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

Task 7 – Scientific roadmap

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Acronyms and abbreviations

AL	Active learning
ARTMO	Automated radiative transfer models operator
ASI	Agenzia spaziale Italiana (Italian space agency)
CAI	Crop angle of inclination
CAR	Carotenoids
CEOS	Committee on Earth observation satellites
CCC	Canopy chlorophyll content
CNC	Canopy nitrogen content
CNN	Convolutional neural network
CR	Continuum removed/removal
DL	Deep learning
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German aerospatial center)
DNN	Deep neural network
DTE	Digital Twin Earth
EC	European Commission
EnMAP	Environmental mapping and analysis program
EO	Earth observation
EVI	Enhanced vegetation index
FRM	Fiducial reference measurement
GEE	Google Earth engine
GPR	Gaussian process regression
IoT	Internet of things
JECAM	Joint experiment on crop assessment and monitoring
k-NN	k-nearest neighbours
LAI	Leaf area index
LCC	Leaf chlorophyll content
LNC	Leaf nitrogen content
LSTM	Land surface temperature monitoring
LUT	Lookup table
LWC	Leaf water content
ML	Machine learning
MODIS	Moderate-resolution imaging spectroradiometer
MSC	Multiplicative scatter correction
MSI	Moisture stress index
NDII	Normalised difference infrared index
NDVI	Normalised difference vegetation index
NDWI	Normalised difference water index
NIR	Near infrared
NMDI	Normalised multi-band drought index
NN	Neural network
PCA	Principal component analysis
PLSR	Partial least squares regression
PRISMA	Precursore IperSpettrale della Missione Applicativa
R^2	Coefficient of determination
RFR	Random forest regression
RFE	Recursive feature elimination
RMSE	Root mean squared error
RTM	Radiative transfer model
SAR	Synthetic aperture radar
SDG	Sustainable development goal
SIWSI	Shortwave infrared water stress index
SVM	Support vector machine
SVR	Support vector regression
SWIR	Shortwave infrared
UAV	Unpiloted aerial vehicle
UN	United Nations

Summary

This report sets out the scientific roadmap developed under the EO4CerealStress project. It reviews the project's achievements, identifies key knowledge and observation gaps, and outlines a research agenda and five-year plan to advance Earth observation methods for crop stress monitoring.

The first part assesses what the project has delivered and where limitations remain. It highlights progress in hyperspectral modelling, multi-sensor data fusion, and machine learning for stress detection, while noting persistent challenges such as data gaps, overlapping stress signals, and the difficulty of transferring models across regions.

The second part defines a scientific agenda to close these gaps. It addresses priorities such as early stress detection with concurrent use of VNIR, SWIR, thermal and fluorescence data, distinguishing co-occurring stressors, understanding the interaction between pests, diseases, and abiotic stressors and scaling insights from UAV and proximal sensing to satellite products. It also calls for a tiered in-situ network, global super sites, regional Sentinel sites, and farmer-contributor nodes supported by standardised protocols and ESA's Fiducial Reference Measurement framework to ensure calibration and uncertainty control.

The final part presents a five-year research plan to move from research to operations within the EC–ESA Earth System Science Initiative on Agriculture and Food Systems[1]. It focuses on multi-sensor fusion, hybrid RTM–ML models, UAV-to-satellite upscaling, and open-access data libraries, alongside collaboration across ESA Agriculture Science Cluster projects and stakeholder engagement through living labs. The plan aligns with future missions such as FLEX, CHIME, and LSTM and connects to programmes including ESA's Digital Twin Earth programme[2], the European Commission's Vision for Agriculture and Food[3], and the CGIAR 2030 Research and Innovation Strategy[4], ensuring scalability and long-term impact.

[1] https://eo4society.esa.int/communities/scientists/ec-esa-joint-initiative-on-earth-system-science
[2] https://dte.esa.int
[3] https://agriculture.ec.europa.eu/vision-agriculture-food_en
[4] https://www.cgiar.org/how-we-work/strategy

1. Assessment of the project's objectives and results

The EO4CerealStress project has four main components, each of which is summarised and then evaluated in this section.

- Improving our understanding of the scientific background and potential of existing and future datasets to monitor multiple crop stressors using EO data.
- Undertaking dedicated field campaigns and radiative transfer modelling to develop a fundamental understanding of the remote signature of individual and multiple stressors.
- Demonstrator cases. The co-implementation of pilots with selected end-users, using existing computational and data infrastructure to develop demonstrator cases;
- Using the experimental data and tools to contribute to improving scientific understanding of the impact of crop stress and develop a roadmap.

1.1. The scientific background

Progress towards the United Nations (UN) Sustainable Development Goal of Zero Hunger (SDG 2) has stalled. Recent assessments show that, globally, we are no longer on track to meet SDG targets on food security, nutrition, and sustainable agricultural practices. The climate crisis and weather-related shocks in particular have a direct negative impact on food production (Saleem et al., 2025). Climate change is disrupting weather patterns, resulting in more frequent and severe extreme weather events such as droughts, floods, heat waves, and storms. These occurrences can have catastrophic impacts on crop production and lead to considerable financial losses for farmers (Fróna et al., 2021; Gornall et al., 2010).

Abiotic stressors, such as extreme temperatures and water scarcity, have significant physiological impacts on crops, hindering their growth and development and ultimately reducing yield and farm productivity. The degree to which these stressors affect crops depends on factors such as the type of stress, the crop variety, management practices, and environmental conditions. While plants can activate various physiological defence mechanisms in response to stress, their capacity for adaptation is limited, particularly under severe abiotic conditions. For instance, many major crops like wheat, rice, and maize lack critical mechanisms such as osmotic adjustment, or altered root architecture, all of which are essential for coping effectively with extreme temperature fluctuations or water shortages.

Certain physical and biochemical characteristics of cereal crops are crucial for monitoring stressor impacts. Physical traits such as plant morphology, canopy height, and leaf characteristics play significant roles in determining lodging resistance. Recent advancements in the retrieval of biophysical traits from multisource data have significantly enhanced our understanding of plant health and growth. Traits such as chlorophyll content, carotenoid levels, nitrogen content, and water content are critical indicators of photosynthetic efficiency and overall plant vitality.

Remote sensing (RS) data offer significant potential for monitoring crop stresses, providing essential insights into agricultural health and productivity. Crop stress, whether caused by extreme weather events, nutrient deficiencies, pest infestations, or poor management practices can have severe impacts on production and yields and nutritional quality of crops. The ability to detect these stresses at large scale as early as possible is crucial for effective intervention and management. RS data obtained from various satellite sensors or other platforms, can help

identify changes in crop physiological traits, which are early indicators of stress and would allow farmers and policymakers to take proactive measures and mitigation strategies.

The advancement of new machine learning (ML) algorithms combined with the physically-based models has opened new pathways for modelling and assessment of crop health and stress. RS and ML-based workflows integrate remote sensing data, environmental variables, and physiological measurements to enable precise and accurate assessments. The integration of various technologies, including spectral and hyperspectral sensors, fine-resolution satellite images, unpiloted aerial vehicle (UAV) data, ML-models, and deep learning (DL), creates a comprehensive framework for detecting and monitoring crop stress. Moreover, DL models are increasingly being used to enhance drought monitoring and assessment, enabling more effective feature extraction and prediction accuracy (Shen et al., 2019).

By using a combination of sensors, we can capture diverse aspects of the stressors and their impacts on crops. For instance, hyperspectral data from the Environmental Mapping and Analysis Program (EnMAP[5]) and PRecursore IperSpettrale della Missione Applicativa (PRISMA[6]) can identify specific stressors in crops, while Sentinel-2 satellite data allows for frequent, large-scale monitoring of crop health. The combination of spectral and spatial data improves detection accuracy compared to using spectral data alone (Canero et al., 2024).

By integrating various sensor types with physical models such as optical and hyperspectral sensors with radiative transfer models (RTMs), we can gather a detailed, multi-dimensional dataset that covers a wide array of parameters, including chlorophyll, water, nitrogen, and dry matter. This integrated approach provides a more thorough and continuous understanding of a crop's response to management and the environment, enabling better monitoring and management of crop stress as observed in wheat lodging (Chauhan et al., 2020).

Monitoring stressors is complicated by the co-occurrence of multiple stresses, either simultaneously or across the growing period (e.g., drought, salinity, nutrient deficiency, heat), which can have either synergistic or antagonistic effects, making it difficult to assess their specific contributions. Proximal reflectance methods (e.g., UAVs) are essential for more precise evaluations, and integrating complementary optical remote sensing can enhance spatial coverage and mitigate weather dependency. However, the limited revisit times of satellite sensors reduce their effectiveness for early stress detection, while proximal sensing offers more flexibility.

While multispectral sensors provide valuable information on canopy conditions their relatively coarse spectral sampling limits the depth of the data. Hyperspectral data can improve spatial and temporal assessments, but high-quality data from missions like PRISMA and EnMAP is often unavailable at short intervals. Due to the infrequent availability of such data, field campaign data and ML models must be used in conjunction with ground-truthing for accurate validation.

EO4CerealStress addressed major knowledge gaps identified in the D1.1 Baseline Document contributing to the development of standardised protocols for EO-based ML model integration and validation. These protocols—developed on soil salinity, drought in irrigated and non-irrigated

[5] https://www.enmap.org
[6] https://www.asi.it/en/earth-science/prisma

systems and wheat lodging—account for the complexity of interactions between various stressors and environmental variables. The project advanced hyperspectral and ML techniques to enhance stressor identification and developed standardised, cost-effective calibration and validation methods applicable across various regions and cropping systems. It also focused on determining optimal resolutions for specific stressor detection and monitoring scenarios while developing methods to address trade-offs between them. Additionally, robust techniques for seamless data integration and fusion were created, providing a comprehensive view of drought impacts on crops in both irrigated and non-irrigated environments.

1.2. The potential of existing EO datasets to monitor crop stresses

1.2.1. Suitability of single and multisource EO data

Freely accessible EO data from Sentinel-2 provides consistency in spectral, spatial, and radiometric characteristics, facilitating the tracking of vegetation changes under stress. Its red-edge bands, sensitive to vegetation stress and growth, have made it particularly valuable. The 5-day revisit time (reduced to 3 days over Europe due to overlapping orbits) enhances the ability to monitor stress impacts with improved temporal resolution. While it supports large-scale monitoring and early warning systems, Sentinel-2 may not detect subtle stress signals as effectively as hyperspectral sensors.

The harmonisation of Landsat 8 & 9 with Sentinel-2 improves observation frequency, while high-resolution thermal data from ECOSTRESS on the ISS and Sentinel-3 can further complement this by enabling monitoring of soil and canopy temperatures and evapotranspiration. These combined observations can support the detection of cumulative heat and drought impacts on crops.

Hyperspectral missions, such as EnMAP and PRISMA, extend the range of observable variables and offer improved transferability of variable estimation techniques. After appropriate processing, these missions can retrieve detailed parameters such as water and pigment content, carbonates, soil salinity, and moisture. They are especially effective at detecting chlorophyll absorption features and offer precise assessments of plant health by analysing full reflectance spectra.

The integration of hyperspectral data with ML and RTMs helps overcome the limited spatial and temporal resolution of these datasets. For example, EnMAP data has demonstrated the ability to detect stress traits like leaf water content (LWC), leaf nitrogen content (LNC), and leaf chlorophyll content (LCC), especially under complex stress scenarios such as combined salinity and nutrient deficiencies. Narrowband vegetation indices derived from hyperspectral data significantly enhance modelling of crop lodging, phenology, and stress detection.

Despite their advantages, hyperspectral datasets pose challenges, including high computational demands and the need for dimensionality reduction, which may lead to loss of crucial stress indicators. While ML approaches can suffer from this, RTMs, though robust, may have limited operational scalability.

The simplicity of processing EO data from a single source makes it an attractive choice for stress monitoring. However, relying on a single data source presents a challenge, particularly regarding temporal gaps. The revisit times in some parts of the globe may lead to missed detections, especially under cloudy conditions, relying on a single sensor may limit early stress identification. To mitigate the limitations of individual data sources, multisource EO integration has proven

effective. Combining data from Sentinel-2 (optical), Sentinel-1 (SAR), and Landsat (thermal) improves temporal coverage and can enables a more holistic analysis whereby:

- Optical sensors track spectral changes in vegetation.
- SAR offers structural data and all-weather monitoring.
- Thermal data helps detect heat and water stress via temperature anomalies.

This fusion approach enhances robustness against data gaps, making it particularly useful for large scale and regional studies. However, data fusion presents its own set of challenges. The complexity of integrating datasets with different resolutions, sensor characteristics, and processing methodologies requires sophisticated fusion techniques. Additionally, ensuring consistent calibration between different sources is crucial to avoid misinterpretations.

1.2.2. Capacity for early stress detection

The combined use of multispectral and hyperspectral is particularly well-suited for early detection of crop stress, offering the ability to capture physiological changes in plants before visible symptoms appear. This early sensitivity is rooted in the ability to monitor subtle biochemical and structural changes, such as chlorophyll depletion or loss of cell elasticity, through detailed analysis of spectral reflectance.

For example, stressors like drought affect cell turgor and stomatal behaviour, leading to reduced cell elasticity and stomatal closure, which in turn raises leaf temperature. These physiological changes can be detected through decreases in near infrared (NIR) reflectance and increases in thermal infrared emissions. According to Franke and Menz (2007), such changes in leaf structure and moisture content correlate with a decline in NIR reflectance, which serves as a reliable early predictor of canopy structural alterations—often preceding visible damage. These spectral shifts are valuable indicators for stress detection, enabling timely and targeted management responses.

Integrating data from Sentinel-2's visible and NIR bands with hyperspectral datasets from missions like EnMAP and PRISMA enhances the multidimensional characterisation of stress conditions. This fusion provides a comprehensive view of plant health, improving the specificity and timing of stress detection.

Moreover, the use of narrowband vegetation indices—tailored to physiological markers of stress has significantly improved the precision of detecting issues such as lodging, phenological changes, and nutrient or water stress. These indices capitalise on the spectral granularity of hyperspectral data, increasing sensitivity to early-stage stress signals.

However, nutrient deficiencies, particularly nitrogen, present more complex challenges. These symptoms are often localised to different parts of the canopy, depending on nutrient mobility, and may co-occur with other deficiencies (e.g., phosphorus or sulphur). In dense canopies, these overlapping symptoms make remote detection more difficult. To address this, combining leaf- and canopy-scale measurements has become common practice. Advanced feature extraction techniques, such as Independent Component Analysis (ICA), have proven effective; for example, phosphorus deficiency symptoms have been detected 15–24 days earlier at the leaf level using ICA (Shi et al., 2022), compared to traditional methods.

ML models such as Random Forest Regression (RFR) and Support Vector Regression (SVR) further enhance the detection of early stress signals when applied to hyperspectral data. RFR, in particular, excels at handling high-dimensional data and producing reliable predictions across varying canopy conditions.

Altogether, the integration of physiological understanding, spectral expertise, and ML approaches strengthens our ability to detect crop stress at an early stage. This enables timely interventions, reduces yield loss, and supports precision agriculture applications by transforming early warnings into actionable intelligence.

1.2.3. Temporal stability of algorithms and products

Temporal stability is critical for long-term, scalable crop stress monitoring. The reliability of spectral band indices or hyperspectral sensitivity to stress can fluctuate due to environmental variation, sensor calibration inconsistencies, or fusion technique limitations. Ensuring product consistency requires ongoing validation and algorithm refinement.

Long-term monitoring efforts must focus on generating consistent data streams that align with standardised methodologies used by global stress monitoring communities. This includes:

- Developing replicable field and EO methods.
- Ensuring accuracy, generalisability, and reproducibility of models.
- Implementing standardised data-sharing and measurement protocols.

The emergence of commercial EO constellations presents opportunities for higher temporal resolution, supporting early detection and field-level interventions. When intelligently integrated, data from various sensor types, i.e., optical, radar, thermal, and hyperspectral, enable a more nuanced understanding of co-occurring stresses, such as overlapping nutrient and water deficiencies.

Current and future EO missions promise to further enhance temporal and spatial resolution. Notable examples include:

- NISAR (launching March 2025) with dual-band L-S radar, which will assist in soil/crop monitoring and water mapping.
- The PREFIRE mission (Spring 2024) and Copernicus Land Surface Temperature Monitoring LSTM (2028) will expand thermal observation capabilities.
- Communities around Sun-Induced Fluorescence (SIF), such as NCEO and NASA JPL SIF, are contributing critical datasets from S-5P TROPOMI for future integration.
- CHIME's (Copernicus Hyperspectral Imaging Mission for the Environment) hyperspectral capabilities will enable detailed monitoring of vegetation biochemistry and soil properties with improved revisit times, addressing key limitations in current hyperspectral missions. This will not only strengthen the ability to detect subtle physiological changes at early stages but also support more accurate, scalable, and frequent stress assessments in operational agricultural monitoring.
- FLEX (the FLuorescense EXplorer mission) will provide global maps of vegetation fluorescence that can reflect photosynthetic activity, plant health and stress. In turn, this is not only important for a better understanding of the global carbon cycle but also for agricultural management and food security. (FLEX - Earth Online)

1.3. Results from the demonstrator cases (pilots)

This section summarises the key findings from the D3.1 Algorithm Theoretical Baseline Document as well as the D3.2 product validation report. We provide a brief outline of the three study areas and data, the best performing RS-data and model combinations for each of the five stresses studied, and the robustness of the findings and methods.

1.3.1. Pilot 1: Multiple stresses in rice

The **Multiple Stresses in Rice** pilot quantified how soil stressors affect rice development and evaluated the potential of Sentinel-2 and hyperspectral missions (EnMAP, PRISMA) for producing accurate, robust crop-stress products. The analysis focused on salinity, nutrient deficiencies, and heavy metals, together with biophysical and biochemical traits sensitive to these stressors. The overarching goal was to understand product accuracy, uncertainty, and consistency, and how these products can support the research community.

The study area is the Guadalquivir marshlands in southern Spain, a floodplain that includes Doñana National Park. Rice is the dominant crop, cultivated under intrinsically high salinity and strict environmental regulations. Exceptional drought in 2023 drastically reduced the cultivated area and the range of observed crop conditions.

EO data comprised Sentinel-2 and hyperspectral EnMAP and PRISMA imagery, complemented with field spectroscopy (ASD) and intensive soil and leaf sampling. Pre-flooding soil campaigns on a 1 km grid measured electrical conductivity (salinity), carbon, nitrogen, and heavy metals. Crop monitoring in selected plots supplied repeated measurements of nitrogen, pigments, canopy structure (LAI), and water content as independent reference data.

Soil properties were estimated using machine-learning regression applied to hyperspectral imagery, Sentinel-2, and laboratory spectra. Alternative datasets combined several preprocessing options and dimensionality-reduction techniques, and models were trained with 10-fold cross-validation. Performance was evaluated using R^2 and RMSE, as reported in the PVR. Hyperspectral models provided clearly superior performance. For soil salinity (electrical conductivity), the selected EnMAP model achieved an R^2 of 0.574, indicating moderate but usable accuracy for mapping salinity patterns at the landscape scale. Sentinel-2 models showed low predictive power for most soil stressors; only Fe reached an R^2 above 0.4, and the remaining Sentinel-2 soil products were discarded due to very low accuracy. For heavy metals, hyperspectral models achieved moderate accuracies for As and Cr, with R^2 values of 0.622 and 0.635, whereas other elements, such as Cd and Zn, showed much poorer performance. Thus, hyperspectral imagery can support soil-stressor products of reasonable exactitude, while multispectral estimates remain considerably more uncertain and often not robust enough for quantitative applications.

Crop biophysical traits were modelled using a hybrid RTM and ML framework. PROSPECT-PRO and 4SAIL generated synthetic spectra spanning realistic ranges of pigments, nitrogen, LAI, leaf structure, and leaf water content LWC. Gaussian Process Regression and other algorithms were trained with these simulations and validated against in situ measurements from the 2023 campaign. EnMAP-based models generally predict leaf and canopy properties with good accuracy. Leaf carotenoids CAR show the best performance, with R^2 = 0.934, and several traits (LNC, LCC, LAI and LWC) reach R^2 values typically between 0.7 and 0.9. Canopy-level traits are more challenging, with CNC achieving moderate-to-high performance and CCC showing higher

residual uncertainty. Sentinel-2-based models systematically underperform EnMAP, but still reach moderate accuracies for traits such as LNC, CNC, LCC and LAI. However, Sentinel-2 is less sensitive to subtle biochemical and canopy-level variations: CAR and LWC present clearly lower accuracies than with EnMAP, and CCC drops to an R^2 of 0.201. Sentinel-2 therefore remains essential for spatial coverage and temporal continuity, while quantitative and robust crop-stress products for biochemical traits require hyperspectral missions as primary data sources.

Stress levels were classified using agronomic thresholds for soil salinity and nutrient availability and then propagated to crop-trait products. Statistical analyses quantified how stress translated into changes in LCC, CCC, LAI, LWC, CAR, LNC and CNC. Salinity alone significantly reduced LCC, CCC, LAI and LWC, revealing declines in photosynthetic capacity, biomass production, and water status. Under combined salinity and nitrogen deficit, stress effects were more pronounced, with marked declines in pigment- and water-related traits. In some cases, LAI did not exhibit significant differences even under severe stress, indicating that structural metrics can remain stable while physiological stress is already advanced. EnMAP-derived stress products showed stronger and more statistically robust contrasts between stressed and non-stressed conditions than Sentinel-2.

From a scientific roadmap perspective, the pilot demonstrates that hyperspectral soil and crop-stress products can reach high levels of exactitude and robustness for many variables, while explicitly documenting residual uncertainty for others such as soil salinity and some heavy metals. The PVR provides R^2 and RMSE values that users can propagate when scaling up or integrating with models, enabling transparent uncertainty quantification. Overall, the combination of hyperspectral imagery, a physically based RTM–ML framework and harmonised validation procedures offers a transferable blueprint for future crop-stress product lines, with Sentinel-2 providing complementary spatial and temporal coverage around hyperspectral acquisitions.

1.3.2. Pilot 2: Drought stress in maize

The ***Drought Stress in Maize*** pilot aimed to develop a comprehensive remote sensing framework for detecting and predicting drought severity in maize fields using Sentinel-2 multispectral data. The study assessed drought stress by integrating remote sensing observations with in-situ measurements of crop water stress indicators.

A range of vegetation and water stress indices were analysed, including the normalised difference vegetation index (NDVI) for vegetation vigour, the enhanced vegetation index (EVI) for canopy structure, the normalised multi-band drought index (NMDI) for water stress, the normalised difference water index (NDWI) for moisture levels, the shortwave infrared water stress index (SIWSI) for soil and plant water conditions, the moisture stress index (MSI) for drought intensity, and the normalised difference infrared index (NDII) for soil moisture shifts.

The study was conducted in the Marchfeld region, a key agricultural area in Lower Austria, northeast of Vienna, covering approximately 60,000 hectares. This semi-arid region, characterised by low precipitation (250–300 mm from May to September) and high evapotranspiration rates, frequently experienced summer droughts, posing challenges for maize cultivation despite partial irrigation from diminishing groundwater reserves.

Field efforts took place from 2018 to 2023, using Sentinel-2 tiles (33UXP and 33UWP), climate records from the SPARTACUS v2.1 dataset for precipitation, and soil field capacity data. The analysis was conducted separately for irrigated and non-irrigated maize fields.

Persistent cloud cover disrupted data continuity, necessitating the development of a reproducible gap-filling approach within Google Earth Engine (GEE). This process used the "COPERNICUS/S2_CLOUD_PROBABILITY" dataset to mask cloud-affected pixels, generated two-week median composites to reduce residual cloud effects, applied linear interpolation to reconstruct missing values, and resampled all imagery to a uniform 10m resolution. These steps ensured comprehensive and reliable datasets for analysis and reduced the risk of uncertainty associated with missing observations.

The study incorporated multiple models, including seven ML algorithms—such as RF, SVR, and k-Nearest Neighbours (k-NN)—along with two DL architectures: Deep neural networks (DNN) and one-dimensional convolutional neural networks (1D-CNN). These models were evaluated to determine their effectiveness in predicting drought severity.

Following a trade-off analysis, DNN emerged as the best-performing model, achieving up to 83% mean absolute error (MAE = 0.13). 1D-CNN and RF also performed well, particularly in non-irrigated fields, where drought effects were more pronounced and easier to detect.

Annual drought maps were generated for the period from 2018 to 2023, highlighting severe drought conditions in 2022, especially in the southern and central Marchfeld region, which experienced substantial drought stress. In contrast, 2020 exhibited milder conditions due to more favourable precipitation levels. Non-irrigated areas proved to be the most reliable indicators, as they bore the greatest impact of drought stress. The use of a consistent legend and probability scale (0–1) for generated maps for all years ensured result consistency and enabled meaningful interannual comparison of drought dynamics.

To evaluate the reliability of drought predictions, a 10-fold cross-validation procedure was conducted to ensure a robust assessment of model performance. Predictions for irrigated fields proved more challenging, as irrigation obscured natural drought signatures, leading to higher error rates. Cloud cover remained a persistent obstacle, though the gap-filling method effectively mitigated data discontinuities. However, occasional misalignments between satellite overpasses and field observations occurred, as maize growth continued regardless of ideal imaging conditions. Reference data were compiled through a network of ~500 points per year, meticulously verified by domain experts in the absence of historical field surveys.

The transparent reporting of accuracy metrics, uncertainty sources, and robustness constraints holds potential for application to maize cultivation in other regions, though adaptations are necessary to account for variations in soil characteristics and climatic conditions. Additional data collection further strengthens its transferability.

The resulting drought maps provide farmers and water resource managers with a practical tool for optimising irrigation strategies and identifying drought onset. These findings underscore the capability of Sentinel-2 imagery for drought monitoring. With further refinement, this approach can significantly enhance agricultural resilience. For the research community, this study provides quantitatively validated, temporally consistent drought-stress maps and well-documented and transferable (ML/DL) model parameterisation to make comparable any single part with other

remote sensing based studies in long-term agricultural drought trend analysis, and considered as a methodological benchmark for development of next-generation agricultural drought monitoring approaches.

1.3.3. Pilot 3: Lodging stress in wheat

Remote sensing has demonstrated to be an effective approach for evaluating crop lodging (Chauhan et al., 2020; Hufkens et al., 2019; Ogden et al., 2002). However, despite encouraging progress, EO-based research for lodging assessment is still developing and have not yet fully matured. As such the use of hyperspectral satellite data which provides extensive spectral information across a wide range of wavelengths—for detecting, quantifying, and analysing crop lodging remains underexplored. Use of hyperspectral data could offer considerable advantages due to its detailed spectral resolution, potentially enabling more accurate identification of lodging severity, improved understanding of lodging dynamics, and enhanced capabilities for predicting the impacts of lodging on crop yields and biochemical and nutrient availability.

In this regard, the ***Lodging Stress in Wheat*** pilot aimed to develop a comprehensive remote sensing framework for detecting and predicting crop lodging severity using Sentinel-2 and hyperspectral measurements at both field and satellite levels. The research focused on understanding the extent and severity of lodging—an often overlooked yet crucial factor in crop stress monitoring and management—and its relationship to the dynamics of crop physiological parameters. This was achieved by integrating remote sensing data with in-situ measurements of crop biophysical and biochemical properties.

The study was conducted on agricultural land owned by *Bonifiche Ferraresi*, a major agri-food organisation in Italy, located in the province of Ferrara in the Emilia-Romagna region. The farm covered approximately 3,850 acres and consisted mainly of silty and clayey soils. A comprehensive field campaign took place from May 3 to May 18, 2023, in wheat fields at the flowering stage, a critical period for lodging occurrences.

A stratified random sampling strategy was used to collect data from both healthy and lodged wheat fields across three spatial scales, ranging from 90-meter to 1-meter plots. This approach ensured that measurements could be analysed using hyperspectral satellite imagery, Sentinel-2 data, and field spectrometry data. Biochemical properties (e.g., carbon, nitrogen, sulphur, water content, dry matter content, and chlorophyll) and biophysical parameters (e.g., leaf area, fresh mass, LAI, crop angle of inclination (CAI), canopy vertical height, and slant height) were collected to calculate lodging scores and explain lodging occurrence and severity.

Hyperspectral data obtained from ASD field spectral measurements and EnMAP (L2A product), as well as Sentinel-2 (L2A product) multispectral imagery was used to assess the relationship between lodging severity and changes in spectral response. Spectral data from the three sensors were analysed to evaluate different algorithms for lodging score estimation, including vegetation indices, ML analysis, and hybrid RTM inversion.

The lodging score assessment, which relied on common performance metrics (RMSE, MAE, and R^2), demonstrated that ML provided the most accurate results. Among the seven ML methods tested, the RFR model performed best, achieving the highest accuracy (MAE = 0.13 ± 0.02, RMSE = 0.18 ± 0.03, and R^2 = 0.59 ± 0.13 as mean and standard deviation).

Accuracy and the associated uncertainty in remote sensing-based monitoring of natural and agricultural ecosystems is a function of remote sensing data, field measurements and data acquisition and modelling algorithms (Figure 1).

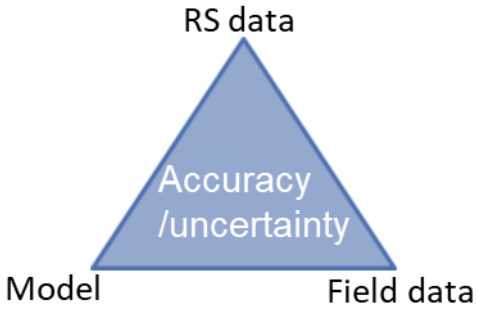


Figure 1. Major drivers of accuracy and associated uncertainty in remote sensing-based monitoring of natural and agricultural ecosystems.

Model-related uncertainty was quantified using the mean prediction value and standard deviation from 100 model iterations. Uncertainty related to field data was minimal, as measurements were conducted with great care, and no sensor malfunctions were observed during the field campaign.

However, when the wet chemical analysis of certain plant traits (e.g., nitrogen and carbon measured using a CHN analyser) showed a weak correlation with spectral data, these lab measurements were repeated using a different CHN analyser with a sufficient number of samples. This approach yielded different and more meaningful results.

The uncertainty associated with remote sensing data in this research was primarily considered in terms of noisy bands located within water and atmospheric absorption regions, as well as those below 400 nm and above 2400 nm. These bands were removed from the raw spectral data before computing the mean spectra and proceeding with further analysis. Additionally, the temporal gap between Sentinel-2 and EnMAP hyperspectral satellite data and the field measurements of crop traits may have introduced another source of uncertainty in the analysis of crop traits using these image datasets.

The workflow followed a systematic methodology, encompassing data collection, processing, model implementation, and the development of score maps using ML models. The approach is replicable for winter wheat across various locations; however, differences in lodging causes, influenced by agricultural management practices and meteorological conditions, may affect model transferability. Additional data is required to successfully train the model for diverse scenarios.

This pilot highlights the importance of maintaining accuracy, quantifying uncertainty, and ensuring product consistency in remote sensing-based evaluations of crop stress using Sentinel-2 and hyperspectral satellite data. The findings provide valuable insights for the scientific community and offer open-access lodging maps for stakeholders, supporting large-scale agricultural monitoring initiatives. Furthermore, remote sensing-based distribution maps of key biochemical constituents, such as chlorophyll, nitrogen, carbon, and sulphur—such as chlorophyll, nitrogen, carbon, and sulphur, direct link to grain quality (Zhao et al., 2005, 2019). In this study, these maps were successfully generated for healthy and lodged wheat with varying

degrees of severity, representing a significant finding that enables the assessment of lodging's impact on both grain quality and nutritional value. Evaluating grain protein content in cereal crops is particularly crucial to meeting diverse market and resource demands.

1.4. Quick wins from early adopters

In the Scientific Analysis & Impact Assessment Task, methods developed over an experimental site in Spain were validated and subsequently applied to a research site in Canada to evaluate their effectiveness and transferability for assessing water stress across multiple crops. Field experiments were conducted using large weighing lysimeters combined with hyperspectral cameras. These experiments leveraged the software tools, spectral indices, and applications developed within the rice pilot science use case, providing quantitative inferences into plant stress responses under controlled yet scalable conditions at the Elora research site. The outcomes contribute to the development of a robust and transferable use case example for future agricultural monitoring applications. The use of a publicly available toolbox for model development (Automated Radiative Transfer Models Operator: ARTMO https://artmotoolbox.com) significantly lowers the barrier to adoption by other user teams. This remains true even when the evaluated stressors, crop types, and growing conditions differ between the pilot site in Spain and the test site in Canada. Further details are in the Impact Assessment Report D5.1 (IAR-Science case Task 5_v2.docx).

Networks such as the Joint Experiment on Crop Assessment and Monitoring (JECAM[7]) provide a potential group of early adopters who could apply similar methods across sites globally. Conducting these joint experiments would benefit from a coordinated approach. In the past, this has involved either a funded researcher or graduate student analysing sites where data is collected or the provision of small amounts of funding and data acquisition, as is currently being done through the JECAM EnMAP-Agricultural Virtual Labs cross-site experiment (https://jecam.org/jecam-experiments-on-going). These types of experiments can enhance the scientific robustness of developed methods while also increasing adoption, as local researchers become familiar with and confident in the applicability of new techniques.

Bonifiche Ferraresi farm, one of the early adopters, is actively monitoring soil salinity across its management units using Sentinel-2 imagery within the QGIS Desktop project. This pilot site also serves as a testbed for other ESA projects, particularly for validating top-of-atmosphere and bottom-of-atmosphere reflectance algorithms for Sentinel-2. As part of the EO4CerealStress project, the farm has gained access to valuable crop quality data, including comprehensive retrievals of biochemical and biophysical crop properties. These insights support a shift toward data-driven decision-making in farm management. The resulting maps enable more timely and precise interventions such as optimising nutrient application, identifying early signs of crop stress, or detecting the extent of potential lodging. Notably, lodging analyses have revealed unusually high nutrient content in affected crops, highlighting significant potential for further research in nutrient management.

As a leading agricultural organisation in Spain, the Andalusian Federation of Rice Growers represents over 1,000 farmers and manages 39,000 hectares of rice fields. Renowned for its

[7] https://jecam.org

dedication to high-quality rice production, the Federation is committed to improving cultivation practices throughout the region. The Federation is keen to expand research collaborations in areas like pest detection and precision agriculture. By adopting advanced technologies such as hyperspectral remote sensing and predictive modelling of soil and crop nutrients, the Federation aims to boost the quality and value of its agricultural products. A key priority is the use of advanced EO data to tackle critical challenges such as crop stress, efficient water use, and enhanced soil health. The Federation actively seeks collaboration with researchers and industry experts to develop predictive models for yield forecasting and early warning systems for crop stress and pest outbreaks (https://www.corporaciontecnologica.com/en/national-projects/sama-challenge-sustainable-agriculture-through-development-system-monitoring). Through ongoing partnerships, the Federation aims to remain at the forefront of agricultural innovation, helping Andalusian rice farmers stay competitive and resilient in a changing environment where salinity and water scarcity pose growing threats to rice production.

1.5. Stakeholder engagement and synergies with other initiatives

EO4CerealStress collaborated with JECAM and conducted a technical webinar on advanced crop assessment using hyperspectral data for JECAM communities. The project team presented results demonstrating the effectiveness of EnMAP hyperspectral data in identifying crop stressors and estimating biophysical variables such as chlorophyll content and LAI. The recording is here: (https://drive.google.com/file/d/1JjHxRDjrmEKLTX5TzuA3jd99eG2F9lXf/view?usp=sharing).

Moreover, the team discussed the development of ML-based lodging detection models using EnMAP data to predict the impacts of lodging stress on crop health. The discussions concluded with an exploration of how EnMAP data could be further used for comprehensive crop assessments, emphasising the integration of hyperspectral data with other remote sensing datasets to improve accuracy and scalability.

During ATBD and PVR development, a Scientific Advisory Group (SAG) meeting was conducted and valuable recommendations and feedback received on the project's development and implementation. Significance of field data realised at higher scale for understanding the interconnectedness of crop physiological responses and stressors, also parameterising models and its potential impact on upscaling. Next step would be to add thermal data fusion for its large applicability in the crop water stress. Their feedback and recommendations are documented in EO4CerealStress- First SAG Meeting Briefing-May2024.docx.

For further collaboration with JECAM and potential ESA projects, an intensive webinar activity organised in May 2025 and early adopters were approached to collect feedback on current EO-based challenges and needs in crop stress monitoring. Webinar included a panel discussion on future directions and opportunities for implementing EO-based stress detection frameworks in other regions. The discussion highlighted the potential of EO data for detecting and monitoring a range of crop stressors, including lodging, salinity, nutrient deficiencies, and drought conditions with examples such as Sentinel-2–based drought prediction for the sub region of Manitoba, Canada, also covered topics . Presentations from JECAM, PRISM, and YIPEEO further illustrated how collaborative networks and advanced modelling frameworks contribute to operational EO applications. JECAM's harmonised experiments and the Canadian Drought Monitor showcased the value of long-term, standardised approaches to stress monitoring; PRISM demonstrated how satellite-based rice mapping and yield forecasting support farmer decision-making and disaster

response in the Philippines; and YIPEEO highlighted the promise of transfer learning to enhance yield prediction accuracy in data-scarce regions.

Panellists emphasised the importance of integrating multi-source datasets, strengthening validation through in-situ observations, and fostering cross-institutional collaboration to advance the operational use and scalability of EO technologies for agricultural monitoring. The webinar drew a diverse and multidisciplinary group of participants, reflecting the growing global interest in leveraging EO for agricultural remote sensing research. In total, attendees represented over 20 countries, including Canada, South Africa, Morocco, China, Indonesia, Pakistan, India, Namibia, Turkey, Lebanon, the UK, Germany, France, Spain, Belgium, Ecuador, Malawi, and Russia. This broad international engagement shows the global importance of EO technologies in addressing agricultural challenges related to climate stress, food security, and sustainable land management. Several attendees were affiliated with ESA-funded projects, GEOGLAM initiatives, and crop modelling consortia, reinforcing the collaborative and integrative focus of the webinar. The participants' backgrounds spanned geospatial analytics, agro-hydrology, environmental biology, IT education and capacity-building, and AI applications in agriculture, ensuring a balanced mix of early-career researchers and senior experts in the field. A blog also published on the event University of Southampton International Webinar – Synergising EO and In-situ Data for Crop Stress Detection and Monitoring (20 May 2025).

EO4CerealStress has developed an interactive Web GIS system for managing and exporting experimental datasets within the team and authorised users, generated from the Algorithm development and validation Task. This system is set to be publicly available through the project website by the end of the project. Following FAIR principles and Open Science, EO products and workflows will be shared on ESA's Open Science Catalogue, EarthCODE, an ecosystem that integrates many platforms and provides a unique access to scientific outcomes via those platforms, link is here: https://earthcode.esa.int.

Whilst a full evaluation of synergies is beyond this report, the Agricultural Virtual Lab (https://agriculturevlab.eu) is a promising platform, set up for non-experts, for sharing research data and tools between disparate teams who are working on collaborative experiments. That said, encouraging users to migrate their existing workflows to such integrated platforms can be challenging. If the main objective is data sharing rather than workflow execution, then the Open Science Catalogue represents a more appropriate approach. This catalogue not only provides comprehensive metadata and provenance information for each dataset but also allows datasets to be linked directly to associated workflows and experiments, including repositories on platforms such as GitHub. This ensures traceability, reproducibility, and discoverability of research outputs, while maintaining interoperability with existing open science infrastructures.

EO4Cerealstress will prioritise the potential users and collaborators to further develop the use of these products, including organisations like ESA's World Cereal, GEOGLAM, FAO GIEWS, NASA Harvest, and others involved in global agricultural monitoring and food security. Some of them have been engaged early in the co-development journey. Such engagements can provide long-term advantages in developing EO-based stress detection products. For example, showcasing results to the government bodies, universities, and organisations can further refine product development, contribute to scientific research, and ensure the product aligns with monitoring requirements within individual organisations with a mandate to monitor crop stress. Showcasing these results to organizations such as GEOGLAM or FAO could highlight the range of available

tools and datasets that are available to their members to help them identify the tools available for monitoring. Organisations such as NASA Harvest which both fund research and development and implement tools for global monitoring could use these models to as a foundation for future model refinement and as a baseline for future tools to be implemented, for example, in their Global Agricultural Monitoring tool box (https://glam.nasaharvest.org)

Such collaboration is vital for operationalising EO-based frameworks and scaling them up for widespread use. It also supports ongoing testing and fine-tuning, ensuring that both scientific and commercial stakeholders, such as cash crop producers, can benefit from the stress detection framework in real-world conditions. While this particular project may be considered a pilot or proof of concept with an emphasis on scientific understanding, early stakeholder involvement will be key to ensuring the practical and large-scale implementation of EO-based crop stress products in the future. This can help socialise users to the range of available tools and technologies that can support future decision-making.

Promoting data sharing, knowledge exchange, and joint activities among ESA Agriculture Science cluster projects can help address common scientific and technical challenges. Synergies with projects such as EO4Nutri (focusing on crop nutrient content estimation) and YIPPEO (improving crop yield forecasting using Sentinel-1 and Sentinel-2 data) are particularly relevant, as both align closely with EO4CerealStress in terms of crop monitoring objectives and methodological frameworks. Similar complementarity exists with EOAgriTwin (digital twin for multi-stress analysis), SaveCrops4EU (yield forecasting and scenario testing), and AgriCEM (dataset generation for CHIME and LSTM missions). Collaborative efforts can foster cross-validation of models, harmonisation of spectral libraries, and development of shared analytical pipelines for stress detection and yield estimation.

By aligning with these cluster projects and other ESA/EC activities, EO4CerealStress can contribute to addressing common gaps in data integration, modelling scalability, and operational deployment. Such collaboration is vital for transforming EO-based stress detection frameworks from pilot-scale demonstrations into operational, user-driven systems, ensuring long-term sustainability and impact across Europe and beyond.

1.6. Summary of main results and challenges

The study on **multiple stresses in rice** demonstrated the superior performance of hyperspectral data from EnMAP and PRISMA compared to Sentinel-2 in detecting key biochemical traits such as nitrogen and carbon content. ML regression models were highly effective in predicting soil and crop parameters with high accuracy, further enhancing the reliability of remote sensing approaches for stress detection. A hybrid methodology that combined RTM with ML proved particularly useful for modelling crop biophysical traits, offering a more comprehensive understanding of crop responses to stressors.

Findings from case-control studies highlighted that salinity had a significant negative impact on rice growth, an effect that was further exacerbated when combined with nitrogen deficiency. The use of EnMAP hyperspectral data provided a stronger contrast in identifying stress indicators compared to Sentinel-2, underscoring the potential of hyperspectral remote sensing for precision agriculture and stress monitoring.

Despite these advancements, several challenges were encountered during the study. Limited variability in crop traits due to drought conditions reduced the robustness of the developed models, as fewer stress conditions could be accurately captured. Sentinel-2's lower spectral resolution made it less effective in detecting subtle biochemical variations, limiting its ability to identify stressors with high precision. Additionally, temporal misalignment between satellite overpasses and field data collection introduced uncertainty in model validation, affecting the reliability of stress assessments. Addressing these challenges will require improved integration of multi-source data and more frequent hyperspectral observations to enhance monitoring capabilities.

The study on **drought stress in maize** demonstrated the effectiveness of combining multiple vegetation and water stress indices—such as NDVI, EVI, NMDI, NDWI, MSI, SIWSI, and NDII—for accurately identifying drought severity. Among the ML models tested, DNN achieved the highest accuracy, followed closely by one-dimensional 1D-CNN and RF. These models performed particularly well in non-irrigated fields, where drought stress signals were more clearly observed.

Annual drought maps covering the period from 2018 to 2023 provided valuable insights into drought trends, with 2022 identified as a year of particularly severe drought conditions. The study also found that non-irrigated fields were more reliable indicators of drought stress compared to irrigated fields, where artificial water inputs masked natural stress responses. The developed methodology showed strong potential for broader application in other agricultural regions, provided that necessary adaptations are made to account for variations in soil characteristics and climatic conditions.

Despite these promising findings, several challenges were encountered. In irrigated fields, the presence of irrigation complicated the detection of natural drought stress signals, reducing the effectiveness of some models. Persistent cloud cover also posed a significant challenge, disrupting data continuity and necessitating the development of a gap-filling approach to maintain data consistency. Additionally, occasional misalignment between Sentinel-2 overpasses and field data collection introduced inconsistencies in model validation, affecting the accuracy of drought stress assessments. Addressing these challenges will require improved data fusion techniques, more frequent field validation, and enhanced cloud-based processing for more reliable and scalable drought monitoring.

The study on **lodging stress in wheat** demonstrated the successful use of hyperspectral and Sentinel-2 data for detecting and predicting lodging severity. Among the ML methods tested, RFR provided the most accurate results. Spectral analysis further confirmed significant changes in biochemical traits associated with lodging stress, highlighting the potential of remote sensing for early stress detection. Additionally, the developed workflow for lodging assessment proved to be transferable to other wheat-growing regions, provided that necessary adjustments are made to account for regional variations in agricultural practices and environmental conditions.

Despite these advancements, several challenges were identified. One key issue was model uncertainty, which stemmed from variations in soil type, weather conditions, and the diverse causes of lodging. These factors introduced inconsistencies in model performance across different study areas. Spectral noise in hyperspectral data, particularly in water and atmospheric absorption bands, also posed challenges, requiring preprocessing steps to remove unreliable spectral regions. Furthermore, temporal misalignment between Sentinel-2 and EnMAP imagery

with field data collection created inconsistencies in stress detection, affecting the accuracy of model validation. Addressing these challenges will require improved calibration techniques, enhanced data fusion strategies, and refined methodologies for aligning remote sensing data with field observations to ensure more robust and scalable lodging detection frameworks.

While our findings provide valuable insights for the scientific community on the use of optical remote sensing data and in particular hyperspectral data, our conclusions may be limited due to the single-season scope, and the use of a single experimental location that result to limited field data. Additional research spanning multiple growing seasons and diverse experimental sites is necessary to strengthen the validity and generalisability of these initial findings using hyperspectral data, though collecting such a multi-seasonal data across diverse experimental locations significantly increases the costs. Such extensive data collection not only requires substantial logistical coordination (including sustained field monitoring, labour-intensive and accurate field measurements, and potentially expensive equipment deployment) but also proper coordination with space agencies (like DLR and ASI) to ensure sufficient acquisition of hyperspectral image data during the seasons and field campaigns. Further, measurements over multiple growing seasons and in different sites to account for variability due to weather, crop varieties, and regional differences adds further complexity and resources demands which needs considerable investment.

1.6.1. Common findings across pilots

Superiority of hyperspectral data. One of the most important findings across all pilot studies was the superiority of hyperspectral data for detecting crop stress indicators. Sensors such as EnMAP and PRISMA consistently outperformed Sentinel-2 in identifying nitrogen, carbon, chlorophyll, and lodging severity. However, despite their higher spectral resolution, these hyperspectral missions suffered from longer revisit times, limiting their practicality for continuous monitoring. This trade-off between spectral detail and temporal frequency remains a challenge for operational applications.

Effectiveness of ML and hybrid approaches. ML and hybrid approaches proved to be the most effective techniques for stress prediction. Models such as DNN, 1D-CNN, and GPR consistently delivered the highest accuracy. Additionally, combining RTMs with ML further enhanced predictive performance by integrating physically based crop behaviour with data-driven learning techniques.

Clearer stress detection in non-irrigated fields. The findings highlighted that non-irrigated fields provided clearer stress signals than irrigated ones. This trend was particularly evident in the rice and maize pilots, where irrigation masked natural stress responses, making it more difficult to detect drought and nutrient deficiencies. Consequently, stress detection models were more reliable in non-irrigated conditions, where natural environmental variations were more pronounced.

The importance of multi-sensor integration. A key takeaway from the pilots was the necessity of adopting multi-scale and multi-sensor approaches. The combination of Sentinel-2, hyperspectral imagery, and UAV-based data significantly improved spatial and temporal monitoring of crop stress. Proximal sensing techniques, including UAV-based field spectrometry, played a crucial role in validating satellite-derived stress indicators, reinforcing the need for integrating different data sources for more comprehensive stress assessments.

1.6.2. Common challenges and recommendations from the pilots

Observational gaps. A major challenge across all pilots was the limited availability of hyperspectral data. While EnMAP and PRISMA provided high spectral resolution, their long revisit times reduced their effectiveness for frequent stress monitoring. Conversely, Sentinel-2 offered more frequent observations but lacked the spectral precision needed to accurately detect biochemical crop traits. To address these limitations, a multi-sensor approach integrating optical, SAR, and thermal datasets is recommended. Combining different remote sensing sources can help mitigate temporal gaps in hyperspectral data, providing a more comprehensive and consistent framework for stress monitoring.

Cloud cover posed another significant obstacle, particularly in regions prone to persistent cloudiness. This resulted in data gaps in satellite imagery, needing the use of advanced gap-filling techniques to reconstruct missing observations. SAR data, which is unaffected by cloud cover, could complement optical EO data, improving temporal consistency in stress detection. Additionally, temporal misalignment between satellite overpasses and field data collection introduced inconsistencies in model validation, making it difficult to precisely correlate remote sensing data with on-the-ground conditions. Standardising data acquisition schedules and incorporating predictive modelling techniques to address misalignment issues would enhance the reliability of remote sensing-based stress assessments.

In situ data gaps. Limited ground-truth data for model calibration was another key challenge. Field data collection efforts were constrained by weather conditions, site accessibility, and logistical limitations, reducing the availability of reference datasets for validation. Expanding field validation efforts and establishing more reference sites with standardised data collection protocols would significantly improve model reliability. Additionally, increasing the use of UAV-based field spectroscopy could supplement ground-truth data, providing finer spatial and spectral resolution to validate satellite-based stress indicators.

Variability in field data collection practices further introduced inconsistencies across different study areas. Differences in soil type, crop variety, and management techniques affected model performance, reducing transferability. Standardising in-situ data collection methods across regions would improve model consistency and allow for more reliable stress detection. Cloud-based data-sharing platforms could also facilitate collaboration and exchange of reference datasets, supporting the development of more robust stress detection models across different agricultural landscapes. Additionally, standards for data collection (such as those developed by groups such as JECAM) could contribute to improved intercomparison between research site results (https://jecam.org/documents).

Long term multi-site experiments are crucial to taking research tools towards operational use and based on robust multi-year testing over multiple field data sites. Data on crop stress is not currently routinely collected at JECAM sites but could be with dedicated resources to support it coupled with a well-defined cross site experiment to guide interested site leads. Such a cross site experiment through a group such as JECAM would support future robust applications for monitoring stress and would leverage field data collection that is ongoing from a wider range of partners.

Model and algorithmic challenges. A fundamental challenge in stress detection was the trade-off between spectral resolution and temporal coverage. Hyperspectral sensors provided high

spectral resolution, improving stress detection, but lacked frequent temporal observations. Meanwhile, Sentinel-2 offered more frequent data but lacked the spectral precision needed to capture subtle biochemical changes. Addressing this trade-off requires the integration of multi-temporal hyperspectral data and ML-based data fusion techniques to generate higher-frequency stress indicators without compromising spectral accuracy.

The computational complexity and scalability of ML models also posed difficulties. These models required extensive training data, making their large-scale application resource-intensive. Cloud-based processing and optimisation techniques are essential to enable real-time stress monitoring and scalable deployment of these models in operational settings. Further investment in high-performance computing infrastructure and automated feature selection techniques could enhance computational efficiency, making large-scale stress detection more feasible. The ESA's Space HPC initiative provides a promising platform to address these challenges by offering high-performance, cloud-integrated computing solutions optimised for EO data processing and AI model training, which can be explored in future (http://commercialisation.esa.int/space-hpc).

Detecting multiple co-occurring stressors remained a challenge, as factors such as drought, salinity, and lodging often overlapped, making it difficult to isolate their individual effects. More advanced models integrating multi-sensor data are needed to effectively distinguish between different stress types and improve classification accuracy. Research into hybrid modelling approaches—combining RTMs with ML—could further enhance the ability to separate and quantify co-occurring stressors. Expanding model training datasets to include diverse environmental conditions and stress interactions would also improve the generalisability of stress detection models.

Stability over time and space. The performance of stress detection models varied significantly across different regions due to differences in soil type, crop variety, and agricultural management practices. ML models trained in one location often required recalibration when applied to other regions, limiting their transferability. In the rice and maize pilots, non-irrigated fields provided more reliable stress signals, while irrigation masked natural stress responses, affecting model accuracy. These findings underscore the need for regionally adapted models that account for site-specific environmental conditions.

Temporal stability was another key challenge, as stress conditions evolved dynamically throughout the growing season. Hyperspectral data provided strong biochemical stress indicators but suffered from limited revisit times, making it difficult to monitor stress progression continuously. In contrast, Sentinel-2 offered frequent observations but lacked the spectral precision necessary for detecting subtle biochemical variations. This trade-off complicated the development of models that remained effective over time.

Detecting multiple co-occurring stressors further affected model stability, as environmental conditions influenced the severity and nature of stress responses. For example, the lodging stress pilot found that variations in weather and soil properties led to different causes and severities of lodging, affecting model predictions. Without the ability to distinguish interacting stressors, models struggled to provide reliable stress assessments across different spatial and temporal scales.

Satellite data availability and coverage further influenced model performance. While hyperspectral sensors provided detailed biochemical insights, their long revisit times created

gaps in data continuity. Differences in cloud cover, satellite overpass schedules, and observational gaps made it difficult to track stress patterns consistently across years. Additionally, temporal misalignment between satellite observations and field data collection introduced uncertainty in model validation, reducing confidence in the predictions.

To improve the transferability of stress detection models, training datasets should be expanded to include diverse soil, crop, and climatic conditions. Cross-site validation should be conducted to test model robustness in different environments, ensuring that models remain effective beyond their original study areas. The development of a standardised database of in-situ measurements can further enhance consistency in model training and validation, making EO-based stress assessments more reliable.

Data assimilation and data sharing : Integrating multi-sensor and multi-temporal approaches is crucial for improving both spatial and temporal model stability. A combination of hyperspectral, multispectral, and SAR data can compensate for gaps in individual sensor observations, creating a more comprehensive monitoring framework. ML-based data fusion techniques can bridge the gap between high-resolution but infrequent hyperspectral data and the more frequent Sentinel-2 observations. Additionally, UAV-based field spectroscopy can be used to fill temporal gaps in satellite data, providing finer details for stress validation.

Refining ML and hybrid modelling approaches can further improve model adaptability across different regions and time periods. Adaptive ML models that update as new data becomes available can enhance long-term performance. Hybrid models integrating RTMs with ML can improve interpretability and reduce sensitivity to local environmental variations. Automated feature selection and transfer learning techniques can also help models generalise more effectively across different agricultural landscapes.

Enhancing field data collection and model calibration efforts will be critical for increasing model reliability. More frequent and standardised in-situ data collection, coordinated across multiple regions, can provide essential validation points for EO-based stress detection. Standardising protocols for data acquisition and sharing will allow for better model comparisons and refinements. Additionally, developing uncertainty quantification methods can help assess model reliability across different spatial and temporal scales, improving confidence in stress assessments.

Cloud-based processing and real-time model updates can further enhance the stability and operational usability of stress detection models. Automated data pipelines can continuously update ML models as new satellite and field data become available, reducing the risk of models becoming outdated. The implementation of an open-access EO-based monitoring platform would also facilitate collaboration between researchers, allowing for continuous model refinement and integration of new training data from diverse agricultural environments.

2. A scientific agenda to improve the detection and monitoring of crop stress

2.1. Knowledge gaps in the current status and future trends of crop stress prevalence

2.1.1. Challenges in multi sensor data integration and fusion

Despite the increasing availability and diversity of EO data sources—including Sentinel-2, PRISMA, EnMAP, UAV-based hyperspectral platforms, SAR, and thermal sensors—significant challenges remain in effectively integrating these datasets. Variations in spectral and spatial resolution, temporal frequency, and sensor-specific calibration protocols often lead to inconsistencies and incompatibilities, complicating the development of robust multi-sensor fusion frameworks.

For example, Sentinel-2 provides high temporal resolution but has limited spectral detail compared to airborne hyperspectral sensors, which offer rich spectral information at the cost of reduced spatial and temporal coverage. Additional differences in overpass timing, data formats, viewing geometries, and atmospheric correction methods further hinder harmonisation across platforms.

These discrepancies make it difficult to construct scalable, consistent monitoring systems capable of reliably detecting crop stress across diverse agricultural landscapes. The fusion process typically demands complex and computationally intensive pre-processing pipelines—including spatial and temporal co-registration, radiometric normalisation, and gap-filling—which often still fall short of fully aligning heterogeneous datasets.

To address these limitations, there is an increasing need for advanced data fusion methodologies that can harmonise multi-source EO data into a cohesive and consistent framework. In particular, ML-based fusion techniques offer promising solutions. These approaches can extract relevant features from disparate sources, dynamically assign weights to each sensor based on context, and intelligently interpolate or reconcile missing and misaligned data.

By using the complementary strengths of different sensors—such as the high spectral resolution of hyperspectral instruments, the frequent revisit of Sentinel-2, and the structural information provided by SAR—ML-driven fusion frameworks can significantly enhance the accuracy, reliability, and scalability of crop stress monitoring systems.

2.1.2. Gaps in understanding individual crop stressors

Different abiotic stressors, such as drought, salinity, nutrient deficiencies, and heavy metal toxicity, pose significant and distinctive threats to crop health, each manifesting through unique physiological responses. However, current spectral data on how these stressors influence plant pigment concentrations, leaf morphology, biochemical processes, and overall plant physiology remains limited, particularly across different growth stages. For example, heavy metal toxicity significantly affects crops by altering leaf pigmentation, cellular structure, and overall plant morphology, particularly in its interaction with plant physiological processes over time. Yet, details reflecting how heavy metals such as cadmium, lead, or arsenic impact leaf spectral reflectance characteristics and how these alterations relate to underlying physiological mechanisms throughout different growth phases remain underexplored.

Salinity stress presents another major challenge, as its spectral signature often overlaps with other abiotic stresses such as drought (water scarcity), nutrient imbalances, and waterlogging. Hence, there is currently no consensus on optimal spectral indices or optimised band combinations that can accurately differentiate salinity-induced symptoms from other concurrent stress factors. Similarly, nutrient deficiencies share spectral similarities with other stressors. Symptoms like leaf yellowing, pigment loss, reduced biomass, and altered physiological processes commonly associated with nutrient deficiency can mimic responses to drought, salinity, and other abiotic stresses, making it difficult to distinguish between them using current EO methods.

A key opportunity lies in developing comprehensive EO-based monitoring systems that integrate spectral data with complementary environmental and physiological parameters. Specifically, measurements of soil moisture and biochemical parameters, temperature, plant pigments, and physiological indicators can provide a clearer picture of nutrient stress dynamics.

Future research should prioritise experiments under controlled conditions that allow for the study of spectral reflectance measurements with assessment of pigment concentration, cell structure, and physiological impairments to understand the temporal dynamics of these stressors individually, and their multiplicative effects across various growth phases. These experiments can be effectively conducted using handheld hyperspectral instruments such as ASD FieldSpec spectroradiometers, which provide high-resolution, ground-based data essential for calibration and validation of satellite observations.

2.1.3. The complexity of co-occurring stressors

Crop stress does not always occur in isolation—multiple stressors often interact, compounding their impact on plant health. However, there is a lack of understanding of how, for example, moderate drought interacts with other concurrent stresses, such as nutrient deficiencies or pest attacks. Similarly, uncertainty remains regarding how heavy metal toxicity interacts with salinity, heat, water deficits, or other abiotic stressors, creating challenges in developing reliable EO-based stress models with high diagnostic skill.

Detection and differentiation of multiple concurrent stressors (e.g., drought + pests + nutrient deficiency) remain under-explored, particularly because these stresses often produce similar spectral responses. Current EO techniques struggle to separate these overlapping signals, making it difficult to determine the primary cause of stress-related crop damage. Additionally, there is insufficient data on how combinations of stressors affect crop physiology and productivity over time. Most studies focus on individual stressors, neglecting the synergistic or antagonistic effects that arise when multiple stressors interact. Research is needed to develop tailored spectral indices and band ranges that can distinguish between different stressors, particularly under conditions where they co-occur. This can be done via the development of new indices from hyperspectral instruments such as CHIME, FLEX, EnMAP, and PRISMA that offer new opportunities to address this challenge due to their advanced spectral and radiometric capabilities. Various methods can be applied to separate overlapping stress responses, like combining data from multiple missions (e.g., FLEX + CHIME or EnMAP + PRISMA) to merge physiological, biochemical, and structural information; developing multivariate and machine learning approaches (e.g., PLSR, SVM, deep learning) trained on hyperspectral data to classify stress combinations; designing new hyperspectral indices optimised for specific spectral regions

identified through feature selection or derivative analysis (e.g., red-edge shifts, SWIR absorption depths); using field and UAV hyperspectral data for calibration and validation of spaceborne models. Advancing research in AI could help disentangle these complex interactions by leveraging hyperspectral data and multi-sensor observations to detect patterns beyond the capabilities of traditional spectral analysis.

2.1.4. Gaps in understanding the interaction between pests, diseases, and abiotic stressors

Pests and diseases are major contributors to crop stress, yet their interactions with abiotic stressors such as drought and nutrient deficiencies remain poorly understood. These interactions complicate EO-based stress detection because they create similar spectral changes to those induced by environmental stressors. For example, pest-induced stress and nutrient deficiency can both cause chlorophyll degradation, leading to similar spectral alteration in multispectral and hyperspectral datasets around the red and red edge regions. However, the stress induced by pest (depending on the pest) usually has an intrinsic relationship with crop biophysical properties, phenological stage and environmental conditions, which could affect other spectral features and assist in discriminating pest stress from nutrient deficiency.

More research is needed to establish unique spectral and structural indicators that can reliably separate pest-related stress from other sources. Overcoming these limitations require comprehensive research on (1) understanding how individual biotic and abiotic factors influence the dynamics of crop physiological traits, and how multiple stressors combination create additive, synergistic, or antagonistic responses (2) how these physiological changes alter spectral reflectance patterns at both the leaf and canopy levels and (3) and how the multiplicative effect and interactions of different stressors affect the spectral signals at leaf and copy levels. Achieving these insights requires dedicated field and laboratory experiments where first individual and then multiple stressors are introduced under control conditions, allowing careful observation of their effects on plant physiological processes and associated spectral characteristics. Additionally, improved understanding of how pests and diseases interact with environmental conditions could enhance the accuracy of EO-based monitoring systems in complex agricultural landscapes.

2.2. EO and in situ data gaps

2.2.1. EO data gaps

Adopting a multi-source EO approach holds considerable potential for improving our understanding of crop stress dynamics and enabling timely, targeted detection. A range of remote sensing indicators should be investigated for early stress identification, allowing specific management interventions to be applied before crop damage becomes irreversible.

Complementary data from different sensors and platforms can capture the early biophysical and biochemical signals of plant stress, often well before visual symptoms appear or yield losses occur. This is particularly critical for implementing site-specific management strategies that mitigate stress impacts and maintain crop productivity. To realise this potential, future research should focus on identifying and validating a broad suite of EO products and indicators that are sensitive to early stress responses.

These indicators include changes in vegetation indices, canopy temperature anomalies, chlorophyll fluorescence, plant morphology and canopy structure, water and biochemical

content absorption features, and spectral shifts observable in the visible, red edge, NIR, and SWIR regions. Integrating such indicators from diverse platforms, such as multispectral and hyperspectral satellites and UAVs, thermal sensors, and radar systems, can offer a more holistic, timely, and physiologically relevant picture of crop health.

A significant gap in current EO capabilities is the limited availability and operational integration of thermal and SIF data. Thermal imaging, especially from upcoming missions like the Copernicus LSTM satellite, provides direct measurements of canopy temperature, an essential early indicator of water stress and stomatal closure. Likewise, the upcoming ESA FLEX mission, designed to deliver high-resolution SIF data, offers unmatched opportunities for monitoring photosynthetic activity and detecting stress early enough to prevent widespread damage. The forthcoming Copernicus CHIME mission will also improve systematic temporal monitoring of both soil stressors and crop biophysical traits, further enhancing our ability to manage and mitigate agricultural challenges globally.

These currently underused datasets, if harmonised with existing EO sources, could significantly enhance both the timing and accuracy of crop stress detection. Notably, the synergistic use of hyperspectral and thermal data represents a promising frontier. While hyperspectral sensors excel at detecting subtle biochemical and pigment-related changes, thermal data capture changes in energy balance and transpiration dynamics. Together, these modalities can provide a more mechanistic understanding of stress physiology and support predictive modelling of stress onset and severity.

Another area for advancement is the application of AI to automate stress detection and differentiate between overlapping stressors, such as pests, diseases, and nutrient deficiencies. AI algorithms can be trained to recognise complex patterns within multi-dimensional datasets, including time-series and cross-sensor inputs, thereby significantly enhancing the diagnostic capacity and operational scalability of EO-based crop monitoring systems.

2.2.2. In situ data gaps

Closing the knowledge gaps identified above requires fit-for-purpose in-situ measurements. Current field observations are uneven in space and time, often collected with non-uniform methods and rarely link physiological and spectral data. This limits our ability to (a) validate satellite products, (b) attribute observed signals to specific stress mechanisms, and (c) generalise findings across crops, climates, and management systems.

Towards an operational network. An operational agricultural field data network is essential as a ground anchor for testing and improving EO-derived products. A tiered structure is recommended:

- Global super sites across major agro-ecological zones, equipped for season-long, co-located observations of biophysical traits (LAI, canopy cover, plant height, phenology), biochemical and physiological parameters (pigment status, canopy temperature, water and nutrient status, pest/disease incidence), and in-situ optical/thermal measurements (leaf spectrometry, canopy hyperspectral/multispectral, thermal infrared, proximal fluorescence, phenocam imagery).
- Regional Sentinel sites with a leaner but standardised set of variables to broaden spatial coverage and capture management/genotype diversity.

- Farmer contributor nodes supplying key variables (phenology, yield, basic management) to enhance representativeness.

Protocols and uncertainty. Standardised protocols and metadata, building on GEOGLAM, JECAM, and CEOS efforts, should guide data collection. ESA's Fiducial Reference Measurement (FRM) framework can be adapted to characterise uncertainty through routine calibration, instrument inter-comparison, replicate sampling, and full uncertainty budgets.

Role of proximal sensing. Proximal sensors deliver high-frequency, high–signal-to-noise measurements at leaf-to-canopy scales under controlled geometry, enabling early detection of physiological changes (e.g., pigment depletion, canopy heating, water status shifts) that precede visible symptoms. Their alignment with satellite bands makes them effective validation anchors at super sites. However, their small footprint and lack of statistical sampling can bias results in heterogeneous fields. Reflectance and thermal metrics remain sensitive to sun–sensor geometry, requiring careful normalisation. Long-term deployments demand rigorous calibration and drift correction, and incur recurring costs for installation and maintenance. Their value is maximised when embedded in a tiered network and used to bridge scales between ground, airborne, and satellite observations.

2.3. Key scientific questions

1. How can multi-sensor and multi-scale EO approaches improve the early detection of crop stress? Early detection of crop stress is crucial for timely intervention and mitigation, yet different sensors have trade-offs in spatial, spectral, and temporal resolution. Sentinel-2 provides frequent multispectral observations but lacks the spectral depth for biochemical analysis. Hyperspectral sensors like EnMAP and PRISMA offer rich spectral information but have long revisit times, limiting their effectiveness for continuous monitoring. To improve stress detection, a combination of multispectral (Sentinel-2, Landsat), hyperspectral (EnMAP, PRISMA, CHIME), SAR (Sentinel-1, NISAR), thermal (ECOSTRESS, LSTM), and fluorescence (FLEX, OCO-3) data should be explored. Future work could be based around:

- Which fusion techniques can best integrate these sources to maximise the timeliness, accuracy, and spatial coverage of stress monitoring? This could be based on an assessment of different (AI-driven) fusion approaches for optical, SAR, and thermal datasets to detect physiological responses (e.g., water loss, canopy changes) across different stressors (Li et al., 2022).
- What are the best methods to calibrate and harmonise these multi-sensor datasets for operational use? This could be based on experiments to optimise the integration of UAV-based hyperspectral and LiDAR data for high-resolution validation of satellite-derived stress indicators.

2. How can ML and RTMs be optimised to improve stress detection and reduce uncertainty? ML and RTM-based models have shown promise in detecting and predicting crop stress, but challenges remain in their transferability, interpretability, and computational efficiency. ML models trained in one location often require retraining for new regions, while RTMs require precise parameterisation of canopy and soil conditions. Future work could explore:

- How can we improve the scalability of ML models to ensure they perform consistently across different crop types, environmental conditions, and management practices? One approach

could be the development and testing of hybrid RTM-ML frameworks that use physically based models to constrain ML predictions, improving generalisability. These frameworks would use transfer learning approaches to adapt models trained in one environment to different geographic and climatic conditions.

- What strategies can be used to improve robustness and reduced uncertainties in stress detection? This would require an assessment of different uncertainty quantification methods to assess uncertainty (e.g., Monte Carlo simulations and Bayesian inference) and reduce prediction errors (e.g., ensemble modelling).

Cloud-based processing would likely be essential for real-time implementation of stress detection algorithms that fuse multiple data sources at large scales. Algorithms hosted on the cloud platforms should be documented in easy-to-deploy formats, like notebooks developed in Python or R and stored on GitHub to facilitate user testing and adoption.

3. How can EO-based models distinguish between multiple and co-occurring stressors? Cereal crops often experience multiple overlapping stressors, including drought, salinity, nutrient deficiencies, heat stress, and pest infestations. These stressors can produce similar spectral signatures, making it difficult to isolate their individual effects. Future work could explore:

- What are the best methods for disentangling co-occurring stresses using EO? This would require multi-sensor integration (e.g., thermal for heat stress, SAR for waterlogging, hyperspectral for nutrient stress) and the development and multi-site testing of stress-specific spectral indices tailored to different crops and stress conditions.

- How can biochemical and structural indicators (e.g., chlorophyll fluorescence, canopy temperature, spectral reflectance) be leveraged to differentiate stress types? This would require an evaluation of different (AI-based) stress classification models trained on large, diverse datasets to separate the spectral and physiological signals of co-occurring stressors.

4. What are the optimal methodologies for scaling unmanned aerial vehicles (UAVs) and proximal sensing data for large-scale stress monitoring? UAVs and ground-based sensors (e.g., UAV hyperspectral data, chlorophyll fluorescence sensors) provide high-resolution, near-real-time stress detection, but their scalability remains a challenge. Efficient and robust means of scaling insights from proximal sensing to regional and national levels using EO data remains a critical question.

- One approach is to develop UAV-satellite hybrid monitoring frameworks to bridge the gap between high-resolution but small-area UAV data and large-scale but lower-resolution satellite imagery. This could include AI models trained on UAV datasets and applied to satellite imagery for upscaling. This would require the development of an open library of UAV datasets. A recent opinion piece (Rufin et al., 2025) raised awareness of the value of opening up commercial imagery archives. A similar effort for UAV datasets could provide valuable insights and training data, perhaps taking the WorldCereal Reference Data Module[8] as an example framework.

[8] https://ewoc-rdm-ui.iiasa.ac.at

- Internet of Things (IoT) technologies have been adopted for automation and decision support on farms (Paul et al., 2022). There is potential to build on these sensor networks for automated ground validation and the integration of IoT-based plant monitoring with EO.Using proximal sensing to capture high-frequency spectral and thermal signals at leaf-to-canopy scales for early physiological stress detection and to provide calibration for upscaling EO products

5. How can novel sensor technologies (e.g., LiDAR, fluorescence, gas emission sensors) enhance EO-based stress detection? Advancements in novel sensor technologies open new possibilities for monitoring stress at the plant and ecosystem levels. LiDAR can capture structural changes related to lodging, while fluorescence sensors can detect early drought stress. Similarly, gas emission sensors can monitor plant volatile organic compounds (VOCs) released under stress conditions. Integrated these sensors into EO-based frameworks would provide a more holistic and early-warning stress detection system. This could explore:

- Combining LiDAR with hyperspectral and SAR data to assess lodging stress.
- Combining fluorescence and thermal imaging for detecting physiological stress responses before visible symptoms appear.

6. How can EO data be operationalised to support precision agriculture and decision-making? Despite advances in EO-based stress monitoring, challenges remain in transitioning these findings into actionable insights for farmers, agronomists, and policymakers. For example, what EO-derived indicators are most useful (and when are they most useful) for early warning, precision irrigation, and targeted fertiliser recommendations?

- The development of any EO-based early warning systems for crop stress requires well designed co-development platforms (such as living labs) that support collaboration with farmers, other initiatives, and policy makers.
- This would require clear criteria for living lab site selection and a user-centric approach to innovation. Continuous attention to user needs and a rapid learning and adaptation cycle will help ensure that the integration of EO data into farm management software and decision-support tools is successful.

2.4. Involvement of stakeholders and future product generators to translate research to operations

Operationalising products. The GEOGLAM philosophy provides a useful foundation: national organisations should, wherever possible, take the lead in operationalising EO monitoring within their own jurisdictions. These organisations, with appropriate capacity development where needed, have the necessary local expertise and contextual knowledge to interpret EO data effectively and apply it meaningfully.

For example, from an Agriculture and Agri-Food Canada's (AAFC) perspective, we aim to operationalise EO datasets ourselves, particularly when suitable products are not already being generated by others.

- AAFC directly uses NASA-produced datasets like the Evaporative Stress Index and GRACE groundwater anomalies, as they meet user needs and are produced consistently.

- In other cases, or datasets, additional processing may be needed. For instance, SMOS soil moisture data is modified because the output from the SMOS operational processor doesn't fully align with requirements.
- In situations where no suitable product exists, such as with crop type mapping over Canada, data is generated in-house from the ground up to ensure adequate accuracy and national relevance.

The decision to operationalise a dataset depends primarily on two factors: the level of effort required to process and maintain it, and the importance of the dataset to our domestic monitoring priorities.

To bring research methods closer to operational use requires more rigorous testing and a clearer demonstration of the benefits these datasets provide. For example, a user would be unlikely to operationalise a hyperspectral product unless there was a dependable, long-term hyperspectral satellite programme in place, one that guarantees consistent data quality, continuity, and spatial coverage.

Early warning and agro advisories. Several user stakeholders are interested in the quality and quantity of crop production (e.g. GEOGLAM, AMIS, IGAD, etc.) The early warning and crop monitoring component of these information systems uses diverse sources of (EO) data to characterise crop condition and anomalies in crop condition. Their narrative reports – in the form of monthly bulletins or special reports in the event of extreme conditions – describe the impact of stresses like drought or flooding, but the EO workflows typically do not detail the presence, duration, and impact of specific crop stresses.

These stakeholders often take a distributed approach to data production, with expert teams nationally and regionally generating data sets for areas as part of national or international monitoring programs. Providing training on the use of methods and tools to detect crop stresses will be a starting point for implementing and testing these tools at this scale. Such collaboration can also operationalise the EO-based stress detection framework and can lead to robust implementation at a large scale. This process will also facilitate continued testing for a long period. By doing so, both scientific and commercial stakeholders (cash crop producers) can benefit from the early adoption of the stress detection framework.

This will also pave the way for impactful and industry-aligned solutions in the realm of early stress detection. EO4CerealStress frameworks on stressors detection and impact assessment based on hyperspectral data can be useful for future hyperspectral imaging missions, i.e., CHIME. Linking the methods to new emerging missions will promote transferability of the methods and enhance their robustness to the user community. Operational users require stability and are often unwilling to invest resources in tools that are experimental or have no long-term prospects for continuity.

Considering the emerging stresses due to changing climates and environments, as well as the increasing co-occurrence of multiple stresses in the same location and season, there is scope to target pest and disease management for future missions. Methodologies for pest and disease detection overlap with EO4CerealStress, and combining their methods can contribute to the expansion of the Joint ESA-EC Earth System Science Initiative. Linking to pests and diseases should include pathologists with expertise in specific diseases and/or leverage existing (largely climate-based) models that assess pest and disease risk. Addressing pests and diseases would

require links to non-RS initiatives such as the Global Burden of Crop Loss[9] and the Global Plant Health Assessment[10].

3. A five-year research plan

We outline a five-year research plan to advance the use and integration of EO-based crop stress detection and monitoring into EO product workflows for research, decision support, and policy support. We describe the future observation status five to seven years from now by accounting for new Copernicus expansion missions, especially those planned towards the end of the five-year duration. In addition to current missions, there is a lot to exploit.

Where relevant, we link our assessment of the priorities, effort, and impact to sections of this report and other resources to justify our ranking. To guide implementation and effort, the priorities consider the evolution of crop stress prevalence and impact from section 2, planned and future EO missions and infrastructure investments, ongoing and future initiatives, and networks of producers and stakeholders for EO-based crop stress products. We do not identify specific projects. Instead, we provide a guide for an ESA research programme for 2026 onwards.

Table 1is a list of the priorities that emerge from the previous sections and the project in general. The ranking reflects the relative importance and, where appropriate, logical sequence of tasks. The columns on anticipated effort, scientific and societal impact are best estimates.

- **Priority 1** tasks are those with high scientific and operational importance, strong support from current pilot findings, and high feasibility or clear pathways to implementation. These include improving early detection with thermal/SIF data, developing fusion techniques, and standardising field protocols critical enablers for future stress monitoring services.
- **Priority 2** tasks are also essential but require higher effort, involve more uncertainty, or depend on future research and infrastructure (e.g., hybrid RTM-ML models, uncertainty quantification, and co-occurring stressor detection). These are immediately necessary for scientific progression but may not be operationalised right away.
- **Priority 3** tasks involve scaling efforts or enabling frameworks (e.g., data libraries, UAV upscaling), which are important for long-term sustainability but depend on groundwork being laid by higher-ranked tasks.
- **Priority 4** broadens the connections between the ESA/EC projects and strengthens stakeholder and early-career engagement.

Table 1 Proposed prioritised task and estimated effort and potential impact

Task description	*Priority ranking*	*Effort (L|M|H)*	*Scientific impact (L|M|H)*	*Societal impact (L|M|H)*
1 Multi-sensor fusion development. Develop advanced fusion techniques combining optical, SAR, thermal, and hyperspectral data for robust crop stress detection. (using data from Sentinel-2, Sentinel-1, Landsat, EnMAP, PRISMA, ECOSTRESS, NISAR).	1st	H	H	H

[9] https://www.cabi.org/projects/global-burden-of-crop-loss/
[10] https://sites.google.com/view/global-plant-health-assessment/home

2 Early stress detection with emerging EO data. Improve early stress detection using thermal imagery and Sun-Induced Fluorescence from missions like LSTM and FLEX. (leveraging upcoming missions like LSTM, FLEX, CHIME, and existing missions such as ECOSTRESS and EnMAP.	1st	M	H	H
3 Hybrid RTM-ML framework design. Further integrate radiative transfer models (e.g., PROSAIL, SCOPE) with ML approaches (e.g., Random Forest, Gaussian Process Regression) to enhance predictive accuracy and interpretability of crop stress detection across varied conditions.	2nd	H	H	M
4 Co-occurring stressor differentiation. Develop advanced AI models (e.g., ensemble classifiers, deep neural networks) trained on multi-sensor datasets to disentangle overlapping stressors such as drought, salinity, and nutrient deficiency, and improve stress classification accuracy.	2nd	M	M	H
5 UAV to satellite upscaling. Develop AI workflows to scale UAV and proximal sensing insights—such as chlorophyll fluorescence, canopy temperature, and biochemical indices—to regional and national levels using satellite platforms like Sentinel-2, PRISMA, and CHIME. Integrate ML to match spatial and spectral scales for crop stress mapping.	3rd	M	M	H
6 Multi-site in-situ data expansion. Establish and maintain global super-sites (including controlled experiments) equipped with co-located field, UAV, and EO sensor systems for consistent calibration and validation of stress detection algorithms across agro-ecological zones.	1st	H	H	M
7 Field protocol standardisation. Develop and implement harmonised field protocols for measuring key biophysical traits (e.g., LCC, LNC, LWC) under various stressors. Align field measurements with satellite overpasses to ensure model consistency and reproducibility.	1st	M	H	H
8 Open-access EO data libraries. Create accessible EO data libraries by consolidating UAV, in-situ, and satellite datasets (from ESA pilot studies and elsewhere). Include metadata standards and harmonised formats to support reproducible ML training and benchmarking across different EO platforms.	3rd	M	M	M
9 Operational EO tools and cloud integration. Operationalise crop stress monitoring services by integrating EO models into cloud-based platforms like [*add suitable platforms here*]. Develop user-friendly interfaces and data pipelines – co-developed in Living Labs for example - for use by farmers, agronomists, and advisory services.	2nd	M	M	H
10 Model uncertainty quantification. Develop uncertainty estimation frameworks for stress prediction models using ensemble approaches, Bayesian methods, and validation across pilot sites. Support better decision-making through transparent confidence intervals and regional sensitivity testing.	2nd	H	H	M

11. Support collaboration and knowledge exchange across ESA agriculture science projects. Establish data-sharing frameworks and coordinated field campaigns to harmonise methodologies and enhance interoperability of EO-based stress monitoring products. Support the involvement of young researchers and early-career scientists, promoting their participation in cross-project research, field experiments, and facilitating long-term capacity building by training workshops or webinar series.	4th	M	M	H

Table 2 presents the priorities and associated activities as a five-year plan (2026-30.)

Table 2 Proposed five year plan based on the task from Table 1

Year	***Activity***
Phase 1 Foundational research and infrastructure. Focus on data collection, protocol standardisation, and fusion method development.	
1-2	6 Multi-site in-situ data expansion. Establish super-sites for calibration/validation. This underpins many downstream tasks.
	7 Field protocol standardisation. Ensures consistency across EO and in-situ measurements.
	1 Multi-sensor fusion development. Early fusion methods will enable future modelling and operational tools.
	5 UAV to satellite upscaling. Runs in tandem with fusion (year 1-2) and early stress and co-occurring stress identification (year 2-3).
Phase 2 Model development and early validation. Focus on building and refining hybrid models and diagnostic tools.	
2-3	2 Early stress detection with emerging EO data. Use new data streams (e.g., SIF, thermal) to advance early warning.
	3 Hybrid RTM-ML framework design. Build interpretable models using fused EO and field data.
	4 Co-occurring stressor differentiation. AI models can begin training with multi-source data from pilot sites.
	9 Model uncertainty quantification. Can start early in tandem with model development to inform validation needs.
Phase 3 Scaling and tool development Apply models at scale and move toward user-facing platforms.	
3-4	8 Open-access EO data libraries. Compile and publish datasets from Tasks 6, 7, and 1 to support reproducibility. 11. Support collaboration and knowledge exchange across ESA agriculture science projects. Strengthen collaboration across ESA and EC projects (e.g., EO4CerealStress, EO4Nutri, YIPPEO, EOAgriTwin, SaveCrops4EU). Establish shared data frameworks and cross-project workshops (eg. Webinar series). Engage key stakeholders, including farmer associations, cooperatives, policymakers, and private sector partners and support early-career scientists through capacity-building activities and mentoring to enhance their skills in agriculture monitoring.
Phase 4 Deployment and services. Translate science into services and prepare for future missions.	
4-5	10 Operational EO tools and cloud integration. Cloud-based platforms for end-users, integrating outcomes of previous tasks.

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