EO4CEREALSTRESS| Use of Advanced Earth Observation-Based Techniques to Monitor Crop Stress

Monday, 23 June 2025 | A.02.03 EO for Agriculture Under Pressure - PART 2

CONSORTIUM
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BOKU, Vienna, Austria
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1. Project Overview

Agriculture is subject to **multiple stressors** (heat, drought, salinity, lodging etc.,). Their combined effects can be more severe and complex, difficult to address.

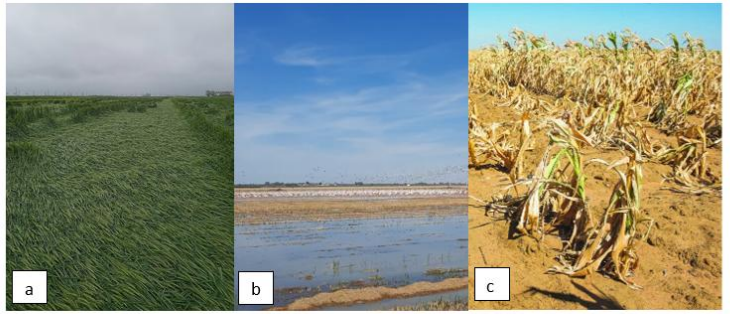
This project follows **a data-centric approach,** synergistically combines multi-source EO data and machine learning techniques to monitor multiple stressors and aims to provide **a scientific roadmap** for the future development of crop stress related EO products.

Target stressors: Heat, Salinity, Toxicity, Water, Lodging Nutrient Stress, Drought

Project Duration: August 2023 – August 2025

Experimental Products:

- Drought Prediction maps (2018 – 2024)
- Lodging Severity and Soil Salinity maps based on field campaigns, Sentinel 2, EnMap, and PRISMA archives (2023 – 2024)
- New Framework for Integrating Hyperspectral Remote Sensing with Machine Learning, Active Learning, and Sentinel-2-Based Deep Learning to monitor multiple stressors

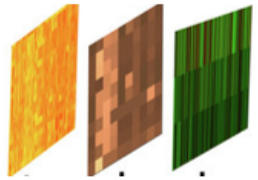


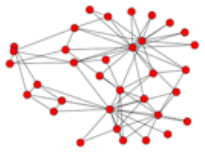
Views of lodged wheat crop in Bonifiche Farm, Italy (a), salinity-affected rice farms in Andalusia (b), and drought-affected maize in the Marchfeld region, Austria (c).

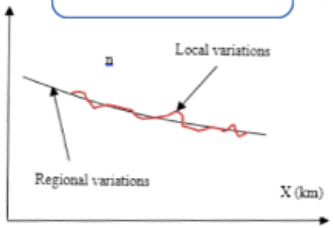
EO4CerealStress Team collecting data in the field campaigns (2023 – 2024) using in-situ instruments

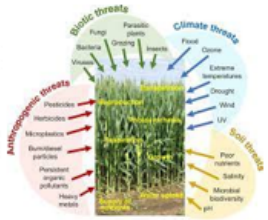
Scientific challenges in using EO & In situ data

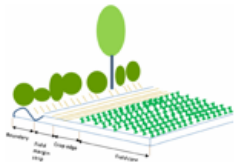
- Integrating diverse datasets
- Disentangling environmental stress sources and types
- Adverse weather conditions, limited data collection opportunities, limited revisit time
- Regional and local variations
- Species-specific methods, a single scale of monitoring
- Applicability and scalability across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







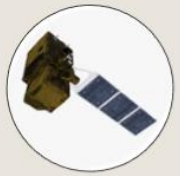




2. Project Framework

EO & in situ data collection

Satellite
(Sentinel, EnMap, PRISMA, 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

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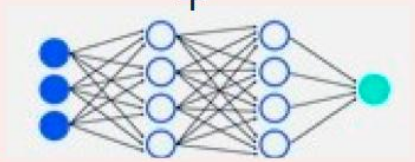

Machine Learning

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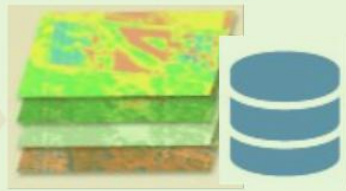
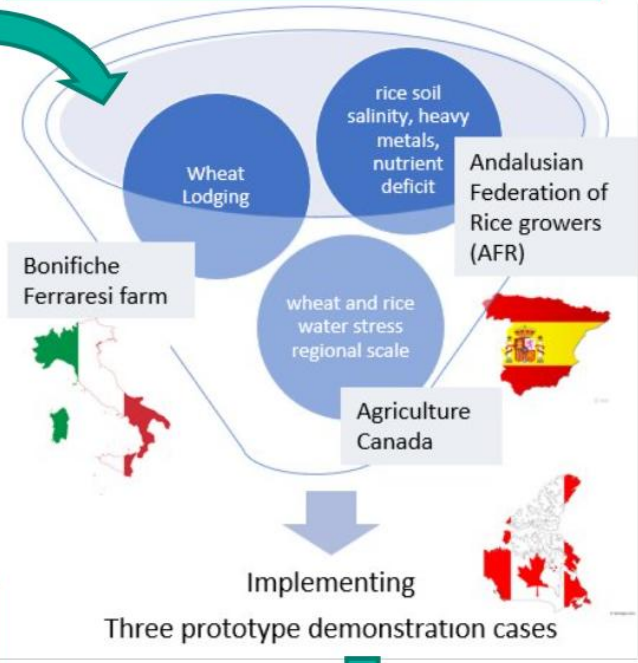
Radiative Transfer Modelling



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

Spectral index-based analysis and empirical regression-based approaches

Simulating plant traits using RTMs- PROSPECT

Calibrations with field samples, multispectral, and hyperspectral UAV, and satellite imagery + analysing

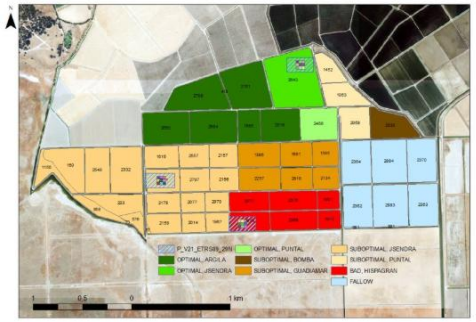
Laboratory analysis on soil, leaves, and grain samples

Machine learning for scenarios-based analysis and impact classification by stress levels

3. Three Pilot Cases

Pilot site I: Andalusia Rice Farm, Spain-(UoSev)

Key Stressors: Salinity, nutrient deficit in soils, and heavy metal toxicity



Study area: 1,260 km²

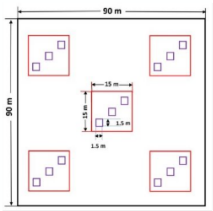
Data Collected/Used: ***EO data*** : Sentinel-2, PRISMA, and EnMap

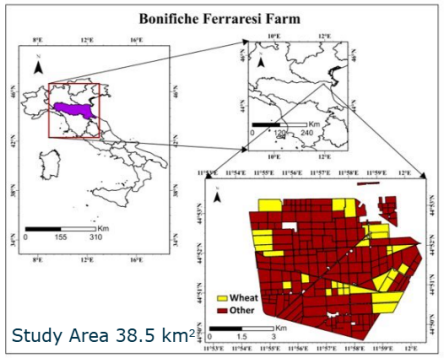
Met data: ECMWF ERA5 data, REDIAM (Andalusian Environmental Information Network), SIAR (Agroclimatic Information System for Irrigation (SiAR) of Spain

Field Data : EC-salinity, organic C, texture, 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

Pilot site II: Bonifiche Farm, Italy-(ITC)

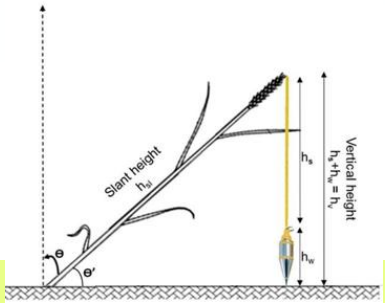
Key Stressor: Lodging in Wheat





Data collected: **EO data**: EnMap, Sentinel-2 **Field data** biochemical/biophysical variables (Slant height, vertical lodged height, SPAD, Lodged area, Canopy height, Plant density, LAI, Cover percentage, Shoot numbers, Point of line failure, Fresh biomass, Tillers), ASD spectral measurements

Derived lodging variables: Crop Angle Inclination, Lodged Area, Normalised Lodging Score Index



$$LS = \frac{LA_{\%}}{100} * \frac{CAI_{\theta}}{90°}$$

Pilot site III: Marchfeld Region, Lower Austria –(BOKU)

Key Stressors: Water Stress (Maize)

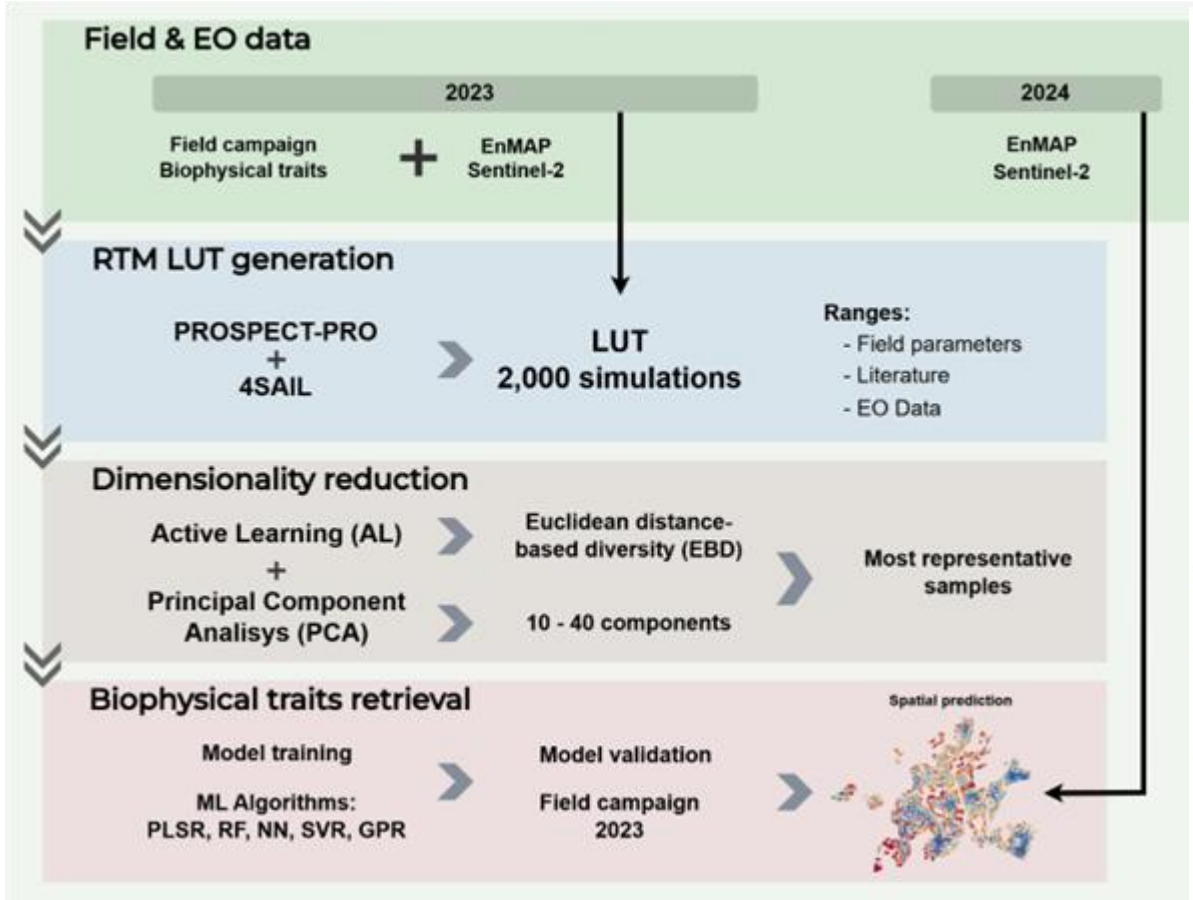
Data Collected:

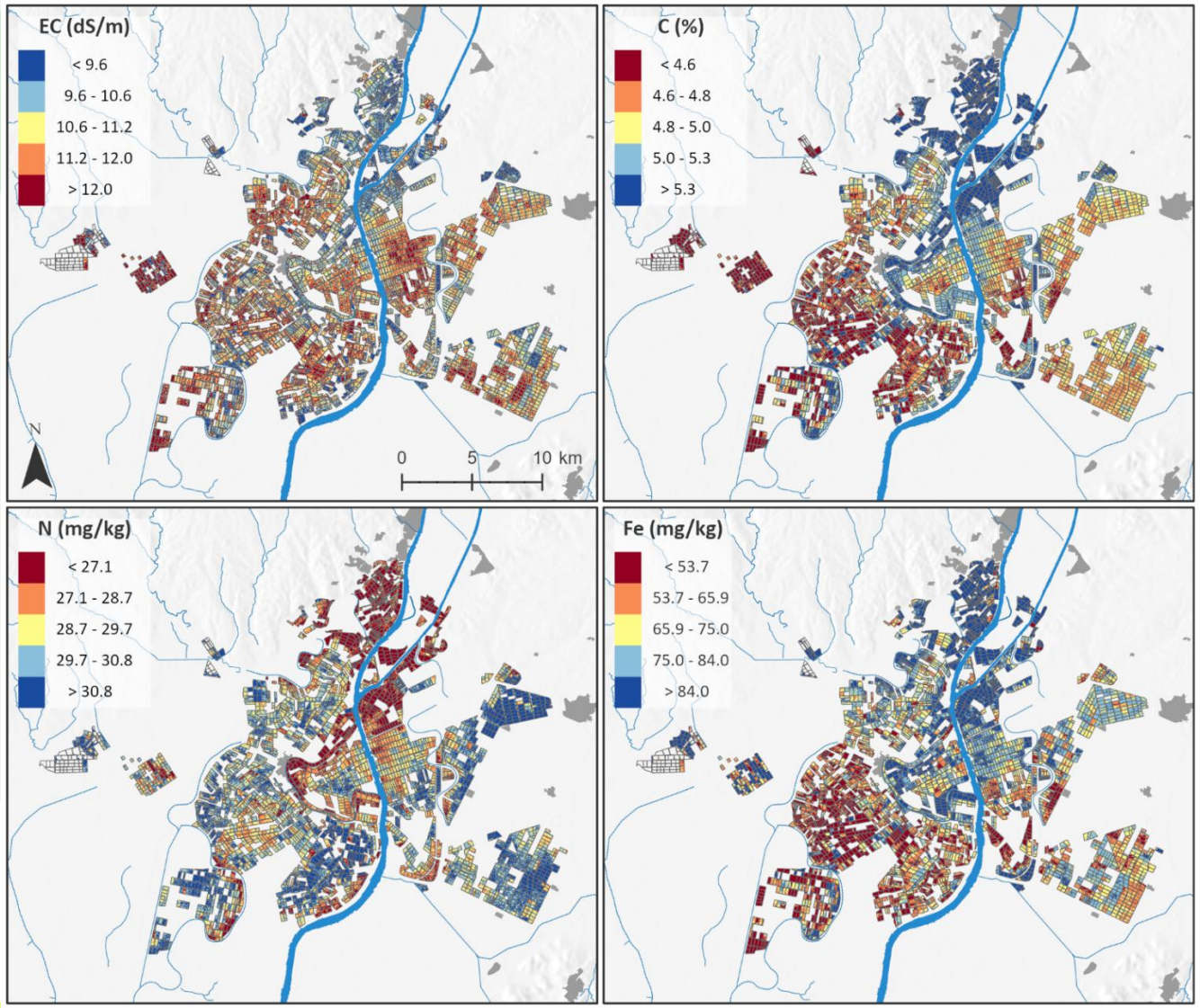
EO data : Sentinel-2 **Met data**: ECMWF ERA5 data , INCA, SPARTACUS v2.1

Field Data yield, Soil characteristics (field capacity, organic carbon content etc.) Expert opinions

Study area: 1,120 km²

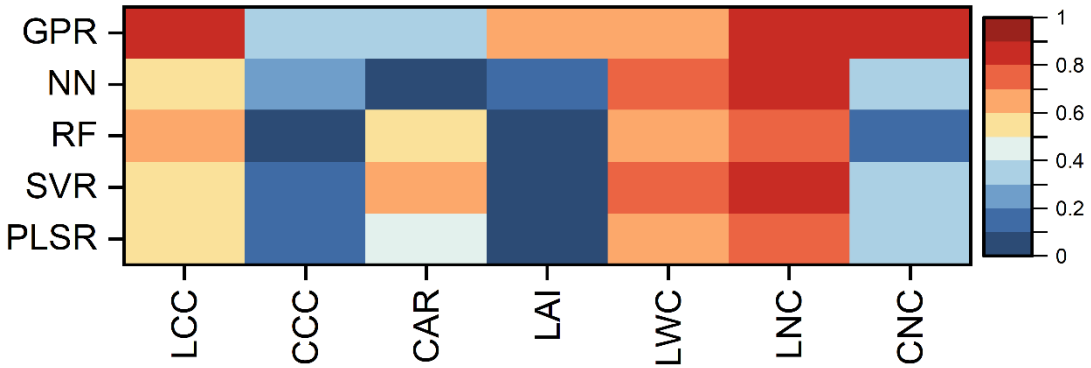
4. Multiple stressor detection



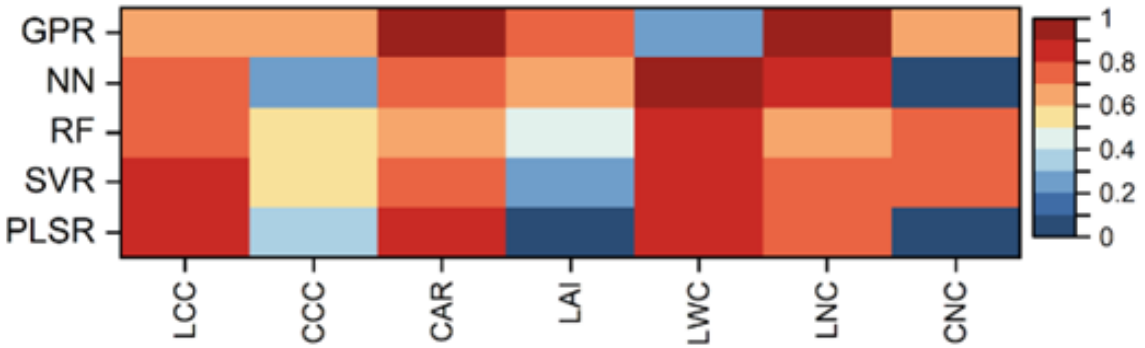


5. Biophysical Traits Modelling

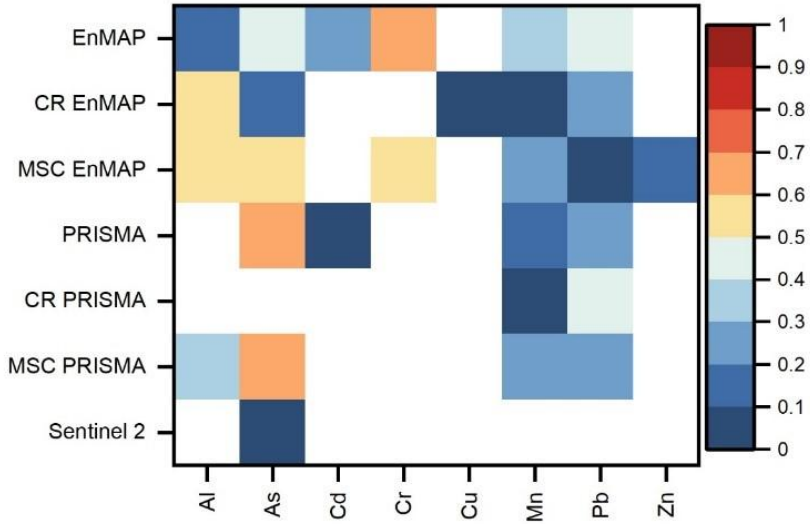
Heatmap of biophysical traits modelling using Sentinel-2



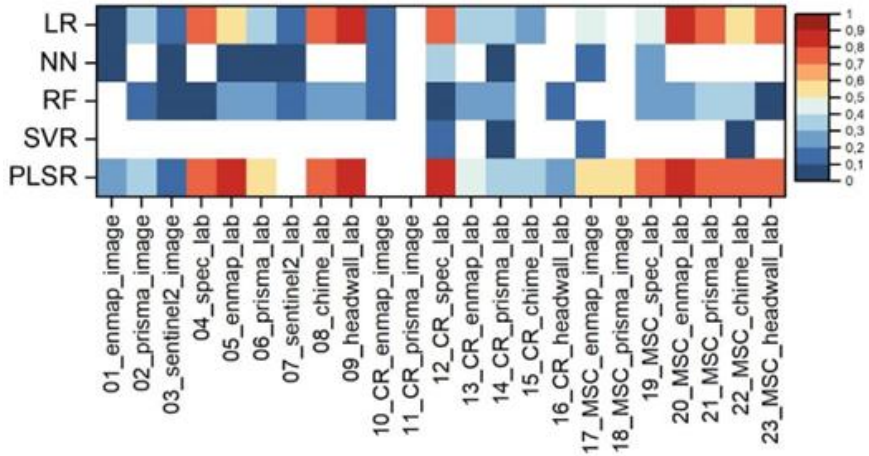
Heatmap of biophysical traits modelling using EnMap



Heatmap of heavy metals in soils using PLSR



Heatmap of EC Modelling in soils using ML



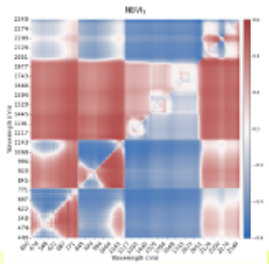
6. Wheat Lodging Estimation framework

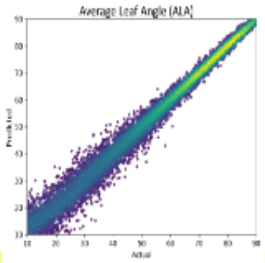
Data Acquisition
- Field Spectral Measurement
- EnMAP
- Sentinel-2

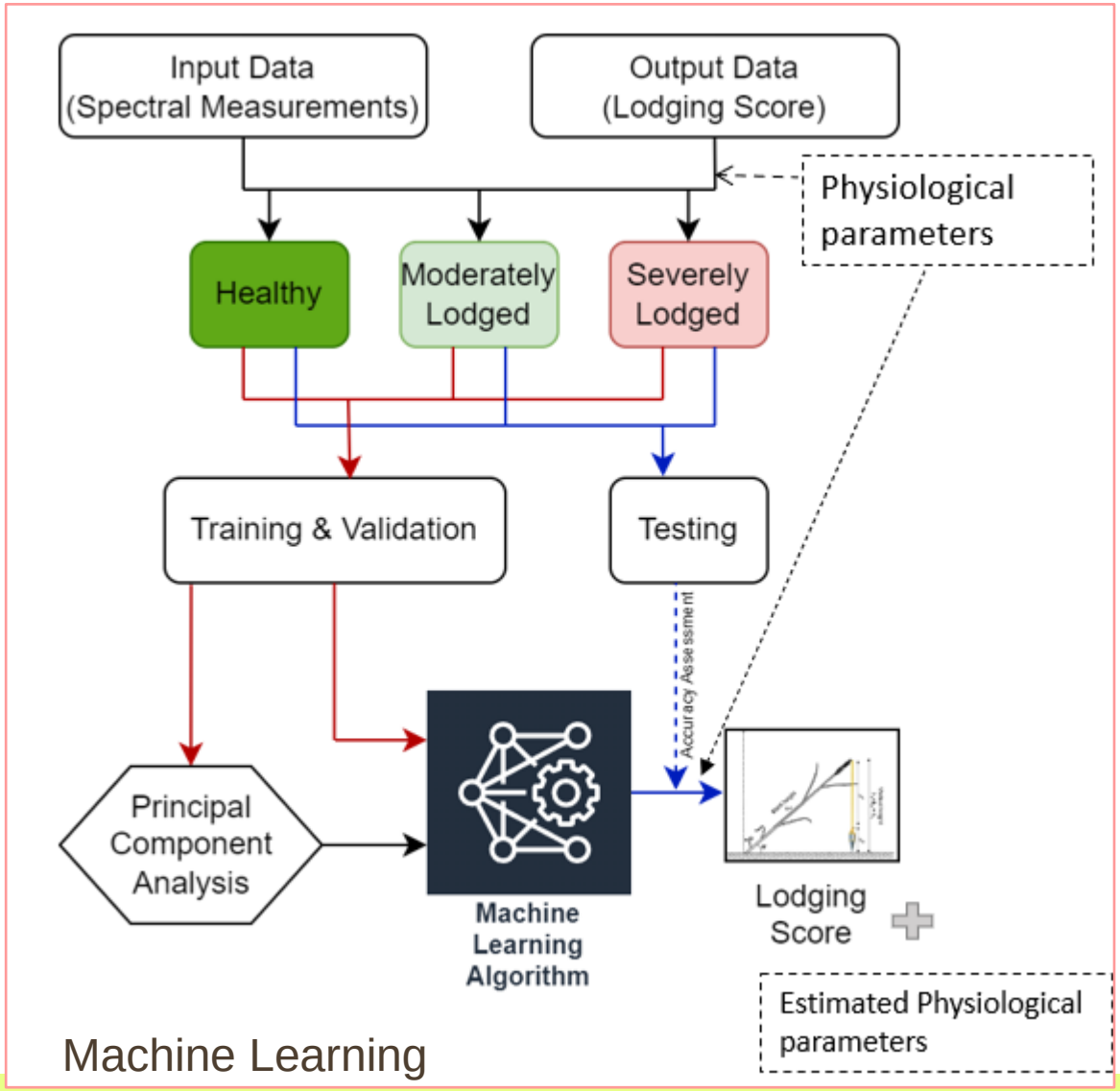
Preprocessing
- Calibration - Gain and Offset
- Noisy Band Removal
- Irrelevant Band Removal
- Atmospheric Water Vapor Absorption Band Removal
- Spatial Resampling
- Outlier Detection
- Mean Spectra
- Smoothing

Alternative Models
- NBVIs: $NBVI_1$, $NBVI_2$, $NBVI_3$, $NBVI_4$, $NBVI_5$, $NBVI_6$
- Machine Learning: PCA-MLR, PLSR, PCA-SVR, PCA-GPR, RFR, GBR, ANN
- Inversion of RTM: LUT based Inversion of PROSAIL

Lodging Estimation

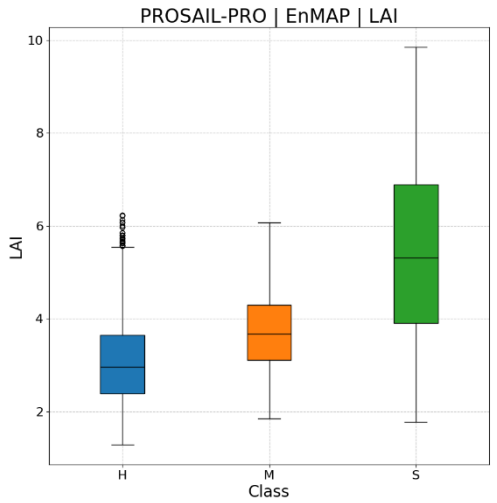


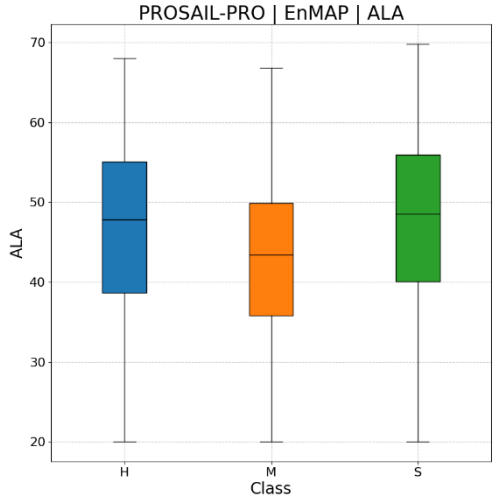


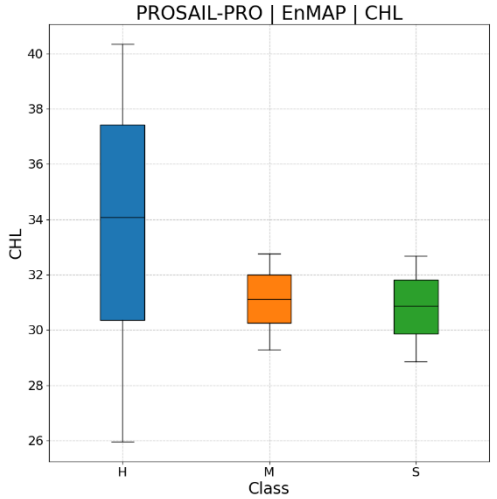


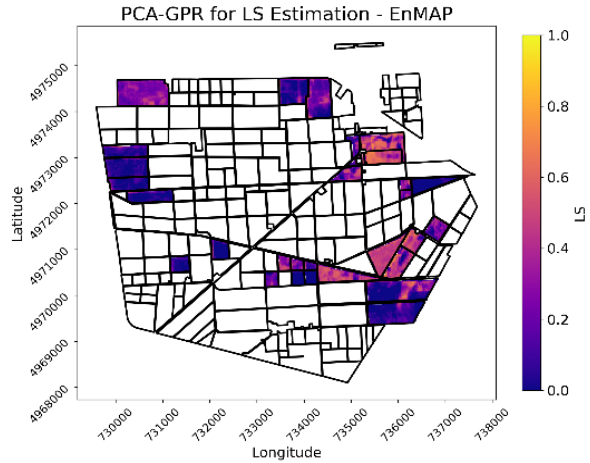
Machine Learning

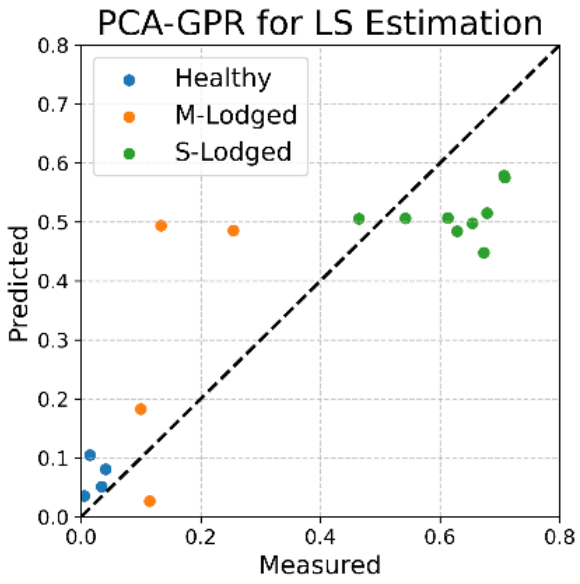
7. Biophysical traits and Lodging

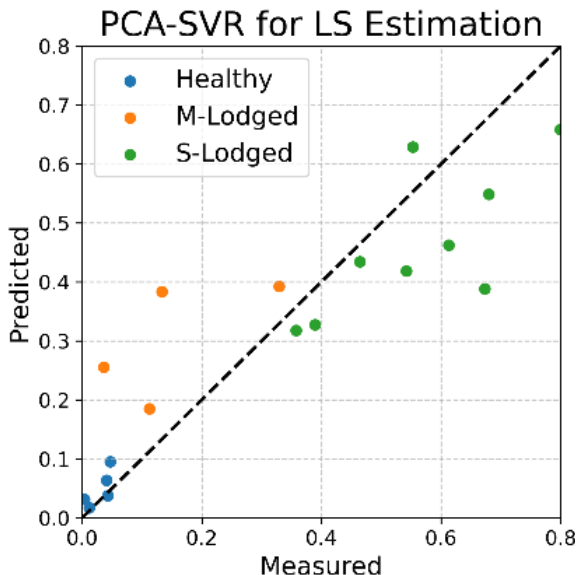


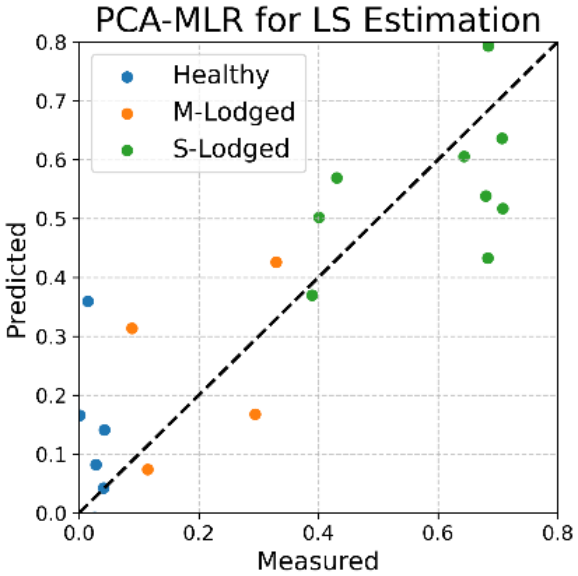


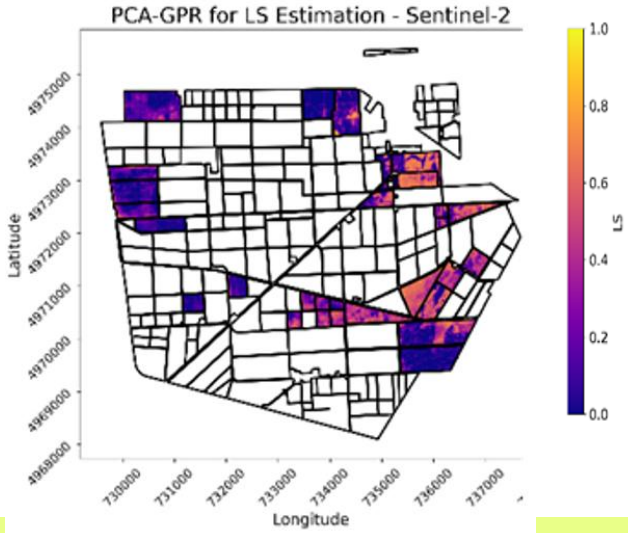






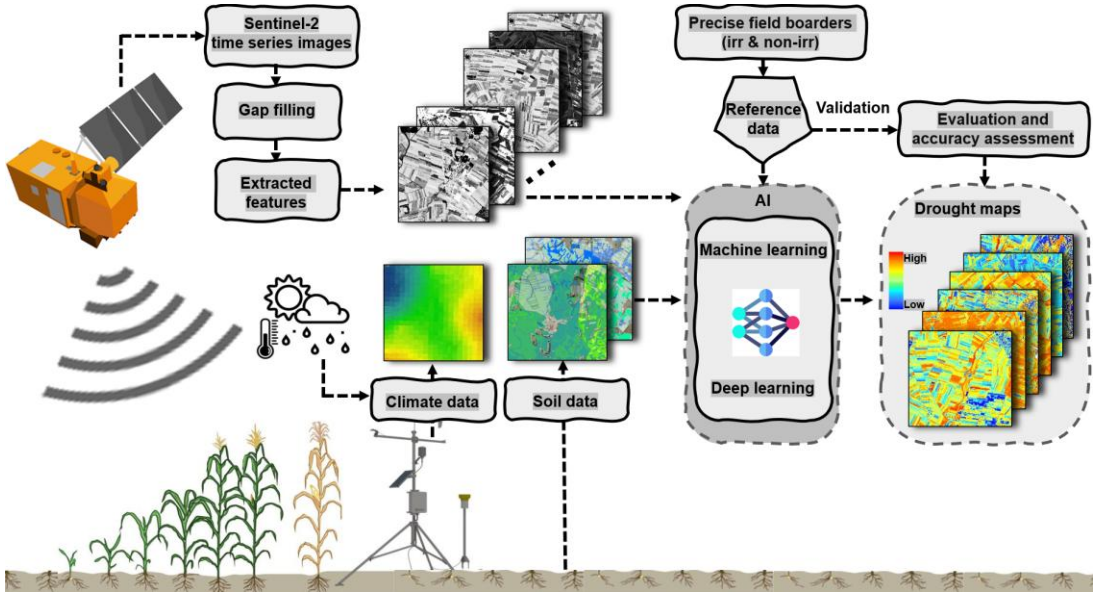






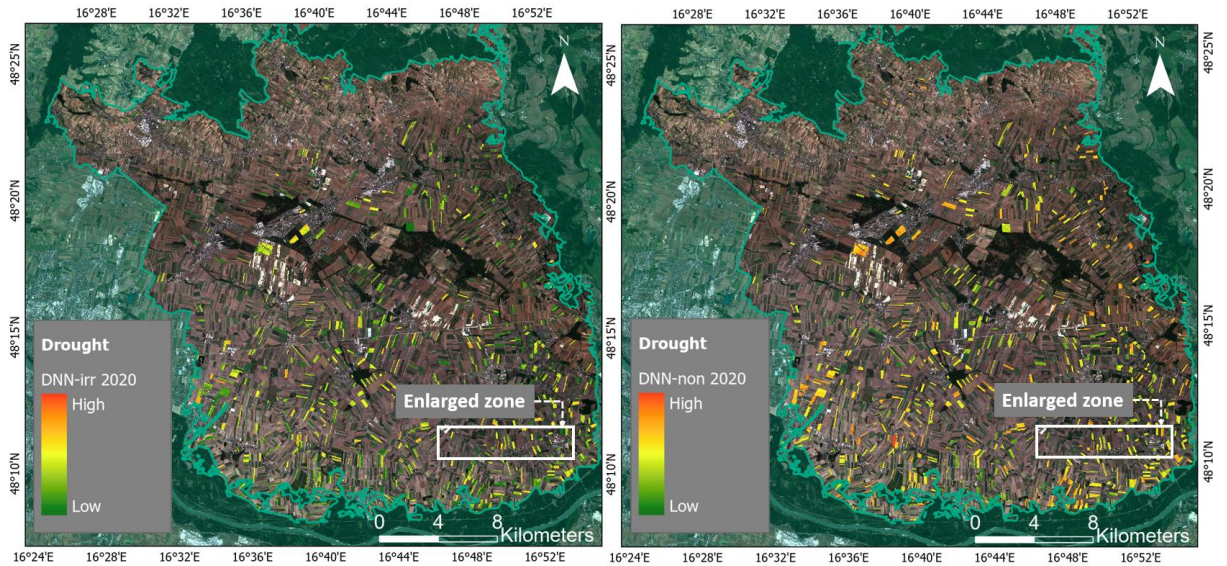
8. Drought Stress Assessment

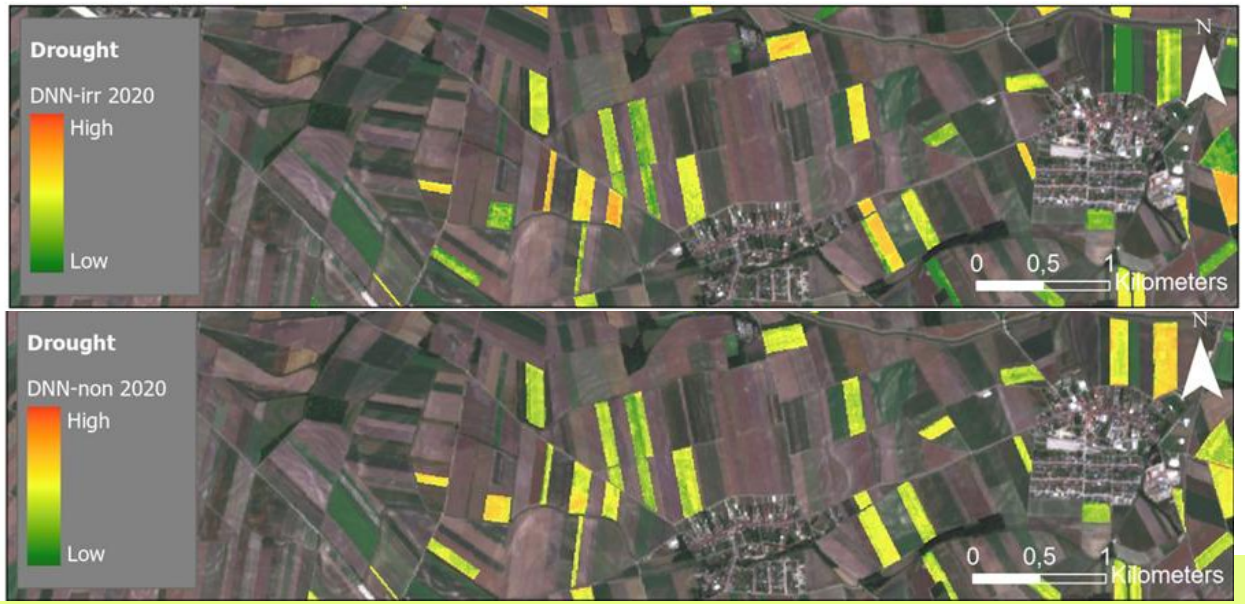
framework of drought stress assessment



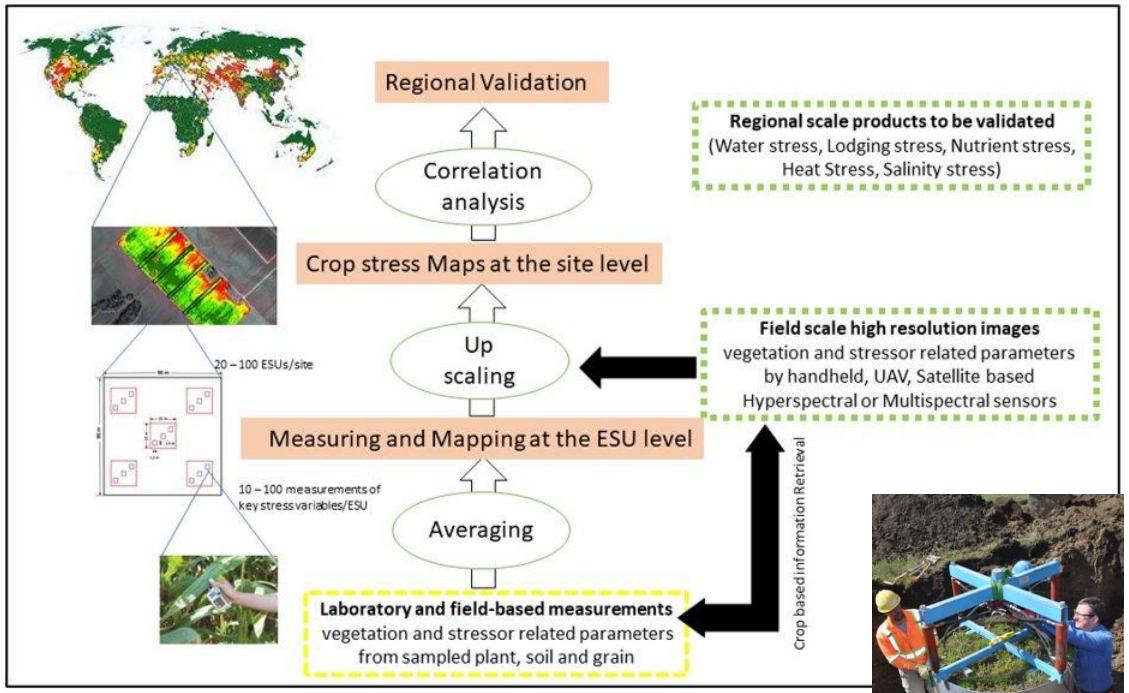
ML vs. DL (Accuracy matrix)

Year	1D-CNN -irr	1D-CNN -non	DNN-irr	DNN-non	RF-irr	RF-non
2018	74.20%	75.58%	76.88%	79.14%	71.93%	73.41%
2019	78.35%	71.15%	77.50%	80.66%	75.27%	72.00%
2020	76.16%	74.94%	77.90%	75.86%	74.49%	75.10%
2021	75.93%	81.27%	77.61%	80.91%	76.86%	78.07%
2022	78.52%	81.35%	73.95%	75.47%	77.00%	72.57%
2023	81.49%	76.94%	78.63%	**83.24%**	81.84%	79.55%
Average	77.4%	76.87%	77.08%	**79.21%**	76.23%	75.12%





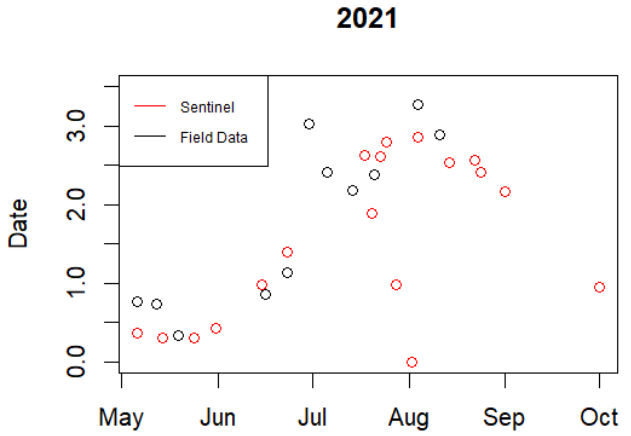
9. Project Validation



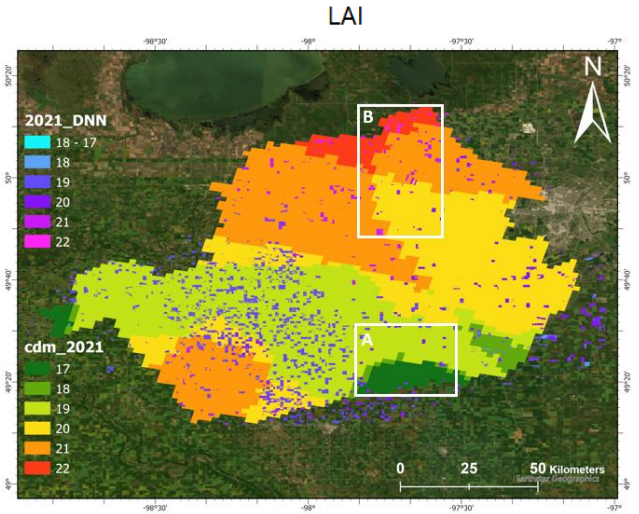
Execution over:

Water Stress Monitoring: Replicating Experiment over cereal crops at Elora Research Site, Ontario

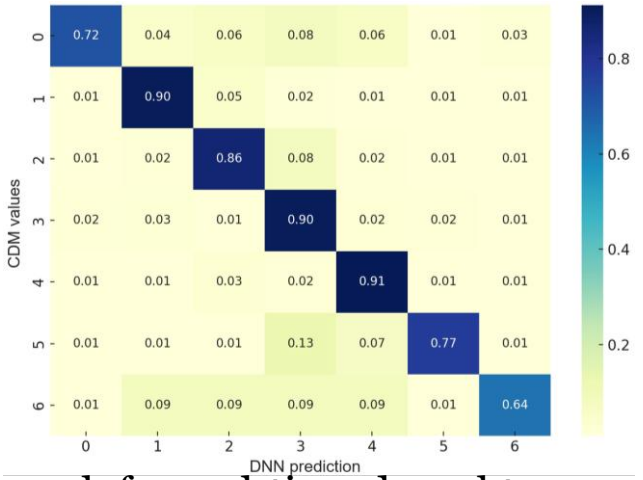
Manitoba District, Canada: Canadian Drought System vs. EO4CerealStress Developed Approach



Used hyperspectral drone data from research site in Elora Canada for 2021 growing season for plots from corn to AAFC generated indicators of crop stress (meteorological, MODIS NDVI, MODIS Evaporative Stress Index) and Sentinel-2 LAI



EO4Cerealstress vs. CDM, Canada



Sentinel-2 with DNN scalable approach for real-time drought monitoring showed promising results for Manitoba district Canada.

10. Scientific Road map

A **Five-Year Research Plan** to Bridge the Gap from Research to Operations: Advancing Agricultural and Food Systems within the EC-ESA Earth System Science Initiative

Challenges: longer revisit times, in-situ data gaps, computational complexity and scalability of ML models, balancing spectral with temporal, limited spectral data

Vision: Establish a worldwide network of 'super sites' to measure key crop variables (biophysical traits, stress indicators, yield) and more controlled experiments.

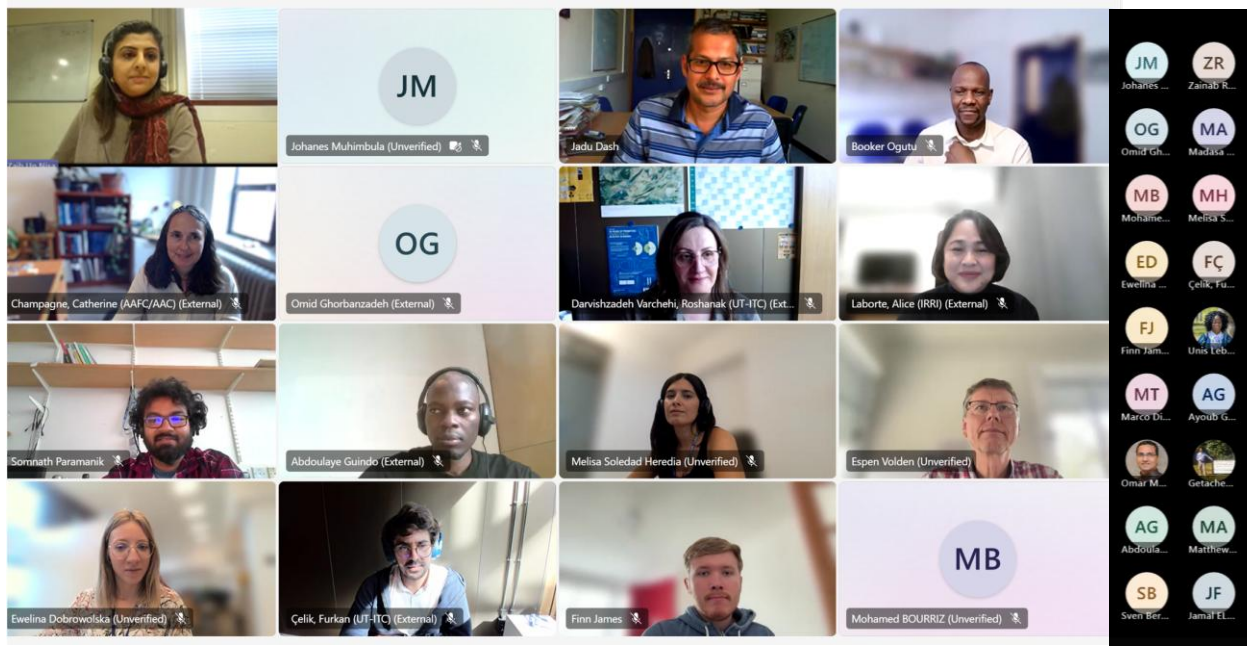
Build on existing efforts: GEOGLAM, JECAM, CEOS for standardized field data protocols focused on satellite validation.

Priority Tasks for Advancing Stress Monitoring

- Fusion of multi-sensor data (optical, SAR, thermal) + ML-based data fusion techniques
- Priority research areas, i.e., Hybrid approaches, Uncertainty quantification, Detection of co-occurring stressors (example Salinity vs. Drought overlapping signatures)
- Scaling efforts via data libraries and UAV integration for long-term sustainability
- For operationalizations, adaptive transferable models with automated feature selection, Cloud-based processing for real-time updates

11. Outreach Activities

University of Southampton hosted a webinar on '*Synergizing EO and In-Situ Data for Crop Stress Detection and Monitoring*' on 20 May 2025, in collaboration with ESA.



University of Southampton hosted a webinar on '*Advanced Crop Assessment Using Hyperspectral Data*' for JECAM, in collaboration with Agriculture and Agri-Food Canada (AAFC) on 17 January 2025.

University of Southampton presented at COST Action PANGOES Working Group 3 meeting on 'Modelling vegetation traits and fluxes from optical remote-sensing data in croplands and forests'.

University of Southampton and ITC presented in EO for Agriculture Under Pressure 2024 Workshop

University of Seville presented in EGU General Assembly 2024

12. Conclusion

1. Hyperspectral sensor data provides a unique ability to monitor **soil and crop parameters** accurate with ground data.
2. Multispectral sensors are even **less effective in detecting trace heavy metals** due to their broader spectral ranges and fewer bands.
3. EnMap and S 2 based maps provide highly detailed spatial representations of crop lodging severity with **upscaling potential**
4. The **challenge of boundary delineation** addressed by Self-Supervised Learning (SSL) semantic segmentation on satellite imagery to update drought maps annually
5. Deep learning models, particularly **DNN and 1D CNN, are highly effective** at extracting complex spatial and temporal patterns from large datasets
6. Stress framework application over Manitoba – transferrable achieving **accuracy nearly 90%**
7. Few Inferences from Scientific Road map:

- Improving early detection with **thermal/SIF data**, developing fusion techniques, and standardising field protocols are critical enablers for future stress monitoring services.
- Scaling efforts or enabling frameworks (e.g., data libraries, **UAV upscaling**) are important for long-term sustainability
- Hybrid RTM-ML models, **uncertainty quantification**, and **co-occurring stressor detection** should be priority areas of research

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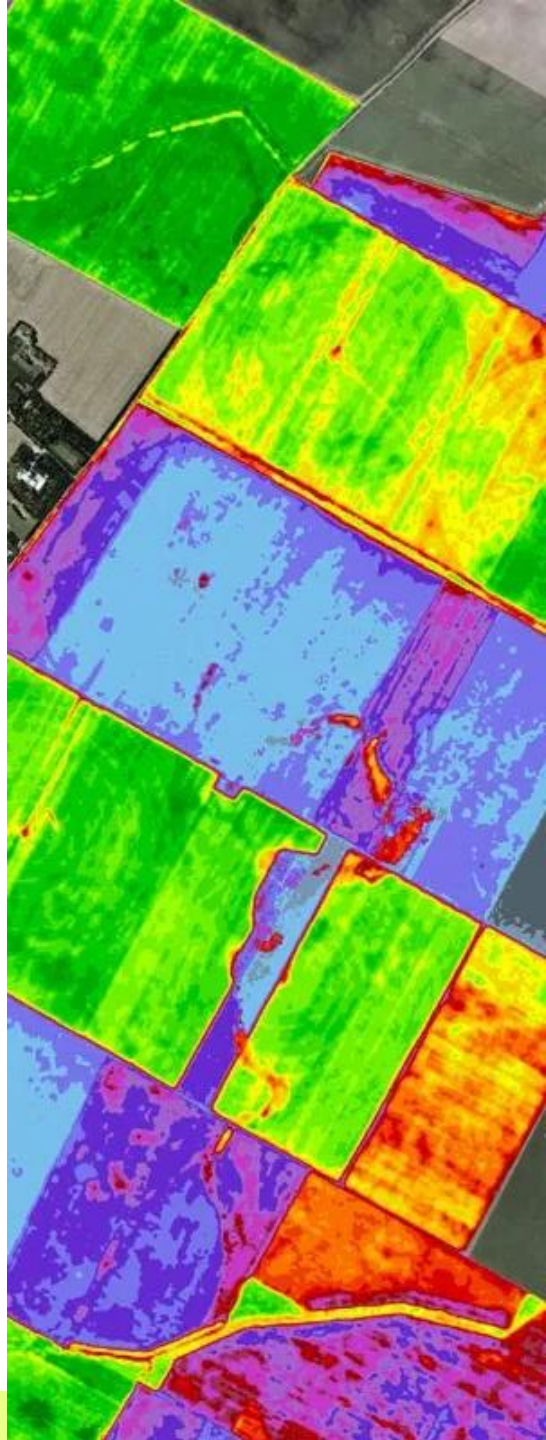
Thank you..