Monitoring abiotic and biotic stressors

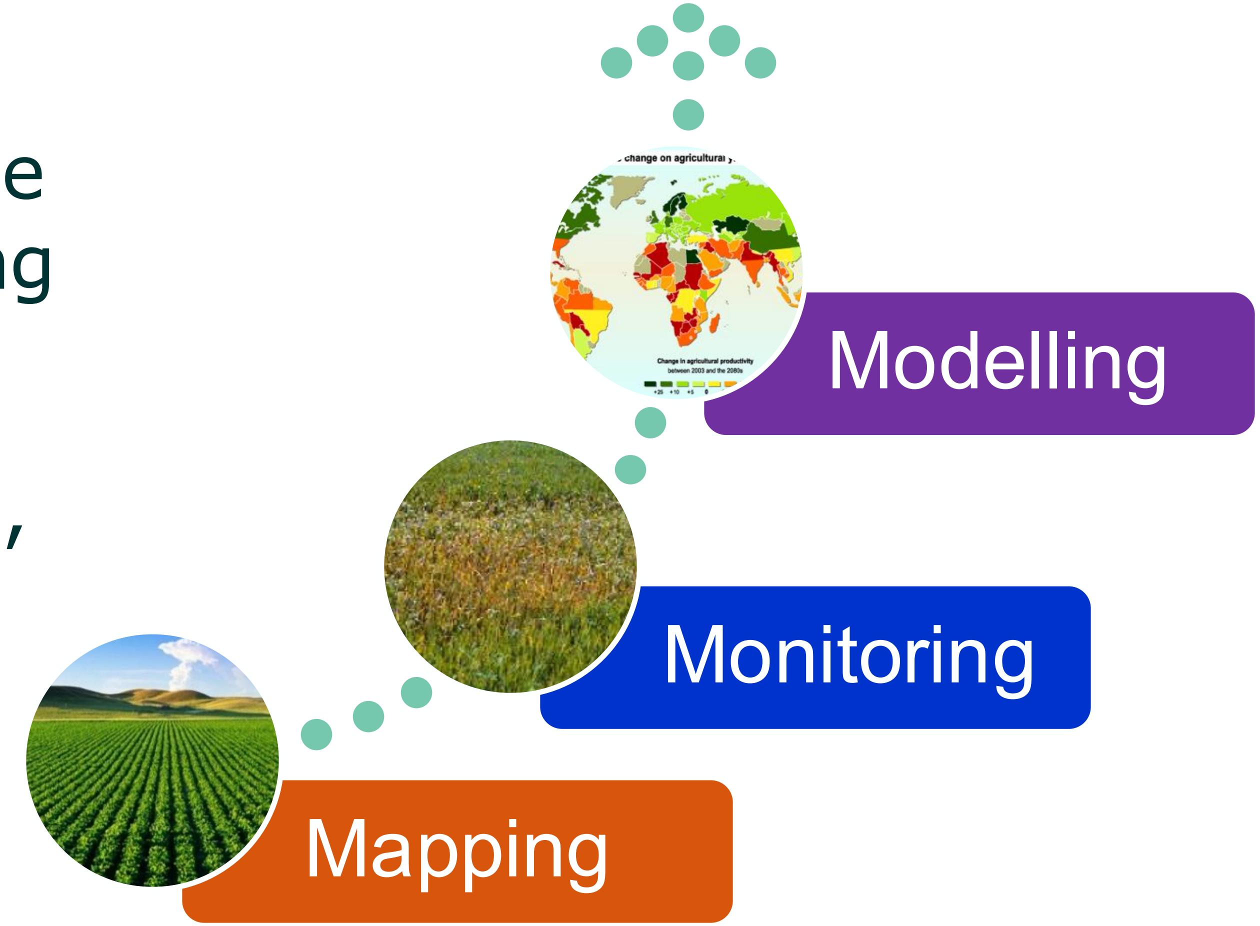
Prof Jadu Dash, University of Southampton

Role of EO in Agriculture

Environmental/climate impact and forecasting

Health and production, pest and disease

Area/type



2

European Earth Observational capabilities

aws

Google Earth Engine

CDSE

JASMIN

Microsoft Azure

→ THE EUROPEAN SPACE AGENCY

Different products

Radiance

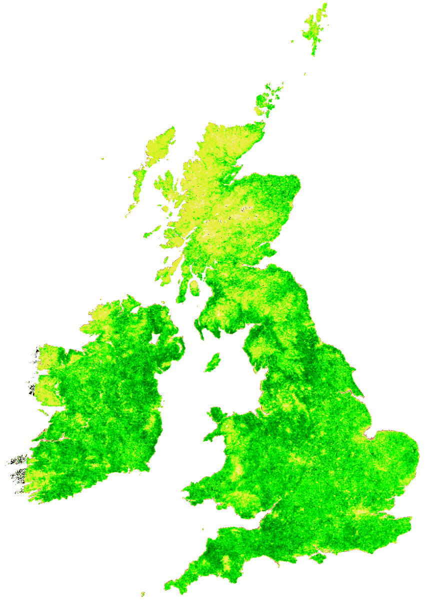
L1

Biophysical

L2

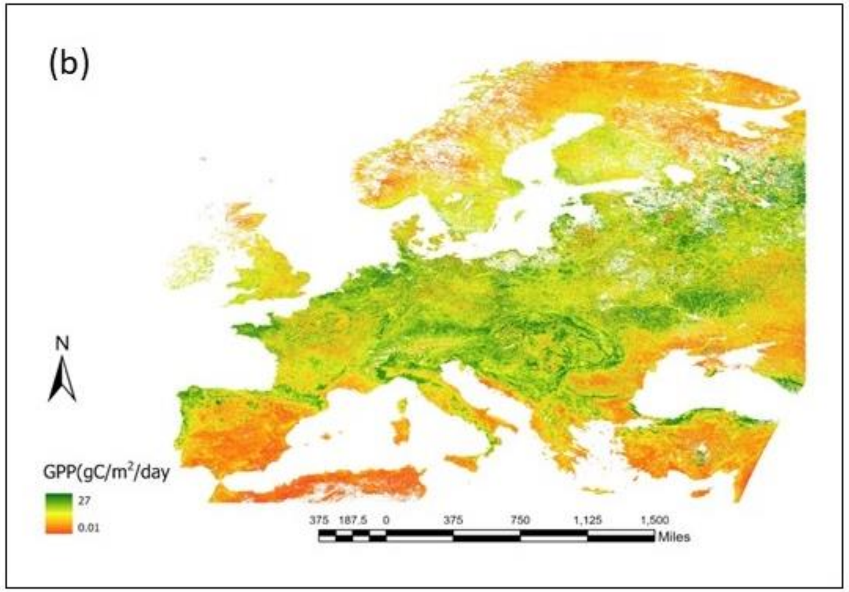
Composites

L3



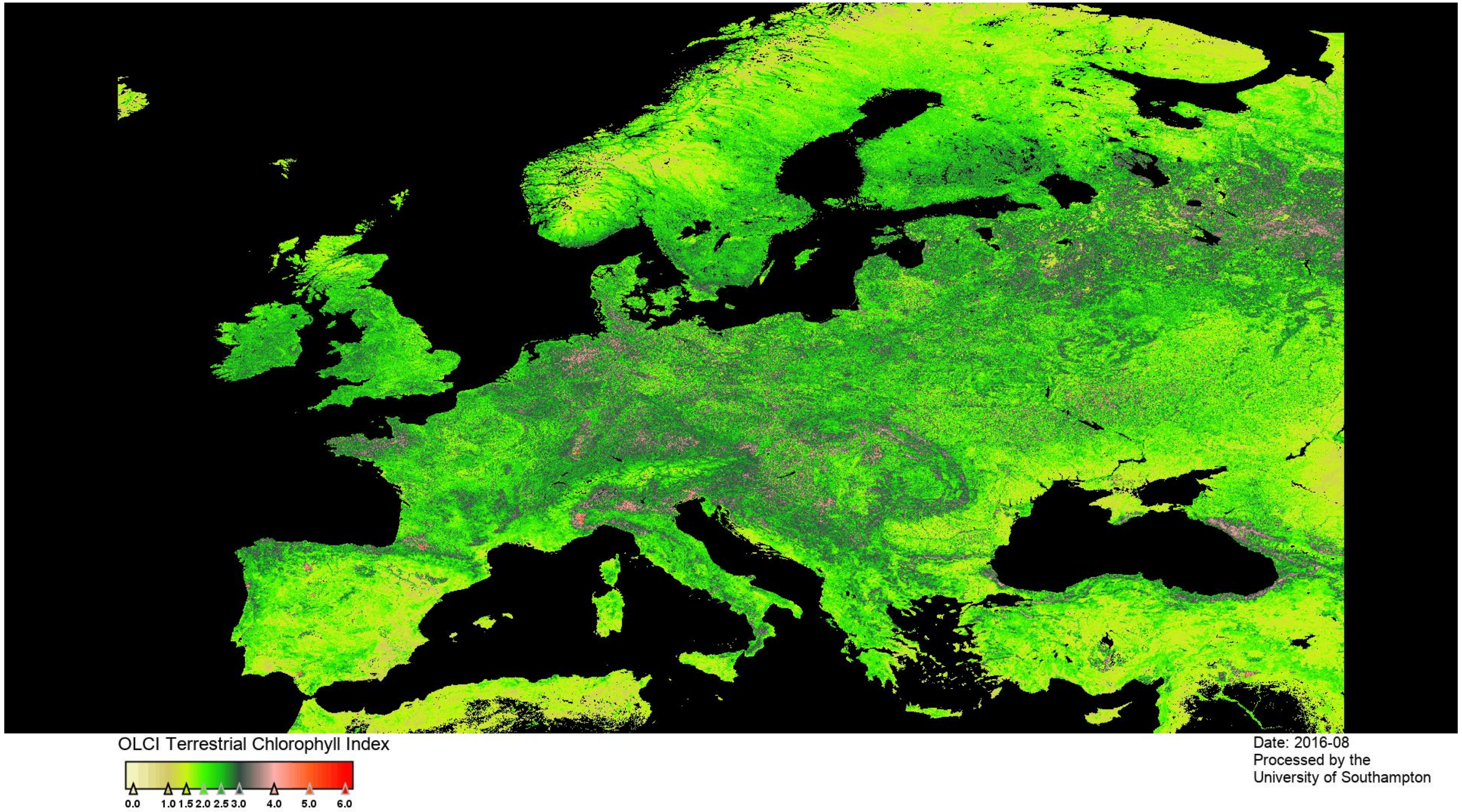
Simulated

L4

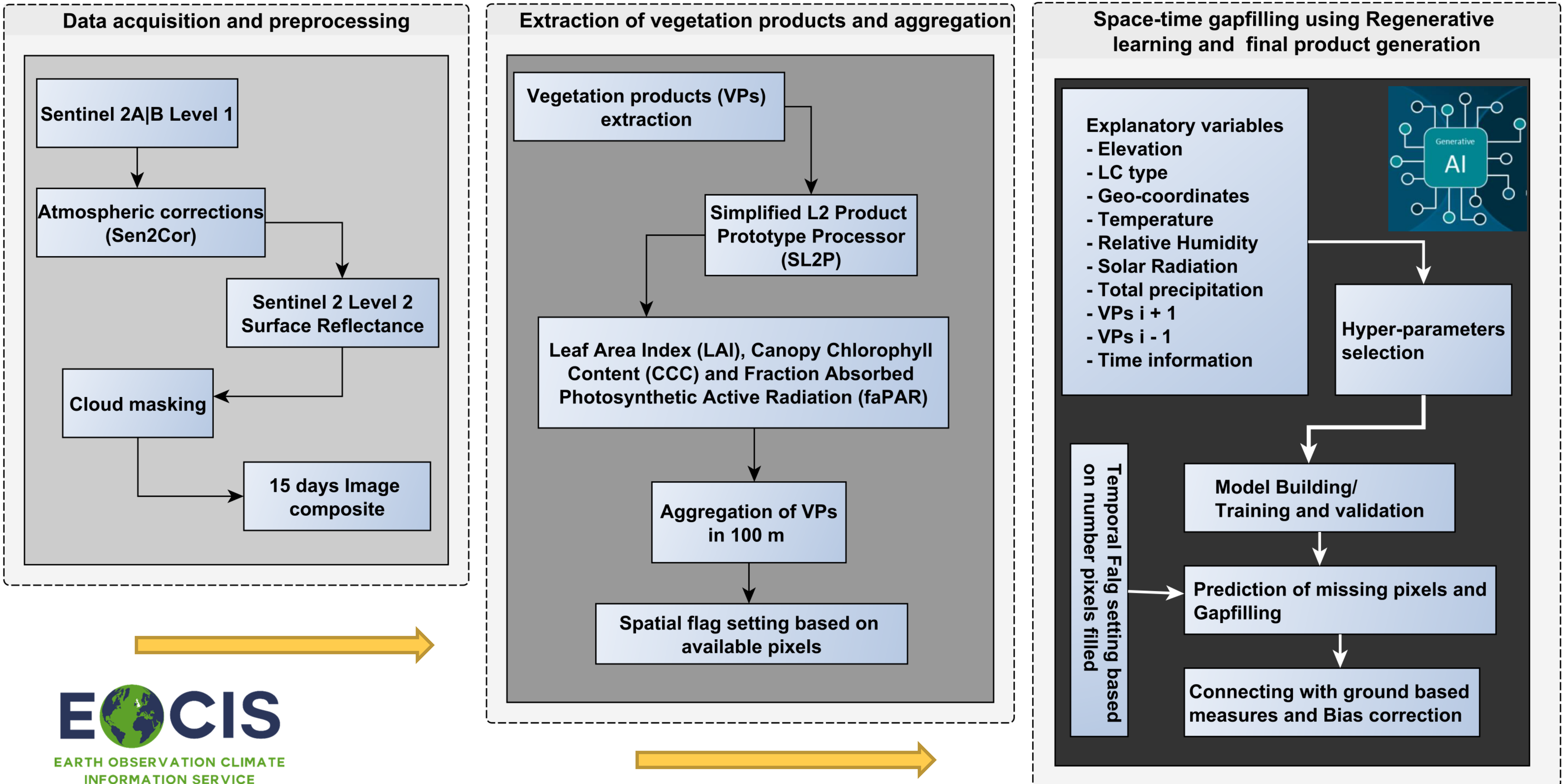


Earth Observation products

Near Daily data acquisition from Sentinel 3

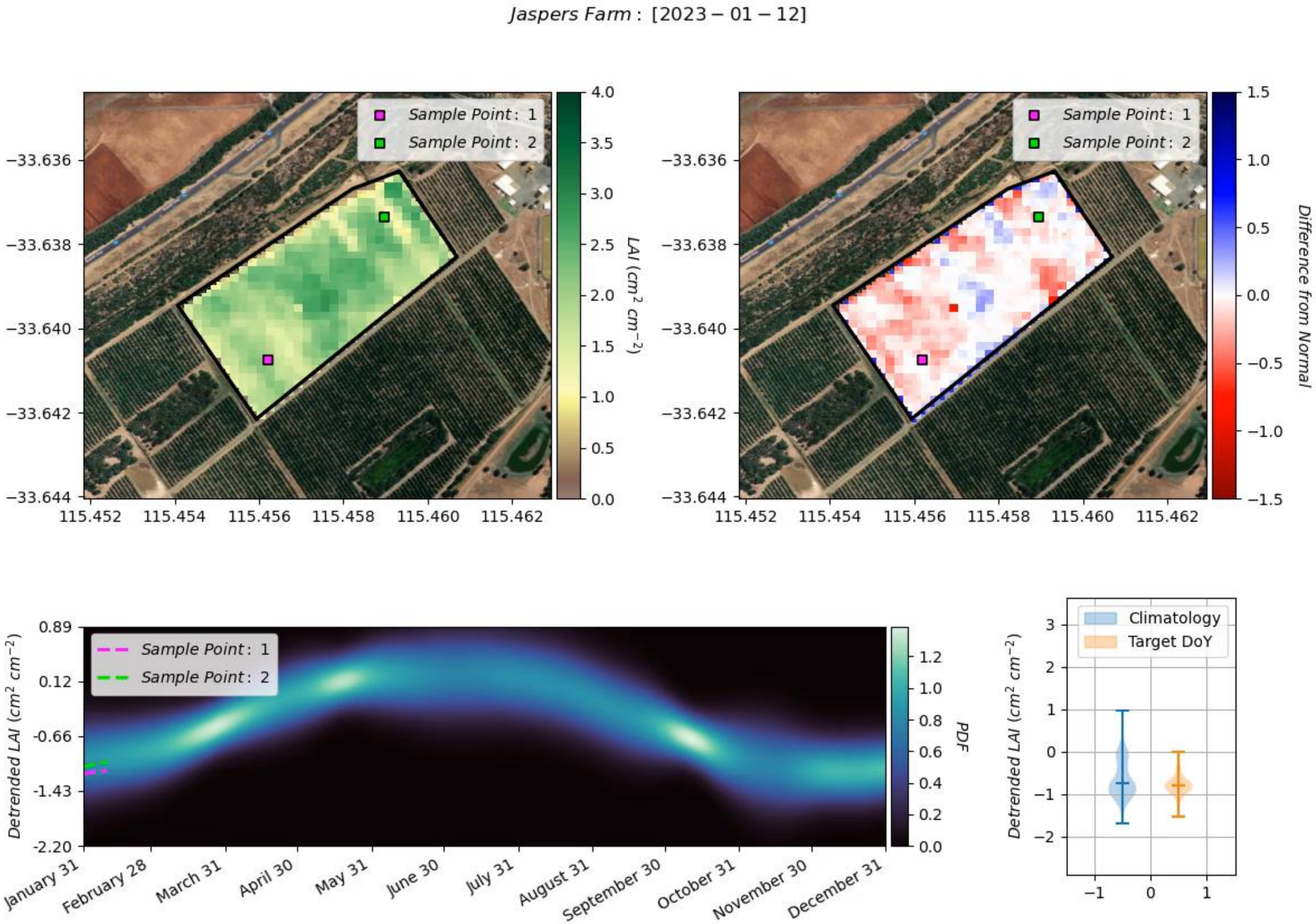


CHUK products



EOCIS
EARTH OBSERVATION CLIMATE INFORMATION SERVICE

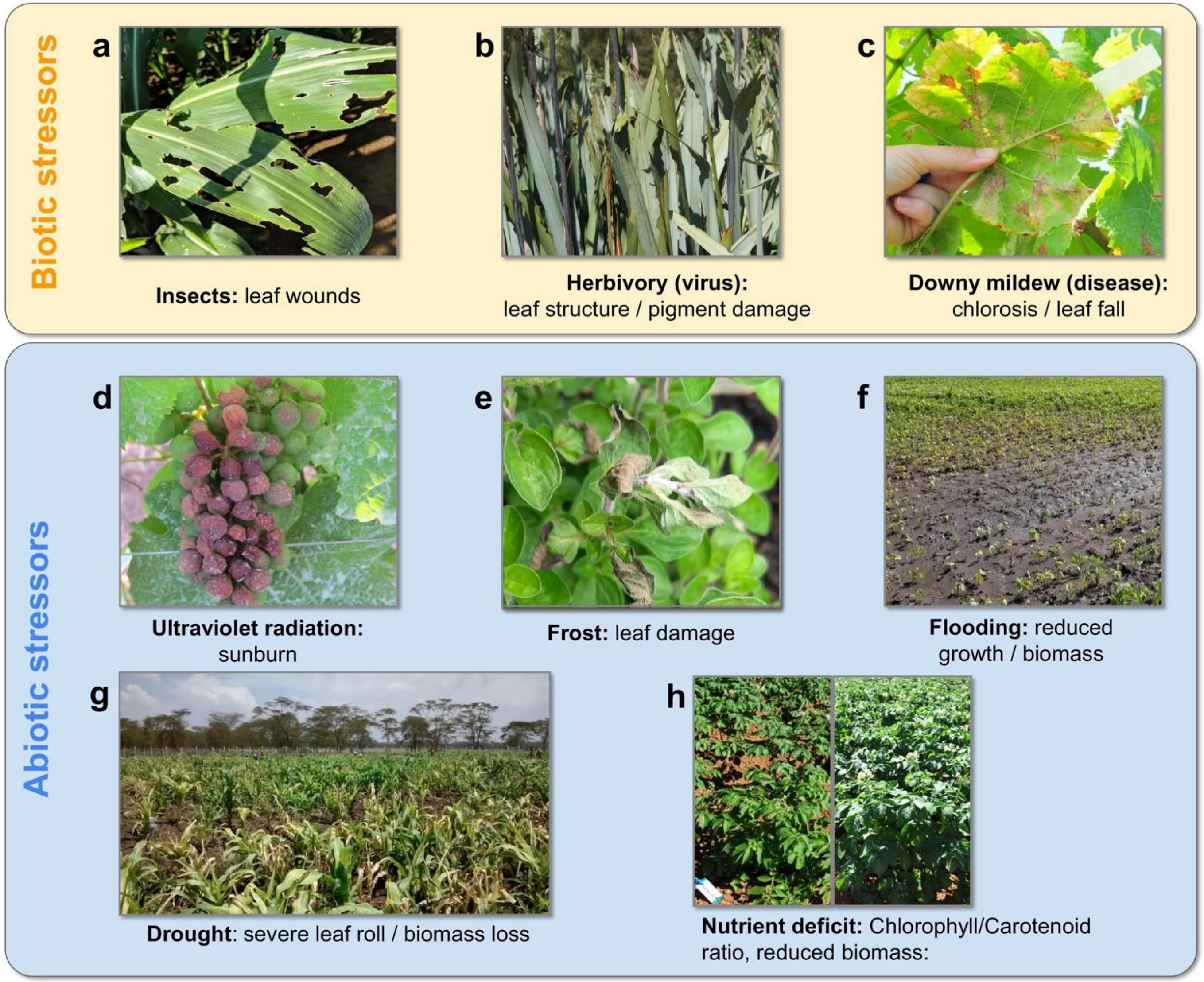
Real time monitoring



EOCROP

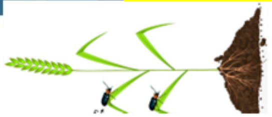
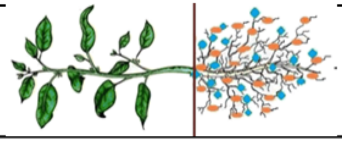
Alex Cornelius

Biotic and Abiotic stresses



Berger, Katja, et al. "Multi-sensor spectral synergies for crop stress detection and monitoring in the optical domain: A review." *Remote Sensing of Environment* 280 (2022): 113198.

Impact of Stressor

Stress	Symptoms	Variables	Signals
 Pest	Texture and structure	pigment conc., water content, Canopy cover, LAI	Variations in VIs, unique dips and peaks
 Lodging	Morphology, canopy structure, shadowing, vegetation density	Canopy height, slant height, vertical lodged height, lodged area %	NIR↑ SWIR↑
 Nutrient	Growth, chlorophyll, pigment content, leaf structure	As, CC, NE,LUE,RUE	Red↓ Blue↓
 Drought	Leaf Turgor, water, leaf angle, chlorophyll	Tc ,ETa, Rn, P, Tmin, Tmax, LAI, Carotenoids, CC	NIR↓ SWIR↓ Vis↑
 Salinity	Yellow leaf, tissue damage, discoloration	CC, WC	NIR↑ SWIR↑ Vis↓
 Heavy metals	Metabolism, morphology, pigmentation, chlorosis	Proline content, fluorescence, soil quality	Hg induce Fluor., NIR↑ for Cu Vis↑ NIR↑
 Heat Stress	Leaf structure, pigments, heat conditions	Tc, LeafT, CC, WC, Leaf pigments	Red↓ Blue↓ LWIR↑

Key methods

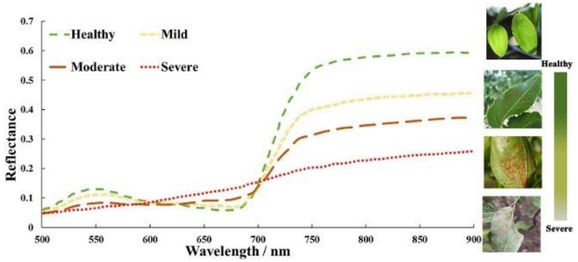
Purpose	Method I	Method II	Method III
Deriving Crop Traits and Stressor Variables	sensor-based crop stress indices (LAI, RECI, TVDI, MTCI,PSI,PRI, CCI, WDI,WSI, SAVI,RVI)	Feature Extraction and Feature Selection (PCA,LDA, ICA,CR, WT, MSC)	Radiative Transfer Models (PROSAIL, DART, SCOPE,SLC)
Applying Techniques	Empirical Regression Models	Machine learning Models Deep Learning	Hybrid Retrieval Method Feature Fusion Data Fusion Ensemble methods Expert Systems

- ❑ purpose of monitoring
- ❑ the scale of monitoring
- ❑ the need for controlled experiments
- ❑ the type of monitoring (qualitative vs. quantitative)

Biotic Stress

- **Direct Pest Assessment**
- **Biophysical & Biochemical Parameters for Early Detection of Invisible Pest Infections**
- **Landscape monitoring through EO data and ancillary information**

Leaf

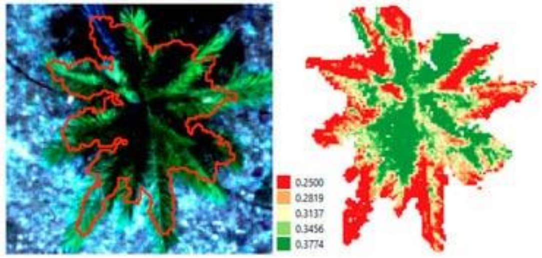


Lu et al., 2022

Preti et al., 2020)

Canopy

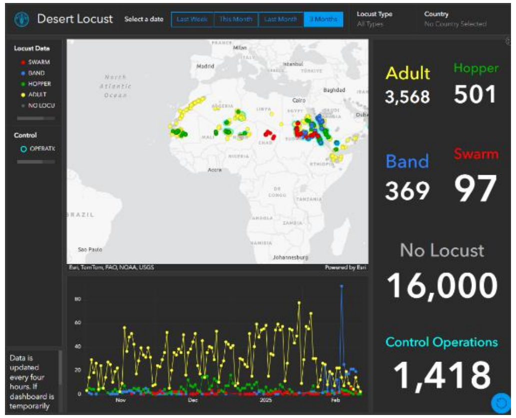
Phytophthora

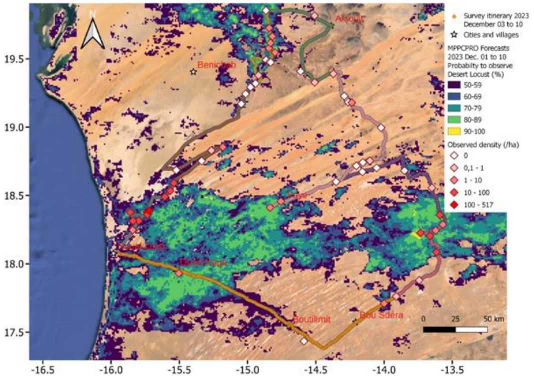


Delalieux et al., 2023

Red Palm Weevil Detection

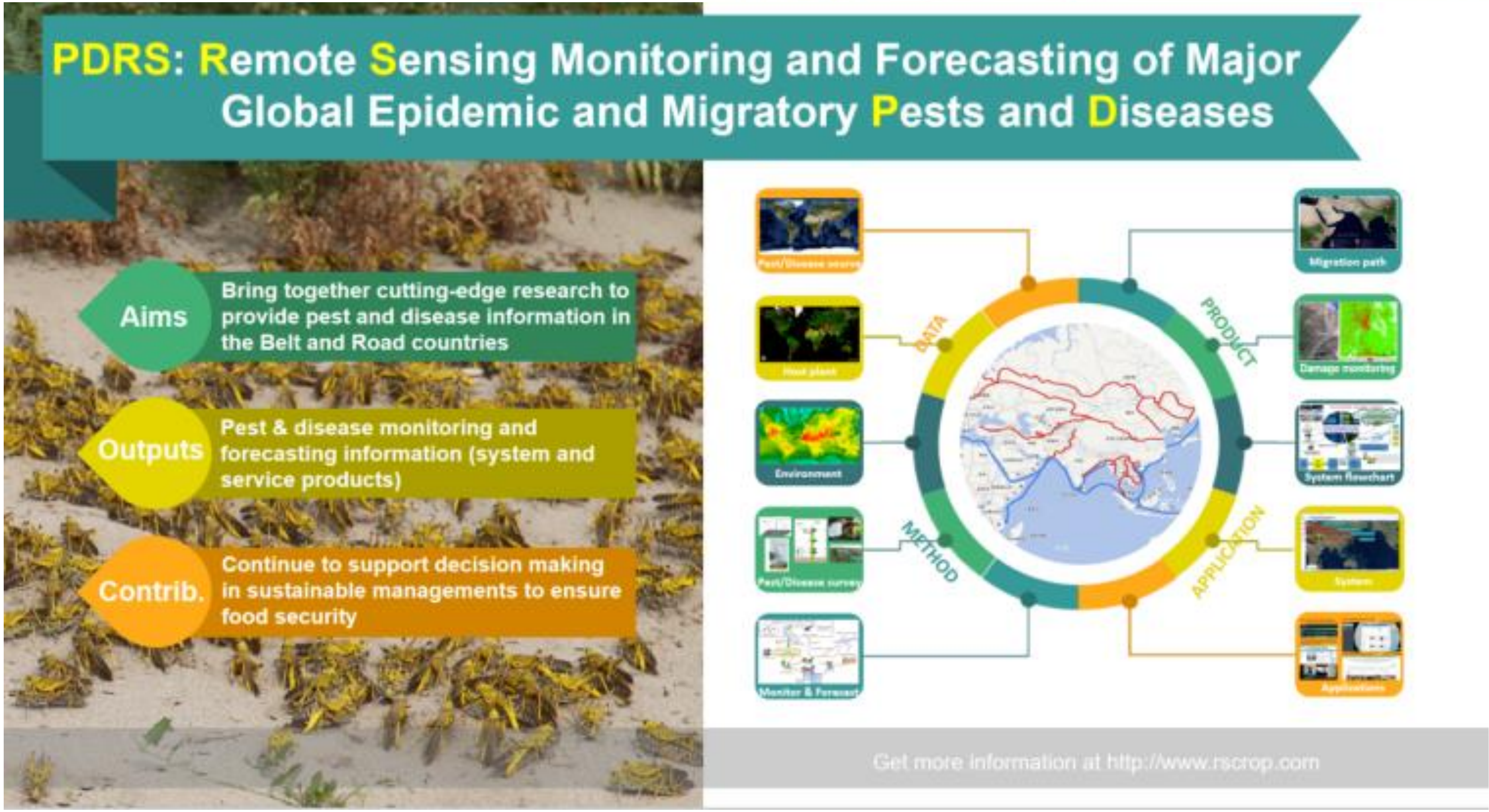
Landscape





(Marescot, et al., 2025)

Biotic Stress



Abiotic stress

1. Land degradation (Yield gap)- Long term
2. EO4Cereal stress: Long->Short term
3. Flash Drought :Short term

Case study: Yield gap in Malawi

Challenges:

Land pressure:

- Cropland expansion
- Continuous farming

Low crop yield:

- Land degradation

Solutions:

- Sustainable intensification
    - ➢ Crop diversification

Research aims:

➢ monitor cropland expansion and estimate remaining arable land

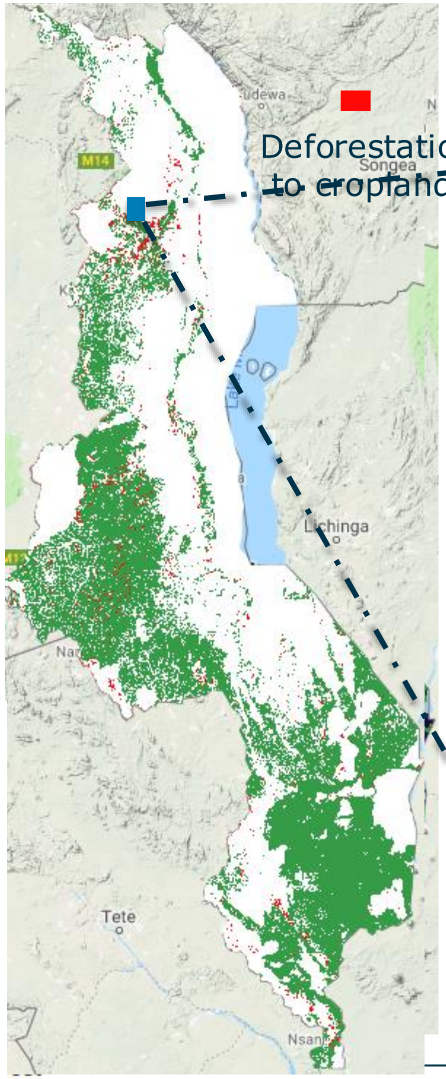
➢ Understand yield gap

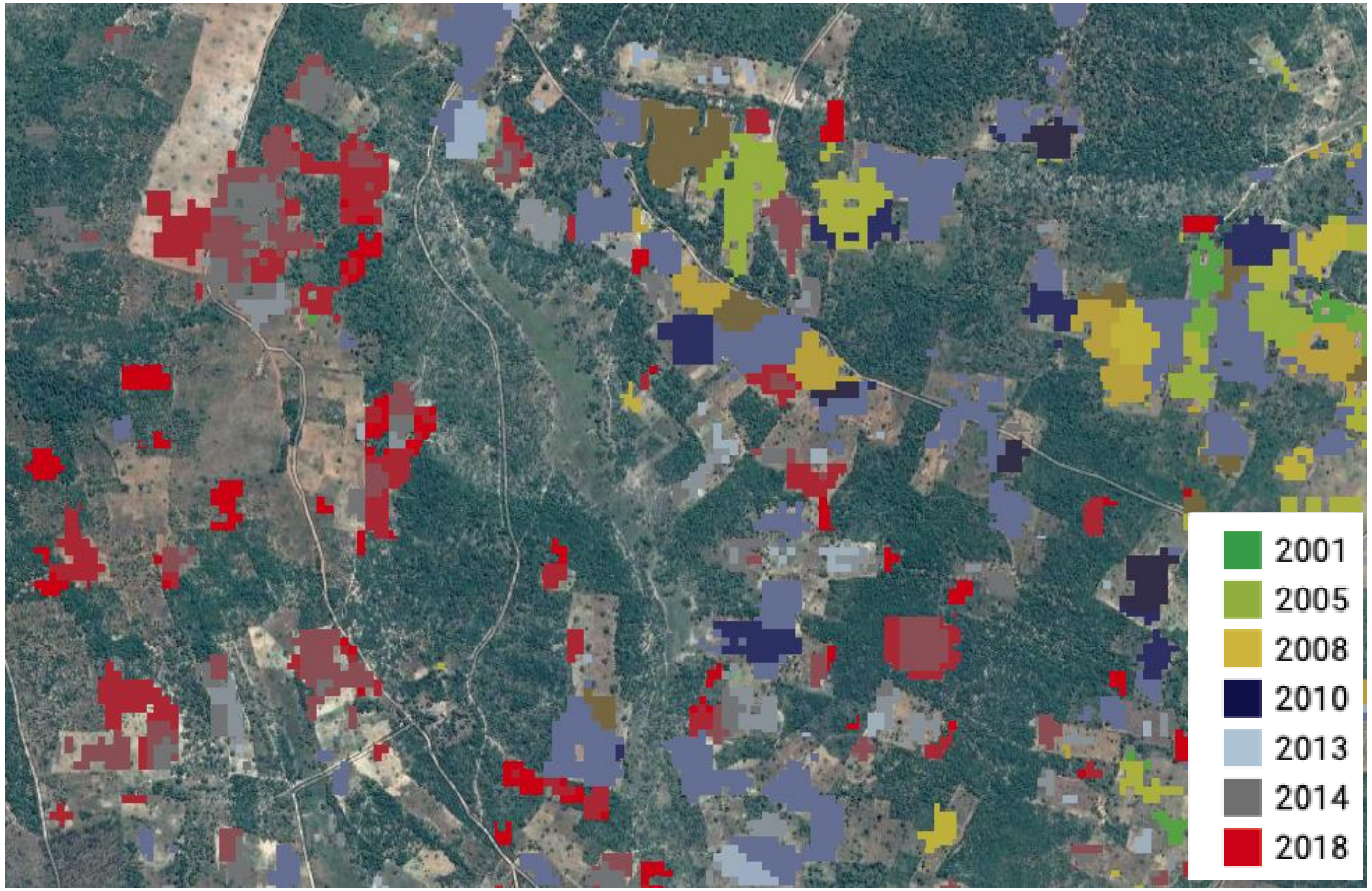
➢ Understand best practices for crop diversification

BRECcIA

Agriculture expansion in Malawi

Cropland extent in 2018

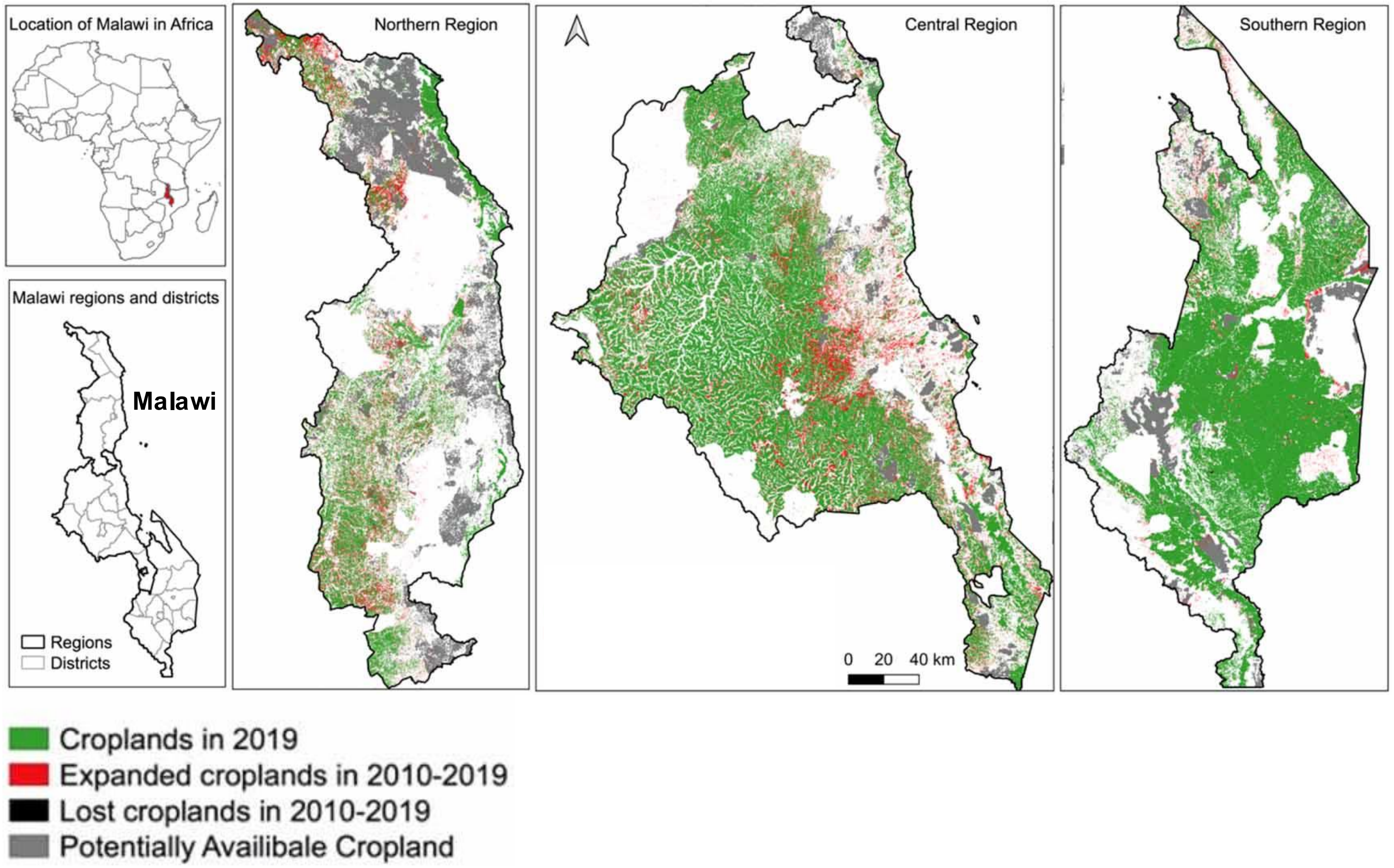


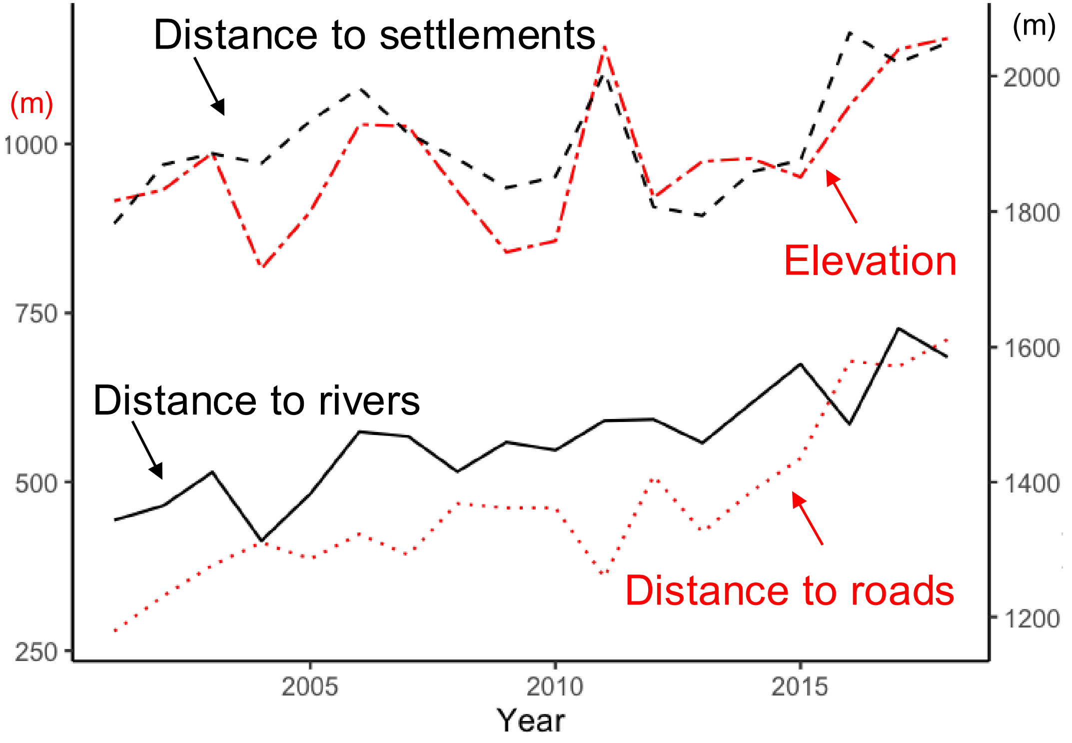


cropland expansion result from forest loss indicated by colored polygon, different color represent the year of forest loss

Agriculture expansion in Malawi

- Rapid cropland expansion rate: 10% (2010-2020)
- Limited potential for future expansion (5%)



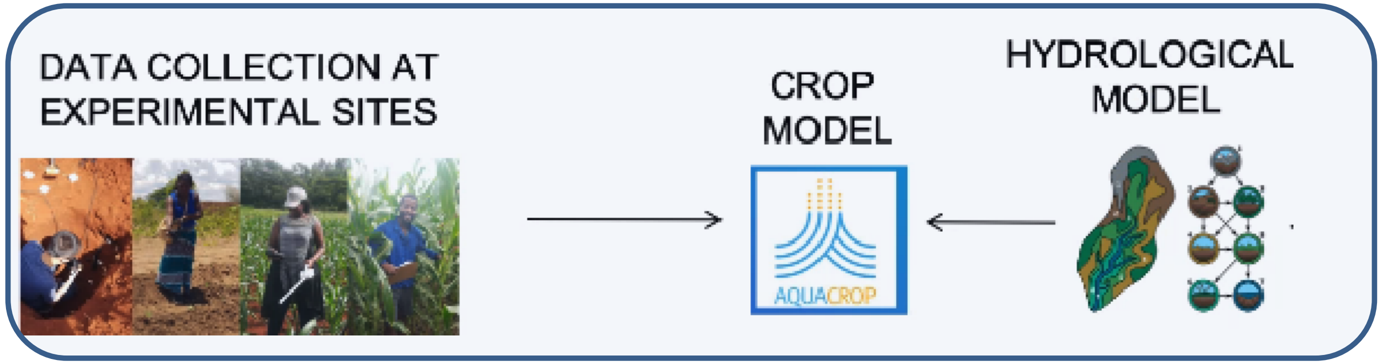


Chengxiu Li, et al., *Environ. Res. Lett.*, 2021

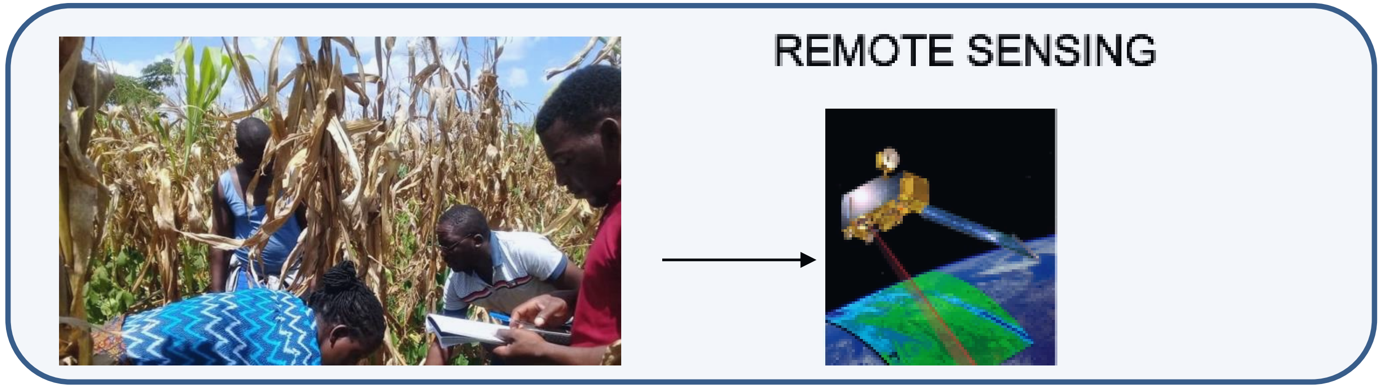
Yield Gap

- Yield gap = Potential Yield - Farm Yield

Potential Yield:



Farm Yield:



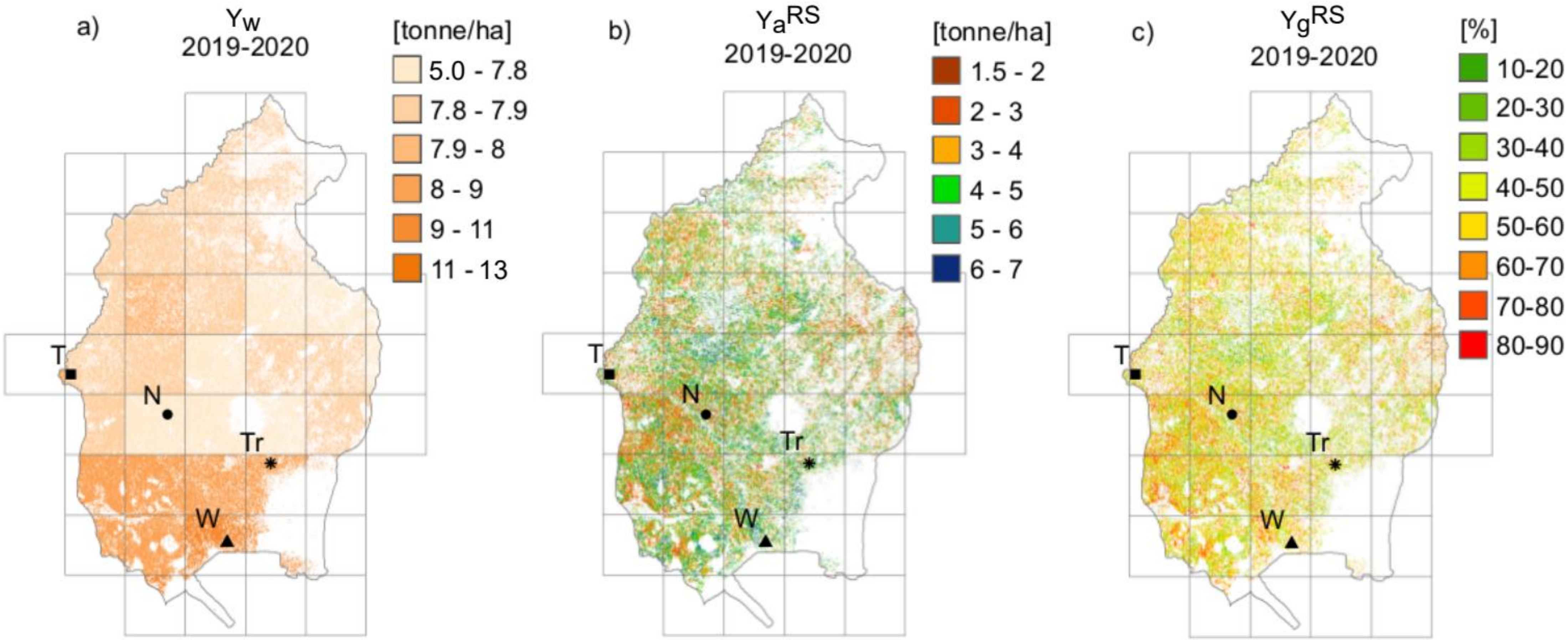
- Socio-economic factors

Management

Socio economic factors

Chengxiu Li, et al., *Remote Sensing.*, 2022, **Daniela Anghileri et al.**, , *Agricultural Systems*, 2024

Yield Gap



Potential Yield (simulated)   Actual Yield (Remote Sensing)   Yield gap (percentage)

EO4CerealStress

- *"Synergistically use of multi-source Earth Observation data and in-situ data - taking advantage of their complementarity - to understand the effects of single and combined stressors on cereal crops"*
- *"To develop products that can be used to monitor these stressors and provide a scientific roadmap for the future development of EO products and techniques for monitoring multiple crop stressors"*

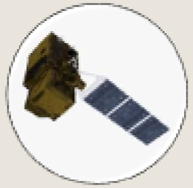
https://eo4cerealstress.org/

University of Southampton
Agriculture and Agri-Food Canada
BOKU University of Natural Resources and Life Sciences, Vienna
Universidad de Sevilla
ITC University of Twente.
University of Guelph

EO4CerealStress: Project Framework

EO & in situ data collection

Satellite
(Sentinel, EnMap, PRISMA, Planet Scope etc.)



Airborne
(UAVs, Drones etc.)

Climate data
(P,T,RH,SM etc.)

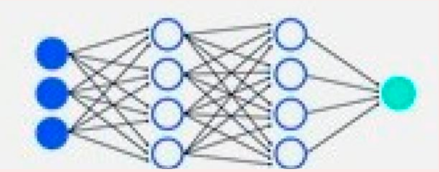
***In-situ* crop measurements**
(Agronomic, Biochemical/Biophysical variables e.g., LAI, CCC, FC etc.)

***In-situ* Soil Properties/Nutrients**
(K, N, P, Cu, As,Cd, Cr, Pb,AI)

Stressor/Effect Estimation - Approach

Empirical Regression based Methods

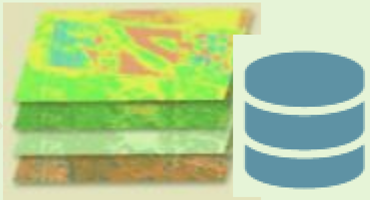
+



Machine Learning

+

Radiative Transfer Modelling



Experimental Products

+

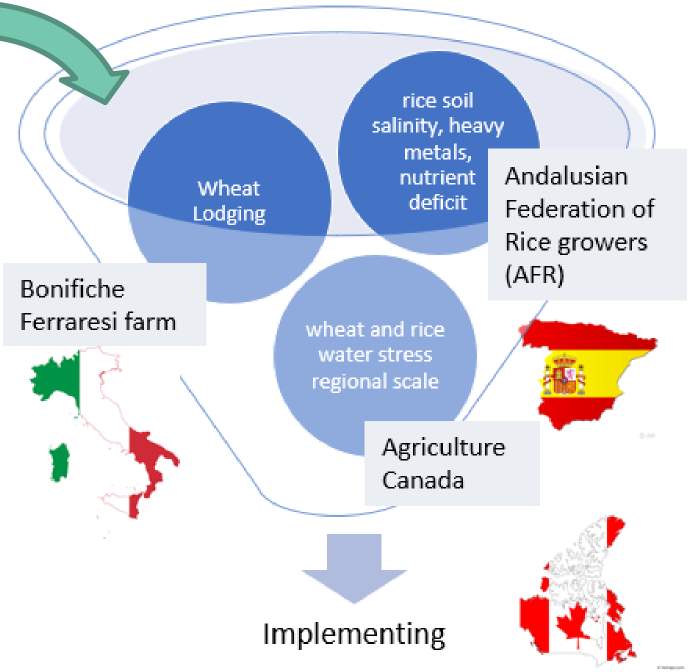
EO based Crop stress indicators

+

Algorithms for cereal crop stress

New algorithm-based Product Development & Validation

Product Evaluation, Scientific Analysis & Impact Assessment

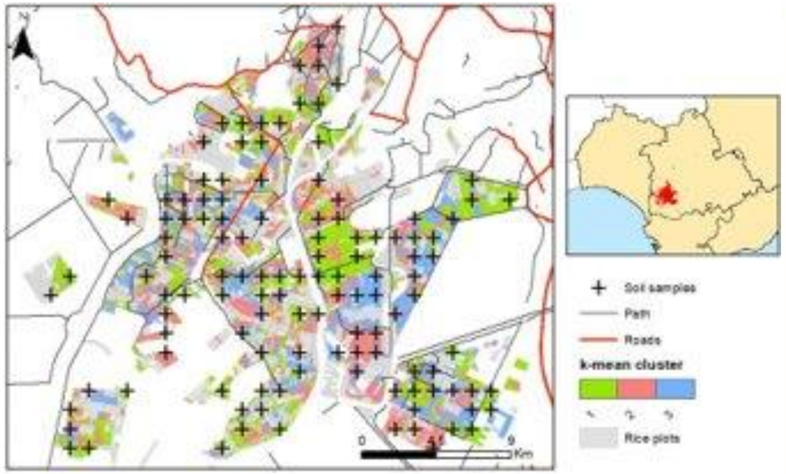


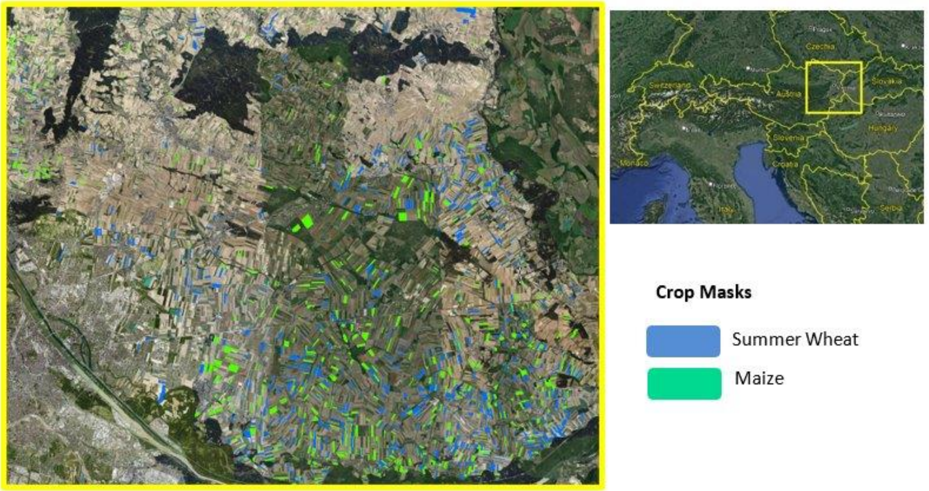
Implementing

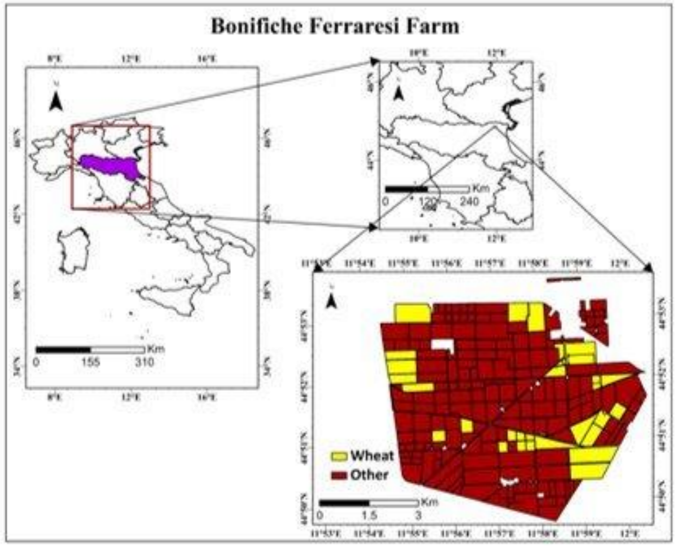
Three prototype demonstration cases

Scientific Roadmap

Pilot sites





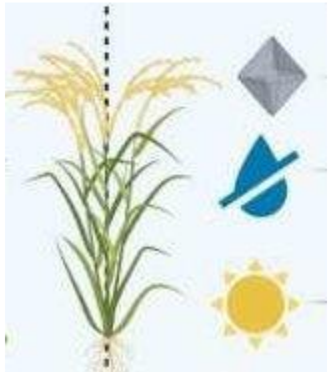


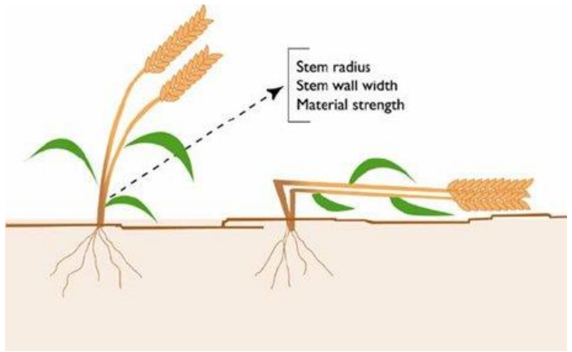
Test site I - Rice cultivation in Andalusia, Spain

Test site II - Marchfeld region, Austria

Test site III - Bonifiche Farm, Italy

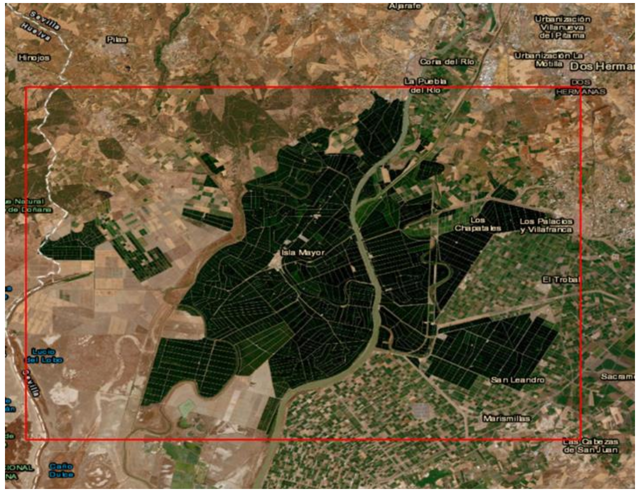
Nutrient stress,
Salinity, Heavy metal,
Water stress



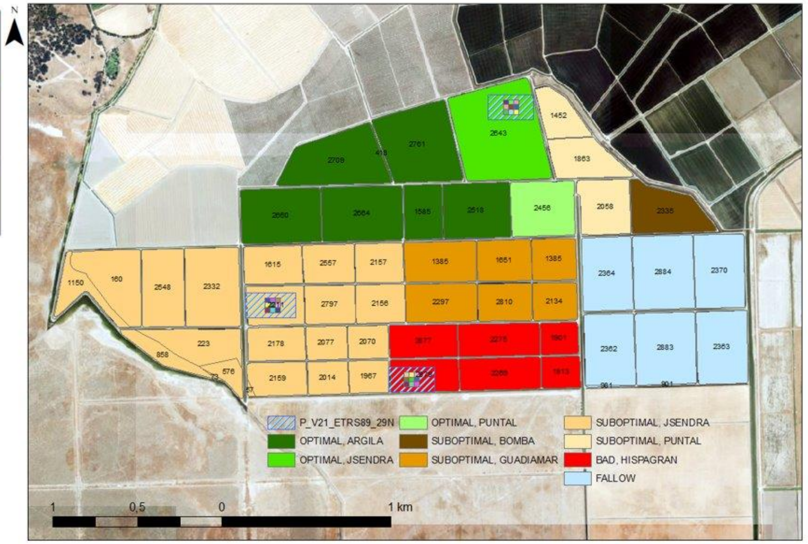


Pilot site I: Andalusia Rice Farm, Spain

- ❑ Salinity, nutrients deficit in soils, and toxicity by heavy metals



- ❑ Relationship between multiple stressors and rice crop status/condition.
- ❑ Data Collected/Used:
  - ❑ ***EO data*** **:** Sentinel-2, PRISMA, and EnMap
  - ❑ **Meteorological data**: ECMWF ERA5 data, REDIAM (Andalusian Environmental Information Network), SIAR (Agroclimatic Information System for Irrigation (SiAR) of Spain
  - ❑ ***Field Data*** *(Campaign in summer 2023):*
    - ❑ Soil Parameters :Electric conductivity-salinity, organic carbon, texture parameters, nutrients -P, K, Ca, Mg, Na and Heavy metals (As, Cd, Cr, Pb,Al, Cu), ASD spectra
    - ❑ Rice Crop Variables: LAI, *CC*, water content, fresh and dry weight, UAV hyperspectral images - VIS-NIR-SWIR , ASD Spectra



- ❑ Study area: 1,260 km^2

Agriculture response to flash drought

Flash droughts are rapid-onset, short-term drought events characterized by a swift decline in soil moisture and precipitation deficits, typically developing over a few weeks.

Since 2018, Europe has experienced persistent sub-seasonal-to-seasonal flash droughts,

Early forecasting of flash droughts is critical but remains difficult due to the rapid development of these events and the complex interplay

Which Remote sensing based indicator provides early signal to Flash drought

Remote Sensing Applications: Society and Environment 39 (2025) 101690

Contents lists available at ScienceDirect

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journal homepage: www.elsevier.com/locate/rsase

ELSEVIER

Potential of sentinel 2-derived canopy water content as an indicator of flash drought: Case studies from European cereal crop areas

Zaib Unnisa*, Booker Ogutu, Jadunandan Dash

School of Geography and Environmental Science, University of Southampton, SO17 1BJ, United Kingdom

ARTICLE INFO

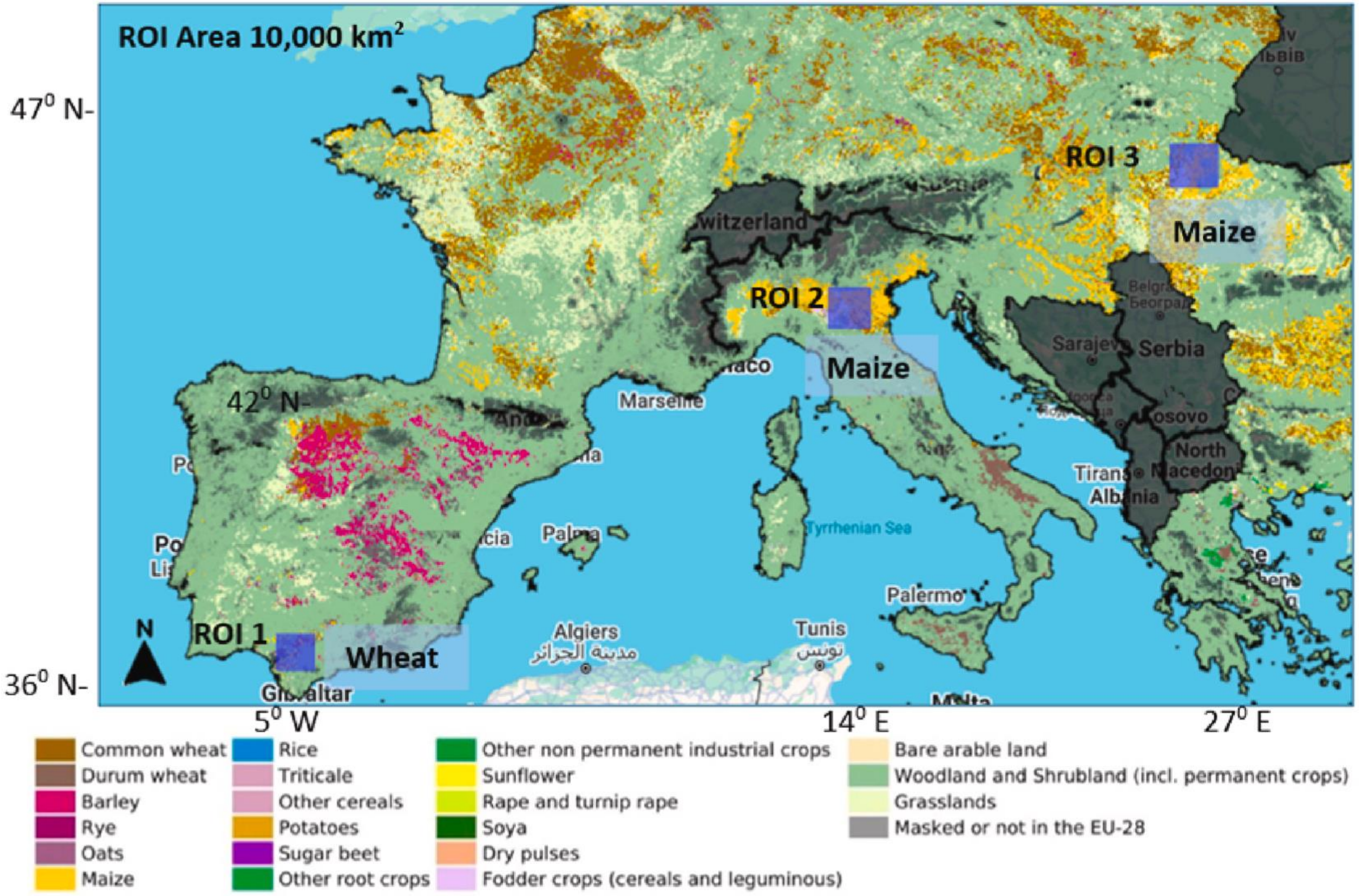
Keywords:
Canopy water content
Drought indicator
Flash drought
Crop stress
Sentinel 2 level 2 processor
Biophysical variables
Evaporative stress index

ABSTRACT

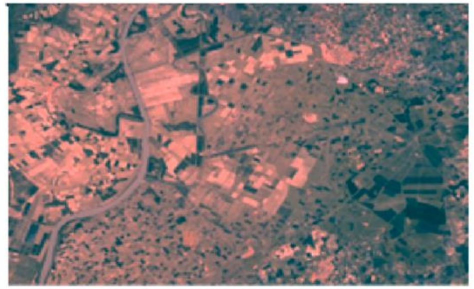
Flash droughts are concerning due to their rapid onset and intensification by heatwaves and rainfall deficit. This leads to rapid soil moisture depletion, causing crops to desiccate and die faster than in slow droughts, especially during critical crop growth stages, which affects the yield. The early detection of flash droughts is possible through the evaluation of the response of plant biophysical variables to these events. To assess that, this study analysed three crop biophysical variables and vegetation index derived from Sentinel-2 across distinct cereal-growing regions in Europe (ROI-1: Southern Spain; ROI-2: Northern Italy; ROI-3: Eastern Hungary) to evaluate their potential for detecting flash droughts. The Evaporative Stress Index (ESI) was used for detecting the drought onset, intensity, and duration, and the response of Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Fraction of Absorbed Photosynthetically Active Radiation (fAPAR), and Canopy Water Content (CWC) were compared using spatio-temporal comparison and Pearson correlation for Wheat and Maize crops in Summer 2022 and Spring 2023 droughts. The findings revealed that CWC showed the earliest response to flash drought over irrigated areas of Spain and Italy compared to LAI and fAPAR. During drought, strong correlations between CWC and ESI (wheat and maize) (in ROI 1, $r = 0.59$ and ROI 2, $r = 0.66$) reflected a higher degree of conformity in capturing drought. However, the sensitivity of CWC to flash drought varied in the rainfed region, with weaker correlation observed in Eastern Hungary, where $r = 0.4$, ROI 3. These results show that there is potential in Sentinel 2-based CWC for early detection of flash droughts, particularly in irrigated systems. It can provide reliable and traceable information about crop stress at the onset of flash drought.

Unnisa, Z., Ogutu, B., & Dash, J. (2025). Potential of Sentinel 2-derived Canopy Water Content as an Indicator of Flash Drought: Case Studies from European Cereal Crop Areas. *Remote Sensing Applications: Society and Environment*, 101690.

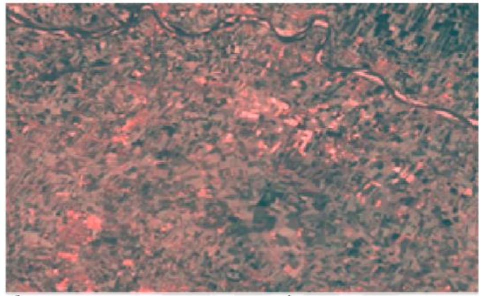
Study area



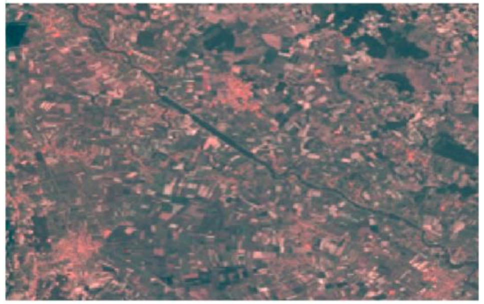
ROI 1: March 2023



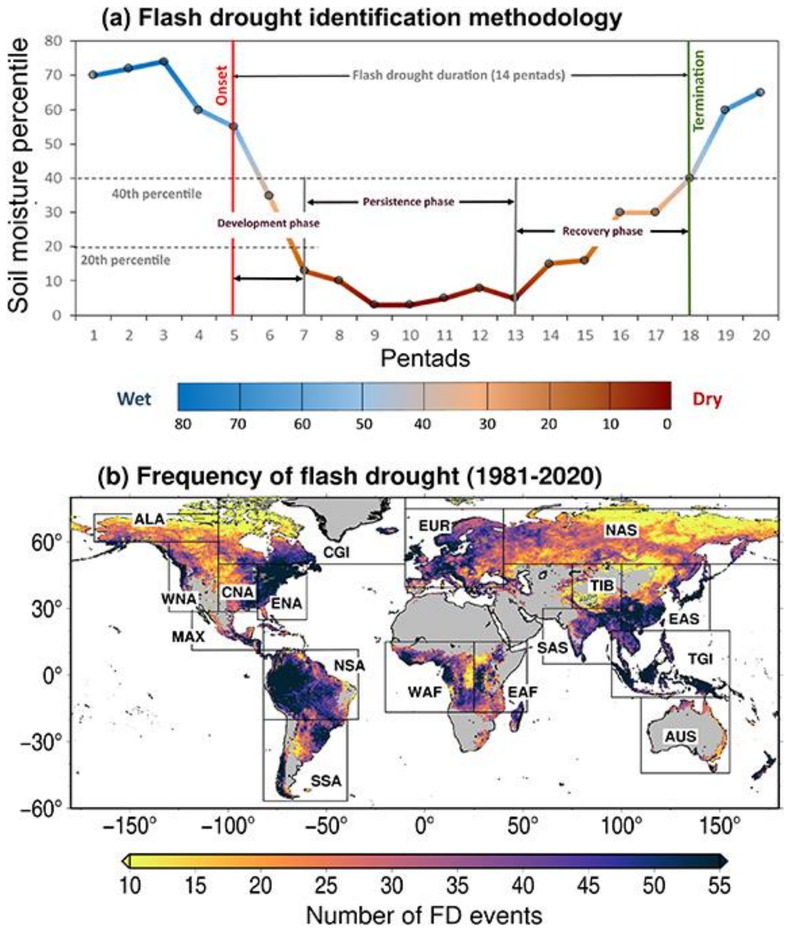
ROI 2: July 2022

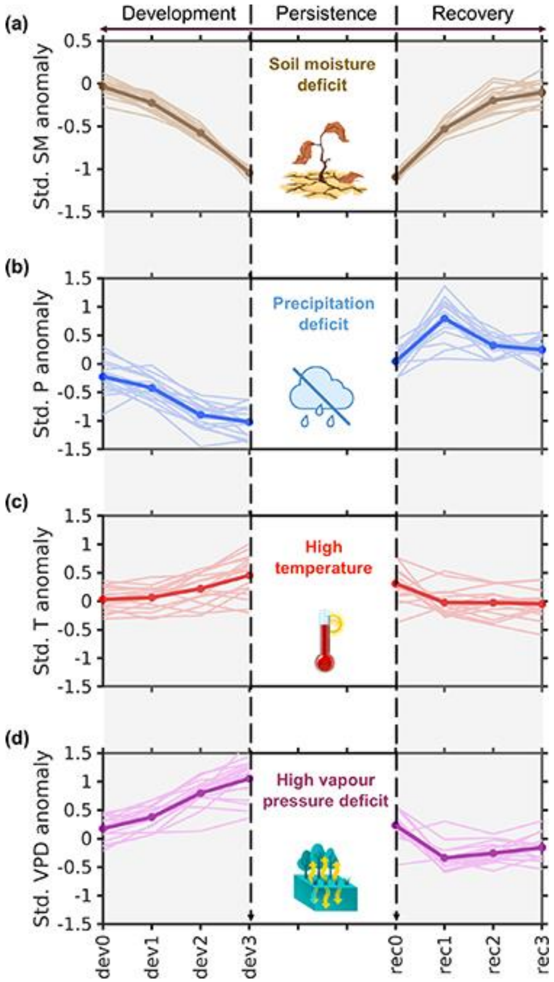


ROI 3: July 2022



Flash Drought indicator





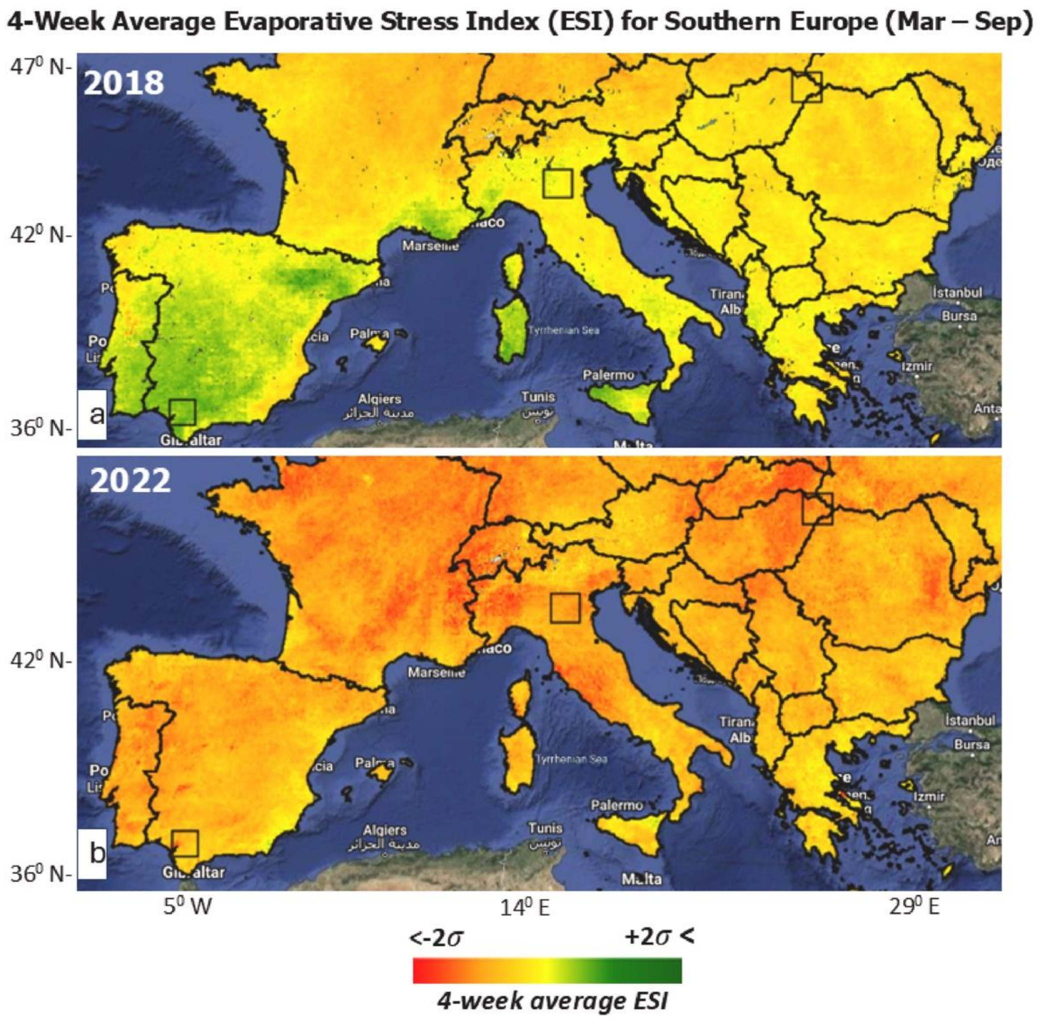
Evaporative Stress Index (ESI)

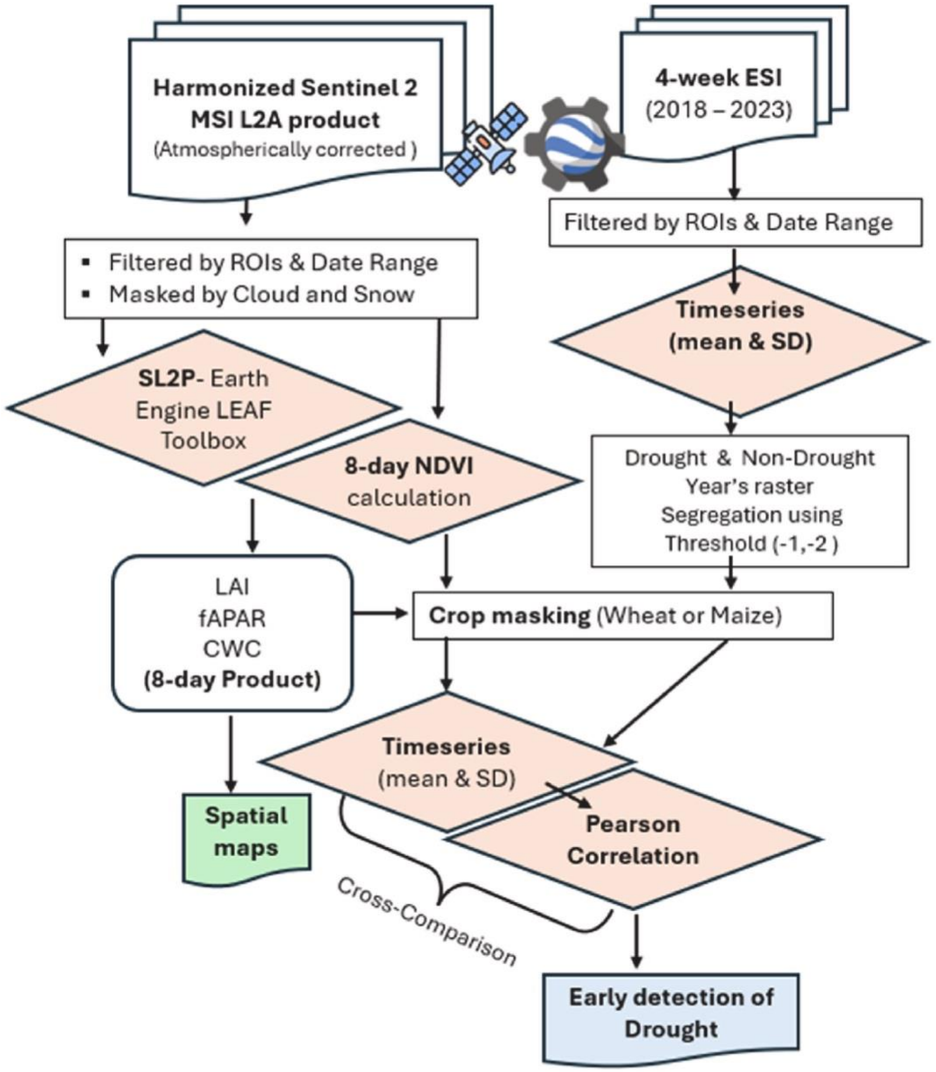
It expresses a weekly varying standardized anomaly (-2σ to 2σ) in fRET relative to long-term baseline conditions,

$$fRET = \frac{ETa}{ETref}$$

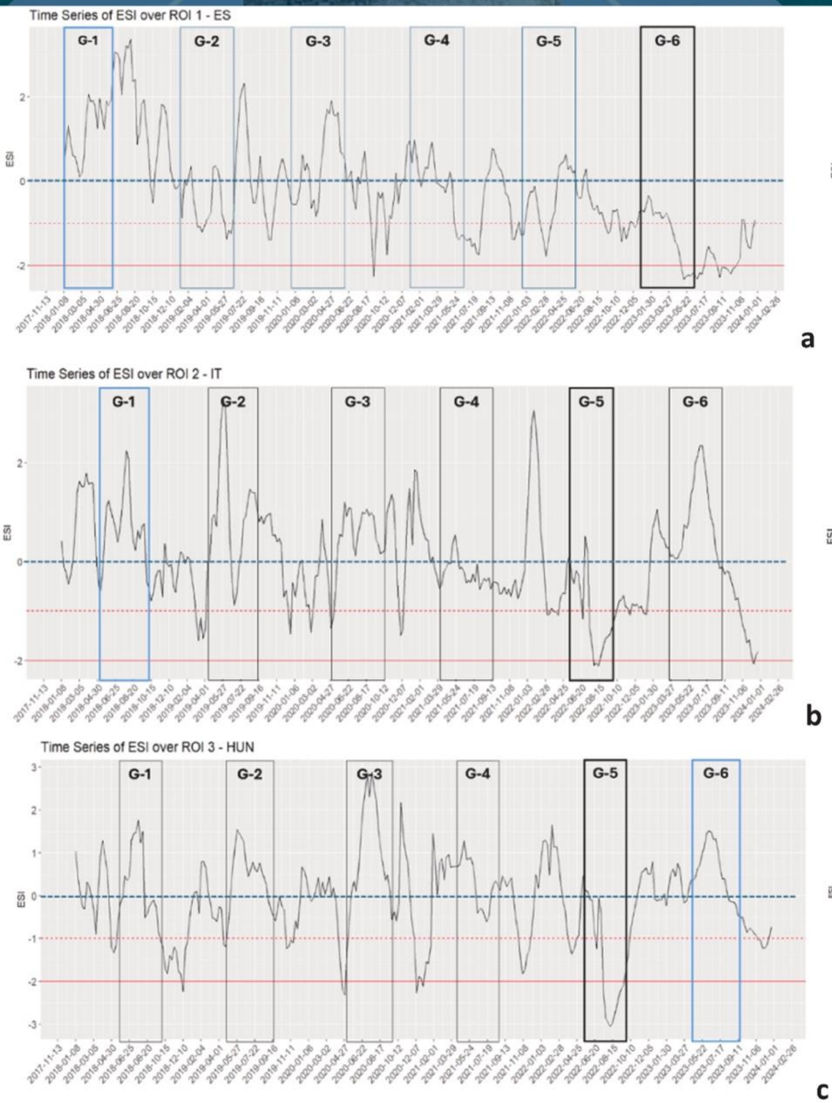
It starts when SM: declines from at least 40th - 20th percentile, It terminates when SM: increases back to above the 20th

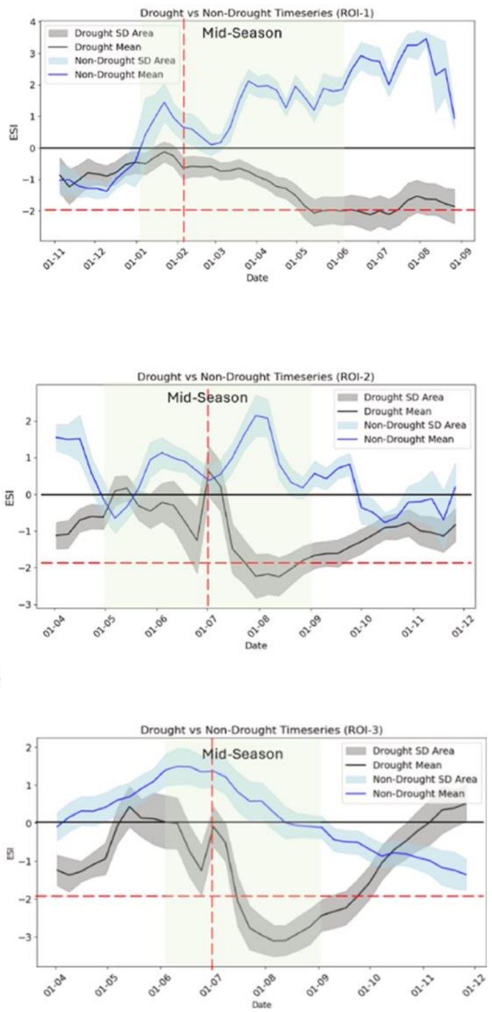
Flash Drought indicator

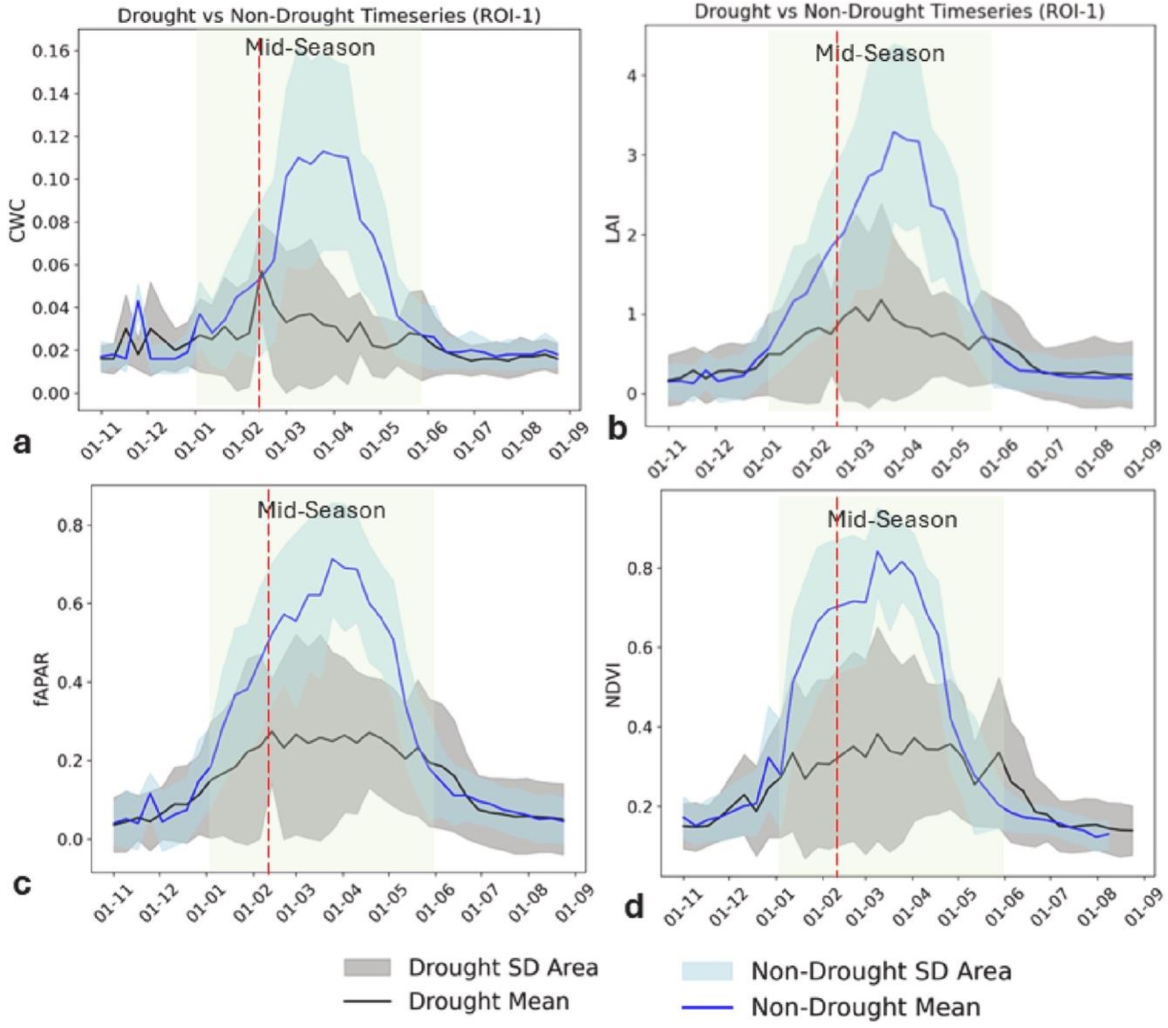




Results

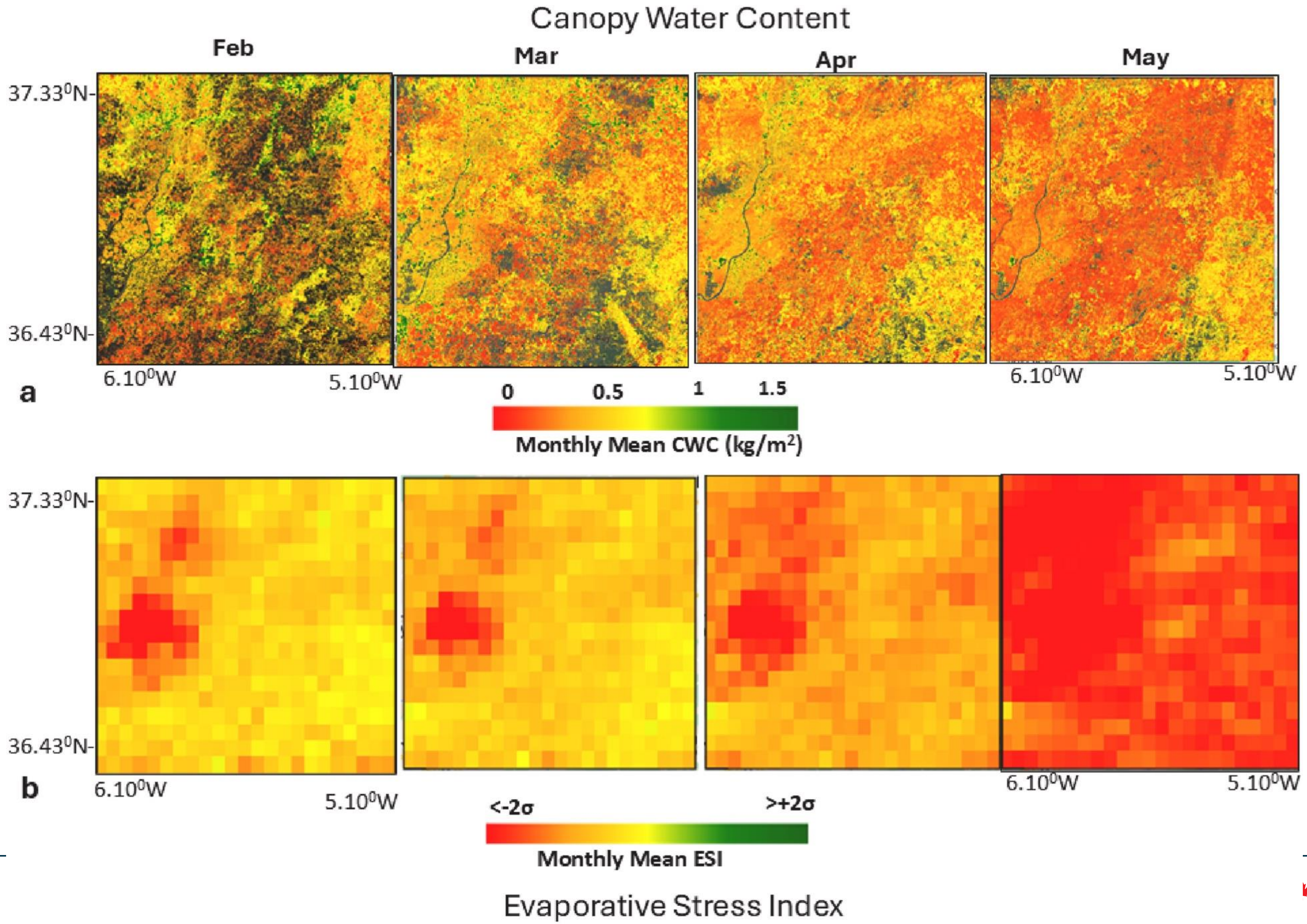






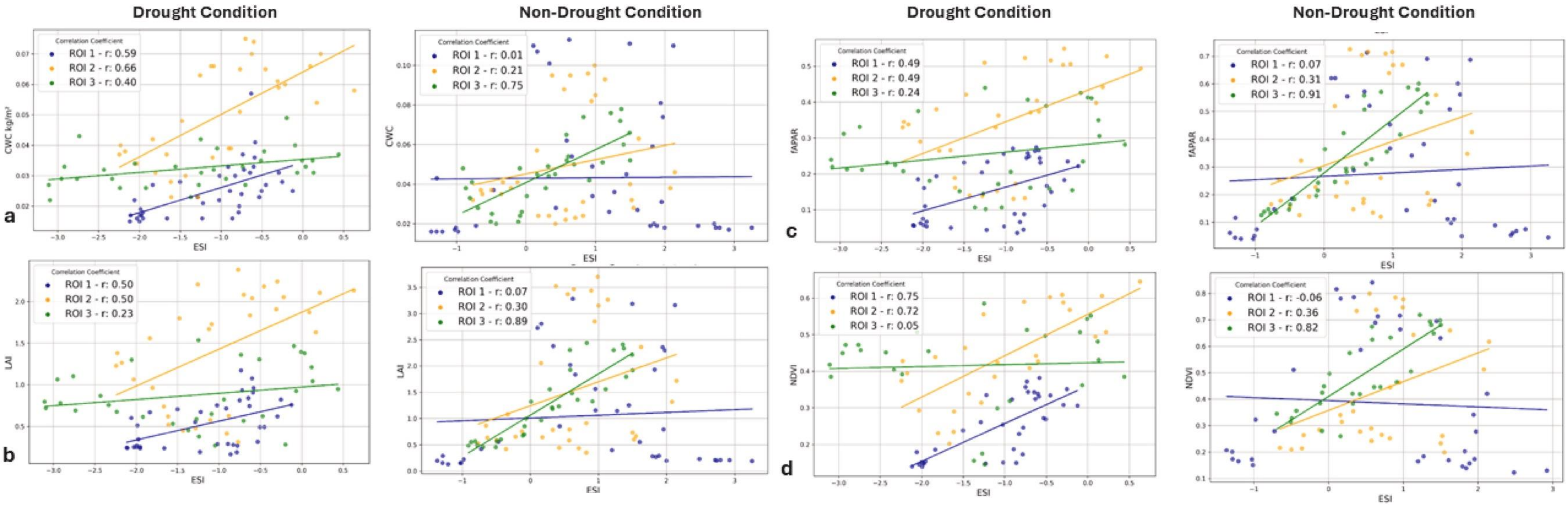
ROI 1- Southern Spain

Results



Canopy Water Content
Feb
Mar
Apr
May
37.33⁰N
36.43⁰N
6.10⁰W
5.10⁰W
a
0
0.5
1
1.5
Monthly Mean CWC (kg/m²)
b
<-2σ
>+2σ
Monthly Mean ESI
Evaporative Stress Index

Results

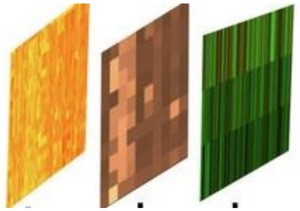


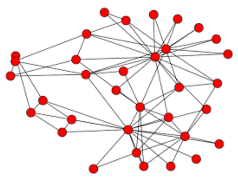
Drought Condition
Non-Drought Condition
Drought Condition
Non-Drought Condition
Correlation Coefficient
ROI 1 - r: 0.59
ROI 2 - r: 0.66
ROI 3 - r: 0.40
Correlation Coefficient
ROI 1 - r: 0.01
ROI 2 - r: 0.21
ROI 3 - r: 0.75
Correlation Coefficient
ROI 1 - r: 0.49
ROI 2 - r: 0.49
ROI 3 - r: 0.24
Correlation Coefficient
ROI 1 - r: 0.07
ROI 2 - r: 0.31
ROI 3 - r: 0.91
Correlation Coefficient
ROI 1 - r: 0.50
ROI 2 - r: 0.50
ROI 3 - r: 0.23
Correlation Coefficient
ROI 1 - r: 0.07
ROI 2 - r: 0.30
ROI 3 - r: 0.89
Correlation Coefficient
ROI 1 - r: 0.75
ROI 2 - r: 0.72
ROI 3 - r: 0.05
Correlation Coefficient
ROI 1 - r: -0.06
ROI 2 - r: 0.36
ROI 3 - r: 0.82
a
b
c
d
CWC kg/m²
CWC
LAI
fAPAR
NDVI
ESI

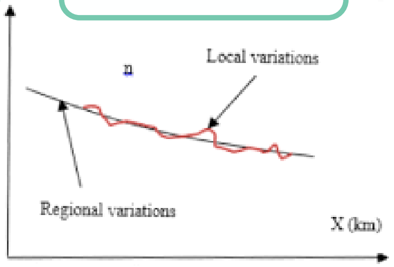
Challenges and Gaps

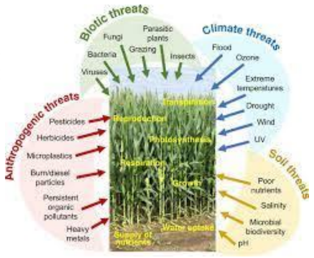
Scientific challenges in using EO & In situ data

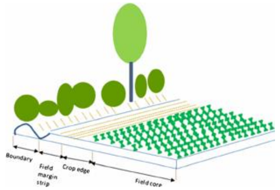
- Integrating diverse datasets
- Disentangling environmental stress sources and types
- Adverse weather conditions, limited data collection opportunities, limited revisit time
- Regional and local variations
- Species-specific methods, a single scale of monitoring
- Applicability and scalability across diverse agricultural settings
- Data assimilation, accessibility of high-quality hyperspectral data











Knowledge gaps

- Optimal resolutions
- Techniques for seamless data integration and fusion
- Methods to upscale local observations to regional
- Standardized protocols for model integration and validation

Results

Strong agreement with ESI: Canopy Water Content (CWC) showed high consistency with the Evaporative Stress Index (ESI) for detecting flash droughts in irrigated regions.

Early detection capability: CWC can capture the onset of flash drought, even during crop growth stages, due to its sensitivity to rapid moisture changes.

Practical value: Incorporating CWC into drought monitoring systems enables early warnings, helping optimize irrigation, diversify crops, and adopt drought-tolerant varieties.

Future validation needed: Results should be verified with CWC derived from other models or ground-based observations to confirm robustness.

Scenario-1

A wheat field shows a steady drop in NDVI over three weeks. At the same time, canopy temperature from thermal sensing is consistently 3–4°C higher than surrounding fields.

Questions

- Is this stress likely biotic or abiotic? Why?
- Which additional indices could strengthen your conclusion?
- How could early detection guide farmer decisions?

Scenario 2

NDVI in a potato field remains mostly stable, but hyperspectral data shows localised declines in specific narrow bands associated with pigment stress. Canopy temperature is normal.

Biotic or abiotic stress? Why?
Which indices or sensors are best suited to confirm this?
Management strategy ?