Summary of the 2025 JECAM Annual Meeting

ESA LPS2025 – Vienna, Austria

Overview

The 2025 JECAM Annual Meeting was held in conjunction with the ESA Living Planet Symposium (LPS) 2025 in Vienna, Austria, on June 26, 2025. The meeting gathered the JECAM network to provide updates, discuss ongoing experiments, new satellite mission opportunities, and future prospects for collaborative research in agricultural monitoring using Earth Observation (EO) data. Scientific presentations were given by many of the sites in a session on "Agriculture Under Pressure" within the Living Planet meeting and a side meeting was held to discuss the results of the AVL/ENMAP joint experiment

JECAM Mission and Network Update

- A February 2024 network-wide survey confirmed 30 active sites across 25 countries on 6 continents, with 28 positive responses and only 1 dropout.
- Recent additions include a new site in the Netherlands and a pending site in Nepal, as well as efforts to renew sites in China.

Major Activities and Experiments

- The main collaborative activity was the ongoing Agricultural Virtual Labs (AVL)/EnMAP JECAM experiment (2024–2025), focusing on the use of hyperspectral data for crop type mapping at 11 sites, with an emphasis on cereals species differentiation.
- The experiment combines over 400 EO data collections from multiple hubs and uses a standardized Jupyter Notebook-based workflow, with cloud infrastructure training provided to participants through AVL platform.
- The project includes coordinated EnMAP image acquisition, shared data storage and processing, and the development of a formal collaborative framework for data exchange and licensing.

Site Presentations

- Presentations of site priorities and activities from JECAM sites in Germany, Brazil, Argentina, Canada, Poland, Ghana, Benin, China, Mali, Belgium, Taiwan and South Africa (slides in attachment)

- Field data collection continues at sites with emphasis on crop type, crop yield, evapotranspiration and crop stress, horticulture and smallholder systems and tools for data collection
- Research interests are in scaling up methods for national mapping (crop type), improving precision of crop maps for complicated classes and distinguishing irrigated and non-irrigated agriculture, evaluation of deep learning models, delineation of field boundaries in commercial and small holder agriculture, crop stress and drought impacts, crop yield modelling, development of data collection tools and transfer learning methods to reduce time to collect crop type information for model training

Potential for New Initiatives

- Updates on new satellite mission opportunities, including the NISAR mission (launch in 2025), BIOMASS satellite, and potential collaboration with PlanetLab, YPS Globe and Earth Daily Analytics.
- Discussion of the GEOGLAM Essential Agricultural Variables initiative (https://agvariables.org/) and research priorities convergence to validate methods for crop type, crop yield, evapotranspiration, field boundaries and land management.
- Roadmap discussions for continuing hyperspectral experiments
- Development of new methods at specific sites that could be tested globally (eg. a hierarchical boundary-guided network for field boundary detection, tested in China and potentially extensible to other sites; neural network architecture developed in Ukraine); A novel index for effective discrimination between wheat and barley)

Perspectives and Challenges

- JECAM aims to maintain its distributed network model and brand visibility while seeking new funding sources at the network level.
- Future opportunities may arise from new calls, such as JRC-EC4GEO, EU Horizon 600, and contributions to GEO from China.
- There are plans to secure regular modest funding (50–100k USD) for annual meetings via multiple sponsors.
- JECAM's legacy includes being a long-established global network leveraged for EO mission priority acquisitions and fostering highly collaborative research across diverse agricultural systems.

Conclusion

- JECAM site leads and co-chairs will continue to seek opportunities to support cross site experiments and fund data collection at sites.

JECAM network dinner on 25 June 2025 in Vienna (LPS venue)

JECAM annual meeting on 26 June 2025 in Vienna (LPS venue)





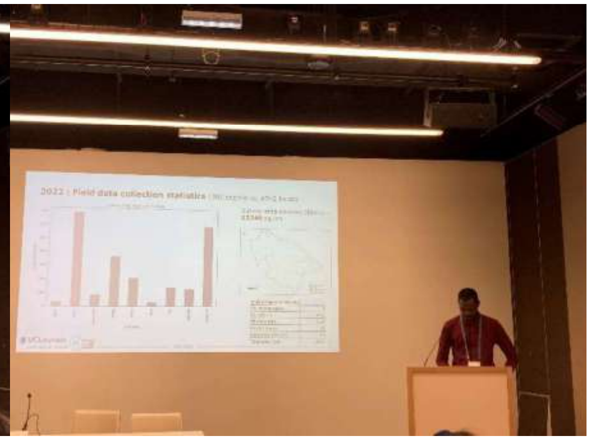

2025 JECAM annual meeting

esa
living planet
symposium
2025

esa
living planet
symposium
2025

esa
living planet
symposium
2025


esa
living planet
symposium
VIENNA
2025



Appendix

Presentation Slides

ARGENTINA JECAM SITE

DIEGO DE ABELLEYRA
INTA,ARGENTINA
DEABELLEYRA.DIEGO@INTA.GOB.AR

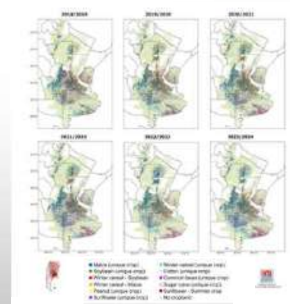
ESA Living Planet Symposium

23-27 June, 2025, Vienna, Austria

1

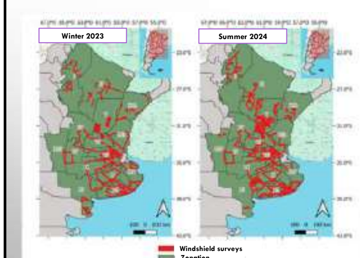
From local to national level crop type classification

2010-2017



2

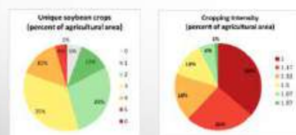
Activities



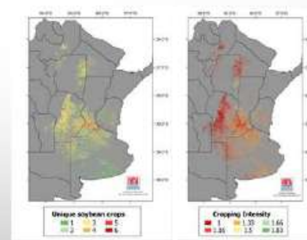
- Thousands of Km surveyed in key agricultural áreas of Argentina to get in situ data during last 6 growing seasons.
- Participation of more than 30 INTA units (Research and Extensión units).
- Common protocol for windshield surveys (available at JECAM web).
- Internal and external funding (Sigma Project, MapBiomas initiative).

3

Crop sequences analysis



Identification of soybean monoculture, rotation processes and agricultural intensification at national level.



4

Developement of tools

App for Wind Shield Surveys (Android based)

Designed for fast registering of georeferenced points along roads in a vehicle. Automatically generate samples for classification at each side of the road.

5

Next steps and additional interests

- Continuity in the generation of National Crop Type Maps:
  - Near real time classification
  - Classification without/less in situ data of current year
  - Improve accuracy of difficult/unfrequent crops
- Identification of Irrigated crops
- Intensive crops mapping (Fruticulture, horticulture)
- Yield estimation

6

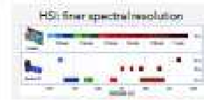
Hyperspectral satellite imagery for cereal discrimination – Belgium JECAM site

Maxime Troiani & Juan Camilo Garcia Peña
UCLouvain

LPS Viena - June 2025

Context & Objectives

- Temporal-based approaches
- Significant processing needed



- Spectral-based approaches
- High dimensionality handling required

UCLouvain

Context & Objectives

- Classify cereals using HSI *>> Benchmark, best way to handle HSI?*
- Compare HSI and MSI -based classification *>> added value at all?*

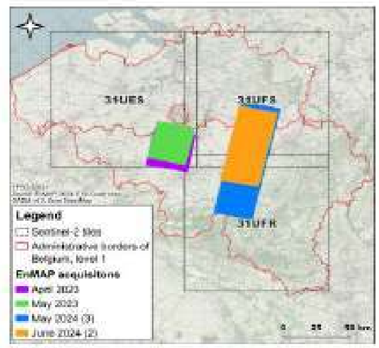
UCLouvain

Data & study area

1. EnMAP
207 bands
Res: 30 m

2. sentinel-2
10 bands
Resampled to 30 m

Year	Month	Day EnMAP	Day S2
2023	April	21	15
2023	May	8	-
2024	May	11	13
2024	June	7	8

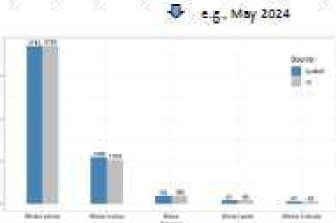


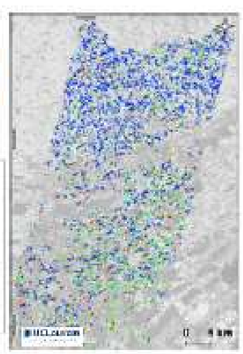
UCLouvain

Data & study area

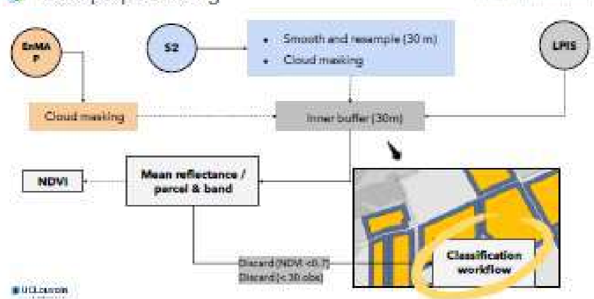
Crop	Winter wheat	Winter barley	Maize	Winter spelt	Winter triticale	Spring Wheat
Date	All	All	Not June 24	Not May 23		Only June 24

e.g. May 2024



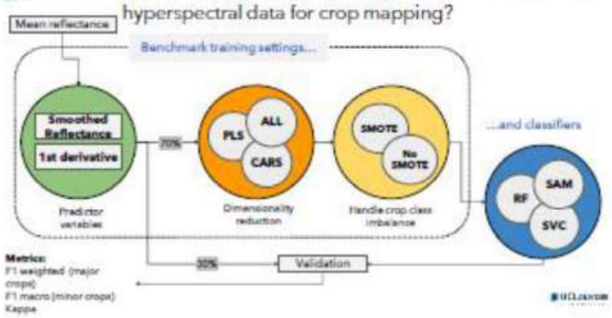


Data preprocessing



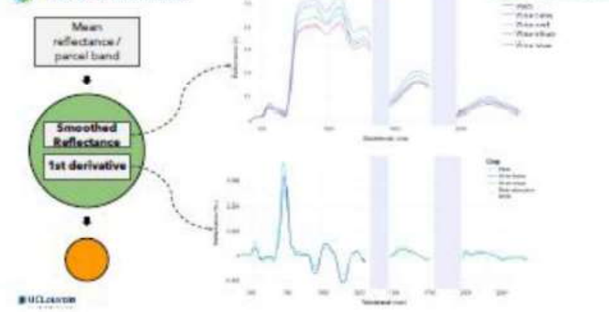
UCLouvain

Workflow on EnMAP: How to leverage hyperspectral data for crop mapping?

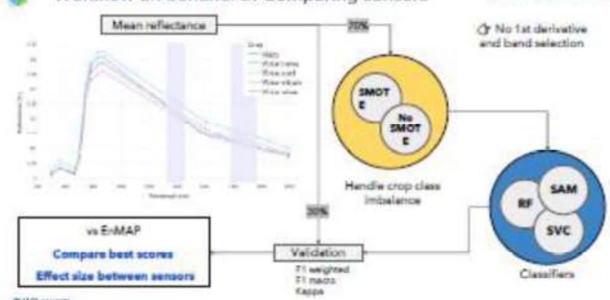


Metrics:
F1 weighted (major crops)
F1 macro (minor crops)
Kappa

Predictor variables



Workflow on Sentinel-2: Comparing sensors



Benchmark results

e.g. May 2024

Classifier	Predictor	Reduction	Smote	F1-M	BAcc	F1-W	Acc	Kappa
RF	Ref	PLS	TRUE	0.76	0.74	0.93	0.93	0.84
SAM	Deriv	PLS	FALSE	0.47	0.66	0.80	0.74	0.54
SVC	Ref	None	FALSE	**0.78**	**0.80**	**0.96**	**0.95**	**0.89**

SVC
- Best overall
- Minor classes always

RF
- Also best
- Minor classes: some

SAM
- Lowest scores
- Ok for major classes

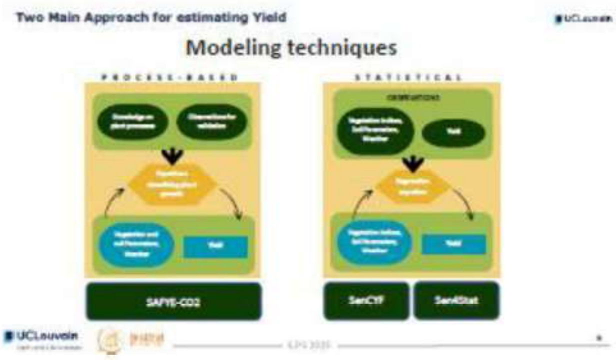
EnMAP & S2 results

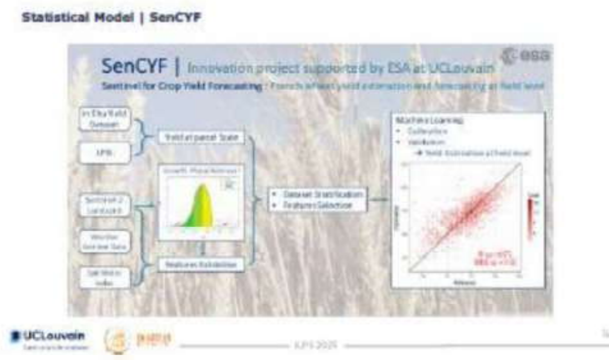
e.g. May 2024

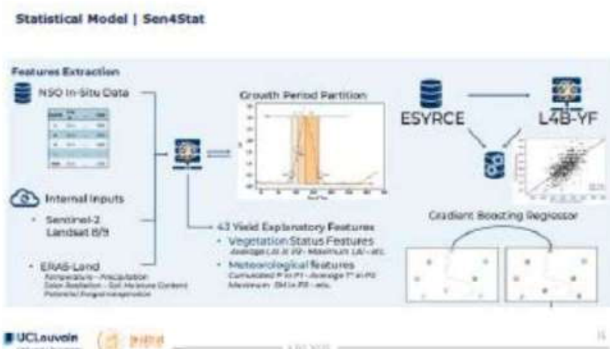
Source	Classifier	SMOTE	Predictor	Features	F1-M	BAcc	F1-W	Acc	Kappa
EnMAP	SVC	NO	Reflectances	All	**0.78**	**0.8**	**0.96**	**0.95**	**0.90**
S2	SVC	NO	Reflectances	All	0.51	0.52	0.89	0.88	0.73

Take home messages

1. **Single date HSI to classify crops?**
   1. Scores above 90%
2. **How to leverage HSI?**
   1. SVC + Reflectance + All bands + No SMOTE
3. **What HSI offers beyond MSI?**
   1. No need of multidate & low processing
   2. HSI comparatively better >> minor crops


Two Main Approach for estimating Yield
Modeling techniques
PROCESS-BASED
STATISTICAL
SAFYE-CO2
SenCYF
Sen4Stat
UCLouvain


Statistical Model | SenCYF
SenCYF | Innovation project supported by ESA at UCLouvain
Sentinel for Crop Yield Forecasting
Yield at parcel Scale
Dataset Stratification
Features Selection
Machine Learning
UCLouvain


Statistical Model | Sen4Stat
Features Extraction
NSO In-Situ Data
Internal Inputs
Sentinel-2
Landsat 8/9
ERA5-Land
Growth Period Partition
ESYRCE
L4B-YF
43 Yield Explanatory Features
Vegetation Status Features
Meteorological features
Gradient Boosting Regressor
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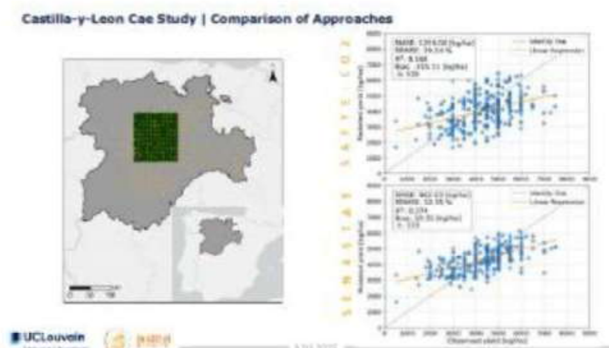
Castilla-y-Leon Cae Study | Comparison of Approaches
UCLouvain


Requirement of EO Compatible and Reliable In Situ Data Collection
Crop Cutting
Plant Counting
Field Production Weighing
Transport Production Counting (bags/containers)
Expert Observation
Farmer Declaration
Limitation : High Cost – Timeliness – Destructive – Bias – etc.
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OBSYDYA

Pilot Monitoring Platform for Agricultural and Landscape Dynamics in Benin

1

OBSYDYA project ID

- European DESIRA project (2023-2026)
- North and Centre Benin + 6 study sites
- Operational Objectives
  - An informational services platform (IS) dedicated to **spatial indicators** (structure and **dynamics of agro-pastoral systems and landscapes**) aimed at national and local stakeholders involved in rural development.
  - Strengthen the capacities of stakeholders - researchers, educators, administrators, advisors, and farmers' organizations - in the use of new **satellite products, processing methods, and spatial analysis**.

2

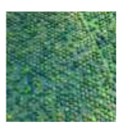
2

Key data sets for JECAM

Agri land use

Soil tillage

Tree crops



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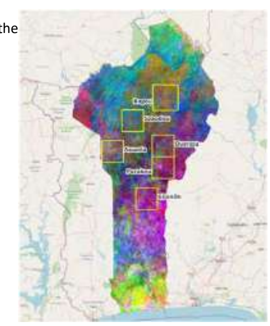
3

Agriculture land use data set

- **6 experimental sites** (50x50 km) spread across the Center/North Beninese agro-climatic gradient
- **Annual agricultural land use [2022-2025]**
  - Focus on the **major annual crop activities** (soy beans, cotton and cereals) **and tree crops** (cashew, mango)



4

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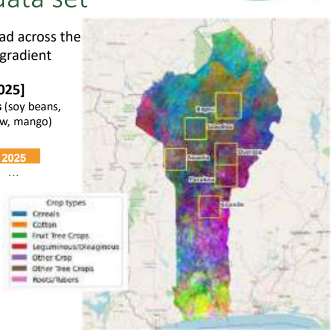
	2022	2023	2024	2025
Ouénou	1 709	3 595	3 114	…
Parakou	1 883	3 590	3 704	
Bagou	3 275	1 980	3 621	
Awanla		1 890	6 245	
Gbanlin		5 202	3 909	
Soaodou		1 589	3 685	
	6 867	17 846	24 278	

≈ 50 000 polygons so far



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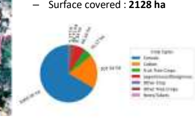
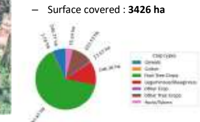
Land use data sets

Bagou Site :
- **3621 annotations** in **2024**
- Surface covered : **2128 ha**



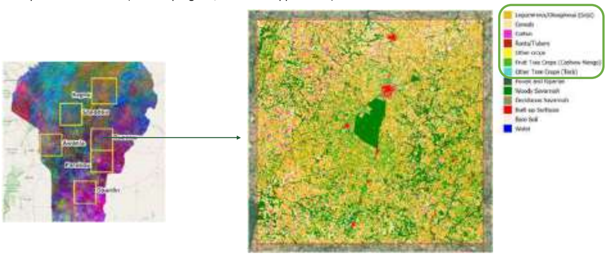
Gbanlin Site :
- **3909 annotations** in **2024**
- Surface covered : **3426 ha**



6

LU classification using MORINGA

- MORINGA land cover tool box (Docker at: https://forge.inrae.fr/raffaele.gaetano/moringa)
- S2 time series + VHSR (SPOT6) image at the end of the rainy season, with OBIA
- Example of Ouénou site (work in progress, test of DL approaches):



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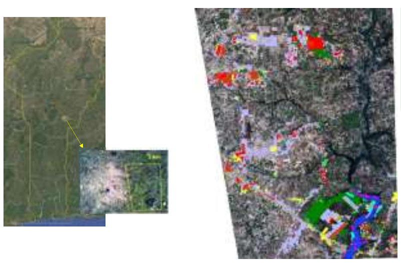
8

Tree crops ground data set

- Parakou site ground data collection (Nov 2023) and vectorization (labelling) -> 16 classes (9 tree crop classes)
- 13% of the area of study (120 km²) were labelled on Pléiades-Néo image (4 décembre 2022)



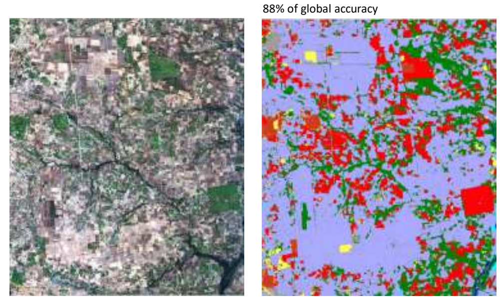
Lelong, C., 2025, "Base de référence spatialisée de l'occupation du sol, périphérie Est de Parakou, Nord-Bénin, 2023.", https://doi.org/10.18167/DVN1/RV9SID, CIRAD Dataverse, V1.

9

9

Application of the U-net model

88% of global accuracy



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10

Soil tillage ground data set

- Increasing mechanization of soil tillage in North Benin.
- Can EO data permit to monitor the adoption of mechanized ploughing ?


Ridge plowing with animal traction


Ridge plowing with power tiller


Tractor with disc plow

11

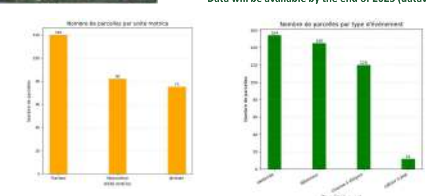
11

Soil tillage ground data set

Records of **379 fields**, in May-June 2024

- Ploughing (start-end dates) : between April-June 2024
- Herbicide use before ploughing
- Ploughing equipment : tractor, power tiller, animal traction
- Tillage type : on-the-flat, ridge, disc

- Work in progress with Sentinel-2 and Sentinel-1
- **Data will be available by the end of 2025 (dataverse)**



12

12

Calendar

- Ground data and maps are open data
- Dataverse in progress :

Dataset	Dataverse	Contact
LULC *	End of 2025, and updates	raffaele.gaetano@cirad.fr
Soil tillage	October 2025	simon.madec@cirad.fr
Tree crops	https://doi.org/10.18167/DVN1/RV9SID	camille.lelong@cirad.fr

* Complementary field campaigns for the characterisation of **natural areas ; An extensive Land Cover / Land Use DB** suitable for **mapping from remote sensing imagery** with ML and DL **based processors**

13

13

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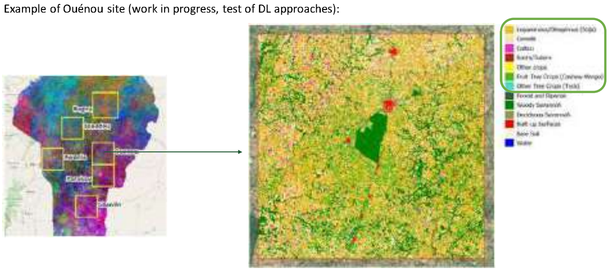

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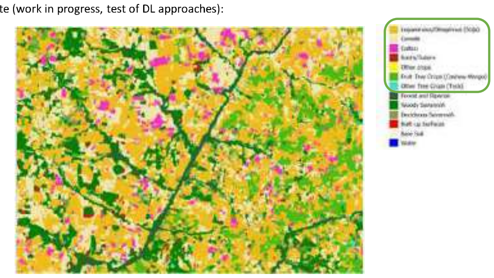

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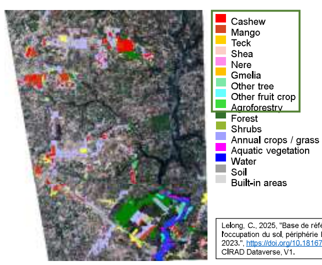

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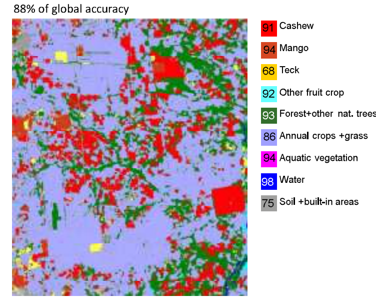

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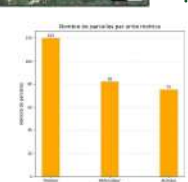

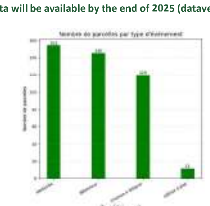

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12

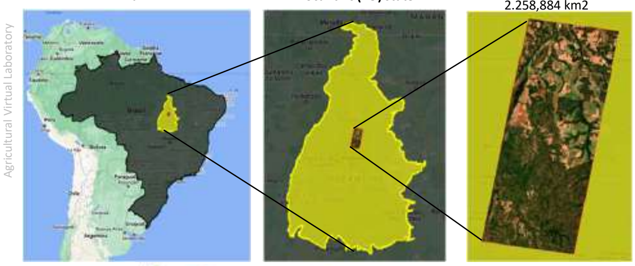
Agricultural Virtual Laboratory

Early Adopters Activities Presentation (Brazil)

JECAM/AVL User Workshop at Living Planet Symposium 2025: 25 June 2025

1

Study area location



2

CROP TYPES IDENTIFICATION AND MAPPING IN TOCANTIS STATE (BRAZIL)

- **Collected fieldwork samples in Tocantins (TO):** soybean (350), millet (70), and pasture (100). **Total** = 520 samples.
  - **Training:** 70% of the samples.
  - **Validation:** 30% of the samples.
  - In addition to the classes mentioned above, it will be possible to obtain information about maize crops in a few months (August), based on MapBiomas LULC Brazilian map. Thus, the main goal of the Brazilian team will be to discriminate spectrally millet and maize.
  - The comparison between EnMap hyperspectral and Sentinel-2 multispectral imagery will focus on mapping millet and maize accurately, timely, and precisely.

3

Identifying crop types:

- Identifying crop types using an auxiliary map from MapBiomas, a great brazilian effort to map all ecosystems and Land Use Land Cover (LULC) using all Landsat time series, and recently, using all Sentinel-2 time series, obtaining 2 products, i.e., one of them at 30m spatial resolution and the other at 10m spatial resolution.
- The map on the left shows a clip of the study area, where the white regions are soybean crops. Usually, in Brazil, after the soybean harvest the farmers grow the maize.

4

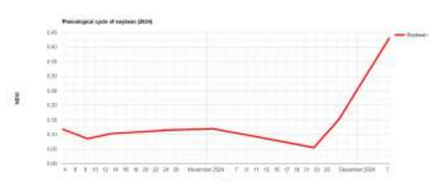
Sentinel-2 Random Forest Classification (2024-10-01, 2024-12-31)

```
Overall accuracy:
1

User accuracy:
[[0,1,1,1]]

Producer Accuracy:
[[0],[1],[1],[1]]

Kappa Index:
1

F1-Score Index:
["NaN",1,1,1]
  0: NaN
  1: 1
  2: 1
  3: 1
```

5

Identifying crop types:

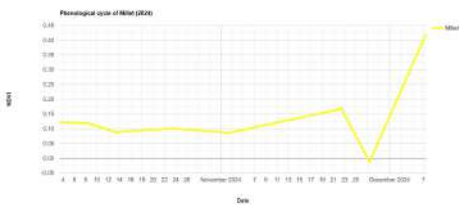
- Soybean temporal profile using NDVI Sentinel-2 time series.



6

Identifying crop types:

- Millet temporal profile using NDVI Sentinel-2 time series.

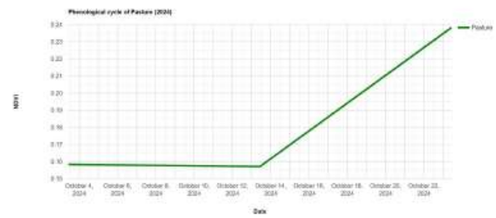


UCLouvain

7

Identifying crop types:

- Pasture temporal profile using NDVI Sentinel-2 time series.



UCLouvain

8

Considerations about the AVL plataform

- **Some AVL plataform considerations:**
  - Working on the AVL plataform, mainly in Jupyter environment, has been a remarkable and enriching experience, as it represents cutting-edge technology in Remote Sensing.
  - It has been a great opportunity to deepen my knowledge of the Python programming language, since I am more used to working on Google Earth Engine using the JavaScript programming language.
  - I would like to congratulate the JECAM/ESA team for this great experience and for the scientific rigor and professionalism with which this experiment has been conducted.

UCLouvain

9

Identifying crop types:

Agricultural Virtual Laboratory

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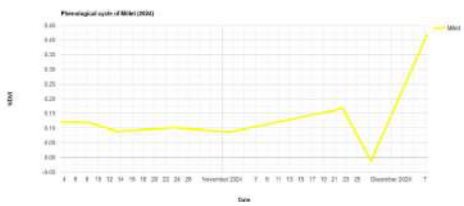

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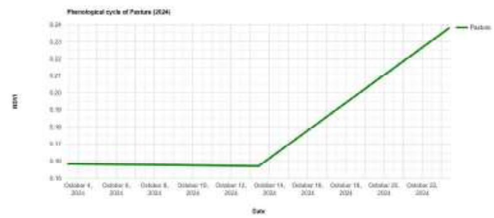

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9

JECAM Updates: Canada

Catherine Champagne
a/Manager Earth Observation
Science and Technology Branch
Agriculture and Agri-Food Canada

Site Leads: Heather McNairn, David Pelster, David Lapen, Taras Lychuk, Kayla Moore

Carman, Manitoba

Site Lead: Dr. Heather McNairn, Dr. Kayla Moore, Dr. Taras Lychuk

- The study site is located in south central Manitoba, Canada (Prairie EcoRegion).
- Land use is dominated by annual cropping. The soil texture varies greatly across the site with heavy clays in the east and loamy fine sands in the west.
- Agriculture and Agri-Food Canada (AAFC) has a permanent in situ soil moisture station network in the area
- The site has been used extensively to develop and validate soil moisture retrievals using Canada's RADARSAT and NASA SMAP satellites. Numerous remote sensing research studies have been conducted in this area which include crop mapping and condition monitoring, crop biophysical parameters (LAI, biomass) retrieval.

- Crop Type(s): Maize, Canola, Spring Wheat, Soya beans
- Current Field Data Collection:
  - Soil Moisture (automated stations), precipitation, solar radiation, temperature, RH
  - Crop Type, planting and harvest dates
- Future Plan:
  - Improve data availability. Available near real-time on Aquarius, ISMN update coming
  - Expand cold regions hydrological data

Casselman, Ontario

Site Lead: Dr. Heather McNairn, Dr. David Lapen, Dr. Kayla Moore, Dr. Taras Lychuk

- The site is located in eastern Ontario, Canada.
- The climate is humid continental with a large seasonal climatic variation, supporting one harvest per year.
- The dominant soil is silt loam.
- Agriculture and Agri-Food Canada (AAFC) has a permanent in situ soil moisture station network in the area
- The site has been used for developing vegetation indices, crop type mapping, watershed evaluation of best management practices

- Crop Type(s): Maize, Soya beans, Wheat
- Current Field Data Collection:
  - Soil moisture to 1 m (automated), precipitation
  - Cope type, planting and harvest dates
- Future Plan:
  - Improve data availability. Available near real-time on Aquarius, ISMN update coming
  - Expand cold regions hydrological data

Ottawa (CFIA), Ontario

Site Lead: Dr. Catherine Champagne, Dr. David Pelster

- The site is located in eastern Ontario, Canada.
- The climate is humid continental with a large seasonal climatic variation, supporting one harvest per year.
- The dominant soil is silt loam.
- Site is in a research farm and has extensive instrumentation (Eddy Flux, N2O, automated weather station, soil moisture, soil temperature, yield)
- The site has been used for developing models, testing new Earth Observation technology

- Crop Type(s): Maize, Soya beans, Wheat, Forage
- Current Field Data Collection:
  - Soil Moisture (automated stations)
  - Crop Type
- Future Plan: 4R Nutrient modelling, ecosystem productivity

Aerospace Information Research Institute (AIR)
Chinese Academy of Sciences (CAS)

Updates of research activities from China JECAM team

Miao Zhang, Bingfang Wu
State Key Laboratory of Remote Sensing and Digital Earth,
Aerospace Information Research Institute, Chinese Academy of Sciences

26th June, 2025

China JECAM site and experiments

Experimental areas

- Located in Handan, Hebei Province
- Construction of ten observation towers
- Equipments for crop conditions monitoring using mounted cameras
- Observation equipments for climate data and flux data

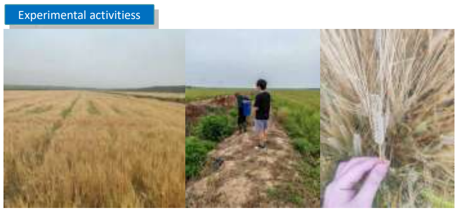
Experimental activitiess and research priorities

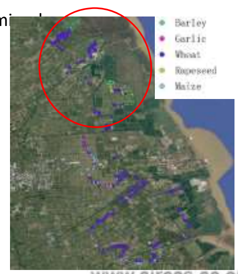
- Survey of crop types
- Collection of crop variables including planting density, biomass, yield, harvest index, etc.
- Digital photos taken during crop survey
- **Research Priorities**
  - Mapping of cropland and utilization, crop type mapping
  - Remote sensing estimation of biomass, harvest index and crop yield
  - Identification of crop diseases, pests and yields using AI approach

Data collection in Jiangsu wheat&barley areas

- The survey was conducted on May 15th, before the peak of growing season.
- The dominant crop is wheat, with some barley farms
- The boundaries of the barley planting plots were determi...
- Digital photos were taken during the crop survey.

Experimental activitiess



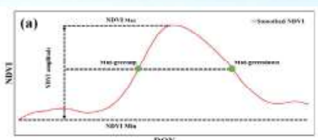


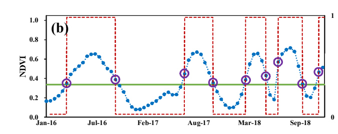
Cropping intensity mapping

Growth to maturity cycle detection

Signal for growth (mid-greenup): the smoothed NDVI time series passes 50% of the NDVI amplitude in the greenup periods

Signal for maturity (mid-greendown): the smoothed NDVI time series reduces to 50% of the NDVI amplitude in the greendown periods





Cropping cycle determination

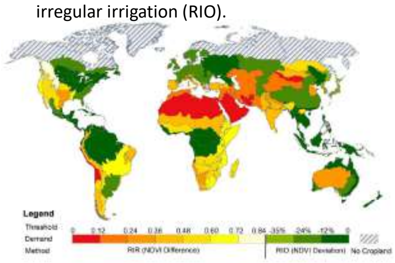
$$N_{pc} = min\{N_{up}, N_{down}\}$$

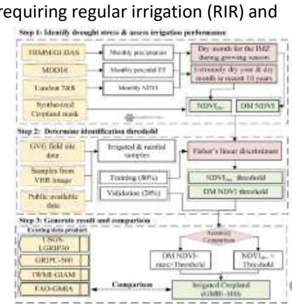
where N_{pc} is the number of the potential cropping cycles; N_{up} and N_{down} are the numbers of mid-greenup and mid-greendown transition points, respectively

Liu Chong et al., Remote Sensing of Environment, 2020

Irrigation mapping

- Poor crop condition under drought stress was considered as rainfed
- A global distinction was made between areas requiring regular irrigation (RIR) and irregular irrigation (RIO).

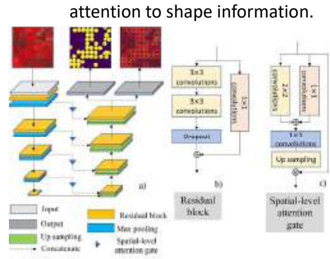


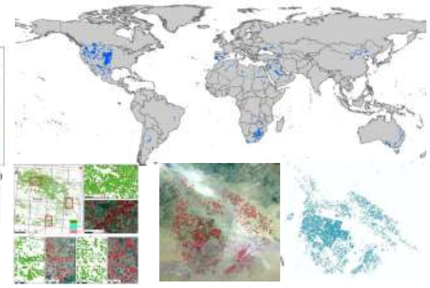


Bingfang Wu et al., Global Environmental Change, 2023

Central pivot mapping

- propose the Pivot-Net model for the circular shape to identify CPIS by adding a spatial attention module, combined with multi-task learning, to make the model pay more attention to shape information.

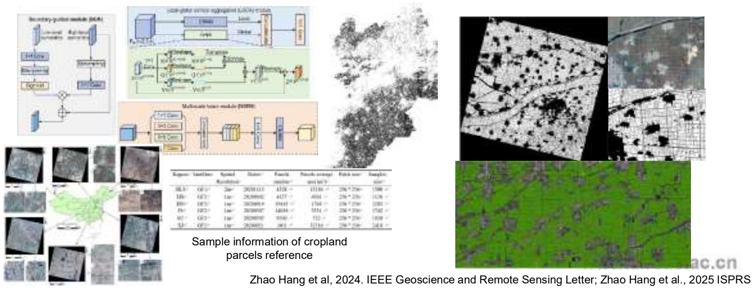




Tian et al. GIScience & Remote Sensing, 2023

Field boundary detection

- Deep learning models were developed based on Pyramid Vision Transformer
- High resolution field parcels was delineated at different region of China

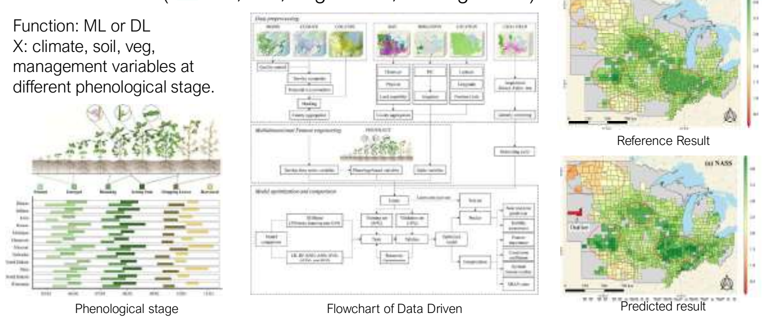


Zhao Hang et al, 2024. IEEE Geoscience and Remote Sensing Letter; Zhao Hang et al., 2025 ISPRS

Data driven yield prediction model

Yield = Function(climate, soil, vegetation, management)

Function: ML or DL
X: climate, soil, veg, management variables at different phenological stage.



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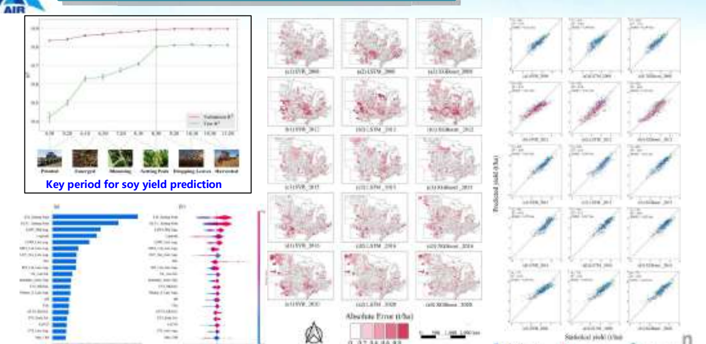
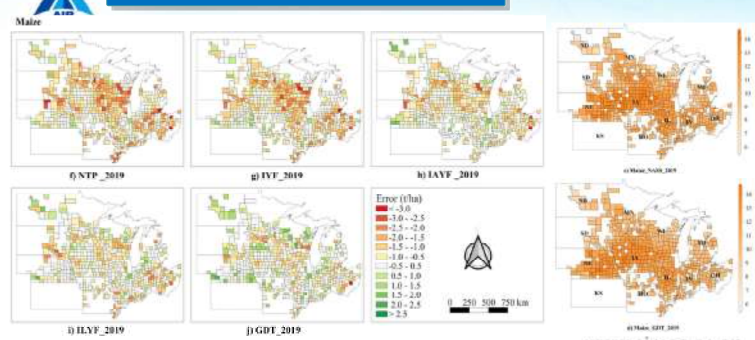


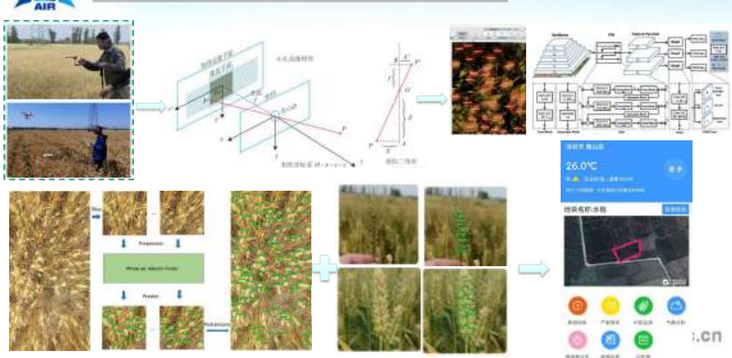
Li, Y., et al. 2023. International Journal of Applied Earth Observation and Geoinformation

Improvement of de-trending for yield prediction



Li, Y., et al. (2024). Global de-trending significantly improves the accuracy of XGBoost-based county-level maize and soybean yield prediction in the Midwestern United States. GIScience & Remote Sensing, 61(1), 2349341.

Yield measurement using AI without destroy crops



Recent publications

1. Hang Zhao, Miao Zhang, et al. A large-scale VHR parcel dataset and a novel hierarchical semantic boundary-guided network for agricultural parcel delineation, ISPRS Journal of Photogrammetry and Remote Sensing, 2025.
2. Li, Y., Tian, F., Zhang, M., Zeng, H., Ahmed, S. et al. (2025). A 10-meter global terrace mapping using sentinel-2 imagery and topographic features with deep learning methods and cloud computing platform support. International Journal of Applied Earth Observation and Geoinformation, 139, 104528.
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4. Xie, Zunyi, Zhao, Yan, Jiang, Ruizhu, Zhang, Miao, Hammer, Graeme, Chapman, Scott, Brider, Jason, Potgieter, Andries. Seasonal dynamics of fallow and cropping lands in the broadacre cropping region of Australia, Remote Sensing of Environment, 2024, 305:114070.
5. Zhao, H., Long, J., Zhang, M., Wu, B., Xu, C., Tian, F., & Ma, Z. (2024). Irregular agricultural field delineation using a dual-branch architecture from high-resolution remote sensing images. IEEE Geoscience and Remote Sensing Letters.
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Thank you!

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Chinese Academy of Sciences(CAS)

www.aircas.ac.cn

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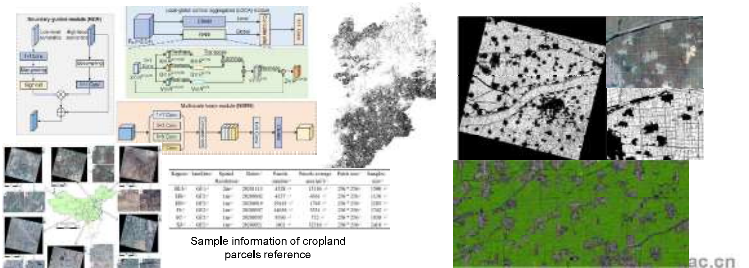

Sample information of cropland parcels reference

Zhao Hang et al, 2024. IEEE Geoscience and Remote Sensing Letter; Zhao Hang et al., 2025 ISPRS

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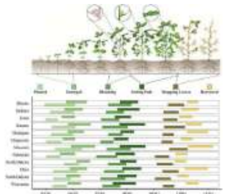
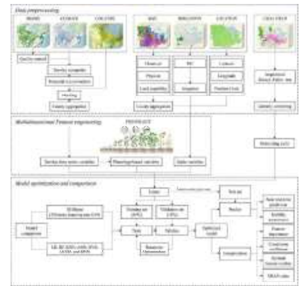
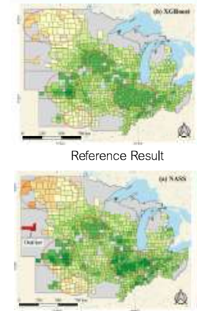


Phenological stage



Flowchart of Data Driven



Reference Result

Predicted result

Data driven yield prediction model

Key period for soy yield prediction

Performance analysis for extreme years

Li, Y., et al. 2023. International Journal of Applied Earth Observation and Geoinformation

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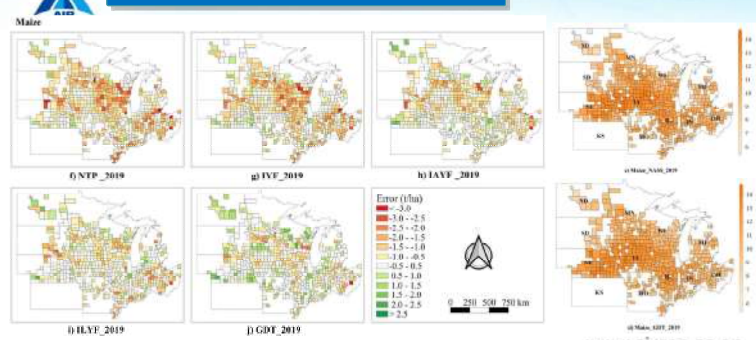

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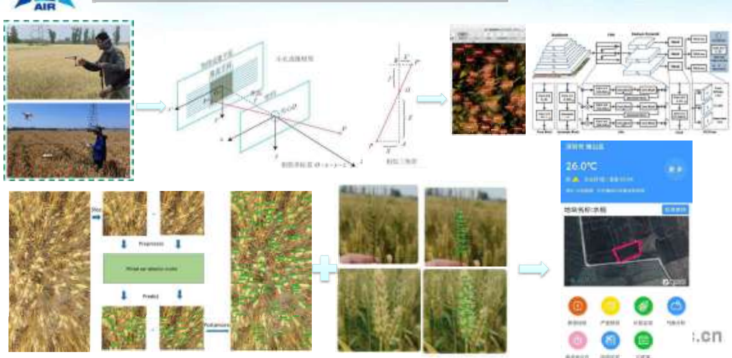

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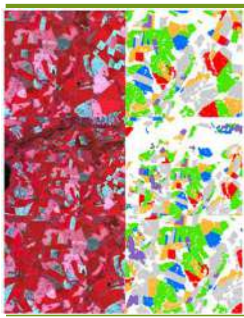


JECAM Meeting 26.06.2025

Joint Experiments on Crop Assessment and Monitoring

Crop classification comparison between EnMAP and Sentinel-2 (AVL workflow)

Site: Demmin, Germany

Prof. Dr. Christopher Conrad
Talha Mahmood

Department of Geoecology
Institute of Geoscience and Geography
Martin Luther University Halle-Wittenberg

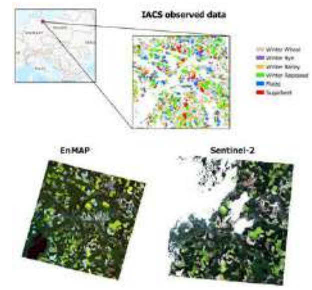
1

Introduction

Study conducted over the DEMMIN site (Germany) — a representative agricultural landscape.

- Evaluate the impact of spectral resolution and preprocessing (e.g., smoothing, derivatives).
- Assess classification performance using a single acquisition from May.
- Identify the advantages of each sensor for operational crop mapping.

EnMap cloud-free image available (2nd May 2024)
Closer best available Sentinel 2 images (30th April 2024)



2

Experiments

Four classifications

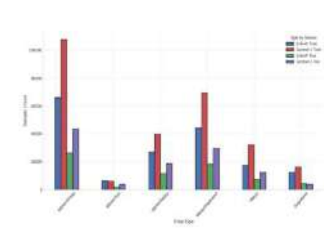
EnMAP Configurations:
1. Raw surface reflectance
2. Savitzky–Golay smoothed spectra
3. First-order spectral derivative (gradient)

Sentinel-2 Configuration:

4. Raw surface reflectance

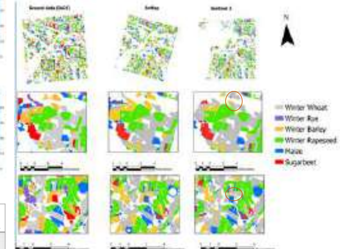
Single acquisition from May used across all tests

Supervised machine learning (e.g., Random Forest)



3

Resuls: Overall Accuracy

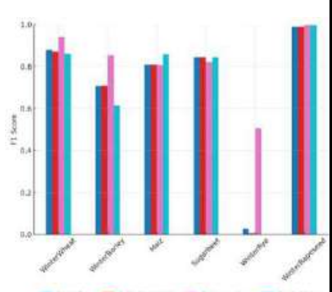


	EnMap Raw	EnMap Smoothing	EnMap Gradient	Sentine2
Overall Accuracy	0.86	0.86	**0.91**	0.84
Kappa Score	0.81	0.80	**0.88**	0.79

4

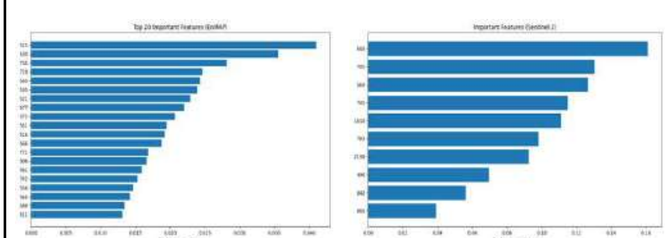
Resuls: Class wise Accuracy

- Using 1st order gradient to EnMAP surface reflectance outperformed all other experiments in class-wise performance, particularly for spectral similar classes, Winter Wheat and Winter Barley
- Sentinel-2 showed higher confusion between Winter Wheat and Winter Barley.
- Winter Rye was misclassified across all configurations
- Winter Rapeseed were classified with high accuracy across both sensors



5

Feature Importance



6

Conclusions

- Applying a first-order spectral derivative improved classification results, achieving the highest overall accuracy (**91%**) and average F1-score (**82%**)
- EnMAP outperformed Sentinel-2, particularly in distinguishing spectrally similar crops such as **Winter Wheat** and **Winter Barley.**.
- All approaches, including Sentinel-2 and EnMAP, struggled to classify **Winter Rye** using a single image from May.
- The limitations in single-date classifications suggest that multi-temporal imagery may provide better discrimination.
- Future efforts should consider integrating SAR time series, which can provide structural properties of crop types.

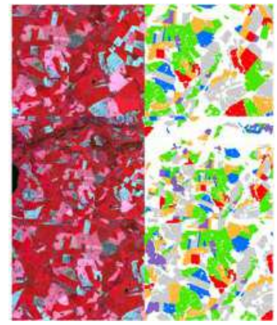
7

Thank you for your attention

Questions?

Talha Mahmood

Department of Geoecology
Institute of Geoscience and Geography
Martin Luther University Halle-Wittenberg
talha2647@gmail.com



8

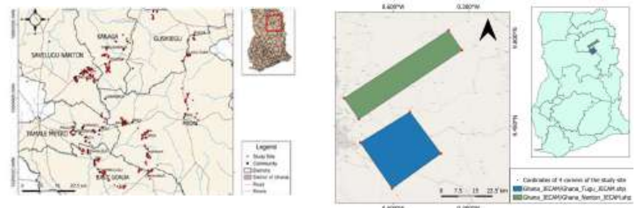
Strengthening JECAM Ghana: Priorities for Agricultural Monitoring

Kofi Asare
Remote Sensing and Climate Center

Ghana Space Science and Technology Institute

1

Study sites - Northern Ghana



- Two study sites: Nanton and Tugu
- Focus: Maize monitoring

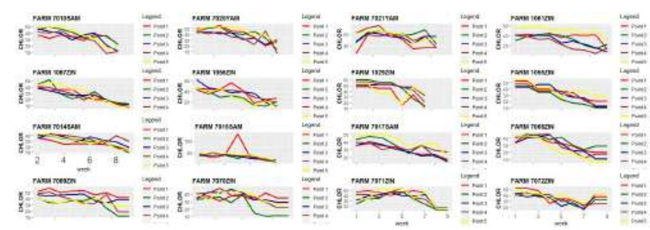
2

Ground data EAV's

Crop location	Often poor information on **crop acreage** Very scarce information on **crop location**
Biophysical variables (context: Essential Ag Vars)	Validate/**understand** limitations of **EO-derived estimates**. Includes: LAI, Chlorophyl

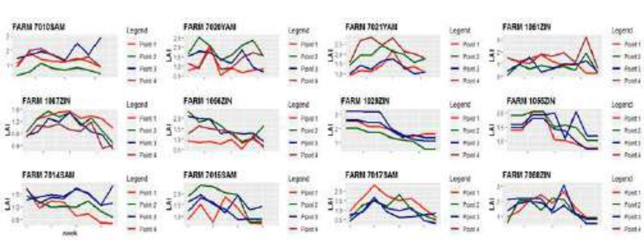
3

Biophysical- Chlorophyl



4

Biophysical - LAI



5

Project activities

- **Field measurement**
  - LAI & chlorophyll dynamics visible
  - Low LAI values
  - Decay of chlorophyll over time
- **Field data collection**
  - At end of the cropping season, 2025
    - Mapping fields and yield estimation
- **Facing challenges**
  - Equipment to collect more data samples
  - Funding for continues data collection

6

Priorities

Priority Area	Goal
Geographic Expansion	Add crops and new regions
Multi-season Data Continuity	Ensure multi-year, diverse datasets
Enhanced SAR Integration	Combine radar + optical for accuracy
Open Data & Validation	Publish validated, open datasets
Capacity Building	Train users, increase local uptake
National Integration	Link data to MoFA systems

7

Thank you

kofi.asare@gaec.gov.gh / asarefi@yahoo.com
+233 244980264

8

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8

JECAM SITE in Poland
Katarzyna Dabrowska – Zielinska

Polish Team:Katarzyna Dąbrowska-Zielińska
Konrad Wróblewski, Szymon Jakubiak, Maciej Bartołd, Dariusz Ziółkowski,
Ewa Panek-Chwastyk, Magdalena Łągiewska, Joanna Kaczorowska
Institute of Geodesy and Cartography

Who we are

Remote Sensing Centre has a long tradition of using Earth Observation data date back to the 1976 year. Activities of the Remote Sensing Department cover the broad range of research and application-oriented works related to the use of various satellite images and products for deriving information on environmental aspects. Our research covers the following topics: **agriculture**, which includes: forecasting of yield, drought detection, crop recognition and crop condition assessment; estimates of **heat** and **carbon fluxes** between surface and air, detection of **soil moisture** changes, **hydrological aspects**, **bioenergy**, **forests**, natural hazards: **floods**, **forest fires** and landslides as well as **land cover** and **land cover changes**

Input data for agricultural drought hazard mapping

Terra MODIS
Gridded 1 km x 1 km, 8-day composite
2000-2024

Sentinels 1,2,3 Copernicus LMS

Ground measurements database

ERA5 data

Daily meteorological data – air temperature and precipitation collected from synoptic, climatic and rainfall stations – resources of the Institute of Meteorology and Water Management

JECAM POLAND STUDY SITE

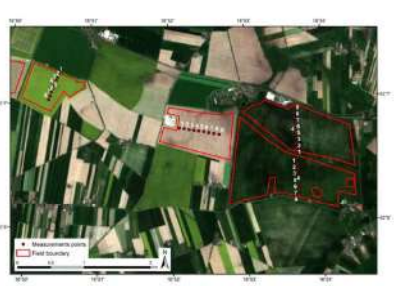
Located at NUTS2 PL41

It is intended that the JECAM experiments will facilitate international standards for data products and reporting, eventually supporting the development of a global system of systems for agricultural crop assessment and monitoring Agriculture and Agri-Food Canada (AAFC) has taken on the secretariat role of the JECAM project on behalf the **GEO Agricultural Monitoring Community of Practice**. (Credits: **www.jecam.org**)

Study site is located in Greater Poland Voivodeship (NUTS 2 PL41), approx. 50 km to Poznan. The site is 25 km x 25 km with the area of focused study and research at 10 x 10 km (highlighted yellow).

Verification of results

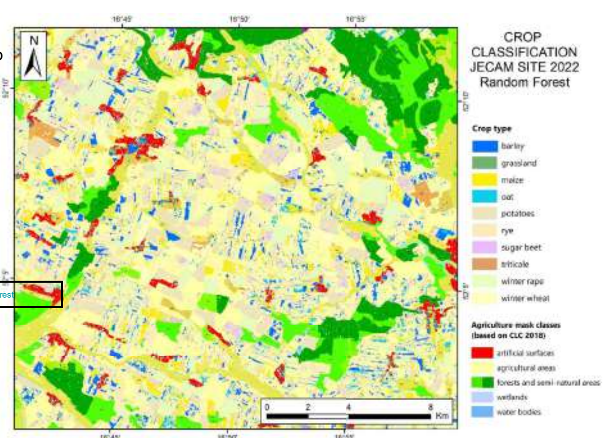
Detailed field measurements
Data standardization



Input: Sentinel-1; from mid-February to the end of June
Overall Accuration = 0.81
Data split: 50/50 for training and validation

10.32614/CRAN.package.randomForest

CROP CLASSIFICATION JECAM SITE 2022 Random Forest



Agriculture Virtual Laboratory (AVL) project, a collaborative initiative focused on developing and utilizing virtual laboratories for agricultural research.
Louvain University

RandomForest
Image for 18/09/2024
Crop categories = 12
Training/validation split 80/20
Overall Accuracy = 0.38
Kappa = 0.11

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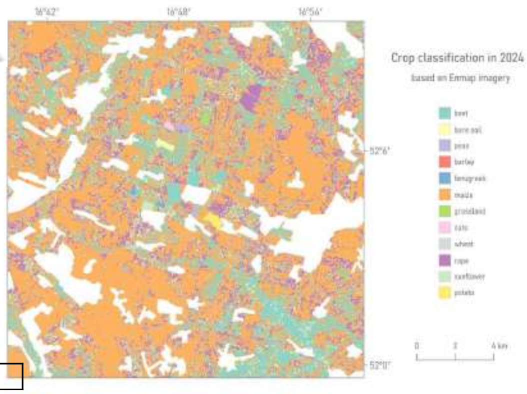


Monthly temperature anomalies relative to the long-term monthly average (1993–2024)

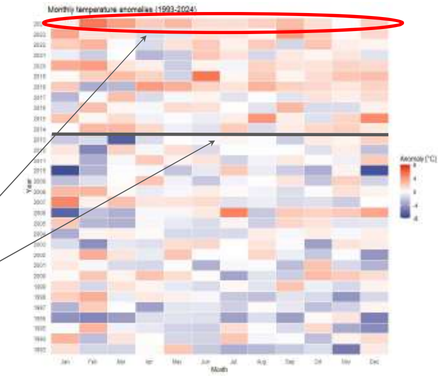
$$A_m = T_m - \overline{T}_{m,\mathrm{ref}}$$

where,

Am - temperature anomaly for a given month;
Tm - average temperature in a given month;
Tm,ref - average temperature for the same month over many years.

2024 is first year without a negative anomaly

Noticeable difference in anomalies since 2014 with predominance of positive anomalies



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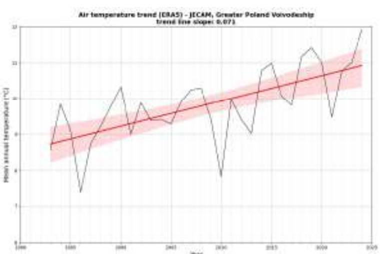

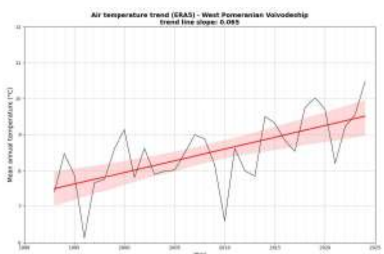

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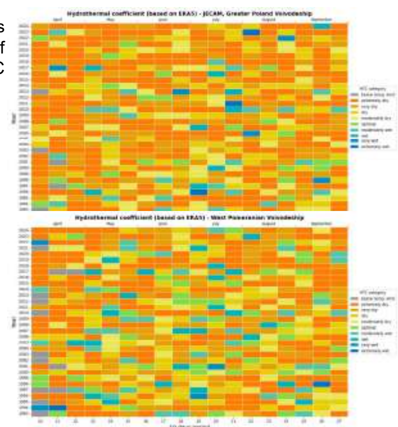

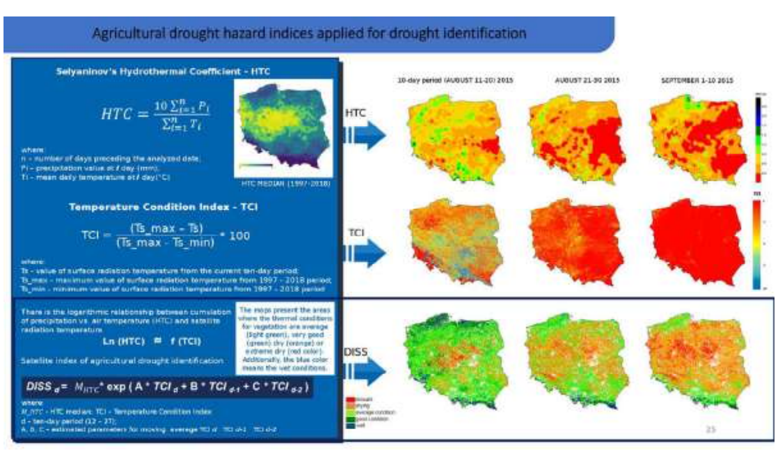

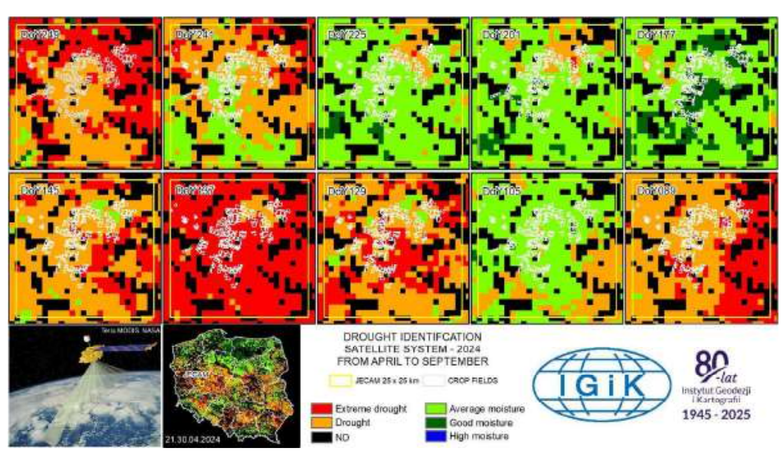

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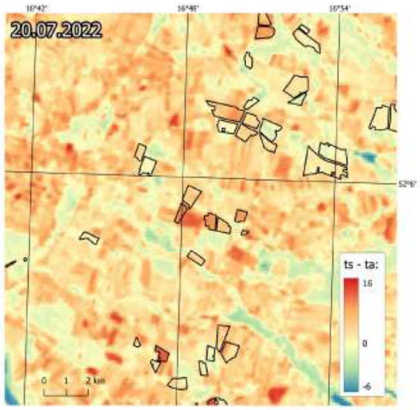

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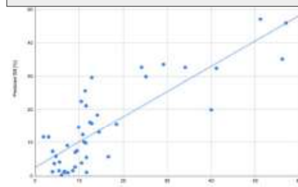
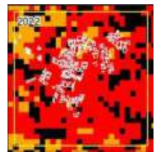
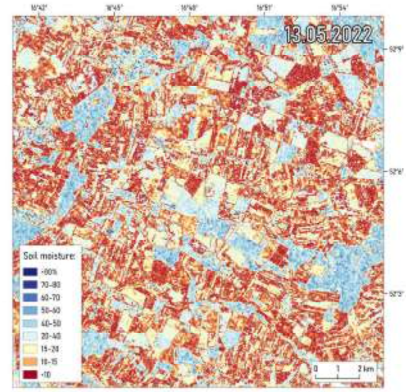


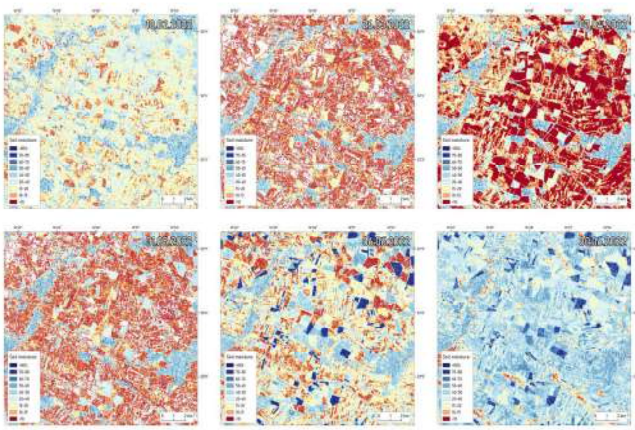


S-1 soil moisture aligns with drought DISS from Terra MODIS in May 2022

AGRICULTURAL DROUGHT
17-24 May 2022

Extreme drought
Drought
ND
Average moisture
Good moisture
High moisture





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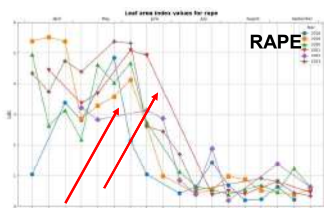
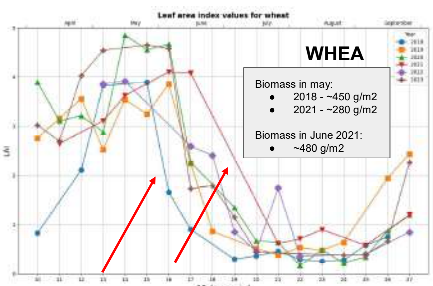
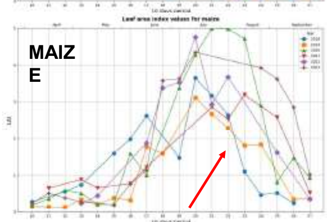
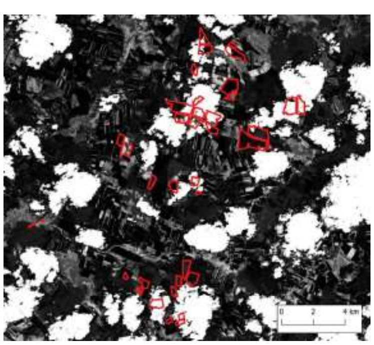
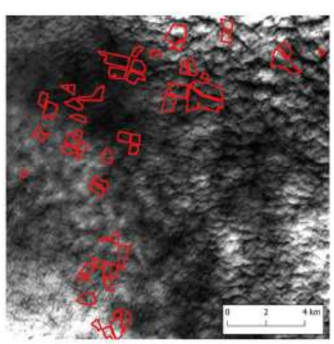




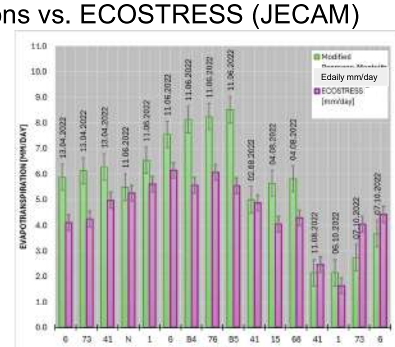


Uncertainties related to LAI from CLMS with cloud and cloud shadow effects and unidentified clouds



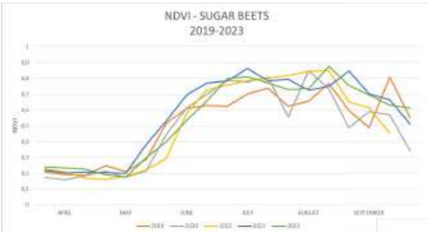


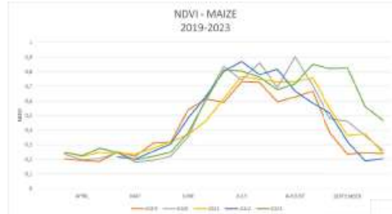
Comparative Analysis of ET Models for winter wheat: Observations vs. ECOSTRESS (JECAM)

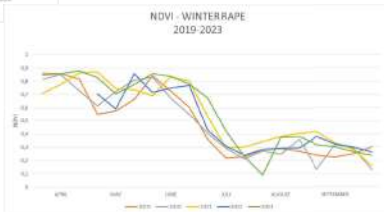


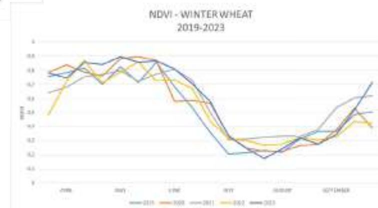
$$LE = R_n - G - H$$

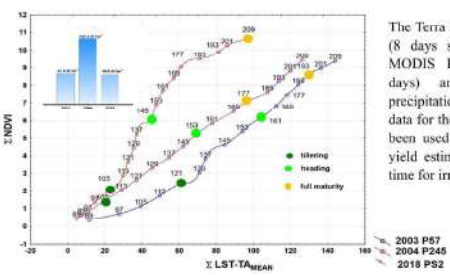
$$H = \frac{\rho c_p (T_s - T_a)}{r_a}$$





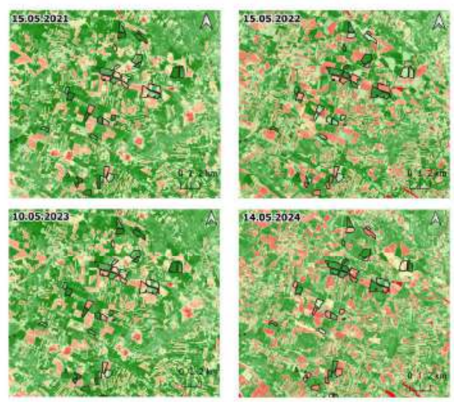






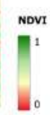
The Terra MODIS (8 days NDVI) and (8 days surface temperature TS), MODIS FAPAR (calculated for 8 days) and meteorological data as precipitation and air temperature. All data for the same periods of time have been used to set the model for crop yield estimates and for estimates the time for irrigation.

$$Yield = 158.88 + 0.58 * \sum_{start}^{matur}(LST - TA) + 43.7 * \log\left(\frac{\sum_{start}^{head} NDVI}{\sum_{start}^{head} LST-TA}\right) + $$
$$+ 20.46 * \log\left(\frac{\sum_{head}^{matur} NDVI}{\sum_{head}^{matur} LST - TA}\right)$$



Temporal variability of NDVI on JECAM site

MAY 2021-2024



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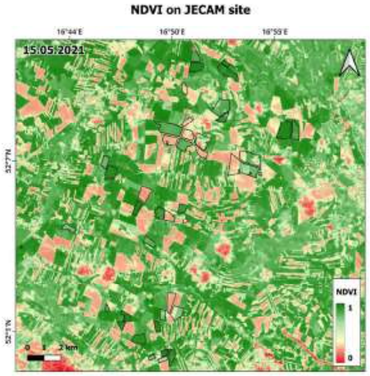

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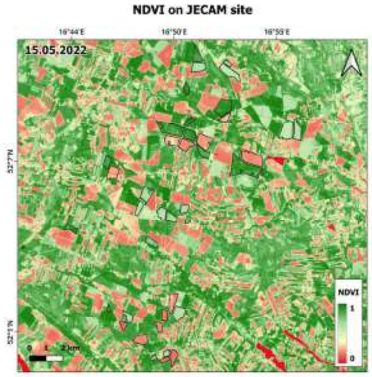

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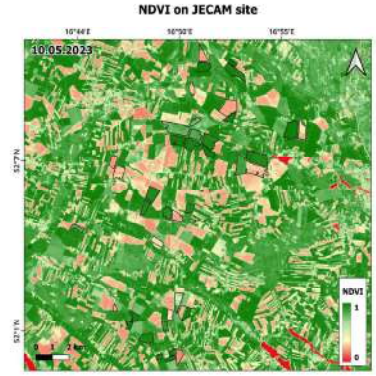

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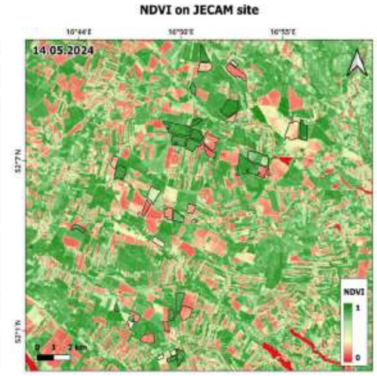

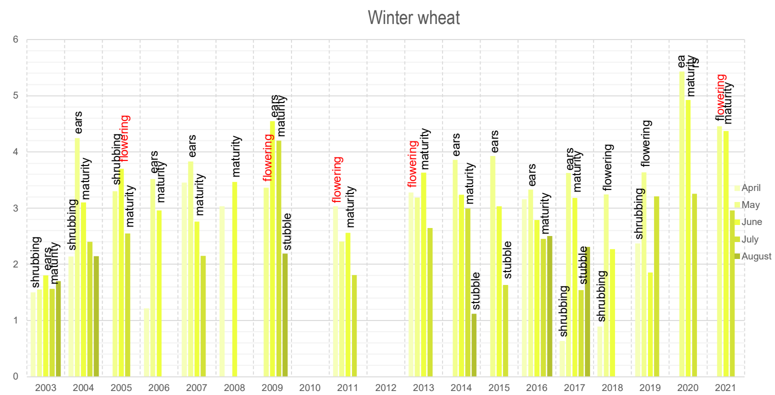

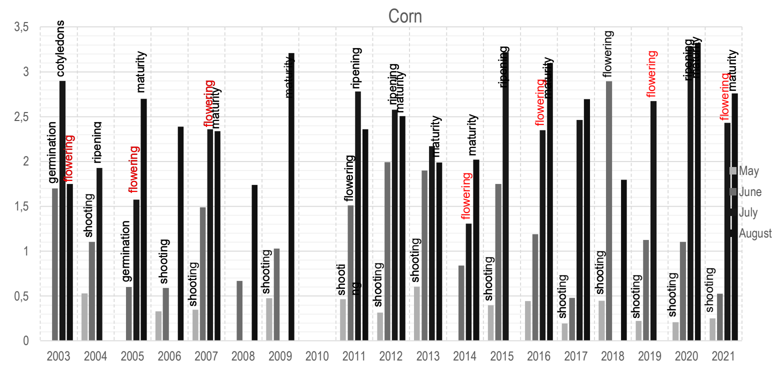

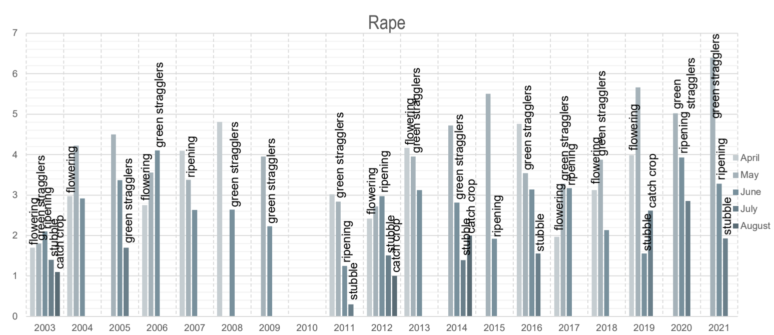

Soil moisture and temperature sond
On JECAM Area

Thank YOU for your attention

Katarzyna Dąbrowska-Zielińska
Katarzyna.dabrowska-zielinska@igik.edu.pl

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Agriculture Virtual Laboratory (AVL) project, a collaborative initiative focused on developing and utilizing virtual laboratories for agricultural research. **Louvain University**

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Image for 18/09/2024
Crop categories = 12
Training/validation split 80/20
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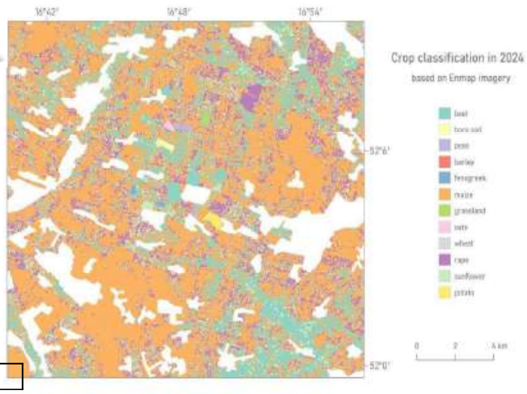

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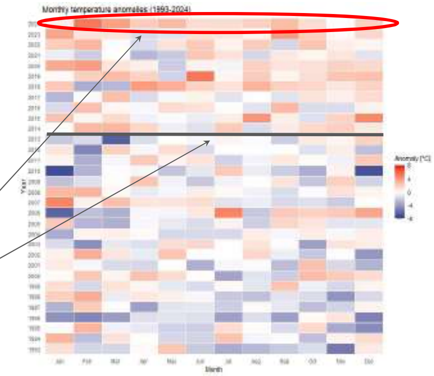
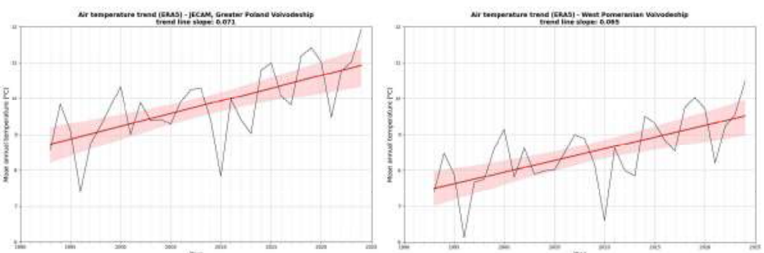


Air temperature trends in the JECAM and west Pomerania



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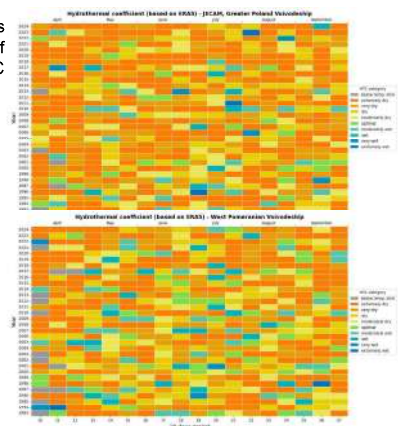

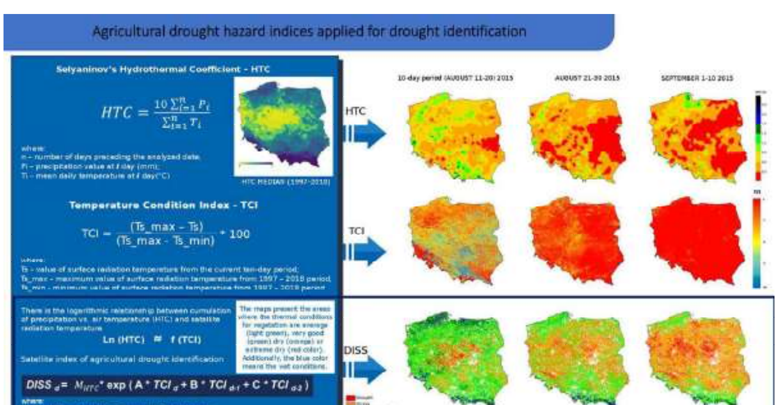

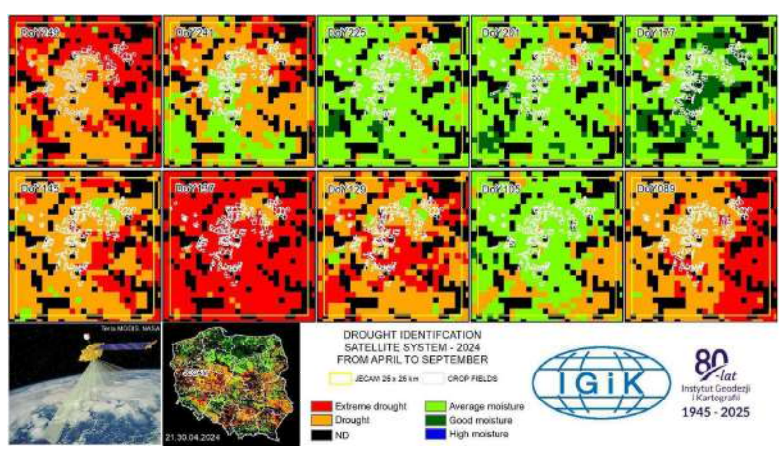

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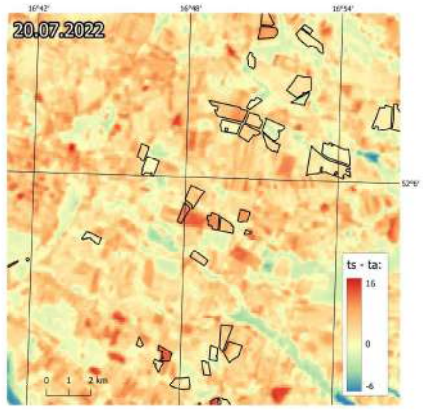

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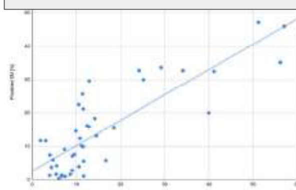
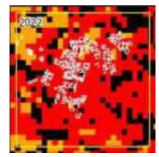
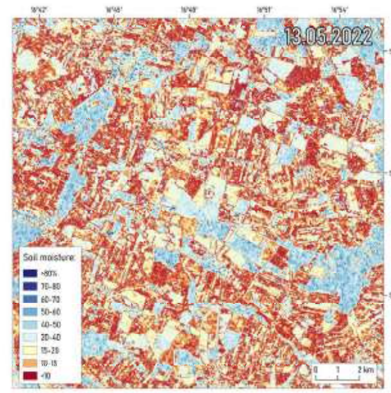


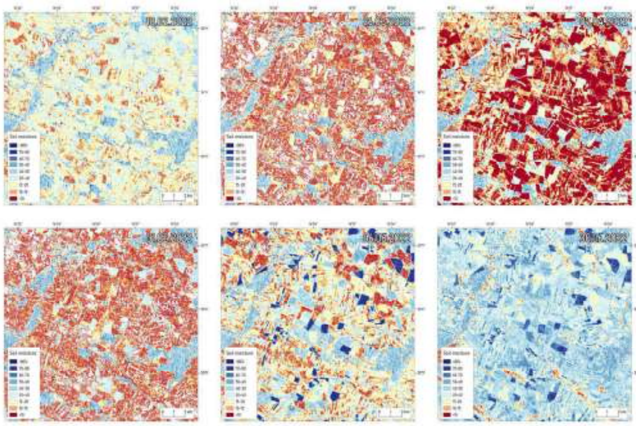


S-1 soil moisture aligns with drought DISS from Terra MODIS in May 2022

AGRICULTURAL DROUGHT
17-24 May 2022

Extreme drought · Drought · ND · Average moisture · Good moisture · High moisture





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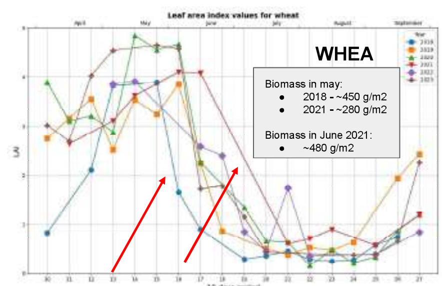
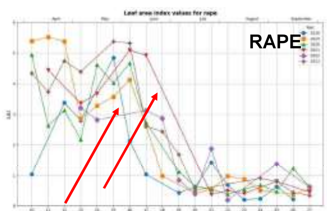
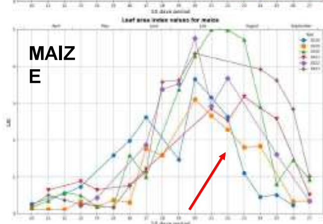
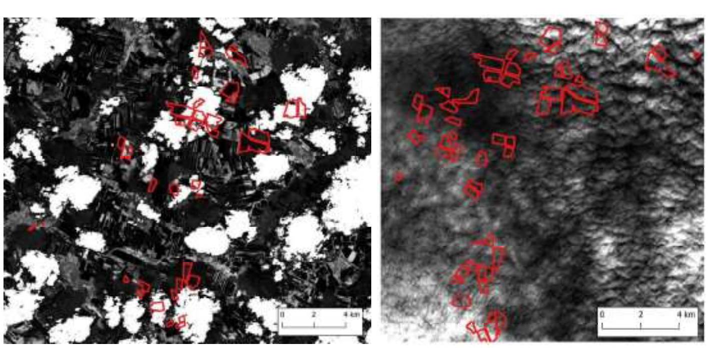
Seasonal variations in crop development, based on LAI satellite observations from 2018 to 2023, revealed shifts in phenological stages.



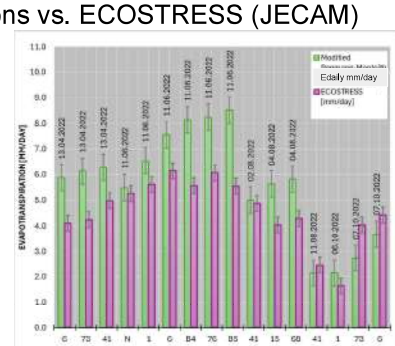




Uncertainties related to LAI from CLMS with cloud and cloud shadow effects and unidentified clouds

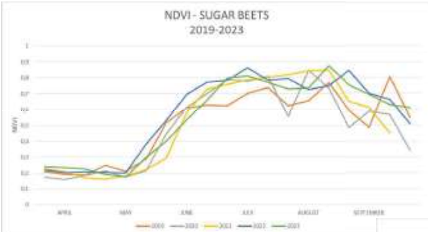


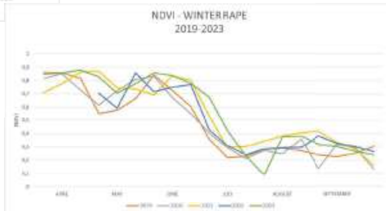
Comparative Analysis of ET Models for winter wheat: Observations vs. ECOSTRESS (JECAM)

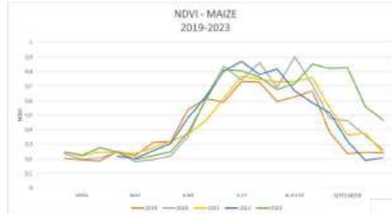


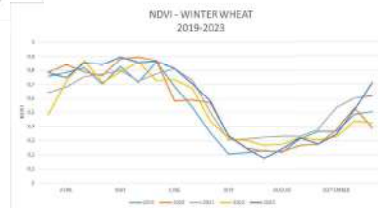
$$LE = R_n - G - H$$

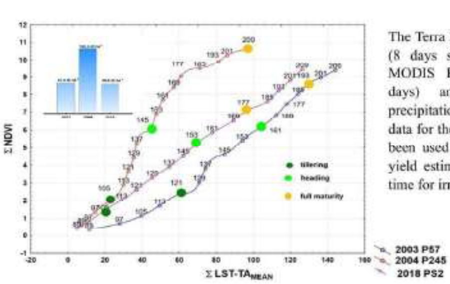
$$H = \frac{\rho c_p (T_s - T_a)}{r_a}$$





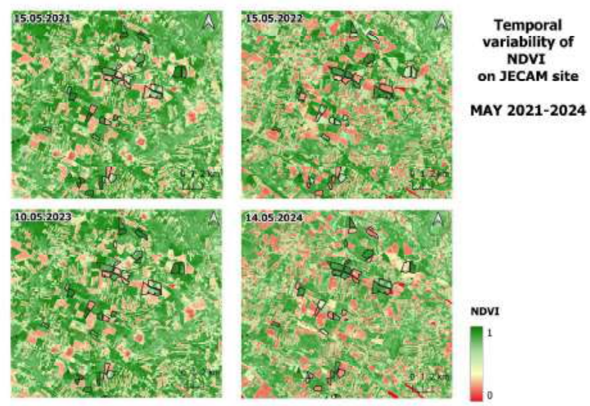






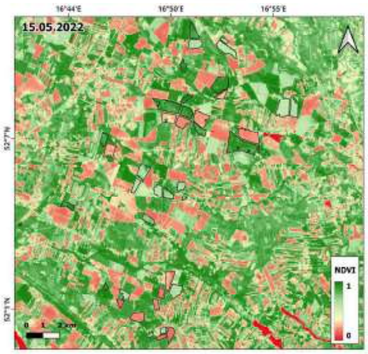
The Terra MODIS (8 days NDVI) and (8 days surface temperature TS), MODIS FAPAR (calculated for 8 days) and meteorological data as precipitation and air temperature. All data for the same periods of time have been used to set the model for crop yield estimates and for estimates the time for irrigation.

$$Yield = 158.88 + 0.58 * \sum_{start}^{matur}(LST - TA) + 43.7 * \log\left(\frac{\sum_{start}^{head} NDVI}{\sum_{start}^{head} LST - TA}\right) + 20.46 * \log\left(\frac{\sum_{head}^{matur} NDVI}{\sum_{head}^{matur} LST - TA}\right)$$



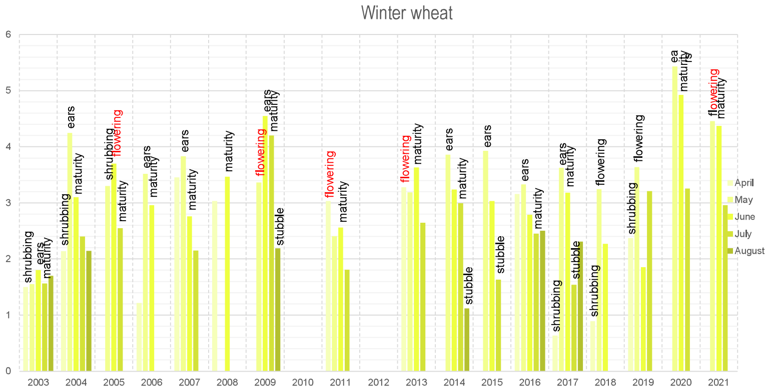
NDVI on JECAM site

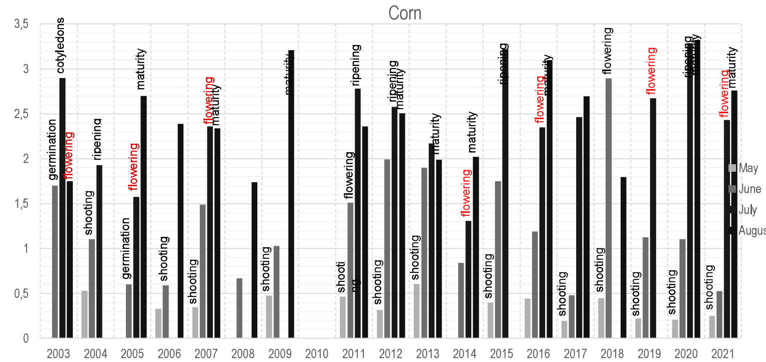
NDVI on JECAM site

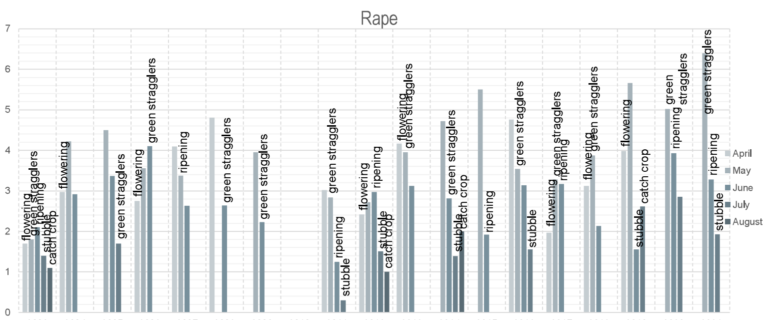


NDVI on JECAM site

NDVI on JECAM site







Soil moisture and temperature sond
On JECAM Area

Thank YOU for your attention

Katarzyna Dąbrowska-Zielińska
Katarzyna.dabrowska-zielinska@igik.edu.pl

www.igik.edu.pl