Using geospatial data to improve targeting of agricultural projects in the context of climate change and resource scarcity

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Who am I?

- 🙋 Darius A. Görgen
- 🎓 M.Sc. Geography, B.Sc. Political Sciences
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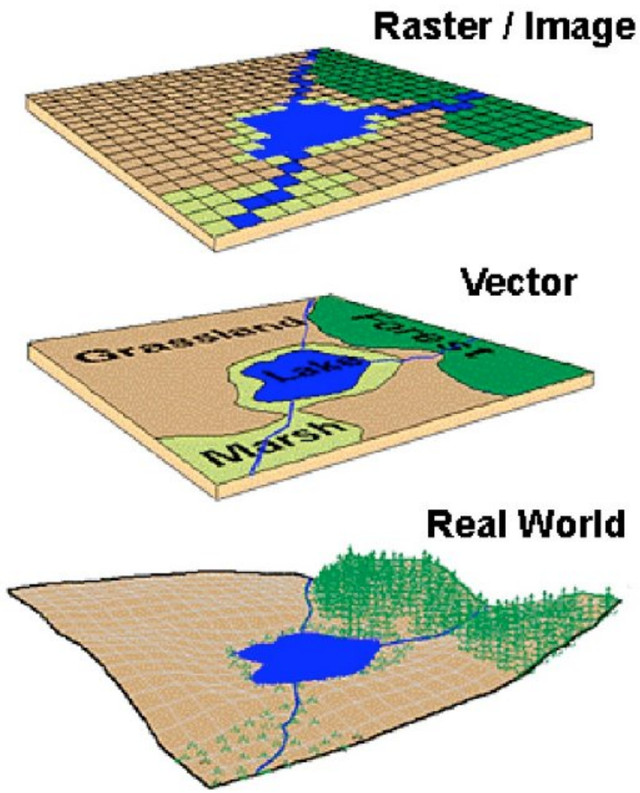
Content

- What is geospatial data?
- From visual interpretation to automated analysis
    i. Counting trees by hand
    ii. Deep Learning for field boundary delineation
    iii. Satellite time series for crop type identification
    iv. Data fusion for crop biophysical monitoring
- Wrap-Up

Geospatial data

Geospatial data



Conceptualization of space in the dominant digital formats.

- Landsat and Copernicus mission provide access to satellite archives for free
- we can look back in time
- we can produce valuable information by intersecting vectors with rasters
- we can derive information for inaccessible areas

Source: Saab (2003)

From visual interpretation to automated analysis

Visual interpretation

A tree plantation near the Jordan EcoPark.

- aerial imagery can help monitoring progress
- VHR images are usually quite expensive
- sensible approach for small areas and simple information requirements, e.g. counting trees

Source: GoogleMaps, CNES 2023

Field boundary delineation

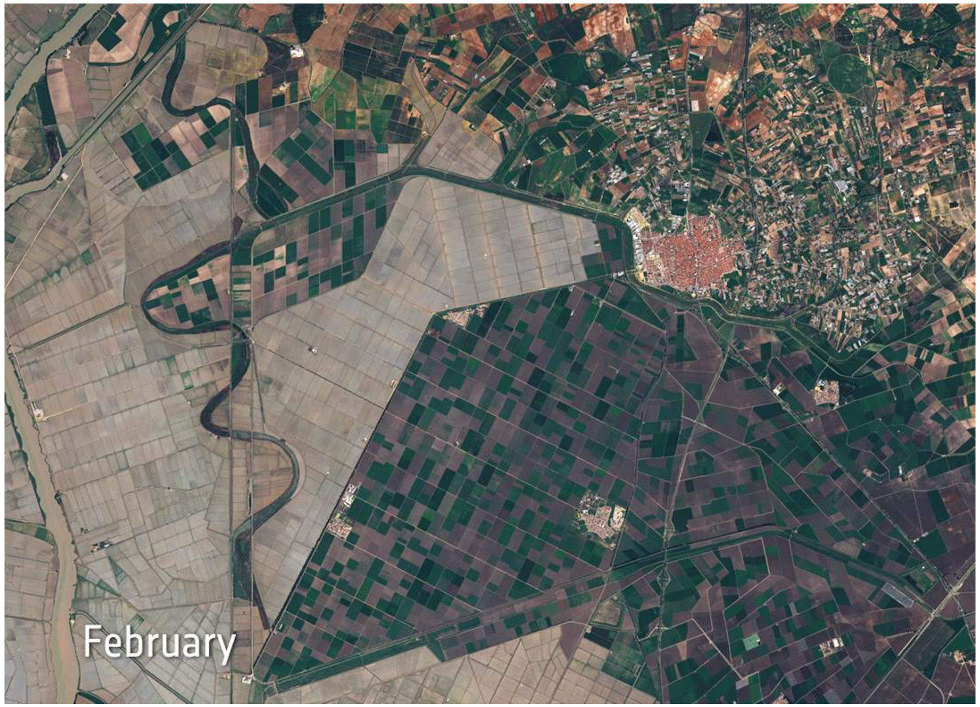
- very often our area is too large for manual interpretation
- we need tools that automate the interpretation of satellite imagery
- Meta AI's Segment Anything Network is already used in the agricultural sector
- field boundaries can be used to inform about the area distribution of farms …
- … but also they might be required for later analysis stages

Screenshot of agricultural boundaries produced by SAM.

Source: lofty

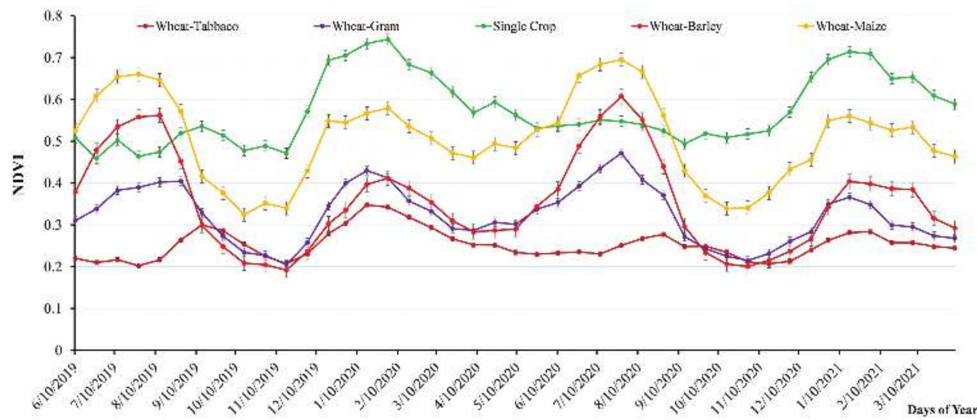
Crop type indentification

Satellite imagery timeseries …



Animation of a Sentinel-2 timeseries over an agricultural area.

… reveal distinct signatures of crops over time.

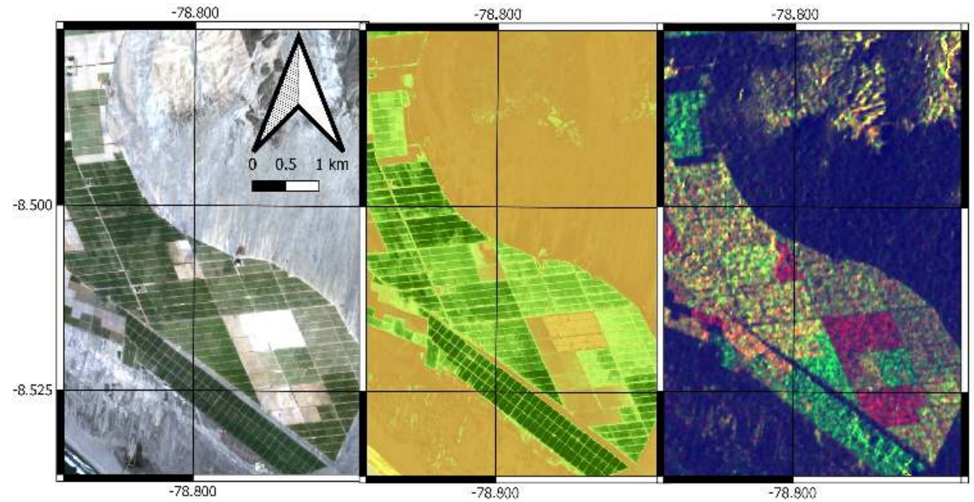


Temporal NDVI profiles of different crop types.

Sources: GeoVille, ESA CC BY-SA 3.0 IGO, Tariq et al. (2022)

Mapping biopyhsical parameters

- monitoring of crop development over time
- derive key parameters such as:
    - crop health
    - growing cycle
    - water consumption
    - yield estimation
- requires large amount of high-quality data collected on ground
- requires the application of advanced statistical methods



Visualisation of an data fusion approach from Sentinel 1 and 2 for crop biophysical monitoring.

Source: Silva-Perez, Marino, and Cameron (2022)

Wrap-Up

- geospatial data can help to better target areas of intervention
- remote sensing can deliver valuable insights, especially in data scarce regions
- *All models are wrong, but some are useful.* (George Box)
- evaluate the low-hanging fruits first
- gold standards require large amounts of high-quality and thus expensive data
- visual interpretation is a valid approach for small areas and simple problems
- if the detail of required information increases, so do the data quality requirements
- regional analysis can reveal key information:
  - area distribution of farms
  - distribution of crop types
  - yield estimation and other biophysical parameters

Thank you for your attention!

Extra Slides

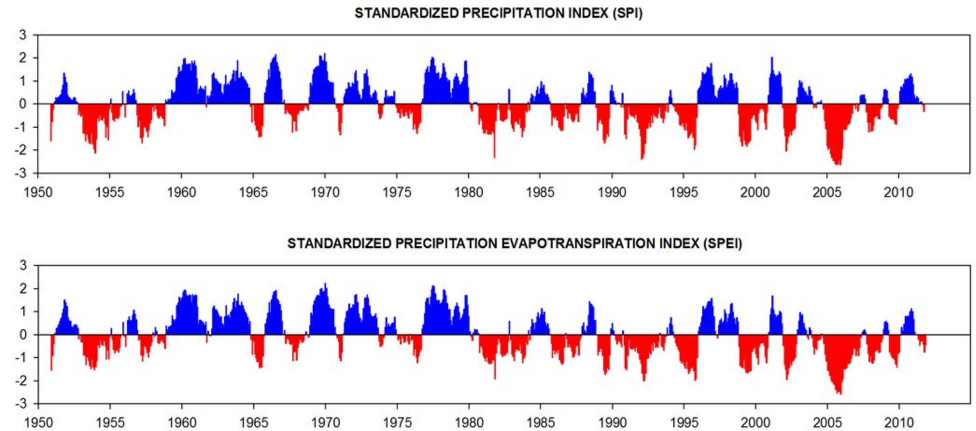
Flooded areas

- determine areas prone to flooding to reduce risks of losses
- assess damages after flood events, e.g. for insurance claims
- support immediate disaster responses

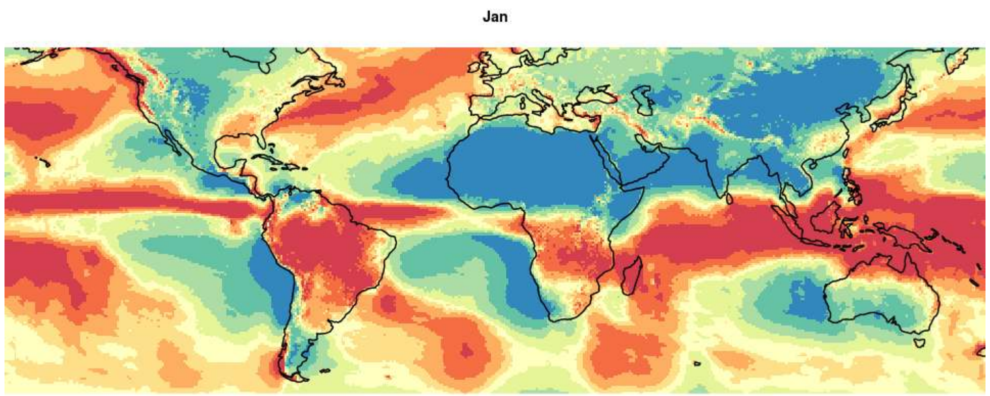
Animation of 2022 monsoon floods in Bangladesh.

Climatological drought

- SPI/SPEI to quantify intensity and duration of meteorological droughts
- SPEI is preferable when temperature or ET_0 data is available
- gridded datasets allow drought analysis even in data scarce regions
- CHELSA has good performance for complex terrains and data-scarce regions
- includes climate projections for different CMIP6 scenarios



Comparison of SPI and SPEI to charachterize meterological drought.

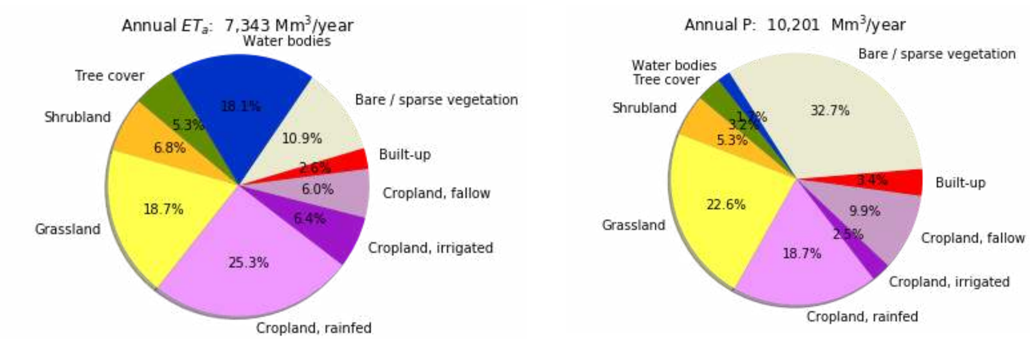


CHELSA animation of average precipitation between 1981-2010.

Sources: Karger et al. (2021), Vicente-Serrano, Beguería, and López-Moreno (2010)

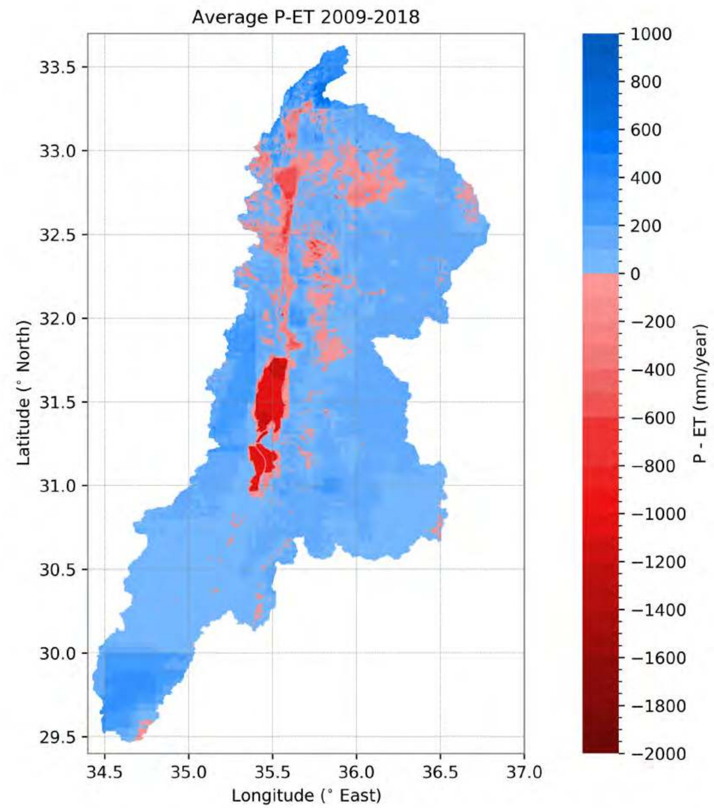
Water accounting

- Water accounting study in the Jordan River Basin by FAO
- Uses remote-sensing based variables by FAO's WAPOR
- Differentiates between water generating ($P > ET_a$) and consuming ($P < ET_a$) land cover classes



(a) ET_a

(b) P



Difference between Precipitation (P) and Actual Evapotranspiration and Interception (ET_a).

Figure 1: Contribution of landcover classes to ET_a (a) and precipitation (b) in the Jordan River Basin.

Sources: FAO and Delft (2020)

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