



Earth Observation for Monitoring Cereal Crop Responses to Multiple Stressors (EO4Cerealstress)

Project Summary (D9.1)

For the attention of:	Dr Espen Volden – ESA Technical Officer – ESA Contract Officer
Author	Zaib un nisa – Project Manager
Reviewed by :	Team members: Roshanak Darvishzadeh, Victor Rodriguez-Galiano, Booker Ogutu, Andy Nelson, Omid Ghorbanzadeh, Catherine Champagne, Aaron Berg,
Approved by :	Jadu Dash

Task lead

University of Southampton, UK

Task Partners:

ITC, The Netherlands

BOKU, Austria

UoSev, Spain

UoG, Canada



DOCUMENT RELEASE SHEET

	Name	Signature	Date
Task lead	Zaib un nisa (UoS)		
Contributing Authors	Victor Rodriguez-Galiano (UoSev), Roshanak Darvishzadeh (UT-ITC), Andy Nelson (UT-ITC), Catherine Champagne (AAFC), Omid Ghorbanzadeh (BOKU), Aaron Berg (UoG), Booker Ogutu (UoS)		
Approval (internal)	Jadu DASH (UoS)		
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1. Project overview

The EO4CerealStress project (2023–2025), funded by the European Space Agency (ESA), delivers a multi-sensor Earth Observation (EO) framework to detect, quantify, and monitor multiple stressors affecting cereal crops, primarily drought, salinity, nutrient deficiency, heavy metals, and lodging. They are among the most significant constraints to cereal production worldwide, are expected to intensify under climate change, have major impacts on crop yield and quality, and can be effectively monitored using advanced Earth Observation and machine-learning approaches. Collectively, they provide a representative framework for investigating crop responses to multiple interacting stressors. The framework is based on:

- Advanced EO datasets (Sentinel-2, EnMAP, PRISMA),
- UAV hyperspectral imagery,
- Field & laboratory measurements,
- Machine learning (ML), deep learning (DL),
- Physical Radiative Transfer Models (RTMs such as PROSPECT, PROSAIL),
- User engagement via international partners.

The project was led by the University of Southampton (UK), with key partners including the University of Seville (Spain), BOKU (Austria), the University of Guelph (Canada), and ITC-University of Twente (Netherlands) and contributions from early adopters Agri-Food and Agriculture (Canada), Andalusian Rice Federation (Spain) and Bonifiche Ferraresi Farm (Italy). The research team has established operational EO stress-monitoring workflows, validated across multiple cereal cropping systems, and provided a five-year scientific roadmap (2026 – 2030) for the long-term development of operational EO products, informed by lessons learnt from project activities and global requirements. The project was executed over three years (Aug 2023 – Mar 2026) and followed the activities shown in **Figure 1**.

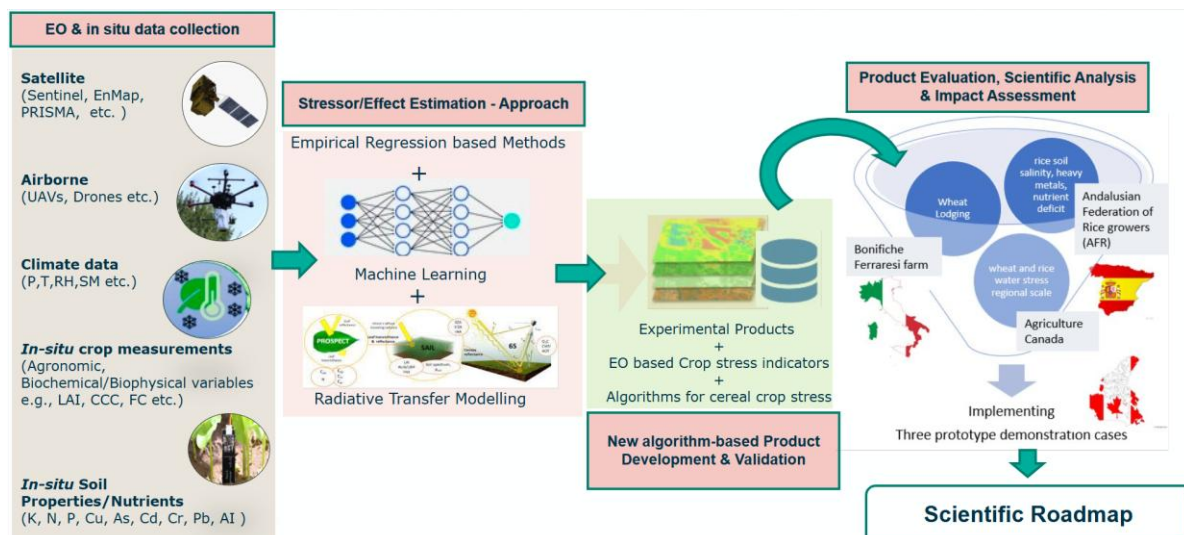


Figure 1. Framework for executing project tasks and activities.

2. Project Consolidation

Cereal crops globally face escalating abiotic stressors, including drought, salinity, nutrient deficiencies, heavy metals, and structural stressors such as lodging. These combined pressures threaten yields, farmer livelihoods, and market stability. Their overlapping physiological responses to different stressors complicate distinguishing stress types using EO data alone. The project utilised an integrated approach to obtain timely, high-resolution EO data (Sentinel 2, PRISMA, EnMap) and to pair them with machine learning, deep learning, and radiative transfer modelling to improve stress detection, early warning, and crop management.

The project aimed to: develop and validate advanced EO-based methods to detect, map, and understand multiple types of abiotic stress in cereal crops, using multi-sensor satellite data, machine learning, and field measurements, while building a scientific roadmap with a five-year research plan (2026 – 2030) for future operational crop-stress monitoring.

Key scientific bottlenecks addressed in the project were:

- Sensor heterogeneity, including mismatches in spatial, spectral, and temporal resolution
- Limited availability of hyperspectral satellite data
- Challenges in scaling observations from leaf to canopy to landscape levels
- Ill-posed radiative transfer model (RTM) inversion problems
- Cloud contamination and inconsistent acquisition conditions
- Lack of standardised calibration and validation protocols
- Limited availability of multi-stressor field experiments
- Persistent difficulty in detecting heavy metal stress using EO data

Key crop variables linked to plant physiology & stress response include *structural variables* such as LAI, AGB, canopy cover, and inclination angle. *Biochemical*: chlorophyll (LCC/CCC), carotenoids (CAR), nitrogen (LNC/CNC), proteins, carbon-based constituents (CBC), *Hydrological variables* such as LWC, EWT, ET, *Environmental variables* such as soil salinity (EC), soil N/C, heavy metals (Fe, Zn, Cr, As, etc.), case by case basis. These variables feed ML, DL, and RTM inversion models that support the validation, detection, and prediction of crop-stress algorithms.

3. Key Advances in Understanding Cereal Crop Stress through Pilot Sites

The project has developed EO products from three crop stress Pilots by focusing on the following stressors (**Figure 2**):

- a. **Pilot One:** Soil salinity, nutrient deficit and heavy metals.
- b. **Pilot Two:** Crop Lodging Stress.
- c. **Pilot Three:** Drought Stress in Maize

Each of these pilots developed an integrated crop stress and severity detection system that combines the scientific strengths of high-spectral- and high-spatial-resolution

multi-sensor EO data, on the one hand, and state-of-the-art machine learning and physical models, on the other.

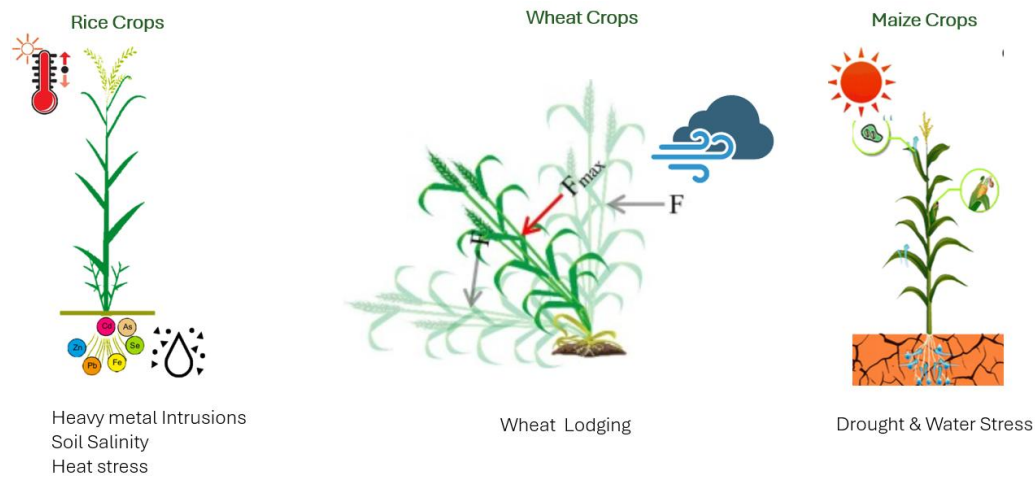
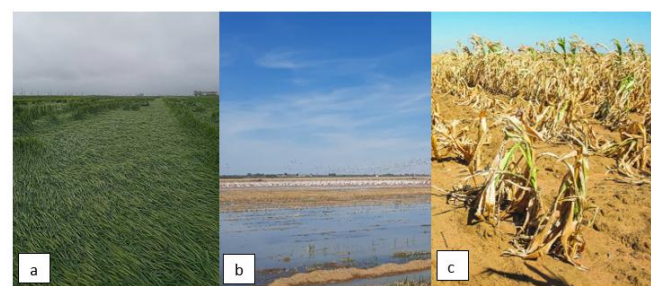


Figure 2. Abiotic Stressors investigated in the project at the pilot sites and demonstration studies.

Figure 3 shows field data collection campaigns conducted in 2023-2024 across three pilot sites.

Pilot One:

The pilot site in Andalusia, Spain, analysed the relationship between multiple stressors and the temporal evolution of rice crop conditions, improved understanding of rice responses to stressors, and evaluated the potential of Sentinel-2, PRISMA, and EnMAP satellite missions for monitoring multiple stress types in rice. It identified the most relevant biophysical and biochemical traits that reflect the impacts of these stressors on rice crops.



Views of lodged wheat crop in Bonifich 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

Figure 3 captures the field activities conducted for the stressor-affected crops.

The study on rice stressors showed that ML approaches combined with hyperspectral data such as EnMap were able to capture fine spectral variations linked to soil and vegetation properties. Soil stressors such as salinity, carbon (C), nitrogen (N), and iron (Fe) are strongly correlated with spectral signatures, enabling reliable modelling when datasets are properly calibrated. Output maps are shown in **Figure 4**. Hyperspectral imagery such as EnMAP and PRISMA, with their detailed spectral resolution, lead to improved derivation of crop biophysical traits and they were accurate with hyperspectral data such as Leaf Chlorophyll Content (LCC) $R^2 = 0.867$, Carotenoid Content (CAR) $R^2 = 0.934$, Leaf Nitrogen Content (LNC) $R^2 = 0.916$, LWC $R^2 = 0.901$, LAI $R^2 = 0.710$, Canopy Chlorophyll Content (CCC) $R^2 = 0.642$, and Canopy Nitrogen Content (CNC) $R^2 = 0.770$. These capabilities make EnMap data particularly useful for detecting soil stressors and their impacts, with peak effectiveness during active crop development (Jul – Sep), particularly in **mid-to-late vegetative and reproductive stages (booting to anthesis)**. The trade-off analysis revealed the strength of the soil property-spectral relationships, with PRISMA and EnMAP performing even better than laboratory ASD spectra; among soil properties, nitrogen-related characteristics produced strong and consistent spectral responses $R^2 = 0.885$, **Iron ($R^2 = 0.818$)**, Carbon (**$R^2 = 0.717$**), Chromium and Arsenic (**~ 0.62**) and Salinity (**$R^2 = 0.574$**). These results are site-specific, which limits the transferability of their trained models across larger regions. Trained ML models will struggle when applied beyond the conditions represented in the training data (e.g., different lithologies or farming systems).

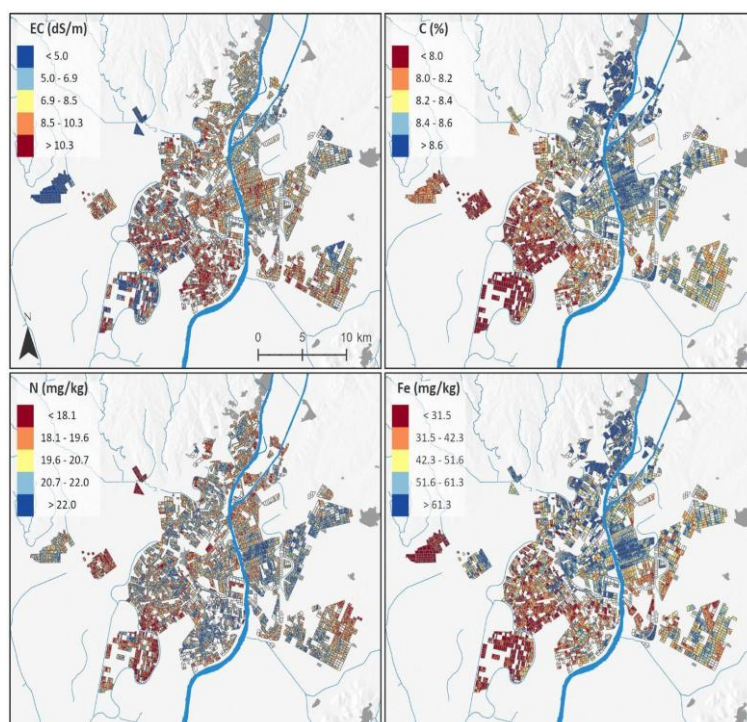


Figure 4. Spatial predictions of the selected soil properties using ML and hyperspectral imagery.

Pilot Two:

At the second pilot site, a comprehensive RS-based detection framework was developed to detect lodging stress in wheat using advanced satellite EO technologies (Figure 5). By integrating field hyperspectral measurements, EnMAP hyperspectral satellite data, and Sentinel-2 multispectral imagery, it accurately identified the timing, spatial extent, and severity of lodging in wheat fields. The analysis employed narrowband vegetation indices, ML algorithms, and Prospect-PRO to evaluate the spectral and structural responses of lodged crops. The comparative performance of these approaches was assessed to determine the most effective methods for operational lodging monitoring using state-of-the-art EO data. In this hybrid modelling framework, machine learning is combined with the PROSAIL model to interpret canopy-level spectral responses. Through PROSAIL simulations, key structural parameters such as the crop inclination angle and LAI are analysed to identify lodged fields and estimate lodging severity. This approach helped isolate the spectral regions most sensitive to lodging, providing new insights into the biochemical and physiological changes in affected crops. Such as, red-edge, NIR and SWIR regions were the most informative spectral domains, with the NIR-SWIR combination providing the highest sensitivity for wheat lodging detection. These findings facilitate a deeper understanding of how lodging alters crop spectral signatures, aiding in the design of more resilient management strategies. The resulting open-access lodging extent and severity maps (shown in the figure 5) can support precision agriculture and sustainable farming practices in large-scale agricultural systems.

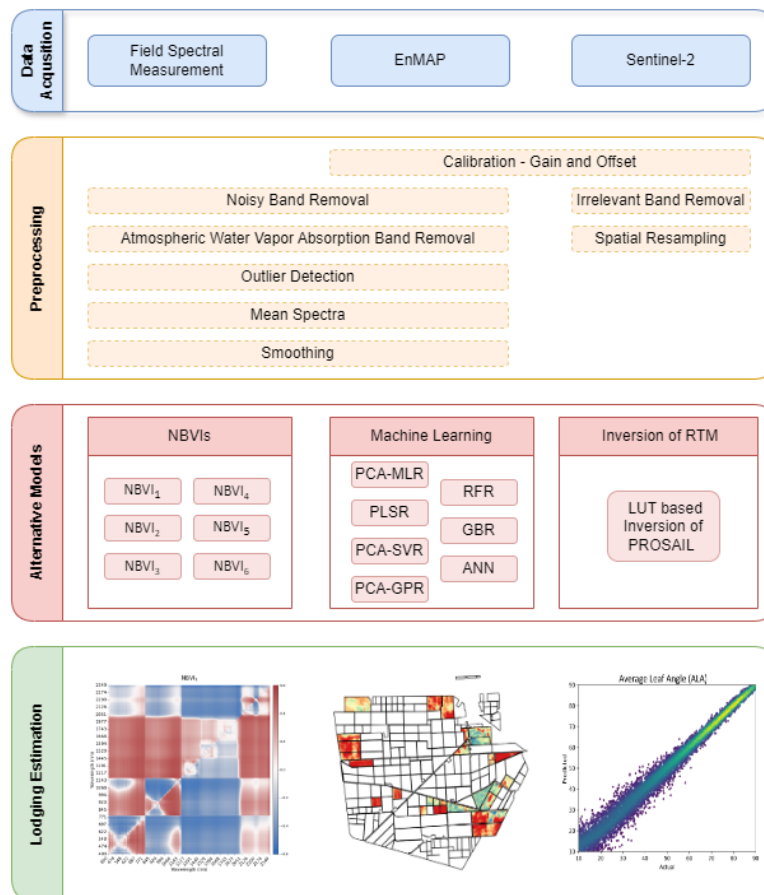


Figure 5. Workflow for each data source, followed by the implementation of multi-method approaches and the outputs.

Pilot Three:

The third pilot site experiment defined drought as crop water stress, expressed through maize condition, inferred from Sentinel-2 vegetation and moisture indices, together with climate data, soil water availability, and validated reference points, rather than relying solely on rainfall deficiency. Advanced drought stress mapping periods were assessed in maize fields in Austria's Marchfeld region by leveraging Sentinel-2 satellite imagery. Other datasets, including ancillary datasets on local climate and soil data, were used in the machine learning and deep learning models. A robust, integrated framework for drought detection and prediction was built by leveraging multiple data sources and analytical deep learning techniques.

By exploiting Sentinel-2's high spatial and temporal resolution, the study demonstrated its potential for monitoring drought severity, and integrating environmental variables can enhance prediction accuracy. Several commonly used machine learning algorithms were applied and compared to identify the most accurate models and vegetation indices for quantifying drought in maize fields. A framework shown in **Figure 6** includes:

- Gap-filling algorithm covering cloud removal, temporal compositing, linear interpolation, VI trajectories and annual feature stacking to address missing or incomplete Sentinel-2 observations.
- Integrating climate and soil datasets with Sentinel-2 band indices for improved drought assessment
- Applying and comparing machine learning model performances with integrated datasets, including Sentinel-2-derived indices
- Selecting the best-performing indices and models based on validation and accuracy assessments.
- Producing annual drought estimates for each growing season between 2018 and 2023.

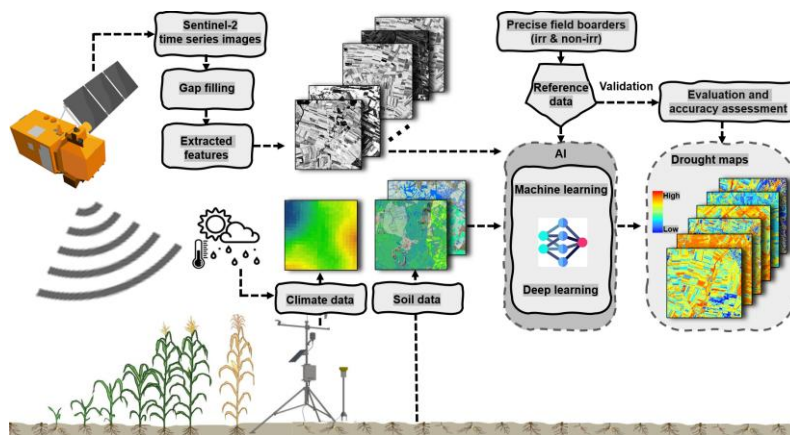


Figure 6. The framework of mapping drought in maize fields within the Marchfeld region, Austria.

This integrated approach provided a scalable, data-driven framework for drought monitoring and management, and can be practically useful for agricultural planning and climate resilience in the Marchfeld region. The 10 m pixel-level Sentinel 2-based drought maps are shown in **Figure 7**, and the resultant accuracy of ML/DL models for irrigated and non-irrigated maize fields is shown in **Table 1**. The DNN model is recommended for future drought assessments in the Marchfeld region due to its robust performance across varying conditions. While CNN showed strength in temporal pattern recognition and RF offered computational efficiency,

DNN's adaptability and accuracy make it the most suitable choice. Overall, all models achieved higher accuracy for non-irrigated fields. DNN was the best performer among them with the highest accuracy of 83.24%. However, greater uncertainty was found in irrigated zones because artificial water supply masked natural drought signals and eluded drought prediction.

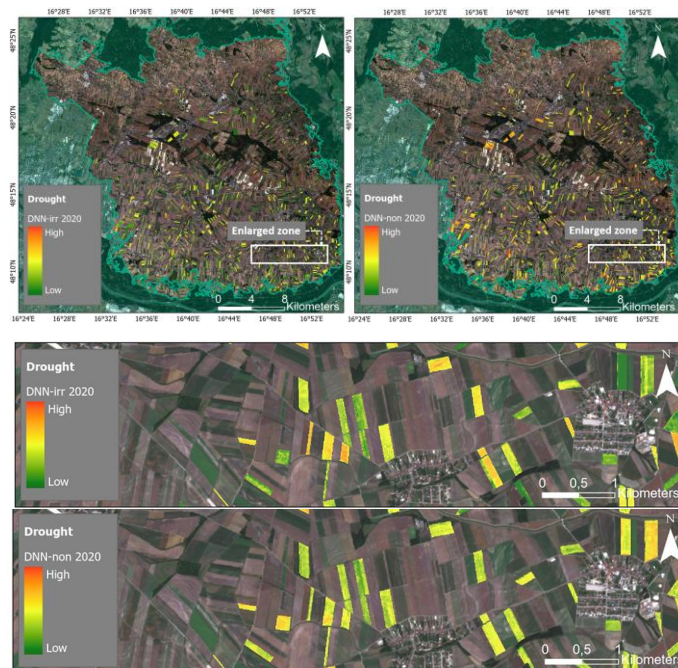


Figure 7 shows drought maps for irrigated and non-irrigated maize fields for the drought year 2020.

Table 1. The accuracy percentage for each DL and ML model in predicting drought.

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%

Dataset Description

A FAIR-compliant database (~7 TB) was created for each pilot site, and datasets were compiled, potentially for use in the project, containing:

- **Hyperspectral Images:** EnMAP, PRISMA, DESIS
- **Multispectral Images:** Sentinel-2 MSI, Landsat, HLS
- **Thermal Products:** ECOSTRESS, Sentinel-3 SLSTR
- **Climate data:** ERA5, SPARTACUS
- **Field campaign data:** Spain (rice), Italy (wheat lodging), Austria (maize drought)
- **Historical campaign data:** HyPlant Germany/Italy, SARSense, SoyFLEX

A harmonised repository was prepared for cross-sensor model transferability testing.

Table 2. Summary of Input and Output datasets used in the pilot sites and access to the stress products.

Pilot	EO Input Datasets	Timeframe	Access to Input Data	Main Output Products	Output Access
Pilot 1: Soil Salinity, Nutrient Deficit and Heavy Metals (Rice, Andalusia)	Sentinel-2 Level-2A multispectral imagery (10-20 m), EnMAP and PRISMA hyperspectral imagery (30 m), hyperspectral UAV imagery (5 cm), ASD laboratory spectroscopy, soil and crop field measurements.	March 2023 to August 2024. Sentinel-2 acquisitions from June-September 2023 and August 2024; EnMAP and PRISMA acquisitions for both bare soil and crop monitoring campaigns.	Sentinel-2 through Google Earth Engine (GEE) ; EnMAP through the EnMAP Data Portal ; PRISMA through the ASI PRISMA Portal .	Soil salinity (EC), soil nitrogen, soil carbon, iron and heavy metal maps, cumulative soil stress maps, and rice trait products including LCC, CCC, CAR, LAI, LWC, LNC and CNC maps.	Available as GeoTIFF products, and experimental datasets within Deliverable D4.1 Experimental Dataset Repository/Project SharePoint .
Pilot 2: Crop Lodging Stress (Wheat, Italy)	EnMAP hyperspectral imagery, Sentinel-2 multispectral imagery, ASD FieldSpec hyperspectral measurements (350-2500 nm), field observations of lodging severity, LAI, chlorophyll, water, carbon and nitrogen content.	2023 wheat growing season; field campaigns conducted during May 2023 and synchronised with satellite acquisitions.	Sentinel-2 from Copernicus Data Hub ; EnMAP imagery ordered through DLR/EnMAP portal ; field spectroscopy acquired during project campaigns.	Lodging Score (LS) maps, lodging severity classes, vegetation-index-based lodging indicators, Random Forest lodging products, and RTM-derived physiological parameter maps.	Analysis-ready products (GeoTIFF maps) provided through D4.1 Experimental Datasets/project SharePoint .

Pilot 3: Agricultural Drought Stress (Maize, Austria)	Sentinel-2 time-series imagery, climate data (SPARTACUS v2.1), soil field-capacity information (eBOD database), irrigation information, and derived vegetation indices (NDVI, EVI, NDWI, SIWSI, SRWI, etc.).	Multi-year period 2018-2023 , covering multiple drought seasons and irrigated/non-irrigated conditions.	Sentinel-2 through Copernicus Data Space Ecosystem (CDSE) ; SPARTAC and soil datasets obtained from open-access repositories.	Annual drought intensity and drought probability maps for irrigated and non-irrigated maize fields at 10 m resolution, generated using RF, DNN and 1D-CNN models
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Input EO datasets were obtained from operational and open-access services (GEE, Copernicus, EnMAP and PRISMA portals), while the resulting validated stress-monitoring products are distributed through the **EO4CerealStress D4.1 Experimental Dataset repository in the project SharePoint and Open Science Catalogue**.

4. Algorithm Specification and Validation Framework

4.1 Radiative Transfer Modelling (RTMs)

RTMs were applied in Pilots 1 and 2 to establish physically based relationships between canopy reflectance and crop biophysical and biochemical traits during stress conditions. The coupled PROSPECT-PRO + 4SAIL (PROSAIL-PRO) framework was used to simulate leaf and canopy reflectance and generate synthetic training datasets for machine learning inversion.

For Pilot 1, a lookup table (LUT) of 2,000 simulated spectra was generated using parameter ranges derived from field measurements of chlorophyll content, carotenoids, leaf nitrogen content, leaf water content, LAI, protein content, and carbon-based constituents. Active Learning and PCA were subsequently applied to retain the most representative simulations and reduce spectral redundancy before model training.

For Pilot 2 (wheat lodging), the same PROSAIL-PRO framework was used to generate a substantially larger LUT consisting of 30,000 simulations, from which 3,000 representative samples (1,000 per lodging class) were selected for modelling. The RTM outputs enabled interpretation of physiological differences between healthy, moderately lodged, and severely lodged wheat, particularly regarding chlorophyll, water, protein, carbon content, and canopy structure.

RTMs were not applied in Pilot 3, where the focus was on time-series analysis of Sentinel-2 vegetation indices, climate variables, and machine/deep learning approaches for drought monitoring in maize.

Overall, the RTM-based framework proved particular use for trait retrieval and physiological interpretation; however, hybrid RTM-ML approaches and data-driven ML models generally provided the highest predictive accuracies for operational mapping applications.

4.2 Machine & Deep Learning

A comprehensive set of Machine Learning (ML) and Deep Learning (DL) algorithms was evaluated across the three pilots, including MLR, PLSR, SVR, GPR, RF, GBR, ANN/MLP, DNN, and 1D-CNN. To address the high dimensionality of hyperspectral datasets (up to 200-250 spectral bands), several preprocessing and feature reduction approaches were tested in pilot site one, including PCA, RFE, Continuum Removal (CR), Multiplicative Scatter Correction (MSC), Wavelet Transform (WT), SPA, and ICA.

The optimal algorithms differed according to stress type and sensor:

- Pilot One (rice stress): PLSR consistently produced the best results for soil-property retrieval from hyperspectral data, achieving R^2 values up to 0.885 for soil nitrogen, 0.818 for iron, and 0.717 for soil carbon. For crop trait retrieval, GPR delivered the

highest accuracies, reaching $R^2 = 0.934$ for carotenoids, 0.916 for leaf nitrogen content, and 0.901 for leaf water content using EnMAP data.

- Pilot Two (wheat lodging): Random Forest Regression (RFR) was identified as the most robust and accurate model for lodging estimation, achieving the highest overall R^2 values (up to 0.83) and the lowest prediction errors across ASD, EnMAP, and Sentinel-2 datasets. While PCA-SVR and PCA-GPR performed well, RFR consistently provided the best generalisation and scalability.
- Pilot Three (maize drought): DNN, 1D-CNN, and RF were evaluated using Sentinel-2 time-series, climate, and soil variables. DNN achieved the highest overall performance, with accuracies exceeding 83% and the lowest MAE values, particularly in non-irrigated fields, outperforming RF and 1D-CNN in capturing complex drought patterns.

Across all pilots, hyperspectral imagery (EnMAP and PRISMA) consistently outperformed Sentinel-2 for stress detection and trait retrieval. PLSR emerged as the most effective model for soil property estimation, GPR for crop trait retrieval, Random Forest for lodging assessment, and DNN for drought prediction. These algorithms were not applied uniformly across all pilots; instead, model selection was tailored to the specific stressor, sensor characteristics, and available ground reference data. Further details are in the ATBD document and PVR (D 3.1 and D 3.2).

5. Validation Framework

For validation, field measurements were collected in close temporal proximity to Sentinel-2, EnMAP, and PRISMA acquisitions during the 2023 and 2024 growing seasons. Established ESUs (30-90 m) were used to ensure plot-scale consistency, while observations from multiple locations captured spatial variability across the study areas. Model performance was assessed using standard metrics, including R^2 , RMSE, MAE, ROC AUC, and uncertainty quantification, supported by robust evaluation strategies such as bootstrapping, 10-fold cross-validation, and active learning. Retrievals and predictions were further benchmarked against in situ measurements from ground-based instruments, including ASD spectrometers, LAI canopy analysers, and lysimeters. The validation over three sites confirms that the developed methodologies at each pilot site perform consistently with, and in some cases advance beyond, existing state-of-the-art approaches. The results reinforce the scientific and operational value of hyperspectral EO data for detailed crop stress characterisation, while demonstrating the complementary role of Sentinel-2 in large-scale monitoring applications. Details on validation results can be found in Section 5, Product validation, in the final report (D 9.4).

6. Scientific Impact Assessment

6.1 Regional Case Study: Canada – Spring Wheat Yield Risk (Prairies)

To estimate crop risk from drought across a large geographic area, the Canadian Prairie region (over 50 million ha), a Bayesian Neural Network (BNN) model was used to combine Canadian

drought monitoring data and satellite-based NDVI anomalies (2010–2021) to predict high-resolution wheat yields with quantified uncertainty. The model achieved accuracy comparable to previous research, with 13–18% error and R^2 values of 0.43–0.70, peaking in early August (Figure 8).

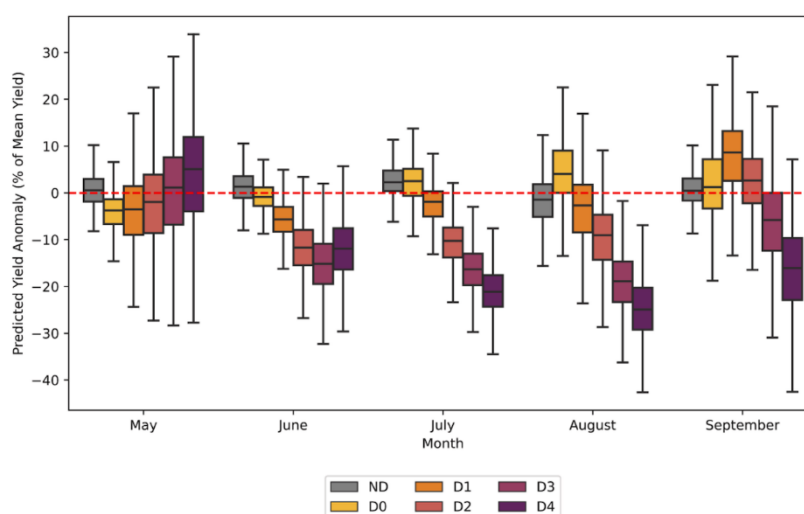


Figure 8. Average yield anomaly predictions (as % of mean yield) for townships across the Canadian Prairies under different drought severities.

The analysis quantified yield impacts under different drought severities using the 2010–2021 period, which included a range of drought and non-drought conditions, to evaluate yield responses. Results showed that droughts from June to August reduce yields in proportion to severity, while abnormally dry conditions can benefit yields, particularly in August. Prediction uncertainty declines significantly from June to July, highlighting July as a critical point for mitigation efforts. The framework also produced operational risk maps that combine yield vulnerability with CDM data, as demonstrated in a case study. These maps are expected to provide near-real-time, actionable insights for farmers and decision-makers.

6.2 Field Scale Case Study: Elora Lysimeter Site (Ontario)

Using the Andalusian pilot site framework, LAI was evaluated with hyperspectral drone data and a Gaussian Process Regression model trained on rice crop data from Andalusia, Spain. The model was adapted for corn crops of the research site in Ontario, Canada. It shows promising results for generating LAI at a fine spatial resolution (~1 m), with approximately 55% of the observed LAI variability explained by the trained GPR model. However, the trained GPR model tended to underestimate the full range of observed LAI variability relative to the Pilot one implementation. Sentinel-2-based LAI also showed a strong relationship with field measurements, suggesting that this dataset could be used in regional analyses of drought impacts and to improve the spatial resolution and physical representativeness of existing drought monitoring approaches. Stakeholders who may use this data include decision-makers (government agencies) interested in monitoring crop conditions to forecast yield or crop losses.

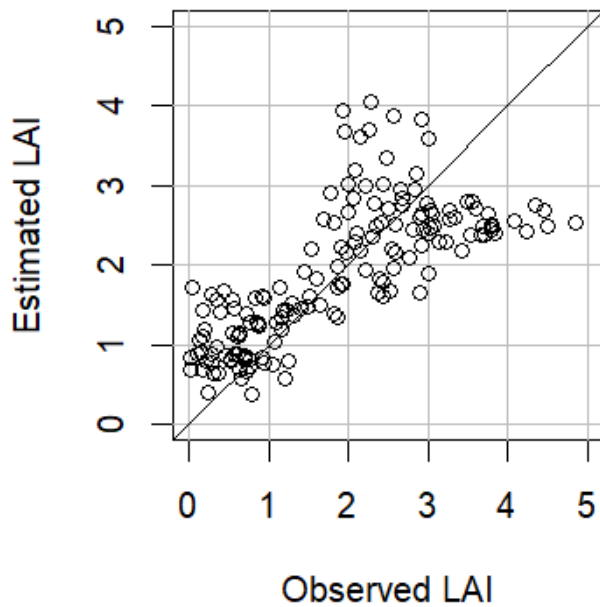


Figure 9. Observed vs. estimated LAI for corn during the 2021 growing season.

7. User-Driven Societal Impact and Operational Uptake

7.1 AAFC feedback on novel DL approach

Agriculture and Agri-Food Canada (AAFC) is the federal authority responsible for supporting innovation, sustainability, risk management, and resilience across Canada’s agri-food sector. As both a policy and operational body, AAFC is a high-impact institutional end user of scalable EO-based agricultural monitoring systems.

Feedback from regular engagement with AAFC confirms that the project’s synergistic approach, combining Sentinel-2–derived indices with CDM-based drought classifications, improves the characterisation of spatial and temporal variability across crops, regions, and growing seasons. The framework’s adaptability, use of harmonised EO inputs, and demonstrated transferability across regions make it well suited for operational early-warning systems and sector-specific risk assessment at the national scale. Future integration of upcoming ESA missions and collaboration with international initiatives such as JECAM further strengthen the pathway toward sustained operational uptake.

7.2 Operational Relevance to Andalusian Rice Federation, Spain

AFR’s long-standing operational experience, extensive agronomic network, and near-complete coverage of rice production in Andalusia position it as a highly credible end user of EO-based agricultural services. Through participation in the EO4CerealStress rice pilot, AFR recognised the tangible societal value of EO technologies for sustainable agriculture. The integration of hyperspectral (PRISMA, EnMAP) and multispectral (Sentinel-2) data enabled a spatially explicit assessment of soil constraints (e.g., salinity, nutrient availability) and crop

biophysical and biochemical traits (e.g., LAI, chlorophyll, nitrogen status), overcoming the limitations of point-based water and soil sampling. These products were successfully integrated into AFR's decision-support platform (SAMA 2.0), demonstrating readiness for operational adoption.

EO-derived stressor maps supported targeted field inspections, improved prioritisation of agronomic interventions, and a deeper understanding of interacting stressors affecting rice production in the environmentally sensitive Guadalquivir marshes. This diagnostic approach enhanced decision-making efficiency, reduced unnecessary inputs, and contributed to improved water and nutrient management.

7.3 Societal benefit to Bonifiche Ferrarsi farm, Italy

Bonifiche Ferraresi, Italy's largest agricultural holding (6,500 ha), represents a strategically important end user for advanced EO-based agricultural services. Managing a highly diversified crop portfolio across multiple regions, the farm already integrates Sentinel-2 imagery into its operational workflows and actively contributes to ESA initiatives, including Sentinel-2 reflectance validation and the EO4Nutri project.

A critical operational challenge identified by Bonifiche Ferraresi is the timely detection and assessment of crop lodging events. Lodging has significant economic implications, yet current monitoring approaches do not allow accurate identification of its onset, spatial extent, or severity at the scale required for rapid farm management decisions and insurance loss assessments. As a result, damage verification and compensation processes can take several weeks, creating delays and uncertainty for both farmers and insurers.

Participation in the EO4CerealStress project introduced the added value of hyperspectral EO data, particularly EnMAP, for retrieving key biophysical and biochemical crop parameters relevant to lodging detection and crop quality assessment. The resulting lodging maps addressed a critical gap in existing monitoring capabilities and were positively evaluated by farm technicians and management. Bonifiche Ferraresi expressed a strong interest in adopting hyperspectral EO products as part of its future operational strategy. The case highlights the importance of combining hyperspectral sensitivity with Sentinel-2's temporal coverage, supported by UAV and field data, to deliver decision-ready products. Bonifiche Ferraresi acts as a key early adopter and testbed, accelerating the transition from research pilots to scalable EO services aligned with Copernicus and future ESA missions such as CHIME and LSTM.

8. Scientific Roadmap & Five-Year Plan

8.1 Challenges and Advances in Remote Sensing of Crop Stress

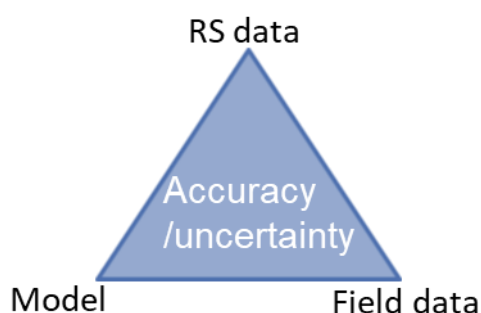
Crop stress monitoring is increasingly constrained by a combination of observational, methodological, and operational barriers. Key challenges include long satellite revisit times for hyperspectral missions, persistent gaps and inconsistencies in in situ measurements, and the growing computational complexity and limited scalability of ML models. These challenges are

compounded by the need to balance spectral richness against temporal continuity, as well as the limited availability of spaceborne hyperspectral data suitable for operational monitoring.

Abiotic stressors (e.g. drought, salinity, nutrient deficiencies, and heat) and biotic stressors (e.g. pests and diseases) often co-occur and interact, producing overlapping spectral signatures that confound traditional stress-detection approaches. Addressing these complexities requires coordinated advances in sensing, modelling, data integration, and validation.

Results from three pilot studies: rice (multiple soil-related stressors), maize (drought), and wheat (lodging), demonstrate the strengths and limitations of current EO capabilities. These pilots highlight the usefulness of hyperspectral missions such as EnMAP and PRISMA for retrieving pigment, nutrient, and water-related traits that act as early indicators of crop stress. At the same time, despite its limited spectral sensitivity, Sentinel-2 provides the temporal density required for operational monitoring.

Across pilots, hybrid RTM-ML approaches consistently outperform single-method solutions, offering improved robustness, physiological interpretability, and transferability across sites. However, critical barriers remain, including sparse and inconsistent in-situ datasets, limited hyperspectral revisit frequencies, model instability when applied beyond calibration sites, and the persistent difficulty of disentangling interacting stressors with similar spectral responses. The scientific roadmap suggests establishing a globally coordinated, tiered network of agricultural “super sites” designed to measure key crop variables, including biophysical and biochemical traits, stress indicators, and yield under both operational conditions and controlled experimental settings. Such sites will underpin sensor calibration and validation, enable process-based understanding of crop stress responses, and support the transition from experimental EO products to reliable operational services.



This vision builds directly on existing international initiatives such as GEOGLAM, JECAM, and CEOS, leveraging their experience to develop harmonised, FRM-aligned field protocols specifically tailored for multi-sensor satellite validation and model benchmarking.

8.2 Priority Research Areas for Advancing Stress Monitoring

To overcome the above limitations, the 5-year research plan prioritises the following interconnected tasks. Over five years, this plan can deliver a coordinated, multi-sensor, and physically grounded framework for early stress detection in cropping systems (**Figure 10**).

Phase 1: Multi-sensor data fusion (High Priority (Years 1–3))

- Integration of optical, SAR, thermal, fluorescence, and hyperspectral observations using advanced ML-based fusion techniques.
- Exploitation of complementary missions, including Sentinel-1, Sentinel-2, EnMAP, PRISMA, ECOSTRESS/LSTM, FLEX, and NISAR, to jointly characterise crop structure, water status, temperature, and biochemical traits.

Phase 2: Advanced modelling and analytics (High Priority (Years 1–3))

- Development of hybrid RTM–ML frameworks that combine physical consistency with data-driven flexibility.
- Explicit uncertainty quantification to support decision-making and operational reliability.
- Improved detection and attribution of co-occurring stressors (e.g. salinity versus drought) with overlapping spectral signatures.

Phase 3: Scaling and sustainability (Low Priority (Years 1–2))

- Creation of curated, open data libraries linking UAV, proximal, and satellite observations for UAV-to-satellite scaling.
- Integration of UAV platforms to bridge spatial and temporal gaps, particularly for calibration, validation, and trait upscaling.
- Emphasis on long-term sustainability through reusable datasets, standardised workflows, and community-driven benchmarks.

Phase 4: Operationalisation (Medium Priority (Years 4–5))

- Development of adaptive, transferable models with automated feature selection to ensure robustness across regions and seasons.
- Cloud-based processing environments enabling near-real-time updates and scalable deployment.
- Alignment with Copernicus operational requirements to facilitate uptake within the future mission ecosystem.

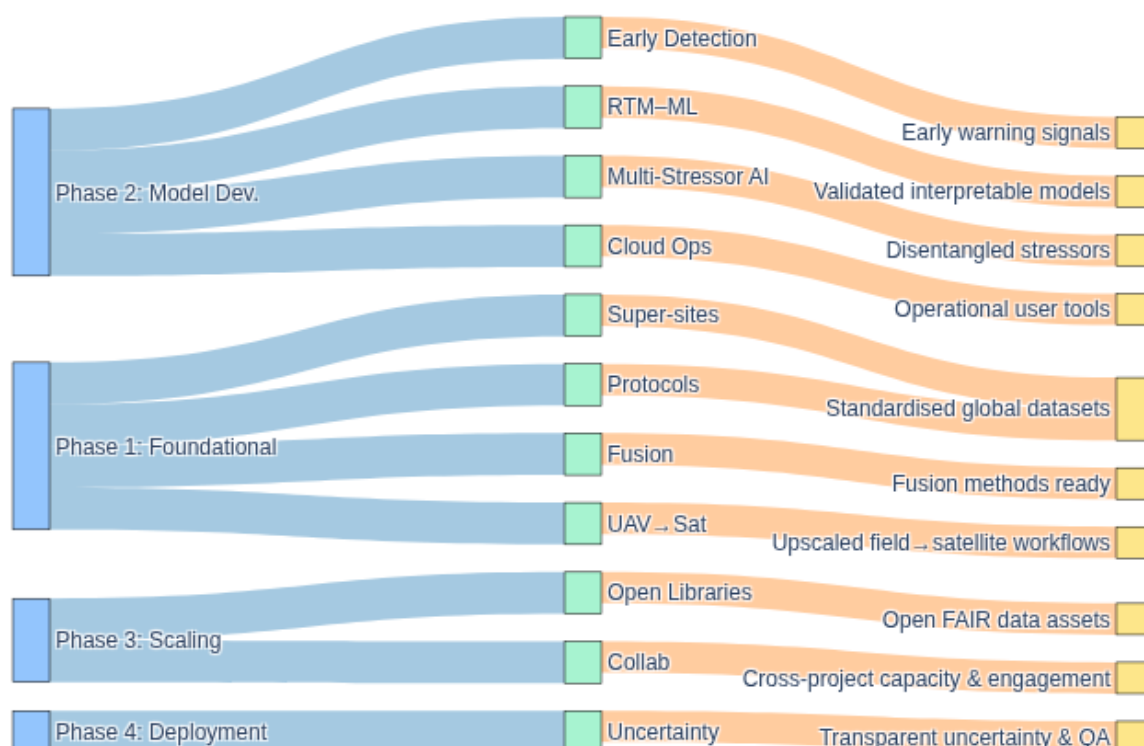


Figure 10: A five-year research plan (2026 – 2030) from the scientific roadmap showing four phases, tasks and expected outcomes.

9. Communication & Outreach

9.1 Scientific Advisory Group meeting, May 2024

The SAG Meeting was held on 8 May 2024 to gather expert scientific guidance on the project's direction, methodology, and future roadmap. The meeting reviewed progress in field data collection for stressor detection, provided expert guidance on evaluating project outputs, standardising field protocols and methodological approaches, and highlighted potential stakeholders, user communities, and collaborative networks relevant to EO-based crop stress detection.

9.2 Webinars (January and May 2025)

UoS hosted a webinar on '**Synergising EO and In-Situ Data for Crop Stress Detection and Monitoring**' on 20 May 2025, in collaboration with ESA. The webinar brought together leading experts to showcase emerging technologies, collaborative networks, and user-centred approaches that are overcoming challenges to provide scalable, precise, and actionable solutions for farmers globally. Representatives from IRRI-Philippines, YIPEEO-Austria, JECAM-AAFC, and the EO4CerealStress team shared the recent advancements in crop monitoring and modelling. A blog also published on the [University of Southampton International Webinar – Synergizing EO and In-situ Data for Crop Stress Detection and Monitoring \(20 May 2025\)](#) (20 May 2025)

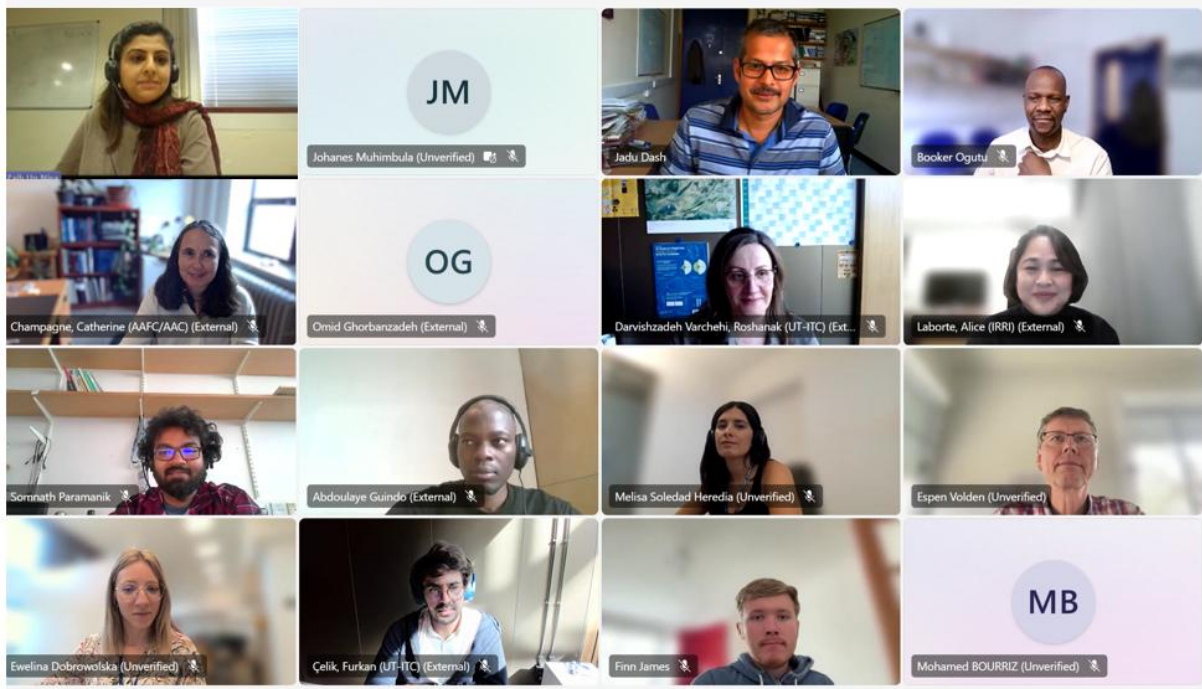


Photo from the webinar held on 20 May 2025.

Another webinar on ‘Advanced Crop Assessment Using Hyperspectral Data’ for the JECAM AVL community, in collaboration with Agriculture and Agri-Food Canada (AAFC), was hosted by UoS on 17 January 2025. The webinar focused on EnMap data processing and featured insights from the EO4CerealStress team, including a newly developed stress assessment scheme shared with JECAM, Canada.



Photo from JECAM webinar held on 17 January 2025.

9.3 Conferences/Publications

Results from project activities were disseminated at the EO for Agriculture Under Pressure workshop 2024, EGU 2024, EARSeL Workshop on Imaging Spectroscopy, COST Action PANGOES WG meeting (Lisbon, Jan 2025), ISRSE40 (Farnborough, UK, Mar 2025), ESA Living Planet Symposium (June 2025), COST Action SUSTAIN WG meeting (Trebinje, Sep 2024) and ESA Living Planet Symposium (June 2025).

Outputs	Count
Reports including DOSTAG	23 (some are public)
Posters	7 (updates on website)
Conferences	7 (updates on website)
Research Articles	1 Published, 3 Submitted, 4 Ready to submit (updates on website)

9.4 Project Reports

A list of reports documenting project activities, some of which are uploaded on the website (<https://eo4cerealstress.org/>) and ongoing publications.

1. Requirements Baseline Report (D1.1)
2. Dataset Description Report (D2.1)
3. Algorithm Theoretical Basis Document (D3.1 - ATBD)
4. Product Validation Report (D3.2 - PVR)
5. Impact Assessment Report- Science Use case (D5.1)
6. Impact Assessment Report- Societal Application (D6.1)
7. Scientific Roadmap (D7.1)
8. Scientific advisory group meeting report
9. Webinar Report (D8.4)

10. Conclusions

The EO4CerealStress project successfully developed multi-sensor, physically informed ML workflows, validated across four countries (Italy, Spain, Austria, and Canada) to evaluate the impacts of multiple stressors on cereal crops, and demonstrated a clear advantage of using hyperspectral EO data for biochemical trait analysis and specific stress identification. Additionally, the project delivered new EO products to detect the impacts of drought, lodging, salinity, nutrient deficiency, and heavy metals on cereal crops. In conclusion, the project developed a scientific roadmap aligned with the priorities of ESA, Copernicus, and GEOGLAM. Overall, the project provides a comprehensive framework for EO-based multi-stressor crop monitoring, strengthening climate resilience, food security, and scientific understanding of multiple stressors in cereal crops.