Leibniz Centre for Agricultural Landscape Research (ZALF)

Towards System Understanding in Agriculture through Multisource Earth Observation

Dr. Gohar Ghazaryan

Remote Sensing for Agriculture

Research Area 4 "Simulation & Data Science"

AK FERNERKUNDUNG 2025, Bochum

Date: 29.09.2025

Technology is the answer
But what was the question?

Cedrid Price, 1960

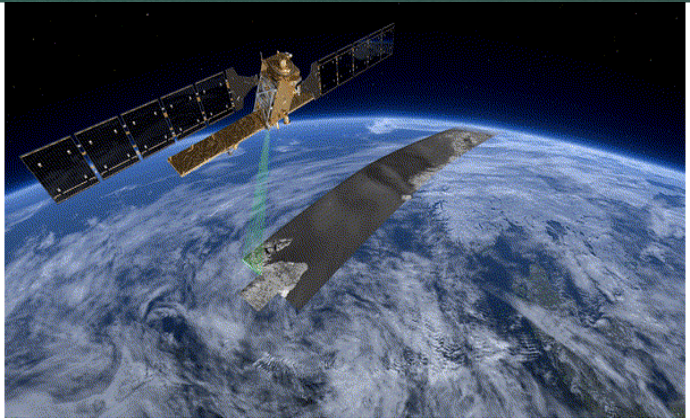
AI is the answer
But what was the question?

Everybody, 2025

Global trends and challenges

- Population growth
- Need for higher production
- Climate change, extreme events, biodiversity loss
- Need for reliable and timely information

Multi-Source Remote Sensing for Agriculture

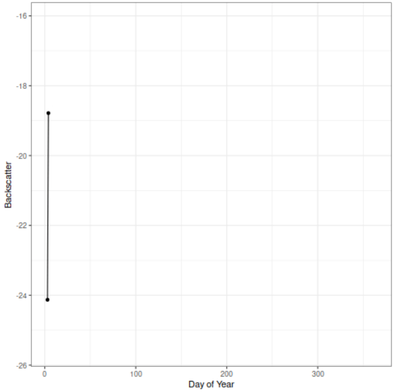


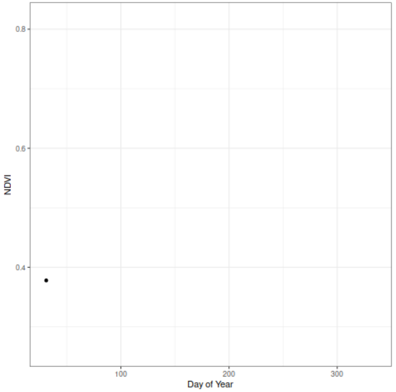
Sentinel-1

Sentinel-2

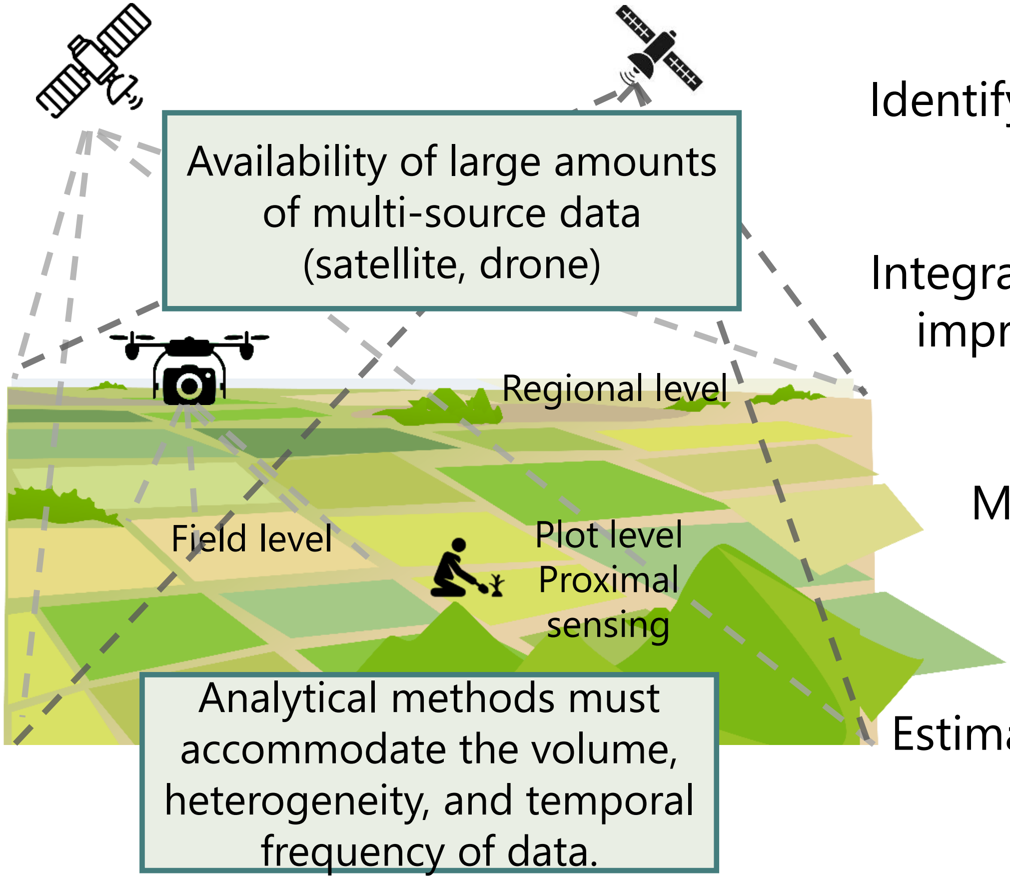
Video credit: ESA

- Sentinel-3
- MODIS
- Landsat
- PlanetScope
- ECOSTRESS
- EnMap





Multi-Source Remote Sensing for Agriculture



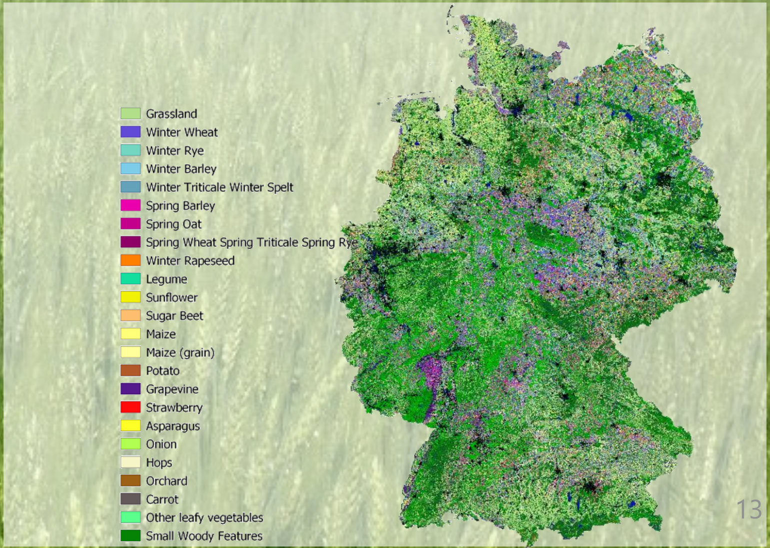
Classification
Identifying crop types, management, land use.

Data Fusion
Integrating optical, radar, and ancillary data to improve accuracy and temporal coverage.

Crop Condition Assessment
Monitoring vegetation health, stress, phenology.

Yield Estimation
Estimating yield using machine learning and time-series analysis.

- EO data can be used to map crop types, land use, and agricultural practices at scale.
- It can serve as a baseline for understanding spatial patterns and tracking land cover dynamics.



https://ows.geo.hu-berlin.de/webviewer/landwirtschaft/index.html

Field level irrigation mapping

Sentinel-2 spectral bands+

NDVI
TC indices (Brightness, Greenness, Wetness)
MNDWI
NDMI

Sentinel-1

VV
VH
VV/VH

Landsat LST

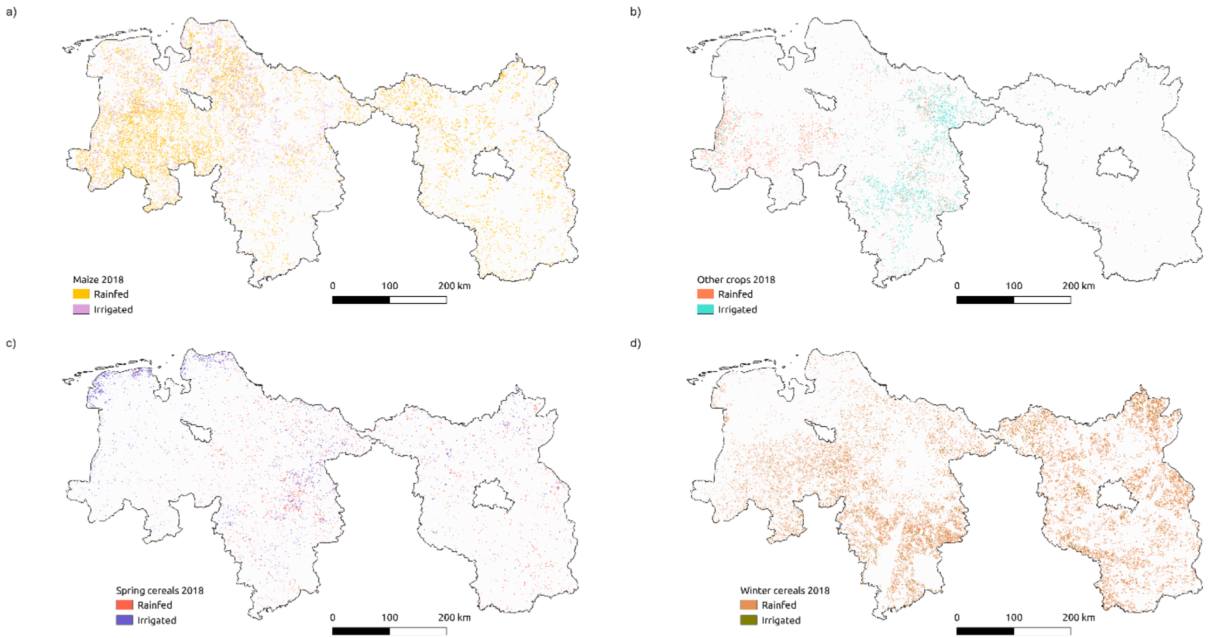
Land Surface temperature

Aggregation Minimum, maximum, Q50, Q25, Median,Q75, IQR,STD

Three periods:
- March- end of September
- April-June
- July-September

Four final classes:
- Spring cereals
- Winter cereals
- Maize
- Other (Potato, Sugar beet)

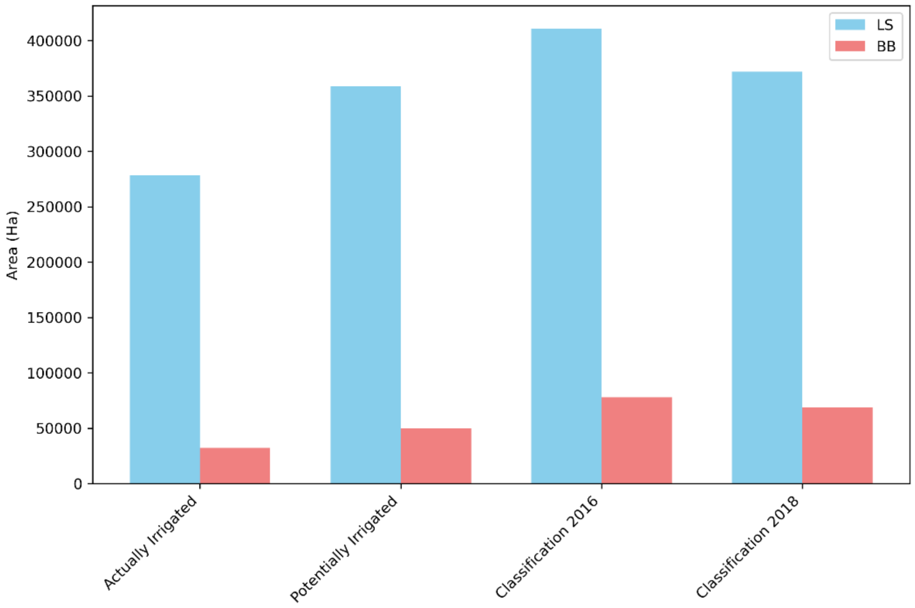
Field level irrigation mapping



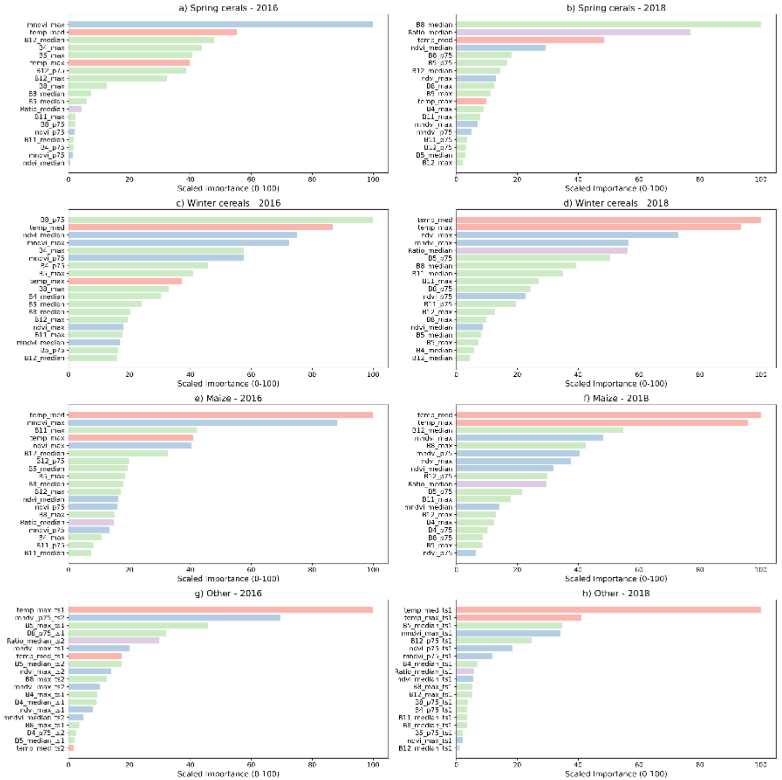
Maps of irrigated areas in 2018 for a) maize, b) other crops, c) Spring cereals and d) Winter cereals

Ghazaryan et al., 2025

Field level irrigation mapping



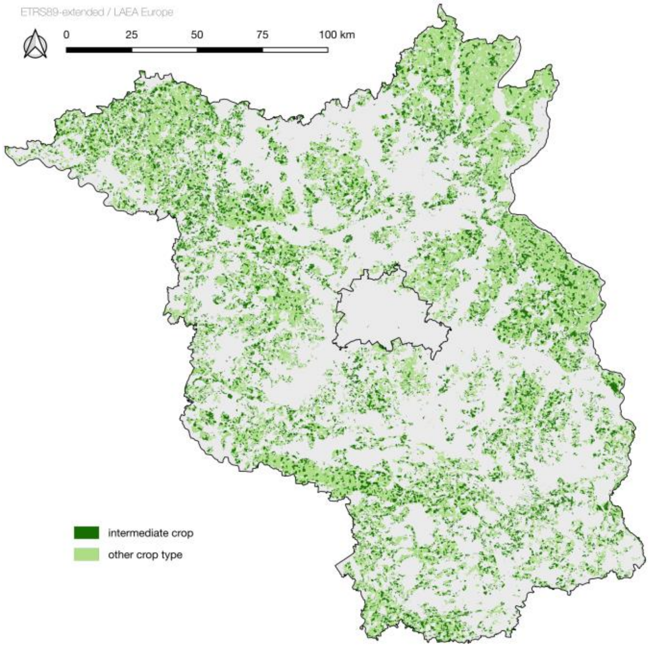
The area estimates of the actually and potentially irrigated areas according to statistics (2019) and the classification results

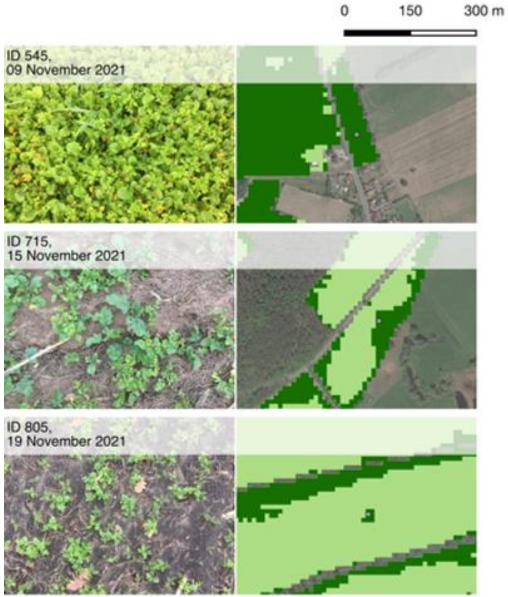


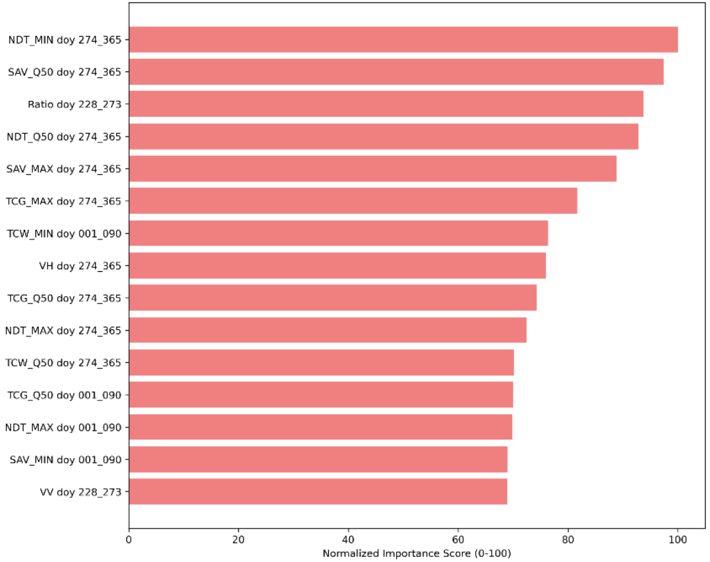
Variable importance (rescaled to 0-100)

Ghazaryan et al., 2025

Intermediate crop mapping





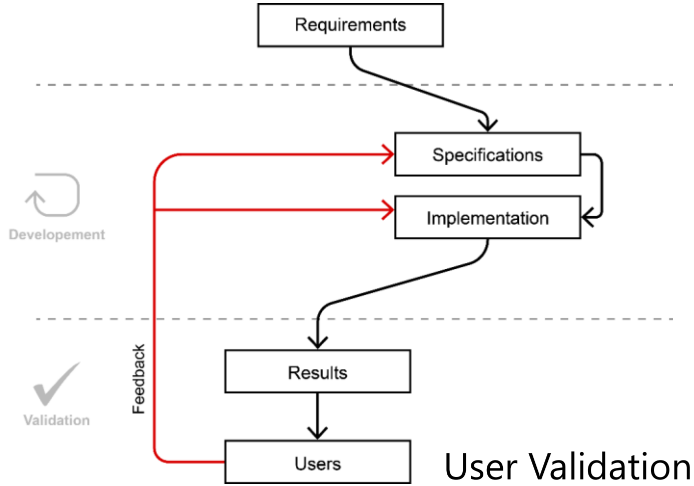


Crop type map of Brandenburg and field images of the three selected crops and the corresponding classification output at pixel level

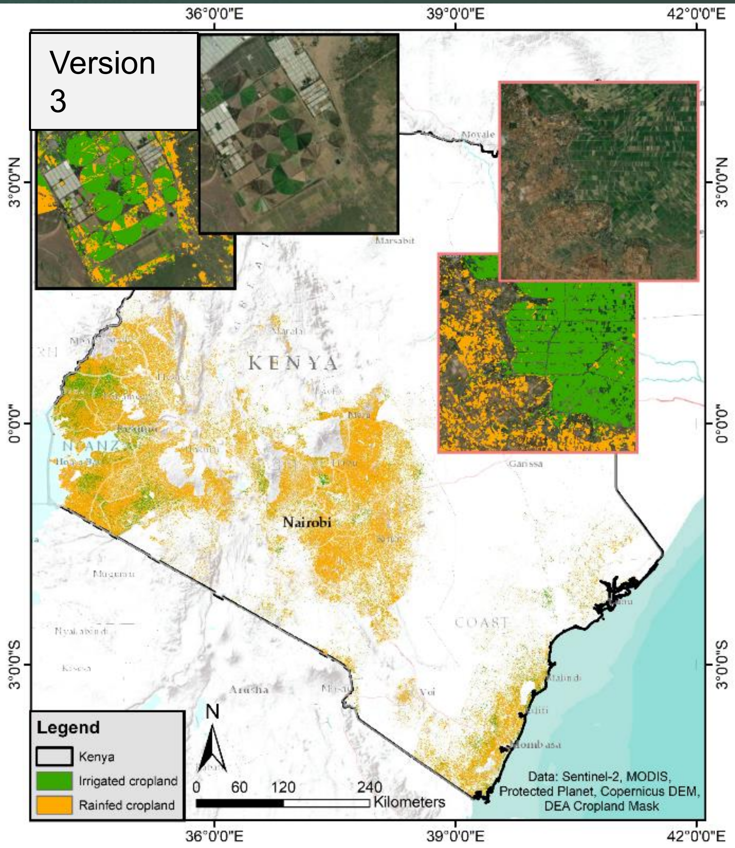
Jensch et al., 2025

Irrigation Systems mapping

		REFERENCE			
		Irrigated	Rainfed	TOT	*User's accuracy (%)*
PREDICTION	Irrigated	**107,353**	2,714	**110,067**	*97.53*
	Rainfed	1,785	**99,693**	**101478**	*98.24*
	TOT	**109,138**	**102,407**	***Total Samples:* 211,545 *Overall Accuracy:* 97.87%**	
	Producers Accuracy (%)	*98.36*	*97.35*		



User Validation Process

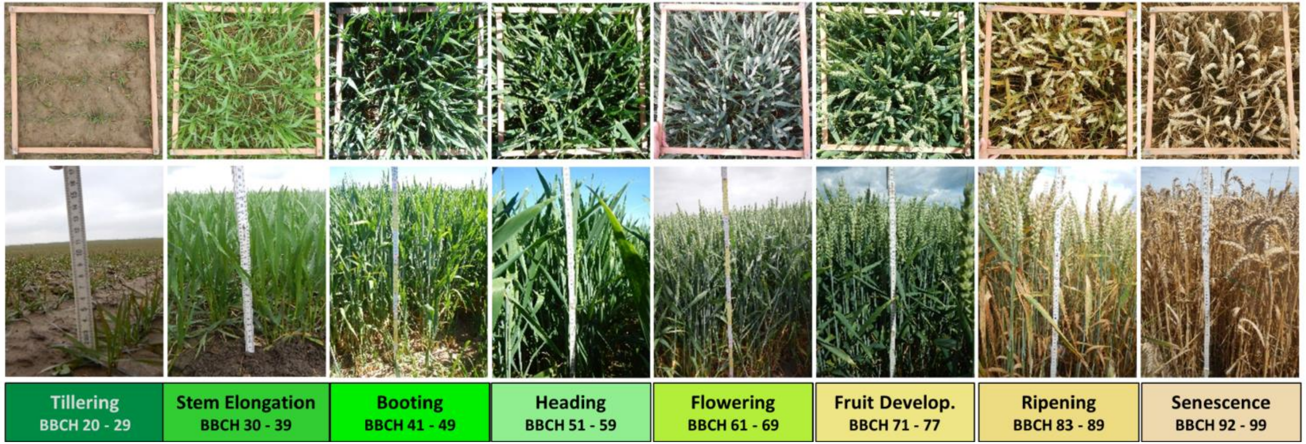


Farming Systems for Kenya: Version 3 – updated training data, updated cropland mask, additional protected areas mask, ET, LST

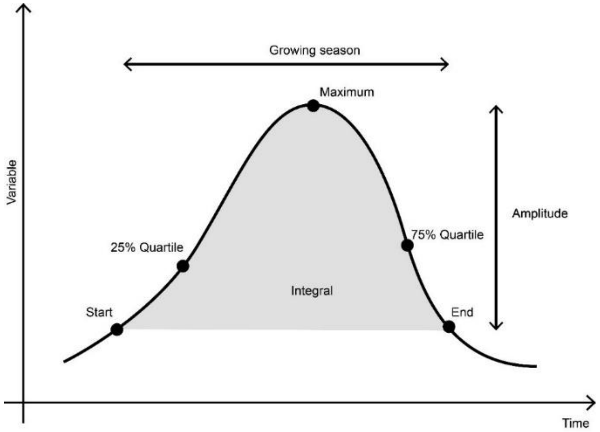
Schwarz et al., 2024

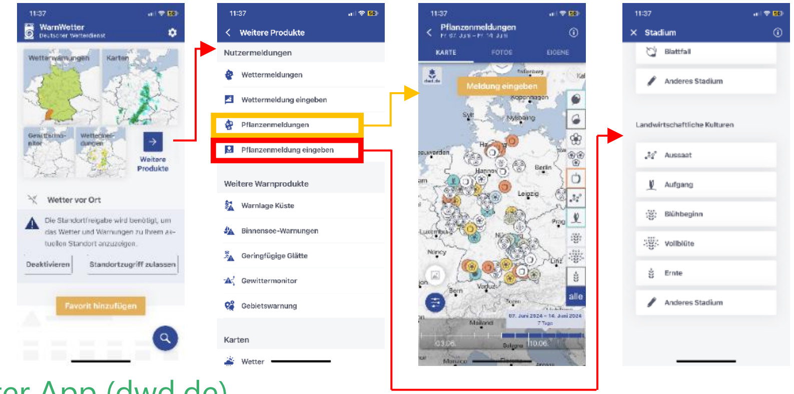
- Crop phenology is critical for agricultural management and agroecosystem assessment
- Temporal signatures can be used for distinguishing land-cover types and for mapping land-use change
- Important information for yield estimation

Crop phenology assessment



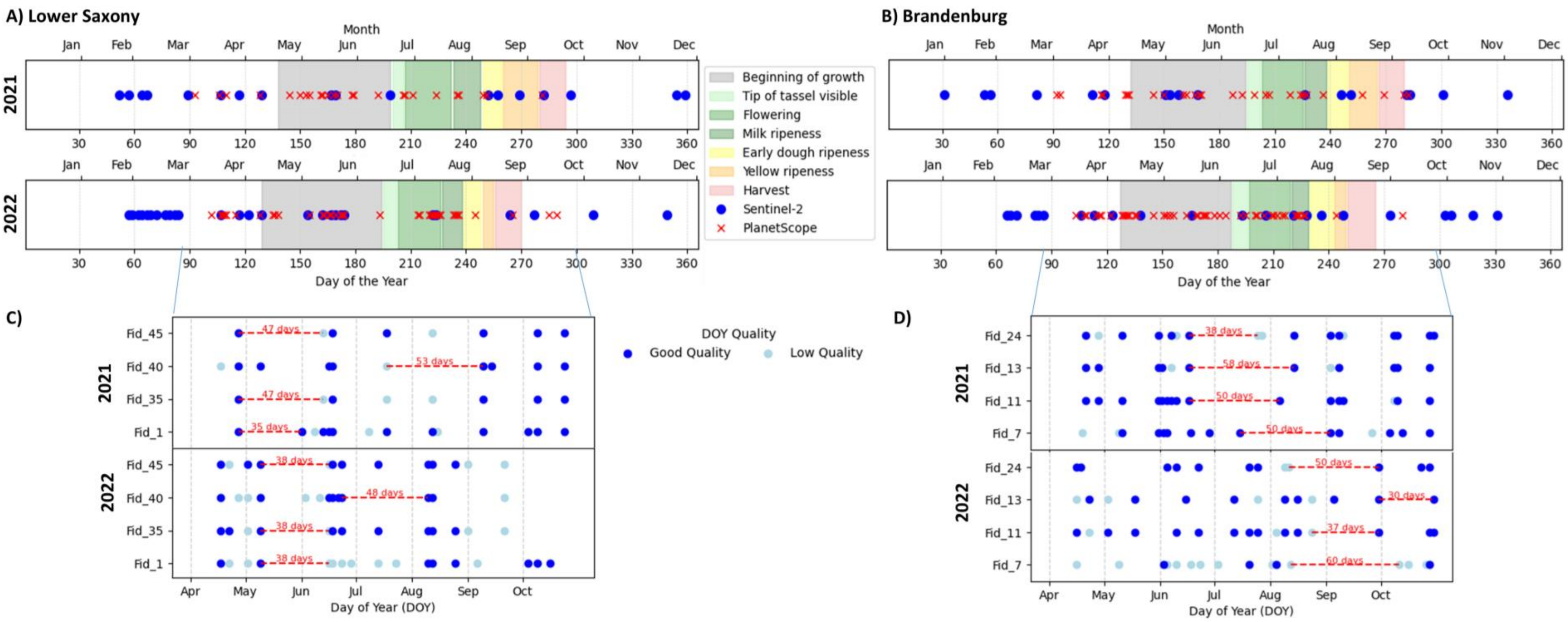
Harfenmeister et al. (2021)





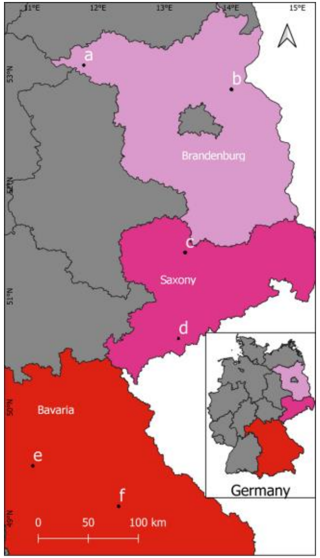
[WarnWetter App (dwd.de)](dwd.de)

Satellite data availability vs maize phenological phases

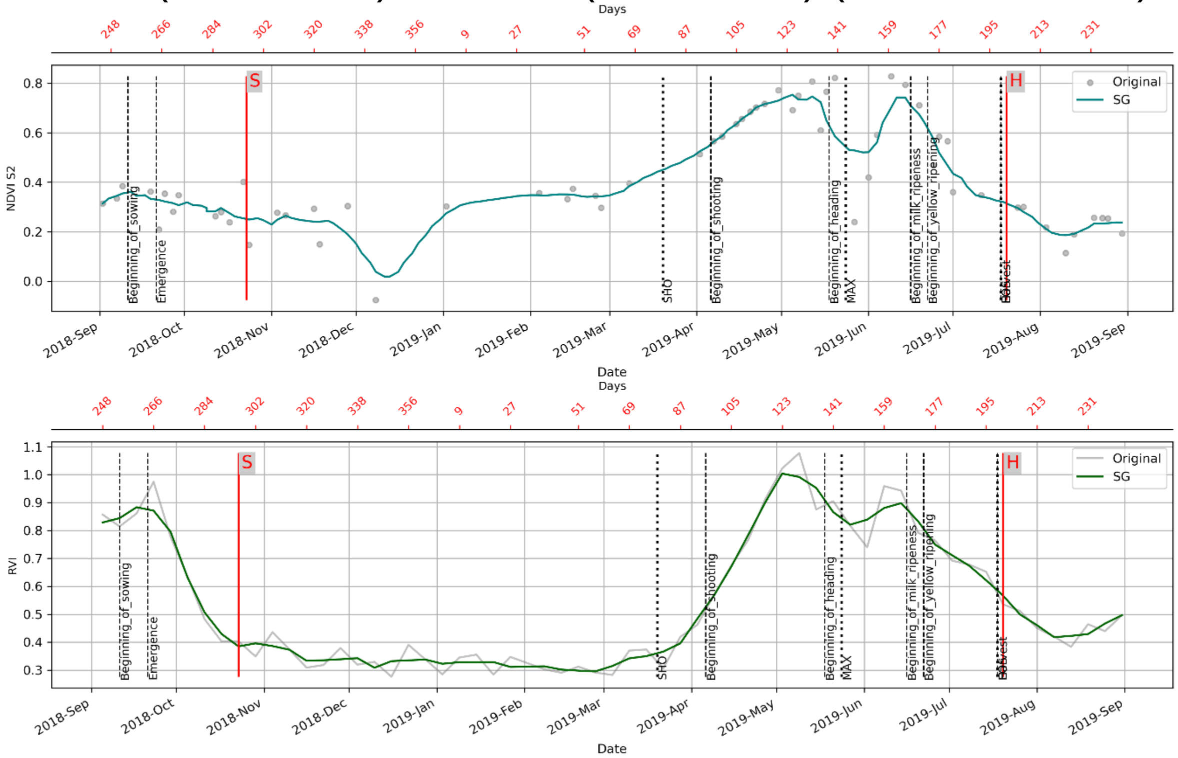


(Main-Knorn et al. 2025, in preparation)

Crop phenology assessment



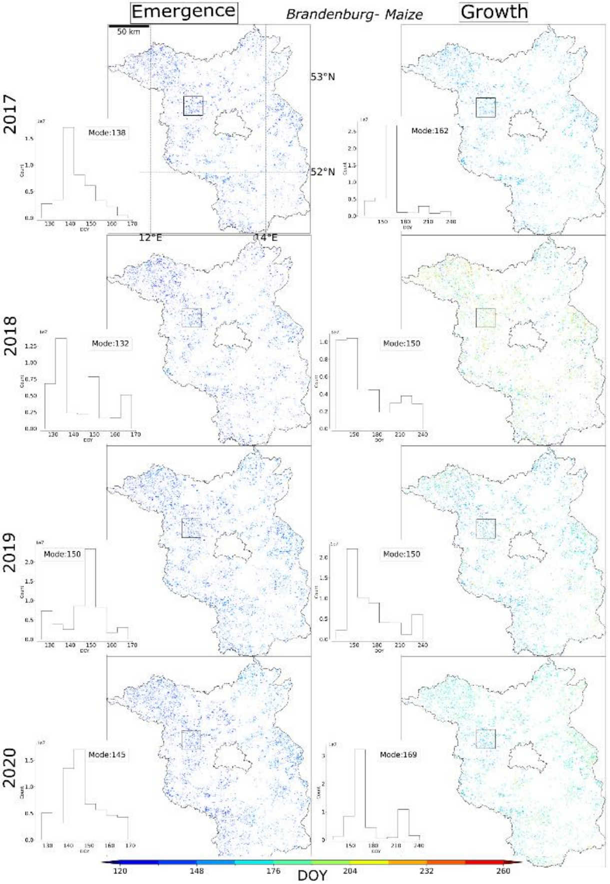
NDVI (Sentinel 2) and RVI (Sentinel 1) (Winter Wheat)

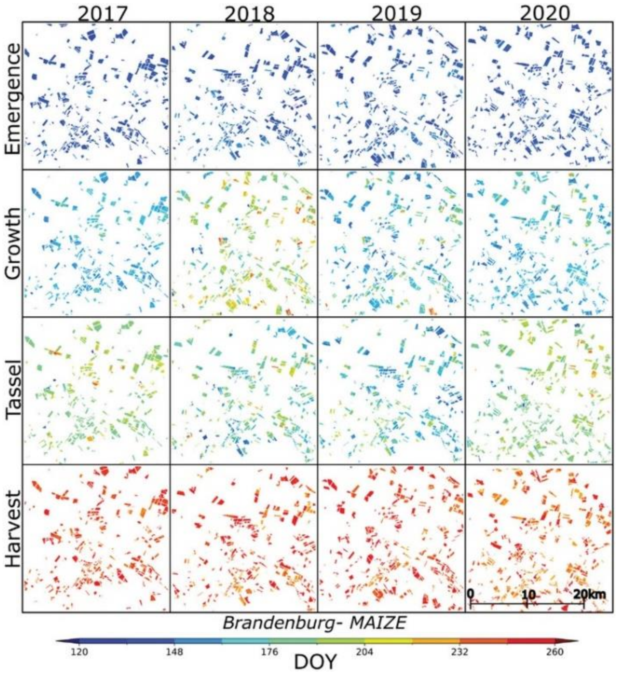


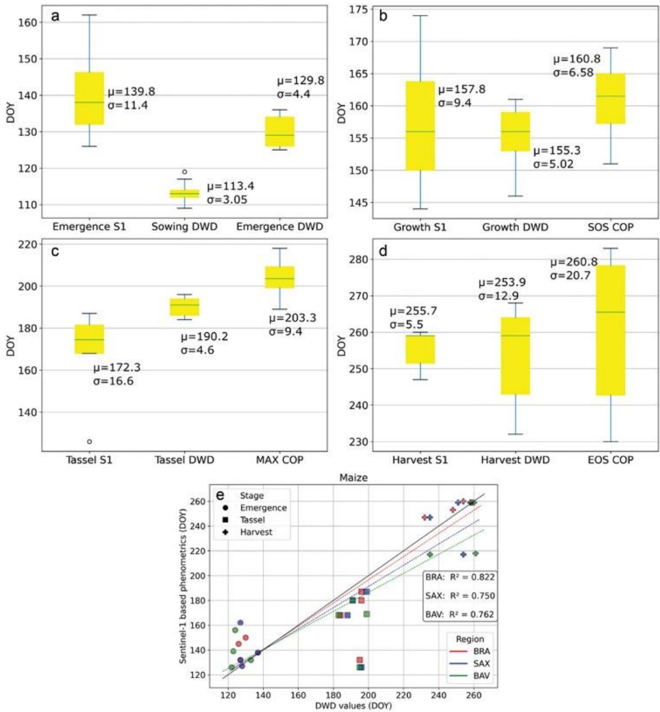
-6 sites in Brandenburg, Saxony and Bavaria
- focus on **maize** and **winter wheat**

Flores et al., 2025

Crop phenology assessment

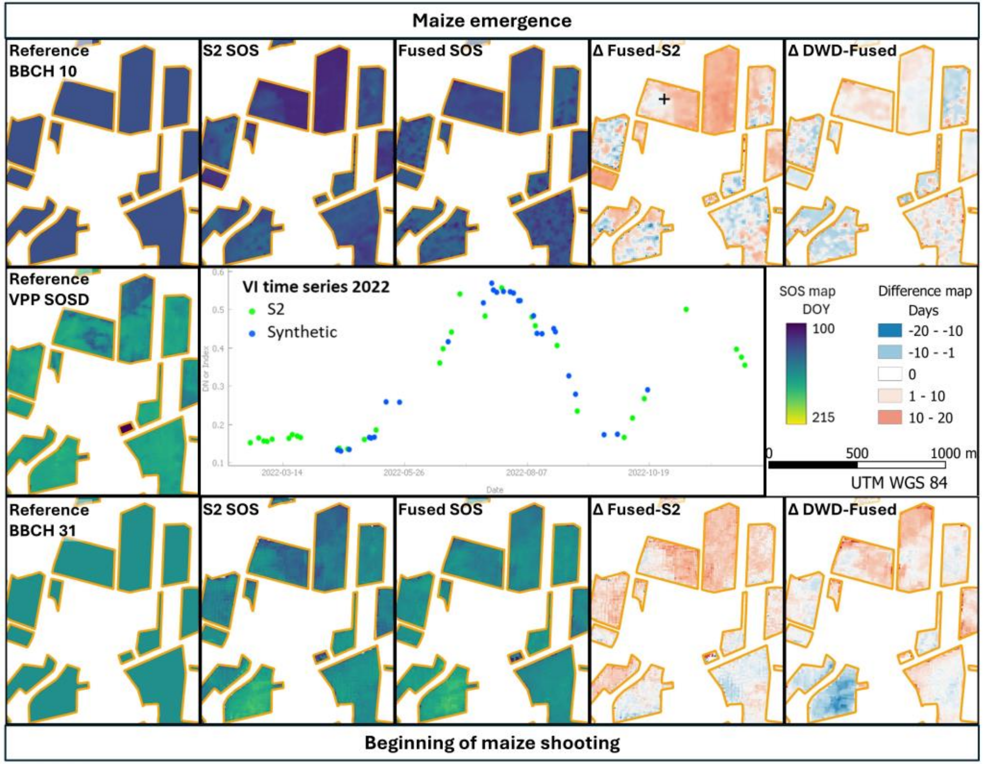


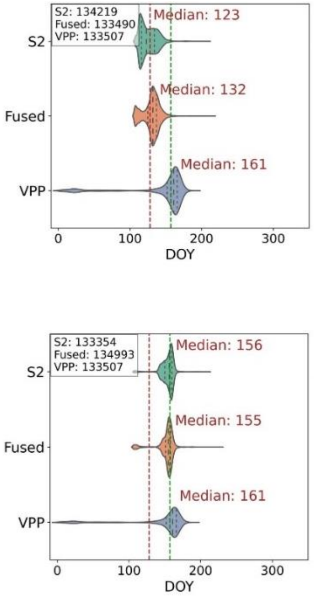




Flores et al., 2025

Crop phenology assessment



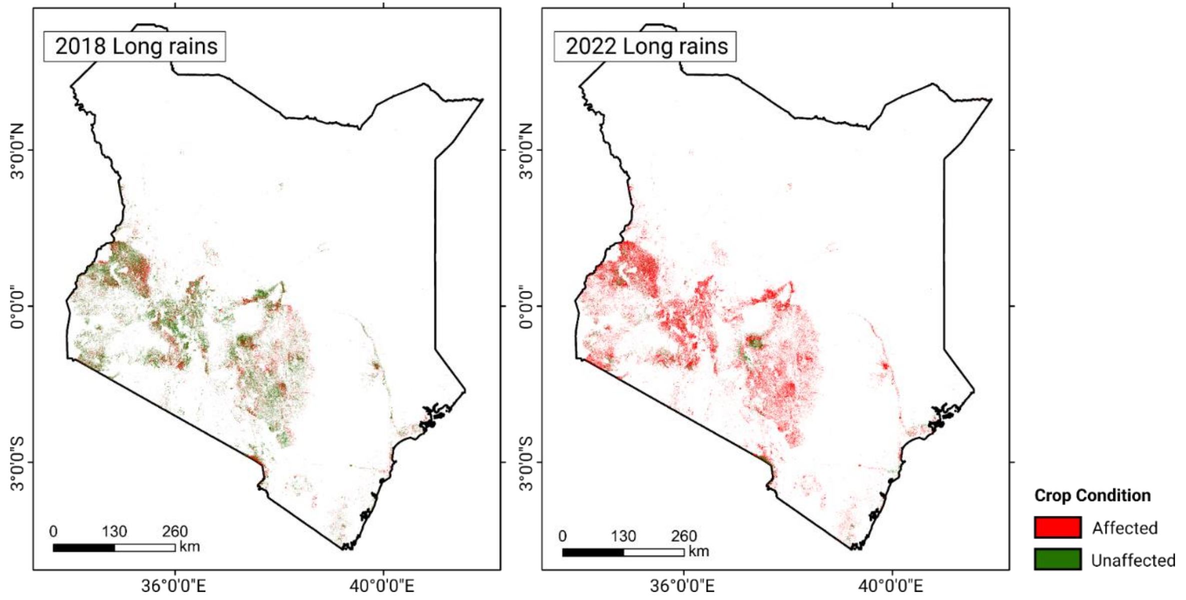


- Dense time series highlight inter-field variability in maize phenology
- PS-based synthetic data increased accuracy in SoS retrieval
- Difference to DWD reference within +/-10days

Main-Knorn et al., (in preparation)

- Accurate information on drought occurrence is essential to mitigate the negative effects on cropping systems.
- This information can be used for policymaking, risk management, and early drought warning systems

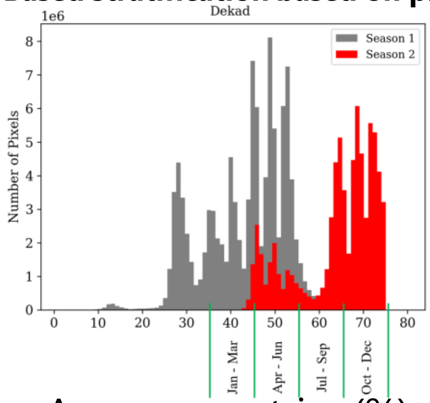
High Resolution Crop Condition



Crop Condition maps for Long rains season for 2018 and 2022. (Data: Sentinel-2, AEZ, ESA World Cover v2), Random Forest Model

Mirmazloumi et al., 2025 (in preparation)

Season Based stratification based on phenology

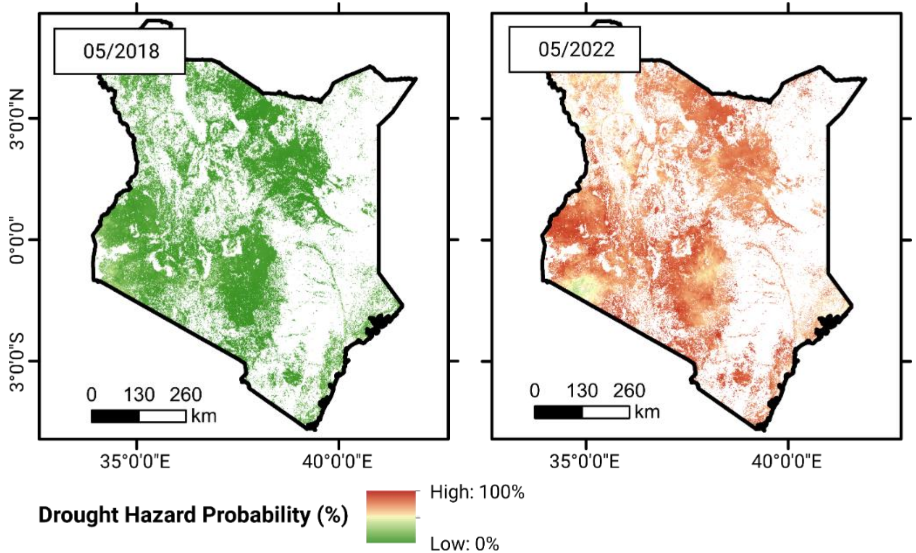


Accuracy metrics (%)

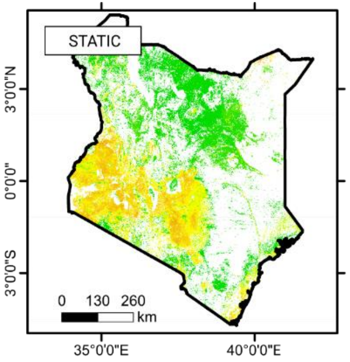
AEZs	Long rains	Short rains
Humid	*68*	*67*
SubHumid	*68*	*65*
Transitional	*64*	*69*
Semi-Arid	*80*	*78*
Arid	*78*	*85*
PerArid	*70*	*66*

National scale Drought Risk assessment

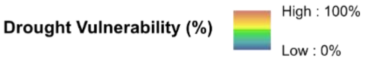
Random Forest for Drought hazard probability

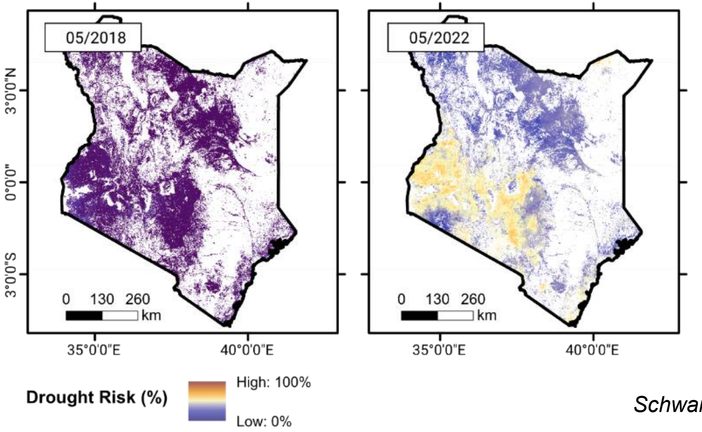


Drought Hazard, Risk and vulnerability for May 2018 and May 2022
(Data: FAOSTAT, Copernicus Land Cover, MODIS, Sentinel-3, TAMSAT)



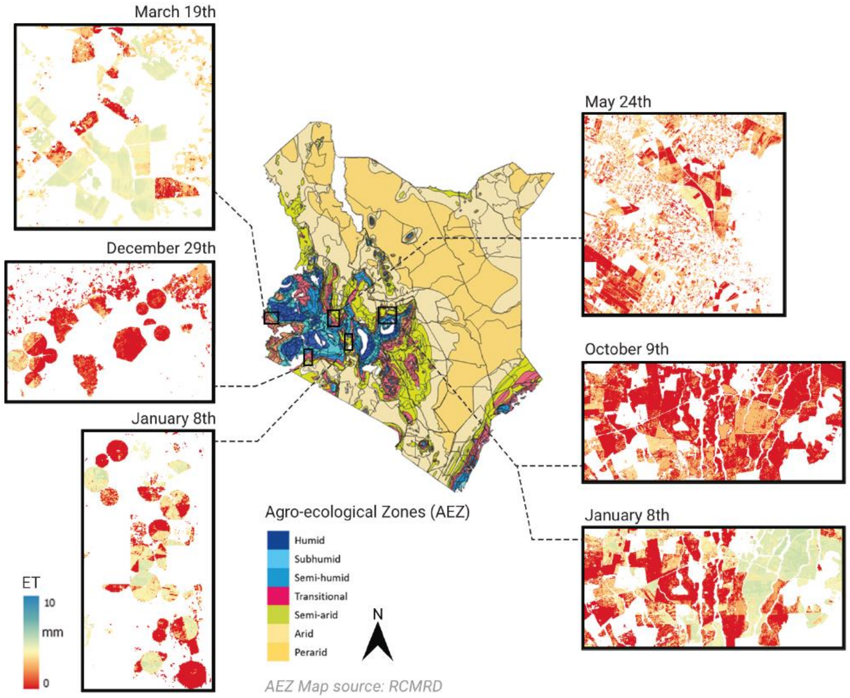
Irrigation as input for Vulnerability



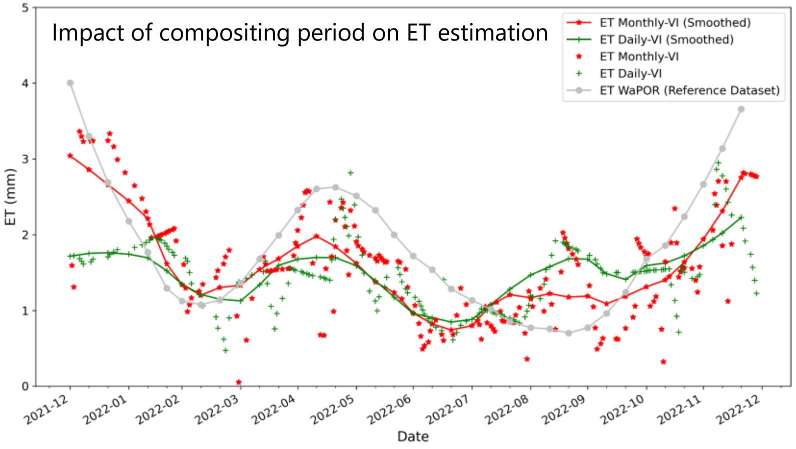


Schwarz et al., 2024

Evapotranspiration



Examples of ET estimation for different time steps/areas

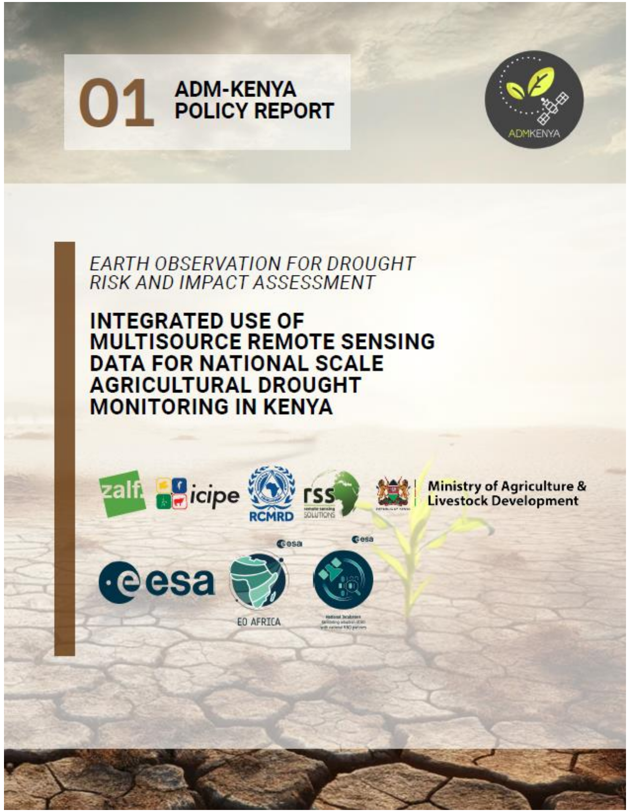


Large scale evapotranspiration estimation

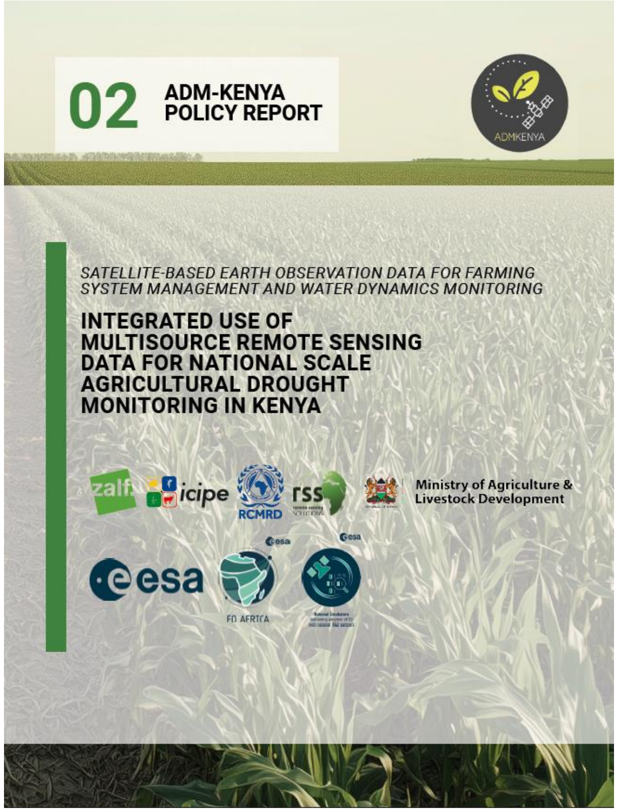
(Data: Sentinel-2, Sentinel-3), Random Forest Model for downscaling, two-source energy balance (TSEB) model

Mirmazloumi et al., 2025 (in preparation)

Policy Reports



https://publications.admkenya.eu/ADM_Kenya_PolicyReport_1.pdf

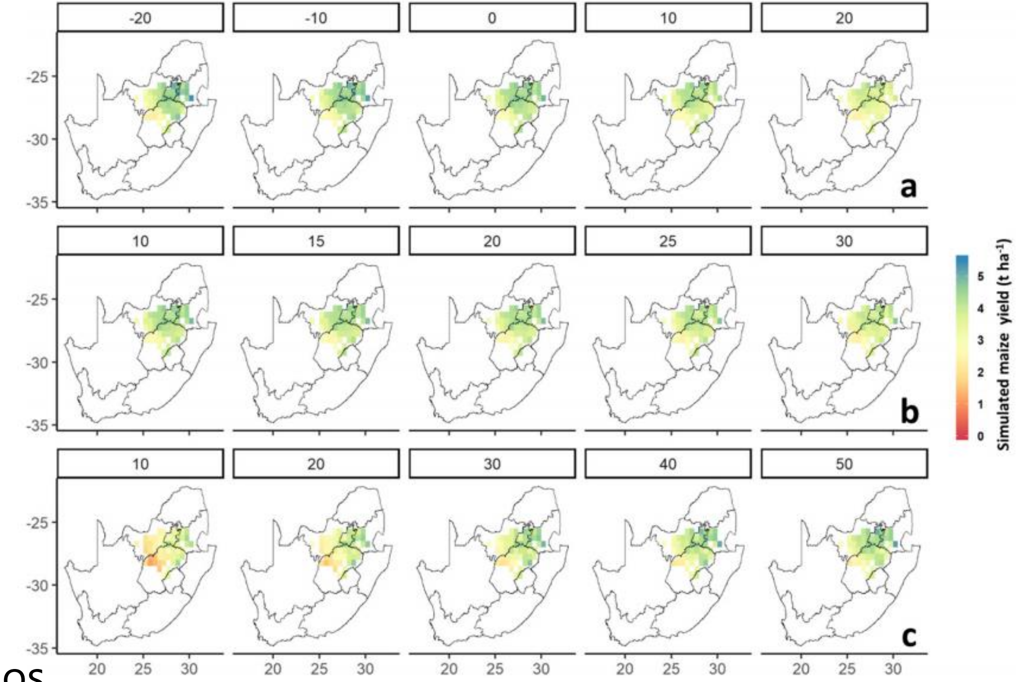


https://publications.admkenya.eu/ADM_Kenya_Policy_Report_2.pdf

- Estimating yields is essential for anticipating food supply, managing risk, and guiding agricultural policy.
- Remote sensing and machine learning provide scalable approaches to estimate production across space and time.

Yield assessment

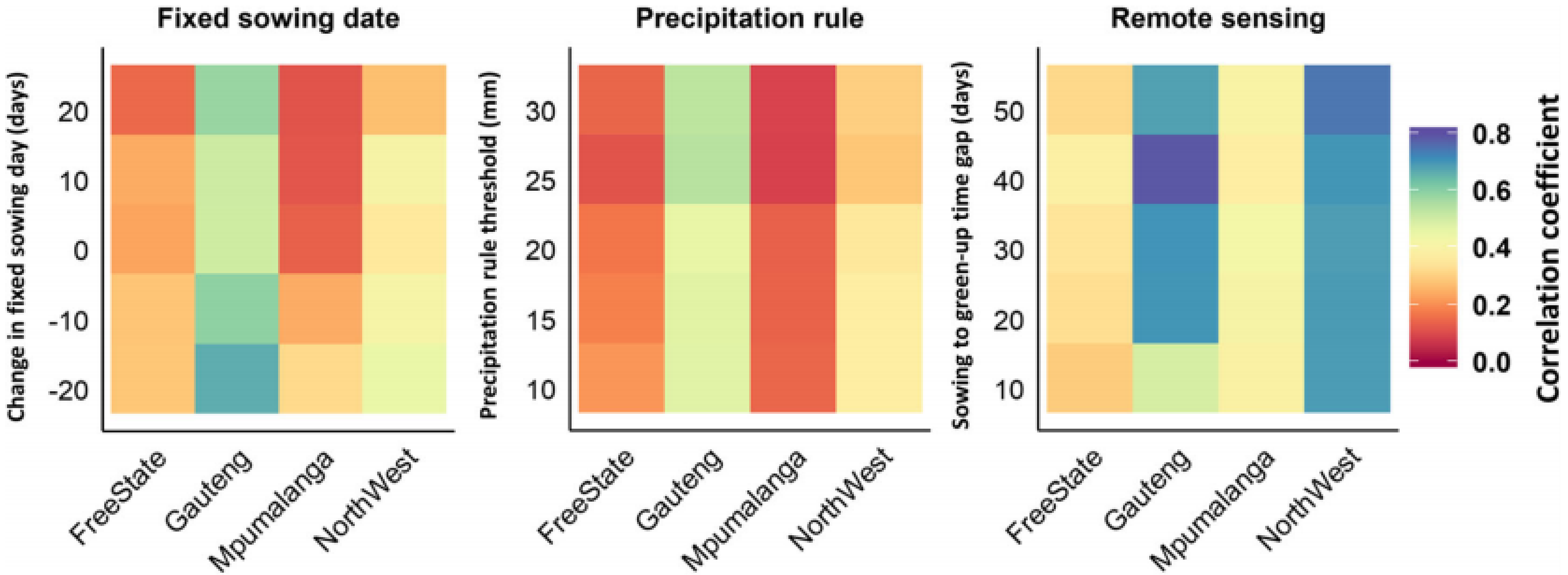
- fixed sowing dates
- precipitation rule – 10,13, 20, 25 and 30 mm as precipitation threshold
- **RS-based sowing dates** – 10,20, 30, 40 and 50 days fro sowing to greenup



Maize yield simulated using sensitivity scenarios based on fixed sowing dates (a), precipitation rule (b), and RS-based sowing dates (c) in the period 2001–2016

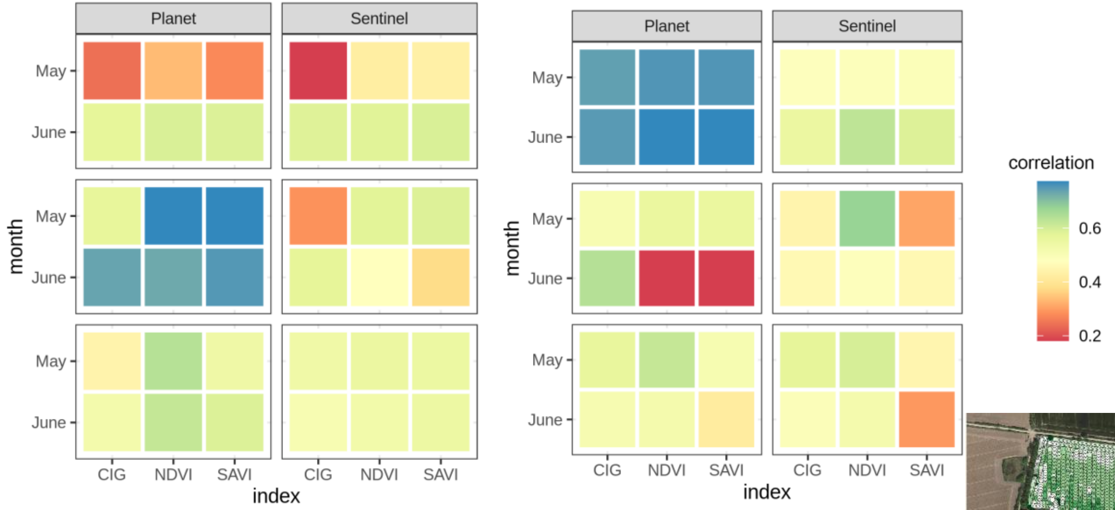
Rezaei et al., 2021

Yield assessment



Correlation coefficients between the anomaly of simulated yield using sensitivity scenarios based on RS-based sowing dates, fixed sowing dates and the dates estimated with the precipitation rule and the observed yield

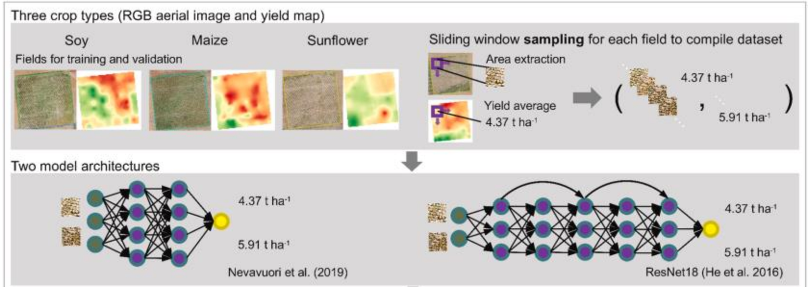
Yield assessment

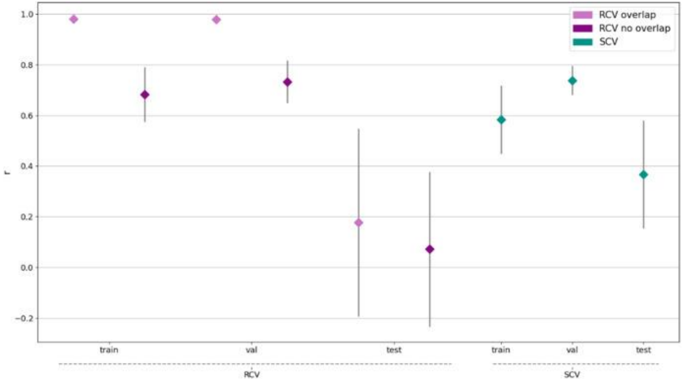


Within-field level analysis of yield correlation with Sentinel and Planet based Vis for a) winter wheat and b) winter barley

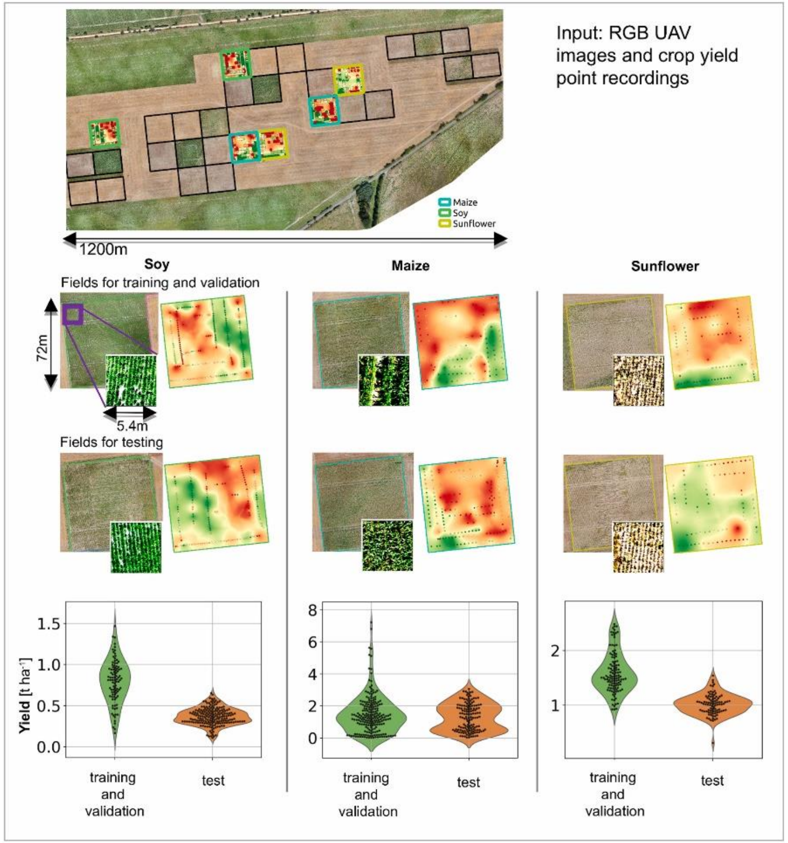
Yield map and estimated yield

Yield assessment





Aggregated model prediction performance over two deep learning architectures for random (RCV) with and without sample overlap and spatial (SCV) cross validation approaches



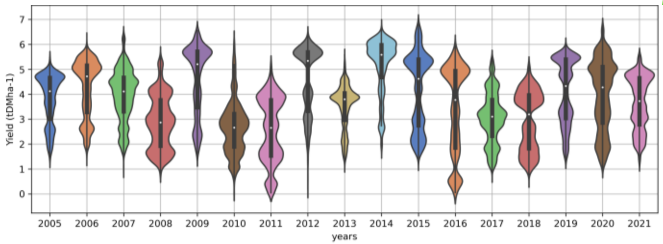
Stiller et al, 2024

Analysis of food systems

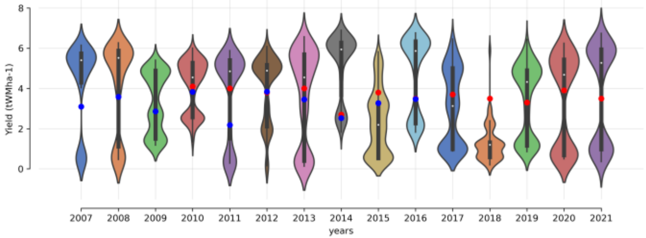
SWITCH

Yield for Winter Barley

Foodshed Berlin



Foodshed Montpellier



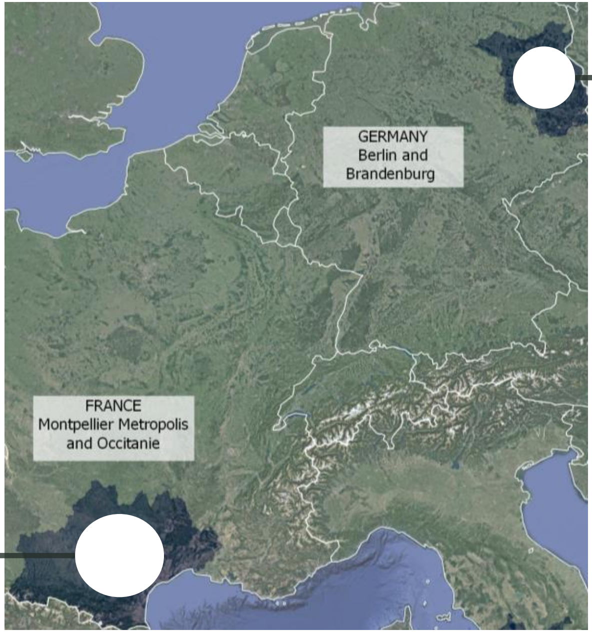
MONICA

Model for Nitrogen and Carbon Dynamics in Agroecosystems

MFSS

Metropolitan Foodshed and Self-sufficiency Scenario

Foodshed around Berlin



Source: Laura Flores

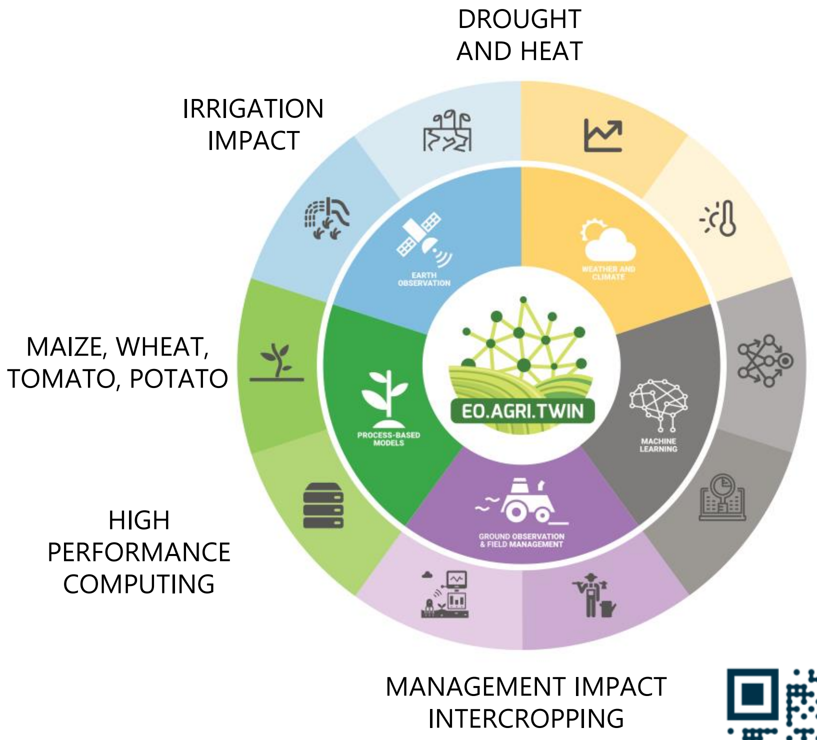
Foodshed around Montpellier

https://switchdiet.eu/

Towards digital twin for agriculture

EOAgriTwin
Earth Observation based Digital Twin for Resilient Agriculture under Multiple Stressors

To create a comprehensive **virtual replica of agricultural systems,** at multiple scales, with a focus on agriculture under **multiple stressors,** and to deliver functional **Digital Twin** to support monitoring of crop condition, simulation of growth dynamics and production under different conditions and stress factors.



Towards digital twin for agriculture

EO.AGRI.TWIN | Leibniz Association | zalf

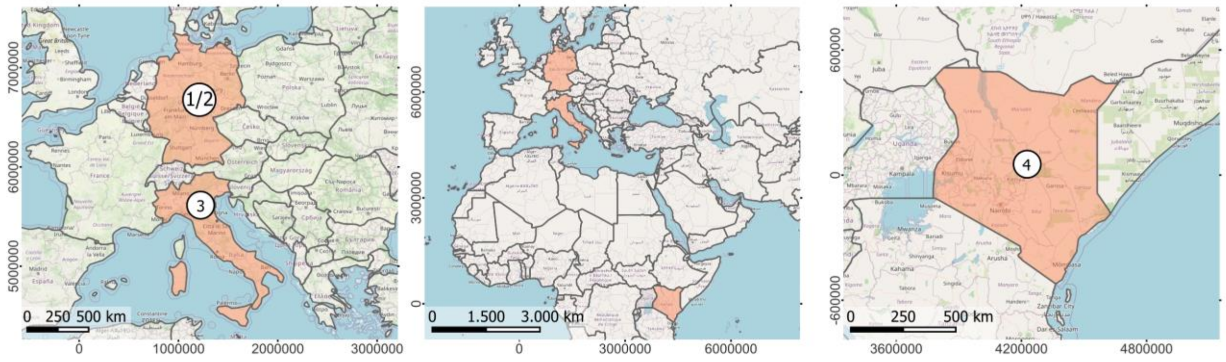
TOOLS AND METHODS

- AI
- Satellite EO Data
- Process-based models

THEMATIC FOCUS

- Drought and heat
- Management Impact
- Biotic Stressors
- Resilience

USE CASES



1. Crop specific drought and heat risk
2. Field-level crop water consumption
3. Drought and disease impact assessment
4. Push-pull and alternatively controlled cereal-based cropping systems

Towards digital twin for agriculture

EO.AGRI.TWIN

EO data combined with diverse modelling approaches help answer key questions

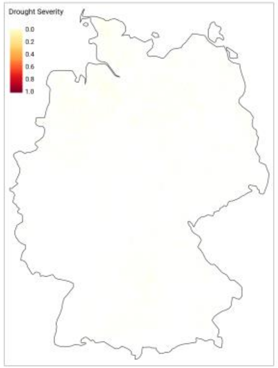
What if

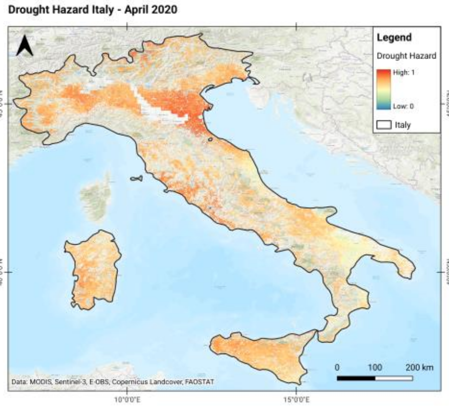
…sease spread and yield?

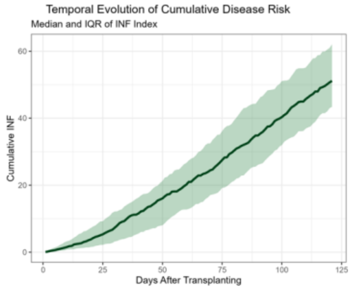
Stakeholder needs, feedback, and integration drives the development.

Management Scenarios and Drought Impact

Silage Maize – 2018 March



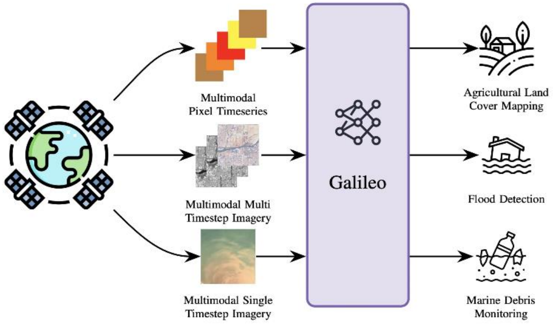




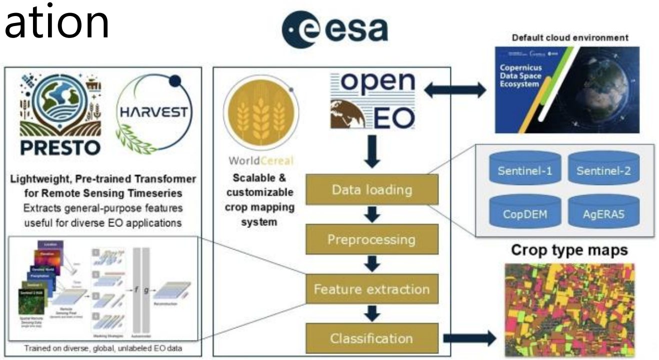
Drought and Pathogen Risk Assessment

Larger Landscape

Towards large scale assessment, Remote sensing foundation models



Tseng et al., 2025



https://esa-worldcereal.org/

Earth Observation Digital Twin Components

EO.AGRI.TWIN

DTE Hydrology

Hydrology

Urban areas & smart cities

https://eof.esa.int/leaddtc/

Thank you for your attention

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Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat, F. (2019). Deep learning and process understanding for data-driven Earth system science. Nature, 566(7743), 195-204.

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https://www.dwd.de/DE/leistungen/warnwetterapp/warnwetterapp.html

Results of the following project were shown:

ADM-Kenya

https://www.admkenya.eu/

EOAgriTwin

https://www.eoagritwin.eu/

KIKompAG - Multi-modal data integration, domain-specific methods and AI to strengthen data literacy in agricultural research

Federal Ministry of Research, Technology and Space

Finanziert von der Europäischen Union NextGenerationEU