



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

Project Final Report (D9.4)

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AAFC	Agriculture and Agri-Food Canada
AFR	Andalusian Federation of Rice Growers
AGB	Above-Ground Biomass
AGL	Above Ground Level (flight altitude descriptor)
ANN	Artificial Neural Network
ASD	Analytical Spectral Devices (FieldSpec spectroradiometer)
ASI	Agenzia Spaziale Italiana (Italian Space Agency)
AUC	Area Under the Curve
BNN	Bayesian Neural Network
CBC	Carbon-Based Constituents
CCC	Canopy Chlorophyll Content
CDM	Canadian Drought Monitor
CDSE	Copernicus Data Space Ecosystem
CGIAR	Consultative Group on International Agricultural Research
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
CNC	Canopy Nitrogen Content
CNN	Convolutional Neural Network
CWSI	Crop Water Stress Index
DESIS	DLR Earth Sensing Imaging Spectrometer
DL	Deep Learning
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DNN	Deep Neural Network
EC	European Commission
ECMWF	European Centre for Medium-Range Weather Forecasts
ECOSTRESS	ECOsysteM Spaceborne Thermal Radiometer Experiment on Space Station
EO	Earth Observation
ERA5	ECMWF Reanalysis v5
ESA	European Space Agency
ET	Evapotranspiration
EVI	Enhanced Vegetation Index
EWT	Equivalent Water Thickness
FAIR	Findable, Accessible, Interoperable, Reusable
FAO	Food and Agriculture Organization
FLEX	Fluorescence EXplorer mission
FLUXNET	Global eddy-covariance flux network
GBR	Gradient Boosting Regression
GEE	Google Earth Engine

GEOGLAM	Group on Earth Observations Global Agricultural Monitoring
GFSAD1000	Global Food Security-support Analysis Data (1-km cropland)
GI	Greenness Index
GNSS	Global Navigation Satellite System
GPP	Gross Primary Production
GPR	Gaussian Process Regression
HLS	Harmonized Landsat–Sentinel
HNDVI	Hybrid NDVI variant
ICOS	Integrated Carbon Observation System
IFAPA	Agrarian and Fisheries Training Institute of Andalusia
INSPIRE	Infrastructure for Spatial Information in the European Community
IPCC	Intergovernmental Panel on Climate Change
ISS	International Space Station
JECAM	Joint Experiment for Crop Assessment and Monitoring
k-NN	k-Nearest Neighbours
LAI	Leaf Area Index
LCC	Leaf Chlorophyll Content
LDA	Linear Discriminant Analysis
LEAF	Landscape Evolution And Forecasting Toolbox
LIDF	Leaf Inclination Distribution Function
LMA	Leaf Mass per Area
LNC	Leaf Nitrogen Content
LR	Logistic Regression
LST	Land Surface Temperature
LSTM	Land Surface Temperature Monitoring (Copernicus mission)
LUT	Look-Up Table
LWC	Leaf Water Content
MAE	Mean Absolute Error
MCARI	Modified Chlorophyll Absorption in Reflectance Index
ML	Machine Learning
MLP	Multi-Layer Perceptron
MLR	Multiple Linear Regression
MOD11A1	MODIS Land Surface Temperature Daily Product
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	MultiSpectral Instrument (Sentinel-2) / Moisture Stress Index (context)
NDII	Normalized Difference Infrared Index
NDVI	ormalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NISAR	NASA–ISRO Synthetic Aperture Radar mission
NMDI	Normalized Multi-band Drought Index

OZA	Observer Zenith Angle
PCA	Principal Component Analysis
PLSR	Partial Least Squares Regression
PRI	Photochemical Reflectance Index
PROSAIL	Coupled PROSPECT + SAIL canopy RTM
PROSPECT	Leaf optical RTM family (incl. PROSPECT-4/5/D/PRO)
PSOIL	Soil brightness coefficient (RTM parameter)
QA	Quality Assurance
RAP	Red Andaluza de Posicionamiento (Andalusian Positioning Network)
RECI	Red-Edge Chlorophyll Index
REDIAM	Andalusian Environmental Information Network
RF	Random Forest
RFE	Recursive Feature Elimination
RFR	Random Forest Regression
RMSE	Root Mean Square Error
ROC-AUC	Receiver Operating Characteristic – Area Under Curve
RTK	Real-Time Kinematic (GNSS)
RTM	Radiative Transfer Model
R²	Coefficient of Determination
SAIL	Scattering by Arbitrarily Inclined Leaves (canopy RTM)
SAMA	Seville agro-monitoring platform
SAVI	Soil-Adjusted Vegetation Index
SCOPE	Soil–Canopy Observation of Photochemistry and Energy
SIAR	Agroclimatic Information System for Irrigation
SIF	Sun-Induced Fluorescence
SIWSI	Short-Wave Infrared Water Stress Index
SLSTR	Sea and Land Surface Temperature Radiometer
SPA	Successive Projections Algorithm
SPARTACUS	Spatial Analysis of Temperature and Precipitation Climatology for Austria
SRIs	Spectral Reflectance Indices
SSL	Self-Supervised Learning
STATcube	Austrian national statistics database
SWIR	Short-Wave Infrared
SZA	Solar Zenith Angle
TOA	Top of Atmosphere
TROPOMI	TROPOspheric Monitoring Instrument
UAV	Unmanned Aerial Vehicle
VNIR	Visible and Near-Infrared
WI	Water Index
WT	Wavelet Transform

Applicable and Reference documents

Reference Document	Project Documents
RD-1.1	Baseline Review Document
RD-2.2	Database Description
RD-3.1	Algorithm Technical Base Document
RD-3.2	Product Validation Report
RD-4.2	Experimental Product Description
RD-5.1	Impact Assessment Report (Science case)
RD-6.1	Impact Assessment Report (Societal Application)
RD-7.1	Scientific Roadmap Document
RD-8.2	Final Workshop Report

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1. Introduction

1.1. Project Overview

Agriculture faces increasing vulnerability due to climate change, as well as multiple biotic (pests, pathogens), and abiotic (drought, salinity, nutrient deficiencies, lodging, heavy metals) stressors. Early detection and monitoring of these stressors are therefore vital for mitigation and avoiding losses. The project's primary goal was to synergistically use multi-source data to conduct a feasibility study and develop Earth Observation (EO)- based products to understand and monitor the effects of individual and multiple stressors on cereal crops. A secondary goal was to engage both the user community and scientists to develop a scientific roadmap. This roadmap includes recommendations to the European Space Agency (ESA) and the European Commission (specifically the Directorate-General for Research and Innovation, DR-RTD) on priority scientific issues that need to be addressed to advance understanding and monitoring of the impacts of multiple stressors on crops.

The project took advantage of the complementarity of advanced EO data sources leveraging, Sentinel 2 mission, hyperspectral sensors (EnMap, PRISMA), and proximal sensing platforms (UAVs, spectroradiometers), combined with Machine Learning (ML) including deep learning (DL)-, and radiative transfer models (RTMs), for individual and combined stressors' detection and impact assessment. The project also provided a scientific roadmap and a five-year research plan for the future development of EO products, frameworks, and techniques for real-time monitoring of multiple stressors. The developed EO products and methods can be used to monitor abiotic stressors. These products can be useful to farmers, agronomists, policymakers, and researchers, providing meaningful insights into crop health and the environmental factors that affect it.

1.1.1. Objectives achieved

- Integrating multi-source EO with AI and ground datasets for stressor analysis.
- Conducting field experiments to evaluate stressor impacts on crop physiology and performance.
- Developing new algorithms of stress detection via combining EO data, in-situ measurements, and RTM/ML models.
- Generating validated experimental datasets for stress detection and demonstrating its use to early adopters for advanced scientific understanding of the impacts of multiple stressors on crop growth status.
- Engaging the user community and scientists in validation and critical assessment of the new EO products and impact assessment studies, and the design of a scientific roadmap for addressing major scientific challenges in synergistic approaches on EO data to monitor single and combined stressors.

1.2. Document overview

This document presents a summary of the ESA-funded EO4CEREALSTRESS project (<https://eo4cerealstress.org/>). Section 1 provides a brief introduction to the project and its goals. Section 2 describes the baseline review conducted before the inception of the EO product development. Section 3 outlines the datasets used, including EO, proximal sensing, and ground-based data. Sections 4 and 5 detail the algorithm development and validation across three pilot sites: soil stress in rice (Spain), lodging in wheat (Italy), and drought in maize

(Austria). Sections 6 and 7 present impact assessments, both scientific and societal, through case studies in Canada, Spain, and Italy. Section 8 summarises the final workshop and stakeholder feedback. Section 9 outlines the scientific roadmap and a five-year research plan for scaling EO-based stress monitoring into operational services.

2. Scientific Consolidation

2.1. Introduction

The baseline study established the project's scientific foundation. It identified the main scientific challenges and knowledge gaps in using EO and in situ data to understand and monitor the impacts of multiple stressors on crops. The study reviewed existing EO products and ancillary datasets for validating new crop stress products and assessed the strengths and weaknesses of current methods and algorithms used for EO- and in-situ-based crop health monitoring. It also identified suitable test areas for generating and evaluating crop-stressor products and explored the ideal requirements for creating experimental datasets, including accuracy, spatial and temporal resolution, and compositing periods. Lastly, the baseline study identified other ongoing projects and initiatives (YIPEEO, EO4NUTRI, EOAGRITWIN, JECAM, etc) within the Agriculture Science Cluster, of which the EO4CEREALSTRESS project is part too and can collaborate to enhance the uptake and value of the EO products.

2.1.1. Crop Stress Monitoring through Remote Sensing

Agriculture is affected by various biotic and abiotic stressors, including drought, pests, diseases, nutrient deficiencies, heavy metals, extreme temperatures, and adverse weather events. Abiotic stresses arise from physical or chemical factors, whereas biotic stresses are caused by infectious agents such as bacteria, fungi, and insects (**Gull et al., 2019; Berger et al., 2022**). The impact of each stressor on crop yield varies according to the type of stress, crop species, and environmental conditions.

Physical and physiological traits of cereal crops are key to agricultural monitoring and food production. Physical traits such as morphology, canopy height, and leaf characteristics influence how crops respond to stress, for example, their lodging resistance and disease susceptibility. Traits like tillering, spikelet and panicle morphology, and root system depth determine nutrient uptake, drought tolerance, and overall yield potential. Physiological traits, including chlorophyll content, photosynthetic efficiency, and carbon assimilation, are direct indicators of plant growth and stress tolerance. With climate change, the prevalence and severity of crop stressors is expected to increase. Therefore, new approaches for monitoring the impacts of these stressors on crops is needed to design early warning systems and to provide critical data and insights for informed decision making. While the volume of multisource agricultural data continues to grow, challenges remain in integrating and analysing these datasets effectively for holistic decision-making.

Remote Sensing (RS) is a non-destructive diagnostic tool useful for early warning systems and mitigation efforts. The integration of automated/semi-automated sensors, satellite and UAV datasets, ML tools, and DL enables comprehensive detection and monitoring of crop stress. Combining spectral and spatial information enhances stress detection compared with spectral data alone. Integrating thermal, optical, and hyperspectral sensors produces a richer dataset for continuous, system-wide monitoring. This project has developed integrated approaches to single and multiple stressors to support timely interventions that can improve farm management and food security.

2.1.2. Scientific Challenges and Gaps

Scientific studies increasingly employ EO data, ML, and RTMs to assess the impacts of multiple stressors on crops. However, integrating these complex tools presents numerous

challenges. A major difficulty lies in combining heterogeneous datasets from EO satellites, ground-based sensors, and climatic records, which differ in format, resolution, and scale. On the other hand, crops often exhibit similar physiological responses to various stressors, both biotic and abiotic, making it difficult to distinguish among the causes of observed stress (**Blum, 2016**). Current methods struggle to separate the combined effects of stressors, as synergistic or antagonistic interactions between stressors can alter plant reflectance and physiology in unpredictable ways.

Proximal sensing techniques, though viable for detailed spectral analysis, face operational constraints such as limited spatial coverage, weather dependency, payload limits, and complex data processing requirements. The transition from controlled greenhouse studies to real-world field conditions introduces additional uncertainty, as spectral models derived in greenhouses often fail to capture the full environmental variability in open fields (**Goldsmith et al., 2020**). At broader scales, data assimilation is limited by data availability, resolution, and cloud interference, while satellite revisit times may restrict early stress detection. Multispectral sensors provide useful canopy-level information but are constrained by coarse spectral sampling, and access to high-quality hyperspectral data from missions such as PRISMA, EnMAP, and DESIS remains limited. Consequently, integrating multi-resolution and multi-platform data to achieve both high spatial and temporal coverage remains a major technical bottleneck. The multiple challenges of using EO data in crop stress monitoring are shown in **Figure 2.1**.

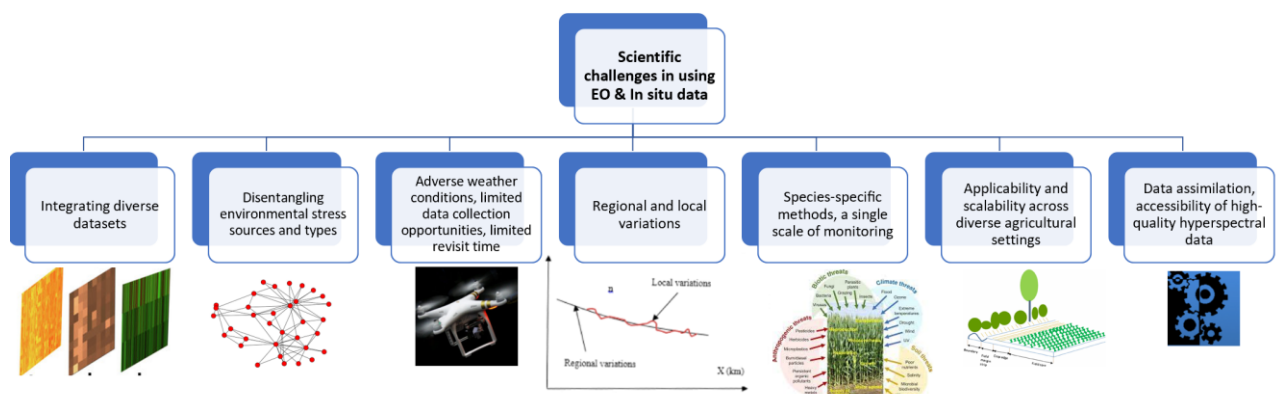


Figure 2.1 shows key scientific challenges in using EO and in situ data in crop stress monitoring.

Key knowledge gaps persist in understanding, modelling, and monitoring multi-stressor effects on crops. First, there is a lack of robust methods for upscaling local and experimental findings to regional or global levels while accounting for spatial and temporal variability. Second, the absence of standardised protocols for model integration and validation hinders comparability and reproducibility, particularly given the complex interactions among stressors and environmental variables. Third, further advances are required in spectral and ML techniques to improve the discrimination and identification of specific stressors that induce similar physiological responses.

There is also a need for harmonised, cost-effective calibration and validation methods applicable across diverse environments and cropping systems. Determining the optimal spatial, temporal, and spectral resolutions for detecting specific stressors and balancing these parameters remains an open challenge. Finally, developing robust techniques for seamless

data fusion and integration across EO, proximal, and in-situ sources is needed. The EO4CEREALSTRESS project aimed to address these challenges and knowledge gaps by developing new methods that leverage synergistic EO data to understand the impacts of stressors on cereal crops. Furthermore, the project evaluated the accuracy, transferability, and operational applicability of our new approaches to support timely interventions for improved farm management and food security.

2.1.3. Existing EO and Ground Datasets

2.1.3.1. Optical Remote Sensing (Coarse to High Resolution)

Over the past three decades, advances in sensor technology have expanded data availability across optical, thermal, and microwave domains (**Figure 2.2**). Key freely available datasets include MODIS (250–1000 m), Sentinel-1-SAR A/B/C (5 – 100m), Sentinel-2 (multispectral, 10–20 m; 60m), and Landsat missions (30 m), Sentinel-3 A/B LST Radiometers (500 m), providing complementary temporal and spatial resolutions for assessing vegetation health and crop stress. High-resolution systems such as PlanetScope and hyperspectral missions like EnMap, PRISMA, and DESIS enable detailed retrieval of soil and crop biophysical parameters (e.g., pigment, moisture, and canopy characteristics). Fusion products, such as Harmonised Landsat–Sentinel (HLS) and GFSAD1000, as well as open-source platforms like FARMA, demonstrate the growing integration of multisensor data to produce high-quality crop information at regional to global scales.



Figure 2.2 presents the evolution of satellite missions towards higher spatial and spectral resolution across optical, thermal, and microwave domains.

2.1.3.2. Proximal Sensing (Aircraft to Handheld)

Proximal sensing techniques bridge the gap between field and satellite observations. UAVs (<1 m resolution) equipped with multispectral or hyperspectral cameras enable high-spatial and temporal resolution imaging for early stress detection at the field scale. Airborne hyperspectral imaging supports broad-scale mapping and can be spectrally aligned with spaceborne missions for calibration and validation. Handheld and fixed spectroradiometers (e.g. ASD FieldSpec, Headwall Hyperspec) provide precise leaf- and canopy-level measurements under controlled and natural conditions (**Figure 2.3**). These data are vital for calibrating and validating EO-based stress indicators and for developing scalable, multiscale approaches that link proximal and satellite observations.

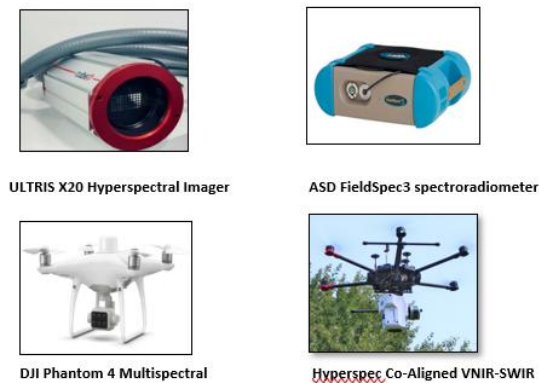


Figure 2.3 shows different proximal sensing tools used for in-situ data collection.

2.1.3.3. Ground Datasets for Calibration and Validation

Existing ground datasets complement EO data by providing in-situ reference information. USDA NASS offers extensive crop condition, soil moisture, and stress data through tools such as CroplandCROS and VegScape. AgMERRA and GGCMi provide gridded meteorological and crop model data for analysing climate-related stress impacts. FLUXNET and ICOS networks supply micrometeorological and carbon flux data from multiple European crop sites for physiological validation. The PhenoCam network delivers high-frequency phenological observations from agricultural ecosystems, enabling phenology and stress-response modelling. Long-term experimental sites, such as Rothamsted Research, offer controlled datasets for studying specific abiotic and biotic stressors under repeatable field conditions. Access to ground data facilitates multiscale, multi-sensor calibration and validation frameworks, which are essential for developing robust EO-based crop stress monitoring systems.

2.1.3.4. Key Crop Variables

A wide range of biophysical and biochemical variables can be derived from EO, proximal, and in situ measurements to assess crop stress and performance (**Figure 2.4**). Above-ground biomass (AGB), Leaf Area Index (LAI), and canopy cover describe structural attributes linked to crop vigour and yield potential. Chlorophyll, nitrogen content, and carotenoids serve as biochemical indicators of photosynthetic activity and nutrient status, with hyperspectral data particularly effective for their retrieval. fAPAR, gross primary production (GPP), and evapotranspiration (ET) quantify crop productivity and water-use efficiency, providing early stress diagnostics. Physical indicators such as crop inclination angle, root and panicle weight, and maturity timing provide insight into mechanical stability, reproductive success, and phenological shifts under stress. Soil moisture remains a critical environmental driver, detectable via microwave sensors and in-situ probes. Advances in LiDAR, SAR, and UAV platforms now enable fine-scale estimation of canopy structure and spatial heterogeneity, while ground spectroscopy and laboratory assays support calibration and validation. Together, these variables form an integrated framework for detecting, quantifying, and modelling multiple crop stressors across scales, supporting timely management decisions and the development of resilient agricultural systems.

Structural Traits	Physiological Traits	Water & Energy	Productivity Indicators
• Leaf Area Index (LAI) • Canopy Cover • Crop Inclination Angle • Root Weight	• Chlorophyll Content • Carotenoids • Nitrogen Accumulation • Grain Protein Content • Photosynthetic Efficiency	• Leaf Water Content • Soil Moisture • Evapotranspiration (ET) • Crop Water Stress Index (CWSI) • Equivalent Water Thickness	• Above-Ground Biomass • Fraction of Absorbed PAR (FAPAR) • Gross Primary Production (GPP) • Maturity Date

Figure 2.4 shows relevant traits used to assess crop stress and performance.

2.1.5. Key Stressor Symptoms and their detection

Crop stressors, both abiotic and biotic, significantly impact crop growth, physiology, and productivity, manifesting as observable changes in plant traits. **Soil waterlogging**, caused by flooding or heavy rainfall, deprives roots of oxygen, leading to stomatal closure, reduced growth, and chlorosis. **Drought stress** reduces leaf turgor, causing wilting, curling, and drooping branches, as well as chlorophyll degradation and changes in carotenoid concentration, while **salinity** disrupts water and nutrient uptake, resulting in leaf tissue degeneration, chlorosis, and yellowing. **Heavy metal contamination** inhibits growth, alters metabolism, impairs water and ion absorption, and induces chlorosis, with specific metals such as Cu and Hg producing distinct spectral responses. **Heat stress** elevates leaf temperature, degrades pigments, and reduces chlorophyll and water content, affecting leaf structure and physiology. **Biotic stressors**, such as disease or pest infestations, alter pigment concentrations, water content, and leaf or stem structure. **Nutrient deficiency** impairs photosynthesis, reduces chlorophyll content, and stunts growth, whereas **lodging** alters canopy structure and vegetation density.

The impacts of the stressors can be detected using key plant variables, including chlorophyll content, leaf water content, LAI, canopy temperature, transpiration rates, nutrient uptake efficiency, proline content, and tissue fluorescence. Spectral signatures from multispectral and hyperspectral sensors reveal characteristic patterns for each stressor, including changes in reflectance across visible, NIR, SWIR, and LWIR ranges, as shown in **Table 2.1**. While all stressors increase reflectance in green areas due to reduced chlorophyll, the timing, amplitude, and wavelength of these changes allow differentiation among stress types. Combining data from optical, thermal, microwave, and LiDAR sensors enhances crop stress detection by capturing physiological, biochemical, and structural variations. Multi-sensor integration, using platforms such as Sentinel-2, EnMap, and PRISMA, requires careful calibration, atmospheric correction, georeferencing, spectral alignment, and noise adjustment to harmonise datasets, enabling accurate spatial and temporal monitoring of crop health. Despite progress in spectral screening, detecting coexisting stressors remains challenging, emphasising the need for comprehensive data fusion to improve crop stress assessment and management.

Table 2.1 shows stressor-specific symptoms, key variables and spectral responses.

Key Stressors & Indicators				 ↑ absorption  ↓ reflectance
Stress	Symptoms	Variables	Signals	
 Pest	Canopy Texture and structure	pigment conc., water content, Canopy cover, LAI	Variations in VIs, unique dips and peaks	
 Lodging	Morphology, canopy structure, vegetation density	Canopy height, slant height, vertical lodged height, lodged area %	NIR ↑ SWIR ↑	
 Nutrient	Growth, pigmentation, leaf structure	As, CC, NE, LUE, RUE	Red ↓ Blue ↓	
 Drought	Leaf Turgor, water, leaf angle, chlorophyll	Tc, ETa, Rn, P, Tmin, Tmax, LAI, Carotenoids, CC	NIR ↓ SWIR ↓ Vis ↑	
 Salinity	Yellow leaf, tissue damage, discoloration	CC, WC	NIR ↑ SWIR ↑ Vis ↓	
 Heavy metals	Metabolism, morphology, pigmentation, chlorosis	Proline content, fluorescence, soil quality	Hg induce Fluor., NIR ↓ for Cu Vis ↑ NIR ↑	
 Heat Stress	Leaf structure, pigmentation, heat conditions	Tc, LeafT, CC, pigment conc., water content	Red ↓ Blue ↓ LWIR ↑	

2.1.6. Methodologies for Stress Detection

Crop stress detection and monitoring rely on a combination of laboratory, field, and RS approaches, each providing unique advantages for understanding plant responses to stressors. Controlled laboratory and field experiments are essential for assessing crop reactions to individual or combined stressors under reproducible conditions, enabling precise control over stressor intensity, timing, and duration. These experiments facilitate scaling from leaf- and canopy-level measurements to broader imaging applications and allow identification of stressor-specific wavelengths for creating targeted vegetation indices (VIs), which are particularly useful for detecting salinity and heavy metal contamination.

Beyond controlled settings, spectral data from ground-based and remote sensors, increasingly analysed with ML algorithms, allow automated detection, predictive modelling, and real-time monitoring of stress responses. **Sensor-based crop stress indices** derived from multispectral and hyperspectral imagery, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Canopy Chlorophyll Content Index (CCCI), Leaf Area Index (LAI), Red Edge Chlorophyll Index (RECI), and Crop Water Stress Index (CWSI), are widely used to assess crop health, detect drought, nutrient deficiencies, water stress, pest infestations, or disease outbreaks, with each index tailored to the stress type and crop. Advanced indices derived from red-edge or shortwave infrared bands enhance sensitivity to subtle changes in chlorophyll and water content, while temporal analysis of these indices enables monitoring of stress progression. Combined indices, such as CWSI and Water Deficit Index (WDI), can disentangle the physiological effects of water and nutrient stress and their interactions. Hyperspectral data provide finer spectral resolution than traditional multispectral data, enabling detection of short-term versus long-term drought impacts: short-term stress affects upper-canopy pigments,

while long-term stress causes structural alterations in lignin and cellulose. Water-deficit monitoring can be done by combining three approaches: developing VIs to detect changes in leaf water content, using ML regression to predict physiological parameters such as leaf water potential and stomatal conductance, and tracking early alterations in pigments and growth traits, such as LAI and ground cover. Overall, integrating controlled experiments, sensor-based indices, hyperspectral data, and ML enhance the precision, accuracy, and scalability of crop stress detection and management.

Feature extraction, feature selection, and spectral preprocessing are essential components of hyperspectral data analysis. Although related, each plays a distinct role in reducing dimensionality, improving information content, and enabling efficient modelling.

Feature extraction transforms raw spectral data into new, informative variables that represent underlying biophysical or biochemical properties. In hyperspectral remote sensing, Spectral Reflectance Indices (SRIs) such as chlorophyll- or water-sensitive indices are widely used to capture plant traits in simplified, biologically meaningful forms. Advanced extraction methods include the Wavelet Transform (WT), which reveals narrow and broad absorption features across multiple scales, and Independent Component Analysis (ICA), which separates mixed spectral signals into statistically independent components.

Feature selection identifies the most relevant wavelengths or derived features while removing redundant information. Common approaches include Partial Least Squares Regression (PLSR) for selecting predictors most correlated with target variables, Linear Discriminant Analysis (LDA) for identifying discriminative features, and metaheuristic or ML-wrapper methods (e.g., Genetic Algorithms, wrapper-based selection) that optimise feature subsets. Techniques such as the Successive Projections Algorithm (SPA) and Recursive Feature Elimination (RFE) iteratively refine the feature set by removing redundant or low-importance wavelengths.

Feature reduction aims to transform the original data into a smaller set of components while preserving variance. Principal Component Analysis (PCA) is the most common approach, offering efficient dimensionality reduction but not selecting original wavelengths.

Spectral preprocessing filters modify raw spectra to improve comparability and reduce noise before extraction or selection. Continuum Removal (CR) isolates absorption features by removing background shape, while Multiplicative Scatter Correction (MSC) normalises spectra to reduce scattering-related variability. These are considered normalisation filters, not feature selection methods.

Together, these processes support robust ML model development for crop stress detection. In particular, multiscale spectral indices, which integrate information from both leaf- and canopy-level measurements, help minimise scale-dependent biases and improve the retrieval accuracy of plant traits under varying stress conditions.

Compared with vegetation indices (VIs) derived directly from satellite data, RTMs offer clear advantages for global applications. Being based on physical laws, they are generally applicable across different environments. RTMs are primarily used for physically based retrieval of crop characteristics; by converting RS signals into biophysical information, RTMs allow detailed analysis in combination with other datasets.

Although RTMs can be simplified using tools like simulated look-up tables (LUTs) or artificial neural networks (ANNs), simplification often comes at the cost of reduced accuracy. Most RTMs are complex and nonlinear, simulating quantitative relationships between plant biochemical parameters and leaf/canopy spectral properties. They can detect changes in

leaf/canopy structure and biochemical composition in response to environmental conditions, making them generally more reliable than VI-based regression models. RTMs are widely used to monitor crop health traits such as chlorophyll content, leaf area index (LAI), and vegetation cover. To extract these variables, RTM inversion schemes are applied to observed reflectance data to identify the best match between simulated and measured spectra. Among RTMs, the **PROSPECT model** and its derivatives are the most widely used for leaf-level radiative transfer simulations. The original PROSPECT model required only three input parameters: structure parameter (N), chlorophyll content (Cab), and equivalent water thickness (Cw). PROSPECT-4 extended this to simulate directional-hemispherical reflectance and transmittance for a single leaf. PROSPECT-5 further included the dry matter parameter (Cm) to account for absorption by cellulose and lignin, and separated chlorophyll into a and b, along with carotenoids. PROSPECT-D introduced anthocyanins to simulate leaf optical properties throughout the plant lifecycle. The most recent **PROSPECT PRO** allows decomposition of leaf dry matter into nitrogen-based proteins and carbon-based constituents, modelling leaf proteins, cellulose, lignin, hemicellulose, starch, and sugars.

At the canopy level, **PROSAIL**, an integration of PROSPECT with the SAIL (Scattering by Arbitrary Inclined Leaves) model, is widely used. Variants like 4SAIL2 simulate canopy reflectance more accurately by accounting for variables such as the fraction of brown canopy area (fB), dissociation factor (D), hotspot effect (hot), tree shape factor (Zeta), crown cover (Cv), LAI, and leaf inclination distribution function (LIDF). PROSAIL is especially suitable for crops and grasslands, as it assumes the canopy behaves as a turbid medium. Other models, such as **SPART**, combine PROSPECT-D and SAILH with hotspot effects and include pigments like chlorophylls, carotenoids, and anthocyanins, along with water content, dry matter, leaf structure, and senescent materials, to scale leaf optical properties to the canopy level.

For RTM applications, synthetic datasets are often created for model validation, sensitivity analysis, training ML algorithms, and developing retrieval methods. These datasets include sensor, vegetation, soil, and atmospheric information, such as soil properties, leaf traits, canopy structure, sun-observer geometry, and top-of-atmosphere (TOA) radiance. Noise and random variations are often added to mimic real-world conditions. Before use, synthetic datasets are validated against ground-truth measurements to ensure accurate representation of crop stress scenarios.

Common RTM parameters include optical thickness (τ), single scattering albedo (ω_0), phase function ($P(\theta)$), albedo (ρ), reflectance (R), transmittance (T), absorption coefficient (α), LAI, and LIDF. Atmospheric parameters such as pressure, temperature, humidity, aerosol properties, and gas concentrations are also considered. RTMs can be tailored to specific applications, including vegetation monitoring, crop remote sensing, or atmospheric radiative transfer, and accurate initial parameter values are critical for reliable simulations and inversion results.

A major challenge in applying RTM inversion is “ill-posedness”, where multiple combinations of model parameters can reproduce the same observed spectrum. This complicates the interpretation of RS data and requires careful handling of uncertainties during inversion. RTM inversions can be performed using several statistical approaches, including numerical optimisation, which iteratively minimises a cost function between measured and simulated reflectance spectra. While accurate, it is computationally intensive for large-scale datasets. A second approach used LUT-based inversion, which precomputes hundreds or thousands of simulated spectra from combinations of input parameters, enabling faster retrievals. Hybrid

approaches combine the speed of ML with the physical realism of RTMs, using RTM simulations as training data and reserving ground measurements for validation (**Figure 2.5**).

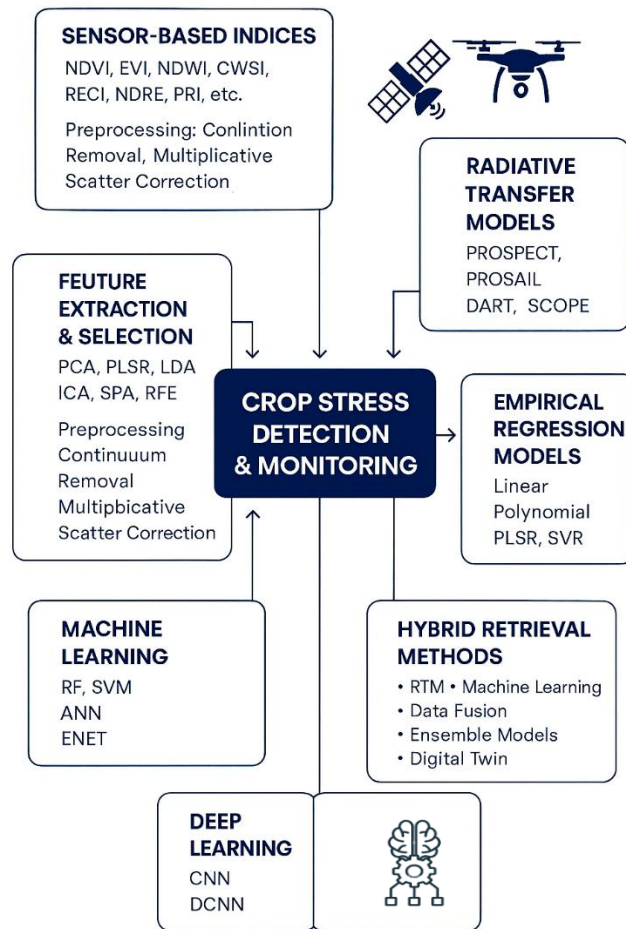


Figure 2.5 shows a schematic diagram of different crop stress detection models and techniques.

RTMs can also be coupled with other models for comprehensive crop monitoring. Integration with crop growth models (CGMs), process-based vegetation models, or phenology models allows RTMs to be trained and constrained, reducing uncertainties in biochemical retrievals and improving parameterisation (**Verrelst et al. 2015**).

Data-driven approaches, including the development of VIs and ML inverse models, rely heavily on large datasets collected from field experiments. However, these methods have some limitations, including a lack of theoretical grounding, low interpretability, limited physical explanations of light transfer in leaves, and limited generalisation across conditions. Therefore, understanding the physical transmission of optical radiation through leaves is critical to improving the accuracy of detecting plant physicochemical parameters using hyperspectral data. ML has surpassed traditional VI-based methods in performance and enables more robust stress detection through its Classification models, Regression models and Automated crop stress detection models.

Studies show that integrating multimodal data with ML or DL improves predictions of crop stress responses. Hybrid methods leverage the strengths of multiple techniques, overcoming the limitations of individual approaches, and are increasingly used in precision agriculture. They can be parametric or non-parametric. Non-parametric methods are flexible, can handle

high-dimensional data, and provide uncertainty estimates, but require more computational effort and careful optimisation. Parametric methods are simpler, computationally cheaper, and easier to interpret, but may be less accurate and less adaptable to complex datasets.

Accurate monitoring requires a clear understanding of data collection and analysis, which varies according to environmental conditions, crop species, traits measured, and growth stage. The monitoring purpose (e.g., precision farming versus environmental assessment), scale (proximal or broad), experimental control, and data type (qualitative or quantitative) must first be defined, as these factors determine the most appropriate processing approach to optimise stress detection and quantification.

For broad-scale monitoring, selecting relevant wavelengths associated with stress-specific symptoms can help create descriptive variables for ML models. Empirical regression models are suitable when robust calibration datasets are available, though they may struggle to extrapolate beyond the training data. RTMs do offer versatility across scenarios but require accurate inputs and significant computational resources, often in combination with other methods. ML can accommodate diverse stress factors and provide precise predictions if properly trained, but deep black-box models may lack interpretability and are susceptible to overfitting without sufficient high-quality data. DL is particularly effective for image-based monitoring at scale, provided ample labelled data is available. Overall, combining multiple approaches tends to yield the most reliable results.

2.1.7. Validation Framework

Effective validation relies on a feedback loop between satellite or airborne monitoring and field observations, with algorithms tested across different crops and growth stages to account for variability in stress responses. Key validation metrics include correlation coefficients, RMSE, bias, accuracy assessments, regression analyses, variance, and temporal comparisons. For hybrid models, metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are used, alongside simple measures like visual inspection, multi-location sampling, and yield assessment.

Validation approaches involve multiple complementary methods: installing ground-based instruments (e.g., spectroradiometers, thermal cameras) at independent sites; using soil moisture sensors and leaf-level measurements (chlorophyll content, leaf water potential, stomatal conductance); comparing high-resolution in-situ spectral data with RS-derived indices; and establishing validation transects to capture spatial variation. Synchronising field and RS data collection reduces temporal discrepancies, while temporal trend analysis helps characterise stress dynamics. Expert agronomist input and experimental data from mobile platforms can further enhance validation. Statistical approaches, such as Monte Carlo simulations or bootstrapping, support uncertainty estimation.

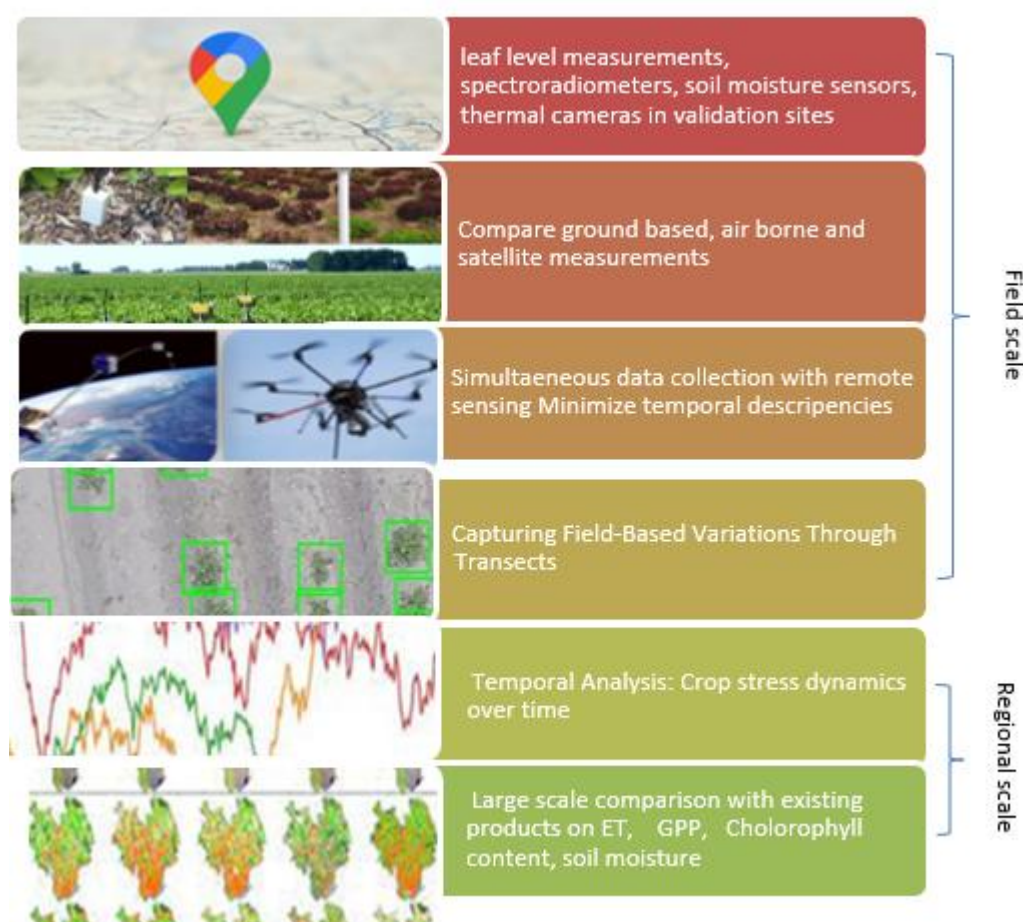


Figure 2.6 presents a common validation approach used for EO products.

Common validation approach involves linking local field measurements to regional and global RS products (Figure 2.6). Validation considers instruments and methods used, sampling schemes, integration with high-resolution imagery (EnMap, DESIS, Sentinel-2, PRISMA), algorithms for deriving crop stress indicators, and comparisons between high- and moderate-resolution products (e.g., CCI Soil Moisture, MODIS ET, LSA-SAF ET, MOD17GPP, Sen4GPP, GDMP). Existing field validation networks, such as Fluxnet, AgMerra, PhenoCam, and EnMap sites, provide support to robust assessment of the new products.

2.1.8. Existing global initiatives

Existing European and international initiatives on crop monitoring can help integrate EO data and advance global approaches to monitoring crop stress. The Copernicus Programme and Sentinel missions provide high-resolution, multi-spectral datasets essential for detecting crop stress at local to regional scales, while JRC and JPI FACCE offer scientific expertise and research networks that enhance the interpretation and application of these datasets. EU-funded projects such as MEF4CAP, INVITE, ScaleAgData, and DIONE demonstrate the practical utility of combining satellite imagery, ground sensors, and ML to improve monitoring of water, nutrient, and pest stress across diverse crops and conditions. Commercial platforms like EOS-Agro and national systems such as Poland's ADMS show the operational feasibility of translating EO data into actionable farm-level recommendations. International programmes, including WaSCIA, GEOGLAM, FAO, CGIAR, AfricaRice, and Canada's Drought Watch, extend these capabilities globally, enabling early detection of drought, nutrient, and disease

stress while supporting food security and adaptive management. Collectively, these initiatives support EO data integration, modelling, and AI-driven analytics, substantially improving the accuracy, spatial coverage, and timeliness of crop health monitoring, from both research and practical agricultural management.

3. Datasets Used

3.1. Introduction

This section provides details on datasets used within the project. It provides insight on in-situ, EO and climatic data to be used in the algorithms for monitoring stressors' impacts; ii) areas of interest for acquiring data; iii) the specifications for the EO4CerealStress data repository, i.e., time frames, extension, temporal and spatial resolution and input products to give a common framework for information shared among partners during the project term.

The project reference database was managed by the University of Seville, with contributions from all other partners. The database contained: historical campaign data, EO data and climatic data for different pilot sites (**Figure 3.1**). This data is stored on the UoS SharePoint and is accessible to the project team. It will be retained for three years from the project end date.

3.1.1. Database

The data repository is built on the Findable, Accessible, Interoperable, and Reusable (FAIR) principles outlined by Wilkinson (2016). The INSPIRE directive is considered for describing metadata and complying with the ISO 19115 and ISO 19139 metadata standards. The metadata generated by the EO4CerealStress framework was validated against the INSPIRE Reference Validator (<https://inspire.ec.europa.eu/validator/home/index.html>).

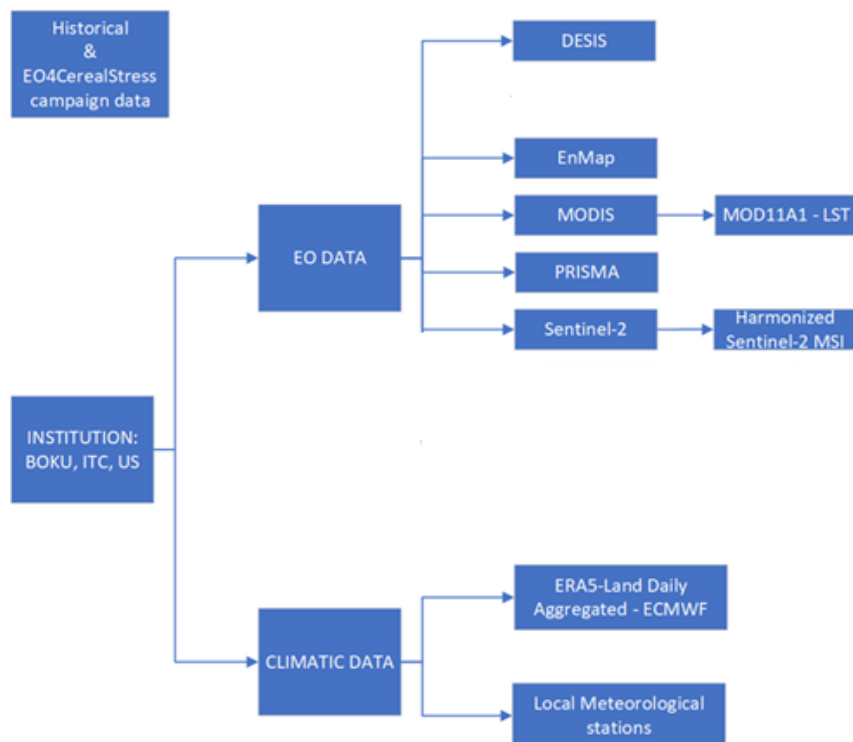


Figure 3.1: Structure of EO4CerealStress Data Repository

3.1.2. Data Categories

A range of historical airborne and field campaign datasets have been compiled to support the validation of EO data within the EO4CerealStress project. These include previous FLEXSense

and SARSense campaigns, as well as more recent fieldwork conducted in 2023 across Austria, Italy and Spain.

3.1.2.1. Historical Campaigns:

Past campaigns such as HyPlant-Italy (2014 & 2019) and HyPlant-Germany (SoyFLEX, 2015) provided high-resolution airborne hyperspectral data (VNIR, SWIR, and FLUO) for various crop types, including maize, grasses, and soybeans. These missions also incorporated extensive ground measurements, including chlorophyll content (SPAD readings), leaf water potential, stomatal conductance, canopy temperature, and flux data. The SARSense (2019) campaign in Germany gathered multi-temporal data for sugar beet, wheat, barley, maize, and rapeseed, complemented by detailed biomass and canopy structure measurements.

3.1.2.2. Multisource EO data

An initial assessment of the data repository requirements for each pilot site, the expected EO products, and the estimated image sizes and acquisition frequencies was conducted. Six main satellite data sources are considered for the EO4CerealStress project.

- i. DESIS (DLR Earth Sensing Imaging Spectrometer): Installed on the ISS, DESIS captures hyperspectral imagery in the visible and near-infrared (400–1000 nm) range with 235 spectral bands and ~30 m spatial resolution. Each image covers ~900 km² and is ~2.3 GB in size. One image has been acquired for the Seville AOI, with further acquisitions planned for other sites.
- ii. EnMAP (Environmental Mapping and Analysis Program): EnMAP collects hyperspectral data from 420 to 2450 nm across 246 bands at a 30 m spatial resolution and a 30 km swath width. The satellite provides a 27-day revisit (4 days off-nadir). Each image (~1.2 GB) is available upon request, and multiple scenes are being acquired for all AOIs.
- iii. PRISMA (PRecursore IperSpettrale della Missione Applicativa): PRISMA's hyperspectral camera (HYC) records 237 bands from 400–2505 nm at 30 m resolution and 30 km swath width. Each scene (~5.6 GB) is available for download upon request. Three images have been obtained for the Spanish AOI, with additional acquisitions planned.
- iv. MOD11A1 – MODIS Land Surface Temperature (LST): The MOD11A1 V6.1 product provides daily global LST and emissivity data at 1 km spatial resolution. From 2000–2023, each AOI (Austria, Spain, Italy) is covered by a single MODIS tile (~8,712 acquisitions), with total data volumes ranging from 0.83 to 1.08 TB per site. Overall storage requirements for MOD11A1 are estimated at <2.75 TB and can be reduced by cropping to AOIs.
- v. Harmonised Sentinel-2 MSI: Sentinel-2A/B provides multispectral imagery across 13 bands with resolutions of 10–60 m and a global 5-day revisit. L2A products are processed using Sen2Cor, with QA bands for cloud masking. For 2019–2023, the expected total data volumes are approximately 1.01 TB (Austria), 1.08 TB (Spain), and 0.58 TB (Italy), totalling <2.5 TB in compressed form. This size can be reduced by excluding high-cloud scenes and by cropping mosaics within the AOI. All these sources will comprise multi-sensor datasets with an estimated total raw volume below 8 TB, before optimisation and processing.

6. Climatic Data: Two main sources of climate information are shortlisted:

- i. ERA5 Daily Aggregates (ECMWF): A global reanalysis providing daily values for temperature, precipitation, wind, pressure and other key parameters on a 0.25° grid

from 1979 onwards. For EO4CerealStress, data from the past three decades (1993–2023) are used to compute climatic normal, with a total storage requirement of less than 3 GB.

- ii. Local Meteorological Stations: Complementary, real-time monitoring data are drawn from national and regional sources to address the delay in climate grid updates. These include the Andalusian Environmental Information Network (REDIAM), the Agrarian and Fisheries Training Institute of Andalusia (IFAPA), the Agroclimatic Information System for Irrigation (SIAR), and the SPARTACUS v2.1 daily gridded temperature and precipitation dataset over Austria (1 km resolution).

Table 3.1a lists the datasets used in the project and their products with sharing status.

EO/in-situ Dataset	EO Product	Acquisition timeframe	Sharing Status
Sentinel-2 MSI Level-2A	Drought maps, lodging severity maps, soil salinity maps, nutrient deficit maps, heavy metal maps, rice crop trait maps (LCC, CCC, CAR, LAI, LWC, LNC, CNC)	25 Jun 2023, 30 Jul 2023, 14 Aug 2023, 29 Aug 2023, 13 Sep 2023, 23 Sep 2023, 03 Aug 2024 (pilot one); 23 May 2023 (pilot two); 2018-2023 (pilot three);	Product published on Open Science Catalogue under license CC-BY-ND-4.0. Data available on request.
EnMAP	Soil salinity, carbon, nitrogen, iron and heavy metal maps; rice crop trait maps; lodging severity maps	22 Mar 2023, 22 Apr 2023, 24 Jul 2023, 20 Sep 2023, 01 Aug 2024 (pilot one); 21 May 2023 (pilot two)	Product published on Open Science Catalogue under license CC-BY-ND-4.0. Data available on request.
PRISMA	Soil salinity, carbon, nitrogen, iron and heavy metal maps; rice crop trait maps	02 Mar 2023, 10 May 2023, 25 Jul 2023, 17 Aug 2023, 30 Jul 2024 (pilot one)	Product published on Open Science Catalogue under license CC-BY-ND-4.0. Data available on request.
UAV Hyperspectral Imagery (Headwall Hyperspec) – Pilot one	High-resolution crop stress maps and calibration/validation datasets for satellite products	2023 field campaign (May-June bare soil; July-September rice) and 2024 campaign (July-August rice season) ; approximately five flights per campaign	Available on request – EO4CerealStress website
ASD FieldSpec 4 Spectroscopy	Reference spectra for model calibration and validation; trait retrieval and lodging assessment datasets	Ricefield campaign 2023 (soil and crop measurements); Italy lodging campaign 30 Apr-18 May 2023 (crop measurements)	Available on request – EO4CerealStress website

Field Measurements (soil, crop biophysical and biochemical variables)	Reference datasets for calibration and validation; soil properties, LAI, chlorophyll, nitrogen, water content, lodging score and drought observations	2023-2024 field campaigns across Spain, Italy and Austria	Available on request – EO4CerealStress website
Climate Data (ERA 5, SPARTACUS, REDIAM, SIAR, IFAPA)	Temperature, precipitation and other climatic variables used for drought modelling and validation	2019-2023	Public, local datasets available on request.
Reference Datasets: Historical HyPlant Italy, HyPlant Germany (SoyFLEX), Sarsense Campaign	Historical airborne hyperspectral calibration/validation dataset, Historical EO and field dataset supporting algorithm testing and validation	2014,2015, 2019	Available on request – EO4CerealStress website

Together, these datasets provide an integrated framework of EO and climatic information to support the assessment of crop stress conditions across the European pilot sites (**Table 3.1**).¹

3.1.2.3. EO4CerealStress Field Data (2023):

Field campaigns were undertaken at three pilot sites: Austria (Marchfeld Region), focusing on maize under water-stress conditions, with soil and irrigation data collected. Spain (Doñana, Andalusia): Studied rice under salinity, heavy metal and heat stress, with extensive plant and soil biochemical and spectral measurements. Complementary datasets (SAMA campaign) included nutrient and heavy-metal analyses of plants, soils, and grains. Italy (Jolanda di Savoia, Ferrara): Investigated lodging in winter wheat through spectral and biophysical measurements such as canopy height, density, biomass, and tiller numbers.

Pilot Sites cover Marchfeld (Austria): 1,120 km², primarily maize, Guadalquivir Marshlands (Spain): 1,260 km², rice cultivation and Jolanda di Savoia (Italy): 6.64 km², winter wheat. These regions represent key European cropland areas affected by different abiotic stressors. For each AOI, roughly 1,000 km² were defined, within which relevant imagery and datasets are being gathered. All products and datasets will be catalogued in the ESA Open Science Data Catalogue ([ESA Open Science Catalog](#) | [ESA Open Science Catalog](#))

¹ Open datasets (Sentinel-2 and ERA5) are publicly accessible through their respective data portals. Project-generated field, UAV, spectroscopy are not publicly distributed but may be shared upon reasonable request, subject to consortium member approval and the licensing conditions of the original data providers. However ready to use EO stress products are available on ESA open science catalogue ([ESA Open Science Catalog](#) | [ESA Open Science Catalog](#)) .

3.1.2.4. Storage Summary

Table 3.2 Summary of space requirements by sensor/product and AOI.

Sensor/product	Time period	AOI: AU	AOI: ES	AOI: IT	Total size
DESI	2023	***	2.3 GB	***	2.3 GB
ENMAP	2023	1.2 GB	3.6 GB	1.2 GB	6.0 GB
PRISMA	2023	***	5.6 GB	***	5.6 GB
S2A/B MSIL2A	2019-2023	0.83 TB	1.08 TB	0.58 TB	2.49 TB
ERA5 Daily	1993-2023	***	***	***	3GB
TOTAL					2.51 TB

Table 3.3 Summary of EO product data size and storage.

EO Product	Time period	AOI: AU	AOI: ES	AOI: IT	Total size
ENMAP	2023	***	17.4 MB	7.58 MB	24.98 MB
PRISMA	2023	***	3.32 MB	***	3.32 MB
S2A/B MSIL2A	2019-2024	12.8 GB	104 MB	8.68 MB	12.912 GB
Meteo Data	2018-2023	3 GB	3.06 MB	***	3.00306 GB
Irrigated & non-irrigated maps	2023 drought	3 GB			3 GB
TOTAL					18.94 GB

4. Algorithm Development

The EO4Cerealstress project has developed advanced EO-based methodologies to monitor cereal crop responses to multiple stressors (soil salinity, nutrient deficits, heavy metals, lodging, and drought). It integrates hyperspectral/multispectral satellite data (EnMAP, PRISMA, Sentinel-2), UAV-based imaging, and in-situ measurements with ML, DL, and RTMs to develop frameworks for monitoring and assessing these stressors (**Figure 4.1**). This activity aims to establish a scientific foundation for future EO products and methods addressing crop stress by evaluating all the methods described in the Figure.

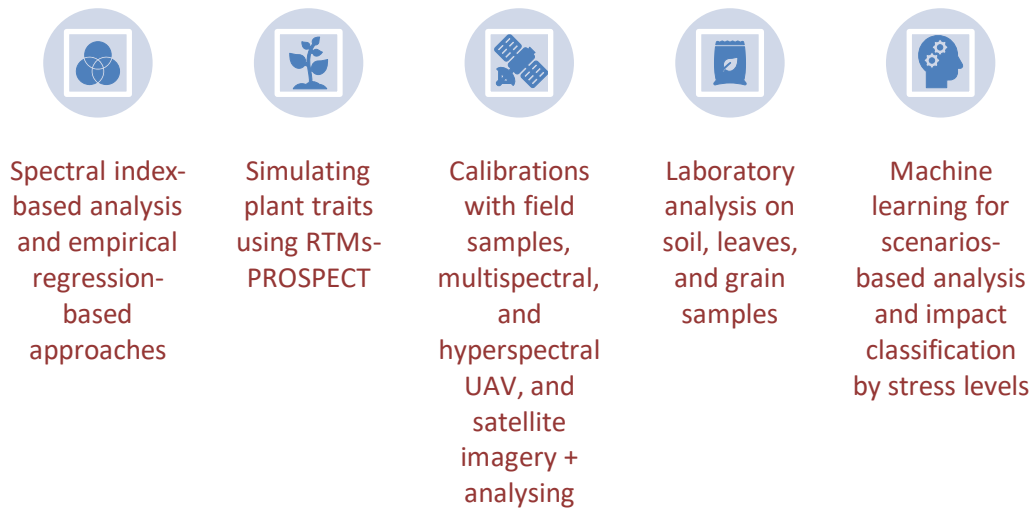


Figure 4.1 provides an overview of the methods used to develop stress detection and monitoring frameworks.

EO4Cerealstress has developed products from three crop stress Pilots by focusing on the following stressors:

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

Each of these pilots develops an integrated crop stress detection system that combines the scientific strengths of high-spectral- and high-spatial-resolution multi-sensor EO data on the one hand and state-of-the-art ML and physical models on the other. This section summarises the scope, algorithm trade-off, algorithm description, and validation of all three crop stress pilots.

4.1. Pilot One: Soil Stress in Rice (Guadalquivir Marshlands, Spain)

4.1.1. Goal

The main goal of this pilot site is to enhance the understanding and monitoring of how different abiotic stressors affect rice cultivation. This is achieved by applying advanced EO techniques and identifying key biophysical and biochemical indicators linked to crop health by:

- Analysing the relationship between multiple stressors and the temporal evolution of rice crop conditions.

- Improving understanding of rice responses to stress factors such as soil salinity, nutrient deficiencies, heavy metal toxicity and high temperatures.
- Evaluating the potential of Sentinel-2, PRISMA and EnMAP satellite missions for monitoring multiple stress types in rice.
- Identifying the most relevant biophysical and biochemical traits that reflect the impacts of these stressors on rice crops.

4.1.2. Pilot Site One Description

The Guadalquivir marshlands, situated in southern Spain, cover approximately 781 km² of flat valley terrain within the former estuary of the Guadalquivir River. The area's Quaternary deposits form a uniform geological landscape of high ecological significance, encompassing the Doñana Natural Park, the largest ecological reserve in Europe and a UNESCO World Heritage Site. The park supports exceptional biodiversity, including endangered species such as the Iberian lynx (*Lynx pardinus*) and the Spanish imperial eagle (*Aquila adalberti*).

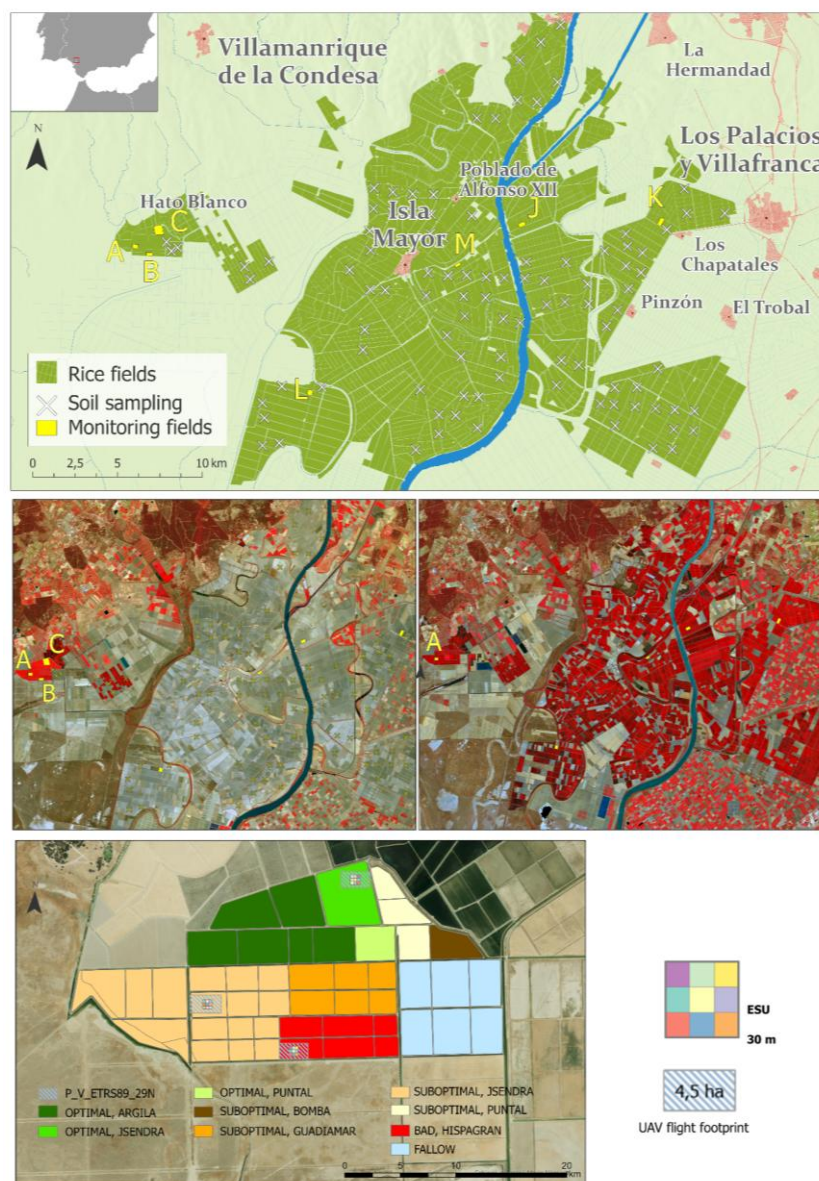


Figure 4.2 Location of Rice crop fields in the Guadalquivir marshlands, ESU design and UAV flight footprint for soil sampling

Agriculture in the marshlands is dominated by rice cultivation, typically restricted in Spain to saline and environmentally sensitive deltaic and marshy regions. Andalusia leads national rice production, contributing roughly one-third of Spain's total output. The Andalusian Federation of Rice Growers (AFR), founded in 1986, represents approximately 960 farms, covering 99% of the regional rice area, with an average farm size of 33.65 hectares. Under normal conditions, around 39,000 hectares are cultivated annually, yielding approximately 350,000 tonnes in Seville province.

During the 2023–2024 study period, the region suffered a severe drought, recording only 310.1 mm of rainfall, significantly below both the long-term mean (464.8 mm) and the previous five-year average (378.5 mm). Reduced river flow and saline intrusion from the sea limited irrigation water availability, resulting in only 2.5% of rice fields (under 1,000 ha) being sown in 2023. One of the few active sites was Hato Blanco Nuevo, located in the western Lower Guadalquivir area, where ~400 ha of seed rice was cultivated using groundwater from Doñana's aquifer, characterised by lower salinity and higher quality.

Field campaigns in 2023 included hyperspectral UAV flights and Elementary Sampling Units (ESUs) over selected monitoring plots, as shown in **Figure 4.2**, to analyse crop health and environmental conditions through both remote sensing and ground measurements.

4.1.3. Field Data Collection

A comprehensive data collection campaign was conducted between **March 2023 and August 2024** across the Guadalquivir marshlands to characterise soil properties and monitor rice crop development using both in situ and RS observations.

- i. Soil Sampling (2023 Campaign) Before the flooding of the rice fields (May–June 2023), a bare soil sampling campaign was undertaken following a 1 km MODIS grid. Spatial variability was accounted for by clustering EnMAP imagery, yielding 100 soil samples averaging approximately 2 kg each. Laboratory analyses determined electrical conductivity, total carbon and nitrogen, and eleven heavy metals (Fe, Al, Cr, Mn, Co, Ni, Cu, Zn, As, Cd and Pb). The samples were spectrally characterised using an ASD FieldSpec 4 spectroradiometer (350–2500 nm range), with calibration against a Spectralon™ reference panel. Results revealed moderate to high salinity levels (average EC 11.15 dS/m) and some variability in metal concentrations
- ii. Rice Crop Data Sampling (2023 Campaign) Following field flooding, hyperspectral UAV flights and field measurements were carried out every 15 days (July–September 2023) in three monitoring plots at Hato Blanco farm. These campaigns coincided with Sentinel-2, PRISMA, and EnMAP overpasses to enable multi-sensor data synergy. Within each field, nine 30×30 m ESUs were established, matching the spatial resolution of hyperspectral satellites.
- iii. At each ESU, measurements included: Leaf sampling for nitrogen, moisture, dry weight, and fresh weight analysis. Pigment analysis, including chlorophyll a, chlorophyll b, and carotenoids, using both SPAD-502 Plus readings and methanol-based extraction followed by spectrophotometric analysis. Canopy measurements of LAI using a LI-COR LAI-2200C under uniform illumination conditions. Due to extreme drought conditions (only 2% of rice area cultivated in 2023), crop variability was limited; all monitored plots exhibited healthy vegetation, benefiting from groundwater irrigation of lower salinity. The 2023 dataset included **142** LAI measurements (mean = 6.04

- m²/m²) and **87** nitrogen samples (mean = 126.4 µg/cm²), with corresponding pigment and SPAD values.
- iv. Rice Crop Data (2024 Campaign) A second field campaign was conducted in August 2024, when ~24,000 ha (66% of the total rice area) was cultivated. Five plots (A, J, K, L, and M) were selected to capture a broader range of crop conditions. The methodology mirrored that of 2023, combining in situ measurements, UAV hyperspectral data, and satellite imagery (EnMAP, PRISMA, Sentinel-2).
 - v. Derived Biophysical Parameters Post-processing included the derivation of key leaf- and canopy-level biochemical parameters, based on literature models (e.g. Berger et al., 2020; Féret et al., 2021; Tagliabue et al., 2022): Leaf Water Content (LWC) from fresh and dry weight ratios, Protein Content (Cp) derived from leaf nitrogen content (LNC) using a conversion factor of 4.43, Leaf Mass per Area (LMA) and Carbon-Based Constituents (CBC), calculated as CBC = LMA – Cp, Canopy Chlorophyll (CCC) and Canopy Nitrogen Content (CNC) derived from leaf-scale concentrations multiplied by LAI. Solar Zenith Angle (SZA) and other RTM input parameters were determined from image metadata and reference studies.

4.1.4. EO Data Collection

A combination of multispectral, hyperspectral, and UAV-based datasets was used to monitor the pilot site for the Guadalquivir marshlands. These datasets were selected to provide complementary spectral, spatial, and temporal information, supporting analyses of both bare soil and rice crops.

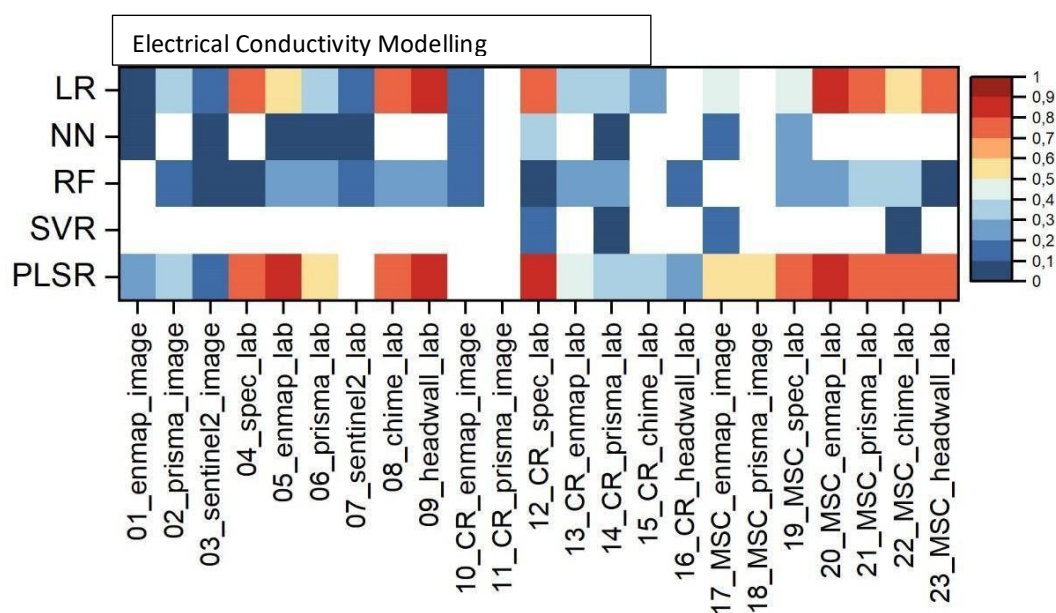
- i. Multispectral Missions (Sentinel-2) For the Guadalquivir pilot area, all available **Level-2A atmospherically corrected** Sentinel-2 images were retrieved from **Google Earth Engine** for the periods **25 July–23 September 2023** and **3 August 2024**. A polygon covering the entire study area (tiles **29SQB** and **30STG**) was used to automatically mosaic the imagery, and a **cloud mask** was applied during download.
- ii. Hyperspectral Satellite Missions (EnMAP and PRISMA) The **EnMAP** (DLR, Germany) and **PRISMA** (ASI, Italy) hyperspectral missions provide detailed spectral data (400–2,500 nm) with **>200 bands**, **30 m spatial resolution**, and a **<30-day temporal resolution**. These datasets enable the detection of subtle spectral absorption features associated with crop stress and soil composition that are not observable in multispectral data. All EnMAP and PRISMA scenes were obtained through their official portals on request, prior to sowing, under bare-soil conditions, and during the rice growth stage (EnMAP [22 March 2023, 22 April 2023, 24 July 2023, 20 September 2023, and 1 August 2024]; PRISMA [2 March 2023, 10 May 2023, 25 July 2023 and 30 July 2024]). The acquisitions covered both bare soil and rice growth stages; details are in **Table 1.3 of the ATBD document**. These missions also act as benchmarks for upcoming operational hyperspectral missions such as **ESA's CHIME**.
- iii. Hyperspectral UAV Acquisitions: Complementary UAV hyperspectral flights were carried out over both bare soils and rice crop plots in temporal proximity to satellite acquisitions, approximately every 15 days, with 5 bare-soil flights in 2023, repeated crop flights in 2023, and 5 crop flights in 2024. The system used was a Headwall Hyperspec Co-Aligned VNIR–SWIR sensor, mounted on a hexacopter UAV with a 1.5 m wingspan and gimbal-stabilised orientation. The instrument captured 270 VNIR and 267 SWIR bands (400–2,500 nm) at a ground sampling distance of 5 cm (at 80 m AGL), with each flight covering approximately 4.5 ha, sufficient to include all 9 ESUs. Pre-flight radiometric calibration employed Spectralon™ reflectance panels (99% and

95%), and a three-step grayscale tarp (56%, 30%, 11%). These reference targets were also measured with an ASD FieldSpec 4 spectroradiometer to ensure consistency between field and UAV data. High-precision georeferencing was achieved using an Emlid Reach RS2 GNSS receiver connected to the Andalusian Positioning Network (RAP), enabling sub-centimetre RTK corrections. All radiometric and geometric corrections were performed using Headwall's proprietary software.

4.1.5. Algorithm & model validation

Multiple validation approaches were implemented to ensure the robustness and accuracy of the models developed for soil and crop trait estimation. Details are in section 1.3 of **RD-3.1 ATBD**.

Soil Parameter Modelling Model validation followed a two-step process. Firstly, hyperparameter tuning was conducted through 10-fold cross-validation to optimise model performance (see *Trade-off Analysis for Soil Salinity, Nutrient Deficit, and Heavy Metals in RD-3.1: ATBD*). Secondly, model deployment used a fixed 80/20 train-test split, with validation performed on the test subset. The predictive accuracy of each model was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE) (refer to the PVR document for full details). The figure shows the comparative performance (R^2 and RMSE) of five ML models (PLSR, RF, SVR, ANN, LR), over spectral features pre-processed by Continuum Removal, MSC, PCA, and RFE methods, evaluated with an 80/20 train-test split. Among them, PLSR was the best-performing ML approach overall when combined with hyperspectral data (EnMAP/PRISMA). The highest predictive accuracy among the soil parameters was achieved for soil nitrogen using PRISMA + PLSR, with $R^2 = 0.885$ and RMSE = 1.406



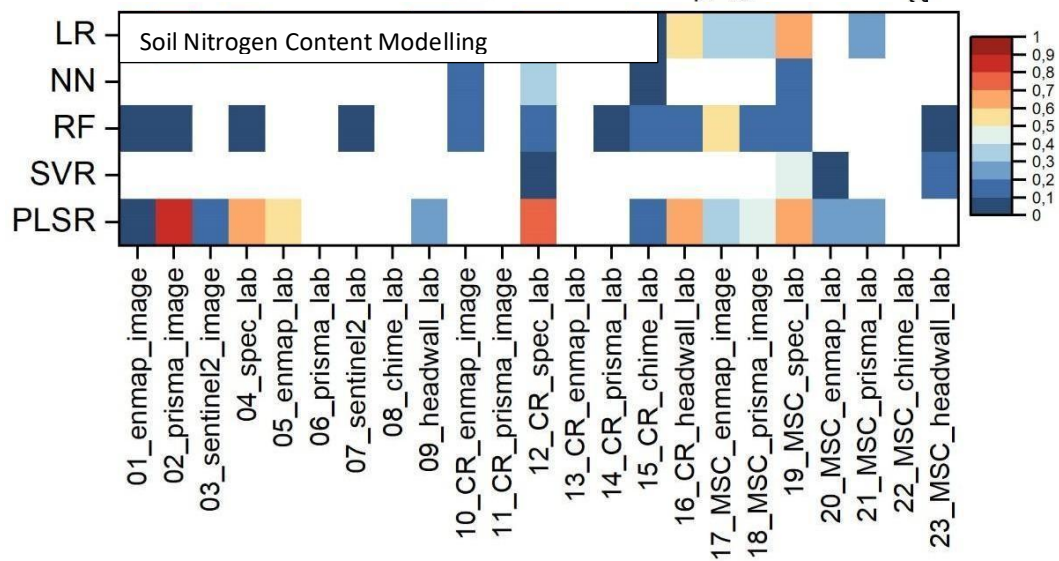
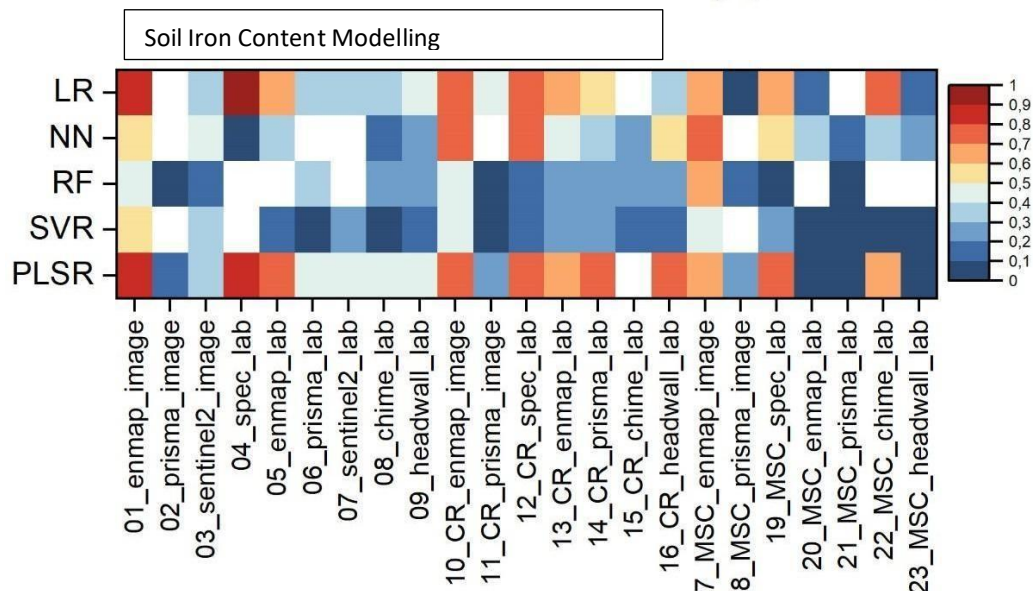
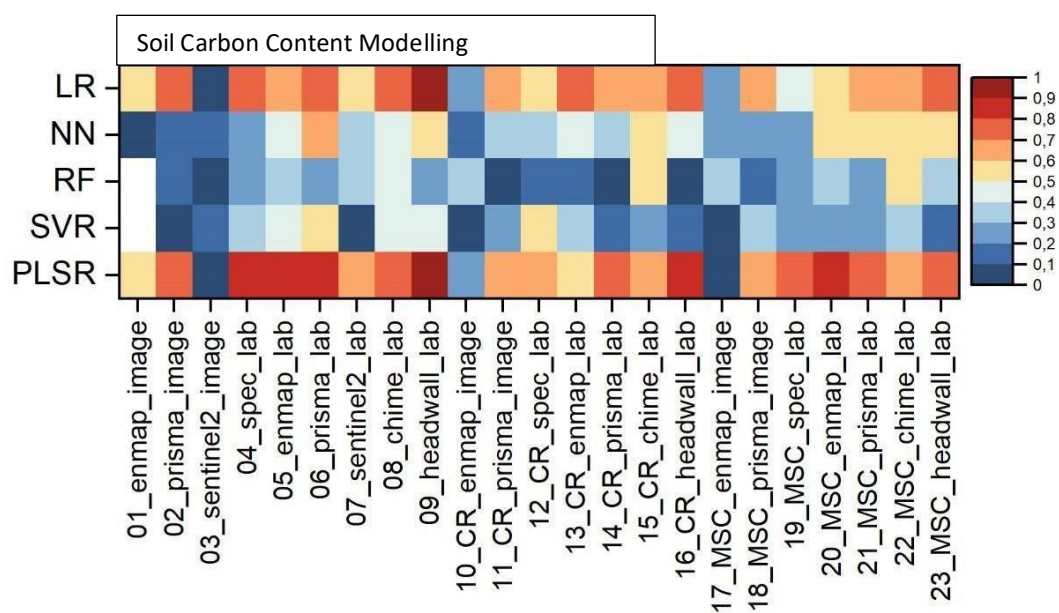
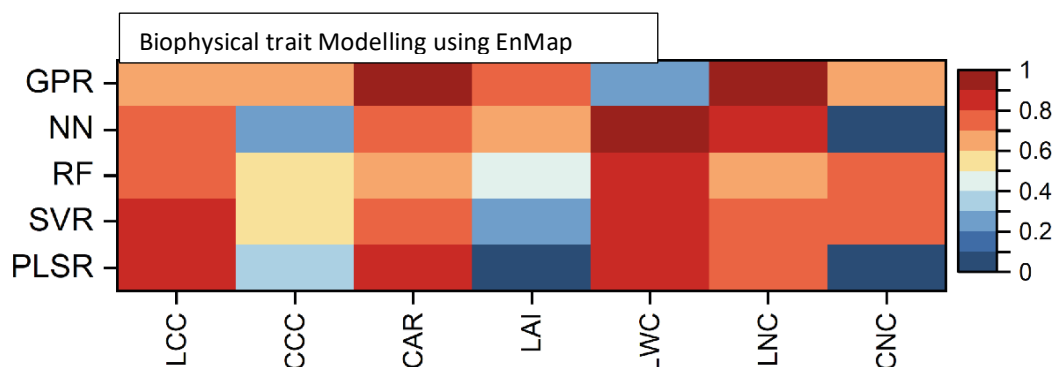


Figure 4.3 Trade-off analysis of algorithm performance for soil salinity (electrical conductivity), carbon, nitrogen and iron content based on R^2 comparison across dataset–algorithm combinations.

Crop Biophysical Trait Modelling Validation of crop trait models employed a fixed test set comprising all available field samples (see **Table 1.2 of RD-3.1: ATBD**). The number and proportion of test samples varied depending on the variable under analysis, as active learning was used to optimise the selection of training data (see **Section 1.2.4.2 of RD-3.1: ATBD**). Differences in rice biophysical and biochemical parameters were visualised using a boxplot and further examined statistically using two-tailed independent-samples t-tests (equal variances assumed). A significance threshold of $p < 0.05$ was used to determine meaningful differences between stressed and non-stressed conditions.

To evaluate the influence of environmental stressors, a case-control analysis was conducted comparing stressed (saline and/or nutrient-deficient) and control zones within the AFR region. This approach assessed both individual and cumulative stress effects: Salinity stress alone, and combined salinity and nitrogen deficit (cumulative stress). Significant reductions in LCC, CCC, LAI and LWC under both salinity and combined stress, with the most pronounced effects observed under cumulative stress. Leaf Nitrogen Content (LNC) remained stable under salinity but slightly increased when combined with nitrogen deficit, likely reflecting compensatory nitrogen redistribution. Conversely, Canopy Nitrogen Content (CNC) decreased under both conditions, indicating reduced nitrogen assimilation at the canopy level. EnMap outperformed Sentinel-2 in predicting these rice traits (**Figure 4.4**). Detailed results are available in **Section 1.3.5 of RD-3.1: ATBD**.

Comparative analysis between Sentinel-2, PRISMA and EnMAP data confirmed that EnMAP's hyperspectral capabilities enable a more accurate detection of crop stress responses, and PRISMA also showed, in some cases, sharper contrasts between stressed and control areas, particularly in nitrogen and EnMAP for iron and salinity (**Figure 4.3**). Sentinel-2 successfully captured general stress patterns but exhibited lower sensitivity to subtle physiological changes.



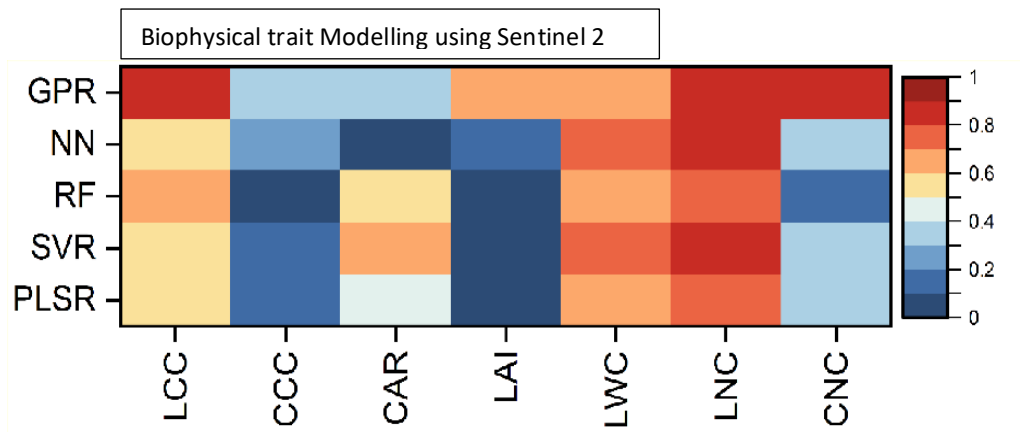


Figure 4.4 EnMap vs Sentinel 2 performance in predicting rice crop traits.

The validation results revealed the added value of hyperspectral observations for precisely quantifying the cumulative impacts of multiple stressors on crop physiology. These findings highlight the importance of integrating hyperspectral EO data into precision agriculture workflows to improve stress detection and support sustainable crop management strategies under adverse environmental conditions.

4.1.6. Strengths and Limits of Multiple Stressors' Approach

The strong potential of ML approaches using hyperspectral EO data stems from their ability to capture fine spectral variations associated with soil and vegetation properties. Soil stressors such as salinity, carbon (C), nitrogen (N), and iron (Fe) show strong correlations with spectral signatures, enabling reliable modelling when datasets are properly calibrated. Crop biophysical traits, including Leaf Chlorophyll Content (LCC), Carotenoid Content (CAR), Leaf Nitrogen Content (LNC), Leaf Water Content LWC, LAI, Canopy Chlorophyll Content (CCC), and Canopy Nitrogen Content (CNC), benefits substantially from the detailed spectral resolution provided by sensors such as EnMAP and PRISMA. These capabilities position hyperspectral EO data as a cornerstone for precision agriculture, supporting data-driven monitoring and management of soil and crop conditions. However, the relationships between soil parameters and spectral features can be site-specific, limiting the transferability of models across regions. With only 100 soil samples, the models developed in this study may struggle when applied beyond the conditions represented in the training dataset (e.g., different lithologies or farming systems).

The high number of spectral bands in hyperspectral sensors relative to the number of samples introduces a dimensionality challenge, requiring the application of dimensionality reduction techniques. For soil-property modelling, Recursive Feature Elimination (RFE) followed by Principal Component Analysis (PCA) was used, and PCA combined with Active Learning (AL) was used for rice trait retrieval. These approaches reduced both spectral dimensionality and the size of the PROSAIL-generated look-up tables before machine-learning training. This has restricted the use of more complex ML algorithms, sometimes favouring simpler, more linear models.. Accurate estimation of crop traits depends heavily on both spectral and spatial resolution. Hyperspectral sensors (e.g., EnMAP) provide superior spectral detail, enabling precise modelling of complex traits. In contrast, multispectral sensors (e.g., Sentinel-2) offer higher spatial resolution and revisit frequency but lack the spectral sensitivity required to capture subtle physiological variations. Soil models trained using laboratory-convolved spectra may not directly translate to the satellite scale due to spatial heterogeneity. Similarly,

crop trait models trained on RTM simulations or UAV-scale data may lose accuracy when upscaled to regional or satellite scales, particularly when using multispectral data.

EnMAP has shown the strongest capacity to preserve trait variability, especially for parameters like carotenoids and CCC, which require narrow-band spectral sensitivity. Both EnMAP and PRISMA can accurately characterise abiotic stressors; their limited data availability and acquisition frequency constrain temporal monitoring. Sentinel-2 can partially compensate for temporal coverage but lacks spectral resolution. The upcoming Copernicus CHIME-A and CHIME-B missions are expected to address this limitation by providing systematic hyperspectral coverage with improved temporal frequency, although challenges related to spatial resolution (e.g., for soil salinity mapping) will likely persist. UAV-based experiments will help assess how spatial resolution affects stress detection. Water absorption bands around 1400 nm and 1900 nm interfere with EO-based detection of soil salinity. Although these regions were characterised using laboratory spectra, they had to be excluded from models using EnMAP and PRISMA data, reducing sensitivity within these spectral ranges.

Estimating heavy metals in soils remains challenging. Despite the fine spectral resolution of hyperspectral data, overlapping spectral features, soil heterogeneity, and environmental factors (e.g., moisture and organic matter) limit accuracy. Multispectral sensors are even less effective due to their fewer, broader bands, which cannot isolate trace-element signatures. For soil property modelling, Partial Least Squares Regression (PLSR) showed the best overall performance, likely because the small sample size favoured simpler, interpretable models. For crop biophysical traits, Gaussian Process Regression (GPR) and Support Vector Regression (SVR) achieved the highest accuracy for traits such as LCC and CAR. EnMAP data revealed stronger, more detailed responses of traits such as LWC, LNC, and LCC under combined salinity and nutrient-deficit stress. Sentinel-2 captured general trends but with lower sensitivity due to its reduced spectral resolution. Overall, the study's insights will support the design of stress-effect products based on narrow-band spectral indices, optimising their operational applicability for sustainable agricultural management.

4.2 Pilot Two: Crop Lodging in Wheat (Ferrara, Italy)

4.2.1 Scope

In this pilot site, a comprehensive RS framework was developed for the detection, quantification, and analysis of crop lodging using advanced satellite EO technologies. By integrating field hyperspectral measurements, EnMAP hyperspectral satellite data, and Sentinel-2 multispectral imagery, it accurately identifies the timing, spatial extent, and severity of lodging in wheat fields. The analysis employed narrowband vegetation indices, ML algorithms, and RTM to evaluate the spectral and structural responses of lodged crops. The comparative performance of these approaches is assessed to determine the most effective methods for operational lodging monitoring using state-of-the-art EO data. In this hybrid modelling framework, ML is combined with the PROSAIL model to interpret canopy-level spectral responses. Using PROSAIL simulations, key structural parameters, such as crop inclination angle and Leaf Area Index (LAI), are analysed to identify lodged fields and estimate lodging severity. This approach helps isolate the spectral regions most sensitive to lodging, providing new insights into the biochemical and physiological changes in affected crops. The findings not only improve lodging detection but also facilitate a deeper understanding of how lodging alters crop spectral signatures, aiding in the design of more resilient management strategies. The resulting open-access product (maps of lodging extent and severity) is shared

with the management team of Bonifiche Ferrarsi farm; it is reproducible and can be used to estimate losses from lodging stress at a larger scale from experimental fields.

4.2.2 Pilot site 2

Bonifiche Ferraresi farm, owned by one of Italy's largest agri-food companies, is one of the pilot sites for monitoring and detecting wheat lodging. Located in the province of Ferrara, in the Emilia-Romagna region, near Jolanda di Savoia, the farm encompasses 3,850 acres of arable land, predominantly on silty and clayey soils (**Figure 4.5**). The area experiences a warm, temperate climate, conducive to the cultivation of a wide range of crops. Farm practices a rotational cropping system across several years, cultivating wheat, barley, corn, rice, soybeans, potatoes, and other horticultural and medicinal crops. Winter wheat is sown between late October and early November and harvested by the end of June, a period during which it is particularly vulnerable to severe lodging. In May 2023, a total of 664.24 hectares were planted with three wheat varieties for the study: emmer wheat (*Triticum dicoccum*), durum wheat (*Triticum durum*), and soft wheat (*Triticum aestivum*). These plots provided the basis for comprehensive monitoring and analysis of lodging events under typical regional cultivation practices.

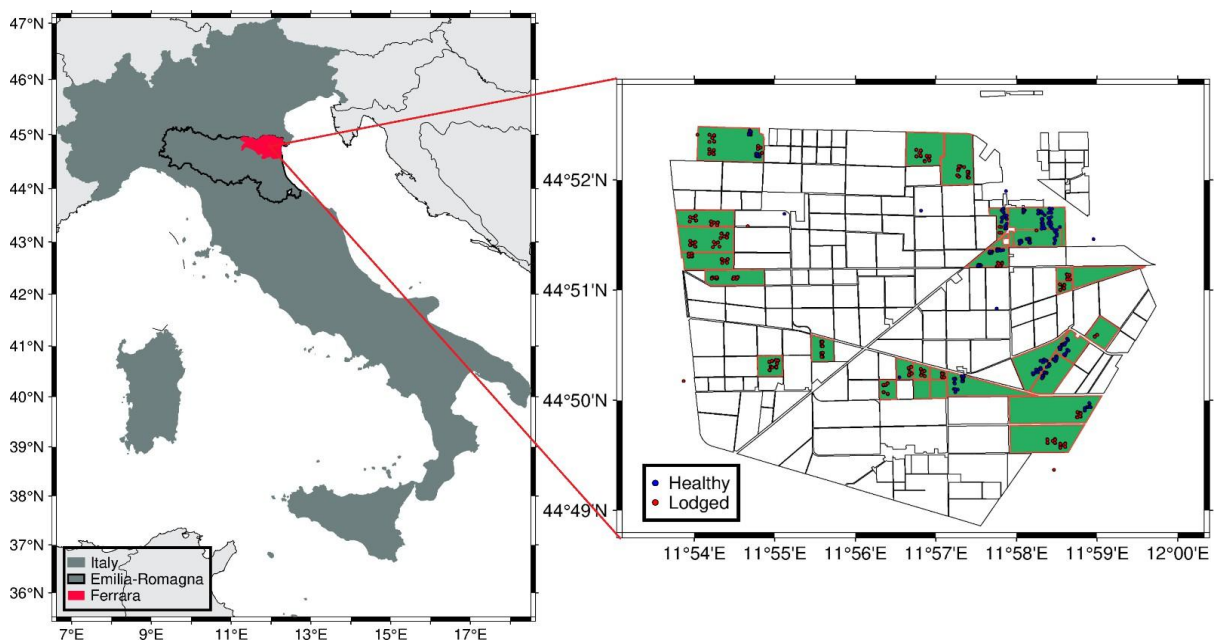


Figure 4.5 presents the location of Bonifiche Ferrarsi Farm in Ferrara, Italy and the sample distribution for healthy and lodged plots.

4.2.3 Field Data Collection

A comprehensive field campaign was conducted from 3 - 18 May 2023 to collect the measurements needed to calculate wheat lodging scores. During this period, the wheat was at the flowering stage, when lodging is most likely to occur. Sampling sites were selected using a stratified random sampling approach to ensure representative and unbiased coverage across the study area.

Sampling was performed at three spatial scales to capture variability at both macro and micro levels: Primary plots (90 × 90 m): designated as the main units for EnMAP hyperspectral data analysis. Subplots (15 × 15 m): five subplots were nested within each primary plot to capture intermediate-scale variability for subsequent Sentinel-2 multispectral analysis. Microplots (1 × 1 m): three microplots per subplot were sampled to examine fine-scale variability in crop characteristics (**Figure 4.6**).

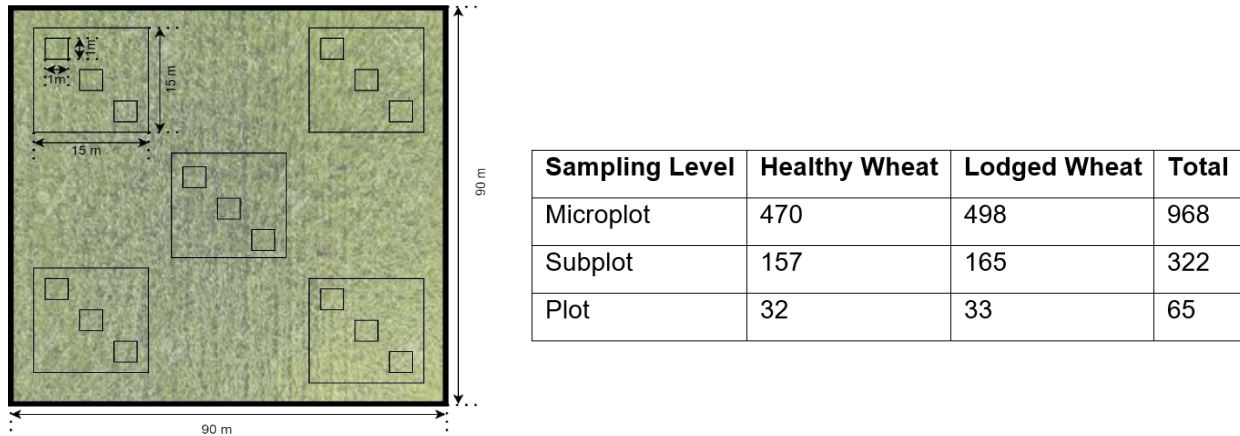


Figure 4.6: Elementary Sampling Unit (ESU) design and number of samples taken over plots

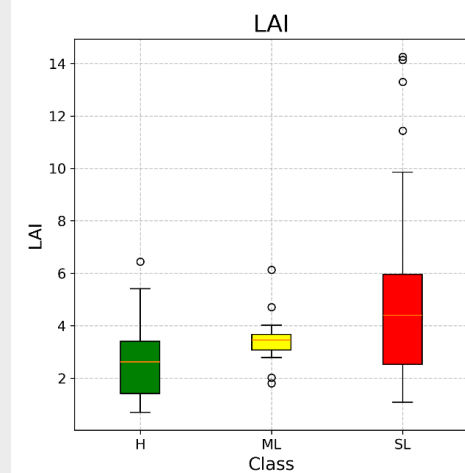
Several biophysical and biochemical lodging parameters were recorded to assess crop physiological status and responses to lodging: Crop Height, Crop Inclination Angle (CAI), and Lodging Score (LS). The CAI quantifies the tilt of plants relative to the vertical. The LS incorporates CAI and the visually estimated lodged area (LA), classifying plots as: Healthy: $0 \leq LS \leq 0.05$, Moderately lodged: $0.05 < LS \leq 0.35$, and severely lodged: $0.35 < LS \leq 0.90$.

$$LS = \frac{LA\%}{100} \cdot \frac{CAI_{\theta}}{90^{\circ}} \quad (\text{Eq. 4.1})$$

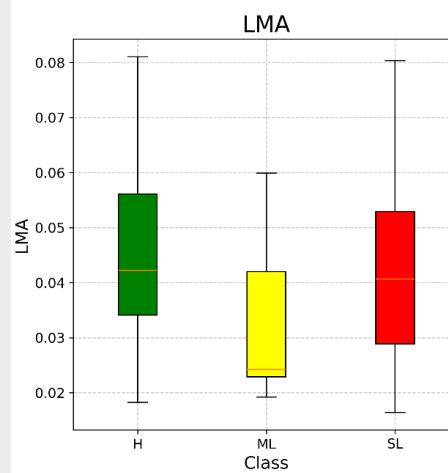
Leaf Area Index (LAI), representing leaf surface area per unit ground area, was measured using destructive sampling to avoid bias from altered leaf orientation. LAI was calculated separately for healthy and lodged microplots, providing key information on canopy density, photosynthetic activity, and water use efficiency. Chlorophyll Content (SPAD): Chlorophyll, an indicator of crop health and nitrogen status, was measured using a SPAD-502 meter. Each microplot was calibrated before measurement, with 10–15 readings averaged per plot to obtain representative chlorophyll values. Equivalent Water Thickness (EWT) estimates leaf water content per unit area, reflecting plant water status and drought resilience. It was calculated from fresh and dry leaf weights and leaf area: Leaf Mass Area (LMA) denotes dry mass per unit leaf area, indicating leaf density and structural integrity. Higher LMA values reflect denser leaves, often associated with environmental stress or low nutrient availability. Carbon (C) and Nitrogen (N) Content Leaf carbon and nitrogen content were determined from dried, ground samples using a Perkin Elmer CHN Analyzer. These parameters provide insights into crop nutrient status, photosynthetic efficiency, and biomass allocation. **Figure 4.7** illustrates distributions of physiological parameters across healthy, moderately lodged, and severely lodged wheat: LAI increased with lodging due to leaf folding and surface area coverage. EWT and LMA showed high variability, with no clear correlation with lodging. SPAD values were generally lower in lodged wheat, reflecting reduced chlorophyll content. Carbon and nitrogen exhibited distinct patterns between lodged and healthy wheat, supporting their use in distinguishing lodging severity.

4.2.4 EO Data Collection and Field-level hyperspectral Measurements

Sentinel-2 Multispectral Imagery Level-2A products of Sentinel 2, which include radiometric, geometric, and atmospheric corrections, were used. A cloud-free Sentinel-2A image acquired on 23 May 2023, closest to the field campaign, accessed through Copernicus Open Access Hub (on 11 September 2023). 2.2.5.2 EnMAP Hyperspectral Imagery. The EnMAP (Environmental Mapping and Analysis Program) image provides 224 spectral bands across the VNIR (420–1000 nm) and SWIR (900–2450 nm) ranges. This broad spectral coverage enables detailed analysis of environmental and vegetation parameters. EnMAP has a ground swath width of 30 km, revisiting the same location every 27 days at the equator, with higher revisit frequency at greater latitudes. For this study, a cloud-free EnMAP image acquired on 21 May 2023, closest to the field campaign, was accessed from DLR on 11 September 2023. Field-level hyperspectral measurements were collected using an Analytical Spectral Device (ASD) spectrometer to capture canopy reflectance for both healthy and lodged wheat at the microplot scale. Measurements were conducted by the Faculty of ITC at the University of Twente during the field campaign from 30 April to 18 May 2023. The ASD spectrometer operates over 350–2500 nm with a 1 nm spectral sampling interval and comprises three sensors: VNIR (350–1000 nm), SWIR 1 (1000–1800 nm), and SWIR 2 (1800–2500 nm). Each microplot was calibrated using a reference white panel before data acquisition. An optical fibre probe with a 25° field of view (FOV) was positioned vertically 10 m above the canopy. To capture canopy variability, ten locations / microplots were sampled under clear-sky conditions, with ten consecutive measurements at each location to minimise error and variability. Following this protocol, 189 microplot-level spectral reflectance measurements were successfully acquired.



(a)



(b)

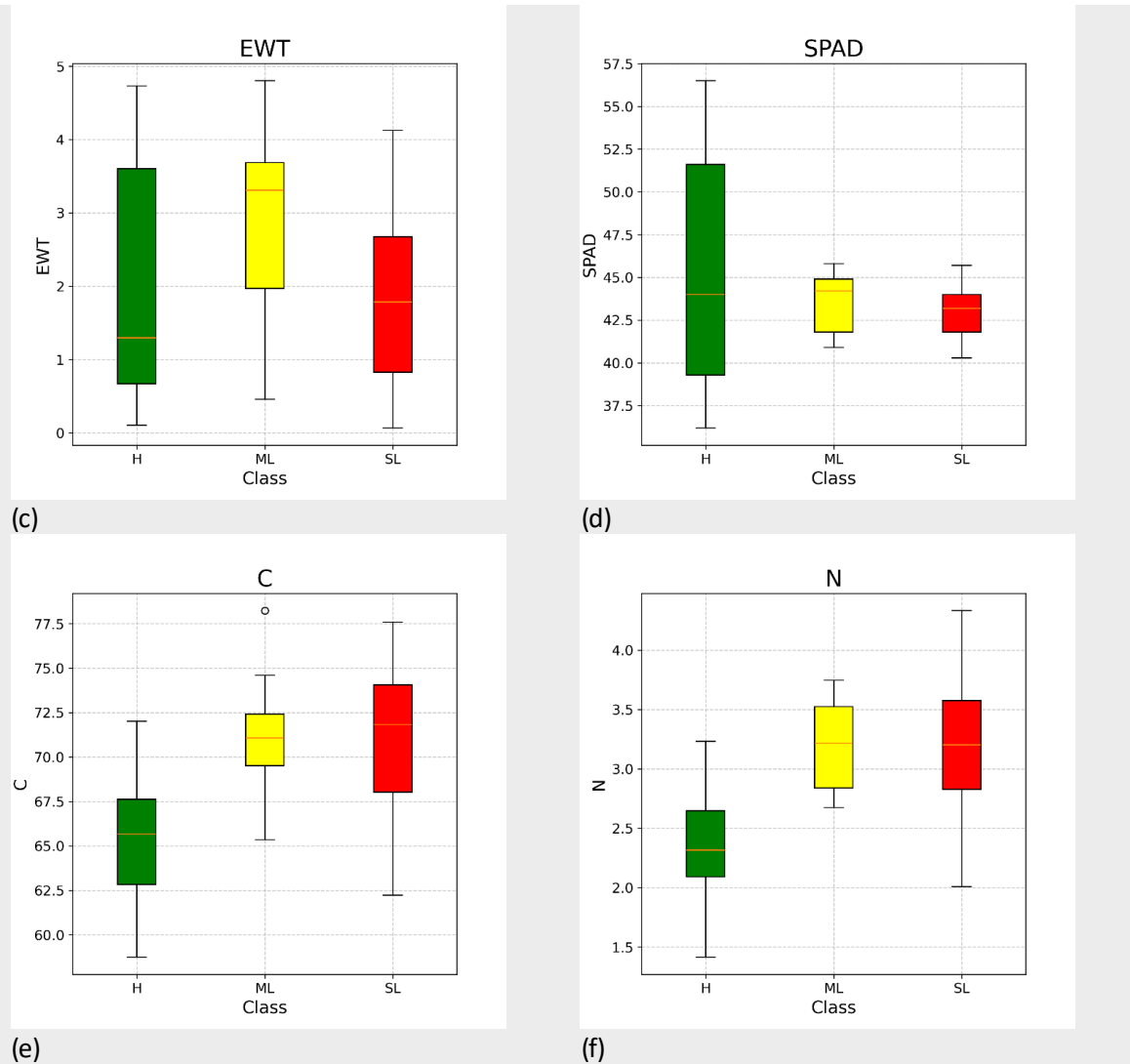


Figure 4.7 presents box plots of biophysical, biochemical, and lodging parameters and their ranges for different lodging severity classes (high, medium, and low).

4.2.5 Algorithm & model validation

For lodging score estimation, pre-processed field spectral measurements (details are in section 2.2.6 Data Processing, ATBD) were utilised to evaluate the effectiveness of three distinct approaches: vegetation indices, ML-based analysis, and hybrid RTM inversion. The spectral analysis aimed to differentiate between healthy, moderately lodged, and severely lodged wheat conditions. Continuum-removed reflectance spectra revealed clear absorption features that varied with lodging severity, particularly in the visible and near-infrared regions. These features were more effective in distinguishing lodging classes than the first derivative of reflectance, which showed limited differentiation.

To harness hyperspectral data for lodging score estimation, narrowband vegetation indices (NBVIs) were computed using all possible two-band combinations across wavelengths from 400 to 2350 nm. These indices were correlated with measured lodging scores, and the most sensitive spectral regions were identified using Pearson correlation coefficients and visualised through heatmaps. The heatmaps highlighted both positive and negative correlations, with certain wavelength pairs showing strong sensitivity to lodging severity.

For model evaluation, the dataset was stratified by random sampling and split into training and test subsets, and each model was run 100 times to ensure robustness. Bayesian hyperparameter tuning was employed to optimise each algorithm's settings. Linear models used three principal components, while kernel-based and ensemble models had various parameters tuned to capture non-linear relationships and improve robustness. Artificial neural networks require careful tuning to manage complexity and prevent overfitting. The hyperparameter search space and selected values for each ML algorithm were detailed to support reproducibility and performance comparison across different data sources.

Each model was evaluated based on its predictive accuracy, robustness, and ability to capture non-linear relationships between spectral features and lodging severity, and a summary is provided in **Table 4.1** and **Figure 4.8**.

- i. Linear Models (MLR and PLSR) are straightforward and interpretable. MLR (Multiple Linear Regression) had no tunable parameters and used three principal components. PLSR (Partial Least Squares Regression) also uses three components but is better suited for handling multicollinearity in spectral data. While both models are computationally efficient, they may struggle with complex, non-linear relationships inherent in lodging phenomena.
- ii. Kernel-Based Models (SVR and GPR) Support Vector Regression (SVR) and Gaussian Process Regression (GPR) are more flexible than linear models. SVR-tuned parameters such as C (regularisation), epsilon (tolerance margin), and gamma (kernel coefficient) make it suitable for capturing non-linear patterns. GPR optimised C, length scale, and noise level, offering probabilistic predictions and uncertainty estimates. These models performed better than linear ones in scenarios with complex spectral-lodging relationships.
- iii. Ensemble Models (RFR and GBR) both combine multiple decision trees. RFR is robust to overfitting and handles high-dimensional data well, while GBR builds trees sequentially to minimize errors. Both models optimized parameters like the number of estimators and tree depth. They performed well, especially with hyperspectral data, thanks to their ability to model intricate interactions among spectral bands.
- iv. Artificial Neural Networks: ANNs were the most flexible and powerful models in the study. They required tuning for architecture (layers and neurons), activation functions, optimisation algorithms, and learning rates. ANNs excelled at capturing non-linear and complex relationships but required careful regularisation to avoid overfitting. Their performance was highly dependent on the quality and volume of training data.

Table 4.1: The performance metrics of the ML models used for lodging score estimation:

Model	Accuracy (R ²)	Interpretability	Non-linearity Handling	Robustness	Computational Cost
MLR	Low	High	Poor	Low	Low
PLSR	Moderate	Moderate	Moderate	Moderate	Low
SVR	High	Low	Good	Moderate	Moderate
GPR	High	Low	Good	Moderate	High
RFR	High	Moderate	Excellent	High	Moderate
GBR	Very High	Low	Excellent	High	High
ANN	Very High	Low	Excellent	Moderate	Very High

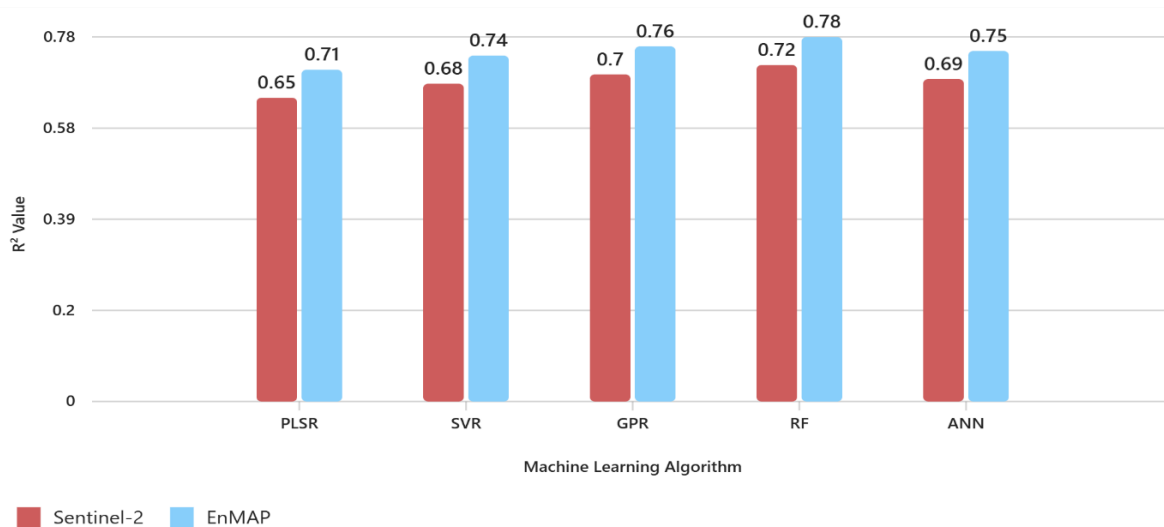


Figure 4.9 shows the performance of ML algorithms tested on Sentinel 2 and EnMap spectral features.

Structural changes in crops (Lodging) were linked to biophysical parameters LAI and ALA, as well as to biochemical traits influenced by agricultural practices. A look-up table (LUT) comprising 30,000 samples was generated using parameter distributions derived from previous wheat studies to simulate canopy reflectance across EnMAP wavelengths. Field-measured spectral data were compared with simulated reflectance using RMSE to identify the closest matches for healthy, moderately lodged, and severely lodged wheat. A final dataset of 3,000 samples was selected, evenly distributed across the three lodging categories. The inversion results revealed that healthy wheat had higher chlorophyll and water content, while lodging severity was associated with increased protein and carbon-based compounds. LAI also increased with lodging severity, whereas ALA showed minimal variation. These findings give a clear indication of the physiological and biochemical shifts caused by lodging, with implications for crop monitoring. Dimension-reduction-based models such as PCA-GPR and PCA-SVR produced smooth, accurate LS maps, particularly with EnMAP data, effectively capturing nonlinear spatial patterns. In contrast, PCA-MLR and PLSR showed greater variability and underestimation in high-lodging areas, especially with Sentinel-2 imagery, indicating limitations of linear approaches.

ML models RFR, GBR, and ANN with a full spectrum were also evaluated. RFR provided the most consistent and detailed LS maps across both datasets, whereas GBR showed slightly greater variability in high-lodging zones. ANN exhibited the greatest variability and underestimation, particularly with Sentinel-2, suggesting sensitivity to spectral noise or overfitting. Additionally, LS maps derived from different NBVIs using EnMAP data revealed similar spatial patterns, with some indices more effective at highlighting high lodging scores. These results demonstrate the potential of specific vegetation indices and ML models in accurately mapping lodging severity across different spectral datasets.

4.2.6 Strengths and Limits of Multiple Stressors' Approach

The major advancement is the pioneering use of hyperspectral satellite data to detect and assess wheat lodging. The project establishes a robust, scalable framework that integrates hyperspectral imagery, field measurements, and advanced modelling techniques, achieving accuracies comparable to those of traditional field-based methods (**Figure 4.9**).

The study fills a key gap in current agricultural monitoring by demonstrating that hyperspectral data, particularly EnMAP, can accurately detect and quantify the extent and severity of lodging over medium- and large-scale agricultural areas. The RFR model effectively estimates lodging severity, especially in healthy and moderately lodged crops. The approach is scalable, extending from microplot to regional satellite applications using EnMAP and Sentinel-2 data. Multi-scale integration of field and satellite data captures fine-scale variability and enables robust validation. The framework combines ML, narrowband vegetation indices (NBVIs), and RTM for comprehensive analysis. Hyperspectral sensitivity allows detection of subtle physiological and biochemical changes (e.g., in chlorophyll, nitrogen, and water content). The method is operationally feasible, offering a cost-effective and timely solution for farm management and insurance assessment.

Key challenges include a limited sample size, spectral variability driven by environmental factors, and potential mixed-pixel effects at satellite resolution. The models are site-specific to the Bonifiche Ferraresi farm and may require recalibration for other regions. Limited temporal coverage of field, EO and hyperspectral data (ASD field spectroscopy (30 Apr - 18 May 2023), Biophysical field measurements (3 May - 18 May 2023), EnMAP acquisition (21 May 2023), Sentinel-2A (23 May 2023)) restricted the analysis of lodging dynamics across seasons. Also, RTM inversion remained computationally demanding, and some external factors (e.g., pesticides, nutrient deficiencies) were not explicitly modelled. Future work should expand sample diversity, extend temporal monitoring, and adapt the approach to other crops and regions. Integrating additional datasets, such as soil, climate, and management data, could improve model robustness and reduce spectral variability.

Several methods were evaluated for estimating lodging scores. While narrowband vegetation indices provided useful spectral insights, they were limited in capturing the multidimensional variability of lodging. ML approaches were therefore explored, with RFR emerging as the most accurate and resilient model with R^2 values of 0.812 (ASD), 0.813 (EnMAP), and 0.833 (Sentinel-2). It outperformed kernel-based (e.g., GPR, SVR) and linear models (MLR, PLSR) in terms of R^2 , RMSE, and MAE. RFR's ensemble architecture effectively handled high-dimensional data and identified the most influential spectral features associated with lodging severity. Although RTM provided valuable physiological insights (e.g., linking lodging with leaf angle, chlorophyll, and nitrogen content), its predictive performance was lower than that of RFR.

Validation against field data confirmed that the RFR-based approach reliably predicts lodging severity using both EnMAP hyperspectral and Sentinel-2 multispectral imagery. Hyperspectral data offered higher sensitivity and accuracy in identifying lodged areas, while Sentinel-2 provided broader coverage suitable for operational monitoring. RTM analysis supported these findings by highlighting physiological stress markers associated with lodging, suggesting its potential for early detection and precision management applications.

Overall, the RFR model proved to be the most effective and scalable algorithm for detecting and quantifying crop lodging. The resulting lodging severity (LS) maps generated from EnMAP and Sentinel-2 imagery accurately represent field conditions, enabling large-scale monitoring and timely decision-making. Nevertheless, operational deployment at regional or continental scales will require additional multi-site and multi-year calibration datasets, assessment of model transferability across environments, and implementation of automated processing workflows. This study demonstrates the power of combining hyperspectral data with advanced modelling techniques, providing a strong foundation for scalable, data-driven solutions in precision agriculture to reduce crop losses and improve management efficiency.

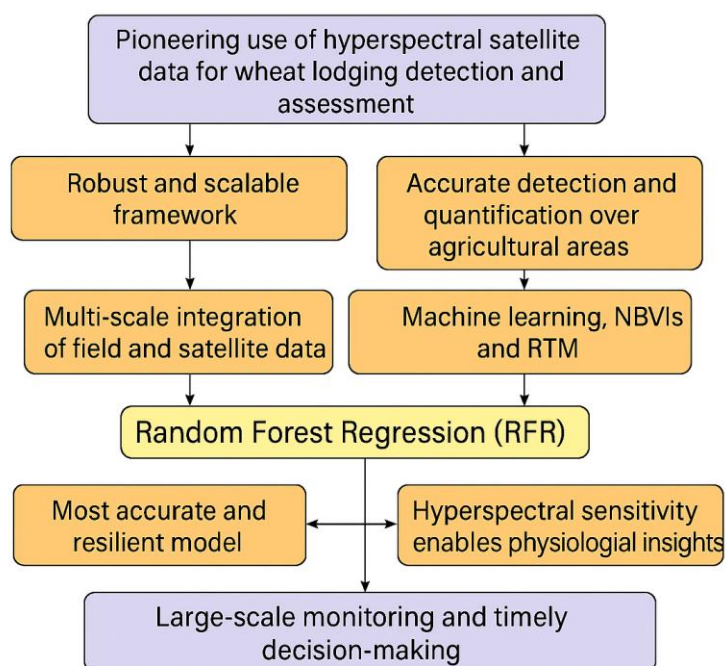


Figure 4.9 Salient features of the Lodging severity detection framework suitable for large-scale monitoring

4.3 Pilot Three: Drought in Maize (Marchfeld, Austria)

4.3.1 Overview

This pilot site experiment has advanced drought mapping in maize fields within Austria's Marchfeld region by leveraging Sentinel-2 satellite imagery, ancillary datasets (such as climate and soil data), and machine/deep learning models. Its goal was to build a robust, integrated framework for drought detection and prediction that leverages the strengths of multiple data sources and analytical techniques.

By exploiting Sentinel-2's high spatial and temporal resolution, the research investigated how this data can be effectively used to monitor drought severity and how integrating environmental variables can enhance prediction accuracy. Several commonly used ML algorithms are applied and compared to identify the most accurate models and vegetation indices for quantifying drought in maize fields. The workflow included.

- Gap-filling methods to overcome missing or incomplete Sentinel-2 observations.
- Integrating climate and soil datasets with Sentinel 2 for improved drought assessment
- Applying and comparing ML models using Sentinel-2-derived indices
- Selecting the best-performing indices and models based on validation and accuracy assessments.
- Producing annual drought estimates for each growing season between 2018 and 2023.

This integrated approach provided a scalable, data-driven framework for drought monitoring and management, and can be practically useful for agricultural planning and climate resilience in the Marchfeld region (**Figure 4.10**).

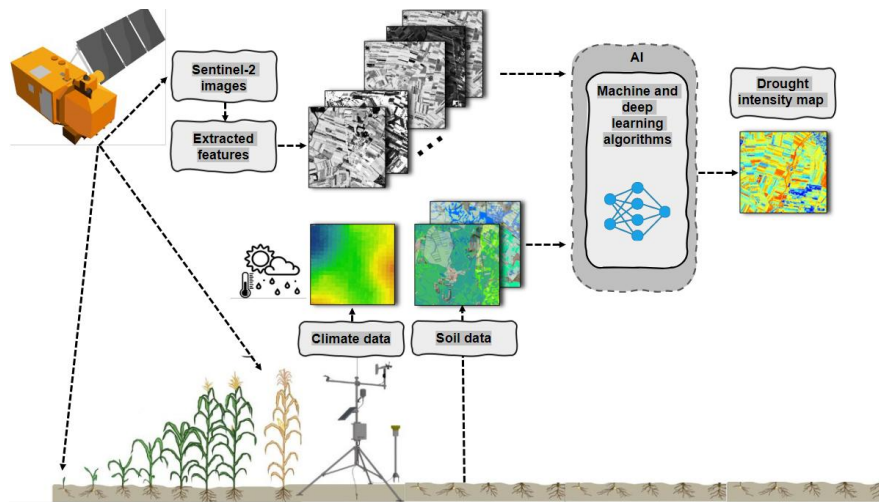


Figure 4.10 Drought Detection framework developed for the Marchfeld region of Austria.

4.3.2 Pilot Site Three Description

The Marchfeld region in Lower Austria, located northeast of Vienna (48.20°N, 16.72°E), covering approximately 60,000 hectares, is one of Austria's most important agricultural zones, characterised by distinct pedo-climatic conditions and a semi-arid climate (**Figure 4.12**). The region typically receives only 250–300 mm of rainfall between May and September, resulting in frequent summer water stress. Although irrigation covers about 21,000 ha, mainly through private wells, it only partially mitigates water shortages due to limited groundwater availability and increasing competition from the urban and industrial sectors.

Climate projections suggest that water scarcity and drought intensity will worsen in the future. The area also exhibits significant spatial variability in soil properties, including spectral and hydrological characteristics, which influence irrigation efficiency and crop performance.

The Marchfeld region has been extensively studied in previous agricultural and environmental research. Building on this legacy, the pilot study begins by collecting and harmonising historical datasets from past experiments, integrating them with local weather, EO, and in-situ crop data to support the development of a comprehensive drought-predicting model.

4.3.3 EO Data Collection

Sentinel-2 imagery was used to monitor vegetation and soil moisture. The twin satellites, Sentinel-2A and Sentinel-2B, each revisit the same area every ten days, achieving a combined revisit frequency of five days. Equipped with a MultiSpectral Instrument (MSI) containing 13 spectral bands (0.4–2.4 μm) at spatial resolutions of 10, 20 and 60 metres, they offer detailed coverage over a 290 km swath. Data were obtained from the Copernicus Data Space Ecosystem (CDSE), which replaced the ESA Data Hub in 2023 and provides open access to satellite products and processing tools.

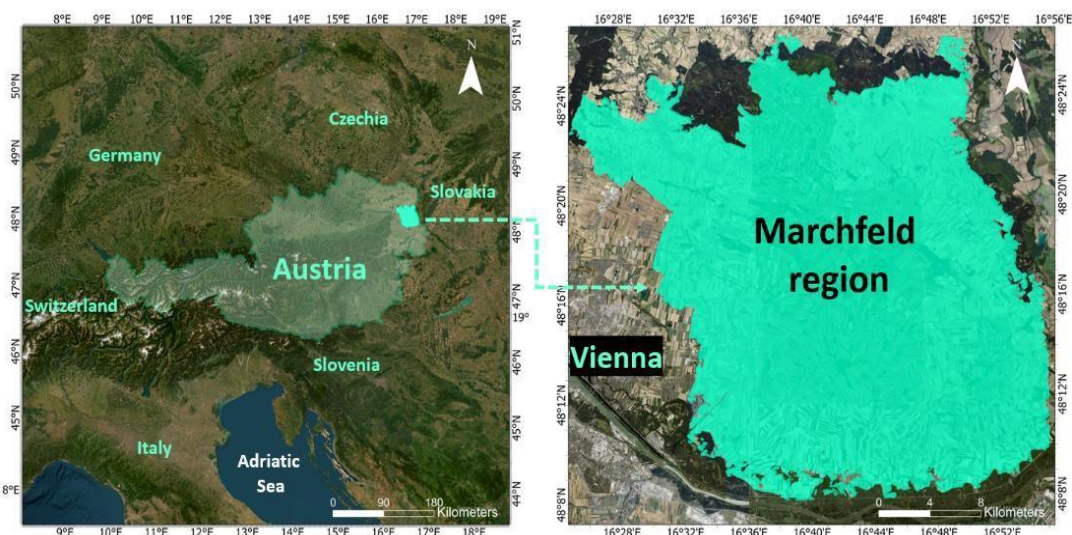


Figure 4.11: Location of the Marchfeld region, the entire study area used for developing the DL-based framework.

4.3.4 Secondary Data Collection

Complementary datasets, including climate and soil information, were incorporated to improve drought detection. Precipitation data support early-season drought mapping, while soil parameters, such as field capacity, serve as essential reference inputs for model training and validation. Daily temperature and precipitation data were obtained from the [SPARTACUS v2.1 open-source dataset](#), available at 1 km resolution and covering Austria since 1961. These data helped identify dry and wet years within the Marchfeld region, supported by maize production statistics from the [STATcube database](#). The year 2022 was identified as the driest year, as reflected in crop yield trends. Soil information was sourced from [the Austrian Soil Mapping Database \(eBOD\)](#), which provides detailed GIS-compatible maps of soil characteristics, including water-holding capacity. This data, provided by the Federal Office for Water Management and the Austrian Soil Science Society, is vital for assessing soil moisture availability and drought resilience. The Marchfeld region lies within the Quaternary alluvial plain of the Vienna Basin, a geologically diverse area that influences soil formation and water retention. [Reference data](#) underpin the training and validation of ML models used for drought mapping. As field surveys were not possible for all years, ground-truth information was compiled using a combination of satellite-derived indices (NDVI, EVI), soil capacity maps, precipitation data, and expert analysis. Fields were classified as “irrigated” or “non-irrigated” based on temporal analysis of Sentinel-2 imagery from 2018 to 2023. This approach ensured the creation of robust and representative reference datasets that reflected real variations in irrigation practices and crop conditions.

4.3.5 Trade-off Analysis of Alternative Models

A range of ML and DL algorithms was assessed to identify the most suitable models for drought detection and classification. The models include [Random Forest \(RF\)](#), [k-Nearest Neighbours \(k-NN\)](#), [Support Vector Machine \(SVM\)](#), [Gradient Boosting \(GB\)](#), [Multi-Layer Perceptron \(MLP\)](#), [Logistic Regression \(LR\)](#), [Decision Tree \(DT\)](#), [Deep Neural Network \(DNN\)](#), and [One-Dimensional Convolutional Neural Network \(1D-CNN\)](#). Each model offers distinct advantages: RF effectively handles large, nonlinear datasets but can overfit; SVM performs well in high-dimensional spaces but requires careful parameter tuning; and DL models such as DNNs and 1D-CNNs excel at identifying complex spatial and temporal patterns, particularly with extensive datasets. Model configurations and parameter tuning are detailed in **the subsequent sections (3.2.5.2–3.2.12) of the RD-3.1: ATBD document**.

Supervised ML and DL models were trained and compared across multiple agricultural seasons (2018–2023) to identify optimal indices and algorithms for accurate drought prediction. Sentinel-2 derived indices (e.g., vegetation and moisture indices) were used to evaluate the models’ performance. Field boundaries, which often differ from official cadastral maps, were refined using a [Self-Supervised Learning \(SSL\) semantic segmentation](#) technique

to ensure a realistic representation of agricultural areas. Drought maps were generated at multiple intervals each year, providing updated pixel-level classifications of irrigated and non-irrigated fields using SSL Semantic Segmentation. Accurate field delineation is crucial given the spatial heterogeneity of agricultural landscapes and the variable crop types. Traditional supervised methods require extensive labelled data, which is often unavailable. Hence, an SSL approach was implemented using the SwAV (Swapping Assignments between Multiple Views) algorithm. SwAV applies contrastive learning principles by comparing augmented versions of the same image to maintain feature consistency without requiring full supervision. The method involves online clustering, where image features are grouped into prototype clusters, and data augmentation, using multiple random crops of Sentinel-2 imagery to strengthen feature learning. A modified ResNet-18-based U-Net architecture was employed, with encoder weights frozen and decoder weights trained to produce probability maps of agricultural field boundaries. This process improved field segmentation accuracy and provided a reliable spatial foundation for further classification. Following segmentation, supervised classification was conducted using both ML and DL algorithms applied to cloud-free, gap-filled Sentinel-2 imagery. Models such as RF, SVM, GB, DT, k-NN, MLP, DNN, and 1D-CNN were trained using reference data to generate probabilistic drought maps. The outputs were validated for accuracy and consistency across seasons, ensuring the robustness and generalisability of the drought prediction framework.

4.3.6 Model Learning and Parameter Tuning

All extracted spectral indices and climate variables (particularly precipitation) are used as input features. Reference points are categorised as irrigated or non-irrigated maize fields, typically comprising around 1,400 non-irrigated and 800 irrigated samples each year. A random-sampling strategy was used to split the data into 70 per cent for training, and 30 per cent for validation, and ten-fold cross-validation was applied to ensure robustness. Stratified sampling and random-seed initialisation preserve the class balance and avoid bias. Documentation of sampling parameters was preserved to ensure reproducibility.

Model Parameter Tuning: A range of ML and DL algorithms were tuned to optimise drought classification accuracy. Random Forest (RF): Key parameters, such as tree number and depth, were fine-tuned to balance accuracy and computational efficiency. k-Nearest Neighbours (k-NN): The choice of k, distance metric (e.g., Euclidean or Manhattan), and weighting method strongly affects model bias and variance and requires careful selection. Support Vector Machines (SVM): require careful tuning of kernel functions and regularisation parameters to maximise classification reliability. Gradient Boosting (GB): The learning rate, number of estimators, and tree depth were optimised for pixel-level drought mapping. Multi-Layer Perceptron (MLP): suited for large datasets, requires parameter regularisation to prevent overfitting. Logistic Regression (LR): used mainly for classification, modelling the probability of drought occurrence between 0 and 1. Deep Neural Network (DNN): Similar in structure to MLPs, DNNs can learn highly complex representations but demand substantial computational resources and careful hyperparameter control. Decision Tree (DT): Provides interpretable, tree-structured classifications but is prone to overfitting; pruning and depth control were applied to improve generalisation. One-Dimensional Convolutional Neural Network (1D CNN): Tailored for sequential data such as time-series imagery, this model captures temporal patterns efficiently using filters along the time axis. **Hyperparameters for each model are found in Tables 3.5–3.13, RD-3.1: ATBD.** Collectively, these tuned algorithms form an integrated drought-mapping framework capable of producing accurate, temporally consistent classifications across the Marchfeld region.

4.3.7 Model Performance

Across the six years, the DNN model consistently showed superior predictive accuracy and lower Mean Absolute Error (MAE), particularly in non-irrigated fields. In 2018, CNN-irr achieved a notable accuracy of 74.20% and MAE of 0.18, outperforming RF-irr. However, the DNN-non model emerged as the most effective in 2019, with an accuracy of 80.66% and MAE of 0.14, underscoring the clearer drought signals in non-irrigated fields. The DNN-irr model maintained strong performance in 2020, while RF-irr peaked in 2023, achieving 81.84% accuracy and an MAE of 0.14.

Figure 4.12 shows drought predictions for 2023 from RF, 1-D, and CNN for irrigated and non-irrigated fields. Overall, non-irrigated fields yielded higher accuracy and lower MAE across all models and years, suggesting that natural drought signals are more discernible without the confounding effects of irrigation. The DNN model, benefiting from its ability to capture complex data relationships, outperformed both CNN and RF, particularly when handling Sentinel-2-derived datasets. While CNNs showed promise in capturing temporal dynamics, especially in non-irrigated fields, RF lagged due to its limited feature-extraction capabilities.

The presence or absence of irrigation significantly influenced model performance. Non-irrigated fields consistently produced clearer drought signals, resulting in higher accuracy and lower MAE. This is attributed to the absence of artificial moisture inputs, allowing vegetation indices such as NDVI and EVI to reflect true drought stress. In contrast, irrigated fields introduced variability that obscured natural drought patterns, thereby reducing model precision. These findings highlight the complexity of modelling drought in managed agricultural systems and underscore the need for refined feature selection or ensemble approaches to improve generalisability.

Drought severity and model performance varied across years and geographical zones. Moderate drought conditions were observed in 2018 and 2019, while 2021 exhibited higher drought intensity, particularly in non-irrigated zones. The year 2020 marked a transitional phase with improved rainfall distribution, slightly enhancing model performance in irrigated fields. In 2022 and 2023, drought severity intensified, especially in southern and central Marchfeld, where non-irrigated fields served as reliable indicators.

Spatial analysis revealed that non-irrigated regions in the southern and central parts of Marchfeld consistently experienced higher drought stress. This geographical clustering of drought severity reinforces the importance of distinguishing between irrigated and non-irrigated fields for effective drought mitigation planning. Vegetation indices such as NDVI, SIWSI, and NDWI proved instrumental in capturing drought-related changes in vegetation and soil moisture.

Drought Prediction Map Using RF, 1D-CNN, DNN

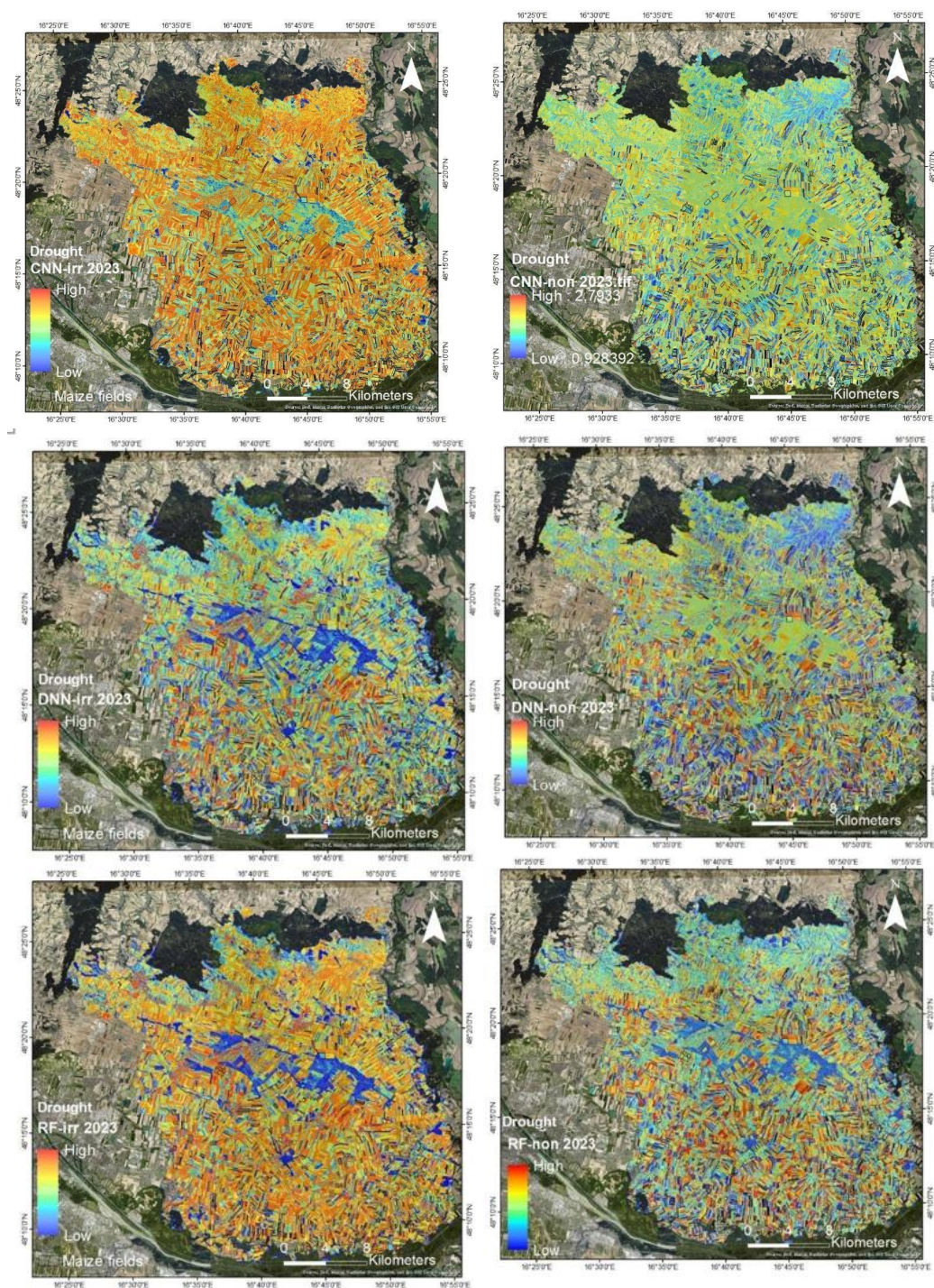


Figure 4.12 Drought Prediction maps for the Marchfeld regions for the year 2023.

The DNN model is recommended for future drought assessments in the Marchfeld region due to its robust performance across varying conditions. While CNN showed strength in temporal pattern recognition and RF offered computational efficiency, DNN's adaptability and accuracy make it the most suitable choice. The findings advocate for a differentiated approach to drought modelling, accounting for irrigation practices and regional variability to enhance predictive reliability and inform sustainable agricultural management. The project's outputs include detailed, pixel-level drought maps at a 10-metre resolution for both irrigated and non-

irrigated fields, which can be found in the SharePoint [Deliverables](#), (RD-4.1 - Experimental Datasets, shared internally) and in the open science catalogue.

5 Product Validation

This section is based on results from three pilot sites and explains the validation of experimental analyses and cross-comparisons of methods for crop stress assessment. The pilot sites have investigated three types of stressors: (1) soil salinity, nutrient deficiency, and heavy metals, (2) crop lodging, and (3) drought stress.

5.1 Pilot One: Soil Salinity, Nutrient Deficit and Heavy Metals

A stratified random sampling strategy was applied across the Guadalquivir marshlands to ensure representative coverage of soil variability. Sampling clusters were derived from a bare-soil DESIS image at the initial stage, when acquisition of EnMap and PRISMA was underway. Soil stressors (salinity, nutrient deficits, and heavy metals) were analysed in relation to rice crop performance through a hybrid modelling approach. A 2,000-spectrum Look-Up Table (LUT) was generated using the PROSAIL-PRO Radiative Transfer Model (RTM) to simulate vegetation spectral responses. Active learning refined the LUT by iteratively selecting spectra that minimised root-mean-square error (RMSE) and excluded unrealistic samples, thereby improving model generalisation.

Partial Least Squares Regression (PLSR) models were developed using in-situ soil measurements and spectral data from ASD, EnMAP, PRISMA, and Sentinel-2. A 10-fold cross-validation was applied to evaluate dimensionality reduction techniques and optimize hyperparameters. A fixed 80/20 train-test split was used to assess model accuracy.

. Biophysical traits of rice crops were validated using field data from the Andalusian Federation of Rice Growers (AFR). Salinity and combined salinity–nitrogen stress were evaluated as single and cumulative stressors, respectively. Stressed and non-stressed areas were delineated using soil salinity (EC) and soil nitrogen thresholds. Salinity stress was defined as $EC > 4 \text{ dS m}^{-1}$, while non-stressed areas had $EC < 4 \text{ dS m}^{-1}$. Nitrogen-deficit stress was defined by deficient soil N levels ($< 20 \text{ mg kg}^{-1}$), whereas areas with optimal or higher N levels ($\geq 20 \text{ mg kg}^{-1}$) were considered non-stressed. areas. This delineation was conducted using EnMAP and Sentinel-2 indices, with statistical validation via two-tailed t-tests ($p < 0.05$) and boxplots. Additional data from the 2024 field campaign were used to further verify model robustness under new environmental conditions. Model performance was evaluated using R^2 and RMSE, providing quantitative assessments of predictive reliability.

5.1.1 Reference Data

Soil Reference Data: 100 soil samples at 20 cm depth were collected to quantify electrical conductivity (salinity proxy), total carbon and nitrogen, iron (Fe), and various heavy metals. Laboratory spectral reflectance was measured with an ASD FieldSpec 4 spectroradiometer after samples were dried and sieved. Preprocessing methods, including Continuum Removal (CR) and Multiplicative Scatter Correction (MSC), were applied to minimise spectral distortions and improve model transferability across datasets. Rice Crop Reference Data: Three rice fields (A–C) at the Hato Blanco farm were selected to represent optimal, suboptimal, and poor growth conditions. Each field contained 9 Elementary Sampling Units (ESUs) arranged in a 3×3 grid (30 m × 30 m), matching the hyperspectral sensor's resolution. Measurements across five field campaigns included leaf nitrogen content, moisture, pigments (Chl-a, Chl-b, carotenoids), and Leaf Area Index (LAI). LAI was recorded with a LI-COR LAI-2200C meter along two transects per ESU. These comprehensive datasets provided high-quality ground-truth for model calibration and validation.

5.1.2 Product Validation – Guadalquivir Marshlands

Hyperspectral models achieved shigh accuracy in predicting soil stressors, with R^2 values indicating accurate estimates of several properties. The best models achieved R^2 values of 0.885 for soil nitrogen (PRISMA-PLSR), 0.818 for iron (EnMAP-PLSR), 0.717 for soil carbon (PRISMA-PLSR), and except moderate 0.574 for salinity (EnMAP-PLSR). (**Figure 5.1**). Sentinel-2-based models exhibited weaker performance due to limited spectral resolution, with only iron (Fe) showing a reasonable fit ($R^2 > 0.4$) (**Figure 5.2**). For heavy metals, hyperspectral models achieved moderate success, particularly for arsenic (As, $R^2 = 0.622$) and chromium (Cr, $R^2 = 0.635$), while cadmium (Cd) and zinc (Zn) predictions were less reliable (**Figure 5.3**). Sentinel-2 results were excluded from further consideration owing to poor accuracy, reinforcing the superior capability of hyperspectral data (e.g., EnMAP, PRISMA) in mapping soil stressors and spatial variability of contaminants.

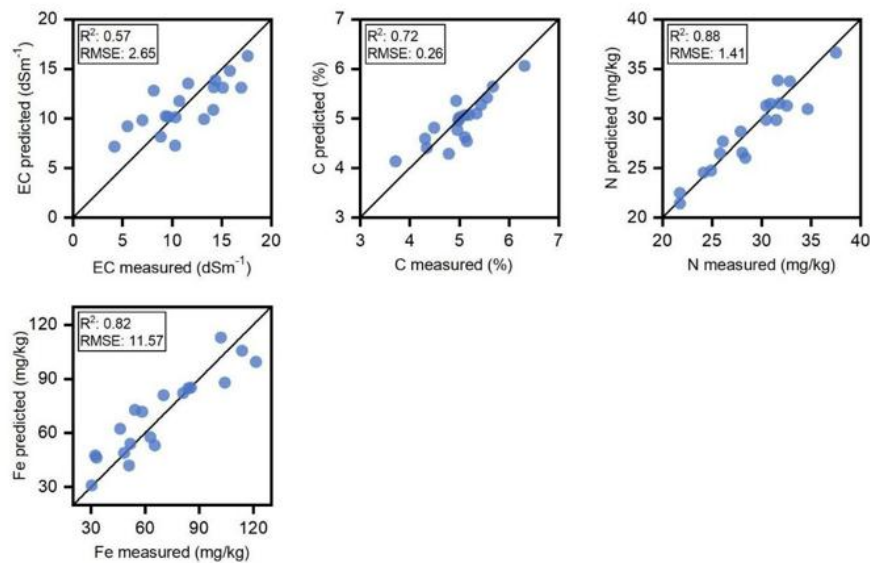


Figure 5.1. Observed vs predicted samples for selected hyperspectral models by soil property. EC (electrical conductivity): selected model: PLSR with MSC EnMAP. C (soil carbon content): selected model: PLSR with PRISMA. N (soil nitrogen content): selected model: PLSR with PRISMA. Fe (soil iron content): selected model: PLSR with EnMAP.

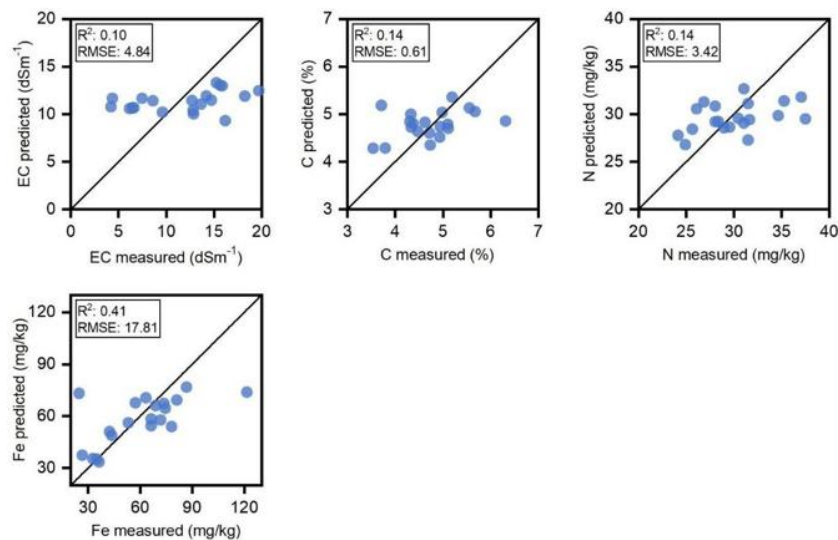


Figure 5.2. Observed vs predicted samples using Sentinel-2 selected model by soil property. EC (electrical conductivity): selected model: PLSR. C (soil carbon content): selected model: NN. N (soil nitrogen content): Selected model: PLSR. Fe (soil iron content): selected model: NN

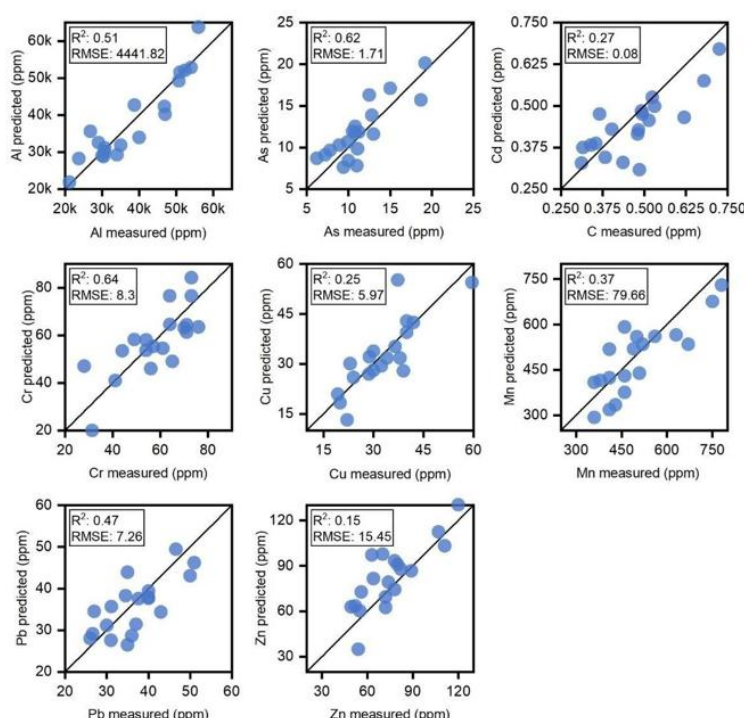


Figure 5.3. Observed vs predicted samples for the selected hyperspectral models by soil heavy metal. Al (aluminium): selected model: PLSR with CR EnMAP. As (arsenic): selected model: PLSR with EnMAP. Cd (cadmium): selected model: PLSR with PRISMA. Cr (chromium): selected model: PLSR with MSC EnMAP. Cu (copper): selected model: PLSR with MSC PRISMA. Mn (manganese): selected model: LR with MSC PRISMA. Pb (lead): selected model: PLSR with MSC PRISMA. Zn (zinc): selected model: PLSR with PRISMA.

5.1.3 Validation of Rice Crop Biophysical Traits and Stress Effects

Figure 5.4 compares observed and predicted values from the hyperspectral models (see Section 1.3.4 of the **RD-3.1 ATBD document “Models for Rice Crops”**). The EnMAP-based models generally demonstrated high predictive accuracy and strong alignment between measured and modelled values, as evidenced by the proximity of the regression line to the 1:1 line and by robust R^2 and RMSE statistics.

Among the hyperspectral models, the leaf carotenoid (CAR) model showed the highest predictive capability, achieving an R^2 of 0.934 and an RMSE of 0.977, indicating excellent agreement between field-measured and modelled data (**Figure 5.4**). The canopy nitrogen content (CNC) model also performed well ($R^2 = 0.770$; RMSE = 3.476), while the canopy chlorophyll content (CCC) model achieved more moderate accuracy ($R^2 = 0.642$), reflecting the additional complexity involved in modelling canopy-level chlorophyll from spectral data. The close clustering of predicted versus observed points around the 1:1 line for most variables confirms that the hyperspectral models captured the spectral variability associated with rice biochemical and biophysical traits.

Figure 5.5 presents the validation results for the corresponding Sentinel-2 models, enabling a direct comparison with the EnMAP results. Overall, Sentinel-2 models exhibited lower

accuracy, which can be attributed to the sensor's reduced spectral resolution and fewer spectral bands. Nevertheless, certain variables achieved satisfactory predictive performance. The leaf nitrogen content (LNC) model, for instance, produced an R^2 of 0.868 with an RMSE of 19.928, representing the highest accuracy among the Sentinel-2 models and only slightly below the performance of its EnMAP counterpart ($R^2 = 0.916$; RMSE = 21.902). The canopy nitrogen content (CNC) model also performed well ($R^2 = 0.861$; RMSE = 1.303), though the hyperspectral version still exhibited greater precision ($R^2 = 0.770$; RMSE = 3.476).

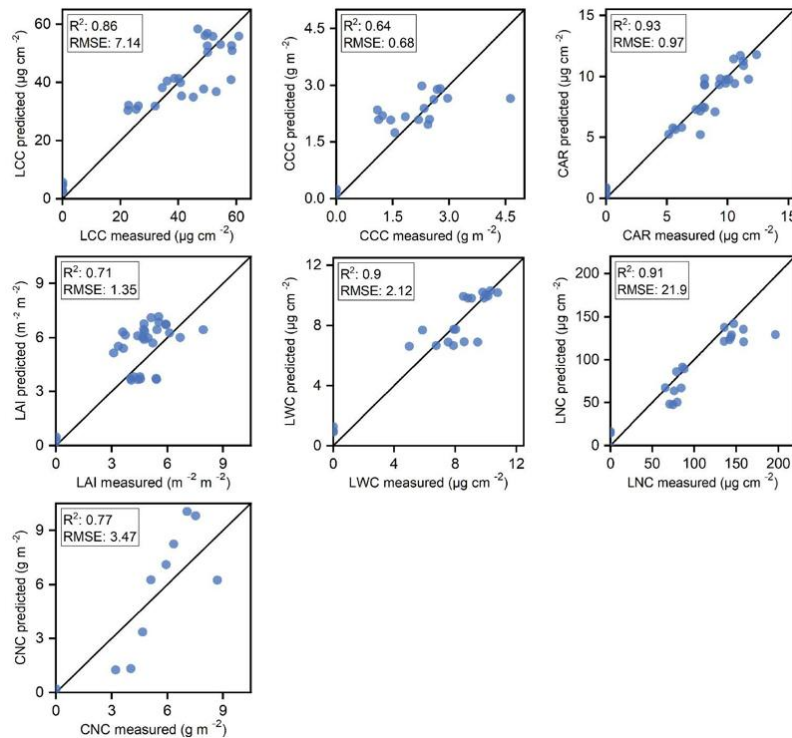


Figure 5.4 Hyperspectral data-based models result in predicting crop traits.

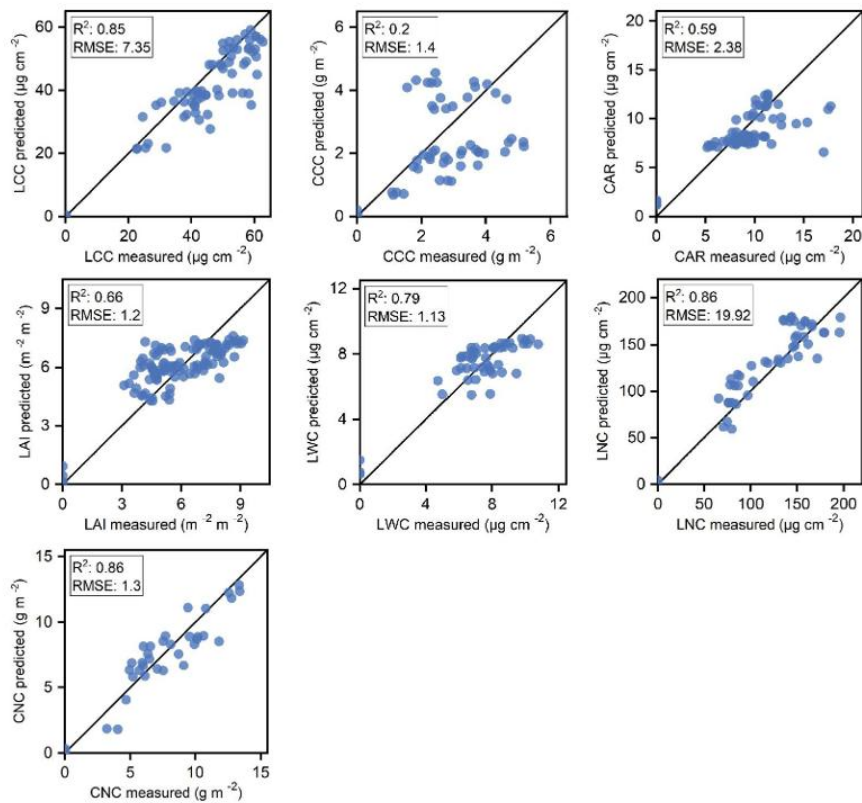


Figure 5.5 Sentinel 2-based predicted crop traits.

Other traits followed similar patterns. LCC and LAI derived from Sentinel-2 data showed reasonable alignment with field observations, with R^2 values of 0.854 and 0.669, respectively. In comparison, EnMAP models for these variables achieved $R^2 = 0.867$ (LCC) and $R^2 = 0.71$ (LAI), demonstrating EnMAP's slight advantage in resolving fine-scale spectral features. The leaf CAR and LWC models showed more pronounced discrepancies between the two sensors: Sentinel-2 yielded $R^2 = 0.597$ (CAR) and $R^2 = 0.792$ (LWC), whereas EnMAP achieved markedly better results ($R^2 = 0.934$ and $R^2 = 0.901$, respectively). The CCC model exhibited the poorest performance overall, declining from $R^2 = 0.642$ with EnMAP to $R^2 = 0.201$ with Sentinel-2, highlighting the difficulty of retrieving canopy-level traits from multispectral imagery.

Collectively, these validation outcomes emphasise the superiority of hyperspectral sensors, such as EnMAP, for accurately retrieving rice crop biochemical and structural properties, particularly for traits sensitive to subtle spectral variations (e.g., CAR and LWC). Nonetheless, the results also confirm Sentinel-2's operational potential for regional-scale agricultural monitoring, where its higher temporal and spatial resolution can offset limitations in spectral granularity. Sentinel-2 models, despite their lower R^2 values, remain effective for traits like LNC and CNC, which exhibit strong, broad-band spectral signatures.

5.1.4 Validation of Stress Effects on Rice

The physiological responses of rice to environmental stressors were evaluated through a case-control analysis comparing areas affected by salinity and combined salinity-nitrogen deficit to unstressed (control) plots within the Andalusian Federation of Rice Growers (AFR). **Figures 5.6** and **5.7** display boxplots for the EnMAP- and Sentinel-2-derived biophysical variables under the different stress regimes.

The EnMAP-based analysis (**Figure 5.6**) revealed substantial reductions in LCC, CCC, LAI, and LWC under salinity stress, indicating significant declines in photosynthetic pigment

concentration, canopy structure, and water retention capacity. These negative effects intensified under combined stress conditions, with even greater decreases in chlorophyll and water-related traits, pointing to a synergistic interaction between salinity and nutrient limitation. The leaf nitrogen content (LNC) remained relatively stable under salinity alone but slightly increased under combined stress, possibly reflecting a physiological redistribution of nitrogen within the plant. In contrast, canopy nitrogen content (CNC) decreased consistently under both stress scenarios, demonstrating an overall impairment of nitrogen assimilation at the whole-plant level. Despite some variation in sample size between stress categories, the observed patterns were consistent, confirming the compounded effects of multiple stressors on rice physiology.

In the Sentinel-2-based analysis (**Figure 5.7**), the same general trends were observed but with smaller contrast magnitudes between stressed and non-stressed plots. While Sentinel-2 successfully detected reductions in CCC, LAI, and LWC, the EnMAP results exhibited clearer separations and stronger statistical significance, owing to its finer spectral resolution. For example, EnMAP data revealed more distinct declines in chlorophyll and water content under combined stress, enhancing separability between treatment groups.

Comparisons between EnMAP- and Sentinel-2-based results show that, although both sensors detect stress-induced differences, EnMAP consistently yields stronger and more reliable separations, particularly for pigment-related variables. For instance, CNC, which was not significant under EnMAP for either stress condition, appeared significant under combined stress using Sentinel-2—likely reflecting the increased uncertainty introduced by multispectral data. Similarly, while LAI was significant in both datasets for salinity stress, the magnitude of the difference was smaller in Sentinel-2 outputs. These discrepancies underscore the influence of sensor characteristics: EnMAP's high spectral resolution minimises uncertainty in biophysical trait retrieval, whereas Sentinel-2's broader bands limit its sensitivity to subtle biochemical changes.

The validation confirms that hyperspectral data provide superior diagnostic capability for detecting both individual and cumulative stress effects in rice. Nevertheless, Sentinel-2 remains a valuable operational tool for large-scale crop monitoring, capable of identifying broad stress patterns when hyperspectral data are unavailable. The statistical validation across both sensors reinforces the robustness of the observed trends and highlights the need for integrated spectral approaches to enhance agricultural stress assessment and management in vulnerable cropping systems.

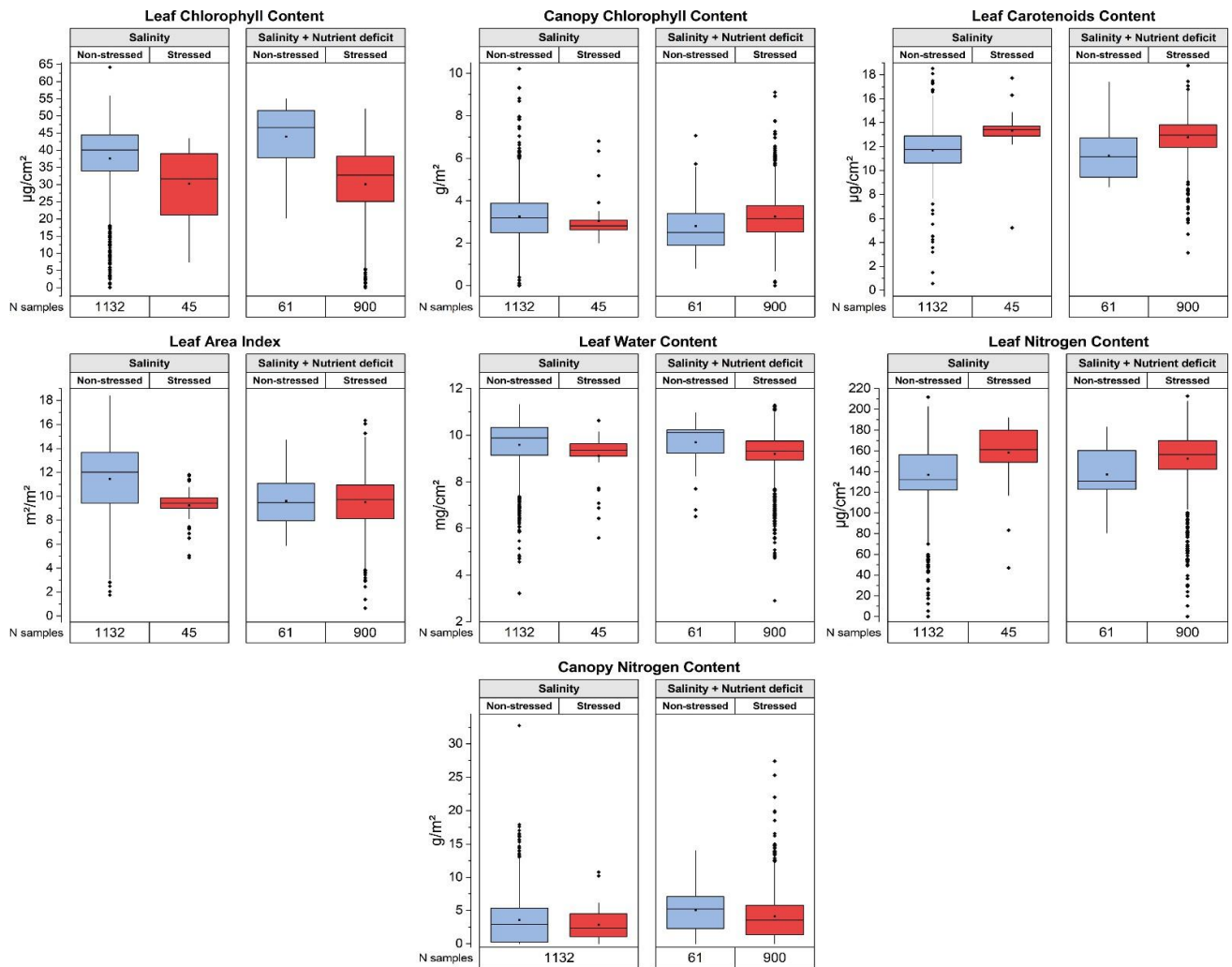


Figure 5.6. Box plots of hyperspectral-predicted crop traits considering stressed and non-stressed areas.

4.3.1.4 Product Validation – Upscaling

Scalability was investigated through multiple methodological approaches (**see RD-3.1: ATBD Section 1.2.4: Trade-off – Exploring Alternative Models**). In situ soil measurements were collected concurrently with spectroradiometer observations to capture detailed spectral signatures of soil properties. These spectra were subsequently convolved to align with the spectral response functions of different optical sensors, ensuring compatibility between ground-based and satellite data. Similarly, crop samples were collected in situ across a structured grid of ESUs, ensuring representativeness of crop variability at the spatial resolution of optical satellite sensors.

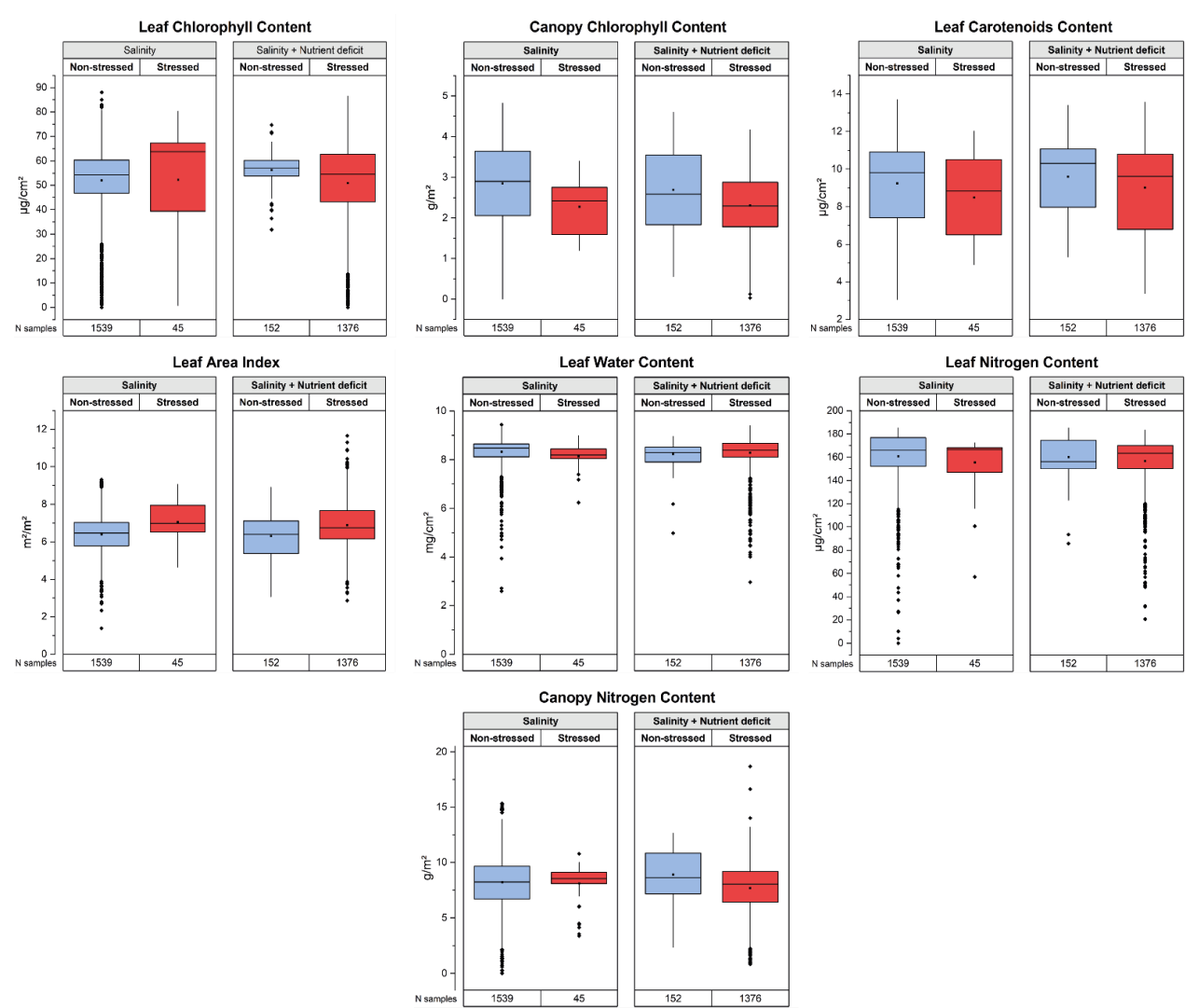


Figure 5.7. Box plots of Sentinel 2-predicted crop properties considering stressed and non-stressed areas.

These field data formed the foundation for training simulations using PROSAIL-PRO. By integrating simulated and measured spectra, the models enhanced their generalisation ability and transferability across sensors. This approach allowed the trained algorithms to be applied first to hyperspectral imagery from EnMAP and PRISMA and, more operationally, to Sentinel-2 multispectral imagery, thereby bridging the gap between local ground-based measurements and regional-scale monitoring.

The high spectral resolution of hyperspectral sensors enabled discrimination of subtle biophysical and biochemical variations, critical for detecting early signs of stressors such as salinity or nutrient imbalance, which are often undetectable with multispectral instruments. By ensuring spectral consistency between ground and satellite data, the approach supported a seamless transition from plot-level observations to landscape-level assessments.

Looking forward, the forthcoming CHIME hyperspectral mission represents a significant advancement in operational scalability. With a higher temporal resolution than existing hyperspectral missions such as EnMAP and PRISMA, CHIME is expected to provide more frequent coverage of agricultural areas and continuous spectral coverage with zero spectral gaps across 400-2500 nm, which will improve the detection of subtle absorption features associated with salinity, nitrogen, water content, and minerals.

5.2 Pilot Two: Lodging Stress

A comprehensive field campaign (**detailed in Section 2.2 of the RD-3.1 ATBD**) was conducted to collect extensive physiological, structural, and spectral data. Field spectrometer measurements were complemented with detailed biophysical and biochemical sampling to create a robust reference dataset for model development. The approach combined three complementary methodologies:

- i. Spectral-index analysis: Narrowband vegetation indices were calculated from field spectra to quantify relationships between spectral responses and lodging severity.
- ii. Machine Learning: Several ML algorithms were evaluated to predict lodging scores based on the spectral and biophysical data.
- iii. Radiative Transfer Modelling (RTM): Simulations of lodged and non-lodged canopy spectra were generated to provide a mechanistic understanding of how lodging alters spectral behaviour.

The crop inclination angle, an important variable in LS computation, was derived from RTM inversion. The relationships between chlorophyll, nitrogen, and water content and different lodging classes (Healthy, Moderately Lodged, and Severely Lodged) were also examined to assess biochemical and physiological drivers of lodging. Among all tested methods (**see RD-3.1: ATBD 2.2.7.3**), RFR consistently achieved the highest predictive accuracy. Model evaluation was based on R^2 , RMSE, and MAE metrics. Data were randomly split into 70% for training and 30% for testing, with 100 model iterations to ensure robustness. Bayesian optimisation initialised with random starting points was used for hyperparameter tuning (**described in RD-3.1: ATBD 2.2.7.3**). Lodging scores, measured at the microplot level, served as target variables, while the input features were the full spectral responses obtained from field spectrometer data. The optimised models were subsequently applied to EnMAP hyperspectral and Sentinel-2 multispectral imagery to predict lodging severity across larger spatial extents. This transition from field-scale to satellite-scale analysis has potential for operational scalability for precision agricultural monitoring and lodging severity assessment.

5.2.1 Reference Data

Data were collected at three spatial scales, microplot (1 × 1 m), subplot (15 × 15 m), and plot (90 × 90 m) in the Fieldwork conducted between 3–18 May 2023 at Bonifiche Ferraresi Farm (Ferrara province, Emilia-Romagna region, Italy), near Jolanda di Savoia, to ensure multi-scale model applicability, refer to Figure 4.6. At the microplot level, detailed biochemical parameters (total nitrogen, total carbon, chlorophyll) and biophysical properties (LAI, LMA, slant height, and vertical height) were recorded, providing fine-scale characterisation of lodging variability. Measurements were aggregated at the subplot and plot levels to evaluate spatial consistency.

Key crop traits were measured using standardised protocols: LAI via destructive sampling; Chlorophyll content measured non-destructively using a SPAD-502 meter; EWT computed from fresh and dry leaf mass; LMA calculated from leaf dry weight and surface area; Carbon (C) and Nitrogen (N) analysed in the laboratory with a CHN analyser. Together, these measurements established the physiological basis for linking lodging occurrence with biochemical and structural factors (**details are in RD-3.1: ATBD 2.2.4**).

5.2.2 Product Validation

Model development and validation were undertaken using data from the Bonifiche Ferraresi Farm, focused on wheat fields, which means applying the models to other crops or regions may alter accuracy due to site-specific spectral, environmental, or physiological differences. Seven ML algorithms were evaluated (**RD-3.1: ATBD section 2.2.7.2**) using the ϵ_{mae} , ϵ_{rmse} ,

and R^2 metrics. RFR achieved the best results, both on average and in the most accurate single run. The best run ($R^2 = 0.812$) indicated a strong correlation between predicted and measured lodging scores. Performance by class was:

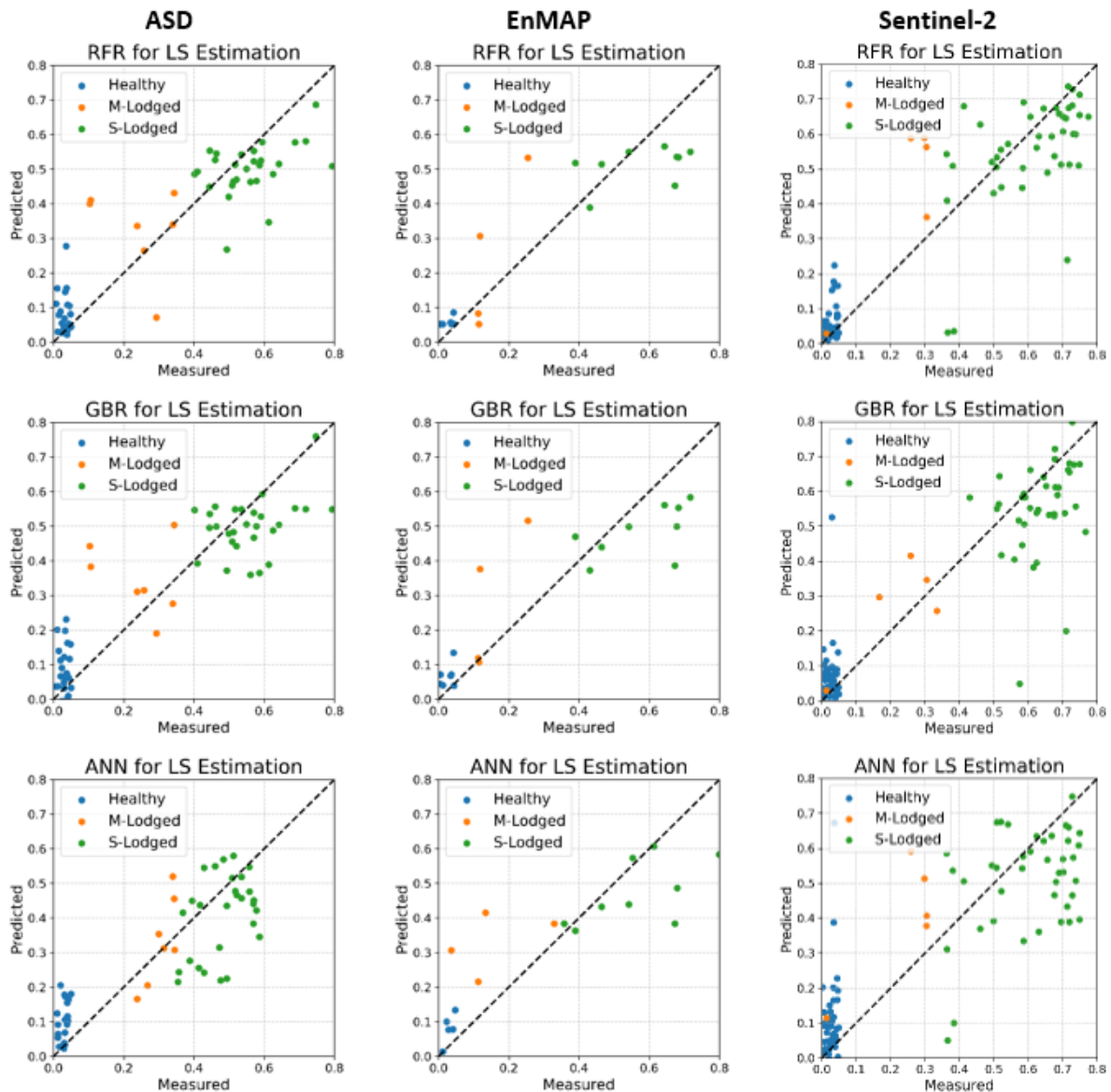


Figure 5.8 The scatter plots of predicted vs. measured LS across the three datasets (ASD, EnMAP, and Sentinel-2) for models without dimension reduction: RFR, GBR and ANN. Each data point is colour-coded by lodging class: Healthy, M-Lodged (Moderately Lodged), and S-Lodged (Severely Lodged).

The model most accurately represented healthy and moderately lodged samples, where spectral–structural distortions are less pronounced. For severely lodged crops, increased variability in canopy reflectance caused greater uncertainty, though overall prediction remained robust. These findings confirm that RFR effectively models the relationship between spectral response and lodging severity and that field-based ASD data provide a strong foundation for scaling up to satellite applications (**Figure 5.8**).

5.2.3 Product Validation – Upscaling

Building upon the field-scale validation, the second phase integrated satellite remote-sensing data to test model scalability. Using the same preprocessing, training, and Bayesian

hyperparameter-optimisation framework, RFR was trained and tested (70:30 split) on EnMAP hyperspectral and Sentinel-2 multispectral imagery. Each dataset underwent 100 independent runs for statistical robustness.

Table 5.1 The accuracy assessment of the RFR model was conducted using the mean values from 100 random runs, with the best performance achieved for EnMAP and Sentinel-2 data.

Data Source	Method	Accuracy mean			Accuracy best		
		ϵ_{mae}	ϵ_{rmse}	R^2	ϵ_{mae}	ϵ_{rmse}	R^2
EnMAP	RFR	0.134 ± 0.021	0.177 ± 0.027	0.586 ± 0.128	0.088	0.117	0.813
Sentinel-2	RFR	0.104 ± 0.011	0.166 ± 0.018	0.702 ± 0.063	0.078	0.122	0.833

For EnMAP, the model showed excellent agreement for healthy samples ($\epsilon_{mae} = 0.024$, $\epsilon_{rmse} = 0.041$, $R^2 = 0.862$). Prediction uncertainty increased for M-Lodged ($\epsilon_{mae} = 0.111$, $\epsilon_{rmse} = 0.162$, $R^2 = 0.611$) and S-Lodged ($\epsilon_{mae} = 0.125$, $\epsilon_{rmse} = 0.152$, $R^2 = 0.652$) categories, partly due to limited training samples. For Sentinel-2, the model performed slightly better overall ($R^2_{best} = 0.833$), although reduced spectral resolution led to greater overestimation in M-Lodged cases ($\epsilon_{mae} = 0.161$, $\epsilon_{rmse} = 0.201$, $R^2 = 0.450$). Predictions remained strong for Healthy ($\epsilon_{mae} = 0.051$, $\epsilon_{rmse} = 0.062$, $R^2 = 0.864$) and S-Lodged samples ($\epsilon_{mae} = 0.061$, $\epsilon_{rmse} = 0.084$, $R^2 = 0.723$) (Accuracy assessment matrices are in **RD- 3.1: ATBD Document Result section 2.2.7.2**). The results shown in Table 5.3 confirm the RFR model's robustness and scalability. Both sensors reliably captured lodging patterns, though EnMAP's hyperspectral data offered superior sensitivity to structural deformation. Sentinel-2, while less precise, provided acceptable accuracy and greater temporal availability, supporting its utility for routine agricultural monitoring. The final model outputs were used to produce lodging severity maps (**Figure 5.9**), illustrating spatial variability across the study area. These maps validated field observations and demonstrated the practical application of ML-based hyperspectral analysis for operational crop-lodging assessment at regional scales.

Thus, Random Forest Regression (RFR) applied to hyperspectral and multispectral data can accurately detect and quantify lodging severity in wheat. Field-level validation yielded $R^2 = 0.812$, while satellite upscaling maintained strong performance ($R^2 = 0.813$ for EnMAP and 0.833 for Sentinel-2). The integrated use of in situ spectroscopy, RTM simulations, and satellite imagery provides a scalable, data-driven framework for precision agriculture. This methodology enables early detection of lodging, supports loss estimation, and contributes to improved crop management and food-security resilience.

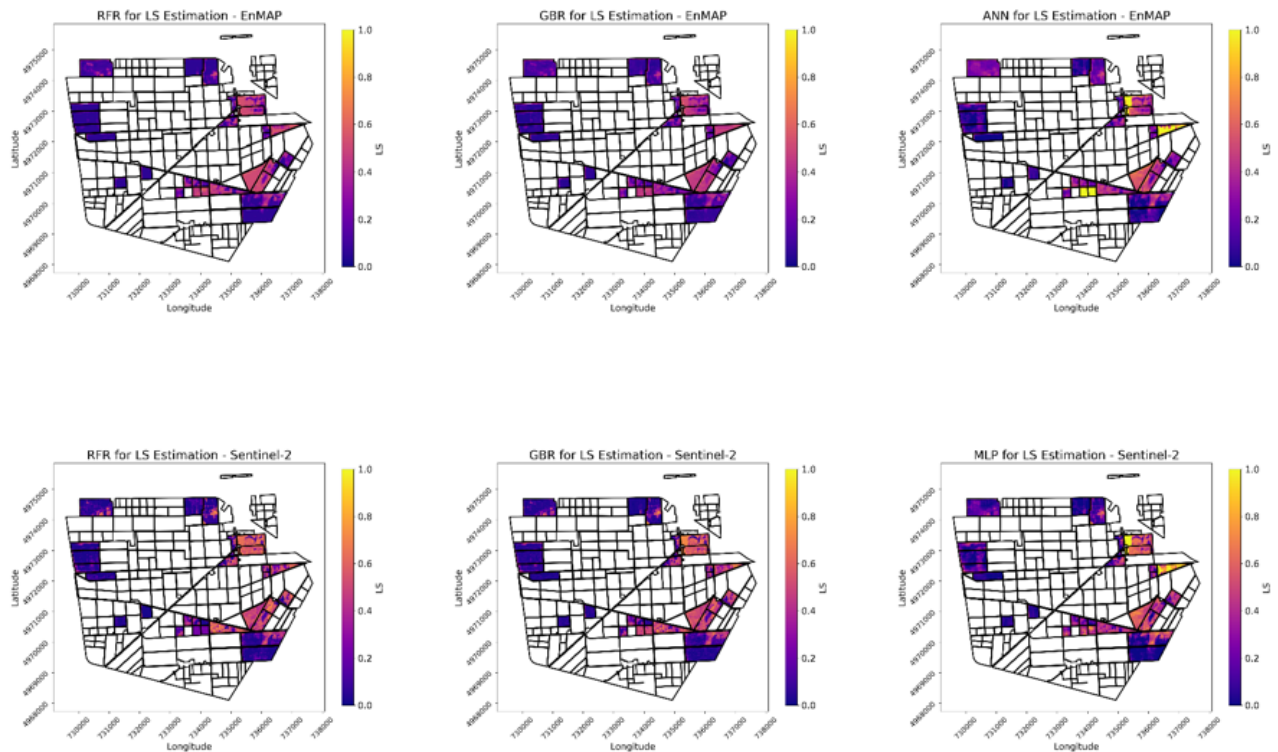


Figure 5.9 LS map produced from ML models for EnMAP data (top) and Sentinel-2 data (bottom).

5.3 Pilot Three: Drought Stress in Maize

Validation of the drought maps was conducted to ensure their accuracy and reliability in detecting drought conditions across maize fields in the Marchfeld region of Austria. The procedure comprises multiple approaches, including comparisons with field- and satellite-based reference data, statistical cross-validation, and performance metric analysis. A 10-fold cross-validation scheme was applied to prevent overfitting and assess model stability. Model performance was quantitatively evaluated using precision, recall, F1-score, and ROC-AUC, providing a comprehensive measure of predictive capability across spatial and temporal scales. This multifaceted validation framework confirmed the consistency of drought estimates over different years and climatic conditions.

The drought maps were produced using three main methodological components. First, feature extraction and vegetation indices involved deriving 28 spectral indices, , from Sentinel-2 , listed in Table 3.3, **RD- 3.1: ATBD Document**.

. These indices were used as indicators of crop health and vitality, enabling the detection of vegetation stress over multiple growing seasons (2018–2023). By integrating these indices with ancillary datasets, including soil moisture, climatic variables, and field capacity maps, the approach provided refined drought characterisation for both irrigated and non-irrigated systems. Second, supervised machine and DL algorithms (RF, SVM, k-NN, GB, MLP, LR, DT, DNN, and 1D CNN) were employed to predict drought conditions at a pixel level. These models processed time-series spectral data to extract spatial and temporal patterns in drought occurrence. Training was based on reference datasets derived from field observations and satellite indices, while independent validation data were used to assess predictive accuracy. This framework enabled adaptive model learning, improving the precision of drought detection across heterogeneous agricultural landscapes. Third, a Self-Supervised Learning (SSL) approach was implemented to enhance spatial accuracy by segmenting maize fields based on actual agricultural practices rather than cadastral boundaries. This improved the

representation of real crop conditions and irrigation patterns, particularly in mixed-use agricultural zones.

Model performance was further assessed using Receiver Operating Characteristic (ROC) analysis, with AUC values quantifying the models' ability to discriminate between drought and non-drought conditions. The combined use of ROC-AUC and cross-validation improved the reliability and robustness of model outcomes.

5.3.1 Reference Data

The reference data used for both training and validation were derived from field surveys, Sentinel 2 based indices, and expert knowledge collected between 2018 and 2023. Experts reviewed Sentinel-2 vegetation indices, soil moisture information, field-capacity maps, precipitation patterns, and irrigation-related information to verify and label maize fields as irrigated or non-irrigated, to ensure the reliability of the ground-reference data used for model training and validation.

Maize fields were categorised as irrigated or non-irrigated using water-source information and local field records. 30% of this dataset was reserved for independent validation each year, ensuring temporal consistency. The spatial distribution of reference samples across seasons strengthened the representativeness of validation results.

5.3.2 Product Validation

Model outputs from ML and DL algorithms were compared with reference data, including soil characteristics, vegetation indices, and irrigation status. These reference data acted as ground truth for assessing the accuracy of satellite-derived drought predictions.

Validation was carried out in three steps. Firstly, model-specific validation evaluated each ML and DL model independently, comparing predicted drought probabilities with reference data to verify the consistency of pixel-level outputs. Secondly, a cross-comparison of models was conducted to identify the most robust and accurate approaches for maize field drought mapping. Error metrics, including precision, recall, F1-score, and area under the ROC curve (AUC), were calculated to quantify prediction performance and guide model refinement. Temporal validation across growing seasons from 2018 to 2023 and spatial validation across the Marchfeld region ensured both temporal consistency and generalizability of the drought maps. For the semantic segmentation of maize fields, precision, recall, and F1-score were employed to assess how accurately models delineated agricultural fields. Precision measured the proportion of correctly identified pixels among predicted positives, while recall quantified the proportion of true field pixels correctly captured. The F1-score provided a balanced measure of model performance, particularly useful for imbalanced datasets where agricultural fields occupy a small fraction of the total area. Both unweighted macro averages (across classes) and weighted averages (accounting for class frequencies) were calculated to evaluate model performance across different land cover types. For the applied Self-Supervised Learning (SSL) model, results indicated high accuracy, with macro and weighted averages of approximately 0.95–0.96, demonstrating reliable segmentation of agricultural versus non-agricultural areas. For drought prediction models, loss metrics such as mean squared error (MSE) and mean absolute error (MAE) were used to assess model training and predictive performance.

Training curves for the SSL model showed rapid loss reduction during early epochs, with validation curves closely tracking training performance, suggesting effective learning and good generalisation to unseen data (Figure 5.10).

Table 5.2: Summary of accuracy assessment values, averages and the standard deviation.

Year	CNN-irr	CNN-non	DNN-irr	DNN-non	RF-irr	RF-non	Year average	year STDEV.P
2018	75,20	76,47	78,10	81,62	67,30	69,62	74,72	4,89
2019	82,81	69,29	81,73	84,40	77,25	67,77	77,21	6,52
2020	79,59	75,31	82,91	78,69	73,47	74,94	77,48	3,23
2021	79,26	87,62	82,29	86,16	75,76	79,17	81,71	4,14
2022	82,59	86,86	77,99	79,03	79,50	69,17	79,19	5,36
2023	86,03	79,26	83,04	90,78		84,07	85,02	3,55
Model average	80,91	79,14	81,01	83,45	76,70	74,12	79,22	
Model STDEV.P	3,16	5,98	1,98	3,92	5,51	5,48		

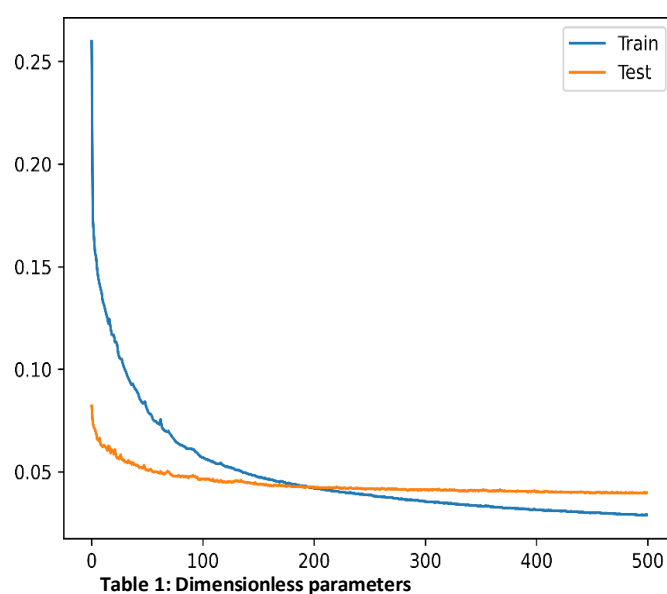


Figure 5.10 Performance of self-supervised learning model.

5.3.3 Product Validation – Upscaling

The performance of three selected models, 1D-CNN, DNN, and Random Forest (RF), was evaluated using ROC curves and AUC. ROC analysis illustrates the trade-off between the True Positive Rate (sensitivity) and False Positive Rate, providing a robust measure of a model's ability to distinguish between drought and non-drought conditions. A 10-fold cross-validation was applied to ensure model robustness and minimise overfitting, with AUC values closer to 1 indicating higher predictive accuracy.

Model predictions were compared with reference data for each year, and drought probabilities were classified across thresholds. Precision and F1-score metrics further quantified model performance, while visual inspection of spatial probability maps highlighted differences in

drought pattern representation. The DNN model consistently produced the highest AUC values and the most accurate spatial predictions, particularly for non-irrigated maize fields.

Variability in model performance across years was assessed using the population standard deviation of AUC values, revealing consistent reliability for the DNN and 1D-CNN models, while RF showed slightly higher year-to-year variability. For additional evaluation, the coefficient of determination (R^2) was applied in a multilinear regression between DNN-predicted drought probabilities and normalized precipitation, confirming the expected inverse relationship: lower precipitation corresponded to higher drought probabilities.

Overall, integrating Sentinel-2 satellite imagery with climate and soil data, combined with self-supervised learning (SSL) for maize field segmentation, improved spatial precision and differentiated irrigated from non-irrigated fields. Across all metrics, the DNN model achieved the highest overall performance (81–83% accuracy), followed by 1D-CNN, demonstrating the effectiveness of DL approaches for reliable, pixel-level drought mapping in Austria's Marchfeld region. These results provide a strong foundation for future improvements through additional data integration and model refinement.

6 Impact Assessment Report (Science Case)

This section presents new findings from large-scale field and regional studies aimed at enhancing the understanding and monitoring of cereal crop responses to multiple stressors, especially drought. The report has two main parts: (1) a regional analysis across Canada's Prairies using EO datasets to evaluate drought effects on spring wheat yields through Bayesian Neural Network models that combine MODIS based NDVI anomalies and Canadian Drought Monitor data, providing high-resolution predictions with uncertainty estimates; and (2) field experiments at Elora Research Station in Ontario using large lysimeters and hyperspectral UAV imagery to assess vegetation indices and model LAI for evapotranspiration (ET) calculation. These approaches collectively demonstrate the potential for operational risk mapping and advanced stress indicators to support precision agriculture and informed decision-making at regional and field levels.

6.1 Case study 1: Drought Impact Assessment in Canada Using EO

6.1.1 Overview

The Prairie region of Canada is a key wheat-producing area, yet it faces chronic water scarcity and limited irrigation infrastructure. Agriculture and Agri-Food Canada (AAFC) produces a monthly drought assessment, released as the Canadian Drought Monitor. The monthly data set tracks the location, intensity, and evolution of drought using a large combination of meteorological and satellite data sources and expert analysis. While the product is important for classifying the intensity and locations of drought, the link to its impact on crop stress has not been established. To address this research gap, a study was conducted to combine the existing Canadian Drought Monitor (CDM; AAFC, 2025a) with an assessment of crop stress detectable in EO data. In this work, we adopted a risk assessment approach using the IPCC's definition of risk as a function of hazard, exposure, and vulnerability to link how drought severity and timing may influence spring wheat yield losses.

6.1.2 Methodology

Town-level Spring wheat yield data (~95 km²) were obtained from AAFC through provincial crop insurance agencies and converted to kilograms per hectare (kg/ha). Across the Prairie Region, yield data were available for 7,320 townships, but a subset of 4,905 was selected based on consistent wheat cultivation (covering at least 75% of years from 2010–2021). The overall model framework is presented in **Figure 6.1**.

Yield data were linearly detrended at the township level using OLS to isolate climate-driven variability, with the rainbow test confirming model suitability in 94.5% of cases. MODIS NDVI (250 m) from Canadian Ag-Land Information System (CALMS) provided weekly township-level NDVI anomalies (2002–2021 baseline), supplemented with historical means and standard deviations to contextualise vegetation conditions. Monthly Canadian Drought Monitor categories (D0–D4) were resampled to weekly intervals and aggregated to townships for alignment with NDVI and yield data. Spring wheat fields were identified using AAFC's Annual Crop Inventory, resampled from 30 m to 250 m using majority filtering to mask non-wheat areas and exclude unseeded wet fields. Bayesian Neural Networks were trained weekly (late April–September) using NDVI and drought data from the current and previous three weeks, incorporating aleatoric and epistemic uncertainty through probabilistic outputs and Monte Carlo weight sampling. Training used leave-one-out cross-validation (2010–2021), Gaussian NLL loss, and Hyperband hyperparameter optimisation. Model performance was assessed

using nRMSE, MAE/MAE%, R^2 , Pearson r , and Interval Coverage Scores, and monthly analyses quantified the effects of drought timing and severity on yields.

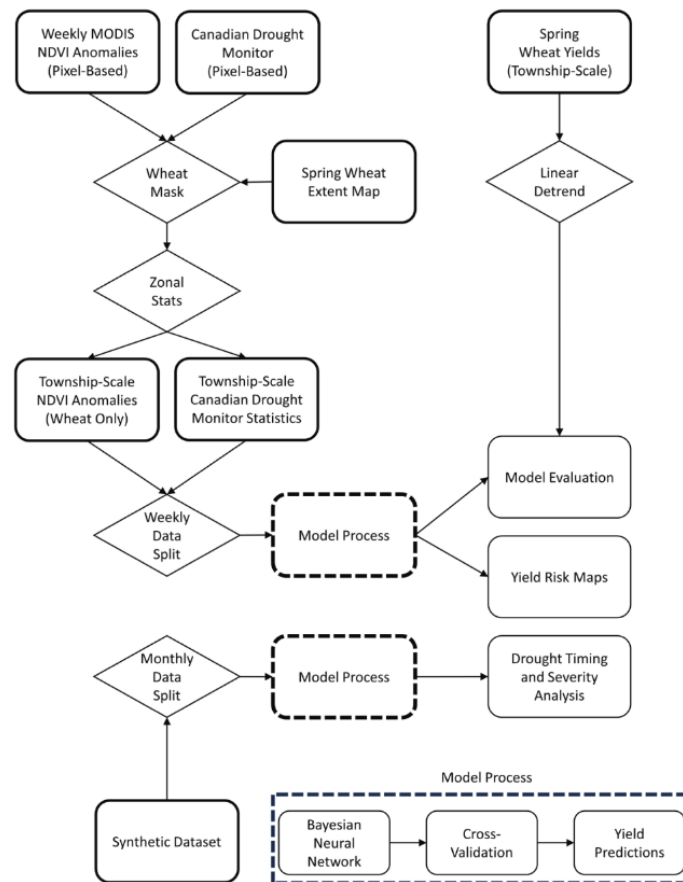


Figure 6.1 Model workflow (Mardian et al. 2024). Data from the Canadian drought monitor (AAFC 2025a) includes MODIS NDVI data; The yield data was a proprietary dataset.

6.1.3 Results

As is obvious from Figure 5.2, prediction accuracy peaked between WOY 29–34, with $R^2 = 0.70$, $r = 0.84$, and mean absolute errors of 400 kg/ha (13%), comparable to or better than previous studies (Mkhabela et al., 2011; Qian et al., 2009). Key advantages of our approach include substantially finer spatial resolution (95 km² vs 35,000 km²), complete spatial coverage from satellite data rather than weather stations, and a simple input structure that relies only on NDVI and CDM data. The BNN was retrained in 2010–2021 data to assess the effects of drought timing and severity. Spring wheat yields responded strongly to drought (ND–D4), with the most significant yield anomalies occurring during June–August; D2–D4 events reduced yields by 12–25% on average and up to 40% in some areas. Prediction uncertainty was lowest in August.

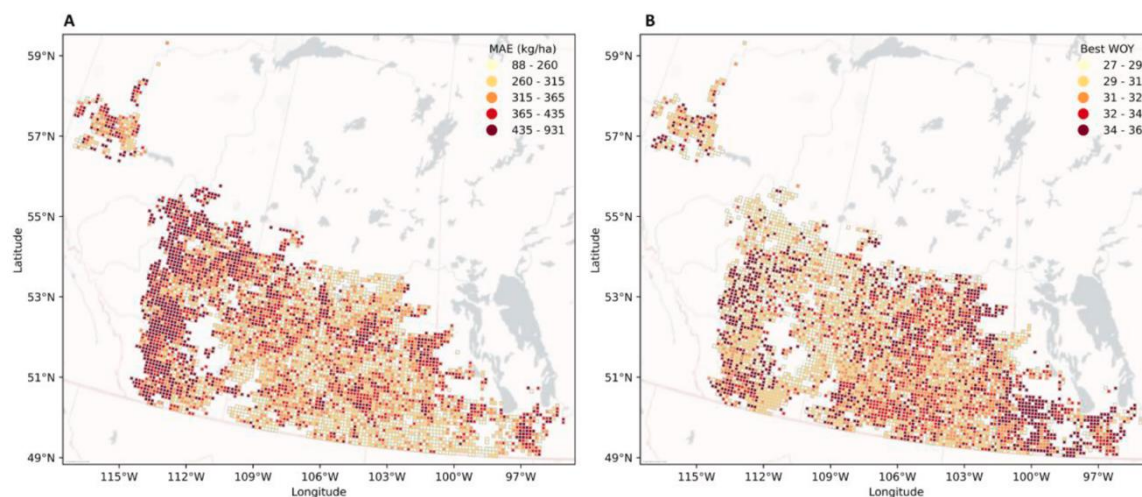


Figure 6.2 (A) Lowest mean absolute error (kg/ha) spring wheat yield predictions and the week of year that this occurred (B)

Drought effects in May were inconsistent and generally weaker due to early crop development and sparse training data, though early water stress still hindered seedling growth. Impacts intensified in June during jointing, varied regionally, and became stronger and more consistent in July, particularly during heading, when model uncertainty also declined. In August, a slight drought (D0–D1) sometimes increased yields by inducing mild stress-enhanced grain filling, reflecting adaptive late-season physiology. Monthly drought–yield relationships are shown in **Figure 6.2**.

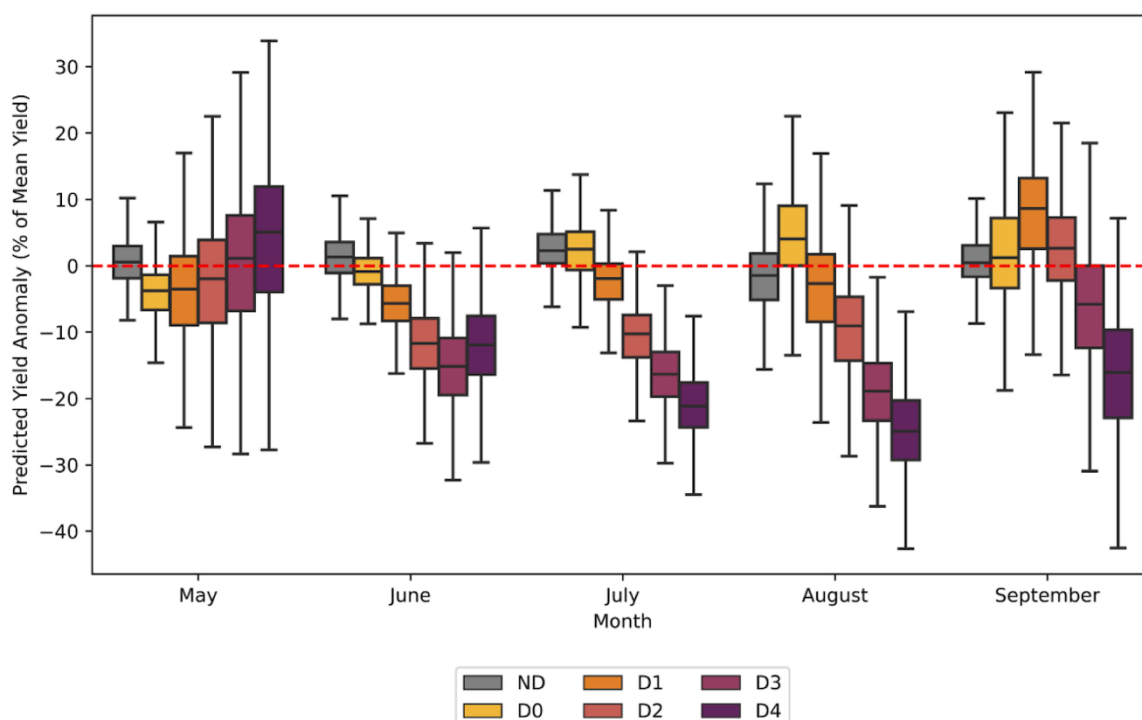


Figure 6.3. Average yield anomaly predictions (as a% of mean yield) for towns across the Canadian Prairies under different drought severities.

Forecast accuracy improved markedly beginning with WOY 27 (July 2–8), coinciding with major growth stages and consistent with earlier NDVI-based findings. Early-season

predictions (WOY 18–21) were weak due to limited vegetation signal, but accuracy increased steadily through jointing (WOY 26) and rose sharply during heading (WOY 27–29). Peak performance occurred around WOY 32 (August 6–12) during the soft dough stage, after which accuracy remained high until WOY 35, when it declined as harvest reduced NDVI. **Figure 6.3** shows mean absolute errors and the timing of peak predictive performance.

6.1.4 Outlook

This study advances understanding of crop stress by integrating the Canadian Drought Monitor into a crop-specific risk framework to predict spring wheat yields across the Canadian Prairies. A Bayesian Neural Network trained on CDM and NDVI data produced high-resolution, spatially continuous yield predictions with quantified uncertainty using only a small set of inputs. Vulnerability analyses showed that wheat is most sensitive to drought in July–August, while mild August dryness can be beneficial. Yield uncertainty declined mid-season, indicating opportunities for earlier mitigation. High-resolution risk maps translate these findings into practical decision-support tools, and the framework is readily adaptable to other crops and regions.

This report section summarises the published study (**Mardian et al., 2024**) and highlights areas for improvement. Risk classes could be refined into explicit yield anomaly estimates, and NDVI-based indicators have known limitations. More sensitive satellite products, such as those emerging from EO4-CerealStress research or future Sentinel Expansion Missions, could enhance early detection of wheat stress and support finer-scale, physiologically meaningful assessments.

6.2 Case study 2: EO4CerealStress Workflow Implementation at the Elora Research Site

6.2.1 Overview

This section explains fine-scale drought indicators developed using advanced EO techniques at the University of Guelph's Elora Research Station in Ontario, Canada. The site is equipped with 18 large weighing lysimeters that provide precise ET measurements for crops like wheat, corn, and soy. The study integrates hyperspectral UAV imagery with field measurements to assess vegetation indices (VIs) and their relationships with ET, aiming to identify indices that better capture crop-specific water-stress dynamics. Nine VIs, including NDVI, HNDVI, and MCARI, were tested across three growing seasons (2020–2022). Additionally, the workflow applied radiative transfer models (4SAIL and PROSPECT-PRO) and Gaussian Process Regression to estimate Leaf Area Index (LAI) from hyperspectral data, and compared the results with field observations and Sentinel-2-derived LAI products. Findings showed strong VI-ET correlations for wheat (NDVI and HNDVI), weaker relationships for corn and soy, and promising LAI estimation performance, though early-season calibration issues were noted. Overall, the workflow demonstrates the potential of hyperspectral and EO-based indicators for improving drought risk assessment and precision agriculture at the field scale.

6.2.2 Methodology

Figure 6.4 shows Elora Research Station in Ontario, where 18 large weighing lysimeters are installed to continuously measure evapotranspiration (ET). Each lysimeter contains a 1.5-m-deep, 1-m² undisturbed soil monolith positioned on a tension load cell capable of detecting mass changes equivalent to 0.01 mm of water. ET was calculated from weight changes in both the soil monolith and its drainage tank. The lysimeters included two soil types, sandy loam from Cambridge and silt loam from Elora, which were managed under two crop rotations:

12 in a corn–soybean–wheat rotation and 6 in a corn–soy rotation. Data were collected weekly from May to September over three growing seasons (2020–2022). Winter wheat was used in 2020, followed by corn in 2021 and soybeans in 2022. ET estimates were aggregated to hourly values, and LAI was measured using a LI-COR LAI-2200c.

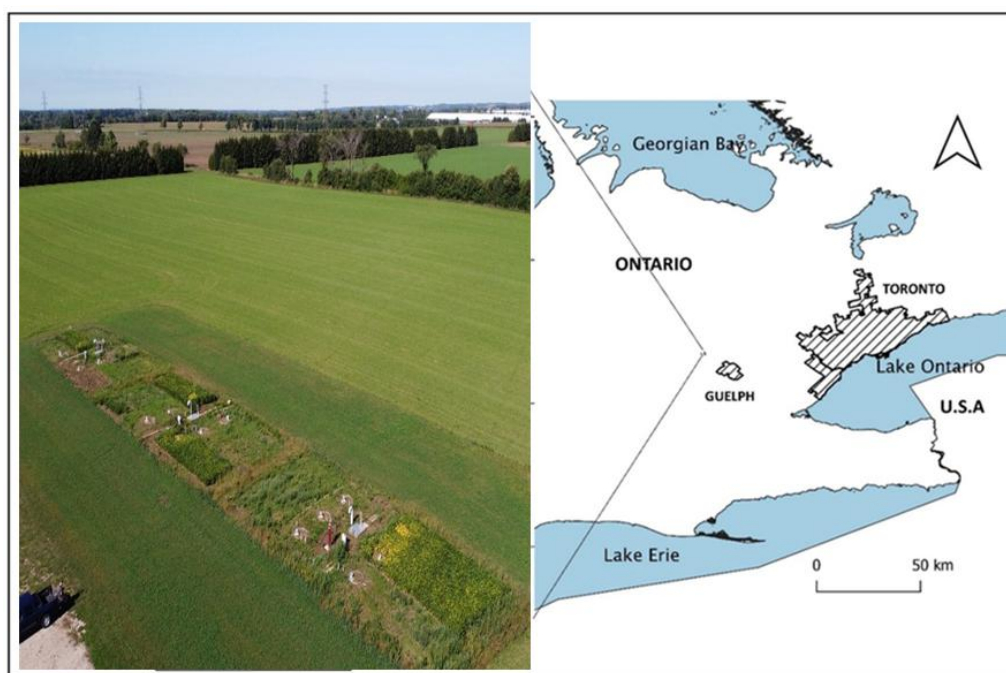


Figure 6.4. The lysimeter site is within the Elora Research Station near Elora, Ontario.

Hyperspectral imagery was collected weekly with Headwall’s Nano-Hyperspec sensor mounted on a DJI Matrice M600 UAV. The sensor records reflectance from 400–1000 nm across 270 bands at 2.24-nm resolution. Flights followed a consistent NE–W pattern with four overpasses and 60% swath overlap. Before each flight, the instrument was calibrated using a white reference panel to set the optimal flight speed. Flights were conducted at 30 m altitude and 1–5 m/s, producing 3.42-cm² pixels. Imagery was processed in Spectral View, and vegetation indices [NDVI, SAVI, GI, RVSI, HNDVI, WI, PRI, MCARI] were correlated with daily actual ET (AET) using Pearson’s correlation.

In addition to index-based comparisons, we used 4SAIL (Verhoef et al., 2007) and PROSPECT-PRO (Ferret et al., 2021) to generate reflectance curves for estimating LAI and for comparison with field measurements. Following the EO4CerealStress method described in section 3.1 for the Andalusia site, we developed a Gaussian Process Regression model using hyperspectral and LAI data collected during the 2021 corn season. Crop-specific parameters, such as carotenoid content and leaf angle, were taken from the literature (Lu et al., 2021) and summarised in Table 6.1.

Table 6.1. Input values for PROSPECT-PRO modelling for the Elora Research Site.

Variable	Short Name	Mean	Min	Max	Distribution
Chlorophyll	CHL	35	20	50	Normal
Carotenoid	CAR	10	0	15	Normal
Anthocyanin	ANT	0	0	0	-----
Thickness of water	EWT	0.02	0.015	0.025	Normal

Leaf Mass Area	LMA	0.0048	0.0035	0.006	-----
Brown pigment	BROWN	0	0	0	Uniform
Protein content	PROT	0.0015	0.0015	0.0015	Uniform
Carbon-based constituents	CBC	0.01	0.01	0.01	Uniform
Leaf structure	N	2.2	1.4	4	Uniform
Soil brightness coefficient	PSOIL	-	0.01	0.05	Uniform
Average leaf angle	LIDFa	30	20	50	Poisson
Leaf area index	LAI	4	0	7	Uniform
Hot spot effect	q	-	0.01	0.5	Uniform
Diffuse/direct radiation	skyl	-	0.2	0.3	Uniform
Solar zenith angle	SZA	-	15	55	Uniform
Observer zenith angle	OZA	0	0	0	Uniform
Relative azimuth	rAA	0	0	0	Uniform
Solar brightness coefficient	asoil	-	0.2	0.28	Uniform

5.2.3 Results

Correlations between vegetation indices and lysimeter-measured actual evapotranspiration (AET) showed that HNDVI and NDVI performed best for winter wheat ($r = 0.84$ and 0.83 ; $SD = 0.12$). Relationships were much weaker for corn, where MCARI ($r = 0.23$, $SD = 0.31$) and RVSI ($r = 0.20$, $SD = 0.29$) were the top indices, but with high variability. For soybean, HNDVI ($r = 0.41$, $SD = 0.27$), NDVI ($r = 0.39$, $SD = 0.27$), and GI ($r = 0.38$, $SD = 0.16$) were most effective. Indices such as PRI, RVSI, and MCARI generally underperformed and often showed weak or negative correlations with AET, especially during the soybean season. Seasonal index performance is summarised in **Figure 6.5** and **Table 6.2**.

Table 6.2. Top indices, their mean correlation and SD for each crop.

Crop	Top Indices	Mean Correlation	SD
Wheat	HNDVI, NDVI	0.84, 0.83	0.12, 0.12
Corn	MCARI, RVSI	0.23, 0.20	0.31, 0.29
Soy	HNDVI, NDVI, GI	0.41, 0.39, 0.38	0.27, 0.27, 0.16

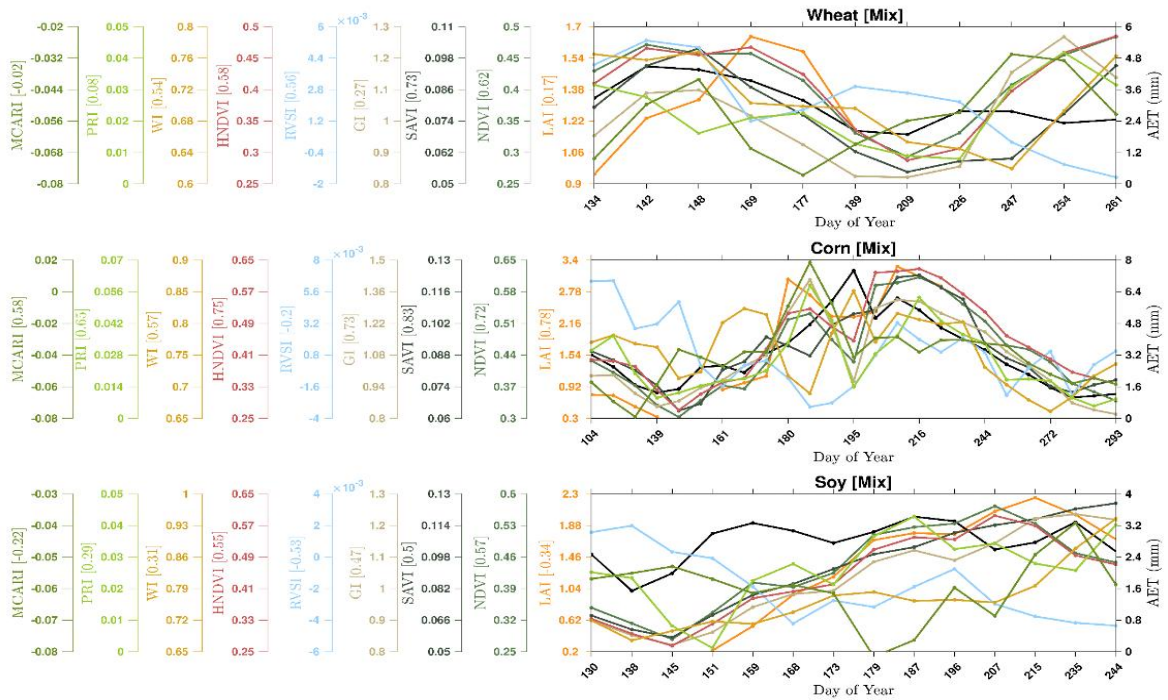


Figure 6.5. Relationships among several vegetation indices (y-axis) and actual evapotranspiration (AET) with correlation shown on the y-axis.

PROSPECT-PRO modelling of hyperspectral data for LAI prediction produced an RMSE of 0.81, $R = 0.74$, and $R^2 = 0.55$ —lower R^2 but lower RMSE relative to results from the Andalusia site ($R^2 = 0.71$; RMSE = 1.353). The model struggled to capture the full range of observed LAI variability (**Figure 6.6a**). A Sentinel-2–based LAI model generated with the LEAF Toolbox was also evaluated. Compared with hyperspectral-derived LAI, the GPR model tended to overestimate LAI in May and June but aligned more closely with observations from July onward, capturing peak and decline patterns that Sentinel-2 products missed (**Figure 6.6b**). Early-season discrepancies likely reflect sensor issues, as the hyperspectral camera recorded unusually low reflectance in the 800–1000 nm region; improved calibration may enhance model performance.

6.2.4 Outlook

Building on the EO4-CerealStress framework from the Andalusia site, we evaluated LAI estimation using hyperspectral imagery and a Gaussian Process Regression model originally developed for rice and adapted here for corn. Results indicate strong potential to produce fine-resolution (~ 1 m) LAI maps, with Sentinel-2–derived LAI showing good agreement with field measurements. These products could enhance regional drought assessments and improve the physical realism of operational monitoring systems. We anticipate that government agencies and other decision-makers will be key users of these tools for forecasting yields and assessing crop losses.

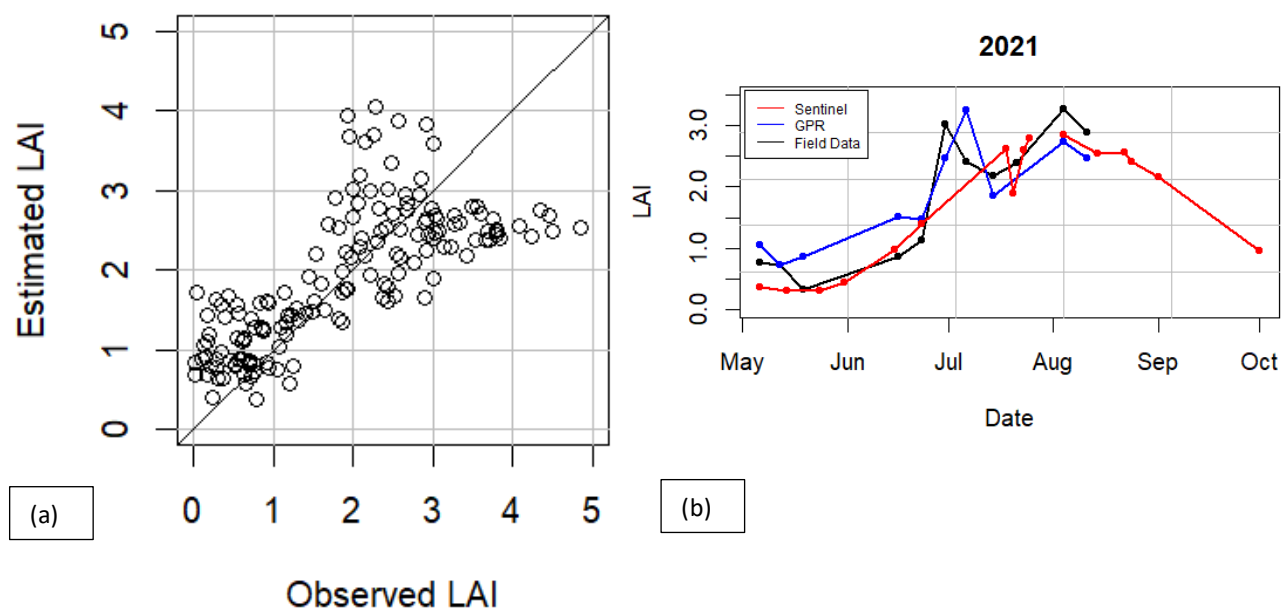


Figure 6.6a. Observed vs. estimated LAI for corn during the 2021 growing season. **b.** Time series of LAI over the 2021 growing season derived from Sentinel-2, hyperspectral data, and site measurements.

7 Impact Assessment Report (Societal Impact)

This section presents a brief overview of the societal impact assessment report of the EO4CerealStress project, which documents early adopters' feedback over agricultural drought monitoring enhancement, lodging stress and other abiotic stressors in soil (salinity, heavy metals, nutrient deficiency) with a synergistic approach of using EO data and DL models. These pilots, co-designed with early adopters such as Agriculture and Agri-Food Canada, the Andalusian Federation of Rice Growers (AFR, Spain), and Bonifiche Ferraresi (Italy), enabled the real-world testing and integration of EO-based solutions into operational agricultural decision-making. Through these collaborations, the project fostered engagement with both users and the wider research community, advancing climate-smart agriculture, crop monitoring systems, and sustainable food systems.

This section highlights the project's key outputs, including drought-stress maps, lodged-wheat maps (with varying severity levels), salinity and nutrient-stress maps, and the Agricultural Science Precursors Dataset. These products collectively demonstrate the potential of EO-based innovations to support early warning systems and provide intelligent, data-driven solutions for farmers and agricultural stakeholders. The section will cover the main scientific findings, pilot stress cases, the approaches and data/methodologies used, and feedback from early adopters. It concludes by outlining pathways to transform the project's scientific advancements into practical, actionable information that can enhance operational and decision-support systems within the agricultural sector.

7.1 Pilot Study 1: Drought Assessment in the Manitoba District, Canada

7.1.1 Overview

In predominantly rainfed regions such as Manitoba's Canadian Red River watershed, meteorological droughts significantly affect land surface conditions, constrain vegetation growth, and reduce crop yields, thereby heightening rural vulnerability. Modern systems like the Canadian Drought Monitor (CDM) have advanced drought assessment by integrating multi-source data, including precipitation, soil moisture, and vegetation health, with expert validation to ensure robust, context-aware drought monitoring across Canada.

In this case study, the EO4CerealStress project aims to validate and demonstrate the adaptability of a DL model initially designed for a specific crop and region, assessing its transferability to other environmentally similar regions and crop types. The study highlights the potential of such models to support scalable, generalised drought monitoring frameworks that can enhance agricultural resilience and operational decision-making across varied agro-ecological contexts.

The primary objectives of Case Study 1:

1. To integrate multi-sensor EO indices (vegetation, thermal, soil moisture) with CDM data in a DL pipeline for agricultural drought assessment.
2. To test whether a DL model trained on maize in Austria remains effective when applied to corn in Canada.
3. To evaluate the model's performance when transferred to soybean crops in the same region.

The study aims to produce interpretable drought maps and identify spatial patterns of stress, enhancing CDM to support climate-adaptive interventions such as crop rotation, soil management, and insurance support.

7.1.2 Field Description

The Redboine Watershed District, located in southern Manitoba (49.60° N, -97.88° W), covers approximately 52,000 hectares and includes the Boyne-Morris River, La Salle River, and Lower Assiniboine (Sturgeon Creek) watersheds. These sub-basins form part of the Red River Basin, which drains northwards into Lake Winnipeg and ultimately Hudson Bay (**Figure 7.1**).

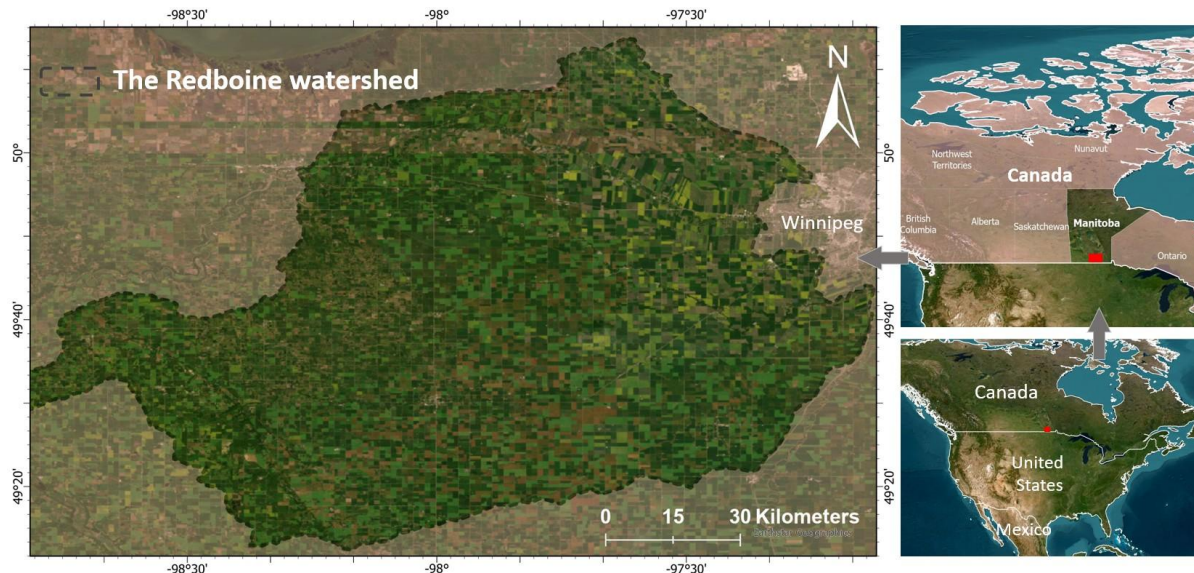


Figure 7.1: Redboine Watershed, Study area for Canadian Drought monitoring

Agriculture dominates land use in the region, characterised by crop rotations involving cereals, oilseeds, pulse crops, and speciality crops such as sunflower, canary seed, field peas, and potatoes, typically grown on fields ranging from 20 to 60 hectares. Soil textures vary from fine clay in the east to coarser, well-drained soils in the west. The area experiences a continental climate, with warm summers, cold winters, and recurring episodes of flooding and drought. Traditional hydrological models often overestimate streamflow during dry years, reducing their reliability for agricultural drought assessment in this environment. Consequently, a more flexible, data-driven approach that integrates vegetation stress indicators and multi-source EO data can be useful for annual drought monitoring. Corn and soybeans serve as the primary indicator crops due to their economic importance and similar growing seasons, both of which are sensitive to soil moisture deficits during critical phenological stages. Their shared vulnerability to drought makes them ideal for this demonstration case.

7.1.3 Data used

- i. Sentinel-2 Imagery: The study employed orthorectified Top-Of-Atmosphere (TOA) reflectance data from the Sentinel-2 satellite mission, selected for its high spatial resolution (10–60 m) and frequent revisit time, which are well-suited to detecting vegetation dynamics and soil moisture variations at the field scale. To ensure consistency across spectral bands, all imagery originally acquired at 20 m and 60 m resolutions was resampled to 10 m, enabling pixel-wise analysis for vegetation index computation and model input standardisation.
- ii. Band Indices: A suite of spectral indices was derived from Sentinel-2 data to assess crop stress and vegetation condition under drought scenarios. Using a customised processing function, indices were computed for each image to capture plant greenness, canopy structure, and water status. These included the Normalised Difference Vegetation Index (NDVI), red-edge NDVIs (NDVI1–3), and water-sensitive indices such as the Normalised Difference Water Index (NDWI) and its shortwave infrared (SWIR) variants. Drought-oriented metrics, including the Normalized Multi-band Drought Index (NMDI) and Moisture

Stress Index (MSI), were also employed to detect subtle moisture variations, while the Enhanced Vegetation Index (EVI), Normalized Difference Infrared Index (NDII), Shortwave Infrared Water Stress Index (SIWSI), and SWIR ratio indices further refined the detection of plant water deficits. These indices collectively leveraged Sentinel-2's NIR and SWIR spectral coverage, enabling detailed spatial assessments of crop drought stress (calculation details are in the **ATBD Document section 3.1**).

- iii. Precipitation and Climatic Data: ERA5-Land: Meteorological and precipitation data were sourced from ERA5-Land, a high-resolution reanalysis dataset by the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset integrates physical modelling and observational data to provide temporally consistent reconstructions of land-surface climate variables. Hourly data were aggregated into daily and seasonal (May–October) means and interpolated to match Sentinel-2's spatial resolution. Analysis of precipitation variability (2018–2023) revealed significant west-to-east rainfall gradients across the Redboine Watershed District, with alternating wet (2019, 2022) and dry (2020, 2021, 2023) years. These fluctuations underscore the region's climate variability and the need for multi-year datasets to capture both extremes and transitions.
- iv. Inventory Dataset| Canadian Drought Monitor (CDM): CDM served as the primary ground-truth dataset for model training and evaluation. CDM provides monthly, expert-interpreted drought assessments across Canada, combining precipitation anomalies, vegetation indices, streamflow data, and established drought metrics such as PDSI and SPI. For this study, seasonal composites (May–October) were generated to represent the growing period of maize and soybean. These composites provided consistent drought class labels, thereby improving the reliability of the model's supervised learning.
- v. Splitting of Annual Training and Testing Data Using CDM-derived drought classes, annual training and testing datasets were produced by linking drought severity labels to Sentinel-2 pixels within actively cultivated maize and soybean fields, as defined by Agriculture and Agri-Food Canada (AAFC) crop inventory maps. These maps, updated annually since 2009, offer detailed EO-based crop distribution information at 10 m resolution. From 2018 to 2023, pixel samples were randomly selected each year to capture temporal and spatial variability in drought and crop conditions. The resulting multi-year, spatially explicit dataset provided a robust foundation for training and validating the DL model, ensuring scalability, transferability, and consistency in drought classification across varying environmental and climatic conditions.

7.1.4 Deep Learning Workflow

A Deep Neural Network (DNN) architecture was employed to model and classify drought categories for corn and soybean crops. Its superior performance in the Marchfeld region. DNNs are particularly well-suited for capturing complex, high-dimensional relationships between EO features and drought conditions. Its network architecture comprises four hidden layers (200, 100, 50, and 25 neurons, respectively), balancing model depth with computational efficiency. The tanh activation function was applied across all layers to introduce non-linearity and facilitate convergence across diverse normalised input features (Dubey et al., 2022). Model training employed the Adam optimiser (Kingma & Ba, 2014) an adaptive gradient-based algorithm effective in handling noisy and sparse datasets, common in EO-based drought analysis. A learning rate of 0.001 was retained from the Marchfeld configuration for stable convergence. The batch size was set at 10, with a maximum of 500 iterations and 100 epochs, ensuring full exposure to training data and convergence of the cost function.

The DNN was trained on multi-annual datasets (2018–2023) comprising labelled Sentinel-2 pixels from maize and soybean fields, with drought classes derived from the CDM. Input features included vegetation indices (e.g., NDVI, EVI), spectral bands, and climate variables. Each annual dataset was randomly partitioned into training and testing subsets, maintaining proportional representation across drought classes. To enhance generalisability and prevent overfitting, a 10-fold cross-validation strategy was implemented. Model performance was

evaluated using the mean F1-score on withheld test data for each year, enabling consistent comparison across seasons and climatic conditions.

7.1.5 Results

The results reveal both spatial and temporal variability in drought patterns, highlighting the complex interplay between local climate conditions, soil characteristics, and crop vulnerability. In 2018, moderate drought was observed in the southwestern watershed, whereas the northern and northeastern areas remained relatively unaffected. A notably wet year in 2019 produced minimal drought stress across most corn fields, with only minor drier patches in the central and southeastern regions. Moderate drought conditions re-emerged in 2020 in the western areas, followed by the most severe and widespread drought in 2021, when high drought classes (17–22) affected the eastern part of the watershed and extended across much of the region. The year 2022 was essentially drought-free, but in 2023 drought conditions returned, affecting large portions of the watershed once more, with the southwestern areas consistently showing the greatest vulnerability (**Figure 7.2**).

Soybean drought maps mirrored maize patterns but exhibited higher spatial variability in drought severity. In 2018, drought stress was moderate, concentrated in central and southeastern zones, while northern and western areas remained relatively unaffected. The watershed was largely drought-free in 2019, but drought severity increased in 2020 and peaked in 2021, primarily affecting eastern and northern regions. By 2023, drought reappeared, demonstrating patterns similar to 2020 but with higher intensity and broader coverage (**Figure 7.3**). These observations underscore the influence of interannual climatic fluctuations on drought stress and highlight areas of recurrent vulnerability within the watershed.

The DL model, originally developed for maize in Austria's Marchfeld region, was recalibrated using Sentinel-2 data and CDM seasonal labels for Canadian conditions. For maize, overall accuracy ranged from 0.65 to 0.86, with mean F1 scores reflecting similar variability, while soybean results ranged from 0.66 to 0.81. The highest performance occurred in 2019, when fewer drought classes and clearer spatial patterns facilitated accurate classification. Conversely, 2021 and 2023 posed the greatest challenge, with more drought classes, sparsely represented categories, and greater similarity between adjacent classes, leading to greater inter-class confusion.

Analysis of the confusion matrices demonstrates a clear inverse relationship between drought class granularity and model performance. As the number of classes increased, the model's ability to discriminate between adjacent classes declined due to overlapping spectral and climatic features. This highlights the critical trade-off in drought classification between spatial resolution and prediction reliability. The findings emphasise the importance of balancing class granularity with model generalisability to ensure reliable drought assessment across diverse environmental contexts.

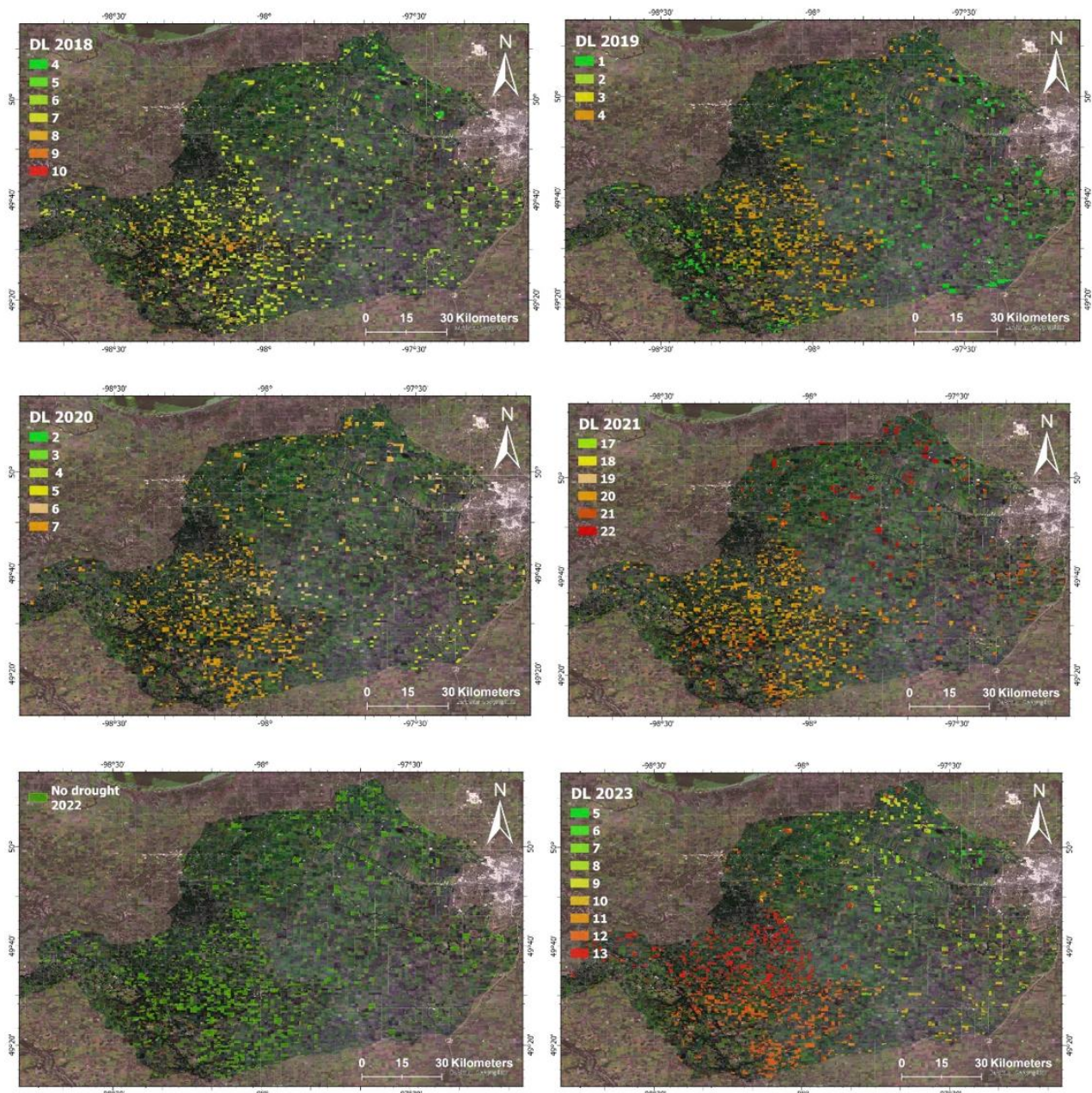


Figure 7.2 Drought maps for Corn fields from 2018 to 2023, using a consistent legend (green = low drought, red = high drought), illustrating annual variations.

Table 7.1 The resulting accuracy assessment metrics for Corn.

<i>Year</i>	<i>Overall Accuracy</i>	<i>Cohen's Kappa</i>	<i>Mean F1 Score</i>
2018	0.728	0.684	0.719
2019	0.859	0.813	0.859
2020	0.738	0.686	0.738
2021	0.7	0.64	0.7
2023	0.654	0.611	0.653

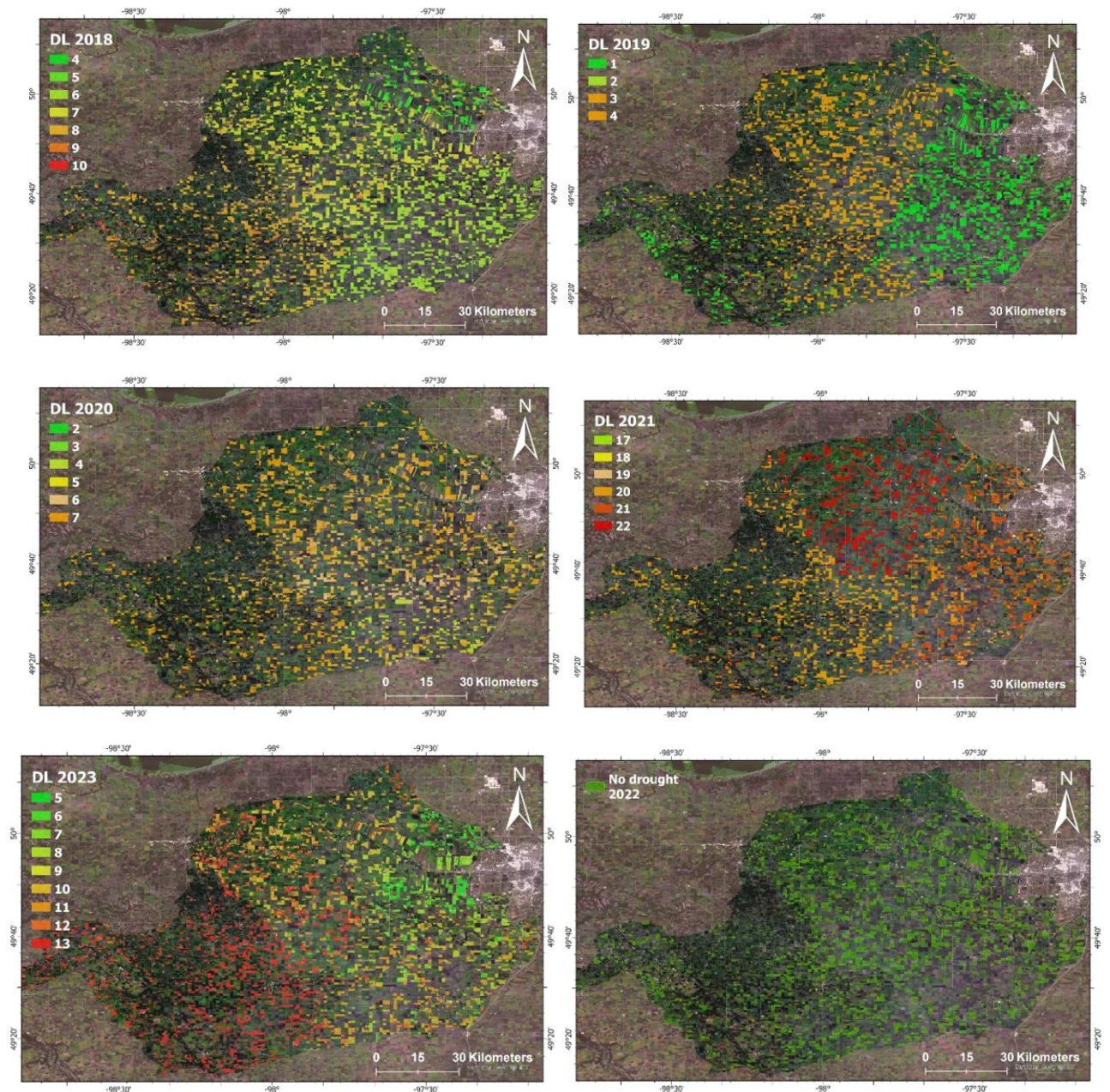


Figure 7.3 Drought maps for soybean fields from 2018 to 2023, using a consistent legend (green = low drought, red = high drought), illustrating annual variations.

Table 7.2 The resulting accuracy assessment metrics for Soybean.

<i>Year</i>	<i>Overall Accuracy</i>	<i>Cohen's Kappa</i>	<i>Mean F1 Score</i>
2018	0.7	0.652	0.689
2019	0.814	0.753	0.814
2020	0.7	0.649	0.707
2021	0.682	0.618	0.68
2023	0.661	0.62	0.66

7.1.6 AAFC Feedback and Assessment

Agriculture and Agri-Food Canada (AAFC) is a federal department responsible for supporting Canada's agriculture and agri-food sector through research, innovation, trade, policy, and sustainability initiatives. AAFC provides funding, tools, and open data to help farmers and producers improve competitiveness, adopt sustainable practices, and respond to environmental challenges, including climate change. Their operational remit also includes market analysis, trade support, and the promotion of Canadian agri-food products.

Currently, AAFC monitors crop stress and forecasts yields using moderate-resolution weekly MODIS NDVI data. While NDVI is widely applied, it has known limitations, including saturation at high vegetation levels, sensitivity to soil background and cloud cover, and difficulty distinguishing between plant structure and biochemistry. Consequently, there is a recognised need for more robust vegetation indicators and advanced modelling approaches to improve drought monitoring and yield forecasting at national scales.

AAFC acknowledges innovative use of Sentinel-2-derived indices and deep learning for drought assessment. Integrating Sentinel-2 data with CDM classifications has produced promising results, particularly in years with clearly defined drought patterns and fewer severity classes. This framework captures spatial and temporal variability across multiple growing seasons, complementing CDM's existing monitoring processes. Its adaptability across crops and regions, alongside the harmonisation of EO inputs, highlights strong potential for operational implementation, supporting early warning systems, crop-specific risk assessments, and more precise field-level impact evaluations.

AAFC representative at the collaborative meeting noted both the challenges and benefits of this synergistic approach: Potential uncertainties in drought reference labels due to interpretive classification; Reduced model accuracy under class imbalance during extreme or complex drought events. Future directions of this study, such as the use of temporal models (e.g., ConvLSTM), transformer-based architectures, and ensemble methods, align with AAFC's goals for scalable, interpretable drought-monitoring tools. Maps developed through the project can assist farmers in anticipating stress, optimising irrigation, and supporting crop insurance decisions (Figure 7.4).

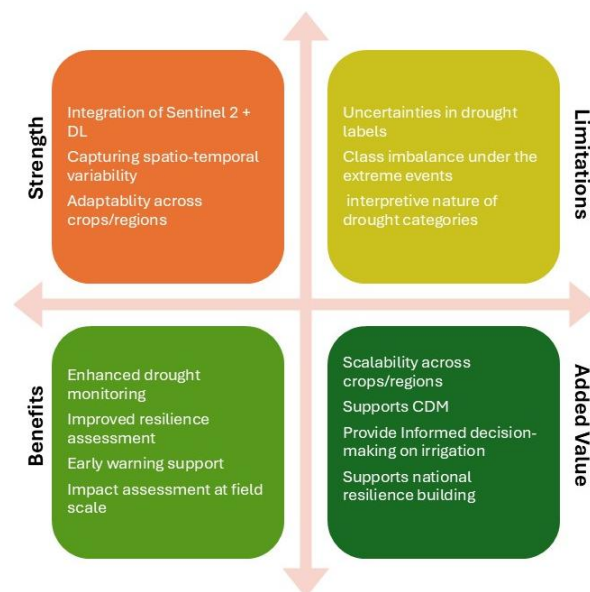


Figure 7.4 Feedback from AAFC as an early adopter from adoption to decision support.

Decision-makers can access granular, spatially detailed insights to guide targeted interventions and policy design, addressing resilience variability driven by natural conditions and land management practices. The transferability of models across crops and regions demonstrates potential for scalability, enhancing the utility of CDM and improving national drought resilience. Overall, AAFC recognises the project's contribution as an important research step toward improving CDM's capacity for timely, data-driven agricultural drought response. While the results demonstrate promising potential for supporting operational decision-making and scientific research, further validation, testing across diverse environmental conditions, and large-scale implementation assessments are required before operational deployment.

7.2 Pilot Study 2: Rice crop stress information in Andalusia, Spain

7.2.1 Overview

This case study focuses on enhancing the understanding and monitoring of abiotic stressors affecting rice cultivation under field conditions. Specifically, the study aims to evaluate the interactions among combined stressors over time and assess their cumulative impact on crop development, physiology, and productivity. Identify key biophysical and biochemical indicators that reliably signal stress impacts, supporting early detection and enabling targeted management strategies to mitigate crop losses. To achieve these objectives, a multi-sensor, multi-temporal RS strategy was employed, integrating high-resolution imagery from Sentinel-2, EnMAP, and PRISMA. Monitoring covered both bare soil periods (March–June 2023 and May 2024) and rice crop growth seasons (July–September 2023 and July–August 2024), ensuring comprehensive temporal coverage. PRISMA: Complemented the dataset with bare soil images (March and May 2023) and crop images (July 2023 and July 2024). On-ground validation was conducted via ESUs, which collected both biophysical and biochemical measurements to evaluate rice responses to stressors, particularly salinity, nutrient deficiencies, and heavy metals.

7.2.2 Field Description

The Guadalquivir Marshlands, located in southern Spain, span a flat valley of approximately 781 km². This marshland encompasses Doñana Natural Park, Europe's largest ecological reserve and one of Andalusia's most important protected areas, renowned for its unique biodiversity. Beyond its ecological significance, the region is a major centre for rice cultivation in Spain. Rice farming is concentrated in saline-prone areas, such as marshes and river deltas, which are subject to strict environmental regulations to protect surrounding natural reserves. Andalusia is the leading rice-producing region in Spain, contributing roughly one-third of national output, with the province of Seville alone producing nearly 350,000 tonnes annually. The 2023–2024 agricultural season was marked by a severe drought, with rainfall totalling only 310.1 mm, well below both the long-term regional average (464.8 mm) and the recent five-year mean (378.5 mm). This climatic anomaly significantly reduced river flow in the Guadalquivir and caused increased water salinity, further exacerbated by seawater intrusion, rendering much of the water unsuitable for rice cultivation. As a result, only 2.5% of the usual rice-growing area, fewer than 1,000 hectares, primarily in the westernmost Lower Guadalquivir sector, was planted in 2023, representing just one-third of the total rice cultivation area in that zone (**Figure 7.5**). This combination of hydrological stress, salinity increase, and reduced rainfall highlights the vulnerability of rice production in the Guadalquivir Marshlands to extreme climatic events.



Figure 7.5. Location map of rice cultivation in the Guadalquivir Marshlands, southern Spain, showing monitoring fields in yellow and cross symbols referring to soil sample data collection during the 2023 field campaign.

7.2.3 Field and RS Data

Between May and June 2023, a detailed field campaign was conducted to characterise bare-soil conditions across the study area. This campaign included five UAV flights equipped with hyperspectral sensors to acquire high-resolution spectral data, complemented by satellite-based hyperspectral imagery from EnMAP on 22 March and 22 April 2023 and PRISMA on 2 March and 10 May 2023. Once the fields were flooded and rice crops began to emerge, hyperspectral UAV and field measurements were conducted approximately every fifteen days from mid-July to late September, capturing the complete phenological cycle of rice, from booting and panicle emergence to flowering, anthesis, fruit development, ripening, and senescence. Field measurements were carefully timed to coincide with Sentinel-2 overpass dates, facilitating calibration and validation of remote sensing observations. Additional hyperspectral satellite acquisitions were obtained from EnMAP (24 July and 20 September 2023) and PRISMA (25 July 2023), providing dense temporal coverage of rice development.

The soil sampling campaign, conducted in line with a 1 km MODIS reference grid, sought to capture spatial variability informed by prior DESIS imagery. A total of 100 composite soil samples were collected, each approximately 2 kg, comprising a central sample point with four subsamples taken 1.5 metres away in cardinal directions. Laboratory analyses quantified electrical conductivity, total carbon and nitrogen, and the concentrations of eleven heavy metals (Fe, Al, Cr, Mn, Co, Ni, Cu, Zn, As, Cd, Pb). In parallel, a time series of Sentinel-2 multispectral imagery was acquired via Google Earth Engine, spanning 25 July to 23 September 2023, with an additional key image from August 2024 to enable comparison with the following season. These images, pre-processed to Level-2A with atmospheric correction and cloud masking, were mosaicked where necessary and covered tiles 29SQB and 30STG, encompassing the rice fields managed by the AFR.

Hyperspectral data from UAVs were collected using a Headwall Hyperspec Co-Aligned VNIR-SWIR sensor covering the 400–2,500 nm spectral range, achieving a ground sampling distance of 5 cm from an altitude of 80 metres. Flights were conducted with a stabilised

hexacopter platform and included in-field calibration with 99% and 95% Spectralon™ panels and a three-step grayscale tarp, while an ASD FieldSpec 4 spectroradiometer provided additional reflectance standards. Geolocation was achieved with sub-centimetre accuracy using a GNSS base station integrated into the Andalusian Positioning Network. Satellite hyperspectral imagery from EnMAP and PRISMA, with 30 m ground resolution and over 200 narrow spectral bands, enabled the detection of subtle biochemical and biophysical variations in soils and crops that are beyond the capabilities of multispectral platforms.

7.2.4 Workflow

A total of 23 datasets were generated for soil property prediction, grouped as follows: Hyperspectral satellite datasets (6 datasets from EnMAP and PRISMA), Multispectral dataset (Sentinel-2) and Laboratory-based ASD spectroscopy datasets (16 datasets). Preprocessing techniques, including CR and MSC, were applied to enhance signal interpretation. Laboratory spectra were resampled to align with satellite sensor resolutions, and spectral regions affected by atmospheric absorption were excluded to ensure comparability. Due to the high dimensionality of hyperspectral data relative to the field sample size (100 soil samples), dimensionality reduction was employed: Feature selection via beta coefficients from linear regression, RFE with 10-fold cross-validation, PCA to remove redundancy before ML model input, and ML hyperparameters were optimised using grid search with RMSE as the evaluation metric.

For biophysical Trait Estimation of rice crops, a hybrid approach integrating the PROSAIL-PRO model with ML was used to retrieve biophysical traits from satellite imagery. A Look-Up Table (LUT) of 2,000 simulated spectra was calibrated using field measurements. PROSPECT-PRO enabled separation of nitrogen- and carbon-based leaf components, allowing retrieval of Leaf Nitrogen Content (LNC) rather than generic dry matter content. Active learning (AL) methods iteratively refine LUT selection, ensuring realistic spectral combinations and improving model accuracy for regression tasks. The study focused on high soil salinity and low nitrogen availability as primary stressors affecting rice in the AFR fields. Both stressors were reclassified using established thresholds:

- Nitrogen: Optimal range 20–40 mg/kg; deviations impair growth.
- Salinity: Progressive negative impact with increasing concentration.

By combining EO data, laboratory spectroscopy, and field measurements, the study provides a comprehensive framework for assessing soil and crop stress, supporting early detection and adaptive management strategies in rice cultivation.

7.2.5 Results

The evaluation of soil properties revealed that hyperspectral data, particularly EnMAP MSC-processed datasets, provided superior predictive accuracy, achieving an R^2 of 0.574 and RMSE of 2.647. PRISMA performance was lower, likely due to differences in environmental conditions and acquisition timing, while Sentinel-2 multispectral imagery lagged in predictive capacity ($R^2 = 0.104$, RMSE = 4.844). Models derived from laboratory ASD-convolved spectra, especially when matched to the EnMAP spectral response, achieved the highest performance ($R^2 = 0.879$, RMSE = 1.547), demonstrating the advantage of high spectral resolution for soil characterisation. Predictive modelling of heavy metal concentrations similarly favoured hyperspectral sensors, with EnMAP achieving robust results for elements such as aluminium and lead, whereas Sentinel-2 consistently underperformed due to insufficient spectral sensitivity.

Cumulative soil stress mapping, integrating salinity and nitrogen data, indicated that most affected areas fell under moderate stress categories, largely located in the western and north-western marshes. High-stress zones with extreme salinity or severe nitrogen deficits were limited and localised, whereas areas adjacent to riverbanks exhibited optimal conditions. These findings highlight the importance of targeted agronomic interventions to mitigate stress and improve productivity in the moderately affected zones.

Analysis of rice crop traits further emphasised the advantages of hyperspectral data. EnMAP outperformed Sentinel-2 for spectrally sensitive traits, including carotenoid and canopy chlorophyll content, while both sensors captured comparable spatial patterns for leaf chlorophyll and nitrogen content. Sentinel-2 performed slightly better for canopy nitrogen content, though it showed reduced sensitivity to spatial variability. These results underscore the critical role of spectral resolution in accurately capturing the spatial heterogeneity of crop traits, even at high spatial resolution.



Figure 7.6 Screenshot of the SAMA 2.0 dashboard displaying a range of soil and rice crop stress indicators monitored during the case study, including electrical conductivity, heavy metal concentrations, and key biophysical indicators, supporting real-time agronomic decision-making

The derived datasets for soil properties, heavy metals, and crop traits were integrated into the SAMA 2.0 platform, a digital agro-monitoring system designed for the Seville Rice Growers Federation (**Figure 7.6**). This platform combines EO data, IoT inputs, and AI tools to support precision agriculture, enabling timely, data-driven management of abiotic stressors such as salinity, nutrient deficiencies, and soil contamination. By linking field-based measurements with high-resolution satellite imagery, SAMA 2.0 allows agronomic teams to assess soil and crop health at the plot level, supporting adaptive interventions that enhance rice production in the Guadalquivir Marshlands.

Partial Least Squares Regression proved effective for estimating soil parameters, while Gaussian Process and Support Vector Regression were most suitable for crop trait estimation. Although Sentinel-2 provides valuable operational monitoring due to its high spatial resolution and frequent revisit capability, hyperspectral data offer more detailed insights into physiological stress responses, particularly under combined salinity and nutrient deficits.

Challenges remain in modelling heavy metals and scaling laboratory-derived models to regional levels, but forthcoming hyperspectral missions such as Copernicus CHIME are expected to improve temporal coverage and further enhance soil and crop monitoring, supporting more sustainable agricultural management in the region.

7.2.6 Andalusian Federation of Rice Growers (AFR) Feedback and Assessment

Established in 1986, AFR serves as the representative body for stakeholders across Andalusia's rice sector. The federation operates with a dedicated team of 60 agronomists and has been systematically collecting geolocated data on rice cultivation since 1998, covering approximately 95% of fields under Integrated Production practices. Each AFR technician oversees around 600 hectares, managing all aspects of the agronomic cycle, from land preparation through laser levelling to ensure uniform water distribution, to ploughing, fertilisation planning, and nutrient management. Fertilisation strategies are carefully tailored, incorporating both macronutrients such as nitrogen (N), phosphorus (P), and potassium (K), as well as essential micronutrients including silicon (Si), magnesium (Mg), sulphur (S), and zinc (Zn). Technicians also determine optimal sowing dates based on local environmental conditions and rice variety. Following field flooding, crop health is monitored weekly, with particular attention paid to phenological development stages.

AFR currently relies heavily on water resource management to safeguard crop productivity, monitoring both water quantity and quality. Water samples are collected daily at key intake points and analysed for sodium chloride concentrations using silver nitrate titration. While this approach provides valuable point-based insights, AFR recognises that these measurements have limited spatial coverage, underscoring the need for complementary monitoring techniques that capture landscape-scale variability. In this context, AFR has highlighted the transformative potential of EO technologies in enhancing field-scale assessments. Through the Rice monitoring case study, AFR has leveraged hyperspectral imagery from PRISMA and EnMAP, along with multispectral Sentinel-2 data, to gain a more comprehensive understanding of soil and crop conditions. Hyperspectral datasets have been particularly effective in mapping soil properties, including salinity, nutrient availability, and heavy metal concentrations, while the integration of radiative transfer models with field measurements enabled the generation of high-resolution maps of rice crop biophysical and biochemical traits, such as Leaf Area Index (LAI), chlorophyll, and nitrogen content, across key phenological stages.

The resulting EO-derived stressor maps, at 30 m resolution, provided AFR with a spatially explicit diagnostic product. These maps allow agronomists to identify areas of the rice-growing region affected by salinity and nitrogen deficits, supporting prioritisation of management interventions. While these products do not directly mitigate stressors, they significantly enhance decision-making by highlighting zones at risk, enabling more informed resource allocation and tailored agronomic practices (**Figure 7.7**). AFR emphasises that integrating these products has enhanced their capacity to understand the complex interactions among multiple stressors on rice crops, ultimately contributing to the long-term sustainability and resilience of rice production in the Guadalquivir Marshlands.

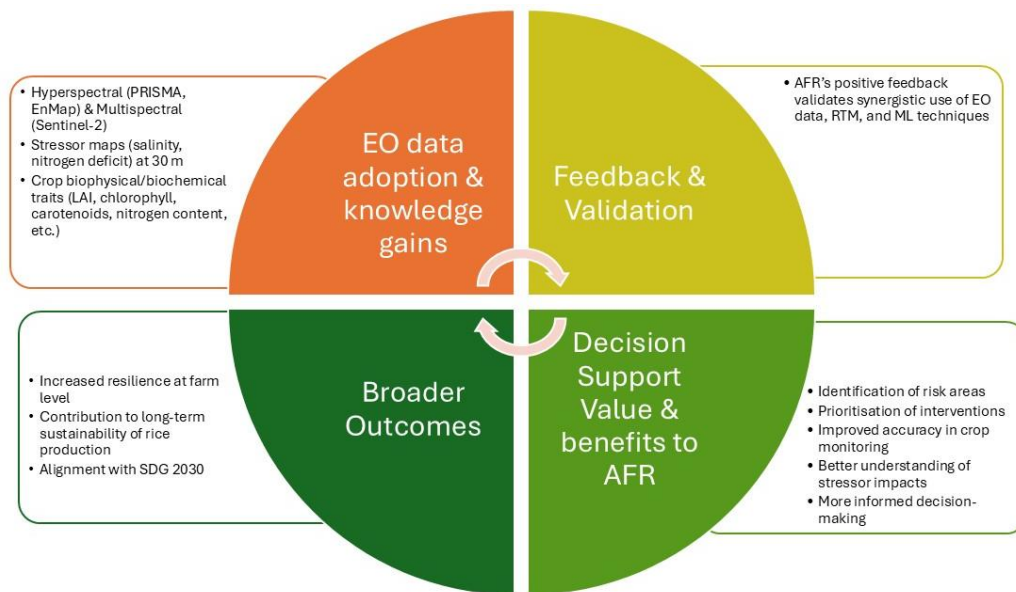


Figure 7.7 Feedback from AFR on adoption of the EO4CerealStress products.

Looking to the future, AFR anticipates that next-generation EO missions, particularly the upcoming Copernicus CHIME hyperspectral satellite, will further improve the early detection of crop stress. The federation recognises that such technologies will be crucial for the continued development of precision agriculture practices, enabling data-driven management strategies that optimise both productivity and environmental sustainability.

7.3 Pilot Study 3: Crop lodging information system in Italy

7.3.1 Overview

Lodging is the permanent displacement of crops from their upright position and represents a significant agronomic challenge, particularly in cereal production. Lodging complicates harvesting and disrupts cereal supply chains, affecting crop production quantity and quality. Early detection and management are critical for mitigating losses, informing insurance claims, and guiding adaptive crop management strategies. Historically, lodging in cereal crops has been assessed through visual field inspections. Synthetic Aperture Radar (SAR) data, which is particularly sensitive to crop structural changes, has enabled effective detection and severity assessment of lodging (**Chauhan et al., 2019, 2020, 2021**). MSI facilitates the calculation of vegetation indices, such as NDVI and SAVI, that act as optical proxies for plant biophysical parameters, capturing lodging-driven shifts in canopy structure (leaf angle distribution and canopy cover), chlorophyll-linked absorption, and scattering pathways that collectively alter canopy reflectance. When combined with ML algorithms, MSI data have significantly improved the delineation of lodging area across different cereal types (**Guan et al., 2022; Chen et al., 2021**). Hyperspectral data allow a detailed assessment of plant physiological status as a proxy for lodging severity, yet hyperspectral satellite-based applications for lodging detection and severity assessment remain unexplored. This pilot has studied wheat lodging detection and severity assessment at different spatial and spectral resolutions using EnMAP hyperspectral satellite data, Sentinel-2 multispectral satellite data, and field hyperspectral measurements taken by an ASD field spectrometer. Spectral reflectance data from multiple sources were pre-treated, calibrated, and standardised to remove noise, producing analysis-ready datasets. Reflectance spectra and derivative features from lodged and non-lodged (healthy) wheat fields were first analysed to quantify lodging-induced changes in canopy spectral response. These

features were then integrated into ML algorithms and RTM to characterise and validate relationships between spectral signals and lodging severity. The combined ML/RTM framework supports robust, reproducible, and quantitative lodging assessment with clear potential for operational deployment. The resulting outputs include actionable lodging maps that depict the spatial distribution and severity of lodging to inform stakeholder decision-making.

7.3.2 Field Description

Bonifiche Ferraresi is one of Italy's largest agri-food companies, located near Jolanda di Savoia, in Ferrara, Emilia-Romagna. The map is shown in section 4.2.2, Figure 4.5. The farm spans approximately 3,850 acres of silty and clayey soils under a warm temperate climate, supporting diverse rotational cropping. In the 2023 season, three wheat varieties, emmer wheat (*Triticum dicoccum*), durum wheat (*Triticum durum*), and soft wheat (*Triticum aestivum*)-were cultivated across 664.24 hectares, with winter wheat sown between late October and early November and harvested by late June, a period particularly vulnerable to lodging.

7.3.3 Data Used

During the field campaign (30 April and 18 May 2023), canopy spectral measurements were acquired using an ASD spectroradiometer, alongside crop biophysical and biochemical properties, including canopy height, crop inclination angle, and lodging area (all three used for the calculation of lodging severity score (LS)). We also measured LAI and chlorophyll content using a SPAD meter. Measurements were collected at three nested sampling scales (microplots, subplots, and plots) to match the spatial resolution of the remote sensing data. Subsequently, field-collected leaf samples were analysed in the laboratory to quantify biochemical traits, including leaf dry matter content, equivalent water thickness (EWT), leaf mass area, and concentrations of carbon, sulphur, protein, and nitrogen. For the remote sensing analysis, a cloud-free Sentinel-2 Level-2A product acquired on 23 May 2023 from the Copernicus Open Access Hub best matched the field campaign period. Similarly, a Level-2A EnMAP hyperspectral product with an acquisition date of 21 May 2023 was obtained from the DLR (German Aerospace Centre), which represents the closest match to the field measurements.

7.3.4 Workflow

Field hyperspectral measurements were pre-processed, with noisy spectral bands removed in the ranges 350–400 nm and 2350–2500 nm, which are prone to instrument-related noise, and water vapour absorption bands between 1340–1420 nm and 1800–1960 nm excluded to minimise atmospheric interference. Outliers were identified and removed using the Interquartile Range (IQR) method, retaining data within the 25th to 75th percentile. The mean spectral reflectance was then calculated to provide a representative measure of canopy behaviour across samples at the microplot level. Finally, the spectral data were smoothed using a Savitzky-Golay filter with a second-degree polynomial across a nine-wavelength window, effectively reducing noise while preserving key spectral features.

From Sentinel-2 multispectral imagery, non-essential bands, those for coastal aerosol, water vapour, and cirrus, were removed. To align with field subplot measurements, bands with 10 m resolution were resampled to 20 m using bilinear interpolation, ensuring spatial consistency with the field data. EnMAP hyperspectral imagery was processed similarly, with noisy bands and water vapour absorption regions removed to maintain data integrity. Outliers were excluded using the IQR method, the mean spectral reflectance was computed, and a Savitzky-

Golay filter was applied to smooth the data. The processed datasets were saved as TIFF files in **D4.1 – Experimental Datasets**, with the full workflow archived in ITC file storage.

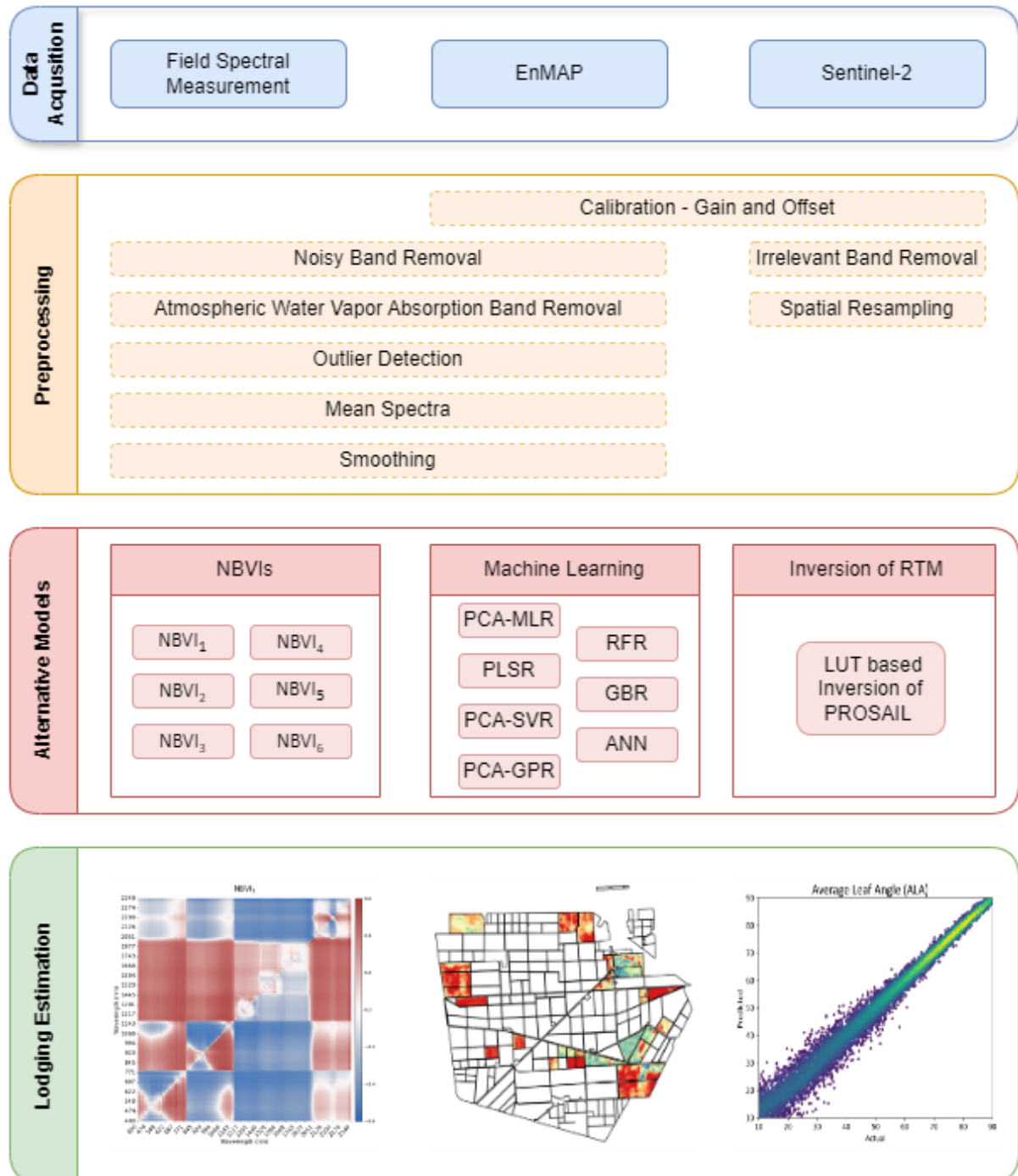


Figure 7.8 Workflow illustrating the data preprocessing steps for each source, followed by the implementation of multi-method approaches and the presentation of results.

Spectral analysis employed continuum-removed reflectance to highlight differences between healthy, moderately lodged, and severely lodged wheat, particularly in the visible and near-infrared regions, while first-derivative spectra proved less effective at differentiating lodging severity. Narrowband vegetation indices (NBVIs) were derived from all possible two-band combinations across the 400–2350 nm range, and Pearson correlation coefficients were used to identify the most sensitive wavelength pairs. Then, five indices showing the strongest correlations with LS were selected as optimal predictors.

ML models were applied to predict LS using both hyperspectral and multispectral datasets. Principal Component Analysis (PCA) was performed to reduce data dimensionality and to extract the principal components, capturing 99% of the variance. Stratified random sampling divided the data into 70% training and 30% testing sets, and each model was run 100 times to ensure robustness. Hyperparameters were optimised using a Bayesian tuning approach tailored to each algorithm. The entire workflow, with the lodging severity map as the output, is shown in **Figure 7.8**.

7.3.5 Results

Spectral analysis of field and satellite hyperspectral data revealed distinct absorption features in the visible and near-infrared regions, which diminished progressively from healthy to moderately and severely lodged crops. These changes reflect both structural canopy alterations and associated physiological stress. Hyperspectral observations are highly sensitive to both biochemical and biophysical changes, enabling lodging to be linked not only to changes in canopy structure (e.g., crop angle and effective LAI) but also to variations in pigment and nutrient-related traits, including chlorophyll, nitrogen, and carbon content.

Heatmaps of Pearson correlation coefficients identified spectral regions most sensitive to lodging, highlighting narrowband indices as effective predictors of LS. The observed positive and negative correlations between lodging and VI values highlight distinct spectral responses associated with structurally and physiologically stressed wheat.

ML approaches were then applied to predict LS using hyperspectral (ASD, EnMAP) and multispectral (Sentinel-2) data. Kernel-based models, particularly PCA-GPR and PCA-SVR, delivered the most accurate predictions, effectively capturing non-linear interactions and spatial variability. Linear models, including PCA-MLR and PLSR, consistently underestimated high LS values and showed greater variability, particularly with Sentinel-2 data, reflecting the limitations of linear approaches for complex canopy stress patterns. The superior performance of ASD data further emphasised the importance of high spectral resolution and signal quality. Radiative transfer modelling (PROSAIL-PRO) provided complementary insights into wheat biophysical and biochemical responses to lodging. Healthy crops exhibited higher chlorophyll content and equivalent water thickness, whereas protein content and carbon-based compounds increased with lodging severity. LAI also rose in severely lodged crops, while average leaf angle showed minor variation. These patterns confirm that lodging alters both structural and physiological traits, with implications for crop health and management. Spatially explicit LS maps derived from PCA-GPR and PCA-SVR models showed coherent, accurate distributions, particularly with EnMAP data. Kernel-based approaches outperformed linear models in capturing non-linear spatial heterogeneity, translating spectral analysis into actionable outputs for stakeholders. These severity-graded maps can provide rapid assessment of crop damage, prioritise interventions, and support insurance or management decisions. RFR emerged as the most effective algorithm, producing accurate and spatially coherent LS maps from both EnMAP and Sentinel-2 imagery. While the results indicate strong performance of Sentinel-2 and EnMAP data for lodging detection and severity assessment, these findings are farm-specific and for a short phenological observation window. Key challenges include temporal misalignment between Sentinel-2 and EnMAP imagery and acquisitions and restricted parameterization in radiative transfer models, which can limit transferability and reduce sensitivity for distinguishing lodging from other stressors. Addressing these constraints will require expanded field sampling across sites and seasons, controlled multi-stressor experiments, and exploitation of upcoming ESA missions such as CHIME and LSTM (**Darvishzadeh, 2025**).

7.3.6 Bonifiche Ferrarsi's feedback and assessment

Bonifiche Ferraresi, Italy's largest farm holding, encompasses over 6,500 ha across several municipalities, with more than 3,850 ha located near Jolanda di Savoia. The farm cultivates a diverse range of crops, including durum and soft wheat, rice, corn, barley, soybeans, and potatoes, as well as horticultural and medicinal plants. The farm is facing longstanding challenges in accurately detecting the timing and severity of lodging events. This limitation complicates operational decision-making and delays insurance assessments, as crop damage estimates by agronomists and loss adjusters can take several weeks, creating a critical gap between damage occurrence and the implementation of mitigation plans.

The pilot demonstrated the potential of EnMAP hyperspectral data for assessing lodging stress. The farm expressed a strong interest in adopting EnMAP data within its operational monitoring strategy. Feedback highlighted that integrating hyperspectral and multispectral platforms can provide both sensitivity to subtle biochemical changes and robust temporal coverage. The farm noted that UAV and field-based measurements would be essential for calibrating and validating lodging detection methods, including ML models, ensuring the transferability of trained models across regions and seasons.

Operationally, producing decision-ready stress severity maps would benefit both farm management and insurance providers by enabling faster responses and streamlining pre-harvest loss verification. The feedback from Bonifiche Ferraresi reinforces the value of synergistic use of hyperspectral and multispectral remote sensing. Hyperspectral platforms, such as EnMAP and PRISMA, offer high spectral resolution for the characterisation of crop and soil biochemical properties, while multispectral sensors, such as Sentinel-2, provide operational spatial and temporal coverage. The lodging framework can potentially be applied to other regions and crops because it was successfully scaled from field measurements to satellite observations (EnMAP and Sentinel-2). However, model accuracy may vary across locations due to differences in environmental, spectral, biophysical, and management conditions. Therefore, additional site-specific calibration and validation are recommended before operational application in new regions or crop types.

8 Final Workshop

This section presents an overview of the final workshop held on 20 May 2025 as an international webinar hosted by the University of Southampton, involving international partners and SAG members. . The event brought together experts, researchers, and professionals from across the globe to discuss cutting-edge EO-based approaches for agricultural stress monitoring. Dr Espen Volden (ESA) opened the session with an overview of ESA's Agriculture Science Cluster, setting the stage for a series of insightful presentations. Prof Victor F. Galiano (University of Seville) explored the synergistic use of Sentinel-2, EnMap, and UAV data for the detection and monitoring of multiple crop stressors, alongside Prof Roshanak Darvishzadeh (ITC), who presented on the integration of in-situ measurements with Sentinel-2 and EnMAP data for wheat lodging estimation. Dr Omid Ghorbanzadeh (BOKU) discussed drought assessment methodologies in Canada employing Sentinel-2-based monitoring techniques. Dr Catherine Champagne (Agriculture and Agri-Food Canada) provided an overview of JECAM and its case studies on crop stress monitoring. The application of stress management strategies in rice cropping systems in the Philippines was addressed by Dr Alice Laborte (IRRI), and Mr Emanuel Büechi (YIPEEO) introduced a transfer learning framework to enhance crop yield forecasts in data-scarce environments. The webinar concluded with a panel discussion on future research directions and collaborative opportunities, featuring Prof Jadu Dash, Dr Volden, Dr Laborte, and Dr Champagne. The event fostered a rich exchange of knowledge and emphasised the pivotal role of synergistic use of EO technologies in stress detection and monitoring. Summary of the webinar can be found on blog post published on Space South Central website. Link is here; [University of Southampton International Webinar – Synergizing EO and In-situ Data for Crop Stress Detection and Monitoring \(20 May 2025\)](#) (20 May 2025)

8.1 Participation

Nearly forty participants from Canada, South Africa, Morocco, China, Indonesia, Pakistan, India, Namibia, Turkey, Lebanon, the UK, Germany, France, Spain, Belgium, Ecuador, Malawi, and Russia attended the event. The broad international involvement underscores the global importance of remote sensing in addressing agricultural issues, particularly those related to climate stress, food security, and sustainable land management.

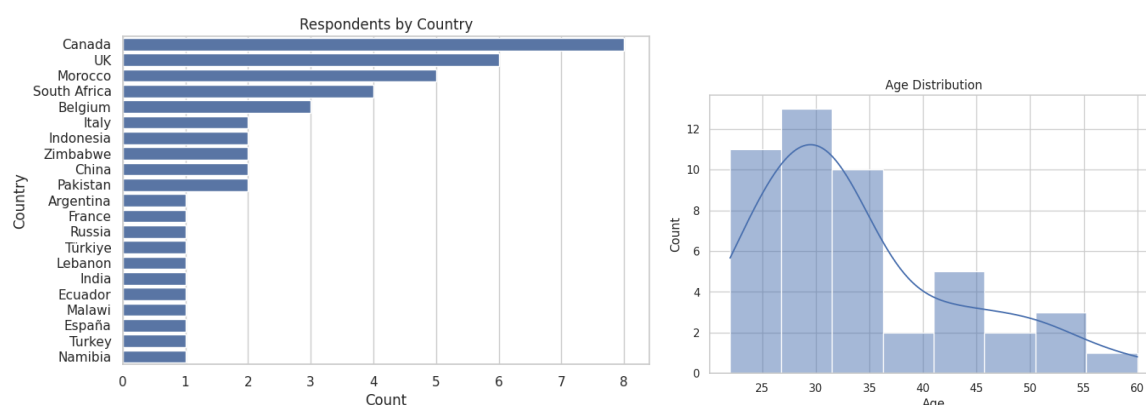


Figure 8.1 Respondents' country and age group.

Several participants were affiliated with key institutions involved in ESA-funded projects, GEOGLAM initiatives, and crop modelling consortia, reinforcing the webinar's collaborative and integrative focus. They came from different disciplines, including Geospatial analytics,

Agro-hydrology, Environmental biology, IT and data systems for public safety, Education and capacity-building, and AI integration in agriculture. A balanced mix of early-career researchers and senior academics was observed.

Respondents by Country

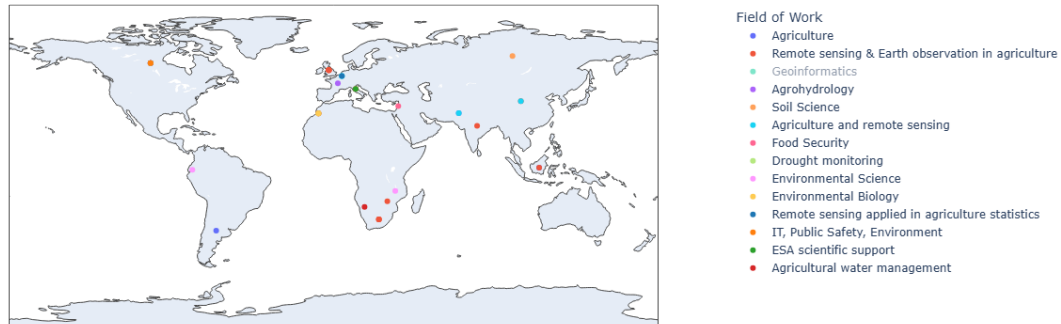


Figure 8.2 Respondents' geographical distribution and field of work.

8.2 Presentation Highlights

8.2.1 Agriculture Science Cluster

The webinar provided an overview of the European Space Agency's (ESA) Agriculture Science Cluster, outlining its transformation from a forum for information exchange into a structured platform for scientific collaboration. Earlier ESA workshops and panel discussions had successfully promoted dialogue and identified synergies across agricultural monitoring projects, yet it became clear that a more formalised approach was required to fully realise collaborative potential. ESA established the Agriculture Science Cluster (<https://eo4society.esa.int/communities/scientists/esa-agriculture-science-cluster/>) to enable coordinated action among research teams, moving beyond simple progress sharing to joint initiatives focused on data integration and collective analysis. A key objective of this collaboration is to integrate crop-stressor research with yield modelling, thereby improving yield forecasting by linking environmental stress factors with crop performance. Several new research initiatives: Digital Twin and EO4Crop, both examining crop stressors and developing new analytical tools, joined the cluster; the Advanced Agriculture Monitoring initiative, preparing for the deployment of hyperspectral, thermal and Synthetic Aperture Radar (SAR) satellite missions due to commence in 2029; Beyond stressor analysis, the Cluster also supports work on irrigation monitoring, crop nutrient estimation, and continental-scale testing of agricultural models. Yield prediction remains a central focus, with stress-specific insights directly informing the refinement of forecasting systems.

8.2.2 Synergising Sentinel-2, EnMap, and UAV Data for the Detection and Monitoring of Multiple Crop Stressors

The University of Seville presented results from the EO4Cereal Stress project, which investigates the combined effects of multiple abiotic stressors on rice cultivation. Extensive field campaigns in 2023 and 2024 integrated soil and crop sampling, UAV-based hyperspectral imaging, and multi-sensor satellite data (Sentinel-2, EnMap, PRISMA). These datasets enabled the estimation of key soil attributes electrical conductivity, organic carbon, and macronutrient content, alongside crop biophysical and biochemical parameters, such as chlorophyll concentration and canopy water content. Using a combination of radiative transfer

modelling and ML, researchers derived high-accuracy spatial maps of both soil and crop variables. Findings confirmed salinity as the dominant stressor, exerting significant negative impacts on photosynthetic activity and plant water retention, whereas heavy metals exerted negligible influence. These outcomes have practical implications for precision agriculture and sustainable rice management, particularly in environments facing similar agro-environmental constraints.

8.2.3 Mapping Wheat Lodging: Integration of In-situ, Sentinel-2, and EnMap Data for Lodging Estimation

The University of Twente's Faculty of Geo-Information Science and Earth Observation (ITC) presented research addressing wheat lodging. Conducted on a commercial-scale farm in Italy (April–May 2023), the study leveraged synergies with a concurrent nutrient estimation campaign to maximise efficiency.

A multi-scale data collection framework was implemented at three spatial resolutions—microplot (1 m²), subplot (15 m²), and plot (90 m²)—integrating field spectroscopy, Sentinel-2, and EnMap observations. Data from 189 field plots were collected around documented lodging events to assess changes in canopy structure and reflectance characteristics. Results showed that near-infrared (NIR) reflectance increased with lodging severity, attributed to altered leaf orientation. A range of ML algorithms (Random Forest, Gaussian Process Regression, Support Vector Machine) was used to classify lodging severity, with Random Forest models based on hyperspectral data achieving accuracies up to 81%. Satellite-based models performed slightly lower due to atmospheric and sensor-related noise. Lodging was found to reduce the accuracy of nitrogen and sulphur retrievals, highlighting the need for correction strategies in yield modelling. Nonetheless, Sentinel-2 and EnMap-derived maps of lodging severity displayed strong spatial consistency, confirming the feasibility of remote sensing-based lodging assessment. The study establishes a scalable, cost-effective framework for monitoring lodging severity, supporting improved harvest planning and yield-loss estimation in cereal production systems.

8.2.4 Drought Assessment in Canada Using Sentinel-2-Based Monitoring

The University of Natural Resources and Life Sciences, Vienna (BOKU) presented its work on drought monitoring through the integration of Sentinel-2 data, ground-based observations, and DL methods. The approach was first developed and validated in the Marchfeld region of Austria, then transferred to the Manitoba region of Canada using reference data from the CDM. Data spanning seven growing seasons (2018–2024) supported the training of multiple models based on vegetation and drought indices (e.g., NDVI, SWIR, moisture metrics) combined with climate and soil variables. Comparative results showed that DL models, particularly a 1D convolutional neural network (1D-CNN), outperformed traditional approaches. Among conventional techniques, Random Forest yielded the most robust and transferable results. Validation against CDM classifications demonstrated strong agreement for years representing moderate (2018), severe (2021), and no drought (2022) conditions. The models successfully captured temporal and spatial drought variability, with only minor misclassifications in extreme drought categories. The spatial drought maps for maize in Canada closely matched CDM outputs, confirming the operational potential of this framework. Future work will focus on refining model calibration, incorporating higher-resolution inputs, and extending applications to additional crop types and climatic zones to enhance climate-resilient agricultural management.

8.2.5 Overview of JECAM: Case Studies on Monitoring Crop Stress

Agriculture and Agri-Food Canada (AAFC) presented an overview of its Joint Experiment for Crop Assessment and Monitoring (JECAM). JECAM fosters international cooperation through shared protocols, best practices, and joint experiments to improve agricultural monitoring and food security. The network operates through voluntary participation and opportunistic funding, uniting research sites across diverse agroecological zones. Core activities include Synthetic Aperture Radar (SAR) intercomparison studies, harmonisation of ground-based validation data, and hyperspectral remote sensing applications for crop classification and stress detection. A notable operational example discussed was the Canadian Drought Monitor (CDM), which integrates MODIS vegetation and evaporative stress indices with meteorological data to provide weekly drought assessments. Looking forward, JECAM aims to transition from relative vegetation indices (e.g., NDVI) to physically based parameters, such as Leaf Area Index (LAI), to enhance physiological accuracy. These developments contribute to GEOGLAM's vision of a "system of systems" for global agricultural monitoring, supporting nations in producing validated, local crop assessments and advancing capacity building in EO-based agricultural science.

8.2.6 Stress Management Practices for Rice Crops in the Philippines

The International Rice Research Institute (IRRI) provided an overview of its efforts to strengthen rice production resilience in the Philippines, a country facing frequent climate shocks and pest pressures responsible for up to 37% of annual yield losses. At the core of these efforts is the Philippine Rice Information System (PRISM), an operational satellite-based monitoring platform integrating Sentinel-1 SAR data with crop growth models. Since its launch in 2015, PRISM has achieved classification accuracies above 95%, producing monthly updates on rice area, crop condition, and yield. It also supports post-disaster damage assessments to inform rapid government interventions, such as seed distribution after floods or typhoons. IRRI has also pioneered an area-based yield index insurance scheme in partnership with the Philippine Crop Insurance Corporation. Using PRISM's satellite-derived yield datasets, payouts are determined objectively and rapidly, overcoming the limitations of traditional field-based insurance. Complementary initiatives include nationwide pest surveillance, an automated pest alert system, and collaboration with the University of Twente to incorporate remote sensing into pest monitoring. Additionally, IRRI is developing drone application protocols for precision management, pest control, and variable-rate input distribution, supported by national funding to promote adoption.

8.2.7 YIPEEO – Transfer Learning to Boost Crop Yield Forecasts in Data-Scarce Situations

The Technical University of Vienna presented findings from the ESA-funded YIPEEO project (concluded in 2025), which aims to enhance crop yield forecasting through transfer learning, a technique that enables models trained on large regional datasets to be adapted to data-scarce local contexts. The project utilised detailed field-scale yield data from Czechia (2017–2022) alongside regional agricultural statistics from Austria and Czechia. Despite privacy restrictions, several open datasets and technical resources have been made available through the project's dissemination channels. Results showed that transfer learning achieved forecasting accuracies comparable to conventional models while requiring only 10% of the training data, demonstrating exceptional data efficiency. This approach is particularly advantageous in regions with limited ground-truth information. Preliminary tests under drought scenarios further indicated that transfer learning could significantly enhance predictive performance where observations are sparse or incomplete. The project marks a notable

advancement in ML applications for EO-driven agriculture, highlighting the role of AI and data transferability in improving food security and climate resilience within the agri-food sector.

8.2.8 Panel Discussion

The panel discussion highlighted the transformative potential of integrating EO and in situ data for scalable and accurate crop stress monitoring. Experts emphasized that combining multi-sensor, multi-temporal, and hyperspectral satellite data with field measurements can significantly improve the timeliness and precision of stress detection, though technical complexity and challenges in scaling local experiments remain significant. Innovative missions such as FLEX, along with complementary Sentinel-2 and Sentinel-3 data, and advanced data fusion techniques, were identified as key enablers, while robust validation against ground truth is essential for building trust and operational relevance. Translating research into actionable tools requires user-centred design, practical implementation strategies, accessible data formats, and sustained institutional support, as exemplified by platforms such as the Agriculture Virtual Lab and Earth Code. The discussion strongly supported the importance of collaboration, data sharing within networks like JECAM, and capacity-building to ensure that tools are not only scientifically robust but also operationally feasible in diverse agricultural contexts. Case studies such as IRRI's PRISM project illustrated that long-term success depends on local institutional commitment and government investment, highlighting the broader challenge of scaling EO-based solutions beyond pilot projects. Overall, advancing crop stress monitoring and management requires a combination of technical innovation, rigorous validation, practical deployment, and strong institutional partnerships.

8.2.9 Participants' Feedback

Participants appreciated the exchange of experiences from ESA projects, JECAM, IRRI, and YIPEEO, which showed how satellite observations, field measurements, and artificial intelligence can be combined to address major agricultural challenges such as drought, salinity, nutrient deficiencies, lodging, pests, and yield forecasting.

Participants' feedback highlighted some important gaps that need to be addressed:

- i. Insufficient funding and the lack of long-term in-situ datasets are among the largest barriers to EO product validation and operational adoption. Reliable ground observations are needed to build trust in satellite-derived products.
- ii. Challenges in integrating heterogeneous datasets from multiple sensors, platforms, resolutions, and acquisition times continue to limit the scalability of crop stress monitoring systems.
- iii. A gap between research outputs and practical farmer applications was repeatedly noted. Many EO products remain technically advanced but are not always delivered in formats that support real-time operational decisions.
- iv. Limited data interoperability and restrictions on data sharing hinder broader collaboration. Several networks rely on case-by-case data sharing arrangements rather than open repositories.
- v. Scaling methodologies from experimental field sites to regional, national, and global levels remains challenging due to differences in environmental conditions, management practices, and data availability.
- vi. Knowledge gaps in key agricultural variables, including evapotranspiration, irrigation mapping, crop yield estimation, and crop boundary delineation, were identified as priority research areas requiring further development.

- vii. Limited engagement with non-research user groups, such as farmers, national agencies, and private-sector stakeholders, was identified as an area requiring greater attention to ensure wider adoption and impact of EO services

Participants were primarily concerned with training, data sharing, and the practical application of remote sensing tools for agriculture. They noted insufficient training in JECAM, though members often conduct technical workshops, underscoring a need for more structured capacity-building. Questions around transfer learning and model generalisation reflected interest in applying models across regions and crops, with concerns about environmental differences limiting direct model transfer. Participants were curious about data sources and model choices, including MODIS vs Sentinel-2, 1D vs 2D/3D models, and timing of UAV vs satellite data acquisition, emphasising the need for clear justification of methodological decisions.

There were questions about estimating crop parameters, such as nutrient levels, irrigation, and LAI, especially under challenging field conditions, such as lodging or uniform water management. Participants sought clarity on outreach to non-research stakeholders, gaps in agricultural applications, and the scalability of approaches like IRRRI's PRISM system, noting that long-term success depends on institutional support and government investment. A recurring question remained about the transferability of the models across regions and crops, using transfer learning to improve efficiency and widen applicability across multiple crops.

8.3 Key takeaways

- i. Integration is critical: Combining Earth Observation (satellite) data with in-situ measurements improves accuracy and timeliness in detecting crop stress.
- ii. Technical challenges: multi-sensor, multi-temporal, and hyperspectral data integration is complex. Scaling local experiments to national or global levels remains difficult.
- iii. Validation matters: Field-based data are essential for algorithm calibration, model accuracy, and building trust in EO products.
- iv. Operational feasibility: Methods must be practical, adaptable to diverse environments, and supported by strong institutional partnerships.
- v. Early stress detection, yield estimation, and their large-scale monitoring can benefit from innovative missions like FLEX, CHIME, LSTM and multi-sensor fusion.
- vi. Practical adoption requires alignment with end-user needs, data validation, training, and sustainable institutional support.
- vii. Collaborative networks (e.g., JECAM) and open platforms (e.g., Earth Code) are central to advancing actionable EO applications.
- viii. Stakeholder engagement is critical: Beyond the research community, successful implementation depends on active involvement of farmers, extension services, policymakers, industry partners, and other end users.
- ix. Moving from pilots to operations requires additional effort: Promising research outcomes must undergo broader testing, validation, and scalability assessments before being deployed as operational tools.
- x. Field measurements remain a bottleneck: Collecting high-quality crop and soil reference data is often resource-intensive and can limit model development, validation, and operational implementation.
- xi. Model transferability requires further work: Ensuring that methods generalise across regions, cropping systems, and environmental conditions remains a key challenge, requiring rigorous validation and methodological refinement.

- xii. Capacity building and data accessibility are essential: Wider adoption requires training opportunities, improved technical capacity, and clear mechanisms for data access, sharing, and dissemination.

9. Scientific Roadmap

This section provides a comprehensive roadmap for advancing EO methods to monitor cereal crop responses to multiple stressors. It begins by assessing the project's achievements, including progress in hyperspectral modelling, multi-sensor data fusion, and ML for stress detection, while highlighting persistent challenges such as data gaps, overlapping stress signals, and limited model transferability. It then defines a scientific agenda to address these gaps, focusing on early stress detection using thermal and fluorescence data, distinguishing co-occurring stressors, scaling UAV and proximal sensing insights to satellite products, and establishing a tiered in-situ observation network supported by standardised protocols and ESA's Fiducial Reference Measurement framework. The final section outlines a five-year research plan aligned with upcoming missions (FLEX, CHIME, LSTM) and initiatives like ESA's Digital Twin Earth and CGIAR's 2030 strategy. Key priorities include multi-sensor fusion, hybrid RTM–ML models, UAV-to-satellite upscaling, open-access data libraries, and stakeholder engagement through living labs. The roadmap aims to transition EO-based stress detection from research to operational services, ensuring scalability, interoperability, and long-term impact for global agricultural monitoring and food security.

9.1 Assessment of the Project's Objectives and Results

The project assessment has four main components. Each is summarised and evaluated here:

- i. Improving our understanding of the scientific background and potential of existing and future datasets to monitor multiple crop stressors using EO data.
- ii. Undertaking dedicated field campaigns and radiative transfer modelling to develop a fundamental understanding of the remote signature of individual and multiple stressors
- iii. Demonstrator cases co-implemented with selected end-users using existing computational and data infrastructure.
- iv. Using experimental data and tools to improve scientific understanding of crop stress and develop a roadmap.

9.1.1 Major results of Dedicated Field campaigns at Pilot sites

The pilot-scale studies emphasise the potential of hyperspectral remote sensing and advanced ML for detecting crop stress, while also highlighting key limitations and research priorities for the future. In the rice experiments, hyperspectral data from EnMAP and PRISMA consistently outperformed Sentinel-2 in identifying biochemical traits such as nitrogen and carbon content. Hybrid approaches that combined RTMs with ML yielded more robust estimates of biophysical parameters and provided deeper insights into plant stress responses. Case-control analyses further demonstrated that salinity and nitrogen deficiency significantly reduced rice growth, with hyperspectral imagery offering clearer discrimination of stress than multispectral data.

Challenges remain, particularly limited trait variability under drought conditions, the coarser spectral resolution of Sentinel-2, and temporal mismatches between satellite and field data. Addressing these issues will require tighter field–satellite synchronisation, improved multi-sensor data fusion, and increased hyperspectral observation frequency.

The maize drought study demonstrated that combining vegetation and water-stress indices enables accurate detection of drought severity, with DNNs achieving the highest predictive performance. Annual drought maps (2018–2023) highlighted strong temporal patterns, including the severe 2022 drought. However, irrigation masked drought signals in irrigated fields, cloud cover and sensor timing mismatches reduced data continuity. Future work should

focus on cloud-resilient processing pipelines, field-informed gap-filling, and stratified modelling that accounts for irrigation practices.

Similarly, lodging detection in wheat benefited from both hyperspectral and Sentinel-2 observations, with RFR providing the most accurate predictions. Although the workflow proved transferable, model uncertainty stemmed from variability in soil and weather conditions, as well as the diverse causes of lodging. Noise in specific hyperspectral bands and inconsistent timing between satellite and field data also affected accuracy. Improved preprocessing, calibration, and multi-sensor harmonisation will be essential for expanding lodging monitoring to broader regions.

While these findings demonstrate the promise of optical and hyperspectral remote sensing for precision agriculture, their generalisability is limited by single-season datasets and single-site experiments. Expanding to multi-season, multi-location field campaigns is crucial but costly, requiring extensive field measurements, long-term logistical coordination, and reliable access to hyperspectral acquisitions from agencies such as DLR and ASI. Investment in broader datasets will be critical for developing scalable, season-independent stress-detection models that support operational agricultural monitoring systems.

9.1.2 Recommendations from pilot sites

Across all pilots, several consistent lessons emerged that point to future directions for EO-based crop stress monitoring. Hyperspectral data from missions such as EnMAP and PRISMA repeatedly demonstrated superior capability in detecting biochemical traits, including nitrogen, carbon, chlorophyll, and lodging severity, compared to Sentinel-2. However, their long revisit times limit operational usability, featuring the enduring trade-off between spectral richness and temporal frequency. ML and hybrid RTM–ML approaches proved consistently effective, with methods such as DNNs, 1D-CNNs, GPR, and RTM-informed ML yielding the highest accuracy. Stress signals were clearest in non-irrigated fields, where natural variability remains unmasked by water inputs. The pilots also highlighted the importance of multisensor integration, noting that combining hyperspectral, Sentinel-2, UAV, and proximal sensing provides a comprehensive and reliable stress assessment.

However, the limited availability of hyperspectral acquisitions and frequent cloud cover created significant observational gaps, while Sentinel-2's coarser spectral resolution constrained biochemical stress detection. These issues highlight the need for multi-sensor fusion combining optical, SAR, and thermal data to ensure continuous spatiotemporal coverage. Temporal misalignment between satellite observations and field campaigns further reduced validation reliability, pointing to the importance of more synchronised data acquisition and the use of predictive methods to compensate for timing offsets.

In situ data limitations were another major barrier. Field data collection was constrained by weather, access, and resource availability, resulting in sparse ground truth for calibration. More consistent, standardised field campaigns across multiple regions and years are needed to strengthen model validation. While JECAM sites offer a potential framework for coordinated multi-site experiments, crop stress data are not routinely collected there and would require dedicated investment and coordinated protocols.

Algorithmic and scalability challenges also emerged in the satellite-based hyperspectral data that offer high biochemical sensitivity but lack temporal frequency, whereas Sentinel-2 provides the opposite; reconciling this requires advanced data-fusion approaches and ML techniques that can generate high-frequency stress indicators without sacrificing spectral accuracy. The computational demands of ML models, especially when scaling to regional or national applications, call for cloud-based processing, automated feature selection, and the

adoption of high-performance computing solutions like ESA's Space HPC infrastructure. Improved modelling of co-occurring stressors such as drought, salinity, and lodging will also require more diverse training datasets and hybrid physical–ML approaches to separate overlapping stress signals.

Variability in soil type, management practices, climate, and crop varieties reduced the transferability of models across regions; thus, spatio-temporal stability remains a central challenge. Irrigation masked stress in the Marchfeld pilot, and hyperspectral revisit limitations in other pilots hindered continuous tracking of stress progression. Expanding training datasets to span diverse environments, conducting cross-site validation, and developing standardised reference databases will improve model robustness. Thus, data assimilation frameworks that integrate hyperspectral, multispectral, SAR, and UAV observations will be essential for producing consistent, multi-temporal stress assessments.

Further progress in stress monitoring will depend on coordinated field data collection, improved data sharing, and the development of adaptive, uncertainty-aware ML models. In this regard, automated, cloud-based pipelines can support real-time model updating as new satellite and field data become available. An open-access EO monitoring platform leveraging multi-sensor data, harmonised field protocols, and scalable ML would create a foundation for operational crop stress surveillance across agricultural regions worldwide.

9.2 Scientific Agenda

The scientific agenda defines how to close gaps and address priorities. 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.

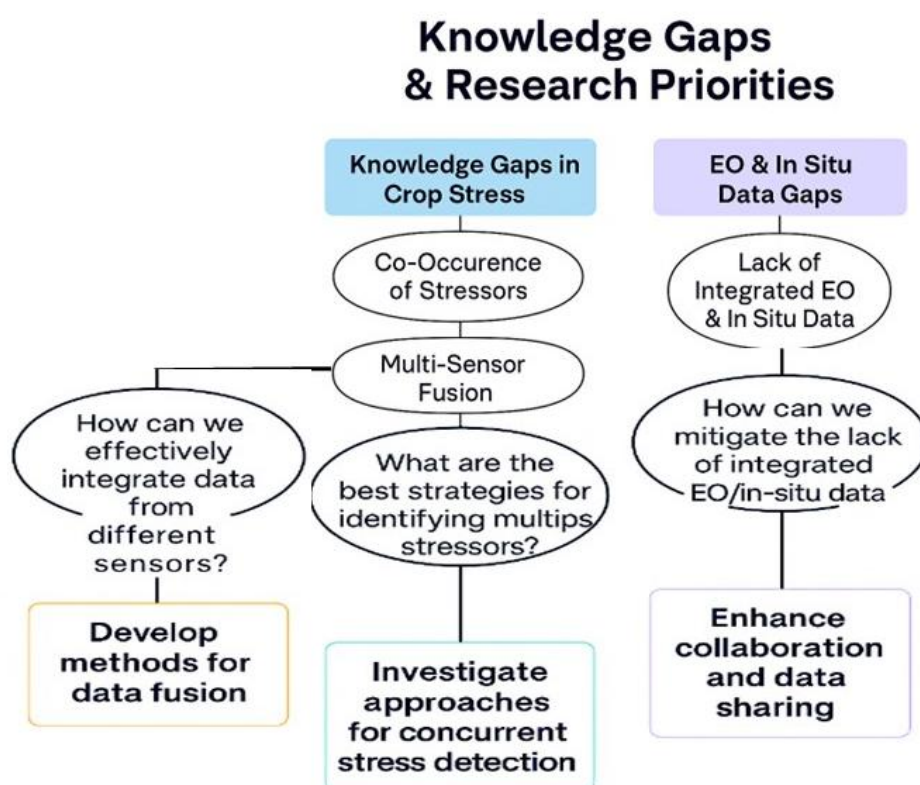


Figure 9.1 summarises the key questions and research priorities defined in the scientific roadmap.

9.2.1 Multi-sensor data integration and fusion

Although the diversity and availability of satellite, airborne, and UAV sensors continue to grow, integrating these heterogeneous datasets into a coherent monitoring framework remains a challenge. The increasing range of EO platforms (Sentinel-2, PRISMA, EnMAP, CHIME, UAV hyperspectral systems, SAR, and thermal sensors) offers complementary capabilities, yet their differences in spectral resolution, revisit frequency, calibration protocols, viewing geometries, and atmospheric correction hinder integration. These inconsistencies limit the development of scalable, multi-sensor stress-monitoring systems and require computationally demanding preprocessing pipelines that are often insufficient for full harmonisation.

Future progress will rely on advanced, ML-driven fusion approaches capable of harmonising disparate sensor inputs, dynamically weighting their contributions, and reconstructing missing or misaligned observations. 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.

Such methods can leverage the spectral richness of hyperspectral sensors, the temporal frequency of Sentinel-2, and the structural and moisture sensitivity of SAR to create consistent, high-resolution stress indicators suitable for operational use.

9.2.2 Gaps in understanding individual crop stressors

Abiotic stressors such as drought, salinity, nutrient deficiency, and heavy metal toxicity induce overlapping physiological and spectral responses, making them difficult to differentiate with current EO methods. For several stressors, particularly heavy metal toxicity, detailed spectral characterisations across crop types, physiological processes, and growth stages are scarce. Salinity, for example, exhibits spectral behaviours that closely mimic drought or nutrient imbalance, and no consensus exists on optimal indices for separating these conditions.

9.2.3 Complexity of co-occurring stressors

Agricultural systems often encounter multiple simultaneous stressors, such as drought combined with nutrient deficiency, pests, salinity, or heavy metal toxicity. These interactions create nonlinear physiological responses and overlapping spectral signatures that current EO approaches struggle to separate. Most existing studies examine single stressors, leaving gaps in understanding their synergistic or antagonistic effects.

New opportunities arise from the next generation of hyperspectral missions (e.g., CHIME, FLEX, EnMAP, PRISMA) that can provide richer biochemical information. Progress will depend on developing multivariate analysis techniques, ML classifiers, and hybrid physical–ML models that can capture subtle spectral interactions associated with co-occurring stresses. Approaches may include designing new hyperspectral indices derived from feature selection, exploiting red-edge dynamics or SWIR absorption features, and integrating data from complementary missions (e.g., FLEX + CHIME) to merge physiological, biochemical, and structural signals. UAV hyperspectral observations will be essential for calibration and validation.

Advances in AI and multi-sensor feature extraction hold promise for disentangling complex, overlapping stress responses. Building comprehensive training datasets that include controlled combinations of stressors will be critical for enabling models to move beyond single-factor detection and toward diagnostic, operational EO-based stress monitoring.

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

Pests and diseases are major contributors to crop stress, but their interactions with abiotic stressors remain poorly understood. These interactions complicate EO-based stress detection, as spectral changes induced by pests or diseases can closely mimic those from abiotic stress, particularly in the red and red-edge regions associated with chlorophyll degradation. Pest-induced stress, however, often has intrinsic relationships with crop phenology, biophysical traits, and environmental conditions, which may be exploited to differentiate it from nutrient or water stress.

Addressing this knowledge gap requires systematic studies that:

- i. Characterise how individual biotic and abiotic factors influence crop physiological traits.
- ii. Examine how these physiological changes modify spectral reflectance at both leaf and canopy scales.
- iii. Investigate how combined stressors produce additive, synergistic, or antagonistic effects on spectral signatures.

Such insights require dedicated field and laboratory experiments in which stressors are introduced sequentially and in combination, enabling careful observation of plant responses and associated spectral changes. Understanding these interactions is essential for developing EO-based systems capable of diagnosing complex stress scenarios in real agricultural landscapes.

9.2.5 Involvement of stakeholders and future product generators

The operationalisation of EO products relies heavily on the engagement of national organisations, which, following the GEOGLAM philosophy, are best positioned to interpret and apply EO data within their own jurisdictions. These organisations possess local expertise and contextual knowledge that are critical for translating EO research into actionable monitoring and management tools. Capacity development, where required, can ensure that local teams can maintain and operationalise EO workflows effectively. For instance, Agriculture and Agri-Food Canada (AAFC) demonstrates a tiered approach to EO product operationalisation:

- i. Direct use of existing datasets: NASA datasets such as the Evaporative Stress Index or GRACE groundwater anomalies are adopted when they meet national monitoring needs and are produced consistently.
- ii. Modified products: In cases where operational datasets do not fully meet requirements, such as SMOS soil moisture data, additional processing and calibration are undertaken in-house.
- iii. In-house generation: For datasets not currently available, e.g., national crop type mapping data, is developed from the ground up to ensure accuracy, relevance, and suitability for domestic monitoring priorities.

Such a decision to operationalise a dataset depends on the resources required for ongoing processing and maintenance, as well as the dataset's strategic importance to national monitoring objectives.

9.2.6 Bringing research into operations

Translating research methods into operational EO products requires rigorous testing and clear demonstrations of their value. As such, hyperspectral products are unlikely to be adopted operationally without a dependable, long-term hyperspectral satellite programme that guarantees consistent data quality, continuity, and spatial coverage.

9.2.7 Early warning and agricultural advisories

National and international stakeholders such as GEOGLAM, AMIS, and IGAD are primarily concerned with crop production quality and quantity. Their EWSs and crop monitoring programmes rely on diverse EO data to characterise crop conditions and identify anomalies. However, EO workflows currently provide limited information on the duration, intensity, or specific causes of crop stress. Operationalisation at scale requires:

- i. Distributed data production: Expert teams at national and regional levels generate datasets for specific monitoring regions.
- ii. Capacity building and training: Stakeholders require training to implement stress detection methods and tools, enabling consistent and accurate use.
- iii. Long-term testing and adoption: Sustained deployment ensures the EO-based stress detection frameworks are robust and reliable for operational use.

Successful integration of EO4CerealStress frameworks, particularly those based on hyperspectral data, into operational workflows can enhance early stress detection capabilities. Linking research methods to upcoming hyperspectral missions (e.g., CHIME) increases transferability and strengthens confidence among the user community. Operational users prioritise stability and continuity; hence, methods must demonstrate long-term viability to gain adoption.

9.2.8 Future directions: pest and disease monitoring

Emerging climatic conditions and the increasing co-occurrence of multiple stressors highlight the need to incorporate pest and disease monitoring into operational EO frameworks. Methodologies for pest and disease detection align closely with EO4CerealStress approaches, and combining these methods can expand initiatives such as the ESA-EC Joint Earth System Science Initiative. Successful integration requires:

- i. Collaboration with plant pathologists and experts in pest and disease management.
- ii. Use of existing climate-based models for pest and disease risk assessment.
- iii. Linking EO approaches with non-remote sensing initiatives, such as the Global Burden of Crop Loss and the Global Plant Health Assessment.

By combining hyperspectral EO techniques with pest and disease monitoring, operational systems can more effectively address the complex, interacting stresses affecting crops, providing actionable insights to farmers, policymakers, and commercial stakeholders.

9.3 Five-Year Research Plan

This five-year research plan outlines a roadmap to advance the integration of EO-based crop stress detection into research, decision support, and policy workflows. It accounts for both current and emerging EO missions, including the Copernicus expansion, LSTM, FLEX, CHIME, and other upcoming hyperspectral and thermal sensors. 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 and connects to programmes, including ESA’s Digital Twin Earth, the European Commission’s Vision for Agriculture and Food, and the CGIAR 2030 Research and Innovation Strategy, ensuring scalability and long-term impact.

The following tasks are prioritised based on scientific importance, societal impact, and feasibility (**Table 9.1**) while building the foundations for operational EO-based crop stress monitoring at regional, national, and global scales.

Table 9.2 Proposed prioritised task, estimated effort, and potential impact

<i>Task description</i>	<i>Priority ranking</i>	<i>Effort (L M H)</i>	<i>Scientific impact (L M H)</i>	<i>Societal impact (L M H)</i>
1 Multi-sensor fusion development. Develop advanced fusion techniques combining optical, SAR, thermal, and hyperspectral data for robust crop stress detection.	1 st	H	H	H
2 Early stress detection with emerging EO data. Leveraging upcoming missions like LSTM, FLEX, CHIME, and existing missions such as ECOSTRESS and EnMAP.	1 st	M	H	H
3 Hybrid RTM-ML framework design. Further integrate radiative transfer models (e.g., PROSAIL, SCOPE) with ML approaches to enhance predictive accuracy and interpretability of crop stress detection across varied conditions.	2 nd	H	H	M
4 Co-occurring stressor differentiation. Develop advanced AI models trained on multi-sensor datasets to disentangle overlapping stressors and improve their classification accuracy.	2 nd	M	M	H
5 UAV to satellite upscaling. Develop AI workflows to scale UAV and proximal sensing insights to regional and national levels using satellite platforms such as Sentinel-2, PRISMA, and CHIME.	3 rd	M	M	H
6 Multi-site in-situ data expansion. Establish and maintain global super-sites equipped with co-located field, UAV, and EO sensor systems to ensure consistent calibration and validation of stress-detection algorithms across agro-ecological zones.	1 st	H	H	M
7 Field protocol standardisation. Develop and implement harmonised field protocols for measuring key biophysical traits under various stressors.	1 st	M	H	H
8 Open-access EO data libraries. Create accessible EO data libraries. Include metadata standards and harmonised formats to support reproducible ML training and benchmarking across different EO platforms.	3 rd	M	M	M
9 Operational EO tools and cloud integration. Operationalise crop stress monitoring services by integrating EO models into cloud-based platforms. Develop user-friendly interfaces and data pipelines – co-developed in Living Labs.	2 nd	M	M	H
10 Model uncertainty quantification. Develop uncertainty-estimation frameworks for stress-prediction models using ensemble methods and Bayesian methods and validate across pilot sites.	2 nd	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.	4 th	M	M	H

- **Priority 1 Tasks:** Focus on high-impact, feasible activities enabling early detection, multi-sensor fusion, standardised field protocols, and in-situ calibration (Tasks 1, 2, 6, 7).
- **Priority 2 Tasks:** Essential scientific tasks with higher effort or uncertainty (Tasks 3, 4, 9, 10).
- **Priority 3 Tasks:** Enabling frameworks and scaling (Tasks 5, 8).
- **Priority 4 Tasks:** Collaboration, knowledge exchange, and capacity building (Task 11).

Figure 9.2 provides a framework for an ESA research programme on agriculture from 2026 onwards. The complete plan of action is shared in the **RD-7.1: Scientific Roadmap, Table 2**.

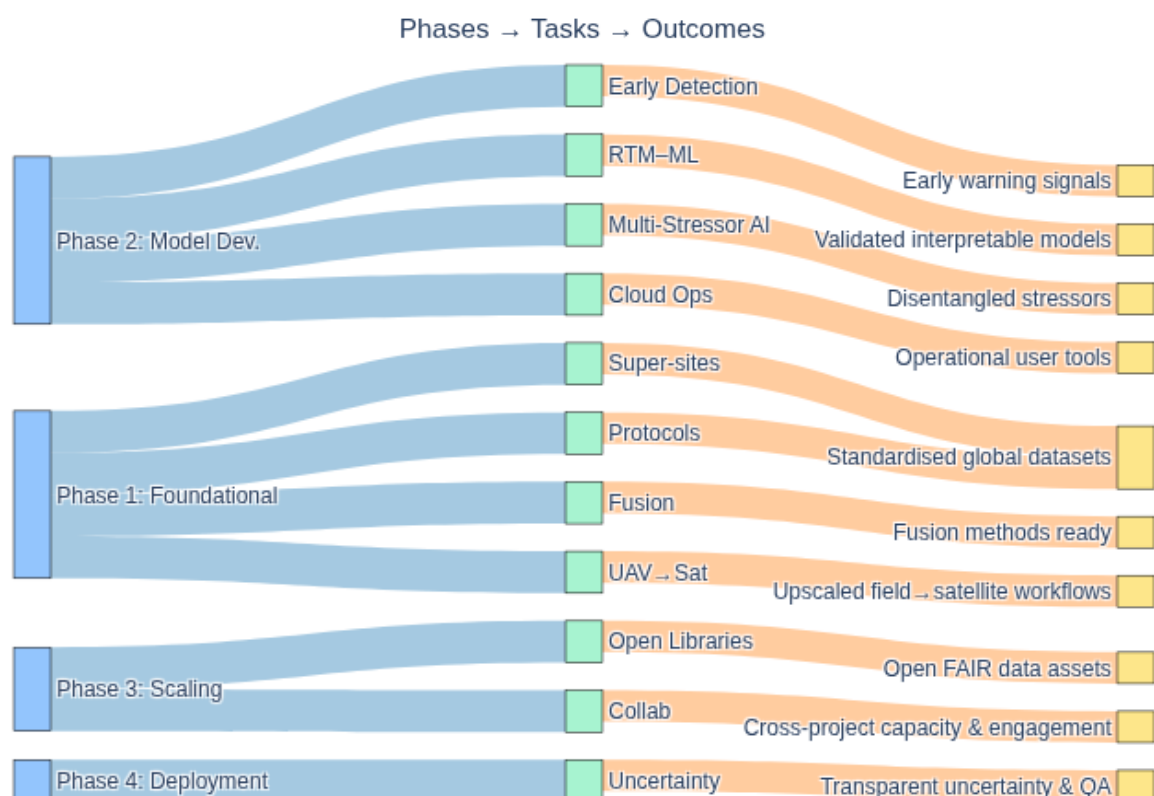


Figure 9.2. Connecting phases of the five-year research plan with tasks and associated outcomes.

10. Conclusion

The EO4CerealStress project has demonstrated the feasibility and value of integrating Earth Observation data, advanced modelling techniques, and field measurements to monitor cereal crop responses to multiple abiotic stressors. Through three pilot studies and complementary case analyses, the project developed and validated innovative workflows combining hyperspectral and multispectral satellite imagery, UAV-based sensing, and ML algorithms. These approaches significantly improved the detection and quantification of stressors such as drought, salinity-nutrient deficiency (co-stressors), and lodging-severity grading, offering actionable insights for precision agriculture and climate-resilient crop management such as Drought maps for Austria and Canada are supporting irrigation planning and crop insurance, Rice salinity and nutrient stress maps in Andalusia are guiding fertiliser and water management and Lodging severity maps in Italy are assisting harvest planning and loss estimation.

The project's impact extends beyond scientific advancement to practical applications, as evidenced by collaborations with early adopters and by their integration into DSS platforms (e.g., the SAMA 2.0 agro-monitoring platform) for operational monitoring. While challenges remain, such as limited hyperspectral coverage, data harmonisation, and the complexity of co-occurring stressors, the scientific roadmap and five-year research plan provide a clear pathway for addressing these gaps. Future efforts will focus on multi-sensor data fusion, UAV-to-satellite upscaling, and operationalisation via cloud-based platforms, leveraging upcoming missions such as CHIME, FLEX, and LSTM.

By bridging research and practice, EO4CerealStress laid the foundation for scalable, interoperable EO-based solutions that enhance food security, support sustainable agriculture, and strengthen resilience to climate change.

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