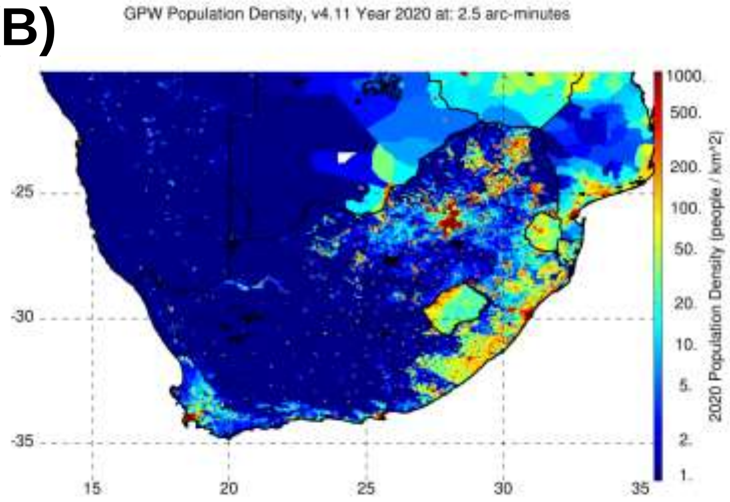
1.0=95th percentile of Frequency*Density
0.0=5th percentile

Risk is greatest in the eastern third of S. Africa, Swaziland, and coastal regions of Mozambique where storms are frequent and population is dense

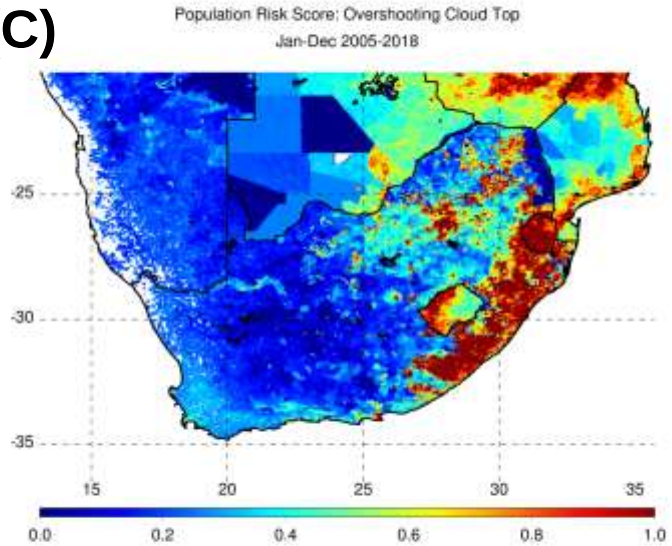
(A)



(B)

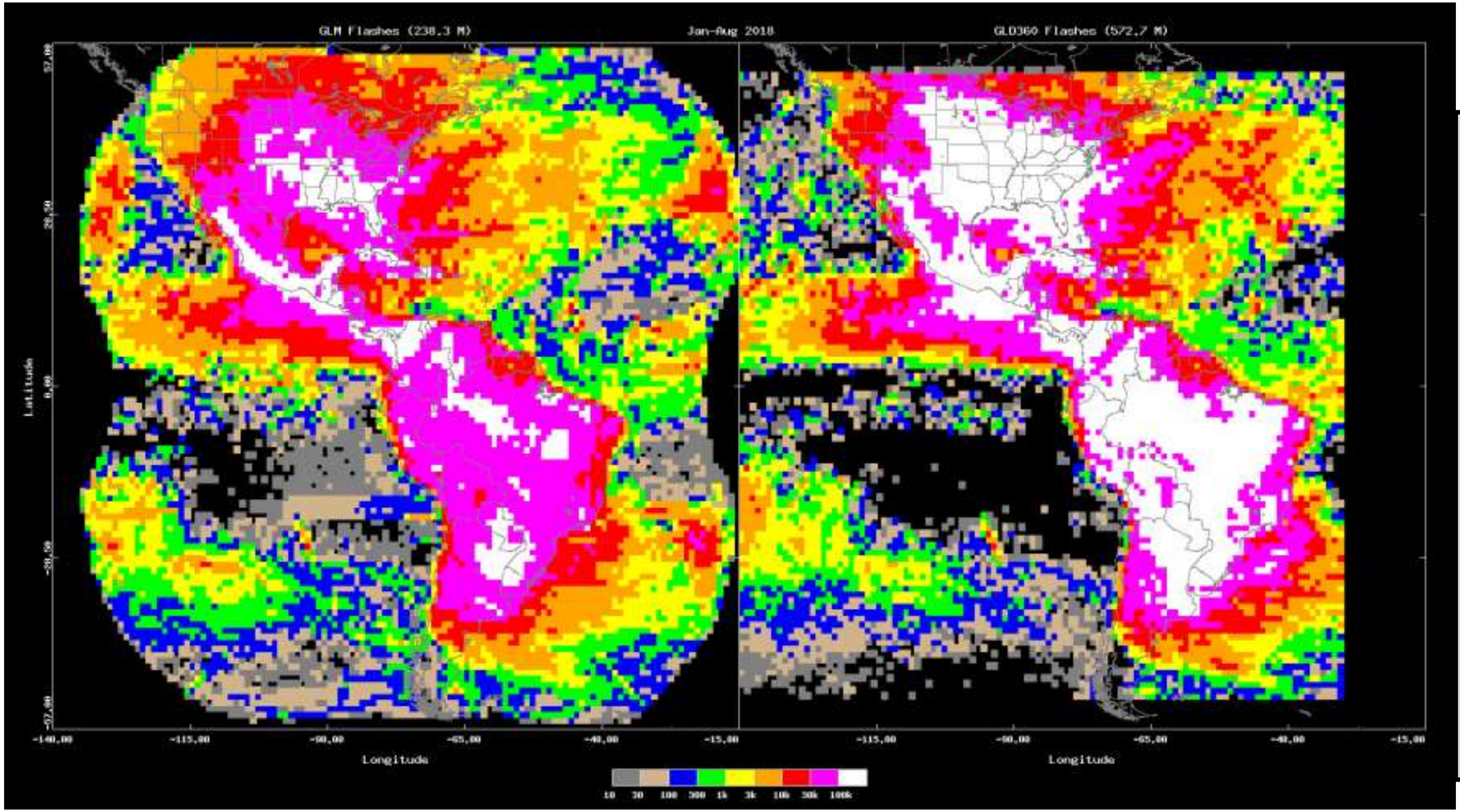


(C)



Using Lightning to Identify Potential Risk Areas

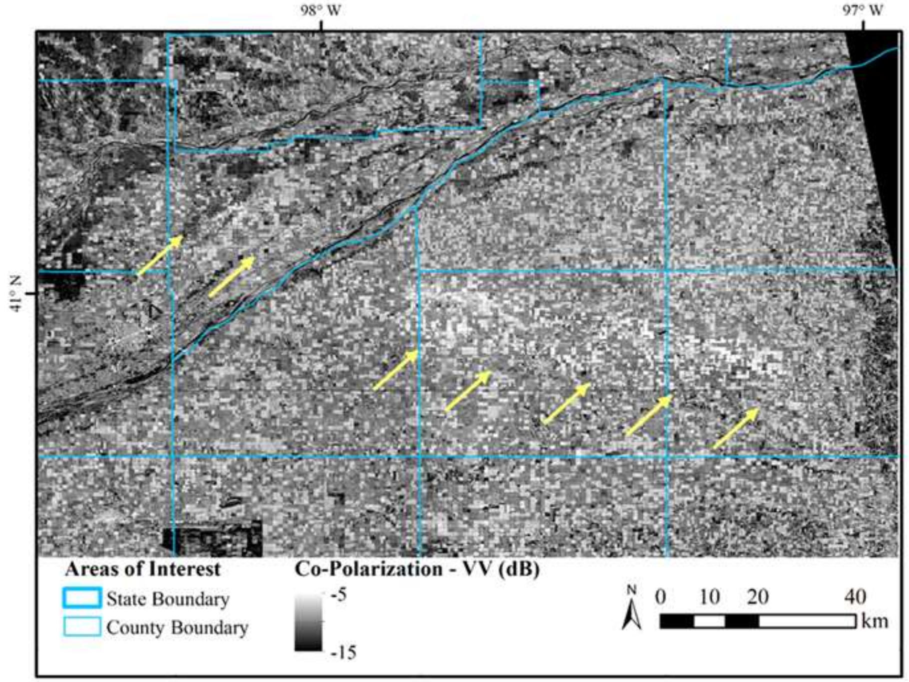
Chris Schultz (NASA MSFC) and Abigail Whiteside (UAH)

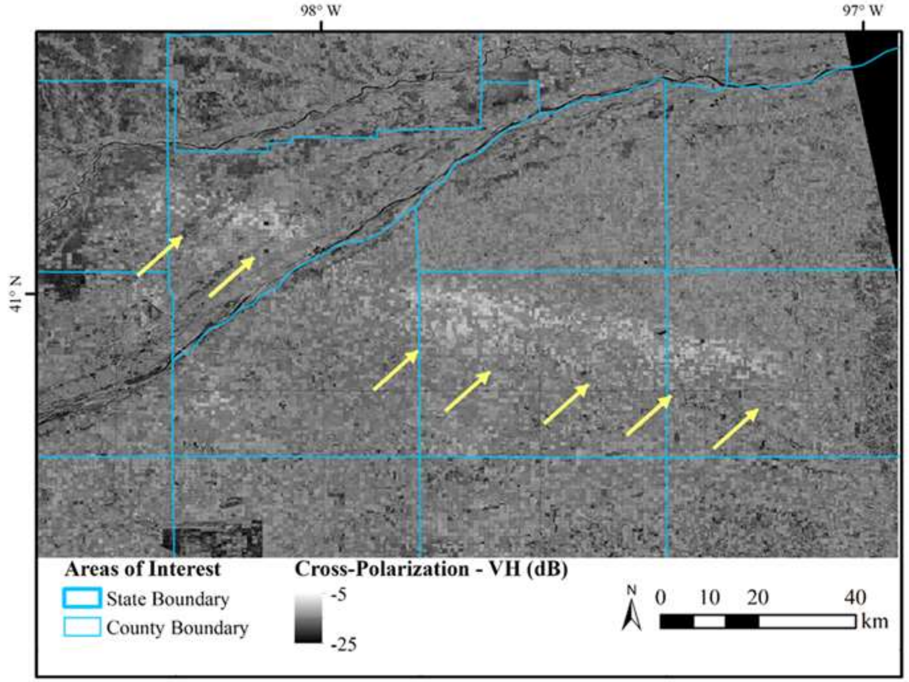


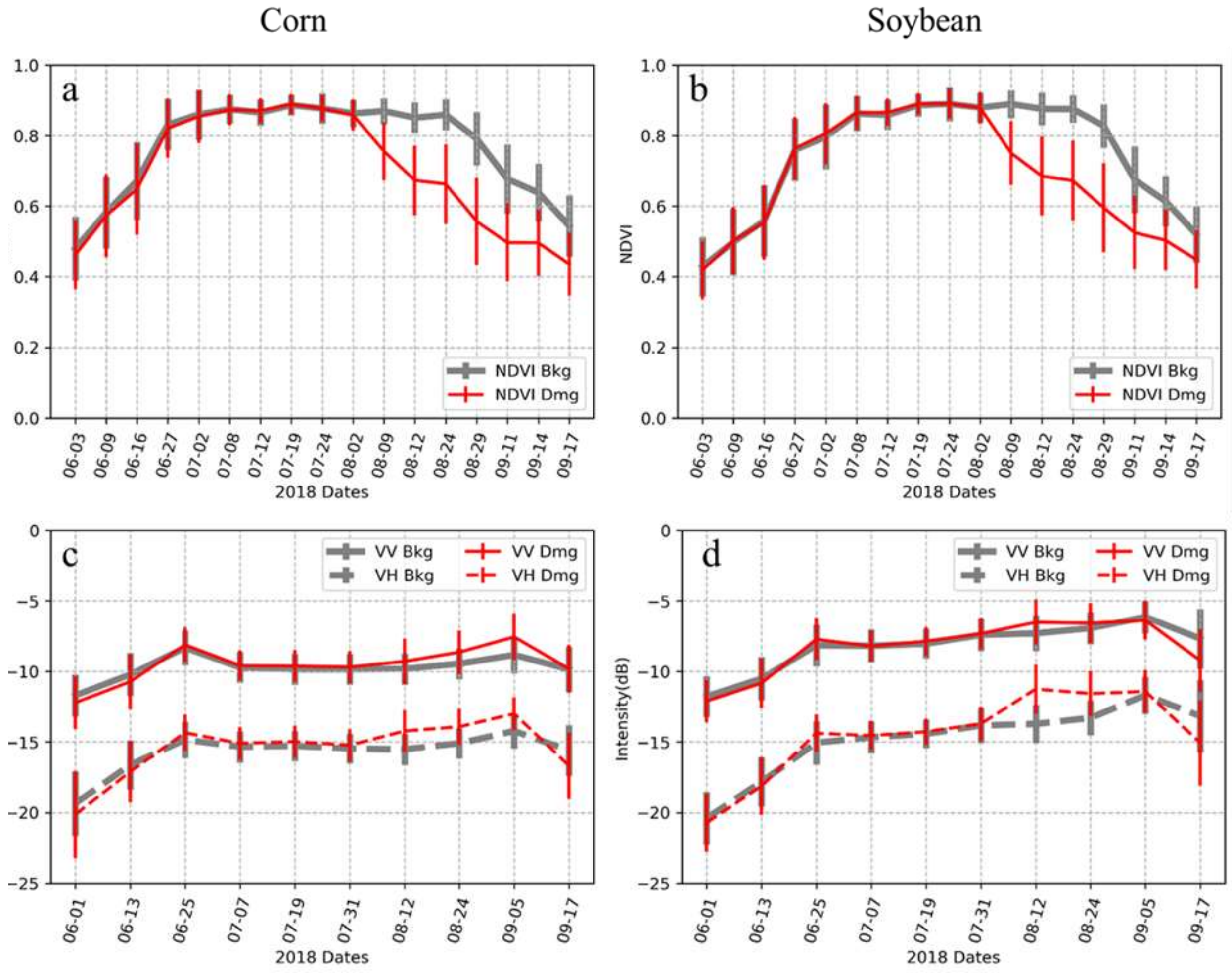
Graphic from M. Bateman, *Preliminary GLM Detection Efficiency and Climatology*, 2018 GLM Science Team Meeting

- **Rapid increases in total lightning (aka lightning jumps) have been shown to precede the observance of severe weather at the surface**

- **South America falls within the GOES-16 Geostationary Lightning Mapper field of view, allowing us to demonstrate how hailstorm detection can be augmented with lightning observations. Space-borne lightning sensors will become increasingly prevalent across the world over the next 10 years.**

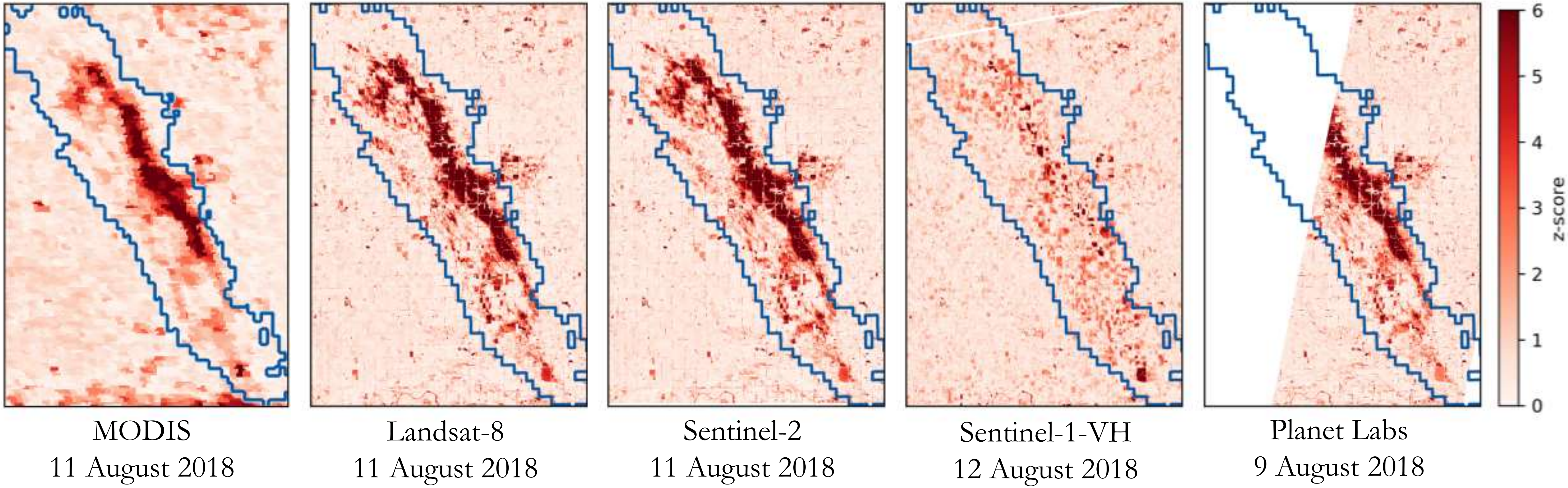






- Identify potential case studies in the United States/South America that overlap with various databases in project
  - Also that have good multispectral instrument/SAR coverage
  - Want to use potential satellite derived datasets at replacements for MRMS
  - Better understand how land-surface imaging of damage swaths can be used to supplement the CAT models or provide data on potential damage
  - Machine learning to identify degrees of damage
- Can we start to understand potential characteristics in satellite derived datasets and the storms that may leave these damage swaths?

Satellite Agnostic Damage Detection



MODIS
11 August 2018

Landsat-8
11 August 2018

Sentinel-2
11 August 2018

Sentinel-1-VH
12 August 2018

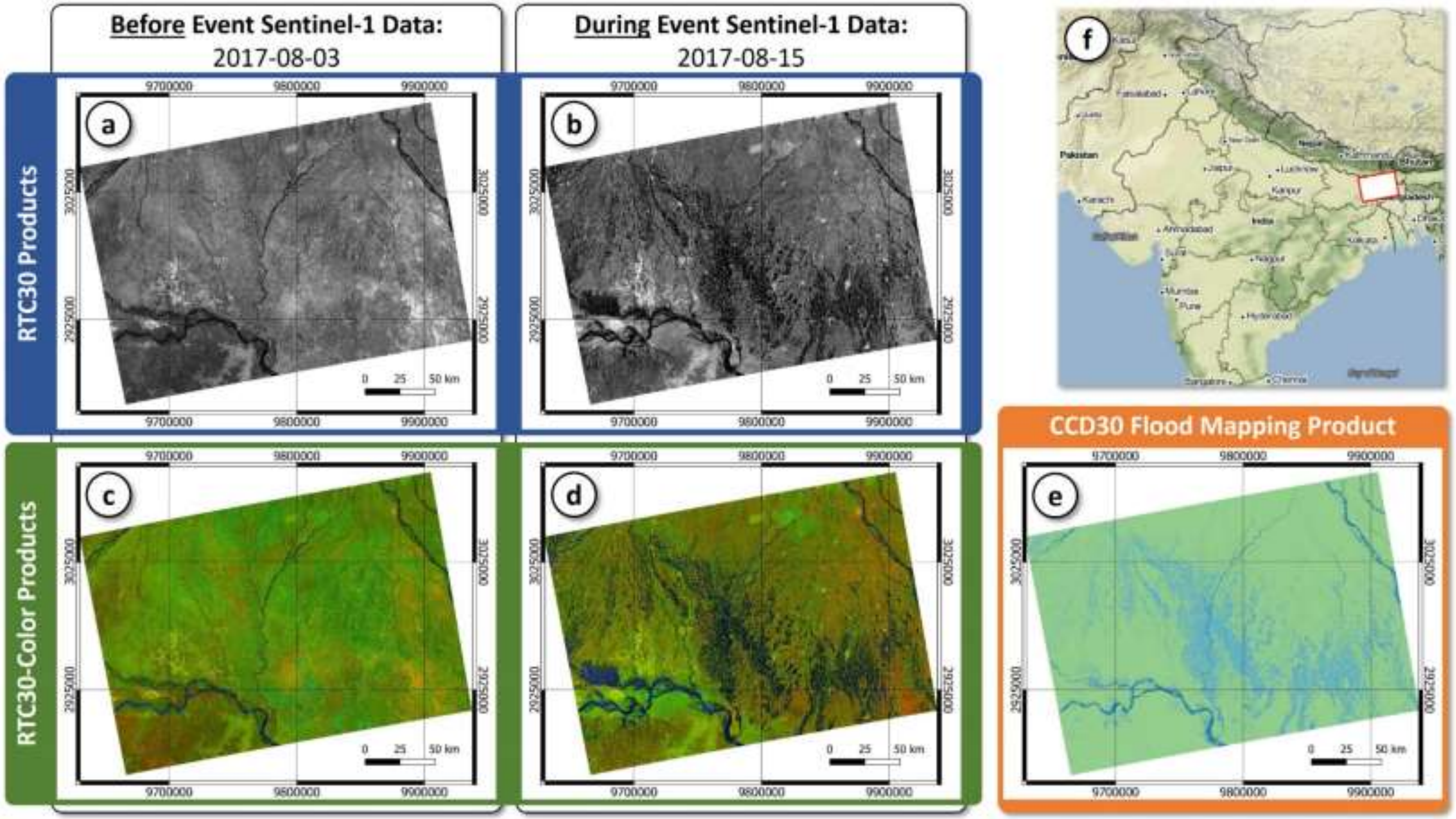
Planet Labs
9 August 2018

- Automated way of combining multiple datasets to identify different degrees of damage
- Incorporate machine learning into the delineation of damage (e.g. classification, clustering, feature extraction)
- Work industry to understand more about the relationship between degree of damage observed on the surface and what is seen from satellite remote sensors.

Integrating SAR Data for Improved Resilience and Response to Weather-Related Disasters

SAR Level-2 and Level-3 data Tailored for the Monitoring of Weather-Related Disasters

- Image Time Series (RTC30)
- Flood Detection (CCD30)
- Color Image Time Series (RTC30-Color)
- Flood Depth (FD30)
- Agriculture and Inundated Agriculture (AG100 & AG100-IN)
- Surface Deformation (DEFO30)



Remote Sensing for Agricultural Monitoring

Earth observation unique and cost-efficient tool to acquire timely and spatially consistent information over large areas with a high revisit frequency

- **Advantages of SAR** (compared to optical remote sensing):
  - **All-weather capability** → Frequent measurements during the short dynamic growing season of crops is possible
  - Independence of sun illumination → day and night operation
  - Sensitivity to dielectric (water content, biomass) and geometrical (plant/canopy structure, surface roughness) properties of the target → complementary information to optical data

- **Disadvantages of SAR** (compared to optical remote sensing):
  - Complex interactions (difficult in understanding, complex processing)
  - Speckle effects
  - Topographic effects, radar shadow
  - Effect of surface roughness

Partner Organizations with their Use Cases

USDA / FAS

- Quantify regions of agricultural activity (product: AG100)
- Assess impacts of severe weather on crop yield and crop area (AG100-IN; FD30)
- Weather impacts from wind and hail (CCD30)
- Track crop recovery (RTC30)
- Crop condition analysis across a growth season (RTC30)

SAR Data Cyclone Idai, March 2019

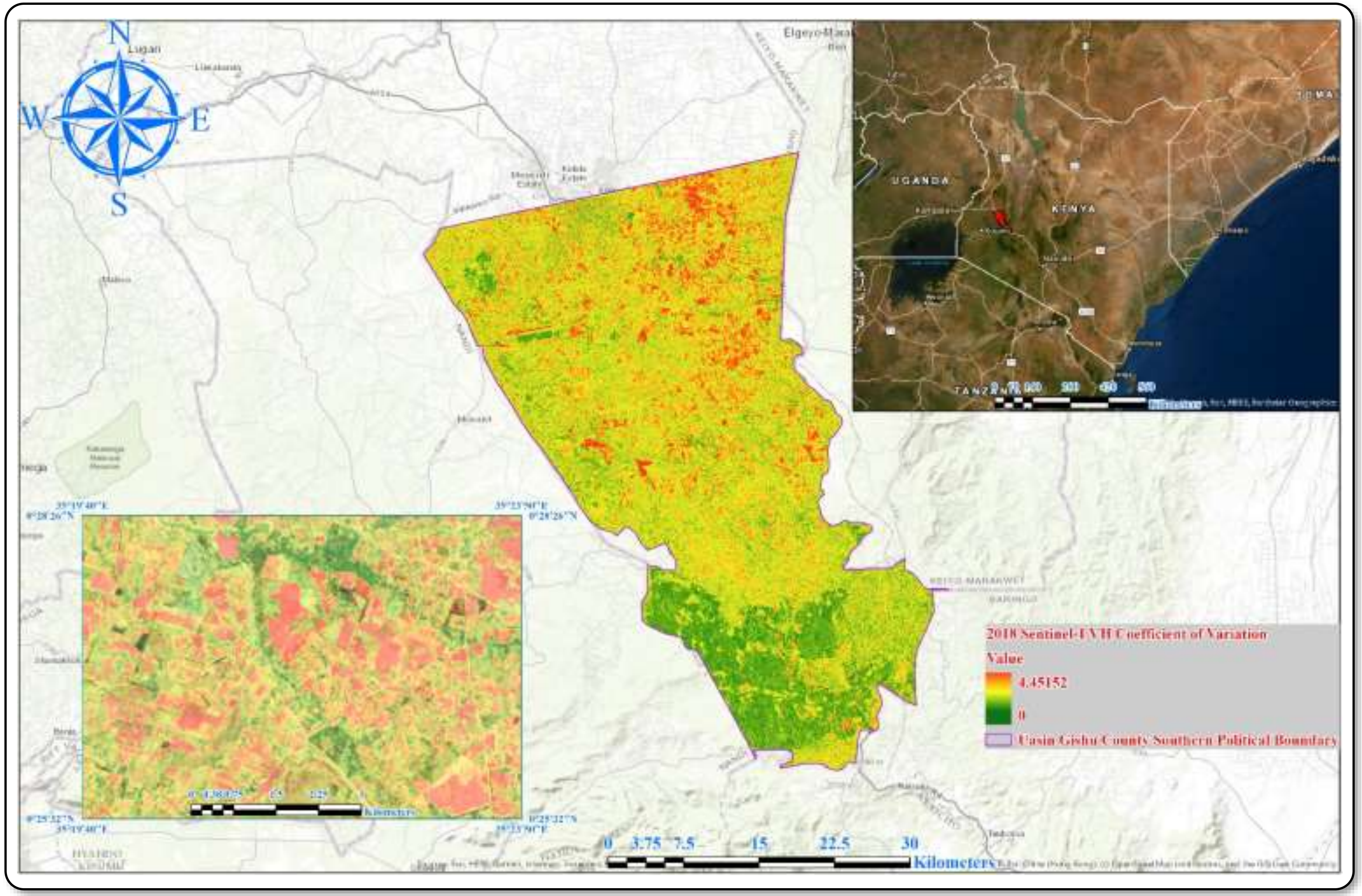
Visualized in NASA Response Portal

Example of Coefficient of Variation for Agriculture Areas

C-Band Sentinel-1 VH Data in Ghana, Africa

- **Study Site:** Uasin Gishu County, Kenya
    - **Top right:** Overview of area
    - **Bottom left:** Sentinel-2 false color image
    - **Center:** Sentinel-1 CoV image

- **Sentinel-1 SAR Data used:**
    - **61 VH-polarization images** acquired between Jan 2017 and Dec 2017



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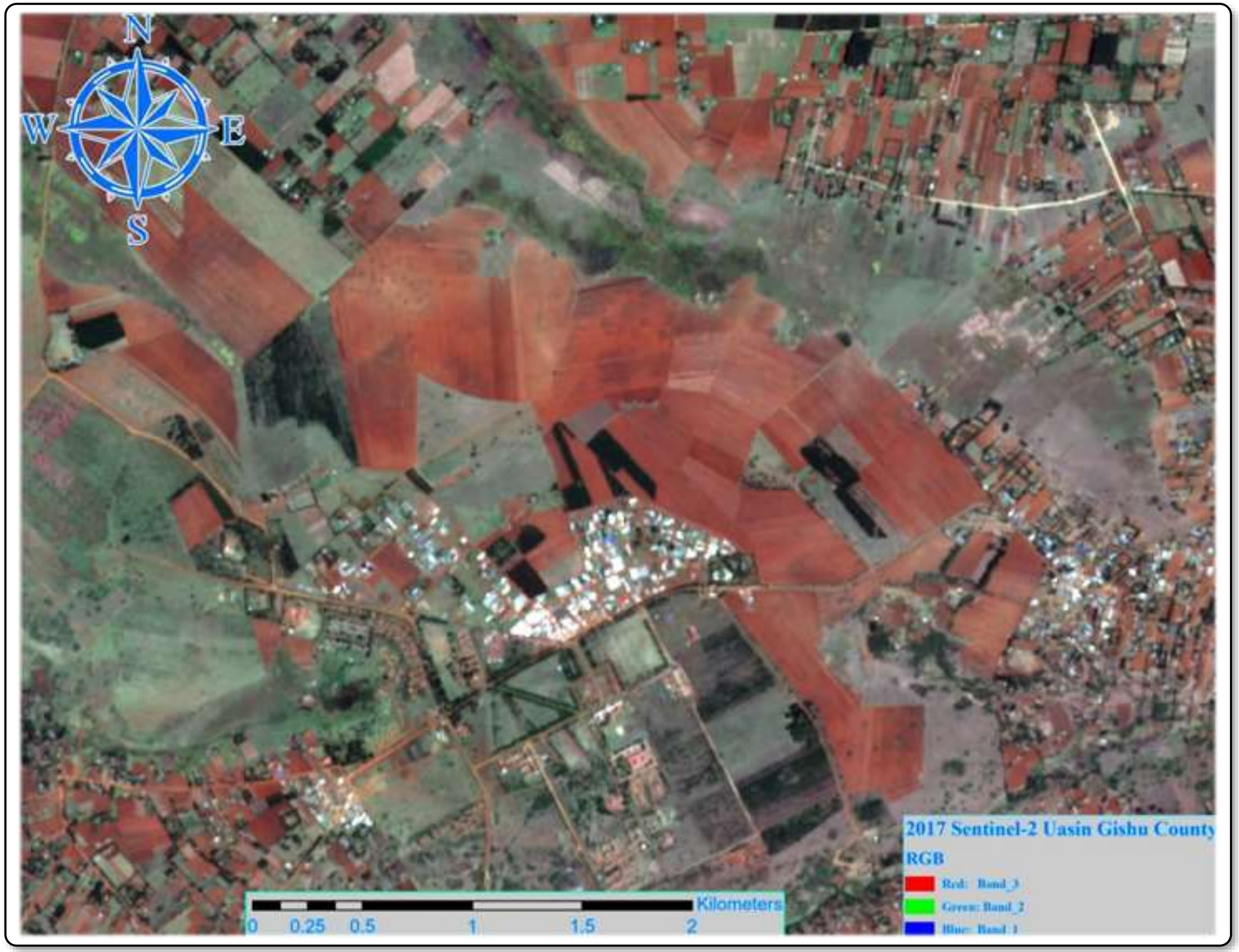
- **Comparison of Sentinel-2 (optical) image and SAR CoV Data**
  - Sentinel-2 image from January 2017
  - SAR data from Jan – Dec 2017

Site A



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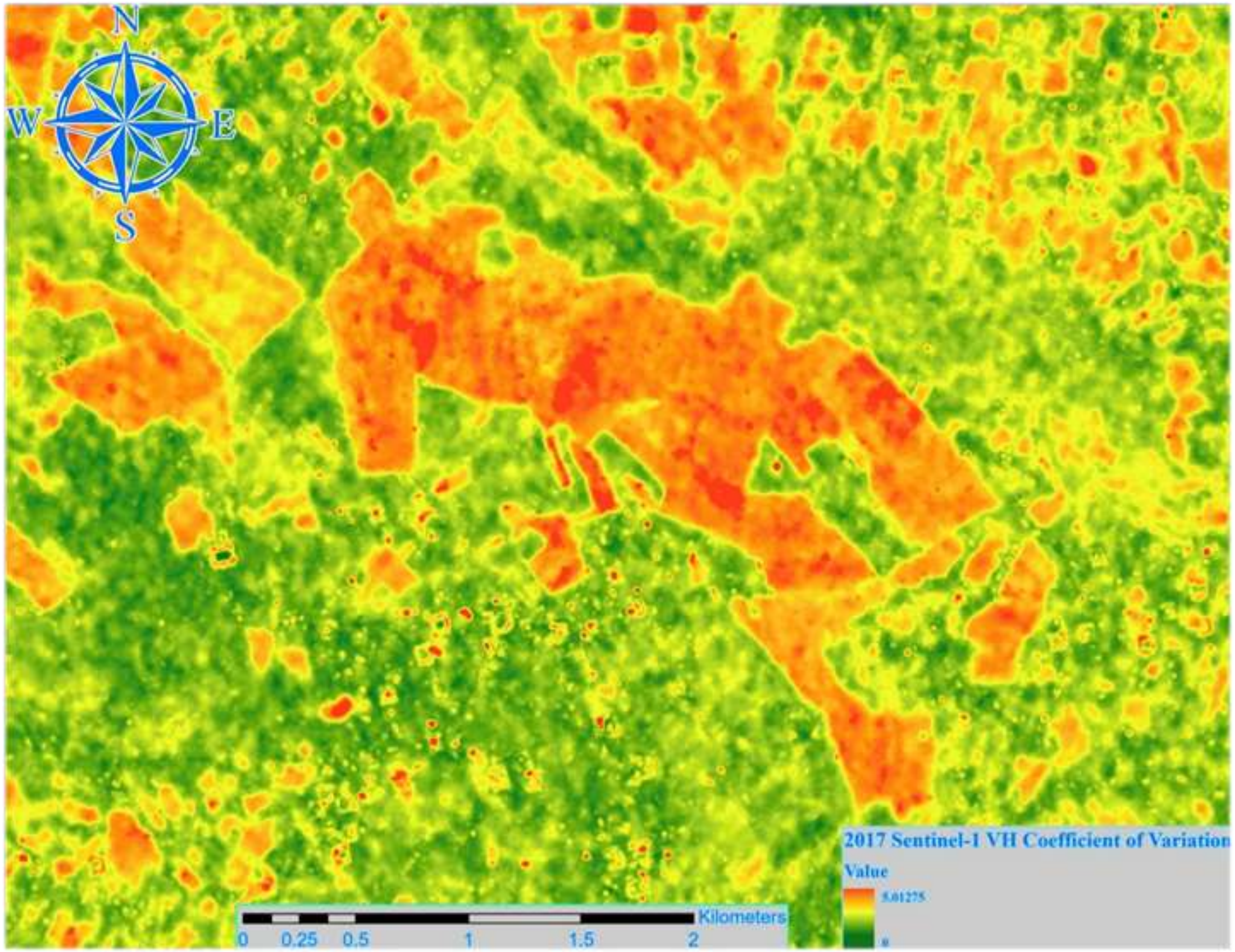

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