EO4CEREALSTRESS

Theme 3: Crop response to multiple stressors

Deliverable 1.1: Requirement Baseline Review Document

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ACRONYMS

ADMS	Agricultural Drought Monitoring System
AFR	Andalusian Farm
AGB	above ground biomass
AgMERRA	Modern-Era Restrospective Analysis for Research and Applications in Agriculture
An	Photosynthesis
ANN	Artificial Neural Network
ASD	Analytical Spectral Devices
AUC-ROC	Area Under the Curve-Receiver Operating Characteristic
AVHRR	Advanced Very-High-Resolution Radiometer
CAP	Common Agricultural Policy
CASMA	Crop Condition and Soil Moisture Analytics
CCC	Canopy Chlorophyll content
CCI	Chlorophyll Content Index
CGIAR	Consultative Group on International Agricultural Research
CGM	Crop growth model
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
CIRCASA	Coordination of International Research Cooperation on Soil Carbon Sequestration in Agriculture
CNN	Convolutional neural network
CWSI	Crop water stress index
DCNN	Deep Convolutional neural network
DESIS	DLR Earth Sensing Imaging Spectrometer
DIONE	an integrated EO-based toolbox for modernising CAP area-based compliance checks
DL	Deep Learning
DSSAT	Decision Support System for Agrotechnology Transfer
EC JPI FACCE	European Commission Joint Programming Initiative on Agriculture, Food Security and Climate Change
EcoStress	Ecosystem Spaceborne Thermal Radiometer Experiment on Space Station
EMR	Electromagnetic radiation
ENET	Elastic net regression
EnMAP	Environmental Mapping and Analysis Program
EO	Earth Observation
EOS	Earth Observing System
ESA	European Space Agency
ESU	Elementary Sampling Unit
ET	Evapotranspiration

EU	European Union
EVI	Enhanced vegetation index
FAO	Food and Agriculture Organization of the United Nations
FAPAR	fraction of absorbed photosynthetically active radiation
FARMA	Fusion approach for remotely sensed mapping of agriculture
FDA	Fisher's Discriminant Analysis
FLEX	Fluorescence Explorer
FLUXNET	Flux network
FSSCat	Federated Satellite System 6U tandem mission for sea ice and soil moisture monitoring
GA	Genetic Algorithms
GaoFen	Chinese high-resolution Earth imaging satellite
GeoGlam	Group on Earth Observations Global Agricultural Monitoring Initiative
GEOSAT	Geodetic Satellite
GLASS	Global Land Surface Satellite
GNDVI	Green NDVI
GPP	Gross Primary Productivity
gs	Stomatal Conductance
HJ-1 A/B CCD	Huan Jing 1A/1B Charge-Coupled Device
HPC	High Performance Computing
HPLC	High-Performance Liquid Chromatography
ICA	Independent component Analysis
ICT	Information and Communications Technology
INVITE	Innovations in plant Variety Testing in Europe
IRRI	International Rice Research Institute
JRC	Joint Research Centre
LAI	Leaf area index
LDA	Linear Discriminant Analysis
LiDAR	Light Detection and Ranging
LIDF	leaf inclination distribution function
LSA-SAF	Satellite Application Facility on Land Surface Analysis
LUT	Look up table
MEF4CAP	Monitoring and Evaluation Frameworks for the Common Agricultural Policy (CAP)
MODIS	Moderate Resolution Imaging Spectroradiometer
MODTRAN	Moderate resolution atmospheric transmission
MTCI	Meris Terrestrial Chlorophyll Index
NARS	National Agricultural Research System
NASA	National Aeronautics and Space Administration
NDRE	Normalized Difference Red Edge
NDVI	Normalized difference vegetation index

NDWI	Normalized difference water index
NIR	Near Infrared
NIRS	Near-Infrared Spectroscopy
NN	Neural Network
NPK	Nitrogen Phosphorus Potassium
OLCI	Ocean and Land Colour Imager
PCA	Principal Component Analysis
PLSR	Partial least square regression
PRISMA	Hyperspectral Precursor of the Application Mission
PROSAIL	PROSPECT + SAIL
PROSPECT	PROpriétés SPECTrales
PSI	Plant stress index
RE	Red- Edge
RECAI	Red edge chlorophyll absorption index
RECI	Red edge chlorophyll index
RFE	Recursive Feature Elimination
RGB	Red, Green, Blue
RS	Remote Sensing
RTM	Radiative Transfer Model
RVI	Radar Vegetation Index
SAIL	Scattering by arbitrary inclined leaves
SAR	Synthetic Aperture Radar
SAVI	Soil Adjusted Vegetation Index
SCOPE	Soil Canopy Observation, Photochemistry and Energy fluxes
SEM	Scanning Electron Microscopy
SLSTR	Sea and Land surface temperature radiometer
SMI	Soil Moisture Index
SMOS	Soil Moisture and Ocean Salinity
SPA	Successive Projections Algorithm
SPA	Soil Plant Atmosphere
SPOT	Satellite pour l'Observation de la Terre
SRI	Spectral reflectance Indices
STMA	Stress Tolerant Maize for Africa
SVM	Support Vector Machine
SVR	Support Vector Regression
SWIR	Shortwave Infrared
TEM	Transmission Electron Microscopy
TOA	Top of Atmosphere
TOC	Top of Canopy
TVDI	Temperature vegetation dryness index
TVI	Terrestrial vegetation index
UAV	Unmanned Aerial Vehicle

USDA NASS	USDA National Agricultural Statistics Service
VegSCAPE	Vegetation Condition Explorer
VHR	Very High Resolution
VI	Vegetation index
VNIR	Visible and near-infrared
WaSCIA	Water Stress and Climate Indices for Africa’
WC	Water Content
WDI	Water Deficit Index
WSI	Water Stress Index
WT	Wavelength Transform

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1. INTRODUCTION

1.1 Purpose and Objective

The overarching objective of the study is to evaluate the synergistic use of multi-source Earth Observation (EO) and in-situ data, to understand the effects of multiple stressors and their cumulative effects on crops. The new and planned European satellite missions are expected to provide data with improved spatial, spectral, and temporal resolution, making them valuable resources for monitoring, and analyzing crop stressors. The project takes advantage of the complementary nature of these data sources to gain insights into the effects of both individual and cumulative stressors on agricultural crops. The synergistic use of EO data, combined with comprehensive data analysis techniques, can enhance our ability to detect, understand, and respond to multiple stressors affecting agricultural crops.

The key aim of the study is to develop products that can be used to monitor these stressors and provide a scientific roadmap for the future development of EO products and techniques for monitoring multiple crop stressors. These products will be useful for farmers, agronomists, policymakers, and researchers, and can provide meaningful insights into crop health and the environmental factors impacting it.

The core objectives of the study articulate around the following elements:

- Exploring and identifying suitable data (both in-situ and EO based) and crop models that can be used to analyze the relationship between selected key multiple stressors and crops growth status evolution.
- Performing detailed field experiments to evaluate the effects of selected stressors on crop growth status.
- Designing and developing algorithms that can exploit existing in-situ data, field campaign data and EO data to monitor multiple stressors and their impact on crop growth status.
- Generating experimental datasets (using the chosen algorithm/s) that can be used to monitor the effect of multiple stressors on crop growth status.
- Demonstrating the use of experimental datasets to advance scientific understanding of the impacts of multiple stressors on crop growth status.
- Working with relevant stakeholders to demonstrate the usefulness of the experimental datasets and scientific findings in mentoring multiple stressors and their impacts on crop growth status.
- Engaging the user community and scientists in validation and critical assessment of the proposed products and impact assessment studies and the design of a scientific roadmap for addressing major scientific challenges in using EO data to monitor multiple crop growth stressors.

This technical note presents the outcome of the first task on the project concerning the Consolidation of Open Scientific Issues. This baseline document hence contains a comprehensive analysis of the scientific basis of the project. In particular it:

- Identifies main scientific challenges and knowledge gaps in using EO and in-situ data to understand and monitor impacts of multiple stressors on crops.
- Identifies up to date EO products and ancillary datasets, that can be used in the development and validation of the new crop stress products.
- Reviews strengths and weaknesses of the current methods and algorithms applied over EO and in-situ data to understand and monitor impacts of multiple stressors on crops.
- Identifies relevant testing areas over which the crop stressor products will be generated and evaluated.
- Evaluates ideal requirements (e.g., accuracy levels, spatial and temporal resolutions, and composite periods) to generate experimental datasets for understanding and monitoring impacts of multiple stressors on crops.
- Identifies other ongoing projects and initiatives with which we could interact all along the project for an enhanced valorization of the EO products.

Ultimately, the research conducted in this project will simplify the data exploitation from the various satellite missions in monitoring the individual and cumulative impacts of various stressors on crops. The recent EO data from both European missions (e.g., Copernicus Sentinel missions, PRISMA, EnMap) and US missions (e.g., Landsat mission) and experimental in-situ data (e.g., FLEXSense campaign data, LSTM, CHIME, SARSense) have potential to address the challenge of monitoring both the individual and combined effects of several stressors on crop growth status, productivity, and ecosystem service. The use of these advanced remote sensing technologies and their integration with data analytics will assist us in addressing global food security challenges. It will advance our ability to monitor crop health, detect stressors, and optimize crop management strategies.

1.2 Document Plan

The remaining sections of the document are structured as follows:

- Section 2 presents the main challenges and knowledge gaps in monitoring multiple stressors in the cropping systems.
- Section 3 reviews the existing ground and satellite databases to be considered in the EO4CerealStress project.
- Section 4 addresses key methodologies for crop stress detection and monitoring
- Section 5 identifies the test areas over which the EO4CerealStress Experimental Dataset products will be generated and summarizes the output EO products.

- Section 6 presents framework for validation and evaluation of the project EO products and describes the validation/evaluation approach to be used.
- Section 7 details the collaborations with the different scientific communities and synergies with other projects which will be undertaken during the project.

2. CHALLENGES IN MONITORING MULTIPLE STRESSORS IN CROP

2.1 Key stressors and their impact on agriculture

Agriculture is subject to various biotic and abiotic stressors, including drought, pests, diseases, nutrient deficiencies, heavy metals, extreme temperatures, and weather events. Abiotic stresses are caused by either physical or chemical factors and biotic stresses are caused by infectious agents such as bacteria, fungi, insects, etc.) (Gull et al. 2019; Dresselhaus and Hückelhoven, 2018). The physiological changes caused by these stressors have a significant impact on plant growth, which has a detrimental effect on agricultural production. The impact of each type of stress on crop yield can vary depending on several factors, including the specific stressor, the crop species, and environmental conditions. Plants can respond to these adverse conditions through various physiological defense mechanisms. However, plants may have limited natural adaptations to cope with certain abiotic stresses. For example, many crops are sensitive to extreme temperatures or lack mechanisms to utilize limited water resources efficiently. Some crops may have developed natural resistance mechanisms against certain pests or diseases. The negative effects of stressors on plant health can be reduced with early detection of these mechanisms and implementation of protective measures. Biotic stresses are often more localized, affecting individual plants or specific fields. They can be managed through various strategies like pesticides, crop rotation, and breeding for resistance (Atkinson and Urwin, 2012). However, a comprehensive monitoring of the state of agricultural crops will contribute to the early and accurate estimation of yield losses and prevent crop failures.

Despite the population explosion and increasing food demand in the last century, farmers continue to suffer from large economic losses due to climate and biotic stressors. Food security is becoming an urgent issue as the global impacts of the climate crisis become more noticeable (Rivera et al. 2023). Climate change is altering weather patterns, leading to increased frequency and severity of extreme weather events such as droughts, floods, heatwaves, and storms. These events can have devastating effects on crop yields and can lead to significant economic losses for farmers (Fróna at al. 2021; Gornall et al. 2010). Moreover, new strains of pathogens and pests are emerging, and plants are developing resistance to pesticides, making it challenging to manage these biotic stressors effectively. Since, many agricultural systems rely on monoculture farming, where a single crop is cultivated over large areas. This practice can increase the vulnerability of crops to biotic stressors (Grant, 2007). Small-scale and resource-constrained farmers often lack access to modern farming technologies, quality seeds, irrigation, and pest management tools. This limits their ability to adapt to and mitigate the effects of stressors. Despite ongoing challenges, the agricultural sector continues to adapt and innovate to meet the growing global demand for food while addressing the economic losses caused by climate and biotic stressors. Sustainable and resilient farming practices are increasingly important in ensuring food security in the face of these challenges.

Certain physical and physiological traits of cereal crops are critically important for monitoring agriculture and food production. Crop physical traits like morphology and canopy height can impact lodging resistance (the ability to stand upright). Leaf characteristics can define photosynthetic efficiency and disease susceptibility. The tillering and morphology of flowers, spikelets, and panicles are related to grain production. Depth of the root system can affect nutrient and water uptake; the fibrous rooting system of cereal crops is well-suited for drought tolerance and adaptive to changing soil conditions. In physiological traits, traits related to photosynthesis and respiration i.e., chlorophyll content, photosynthetic efficiency, and carbon assimilation rates are direct measures for plant growth and maintenance. Crop health is usually tested through its efficiency in physiological processes and tolerance to stress i.e., nutrient uptake efficiency, resistance to fungal, bacterial, and viral diseases, heat tolerance, deep root systems, reduced transpiration rates, and osmotic adjustments in drought conditions. Understanding and monitoring these traits and crop efficiencies are essential for sustainable and productive agriculture. Though the amount and quality of multisource data is constantly increasing, integration, analysis and making the best decisions possible using this data in a holistic manner is still a challenge.

Remote Sensing (RS) technologies serve as a diagnostic tool that can act as an early warning system, allowing the agricultural community to counter potential problems before they can negatively impact crop productivity. It has non-destructive method of data acquisition, making it an inevitable tool to meet multiple goals in agriculture, such as monitoring crop production, choosing economically viable activities, reducing negative environmental impacts, contributing to climate mitigation and minimizing resource depletion. The integration of sensors, automatic data recording, satellite datasets, Unmanned Aerial Vehicles (UAV) datasets, Machine Learning (ML) technology and decision support systems can provide a holistic framework to detect and monitor crop stress. Combined use of sensors can capture different aspects of the agricultural environment. For example, Environmental Mapping and Analysis Program (EnMAP)'s hyperspectral data for identifying specific stressors in crops and Sentinel 2 for frequent and large-scale monitoring of crop parameters. The combination of spectral and spatial information can enhance detection performance in comparison to the use of spectral capacities alone. By combining various soil moisture, thermal, optical, and hyperspectral sensors, we can obtain a precise and more comprehensive dataset covering a wide range of parameters, such as soil moisture, temperature, spectral reflectance, and more. This can give us a holistic understanding and continuous monitoring of the agricultural system. This project will focus on the integrated use of sensors and deriving a large set of crop variables to improve understanding of the stressors and their effects which will support timely interventions for crop management and food security.

The use of RS data in agriculture monitoring has increased since 1970s. Increasing publications in the field of precision farming and environmental monitoring are giving birth to a wide diversity in RS applications in plant stressors as observed by Lasalle et al. 2021 in their work and growing trend is shown in the figure 1. Lasalle et al. (2021) reviewed articles published until 2020, following themes, "Hyperspectral", "field/reflectance spectroscopy", "imaging Spectroscopy", and "leaf optical/spectral properties" further covering keywords of "plant or vegetation stress", "stressor", "stressful Conditions", and "plant or vegetation health". Through Google Scholar and Scopus search engines, a total of 466 peer-reviewed articles have been identified since 1970. Following the same meta review technique, a total of 65 documents were recently published from 2021 onward as retrieved through SCOPUS Database. Nevertheless, this review study found two major gaps in the current methodologies.

- Discrimination of plant stressors with similar effects on plants
- The transferability of the methods across scales.

Further research gaps are discussed in the following section.

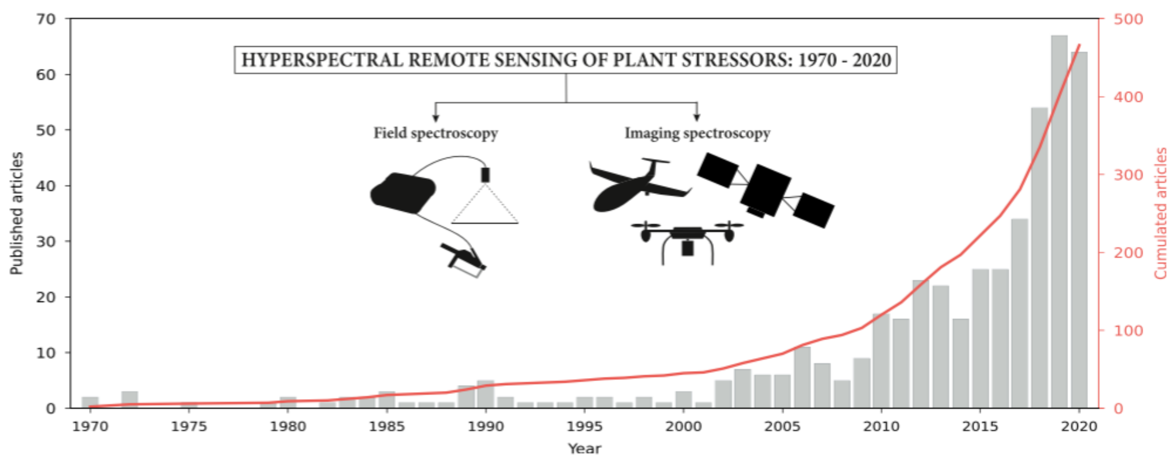

Figure 1. displays emerging trend of hyperspectral remote sensing for monitoring plant stress since 1970. (Lasalle, 2021)

2.2 Main scientific challenges and knowledge gaps in using EO and in-situ data

Scientific studies are growing in assessing the impact of multiple stressors on crops using EO data, machine learning and radiative transfer models (RTMs). Several challenges may arise when integrating stressors in modeling, including accurately quantifying interactions between stressors, handling uncertainties in modeling multi-stressor interactions, addressing data requirements, and validating model predictions with real-world data (Rapaport et al. 2015; Radoglou-Grammatikis et al. 2020). From implementation perspective of this project, some scientific challenges could be:

1. Integrating diverse datasets from different sources (EO satellites, ground-based sensors, climate records) is challenging due to variations in data formats, resolutions, and spatiotemporal scales.

2. A single or numerous stress sources, as well as biotic or abiotic stress combinations, can cause plants to have very similar physiological responses, making their evaluation problematic (Blum, 2016). To date, few studies have focused on disentangling environmental stress sources. The distinction between biotic and abiotic stresses is a difficult undertaking.

- Effects of the multiple stressors (e.g., drought, pests, diseases, nutrient deficiencies) can be synergistic or antagonistic on plant health and reflectance, which is a major limitation of the current methods as most cannot unravel the contribution of individual stressors to the response observed, which is only possible through proximal reflectance measuring methods i.e., drones, UAVs, handheld devices, towers etc.
- Some technical challenges are associated with proximal hyperspectral sensor's setup, data processing, and sample type.
- Proximal sensing has limited spatial coverage. Some platforms are weather-dependent, and adverse weather conditions can limit data collection opportunities. Some like UAVs can have payload constraints, limiting the number of sensors and the size of cameras that can be carried, which may affect the spectral range and resolution of collected data.
- Balancing the need for high temporal and spatial resolution data with the limitations of available satellite sensors and resources consistency
- Crops and stressors can exhibit significant regional and local variations, making it challenging to generalize findings.
- Challenge lies in assessing the effectiveness of stressor mitigation strategies while ensuring their applicability and scalability across diverse agricultural settings.
- Most RS methods are either species-specific or dedicated to a single scale of monitoring (leaf, canopy, images) and context oriented, such as precision farming requires monitoring stress over mono specific crop fields while environmental monitoring requires methods that can be applied at a broad scale over mixed canopies.
- The transition from controlled greenhouse experiments, where these methods are often developed, to complex and variable field conditions introduce uncertainties. Greenhouse conditions may not adequately represent the full spectrum of environmental factors and stressors encountered in the field, making it difficult to accurately assess how well the strategies will perform in practical, real-world scenarios, as observed in spectral response models developed for salinity and foliar nitrogen, primarily based on greenhouse experiments. These models may not be readily applicable in field conditions due to limited factors considered in greenhouses and the presence of multiple stresses in the field. (Goldsmith et al. 2020).
- On a large scale, the application of data assimilation is generally limited due to the availability and quality of the data from RS. Relatively high-resolution data from RS can provide accurate estimates of crop variables, they may be limited by scale, repeat time, and the availability of cloud-free imagery.

- A significant challenge in remote sensing is the retrieval of desired information. Multispectral sensors primarily offer canopy structural measurements, such as photosynthetically active leaf area, but their results can be limited due to comparatively coarse spectral sampling.
- To address spatial and temporal assessment needs, the spectral domain is often combined with hyperspectral remote sensing. However, the accessibility of high-quality hyperspectral data from missions like PRISMA, EnMap, and DESIS is not common.
- In cases where hyperspectral data availability is limited, the use and processing of existing hyperspectral data from field campaigns, as well as the development of accurate machine learning models for remote sensing applications, can be computationally intensive and may require adequate ground-truthing for model validation.
- Satellite-based sensor platforms are valuable for larger-scale monitoring, providing measurements over broader areas. However, they often suffer from limitations in data resolution, and cloud coverage can significantly affect the quality of information collected.
- Satellite-based sensors can revisit areas on a daily to weekly basis, but their limited revisit time may hinder their effectiveness, especially for detecting early signs of stress. Nevertheless, proximal sensing offers flexibility in terms of timing.
- Satellite sensors may not always be suitable in specific environmental conditions, such as those observed in the aftermath of frost events. These conditions may not be conducive for gathering spectral data.
- There is still uncertainty regarding the ability of satellites with spatial resolutions of 1-30 meters to confidently detect certain stress signals (as discussed in Murphy et al. 2020).
- One significant gap exists in the combined use of high to low-resolution sensors for gathering spectral signals. Since different stressors can generate similar stress reactions, remote sensing alone often cannot distinguish between different abiotic stresses.

Some key knowledge gaps are found in:

1. Developing methods to upscale local observations to regional and global assessments while accounting for spatial and temporal variability
2. Developing standardized protocols for model integration and validation that consider the complexity of interactions among stressors and environmental variables.
3. Advancing spectral and machine learning techniques to improve the discrimination and identification of specific stressors.
4. Developing standardized and cost-effective methods for calibration and validation that can be applied across diverse regions and ecosystems.
5. Determining optimal resolutions for specific stressor detection and monitoring scenarios and developing methods to address trade-offs between them.
6. Developing robust techniques for seamless data integration and fusion, enabling a holistic view of crop conditions, remains a priority.

EO4CerealStress aims to address significant knowledge gaps by compiling an experimental database that considers both single and multiple stressors while accommodating various field scenarios and variabilities. The project will focus on developing new spectral algorithms to improve accuracy and precision in stress detection. To achieve these goals, the project will collect extensive field data, including information on soil types, crop stress indicators, and crop performance. Moreover, existing data on crop yield and management practices from farmers, extension services, and government agencies will be incorporated into the project. This database will undergo standardization, cleaning, gap-filling, and other preparations to make it ready for use in detecting the impacts of stressors on crops.

3. EXISTING GROUND AND SATELLITE DATASETS ON CROP STRESS

This section deals with the available ground and RS datasets that can be used in the development and validation of the new EO-based products for understanding and monitoring the impacts of multiple crop stressors.

3.1 Optical Remote sensing: Coarse to high resolution satellite sensors

In the last three decades, Remote sensing has become one of the main sources of the data that can be used to provide spatial information on crop status in a comprehensive and nondestructive manner at regional to global scale. The availability of Data sets from RS has evolved significantly due to improvement in technology and development of new sensors (both in the optical and microwave domains). A list of available RS data is given in Table 1.

Table 1. provides a list of satellite data for the years (2015 – 2023).

Satellite	Sensor	Spatial Resolution	Temporal Resolution	Spectral Resolution	Datasets
		Coarse Resolution			
SMOS (2009 – present)	Microwave	35km	3 days	L-Band (19.4 – 76.9cm)	Brightness temperature, Soil moisture
MODIS (Terra: 1999 – present, Aqua: 2002 – present)	Multispectral	250 – 1000 m	1 – 2 days	36 bands (0.4 – 14)	Black sky FAPAR, GPP, Landcover, ET, NDVI
		Fine Resolution			
Landsat 7 (1999 – present) Landsat 8 (2013 – present)	Multispectral	30 – 120 m	16 days		Cropland products (30m – South Africa)

Sentinel 1 (2013 – present)	Radar	5 * 20 m	6 days	C-Band (3.75 – 7.5 cm)	Level 1 to 2
Sentinel 2 (2015 – present)	Multispectral	10,20, and 60	5 days	10 bands (0.4 – 1.3)	Level 1C to Level 2A
Sentinel 3 (2016 – present)	Multispectral	300m	27 days	21 bands (0.4 – 1)	Level 1B
HJ-1 A/B CCD (2009 – present)	Multi + Hyperspectral	30 m	2 – 4 days	4 bands (0.4 – 0.9)	Level 1 - 2
GEOSAT-1 (2009 – present)	Multispectral	22 m	Daily	3 bands (0.4 – 1.3)	Multiple, Level1 a,b,c
SPOT 5 (2002 – 2015) SPOT 6 (2012 – present)	Multispectral	2.5 – 30 m	1 – 26 days	4 bands (0.4 – 0.8)	Level1A to Level2B
Rapid Eye (2003 – 2020)	Multispectral	6.5 m	1 – 5.5 days	5 bands (0.4 – 0.8)	Level 3a
GaoFen-1 (2006 – present)	Multispectral	16 m	4 days	4 bands (0.4 – 0.8)	Level 1
EnMap (2022 – present)	Hyperspectral	30m	4 – 27 days	246 bands (0.4 – 2.5)	Level 1B, 1C,2A
PRISMA (2019 – present)	Hyperspectral	30m	29 days	Bands 239 (0.4 – 2.5) <12nm	Level0 to Level 2
PlanetScope (2016 – present)	Multispectral	3 – 5m	Daily	8 bands (0.4 – 0.85)	Level 1B to 3B, Multiple
ECOSTRESS (2018 – Present)	Thermal	100m	3 days	6 bands (0.8 – 1.2)	LST, Evaporative Stress Index
DESIS (2018 – present)	Hyperspectral	30m	3 – 5 days	235 bands 0.4 – 1 (3.3 nm)	Level1A to 2A
FSSCat (2020 – 2021)	Hyperspectral	75m	***	50 bands 0.4 – 1.3 (18nm)	Level 1C

Many optical medium-resolution satellite sensors provide freely available data that can be valuable for crop stress assessment. Some key satellite missions and sensors that researchers commonly used for monitoring crops and studying crop stress are shown in Table 1. MODIS sensors, aboard NASA's Terra and Aqua satellites, provide daily global coverage at a coarser spatial resolution (250 to 1000 meters). Although the spatial resolution is lower compared to other sensors, they are still valuable for long-term monitoring of vegetation and crop health at large scale. They are valuable for monitoring crop health and detecting stress conditions. Sentinel-3's Ocean and Land Colour Instrument (OLCI) and Sea and Land Surface Temperature Radiometer

(SLSTR) instruments can also be useful for monitoring crops. Sentinel-3 (S3) satellite measures visible and infrared radiance since 19 April 2016, with a revisit time of 1.1 days (Donlon et al. 2012). Its high revisit time and the early overpass time (before 11:20 a.m.) enable the monitoring of vegetation over the growing season and limit the problem of clouds. Sentinel-2A and Sentinel-2B provide high-resolution multispectral data (10 meters for some bands) with a revisit time of 5 days. PlanetScope operated by Planet Labs offers daily global coverage at a high spatial resolution (3 to 5 meters). Its frequent revisit time and high-resolution data are advantageous for detecting and monitoring stress factors. Compared to conventional multispectral EO systems, emerging hyperspectral satellite missions give a variety of observable variables, higher accuracy of information and transferability of variable estimation techniques. Examples of sources of hyperspectral data include i.e., EnMap, PRISMA, DESIS. They can give detailed soil and crop parameters after processing such as the ratio of vegetated to bare soil area, water and pigment content of plants, soil organic, clay, carbonates and salt content, and soil moisture. Their entire spectral information within hyperspectral data can be harnessed from machine learning approaches with enhanced spectral analyses. Their spatial and temporal resolution are being fully exploited by linking empirical and physical approaches and generalized empirical models, further details are in the section 4.

Some of the existing datasets and application examples from different studies are:

- The Harmonized Landsat Sentinel-2 (HLS) is a Level 3 product providing high quality crop related information at 30 m resolution, easy to use for cover crops, irrigation, and tillage practice assessments, available on USGS Earth Explorer and Landsat Look viewer.
- GFSAD1000 is providing cropland extent at 1km prepared from integration of multi-sensor remote sensing data (e.g., Landsat, MODIS, AVHRR), secondary data, and field-plot data providing Landsat derived rainfed and irrigated cropland product.
- In another study, a global scale high resolution FAPAR product (30m) is generated from the fusion of Landsat and Glass through a hybrid algorithm developed from the integration of physically based radiative transfer models and machine learning (Jin et al. 2022).
- Different Sensors data can be harmonized to retrieve crop performances. One of the examples is Jiri Tomicek et al (2022)'s work in the Czech Republic in which a dense seasonal trajectory generated with harmony of Sentinel-2 MSI and Landsat OLI and tested for the six agronomic crops: winter wheat, spring barley, winter rapeseed, alfalfa, sugar beetroot, and corn. A simple linear transformation was applied on vegetation indices i.e., (NDVI, MSAVI, and NDWI_1610) using an artificial neural network for which training data derived from the PROSAIL radiative transfer model. By merging Sentinel-2 (A/B) and Landsat (8/9) satellites, a dense harmonized LAI time series can be created.
- Example of an open-source applications from fusion of multiple sensors like FARMA which enables large area mapping with modest computing power, its application assessed over WorldView VHR optical, Sentinel-1 Synthetic Aperture Radar, and Sentinel-2 and Sentinel-3 optical imagery, such fusions facilitate efficient agriculture mapping and monitoring broadly (Thomas et al. 2020). It could be a tangible approach for regional scale very high-resolution mapping; however, high cost of commercial satellites could be a potential constraint.

3.2 Proximal sensing through Aircraft to Handheld Cameras:

The use of proximal sensing tools in crop monitoring and stressor detection is continuously evolving, offering new opportunities to enhance agricultural practices and address challenges related to crop health and productivity. It is one of the most promising technologies for the assessment of plant physiology, as well as their reactions to stress by combining spatial and spectral information. It can be with non-imaging sensors without the spatial field of view or imaging sensors, or it can be of varied spectral ranges from multispectral to hyperspectral domain depending installed camera devices. The multispectral UAVs and affordable field sensors provide non abstracted data at high spatial and temporal resolution. UAVs provide relatively low-cost imaging at high spatial resolution, low altitude, and user-preferred temporal resolution. Therefore, they are well suited for field scale application.

In fact, hyperspectral UAVs equipped with remote sensing payloads have become increasingly popular for crop monitoring. They offer flexibility in data collection, allowing for rapid and high-resolution imaging of fields and providing timely and localized information about crop stressors, enabling precise interventions. UAV-based wall-to-wall ultrahigh-resolution canopy map is a cutting-edge mapping technique that leverages drones to create a comprehensive and highly detailed map of the canopy cover in a specific area, providing valuable data for crop cover. Compared to satellite imagery in which some are relatively expensive (e.g., RapidEye) and are susceptible to cloud conditions (e.g., Sentinel-2), they are flexible in spectral range allowing for precise data collection. Pest is one of the main biotic stressors of crop, for which hyperspectral imaging has been preferred in proximal sensing for detection. Most studies exploited very-high-resolution UAV images (<1 m) covering the VNIR domain to detect pest injury in crops, while those on wild vegetation have mostly used high-resolution airborne images (1 – 5 m). The selection of appropriate platform varies by research problem and focus.

3.2.1 Handheld and fixed Spectroradiometers

Handled and fixed spectroradiometers are used to collect leaf and canopy spectra under both controlled and natural conditions. These proximal measurements are commonly used for calibrating stress monitoring methods intended to be applied to airborne or satellite imaging spectroscopy (Lassalle et al. 2019a; Sanches et al. 2013a). Non-imaging sensors like the ASD FieldSpec are indeed lightweight, portable, and relatively easy to use. Measurements performed with a leaf-clip and an internal light source in ASDs are best-suited to avoid the influence of the environment of the measured spectrum, including light illumination, atmospheric noise, clouds, shadows, and surrounding materials. Some other examples are shown in table 2 with specifications.

Table 2. shows specifications of some widely used proximal instruments.

Proximal Instrument	Spectral range	Spectral resolution	Spectral band
ASD FieldSpec3 spectroradiometer	300–2500 nm	3 nm between 350–1000 nm, 10 nm between 1000–2500 nm	2151

ULTRIS X20 Plus hyperspectral mounted on aircraft	350 – 1000 nm	350–1000 nm,4nm	164
DJI Phantom 4	450 – 840nm	16 – 26nm	6
Field Spec Pro FR2500	350–2500 nm	3 – 8nm 3 nm @ 700 nm, 10 nm @ 1500 nm, and 10 nm @ 2100 nm	1512
Headwall Hyperspec Co-Aligned VNIR-SWIR Imaging Sensor	400 – 2500 nm	350 – 2500 nm, 1 – 3 nm spacing	537

ULTRIS X20 Hyperspectral Imager

ASD FieldSpec3 spectroradiometer

DJI Phantom 4 Multispectral

Hyperspec Co-Aligned VNIR-SWIR

By varying the acquisition footprint, canopy reflectance can be studied from the scale of a single plant to that of a complex species community. Drones can also be equipped with custom sensors to assist in detecting abiotic stresses in their early stages. They can provide canopy-scale data with high spatial resolutions (<1m); nevertheless, they have some limitations regarding payload and flight time. Sensors mounted on land-based devices can give a high spatial resolution, allowing them to measure plant parameters at the leaf or canopy scale, with spatial resolutions of up to one centimeter (Zhou et al., 2021). One advantage of proximal hyperspectral sensors, such as the co-aligned VNIR-SWIR camera with 537 channels from Headwall, is that they can be configured to match the spectral settings of satellite-borne missions like PRISMA, Enmap, and CHIME. This capability is demonstrated in the rice pilot project undertaken by the University of Seville. The other means of proximal sensing are displayed in figure 2.

Figure 2. Various proximal sensing platforms for spectral data collections (a) leaf reflectance using a leaf-clip attached to a spectroradiometer, (b) canopy reflectance using a fore optics fixed at nadir, (c–d) close-range hyperspectral imaging of (c) leaf samples and (d) plants, (e–h) canopy reflectance in the field using a spectroradiometer (e) a fixed at nadir, (f) handled, and (g) mounted on a goniometer system and (h) a mobile platform, (i–j) tree canopy reflectance using (i) a tower and (j) a telescopic boom lift, (k–l) canopy reflectance using a spectroradiometer mounted on (k) a motorized vehicle and (l) a tractor. (m) Drone- and (n) airborne-embedded hyperspectral imaging spectrometers proximal and images. (Lassalle, 2021)

In ground-based measurements, data can be acquired even at finer spatial resolutions and without consideration of sensor size or weight, but sampling is slower and may be affected by environmental drift, as occurs in large-scale studies (Liu et al. 2020b). In this case, a multiscale imaging technique would be beneficial for obtaining comprehensive information about plant stress over a wide area with a high level of spatial and spectral resolution. Applying multisource remote sensing data, such as multi-spatial, multitemporal, and multi-angular, increases the estimation accuracy. In case of limited access to high spectral resolution, a multisensory approach can be adopted but a major challenge would be the scaling effect if the land cover is heterogeneous at the pixel scale.

Hyperspectral data from airborne platforms or drones have the potential to provide more precise spectral information regarding crop stress, particularly in the red edge, NIR, and SWIR regions. Proximal measurements at the canopy scale with UAVs make a good transition between leaf-scale proximal spectroscopy and broad-scale imaging. Airborne imaging also known as plane-borne hyperspectral imaging is a reliable solution for monitoring plant stress at a broad-scale with high to very-high spatial resolution (50cm–10 m). Secondly, airborne hyperspectral images can be degraded to lower spatial and spectral resolutions to assess the accuracy of stress monitoring under varying sensor specifications. This can be applied to evaluate the compatibility of stress monitoring methods with operating satellite spectrometers and to formulate recommendations for future sensor specifications. Some of the aerial campaign data from new hyperspectral missions is now available. Over the last 5 years, ESA and other agencies have undertaken these airborne campaigns to collect test data for several planned and new Satellite missions (e.g., EnMap, CHIME). Their grographical locations are displayed in the figure 3. This data can be used for multiscale study of finding the relation between crop biophysical variables and EO-based stress signature.

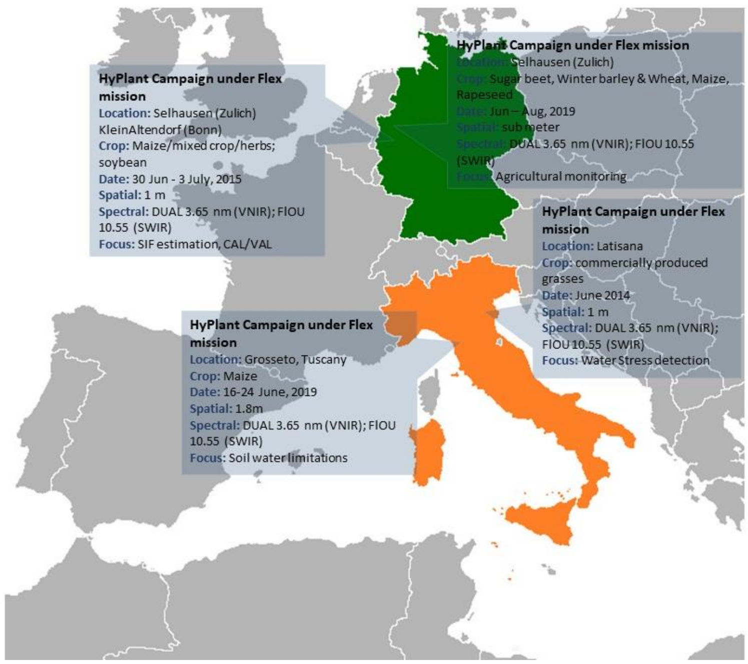

Figure 3. Location of historical aerial campaign data archived for cal-val activities of new hyperspectral missions.

Each data source has its own advantages and disadvantages. Combined proximal hyperspectral sensing with airborne or satellite imagery, from leaf to satellite scale, could be a viable solution to detecting crop stress in the landscape. It can set our baseline expertise to harness the new satellite missions, which are under development and can provide even more accurate information about crops and the environment (Lassalle, 2021). UAV hyperspectral cameras offer very-high spatial (<1 m) and spectral resolutions to field operators and enable timely flights over a specific area.

3.3 Existing Ground Datasets for Monitoring and Validation

There are several existing ground datasets related to crop stress and agricultural monitoring that can be exploited for sensor/model calibration and validation activities.

- Some contextual information can be taken from USDA NASS that provides comprehensive agricultural data, including crop condition reports, crop production statistics, and crop stress-related information. For example CroplandCROS (https://croplandcros.scinet.usda.gov/) web application give access to crop statistics, there are other streams like crop-CASMA (crop condition and soil moisture analytics), VegScape (vegetation condition explorer based on some primary indices), datasets on Crop Progress and conditions, crop sequence boundaries (interactive maps), disaster analysis etc. All this information can be harnessed for cross comparisons and can be helpful in methodology development.
- AgMERRA (Agricultural Model Intercomparison and Improvement Project Modern-Era Retrospective Analysis for Research and Applications) and Global Gridded Crop Model Intercomparison (GGCMI) phase 1 dataset are examples of global gridded dataset that contains information on various meteorological variables, such as temperature, precipitation, and radiation. Researchers use this dataset to study the impact of climate stress on crops, testing of crop model performance, and assess productivity in relation to environmental impacts. They can be retrieved by the following links:
    i. AgMERRA: https://data.giss.nasa.gov/impacts/agmipcf/agmerra/
    ii. GGCMI: https://data.agmip.org/cropsitedb
- FLUXNET is a global network of micrometeorological tower sites that measure various atmospheric and ecosystem variables, including carbon dioxide, water vapor and energy fluxes. These measurements are valuable for studying the physiological responses of crops to environmental stress. There are hundreds of sites monitoring all over the world with a huge wide network. Some potential crop sites could be Groningen, Netherlands (Wheatfields), El-Saler Sueca, Spain (Rice and rainfed crops), Gebesee, Germany (cereals, potato, sugarbeet) Roskilde, Denmark (Wheat and Maize), Oensingen, Switzerland (intensive crop rotation), Lonzee Belgium (rotational cropping system), Lamasquere and Aurade, France (maize, wheat, rapeseed), These sites can give micrometeorological, crop rotation, soil moisture, vegetation parameters information on a large temporal scale. ICOS Observational data product on Summer 2018 Drought in Europe compiled from 52 stations in FLUXNET (https://www.icos-cp.eu/data-products/YVR0-4898) is also available and can be used for crop stress product validation.
- The Phenocam network consists of cameras placed in various agricultural ecosystems in America. These cameras capture high-frequency images of vegetation, allowing researchers to monitor changes in crop phenology and assess stress responses. Phenocam Dataset v2.0 provides a time series of vegetation phenological observations for 393 sites and products consisting of 1783 site years of observations across diverse ecosystems of the world (mostly North America) from 2000-2018. This data can be used for phenological model validation and development from this link https://daac.ornl.gov/VEGETATION/guides/PhenoCam_V2.html . Camera images are also available by university of Seville over rice crop fields.
- Agricultural research stations and universities often conduct field experiments to study crop stress responses to different factors, such as drought, nutrient deficiency, and pests. Data from these

experiments can be valuable for understanding crop stress mechanisms, such as Rothamsted Research station (https://www.rothamsted.ac.uk/north-wyke-farm-platform). There could be reproducible controlled experiments that can be used to evaluate the intensity and duration of exposure to a single or multiple stressors (Tirado et al. 2021). Care is needed as some of these data may not be very useful because several stress exposure situations cannot be replicated in an experimental setting, sometimes the stressor is hard to manipulate, or the species are particularly challenging (Grieco et al. 2022a). However, their field measurements of leaf or canopy reflectance can be used as calibration data to test airborne and satellite-based imaging procedures (Laroche-Pinel et al. 2021).

3.4 Key Crop variables for stress monitoring

Some key remote sensing variables that can be gathered from different RS and ground resources:

1. **Above-ground biomass:** advanced remote sensing techniques, such as LiDAR (Light Detection and Ranging) and synthetic aperture radar (SAR), are now being used for estimation of AGB, especially in forests and areas with complex vegetation structures. These techniques provide three-dimensional information about vegetation structure, which can improve AGB estimation accuracy. Regression models, such as linear regression or machine learning algorithms, are used for establishing statistical relation between sensor-based vegetation indices and ground based AGB measurements such as biomass harvesting, allometric equations, or forest inventory plots.
2. **Leaf Area Index**: LAI is an essential vegetation parameter that quantifies the total leaf surface area in a unit area of land or canopy. It can be measured through both remote sensing and in-situ methods. It is crucial for assessing crop stress because it provides insights into the vegetation's health, growth, and response to environmental conditions. It is measured through various ways such as
   - **2.1.** LAI-2000 Plant Canopy Analyzer measures the amount of photosynthetically active radiation (PAR) both above and below the canopy. It calculates LAI by analyzing the ratio of these measurements.
   - **2.2.** Hemispherical Photography cameras capture hemispherical images of the canopy, which can be used to calculate LAI based on the proportion of the hemisphere covered by leaves. This method provides a visual representation of the canopy structure.
   - **2.3.** LIDAR (Light Detection and Ranging): LIDAR data provides high-resolution 3D information about canopy structure, including leaf distribution. LAI can be estimated from LIDAR data by analyzing the point cloud information.
   - **2.4.** Hyperspectral Imagery: Hyperspectral sensors capture detailed spectral information, enabling LAI estimation by analyzing the reflectance data at different wavelengths. This information can be used to infer leaf density and cover.
   - **2.5.** Remote sensing platforms like satellites and aerial imagery are used to estimate LAI over large areas. These images capture the reflection and absorption of different wavelengths of light,

which are used to derive LAI values. Sensors on satellites such as MODIS, Sentinel and Landsat are freely employed for this purpose.

3. **Crop inclination angle:** Crop inclination angle, also known as crop lean or lodging angle, is the angle at which the crops lean or tilt in the field. It can be measured both through remote sensing and in-situ methods. Specialized instruments like clinometers or inclinometers, sometimes they are called tilt meters, a tilt sensor or slope gauges can be used to measure the inclination angle more precisely. These devices are placed on or near the crop and provide an angle measurement. Drones equipped with cameras and sensors capture high-resolution imagery of crops from different angles can be used to measure the inclination angle of the crops. Crops that are inclined at a certain angle are at higher risk of lodging, which is when the crops fall over due to various factors like wind, rain, or disease. Understanding the inclination angle helps predict lodging risks and take preventive measures.
4. **Leaf/Canopy nitrogen accumulation:** Nitrogen is a critical component of chlorophyll and other leaf pigments involved in photosynthesis, so changes in leaf nitrogen content can influence the way vegetation reflects light in certain spectral bands which can be detected with several remote sensing technologies such as multispectral or hyperspectral satellite or aerial imagery covering the area of interest and wavelength range in the visible, near-infrared, and sometimes shortwave infrared parts of the electromagnetic spectrum. Field measurements of leaf nitrogen content, often come through leaf sampling and laboratory analysis, then statistical models or relationships between vegetation indices and the actual leaf nitrogen content measured in the field are developed. Model calibration is essential for accurate nitrogen estimation.
5. **Canopy cover:** Canopy cover is a direct indicator of the overall health and vigor of crops. A dense and healthy canopy typically indicates that the crop is growing well and is less stressed. Conversely, a sparse or thin canopy may suggest crop stress factors such as water scarcity, nutrient deficiencies, or pest damage. Canopy cover information can be generated from coarse to medium satellite resolution datasets.
6. **Soil Moisture:** Monitoring soil moisture levels can help detect early signs of drought stress in crops. As soil moisture decreases, plants experience water stress, which can result in reduced growth, yield losses, and crop failure if not addressed. Changes in soil moisture may also indicate areas where crop health problems are developing. It can help in the early detection of diseases and pests that thrive under certain moisture conditions. This can be measured from sensor probes and Microwave sensors.
7. **Chlorophyll content:** Chlorophyll, light absorbing tissue, plays a critical role in photosynthesis. Fluctuations in chlorophyll levels due to stress may lead to changes in the interaction between plants and light. It requires hyperspectral image sensing in high resolution. Ground-based spectroscopy instruments are often used to measure the spectral reflectance of vegetation in the field. It can be measured in labs and deduced using handheld instruments such as SPAD and generated at landscape scale from satellite sensors.
8. **Fraction of absorbed photosynthetically active radiation (FAPAR):** FAPAR is a critical parameter for vegetation photosynthesis and primary production estimates. It can detect stress in crops before visible symptoms appear. When crops experience stress due to factors like water scarcity, nutrient deficiency, or disease, they may reduce their photosynthetic activity. This reduction in

photosynthesis can lead to a decrease in FAPAR, allowing for early stress detection. FAPAR over the growing season provides insights into the temporal dynamics of crop stress. Remote sensing satellites, such as MODIS (Moderate Resolution Imaging Spectroradiometer) and other VIIRS (Visible Infrared Imaging Radiometer Suite), have spectral bands that are sensitive to vegetation and photosynthetically active radiation. These bands capture the reflected sunlight from vegetation, providing valuable information for FAPAR estimation. Ground-based instruments, such as spectroradiometers, are used to measure the amount of photosynthetically active radiation at the ground level.

9. **Grain protein content:** Grain protein content is typically measured through laboratory-based techniques, primarily near-infrared spectroscopy (NIRS) and traditional wet chemistry methods. Remote sensing technology does not directly measure grain protein content; however, change in nutrient content at the leaf and canopy can be translated and linked to the content in the grain.
10. **Maturity date:** Delays or unevenness in maturity, as well as premature senescence, can signal various stress factors, including water stress, nutrient deficiencies, temperature extremes, and pest or disease damage. Monitoring crop maturity is essential for timely intervention and effective crop management in response to these stressors. Change detection techniques applied to time-series remote sensing data can identify changes in crop conditions over time. Sudden changes or anomalies in crop phenology or growth patterns compared to historical data or expected growth stages can be indicative of stress factors.
11. **Evapotranspiration:** ET is a direct indicator of water use by crops but cannot be directly measured with satellite data. It can detect early signs of water stress in crops. When water availability is limited, crops may reduce their transpiration rates, leading to lower ET values. Measuring ET can be done using various methods, ranging from simple on-site measurements (eddy covariance, lysimeter, soil moisture sensors) to more complex remote sensing techniques (energy balance models, ecohydrological models etc.).
12. **Gross primary production:** Decreases in GPP can serve as an early indicator of crop stress. Various stress factors, such as water scarcity, nutrient deficiencies, pest damage, and disease, can limit photosynthesis and result in lower GPP. Photosynthesis models, Light use efficiency models, such as the Farquhar model, can estimate GPP based on environmental variables, leaf-level data, and physiological parameters. These models require detailed data on leaf characteristics and environmental conditions. It can be directly measured by eddy covariance method.
13. **Root weight:** Estimating root biomass using remote sensing remains a challenge, advances in technology and modeling techniques are improving our ability to indirectly assess root health and stress. Remote sensing technologies, such as digital imaging and specialized root cameras, can be used to capture images of roots within the rhizotron. Ground penetrating radar (GPR) uses radar pulses to image subsurface structures, they can provide information about root density and distribution in the soil profile. Deeper roots will access moisture at greater depths, which can be detected by soil moisture sensors.
14. **Panicle weight:** Panicle weight can serve as an indicator of stress during the reproductive stage of crop growth. It is an essential variable for crop stress monitoring, particularly in cereal crops. Environmental stressors, such as drought, nutrient deficiencies, or pest damage, can reduce panicle

size and weight. Measuring panicle weight directly using remote sensing is challenging because panicles are typically located below the canopy and are difficult to distinguish from other plant components. Crop growth models, such as the DSSAT (Decision Support System for Agrotechnology Transfer) model, can estimate crop development stages and predict panicle weight based on weather data, soil properties, and management practices. Combining remote sensing data with ground-based measurements and modeling approaches can provide valuable information about panicle weight.

15. **Carotenoids**: Carotenoids, particularly beta-carotene, give plants their orange and yellow colors. Changes in these colors can be visible indicators of stress. Under certain stress conditions, chlorophyll degradation occurs, leading to a decrease in green pigments and an increase in carotenoid pigments. This change in pigment composition can be monitored as an indicator of stress as deciphered in Figure 4. Measuring carotenoids and xanthophylls in plants is typically done through laboratory-based chemical analysis or spectroscopy e.g., High-Performance Liquid Chromatography (HPLC), Spectrophotometry, Fluorescence Spectroscopy, Mass Spectrometry, Colorimetric Assays.

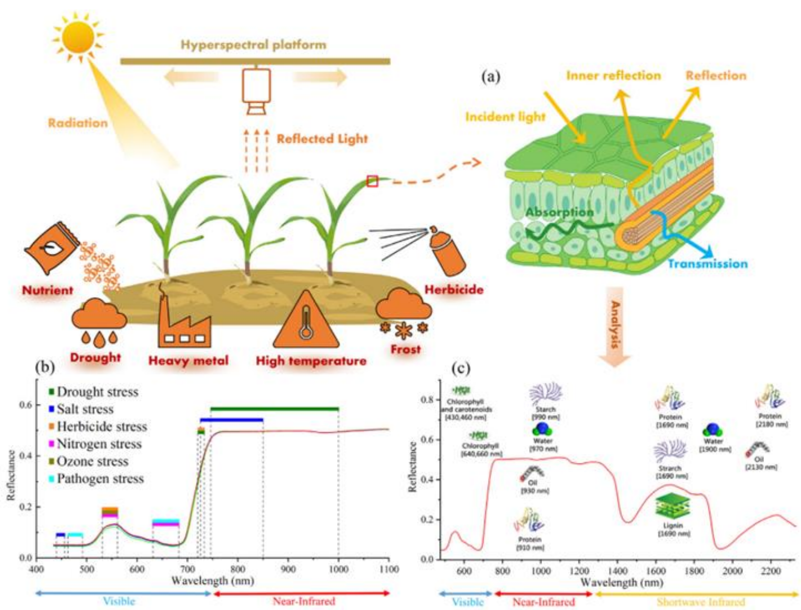

Figure 4. a) is giving cross sectional view of mesophyll tissue, b) plant responses to different stressor at canopy spectra c) is giving sensitivity of leaf molecules and tissue in the range of EMR spectrum detectable by spectrometers.

Leaf spectroscopy provides a good basis for building spectral libraries. Canopy reflectance supports scale-up the models of symptom detection calibrated at leaf scale towards broad-scale monitoring of crops. Figure 4 illustrates part of leaf and canopy spectra relevant to different stressors i.e., drought, salinity, herbicide, nitrogen, ozone, and pathogen. Such as.

1. In stress conditions, depleted chlorophyll can be detected in a broad spectrum as low reflection at 530-630 nm, and increased reflection at 700 nm in visible domain. Chlorophyll absorbs light in specific spectral bands which hyperspectral sensors can better detect by analyzing reflectance spectra.
2. Reflectance around 960 nm is affected by cell elasticity, which decreases when the plant is subjected to drought. Stomatal closure can raise leaf temperature and it can be seen in the infrared range.
3. The blue and red regions can be indicators of salt stress and are useful in characterizations of chlorophyll content, photosynthetic activity, and cellular architecture.
4. Salt stress causes closing and limiting of mesophyll stomata, or changes in cellular metabolism which adversely impact photosynthetic processes (Sytar et al. 2017).
5. Changes in the leaf structure and moisture content are associated with a reduction in reflection in the NIR region, which is also regarded as a reliable predictor of changes to canopy structure (Franke and Menz, 2007).
6. Plant leaves become discolored and disfigured due to inadequate nutrition, it can be seen in the visible and shortwave region (1325 – 1575 nm) owing to pigmentation changes and the yellowing of leaves leads to higher reflectance in the green-red region (Li et al. 2020).
7. In necrosis state, reflectance increases in the visible range while in non-necrotic areas, the reflectance decreases.
8. Nitrogen deficiency is the most studied stress followed by phosphorus, iron, and sulfur. Because it directly affects plant productivity. As it affects only a part of the leaf (young or old), the resulting symptoms become difficult to detect over a complex canopy with mixed leaf ages. For that reason, the coupling of leaf- and canopy-scale measurements is often recommended. Plant response from nitrogen deficiency can coincide with phosphorus deficiency, but it was possible to diagnose P deficiency 15 to 24 days in advance at leaf scale using Independent Component Analysis (ICA) for feature extraction.
9. Physical characteristics of leaves can also help in stress detection such as changes in tissue morphology, cell wall characteristics, and epidermal thickness, influence the leaf's spectral characteristics. These changes are mostly detected by lab techniques e.g., tissue sectioning, Scanning Electron Microscopy, Transmission Electron Microscopy (TEM). However, UAVs can also provide finer-scale data for more localized assessments of vegetation health and potentially detect changes in tissue morphology.

3.5 Crop stressors, their effects, associated symptoms in crop traits, and key measuring variables

Crop stressors can manifest in various ways, and their symptoms can be observed in different crop traits. Some stressors and their effects are:

- Soil waterlogging which is usually caused by severe weather conditions, such as flooding, heavy rain, and storms. It can cause plants to suffer from water deficiency by blocking their stomata due to the lack of oxygen (Kaur et al. 2020).

- Severe drought stress causes the loss of leaf moisture resulting into wilting and curling of leaves, and drooping of branches, followed by the degradation of chlorophyll levels and an overall reduction in leaf surface area. In fact, minor to moderate drought conditions can affect the concentration of carotenoids in plants.
- Salt accumulation causes degeneration of leaf tissue and changes the interactions between plants and water and nutrients, resulting in a reduction of chlorophyll and disease resistance (Lassalle, 2021) that causes subtle discoloration or yellowing of the leaves. It has been mostly addressed in grass and shrublands under controlled environment studies (greenhouses).
- Heavy metals have long-lasting effects for example they are easily absorbed by plants leading to inhibition of their growth. Moreover, the pollutants can also make their way into the food chain, potentially posing grave health risks (Wang et al. 2018). Metallic stress can affect plant metabolism, mineral nutrient transport, and water uptake, and can alter pigmentation and leaf structure (Ruffing et al. 2021). The heavy metal stress in rice plants minimizes water absorption and ion channel function, because of which the plants usually suffer from water shortages and excessive amounts of free proline accumulations, which measurement could be an indicator (Choudhary et al. 2007).

Both monitoring of nutrient deficiency and gas stress monitoring coincides in their reflectance, data processing, and methods are quite similar, which could be beneficial. As with most of the stresses, common plant symptom is increased reflectivity in green areas as chlorophyll levels are reduced (Goldsmith et al. 2020). Moreover, changes in reflectance between species with different leaf morphologies may differ significantly. Spectral signatures can measure and detect these stressors. Table 3 presents some common crop stressors, their associated symptoms in crop traits, and key measuring variables with spectral signatures. This table can assist in choosing future datasets to monitor key crop stressors and their associated measuring variables.

Table 3. describes associated symptoms, key leaf and canopy variables and detectable spectral signatures of some prominent crop stressors.

Crop Stressor	Crop Traits/Symptoms	Key Measuring Variable	Spectral Signature
Lodging	Morphology, flattened or bent canopy structure, shadowing, changes in vegetation density	Canopy Height, light interception, leaf orientation (horizontal)	Lower reflectance in NIR and SWIR
Nutrient Deficiency	Growth and Maintenance, decreased chlorophyll content, changes in leaf structure and pigment content	Chlorophyll content, Photosynthesis Efficiency, Carbon assimilation rates, nutrient uptake efficiency	lower reflectance in the red and blue
Drought Stress	reduced leaf turgor, morphology, degradation of chlorophyll levels, decreased water content and changes in leaf angle.	Canopy Temperature, Transpiration, Precipitation, Radiation, Daily maximum and minimum Temperature, Crop water stress Index, Leaf water content, Chlorophyll content, LAI, carotenoids	reduced absorption in the NIR and SWIR, increased reflectance in the visible portion

Salinity and Water logging	Tissue degeneration, reduction of chlorophyll, discoloration or yellowing of the leaves	Chlorophyll and water content	increased absorption in the NIR and SWIR decreased reflectance in the visible portion
Heavy metals	Metabolism, mostly physiological changes in leaf morphology and pigmentation, reduction in water and ions absorption, stress-induced chlorosis (yellowing of leaves), spread not uniform across a field	Proline content, soil quality and composition data, fluorescence in plant tissues	Unique absorption bands in the visible or NIR regions for Pb and Cd increased reflectance at specific NIR wavelengths for Cu Hg induce fluorescence in plant tissues
Disease or Pest infestation	altered pigment concentrations, water content variations	texture and structure of plant stems and leaves	variations in reflectance in the visible range, unique spectral features, dips, or peaks at specific wavelengths
Heat Stress	High temperature conditions, changes in leaf structure and pigments	Leaf Temperature, Chlorophyll content, water content, leaf pigments	High reflectance in the longwave infrared (LWIR) region, some signatures in visible and NIR, lower reflectance in red and blue changes in the position and shape of absorption features in SWIR.

All stressors do not affect plant reflectance exactly in the same way and at the same time, so they can be distinguished by exploiting the time and amplitude differences of reflectance changes which can differentiate among stressors. The specific spectral responses to crop stressors can vary depending on crop type, stress severity, and timing of stress development. Spectral screening methods can disentangle abiotic and biotic stress sources, most studies at this stage are still focused on a single stress level. Detection of coexisting stresses remains challenging and under-explored. Combining data from optical sensors, such as multispectral and hyperspectral imagery, with data from other sensors like thermal infrared, microwave, and LIDAR, allows for a more comprehensive assessment of crop health. Integration is essential for gaining more accurate and precise measurements and it will reduce errors and uncertainties in the results. Information from Sentinel-2 on soil moisture and vegetation indices can be combined with EnMap's hyperspectral data about crop stressors at a more detailed level. Combining both data sources will provide insights into spatial variations in crop stressors. Similarly, PRISMA's hyperspectral data, with its fine spectral resolution, can provide detailed information about the biochemical and physiological status of crops. Merging PRISMA data with Sentinel's multispectral data can allow frequent and wide area monitoring of crop health. However, combining data from Sentinel, EnMap, and PRISMA, for crop stress monitoring requires careful calibration and correction to ensure that the data from various sources are consistent, accurate, and compatible. It requires a series of steps such as sensor-specific radiometric calibration, atmospheric correction, georeferencing, spectral band alignment, spectral smoothing, temporal alignment as well as sensor-specific noise and uncertainty adjustment. Most importantly, data fusion techniques can merge information from different sensors into a single dataset seamlessly are needed. This can involve using statistical or mathematical methods to harmonize data. Then these sensors can complement each other in cross-validating and calibrating. This will ensure data accuracy and reliability, which is essential for making informed decisions in crop stress management.

4. KEY METHODOGIES OF CROP STRESS DETECTION AND MONITORING

Laboratory and field-based controlled experiments are the most common approach for assessing the response of one or more crop species to single or several combined stressors, and for determining the influence of environmental variables on this response. Lab-based experiments are reproducible and give a full control of the stressor intensity, timing, and duration of exposure. Also, they are well suited for scaling-up the methods from proximal leaf- and canopy-scale measurements to broad-scale imaging. For instance, by identifying the wavelengths affected by the stressor one can create stressor-specific Vegetation Indices (VI), this method has found to be suitable for heavy metals and salinity contaminations. However, several stress monitoring methods have also developed without controlled experiments in field or imaging spectroscopy for pest diseases; soil contaminates and natural ecosystems but mostly are not aimed for broad-scale monitoring. Spectral data from remote sensing and ground-based sensors is increasingly processed and analyzed using machine learning algorithms. These algorithms can identify patterns and correlations between various data points, helping to detect and predict crop stress thereby being quite useful for pattern recognition, automated detection, predictive modeling, data fusion and real-time monitoring. The integration of advanced technologies and data-driven approaches continues to enhance our ability to monitor and manage crop stress effectively.

The subsections below discuss various methods, including vegetation indices based empirical approaches radiative transfer models (RTMs), machine learning, and deep learning, for monitoring and managing crop stress.

4.1 Deriving sensor-based crop stress indices

Multispectral sensor-based crop stress indices are valuable tools for monitoring crop health and identifying stress factors such as drought, nutrient deficiencies, pest infestations, or disease outbreaks. The choice of index depends on the specific crop, the type of stress being assessed, and the availability of multispectral data as shown in table 4. For example, Sentinel 2 based Canopy Chlorophyll Content Index (CCCI) has been used for estimating chlorophyll content in maize. The NDVI is a key indicator of crop stress, as it reflects changes in vegetation density, photosynthetic activity, and overall health. Decreased NDVI values can indicate stressors like drought, disease, or nutrient deficiencies. Enhanced vegetation index (EVI) is an improvement over NDVI that corrects for atmospheric influences and enhances sensitivity to changes in vegetation canopy. NDWI which is sensitive to changes in water content in vegetation, can be used to detect water stress and areas affected by flooding or waterlogging. LAI is valuable for understanding crop growth and stress. A decrease in LAI can be indicative of stressors such as drought or pest infestations. New indices are developing with emerging sensor technologies like the indices created by the red edge (RE) bands (680–780 nm) which are useful to enhance the precision of the estimates. Cui et al. (2019) succeeded in increasing the accuracy of predicated LCC by proposing a new VI called red edge chlorophyll absorption index (RECAI) and integrating it with classical VI (TVI). Also, short wave Infrared domain directly and Red-Edge bands can be indirectly correlated with water status by affecting chlorophyll concentration. Currently multiple indices in combination are used to gain a more comprehensive understanding of vegetation characteristics and conditions. Further, temporal analysis of spectral indices can monitor the progression and persistence of stressors and can provide insights into the dynamic nature of crop stress. Table 4 shows some key indices specific to certain stressors, they can be used as single or in merger for single or multiple stressors.

Table 4. List of key spectral indices and their application for crop stress detection.

Vegetation indices	Formula	Application
Normalized difference Vegetation Index (NDVI)	(NIR - Red) / (NIR + Red)	Drought and Nutrient deficiency
Enhanced Vegetation Index (EVI)	2.5 * ((NIR - Red) / (NIR + 6 * Red - 7.5 * Blue + 1))	Used for monitoring the condition of vegetation, especially in complex canopies or where vegetation stress may be a concern
Water Stress Index (WSI)	((SWIR - NIR) / (SWIR + NIR))	For water stress detection
Water Deficit Index (WDI)	WDI = PET – AET ET calculation using Penman-Monteith equation, the Thornthwaite equation, or the Hargreaves-Samani method.	for assessing water stress or drought conditions
Chlorophyll Content Index (CCI)	(RedEdge - Red) / (RedEdge + Red)	detect nutrient deficiencies and disease stress
Soil Adjusted Vegetation Index (SAVI or SAVI2)	SAVI = ((NIR - Red) / (NIR + Red + L)) * (1 + L) L = soil adjustment factor SAVI2 = ((NIR - Red) / (NIR + Red + L1)) * (1 + L2) L1, L2 = constants for soil adjustment factor	used for monitoring vegetation health and detecting changes over time particularly in agricultural and arid regions where soil brightness affects vegetation index values.
vegetation temperature condition index (VTCI)	(Tc - T_max) / (T_max - T_min) Tc = current temperature of the vegetation (e.g., from thermal infrared data) T_max = maximum temperature for healthy plant T_min = minimum temperature for healthy plant	assessing the impact of factors like drought, disease, or environmental stress on vegetation temperature condition

Radar Vegetation Index (RVI)	(σ_vv - σ_hh) / (σ_vv + σ_hh) σ_vv = radar backscatter in the vertical polarization (VV) channel. σ_hh = radar backscatter in the horizontal polarization (HH) channel.	for vegetation analysis in challenging environmental conditions (clouds)
Crop Water Stress Index (CWSI)	CWSI = (Tc - Te) / (Tc - Td) Tc = canopy T Te = reference T for well-watered crop Td = Dewpoint T	Used for monitoring crop water stress levels and guiding irrigation management decisions.
Red Edge Chlorophyll Absorption Index (RECI)	(NIR/Red Edge) - 1	for assessing chlorophyll content and plant health
Normalized Difference Red Edge (NDRE)	(NIR - Red Edge) / (NIR + Red Edge)	for detecting subtle changes in chlorophyll content and can reveal early signs of stress
Green Normalized difference Vegetation Index (GNDVI)	(NIR - Green) / (NIR + Green)	for detecting stress in crops with senescing or yellowing leaves
Temperature vegetation dryness index (TVDI)	TVDI = VTCI * NDVI	for combined effects of temperature and vegetation health on water stress
Plant Stress Index (PSI)	PSI = (R - NIR) / (R + NIR) * (R - SWIR) / (R + SWIR)	to assess plant health and stress levels.
Normalized difference Water Index (NDWI)		changes in water content in vegetation
photochemical reflectance index (PRI)	PRI = (ρ 531 - ρ 570) / (ρ 531 + ρ 570) ρ = reflectance value at 531 nm and 570 nm wavelength in the green region[1]	sensitive to changes in chlorophyll content and the xanthophyll cycle, due to factors like water stress, light stress, or nutrient deficiencies
Soil Moisture Index (SMI)	SMI = (Current VMC - Wilting Point) / (Field Capacity - Wilting Point) VMC = Volumetric water content expressed as %	help identify areas of water stress or excessive moisture
Meris Terrestrial Chlorophyll Index (MTCI)	MTCI = (ρ800 - ρ680) / (ρ800 - ρ670) ρ = reflectance values at specific wavelengths (800, 680 and 670 nm) in the NIR and red regions. [2] (https://www.indexdatabase.de/db/i-single.php?id=169)	Sensitive to variation in chlorophyll content

Sometimes, selecting the right indices is crucial because different stressors may exhibit unique spectral signatures. Like, changes in canopy temperature are not just in response to biotic stresses but can be due to abiotic stress. Nitrogen deficiency (N) and water stress (drought and salinity) are the most prevalent limiting conditions for crop production, and they commonly co-occur. Using crop water stress index (CWSI) and water

[1] The specific bands may vary based on the band combination of each sensor or instrument.
[2] The specific bands may vary based on the band combination of each sensor or instrument.

deficit index (WDI) together can estimate the physiological impacts of water stress and N nutrition separately, and their interactive effects can also be addressed (Zhao et al. 2022). Most of the spectral indices are not able to distinguish between short- or long-term drought stress, for which hyperspectral signatures can be useful, because they provide a much finer level of spectral detail compared to traditional multispectral data. Short-term drought stress may primarily affect the upper canopy, leading to specific changes in chlorophyll content and water content. On the other hand, long-term drought stress can cause more significant structural changes within the plant, leading to altered lignin and cellulose content. Hyperspectral data can capture these nuanced differences. Water-deficit has been subject to numerous studies for decades from small-scale greenhouse trials with individual plant pots and various levels of irrigation based on the soil's field capacity to the species' needs in irrigation at large scale. Monitoring water-deficit from hyperspectral data typically follows three different approaches [1] detecting alterations in leaf water content through developing VIs from leaf and canopy spectra to establishing a threshold and linking it to regression models,[2] Using ML regression algorithms for predicting physiological parameters affected by water deficiency, such as leaf water potential, stomatal conductance, and non-photochemical quenching. [3] Through VIs and ML tracking early alterations in leaf pigments and plant development (e.g., LAI, ground cover) resulting from water-deficit.

4.2 Feature Extraction and Feature Selection

Feature extraction and feature selection are two essential techniques in dealing with spectral data, as they help in reducing the dimensionality of sensor's data, enhancing the quality of information, and improving the efficiency of data analysis. Extraction involves transforming raw data into a set of meaningful and informative features. This process aims to highlight the relevant information in the data while reducing redundancy. While selection involves choosing a subset of the most relevant features from the original dataset. The purpose is to eliminate irrelevant or redundant features. The most used techniques are principal component analysis (PCA), Partial Least Squares Regression (PLS), and linear discriminate analysis (LDA). PCA is primarily a dimensionality reduction technique. It identifies and transforms correlated variables (features) into a new set of uncorrelated variables called principal components while retaining as much of the original data's variability as possible. These components capture the most variance in the data. PLS, unlike PCA, is more of a feature selection and regression technique. It finds a set of orthogonal factors that explain the maximum variance in the response variable (dependent variable) by modeling the relationship between features and the crop response. It selects a subset of features that contribute the most to predicting the targeted stress. LDA is another feature selection technique primarily used in the context of supervised classification. It finds the linear combinations of features (discriminant functions) that maximize the separation between different classes that could be stress levels. It is used for pattern recognition, classification, and reducing the dimensionality of feature space while enhancing the class separability. It helps identify the most discriminative features. However, algorithms based on metaheuristic approaches such as genetic algorithms (GA) are gaining ground in the field of feature selection. The features are then used in the training phase to build the ML model.

These methods are common in hyperspectral remote sensing in which its better helps in identifying the characteristic spectral bands sensitive to material concentration in plants, and thereby establishing the relationships between plant response and environmental stress (Herrmann et al. 2010). The preprocessing of spectra applying techniques such as Continuum Removal (CR), Multiplicative Scatter Correction (MSC). The CR eliminates the background signal or "continuum" from a spectrum that is unrelated to the crop physical properties of interest, leaving only the relevant spectral features. Other technique, MSC normalize spectral data by fitting a model to the measured spectrum and dividing the spectrum by this modeled scatter component. This process helps to reduce unwanted spectral variability and scatter in the measurements. These preprocessing techniques are critical for improving the quality of spectral data, reducing noise, and making it more amenable to analysis and further processing. There can be two ways of processing spectra, either integrating complete reflectance directly into machine learning algorithms, or converting spectral signatures into abstracted variables. The former method complicates choosing optimal wavelengths for monitoring a particular stressor. Therefore, spectral signatures must often be converted into abstract variables, such as principal components, to reduce dimensionality or select features. Or developing spectral reflectance indices (SRIs) that are related to plant characteristics, such as chlorophyll and water content, can be useful for subsequent analyses to assess plant status. In fact, indices based on WC, photosynthetic efficiency, pigment content, and red/NIR reflectance, and their driven regression models (SRI (spectral reflectance indices) based models) compared to machine learning methods like PLS that uses all available wavelengths including noises, are better in predicting physiological traits based on hyperspectral data.

The wavelet transform (WT) method is one of the viable methods for analyzing the hyperspectral spectrum that converts the original reflectance spectrum into coefficients resolving at high scales (e.g., small narrow bandwidth absorption features) and low scales (e.g., broad absorption features). Other examples are successive projections algorithms (SPA), Recursive Feature Elimination (RFE) and ICA. SPA is widely used in the wavelength selection of spectral data. Its advantage is extracting several wavelengths from the whole band in faster and efficient way, which eliminates the redundant information in the original spectral matrix. It starts with an empty set of selected features and iteratively adds one feature at a time to the selected set. At each step, the algorithm selects the feature that provides the best discrimination between classes or maximizes some relevant criterion. This process continues until the desired number of features is reached or a predefined stopping criterion is met just like forward selection. RFE starts with the entire feature set and repeatedly trains a model, such as a machine learning classifier, and removes the least important features. This process continues until the desired number of features is reached or a predefined stopping criterion is met. Thereby it eliminates the redundancy of features, select the optimal feature combination, and reduce the feature dimension. Like SPA, RFE also a type of wrapper method. They can be computationally intensive, especially for large feature sets, However, their accuracy for hyperspectral data is comparable in lodging stress detection (Sun et al. 2023). Unlike them, ICA can separate a set of observed mixed signals into statistically independent and non-gaussian source signals or components assuming that the observed signals are linear combinations of these hidden source signals but with different mixing coefficients.

Feature selection plays a vital role in machine learning as it helps determine the best set of features to create an effective machine learning regression MLR model. It is more advisable to first evaluate the plant's spectral signature to identify the level of stress at which the plant has been exposed, deriving from graphical analysis of leaf and canopy spectra. Later, dividing data analysis into three general approaches: statistical analysis, prediction models, and classification models. In this step, multiscale spectral indices are more appropriate as compared to indices based on a single scale. The reason is leaf-scale hyperspectral measurements are less sensitive to external conditions such as lighting, climate, and humidity when compared to canopy-scale measurements. Leaf scale measurements reflect the effect on leaf biochemical characteristics. While canopy scale studies assess the effect on the structure of plants. Thus, combining multiscale spectra will reduce inherent bias in scale transferability.

4.3 Deriving Crop traits from Radiative Transfer Models

Compared with VIs retrieval directly from satellite, RTM have clear advantages for global applications, because they are based on physical laws and therefore generally applicable. They are mainly used for physical based retrieval of crop characteristics for improved quantification of their responses to environmental changes. RTMs allow the conversion of remote sensing signals into valuable vegetation biophysical information, which is used for analysis with other datasets. They can be simplified using tools such as Simulated Look-Up Tables (LUT) and trained Artificial Neural Networks (ANN) however simplification may lead to some loss of accuracy. Mostly RTMs are complex and nonlinear, their simulation shows quantitative relationships between plant biochemical parameters and leaf/canopy spectra. Also, it helps in investigating plant physiological changes with environmental conditions and can detect alterations in leaf/canopy structures and their biochemical parameters through reflectance and transmittance signals. They considered better than VI based regression models. RTMs can be used to monitor various aspects of crop health, including chlorophyll content, leaf area index, and vegetation cover. To retrieve plant variables, the RTM inversion scheme needs to be applied to the reflectance data. The inversion gives best match between a simulated and measured reflectance spectrum.

Among RTMs, The PROSPECT model and its improved versions are most widely used RTM that can accurately simulate radiative transfer in leaves. Initially PROSPECT model was simple and required only three input parameters: structure parameter (N), chlorophyll content (Cab), and equivalent water thickness (Cw). It is advanced to the PROSPECT-4 model capable of simulating directional-hemispherical reflectance and transmittance for a single leaf. It is further optimized with additional parameter Cm (dry matter) for simulating EMR absorption and reflectance through internal parts i.e., cellulose and lignin it was further upgraded to PROSPECT-5 to separate chlorophyll into chlorophyll and carotenoids at tissue level which is validated through several independent datasets (Feret et al. 2008). PROPECT-D model formed with addition of anthocyanin in PROSPECT-5 along with chlorophylls and carotenoids for the dynamic simulation of leaf optical properties throughout a complete lifecycle (Feret et al. 2017). However, the most recent PROSPECT PRO allows for decomposition of leaf dry matter into nitrogen-based proteins and carbon-based constituents and is capable of modelling leaf proteins as well as cellulose, lignin, hemicellulose, starch, and sugars (Feret et al. 2021). PROSAIL, which is an integration of the leaf level PROSPECT model and canopy-level SAIL (Scattering by Arbitrary Inclined Leaves) model, is also a very common leaf and canopy RTMs. Both have continuously been revised and improved. For example, 4SAIL2, which is an amended version of the turbid medium SAIL model, simulates the top of the canopy reflectance. This model is a function of a series of variables: The fraction of brown canopy area (fB), the dissociation factor (D), hotspot (hot), tree shape factor (Zeta), crown cover (Cv), leaf area index (LAI), and leaf inclination distribution function (LIDF a and b). PROSAIL a 1D model is more suitable for crop and grass than forest canopies because it assumes that a vegetation canopy is a turbid medium. Due to its simplicity and reasonable accuracy, it is suitable for satellite applications. Another RTM model example is SPART in which PROSPECT-D and SAILH with hotspot effects is used (Feret et al. 2017). It includes the absorption of chlorophylls, carotenoids and anthocyanins pigments and requires the content of these leaf pigments, senescent materials, water content, dry matter, and leaf internal structure as input. SPART can up-scale leaf optical properties (i.e., leaf reflectance and transmittance) to canopy optical signals by considering the canopy architecture. Some of the RTM models and their application in crop stress monitoring is shown in Table 5.

Table 5. Some common radiative transfer models used in crop stress studies.

Radiative transfer models	Function	Usage
Soil Leaf Canopy [***PROSPECT 4 leaf RTM, 4SAIL2 canopy RTM, Soil Model Hapke***]	simulates canopy reflectance over the spectral range [400 and 2500 nm] with a spectral resolution of 1 nm. require less parameters	Quantifies fCover by simulating reflectance by most of the input variables (e.g., chlorophyll, water content etc.)
Discrete anisotropic radiative transfer DART	simulates multiple scattering in heterogeneous 3-D scenes. require a higher number of input variables	Used for spatially heterogenous dense canopy
PROSAIL [***PROSPECT D – leaf RTM and the canopy bidirectional reflectance model (4SAIL)***]	requires only a few input variables. especially efficient to large images	Used for retrieving green fraction (GF), LAI, LCC and canopy chlorophyll content (CCC)
Soil Canopy Observation of Photosynthesis and Energy fluxes SCOPE [***seven RTMS –one for leaf, 5 for whole stand, one for soil BSM***]	Simulates solar-induced chlorophyll fluorescence (SIF), energy balance fluxes, gross primary productivity (GPP) and directional thermal signals	Used for homogenous complex multilayer canopies, investigates vegetation physiology under various weather conditions

Regarding RTM application, the first synthetic dataset is prepared for model validation, sensitivity analysis, training of machine learning model and algorithm development. It is comprised of information about sensors, vegetation, soil, and atmosphere e.g., soil properties, leaf properties, canopy structure, sun-observer geometry, and the corresponding TOA radiance. The choice of RTM varies by different scenarios such as PROSAIL used for soil and canopy characteristics, MODTRAN for simulation of atmospheric conditions. To make the synthetic dataset more realistic, some noise, random variations and uncertainties are added to the simulated measurements. Prior to use as RTM input, synthetic data is first tested and validated with ground dataset to ensure its accurate representation of crop stress scenario. Some common parameters used in RTMs are Optical Thickness (τ), Single Scattering Albedo (ω0), Phase Function (P(θ)), Albedo (ρ), Reflectance (R) and Transmittance (T), Absorption Coefficient (α), Leaf Area Index (LAI), Leaf Inclination Distribution Function (LIDF) and atmospheric parameters include atmospheric pressure, temperature, humidity, aerosol properties, and gas concentrations. RTMs can be highly specialized for applications, such as atmospheric radiative transfer, vegetation modeling, or crop remote sensing, which further influences the parameter choice. Accurate initial parameter values can improve the accuracy of the RTM's simulations. This is especially important when fine-tuning RTMs for crop applications or when using them for inversion (retrieving model parameters from observed data), some parameter used as input and can be retrieved from RTMs are provided in Table 6.

Table 6 List of the parameters used often in RTM models, ranges and initial values may differ case by case depending on the specific application, the target material or medium, and the instrument or sensor being used.

Parameter	Description	Unit	Range	Initial value
B	Soil brightness	–	[0,0.9]	0.5
ϕ	Soil spectral latitude	Degree	[−30,30]	0
λ	Soil spectral longitude	Degree	[80,120]	100
SMp	Soil moisture volume percentage	–	[5,55]	20
Cab	Chlorophyll a and b content	$\mu g\ cm^{-2}$	[0,80]	40
Cdm	Dry mass per unit leaf area	$g\ cm^{-2}$	[0,0.02]	0.01
Cw	Equivalent water thickness	cm	[0,0.1]	0.02
Cs	Senescent materials	–	[0,1]	0
Cca	Carotenoid content	$\mu g\ cm^{-2}$	[0,30]	10
N	Leaf internal structure parameter	–	[1,4]	1.5
LAI	Leaf area index	$m^2\ m^2$	[0,7]	3
LIDFa	Leaf inclination determination parameter a	–	[−1,1]	−0.35
LIDFb	Leaf inclination determination parameter b	–	[−1,1]	−0.15

AOT550	Aerosol optical thickness at 550 nm	–	[0,2]	0.325
UO3	Ozone content	cm-atm	[0,0.8]	0.35
UH2O	Water vapour	g cm^{-2}	[0,8.5]	1.41

A significant challenge in applying RTM inversion mode is the issue of "ill-posedness" which means there can be multiple different combinations of model parameters that can reproduce an observed spectrum. This challenge complicates the accurate interpretation of remote sensing data and necessitates careful consideration of uncertainties in the inversion process. It is resolved by various statistical means such as numerical optimization, look-up table (LUT)-based inversion and hybrid approaches. All these approaches have their own advantage such as Numerical optimization minimizes a cost function value between the measured and predicted reflectance spectrum in an iterative manner. This method requires significant computing power and is time-intensive if applied to a huge number of pixels. In contrast, the LUT-approach uses a high number of simulations to produce several hundred or thousand reflectance spectra from numerous combinations of input variables. Hybrid approaches combine the fast computation power of machine learning and generalization level of RTMs. In this approach, RTM simulations are used as training data, leaving ground measurements only for validation. Yang et al. (2021) provided an improved retrieval of land surface biophysical variables from time series of Sentinel-3 OLCI TOA spectral observations by considering the temporal autocorrelation of surface and atmospheric properties, this has reduced inversion problem – ill posedness, in which multi-sensor integration takes place at the lower-level product of TOA radiance by using SPART model, instead at the higher product scale (e.g., LAI and fPAR). Thus, retrieval of land surface properties can be directly from OLCI TOA observations without atmospheric correction. In this way, the temporal continuity of the land surface and atmospheric properties used as prior information reduces the ill-posedness of model inversion problems and improves the retrieval accuracy. It helps to mitigate unrealistic short-term changes in the retrieved variables (FAPAR, LAI).

Besides retrievals, RTM can have multiple advantages. They can be combined with crop growth model (CGM) or process-based models, vegetation growth and prognostic phenology models (Fang et al. 2008) to get information about how crop changes over time in response to environmental conditions. By using crop models, RTMs can be trained, constrained, and the uncertainties in their biochemical retrievals can be reduced likewise. It allows for better parameterization of the RTMs and helps to match model outputs with observed data, leading to more reliable and meaningful results (e.g., Verrelst et al. 2015). Therefore, coupling of Radiative Transfer Models (RTMs) with other models gives more comprehensive analysis and monitoring of crop health. The Soil-Plant-Atmosphere (SPA) model, simulate water movement in the soil and its effect on plant water stress its integration with an RTM simulates changes in soil moisture and its influence on canopy reflectance and temperature, aiding in the detection of drought stress. Coupling with crop growth models like DSSAT allows researchers to simulate crop development and stress responses such as crop phenology, leaf area index, and nutrient uptake, helping to detect nutrient deficiencies or disease-induced stress. Coupling an RTM with a regional climate model provide insights into how variations in temperature, precipitation, and solar radiation influence crop health. Machine learning models, such as neural networks or random forests, can be trained using synthetic data generated by RTMs to detect crop stress from remotely sensed imagery. The combination of RTMs and machine learning enables the development of accurate stress detection algorithms. In some studies, LUT approach is used in which a discrete sample of model input is extracted from the full parameter space, and the corresponding model output is simulated by the forward radiative transfer model. Some studies used emulators as facilitators for developing simple relationships between model input and output by relying on machine learning techniques (Berger et al. 2020; Verrelst et al. 2019).

4.4 Applying Empirical Regression Models

Empirical regression methods use a learning dataset to calibrate a parametric or non-parametric model. The learning dataset consists of independent variables and dependent variables, where the independent variables can be spectral reflectance from multispectral/ hyperspectral image, vegetation indices, principal components, and even contextual descriptors. Dependent variable could be cropping performance related indicators like GPP, Yield, Biomass, Productivity and so on. The learning data can be generated using field experimental measurements of crop stress related variables, e.g., chlorophyll content, water content, LAI etc. In such cases, the resolution of the outcome stress variable map is determined by the scale of experimental measurement, for instance, measurements taken at a 10 m by 10 m sample plot, resulting in the degraded resolution of aerial mapping, if the parametric approach is used, non-parametric models have gained more attention (Zhang et al. 2021). Or otherwise the original resolution can be maintained through a wall-to-wall UAV map which requires rigorous and challenging co-registration between the two data sources i.e., satellite images and airborne images. The other challenge is empirical functions are constrained by the representativeness of the calibration dataset over the targeted areas that are related to atmospheric conditions, sun-sensor geometry, land cover (vegetation type, tree species even crop cultivar), phenological stages, and topography (Baret and Buis, 2008). So, when an empirical inverse model is calibrated over one scene applied to a new scene, it usually requires re-calibration based on the learning data of the new scene. In parallel, processed spectral signal-based regression models have a wide range of applications, including estimating crop yields, and monitoring soil properties. Once spectral data is collected from appropriate sensors, instruments, or spectroscopy techniques across a range of wavelengths. This data is preprocessed by various techniques like baseline correction, noise reduction, and wavelength selection to improve data quality. Then relevant features or spectral indices from the processed data are extracted for regression tasks.

Regression models are versatile tools applicable to various scenarios with both small and large numbers of variables. The choice of the specific regression model depends on the characteristics of the data and the goals of the analysis. For instance, a study by Asargew et al. (2024) conducted a glasshouse experiment to investigate changes in the linear relationship between stomatal conductance (gs) and photosynthesis (An) owing to water stress in rice and the association with soil moisture content. They employed a linear regression model- Ball-Woodrow-Berry to identify water stress in rice crops by analyzing relationship between gs and An. They found severe water stress had a significant effect and can reduce the slope of the linear relationship between gs and An by 30 % compared with normal water stress. Only in severe stress conditions, An and gs were strongly correlated with soil water content. For a relatively complex nature of the interactions with large set of variables polynomial regression technique is better. For instance, Gomez et al. (2022) studied water stress mechanisms in commercial crops (pineapple) to explore the influence of plant metabolites on shoot biomass in response to water stress. The statistical analysis of relationships conducted between commonly used biochemical markers of water stress and growth in crops. The study highlighted the efficacy of polynomial regression in quantifying the influence of plant metabolites (chlorophylls, carotenoids, phenolics, and aldehydes) on shoot biomass in response to water stress (Gomez et al. 2022). When dealing with a larger number of variables, multiple regression or other advanced techniques can be employed. Such as an airborne survey over an experimental farm in Italy used airborne hyperspectral images to assess maize fields with different irrigation levels. Field measurements of crop indicators like leaf water content, chlorophyll fluorescence, leaf temperature, and leaf area index were then analyzed using an ordinal logit regression model (an extension of binary logistic regression to handle more than two ordered categories)[3]. Results indicated Photochemical Reflectance Index (PRI_{570}) has strong relationships with LAI. PRI can be used in mapping stress classes and optimizing irrigation management in precision agriculture (Rossini et al. 2013). These examples illustrate the versatility of regression models in leveraging data of different types for crop stress detection and monitoring.

Some complex regression models are:

1. Partial Least Squares Regression (PLSR): Effective for dealing with multicollinearity in spectral data.
2. Support Vector Regression (SVR): Useful for modeling complex relationships.
3. Random Forest Regression: Robust and capable of handling high-dimensional data.

Because SVM and RF are non-linear, able to learn complex relationships and form high-dimensional datasets While using these high-performance models, the selected dataset is divided into training and testing subsets to evaluate model performance. This division of dataset is not needed if performance check is done through k-fold cross-validation in which only one set of observations, is resampled automatically and iteratively that help in assessing model generalization. Hyperparameter tuning of the regression model is important for accurate results. It is done by adjusting parameters related to model complexity, regularization, or kernel functions (for SVR). Once the regression model is trained and evaluated satisfactorily, it can be deployed for making predictions on new, unseen spectral data. It is necessary to periodically retrain or update the regression model as new spectral data becomes available or as conditions change. However, low-quality data can adversely affect model performance.

[3] Ordinal logistic regression, also known as ordered logistic regression or proportional odds model, is a statistical technique used for modeling the relationship between an ordinal dependent variable and one or more independent variables. Ordinal variables are those that have a meaningful order but the intervals between the categories are not necessarily equal. Model assumes that the relationship between the independent variables and the cumulative odds of being at or below a particular category is the same for all levels of the dependent variable.

4.5 Applying Machine Learning

Data-driven methods that include the development of vegetation indices in specific spectral bands and the construction of machine-learning inverse models require large sample data through field experiments. Those methods have certain shortcomings e.g., lack of theoretical support, low interpretability, lack of physical explanations of light transfer mechanics in plant leaves, and low generalization. Therefore, it is important to investigate the physical transmission of optical radiation in leaves, to gain a thorough understanding of the mechanisms of interaction between plant leaves and optical radiation and thus to develop plant physicochemical parameter detection methods with improved accuracies based on hyperspectral data. Machine learning approach has overpassed VI-based traditional diagnostic methods in performance. Some of the examples are:

1. Classification models, which involve combining input variables to predict classes related to plant condition (healthy/stressed). The labeled training data could be reflectance or transformed-reflectance (derivative, continuum removed, etc.) data, VI, or biochemical parameters retrieved by regression or RTM inversion. They can be assessed on a test dataset by comparing the predicted and true classes. Such methods can be applied to new reflectance measurements to predict plant stress but are skill- and computationally demanding.
2. Advanced regression models use same training datasets as classification model and can ingest several inputs variables like classification models. They can predict a continuous response variable such as the stressor itself (e.g., concentration of soil contaminants) or a biochemical or physiological indicator of plant stress (e.g., pigment contents, stomatal conductance). However, a common challenge to these methods is data dimensionality issue, the information in each spectral region can be highly redundant, making it difficult to identify the most suitable bands to monitor a given stressor.
3. Machine learning algorithms are being applied to remote sensing data for automated detection and classification of crop stressors. These algorithms can process vast datasets, identify patterns, and make predictions, enhancing the efficiency of crop monitoring and management. Several ML algorithms exist that can detect stress at an early stage and can distinguish plant stressors with similar effects on plant reflectance. Some can handle nonlinear relationships between the stressor intensity and the spectral response of plants. Some non-parametric examples are Linear or Quadratic Discriminant Analysis (LDA/QDA), Partial Least Square Regression (PLSR), Support Vector Machines (SVM), Random Forest (RF), Elastic net (ENET) regression, and Neural Networks (NNs). Their functional units and specific advantages are listed in Table 7.

Table 7. Examples of Machine learning algorithms, their functional use and advantage for crop stress monitoring

Methods	Function	Advantage

LDA	linear combination of input variables into a reduced project space	maximizes the separability of plant health classes
PLSR	a series of principal components (latent vectors) from the input variables	Quantify plant stress
SVM	Separate the plant classes (e.g., healthy/stressed) by defining a linear function that minimizes a cost function	maximizes the margins of a hyperplane and minimizes an approximation error
RF	averaging a series of independent decision trees to model the relationship between input variables and plant health classes	handles nonlinear relationships and informs on the importance of each input variable
ENET (penal-ized least square method)	Uses Ridge and Lasso regression	performs variable selection under multicollinearity
NNs (Multilayer Perceptron)	split layers in nodes which relate to those of another layer, layer can be reflectance data, VIs, or biochemical	output layer returns the plant health (e.g. healthy/stressed)

Some simple and advanced machine learning models, such as multivariate linear regression, random forest, artificial neural network, SVM, Gaussian process, and partial least square regression (PLSR), have been widely used to retrieve agricultural variables from RS data with the input of multiple features or continuous reflectance spectra (Schwieder et al. 2014). Nevertheless, training an SVM with high-dimensional data can be extremely slow, while ANN is prone to overfitting, and the parameter setting in ANN is more complicated. Compared to SVM and ANN, RF has proven to be a very robust machine learning algorithm for the retrieval of vegetation parameters, like CCC (Abdelbaki, et al. 2021). it has a high accuracy nearly 97%, can run effectively on huge datasets; is able to process input data with high-dimensional features. It can evaluate the importance of each variable. It can obtain unbiased estimates of internally generated errors. It can also give good results for the discrete values of inputs (Timsina et al. 2021).

ML techniques are also an efficient way to merge datasets of different natures, such as integrating in-situ data (soil data, farming management practice data from field surveys, weather variables) with datasets from various RS sources. It allows the complex relationship between variables to be statistically characterized and permits real-time computations, which is of strong interest for agricultural applications. Most phenotypic studies concerned with multispectral cameras use ML algorithms to develop the relationship between vegetation indices and crop traits such as leaf area index (LAI), nitrogen content, and chlorophyll content. They are now the long-lasting goals for RS applications in agriculture to be met. The rapid improvements in machine learning and sensor technology have provided cost-effective and thorough crop assessment and decision-making solutions. Machine learning techniques can process large hyperspectral data to detect subtle changes in crop health caused by various stressors, providing valuable insights for crop management. Also combining hyperspectral and meteorological data with machine learning improves crop yield predictions by considering the effects of multiple stressors on crop development. From these integrations, decision support systems can be developed using machine learning models by incorporating hyperspectral, environmental, and RTM data to assist the user community in making informed decisions for crop stress management. Using preprocessed spectra and machine learning algorithms, drought detection can be achieved a very high accuracy (Dao et al. 2021).

4.6 Applying Hybrid Retrieval Method

This section explores hybrid approach that integrates sensor data with complementary field data sources to enhance stressor monitoring and prediction. Data integration of multiple data sources i.e., data from various sensors, such as optical, thermal, and microwave, along with ground-based observations, weather data, and soil information enhances the accuracy of stress detection and predictive modeling. A study by Fei et al. (2023) showed that the use of multimodal data fusion and deep learning methods on UAV data resulted in good crop yield prediction. In another study, Ahmed et al. (2021) used hybrid machine learning approach and considered several soil management variables and harvest management features: Planting date and density, date of nitrogen application (both at planting and side-dress application), grain yield, harvest key, fresh and dry biomass, fertilizer rate, and nutrient uptake for nutrient stress management. Important is that these hybrid methods should be portable and independent from field measurement (Asma and Thomas, 2022). Hybrid approach leverages the strengths of different methods to address the limitations of individual techniques. In fact, nonparametric hybrid approaches are found to be highly accurate for the quantitative assessment of crop traits in optical remote Sensing. Most advanced crop-related research surrounds combining RTM and machine learning (ML) methods in a symbiotic manner such as integrating shallow or deep neural networks with RTM using remote sensing data to reduce errors in crop trait estimations that improve control of crop growth conditions in very large areas and are serving many precision agriculture applications now.

However, hybrid methods can be classified into parametric or non-parametric based on their retrieval approach. The advantages and limitations of a parametric and non-parametric hybrid method can be seen in Table 8 which can help in choosing an appropriate approach in the project.

Table 8. advantages and limitations of parametric and non-parametric hybrid retrieval methods.

Hybrid Retrieval method	Advantages	Limitations and cautions
Non-Parametric regression	Uses physical laws	Accuracy of results depend on RTM model type and design of LUT
	Accommodated to any data type with linear or nonlinear relationships	Needs knowledge for optimization and realistic results
	Trainable with full spectrum information, band selection or transformed spectrum	Model complexity increases as model progresses
	Perfectly implementing global maps and faster in calculation	

	Transparent inferential can give uncertainty information for assessing retrieval quality	Fast at calculating global maps with perfect execution
	Can handle high dimensionality and large training data	Training is computationally expensive
Parametric	Preserves physical principle	Accuracy of results depend on RTM model type and design of LUT
	Absorption and scattering features of spectrum to be considered	When using hyperspectral data, spectral range should be chosen carefully to generate a complex or simple VI
	Statistical relation between variable and spectral response can be taken	Limited representatives of relation between VI and target variable using curve fitting function
	Simple to apply and computationally inexpensive	Uncertainty calculation not provided, so accuracy can be challenged
	Interpretation is straightforward	Covariate with other variables related to absorption features is not considered
		Mapping crop traits over a large is not easy

EO and in situ data integration can be done in several ways:

1. **Feature Fusion:** Combine extracted features from different sources into a unified feature space for modeling. One example of feature fusion found in synergy of Sentinel-1 and Sentinel-2 Time Series for Cloud-Free Vegetation water content mapping in which several multiple-output Gaussian processes (MOGP) models evaluated to fuse efficiently Sentinel-1 (S1) Radar Vegetation Index (RVI) and Sentinel-2 (S2) vegetation water content (VWC) time series over a dry agri-environment in southern Argentina in Figure 5.

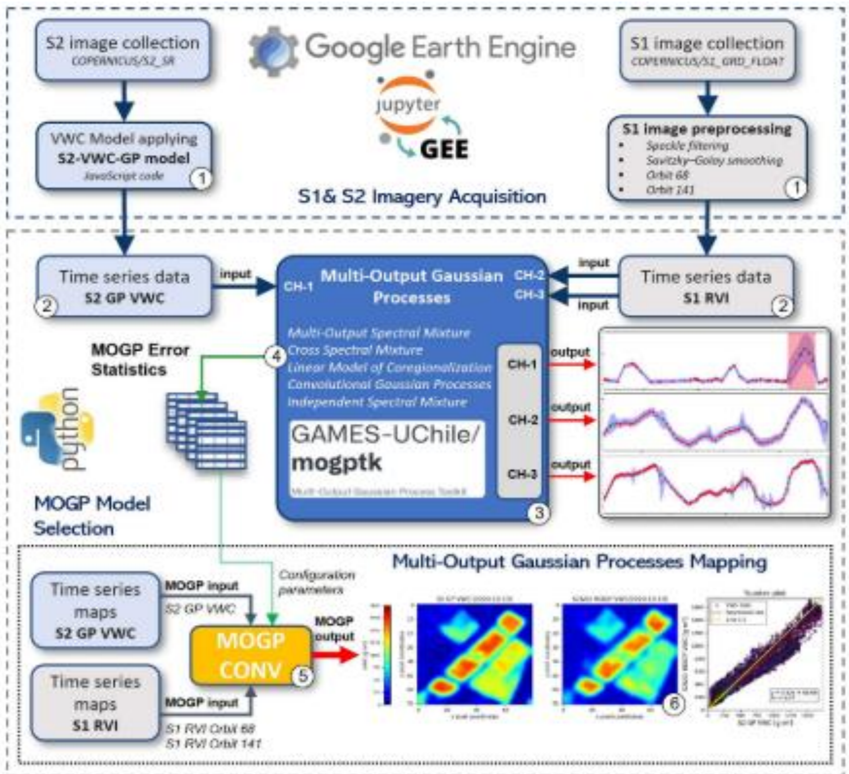

Figure 5. illustrates example of feature fusion for canopy water content mapping using time series of Sentinel 1 and 2 with machine learning technique – Multi output Gaussian process (Caballero et al. 2023).

2. **Data Fusion:** Merge data from different sensors and in-situ information at the data level, such as fusing multispectral, hyperspectral, and thermal data for enhanced stress detection. One exemplary application found in Gopi and Periasamy (2023)'s work in which MLR models are used on the feature space derived from in situ and S1 SAR (L, S) bands by which enhanced soil moisture product generated and linked to plant water content modelled by Water Cloud Model, the resultant crop health schema with combination of MLR and WCM provided PWC and Soil moisture maps for detecting healthy and stressed sorghums and cotton crops. Figure 6 illustrates significance of non-parametric hybrid approach and its framework difference with a parametric approach.

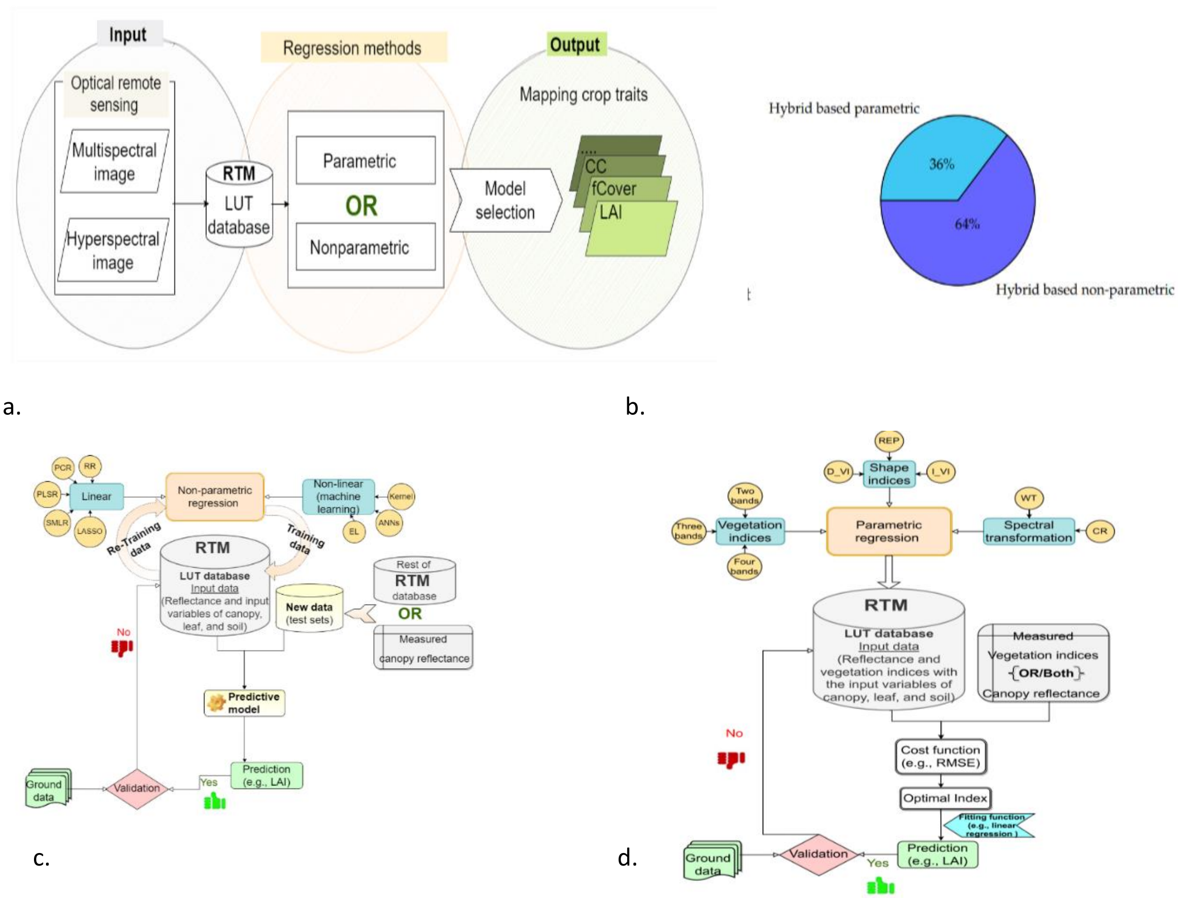

Figure 6. a) Example of hybrid retrieval methodology and b) popularity of hybrid based nonparametric methods [2002 – 2-22] (Source: Asma and Thomas et al. 2022) c) methodology design of parametric hybrid method based on VIs and RTMs d) integrating RTM with machine learning methods as example of non-parametric hybrid methodology.

3. **Ensemble Methods:** Utilize ensemble techniques like stacking or boosting to combine predictions from multiple models trained on different data sources. This category application is found mostly in crop yield predictions or selection of suitable cropping systems, but not for crop stress monitoring as such. The gradient boosting decision tree (GBDT), random forest (RF), extreme gradient boosting regression (XGBR), and a stacking ensemble ML algorithm have good

performances in solving regression problems (Aldress et al. 2022), Figure 7. Zewei et al. (2023) tested these ensemble methods on simulating soil salinity dynamics over cotton crops and proved the ML models, especially the XGBR and stacking ensemble ML algorithm, are useful tools to predict soil salinity, EC, cotton yield and ET. The use of the model is relatively simple, and the accuracy and stability are satisfactory. They can be used for real-time prediction of soil salinity, ET and cotton yield under drip irrigation in the future.

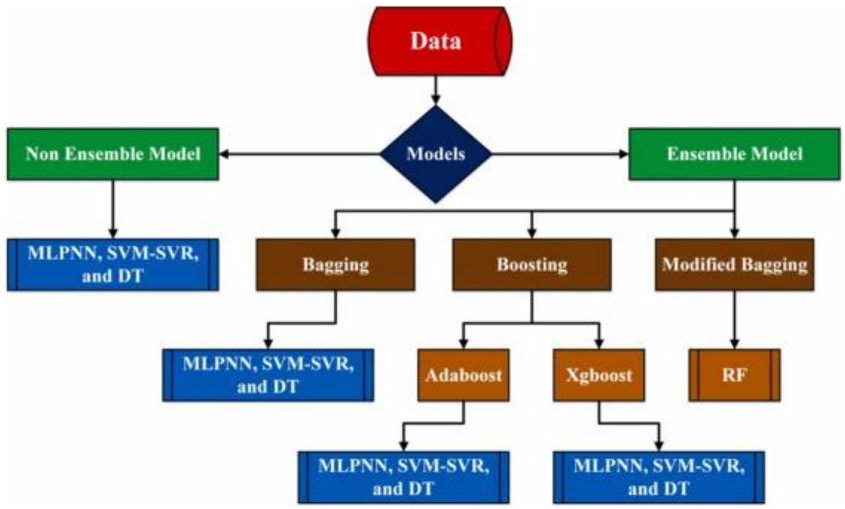

Figure 7 indicates the type of ensemble models known to be the best data mining techniques and their differentiation from other conventional ML techniques. (Aldrees et al. 2022)

4. **Expert Systems:** Combine domain knowledge via field sensors and rules-based approaches with data-driven models to improve interpretability and accuracy. Its major example is Digital Twin which is still developing by which farmers can manage operations remotely based on (near) real-time digital information instead of having to rely on direct observation and manual tasks on-site. An example is shown in figure 8. This allows them to act immediately in case of (expected) deviations and to simulate the effect of interventions based on real-life data. Verdouw et al. (2021) explain how Digital Twins can advance smart farming.

A well-designed hybrid retrieval method for crop stress detection can provide more accurate and reliable results compared to using a single data source or method. It leverages the complementary information available from multiple sources to enhance the monitoring and management of agricultural systems.

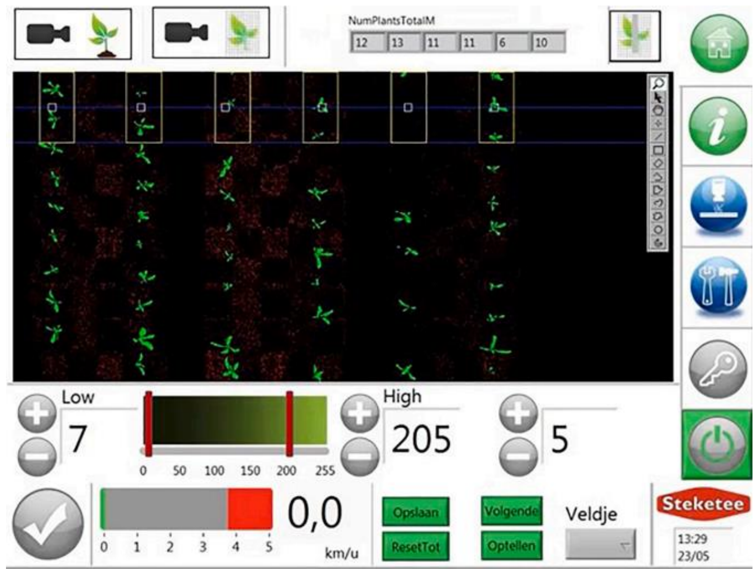

Figure 8. shows outcome of Smart Farming called Digital Twin as the next phase of Precision Agriculture for up-to-date information about farm operations. (Verdouw et al. 2021)

Nonparametric nonlinear methods are more powerful in extracting information from subtle differences in reflection by supporting covariance between biochemical and biophysical variables. Nowadays, deep learning (DL), as extending machine learning, is starting to be explored for crop monitoring using hyperspectral images. DL has the advantage of handling a large data size of training samples to possibly improve the targeted variable. It can provide estimates of uncertainty and the use of the complete optical spectrum information. It is gaining momentum recently for image classification also the convolutional neural network based on DL is being applied widely. In the study by Chandal et al. (2021) a comparative assessment of three deep learning models (Alexnet, GoogLeNet and Inception V3) is provided for identifying the water stress conditions of three crops (maize, okra, soybean), in which GoogLeNet DCNN model is efficient classifier for the water stressed conditions for different types of crops. This model can be used for real-time embedded image-based system of detecting the onset as well as extent of abiotic stresses in crops. A recent review on deep learning-based computer vision techniques by Orka et al. 2023 revealed that most of the work targeted various micro and macronutrient deficiencies in crops covering rice and potassium shortage represent the most researched crop and abiotic stress. Some are found on water-related stresses including drought and submergence, but no research exists on the cognition of early indicators of water, heat stress or nutritional inadequacies. This project can contribute to addressing the gaps in current research related to early indicators of water and heat stress as well as nutritional inadequacies in crops, ultimately making a valuable contribution to the sustainable crop production.

4.7 Best approach in developing new methods

While developing new methods, the accurate monitoring of plant stress needs a proper understanding of data collection, and analysis, which may vary depending on the conditions, the crop species, measured characteristics, and the stage of growth. A thorough understanding of crop light interactions, sensors, imaging platforms, and processing algorithms must be acquired to ensure that crop phenotyping meets the required criteria. First there is need to identify the purpose of monitoring (precision farming vs. environmental monitoring), the scale of monitoring (proximal vs. broad scale), the need for controlled experiments, and the type of monitoring (qualitative vs. quantitative). This will determine the most suited processing approach to maximize the accuracy of stress detection and quantification. For broad-scale monitoring, relevant wavelengths linked to stressor-specific symptoms can help to develop descriptive variables for machine learning models. Empirical regression models can be suitable for large-scale monitoring when a robust calibration dataset is available for the specific region and conditions of interest. However, they may struggle with extrapolation beyond the training data. On the other hand, RTMs are versatile and can simulate various scenarios. They require accurate input parameters and can be computationally intensive. They are often used in conjunction with other techniques for large-scale monitoring. Machine learning algorithms can handle a wide range of stress factors and provide accurate predictions when properly configured. They may lack interpretability, especially deep black-box models. They require substantial training data and can overfit if not properly regularized. Also, model response accuracy truly relies on data quality and size (Barbedo, 2019). Deep Learning is powerful for image-based monitoring, making it suitable for large-scale monitoring when a significant amount of labeled image data is available. The best approach is to combine multiple techniques to leverage their respective strengths in large-scale crop stress monitoring, ensuring both accuracy and interpretability.

5. TEST AREAS FOR EXPERIMENTAL DATASET

The project will consider three major grain crops of the world: rice, wheat, and maize. They are staple foods for billions of people and understanding how these crops respond to stress is vital for global food security. They are not only consumed directly but are also used as feedstock for livestock and as raw materials in various industries. Stress-induced reductions in yield can have widespread economic implications. Any threats to their production could lead to food shortages and price spikes, affecting vulnerable populations the most. They occupy vast agricultural lands, and their production often involves the use of pesticides, fertilizers, and irrigation, which can impact ecosystems and water resources. Studying their responses to stress can help develop more sustainable agricultural practices which can lead to the development of more stress-tolerant varieties through breeding or genetic modification. Improved crop varieties can help farmers mitigate the impacts of stress and increase overall crop yields.

Field protocols for measurements of different biophysical and biochemical parameters and stress conditions are required in the test areas to understand the relationship between key stressors and their remote signature. Our proposed test sites should cover a wide representation of different stress conditions. For which a trade-off analysis required for the selection of the state-of-the-art methods including time series analysis, RTM, machine learning, quantitative spectral analysis (e.g., spectral derivatives and continuum removal), and spectral indices as described in above sections. The knowledge gained on the cumulative effect of multiple stressors using such multi-source and multi-model approach may also require cloud computing and HPC framework. The datasets from in situ measurement of crop parameters and stress conditions, simulated data using radiative transfer models, and existing data in different crop stress conditions will provide a complete assessment of the cropping systems. A detailed cross comparison and verification would be needed in the selection of final methods and algorithms. The resulting EO-based stress maps/products from test sites can be cross compared and verified with simulated datasets generated by the machine learning or radiative transfer model to gain a thorough understanding of the range of validity, limits, and benefits of the different existing products.

This field scale investigations can be scaled up to regional scale analysis using regular RS monitoring data. But the main requirement is, test sites should represent different stress conditions (nutrient stress, water and heat stress and lodging) in cereal crops for testing the performance of various crop traits retrieval methods. For testing the robustness of selected methods, validation data will be comprised of in situ measurement of crop parameters and stress conditions, simulated data using radiative transfer models (RTM), and existing data in different crop stress conditions. In this project, three pilot sites are consolidated on which a large set of information is accessible and detailed measurements are available through various field campaigns.

5.1 Test site I - Rice cultivation in Andalusia, Spain

Andalusia, with about a third of all Spanish rice production, is the first rice producing region, although the area dedicated to this crop varies considerably depending on problems in the availability of water for flooding. Currently, the area under rice cultivation is close to 39,000 ha (Figure 9). This area uses different water sources (water from wells, river channels) for irrigation that accounts for about 80% of total water withdrawals in the region, out of which, 71% of irrigation water is derived from surface water, 28% from groundwater, and 1% from non-conventional water resources (i.e., reutilisation, desalinisation). Drip irrigation systems cover 64% of irrigated land, whereas sprinkler systems and surface irrigation span 13% and 23% of irrigated land, respectively. Arable crops account for 30% of the agricultural water withdrawal in the region (mainly due to rice and cotton production), followed by fruit trees (22%), olive trees (19%), and vegetables (10%). Rice cultivation in Spain is limited to areas with high salinity and significant environmental restrictions, such as deltas and marshes belonging to or close to natural parks.

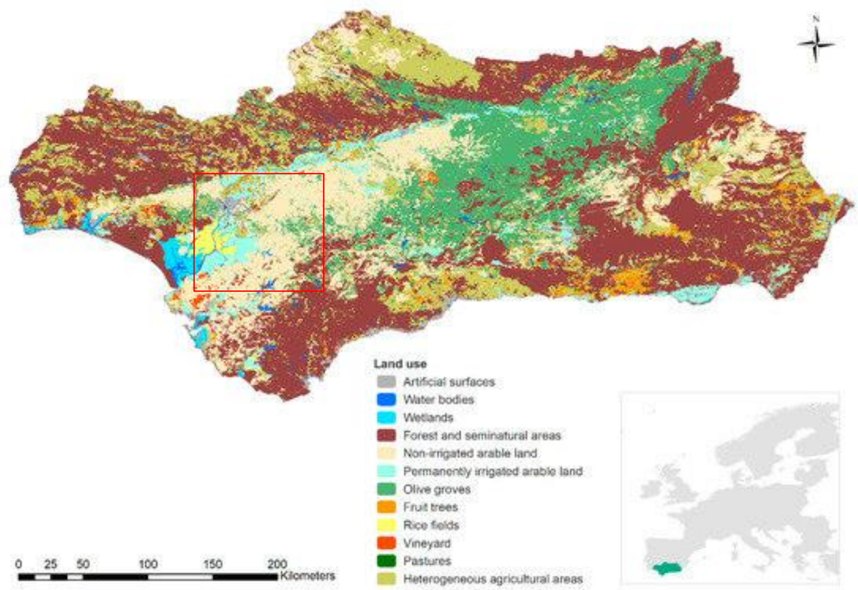

Figure 9. Types of Land use in Andalusia showing rice cultivation mostly in the west marked by red box (Source: Pilar and Maria, 2019)

An extensive field campaign has been carried out recently in the summer of the year 2023 to characterize the agronomic parameters of the AFR soils that can give information on stressors related to salinity, deficit or excess of nutrients, and heavy metal toxicity. Field data is accessible from five different campaigns in line with the Sentinel-2 acquisition dates and EnMap for the rice growing season (May – June 2023). Field measurements of chlorophyll, LAI and reflectivity have been taken using SPAD, LICOR 2200-c, and ASD FieldSpec 4 spectroradiometer during key growth stages of rice development (tillering, productive tiller critical stage (N-n), jointing, booting, heading, and filling stage). 100 soil samples in the month prior to rice planting have been collected to analyze different agronomic parameters in the laboratory, such as: electrical conductivity, nutrient content (KNP) and heavy metals. Soil samples are also measured using an ASD FieldSpec Pro spectrometer (400-2500 nm). Agronomic parameters are estimated using in situ measurements i.e., above, and below canopy LAI from Licor 2200c following LICOR protocol, leaf pigments using SPAD 502, reflectance using ASD and a Hyperspectral drone system (537 channels -VIS-NIR (400-1000 nm), SWIR (900-2500)), and spectral information also extracted from the new European hyperspectral mission EnMap, acquired during the month prior to seeding.

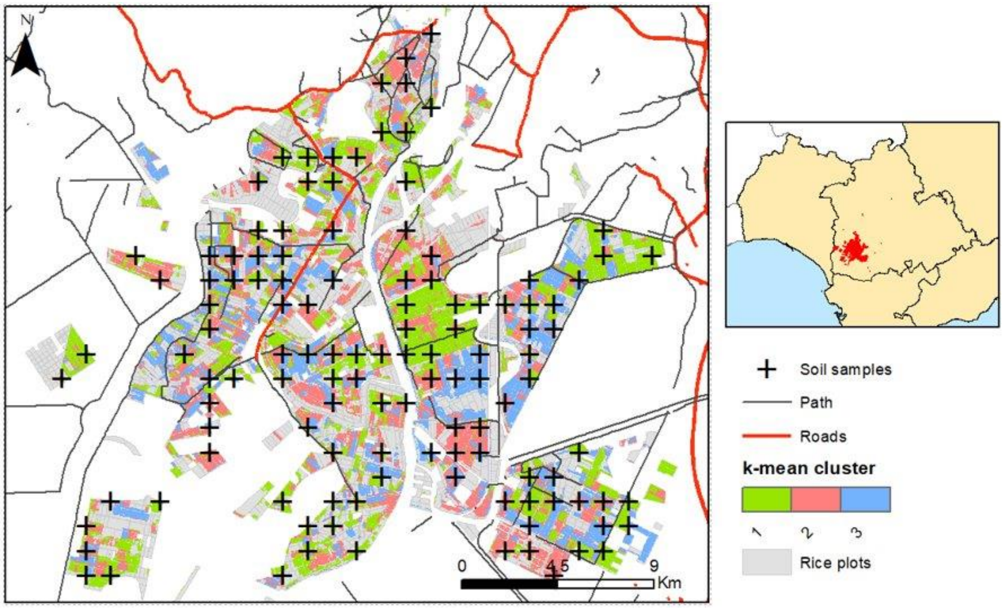

Figure 10. 100-point locations showing stratified random soil sampling in rice farm, Andalusia.

Additionally, the spectral measurements of soil samples (Figure 10) measured with the spectrometer is being convolved to the EnMap spectral response function to obtain the Look Up Table (LUT) that acts as an additional model calibration/validation set, to compare new retrieval approaches. Rice grain samples are being collected form every experimental plot to analyze proteins and trace elements (i.e., As). Chlorophyll content and LAI information from Sentinel 2, PRISMA and EnMAP, along with in situ measurements from field campaigns. This information can be used to quantify and improve understanding of rice crop cumulative response to multiple stressors by which the potential of new European hyperspectral missions in agricultural monitoring such as EnMap can be evaluated. This experimental data is sufficient to model soil agronomic parameters, chlorophyll, LAI, and yield, from open-source algorithms such as Partial Least Square Regression (PLSR) or Random Forest, in a High-Performance Computing (HPC) environment.

5.2. Test site II - Marchfeld region, Austria

The Marchfeld region (ca 60,000 ha) is one of the major crop production areas of Austria for grain and vegetables and hence crop failure due to stressors may have severe consequences for food security. The area is generally flat with an altitude of ~ 160-180m above sea level (Figure 11). Around 75% of the area is used for agriculture and 30 % is irrigated. There are 884 farms with more than two-thirds (72%) professional farms where farming is the only source of income with average farm size around 55ha. It has semi-arid climate with often severe precipitation shortages (typically only 250 - 300 mm of precipitation during May-September). Therefore, water stress is a major threat to crop production areas as groundwater resources are increasingly limited in this area. Water needs during summer months can only be partially alleviated through irrigation, groundwater in the Marchfeld region must be distributed in the urban and industrial sectors, leading to high pressure on the quantity and quality of water resources. Water stress is projected to further increase in the future due to climate change. Soils in the region is highly heterogenous and have low to moderate water storage capacity (Eitzinger et al. 2013; Thaler et al. 2012). This field has been under observation for long time. Hence, a wealth of information is available on weather, crop status and performance (e.g., ET, structural and biochemical crop characteristics, crop yields) as well as soil optical and hydrological properties (e.g., field and lab spectrometer measurements under different soil wetness conditions; soil properties such as texture, field capacity and organic carbon content). Several high-resolution vegetation indices maps are available for stressed and non-stressed fields. The list of available datasets is shown in Table 9.

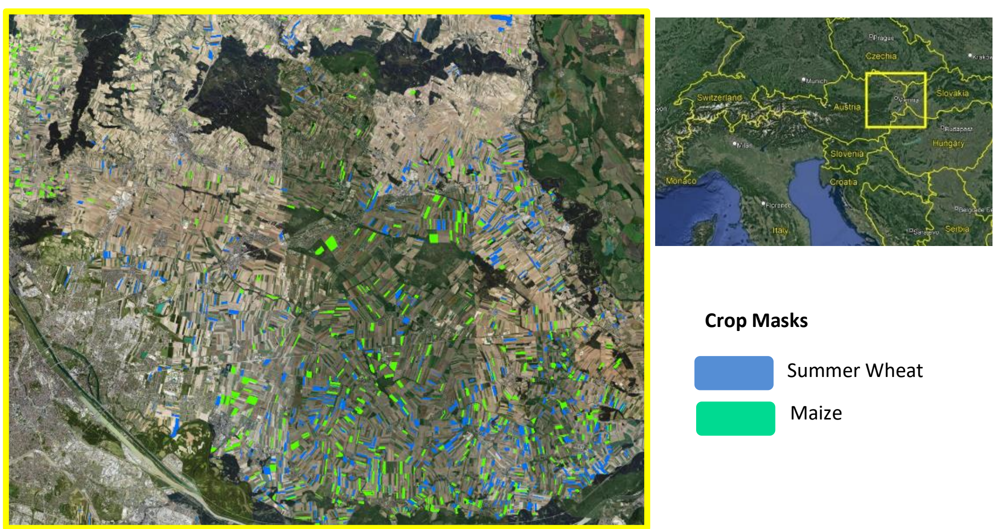

Figure 11. RGB image of Sentinel 2 displaying maize and summer wheat crop parcels in Marchfeld region under observation since 2017.

Table 9. shows the available dataset for Marchfeld site.

Product	Instrument Dataset	Spatial resolution	Temporal resolution	Temporal Coverage	Spatial Extent
Reflectance VI	EnMap, PRISMA, S-2	30m, 10m	variable/5	2022+, 2019+, 2017+	Sites
Air-temperature, Precipitation, Humidity, Wind speed	INCA, SPARTACUS v2.1	1 Km	Hourly/Daily	2011-2021, 1961+	Sites

5.3. Test site III - Bonifiche Farm, Italy

Bonifiche Ferraresi farm situated in Jolanda di Savoia (44°52′59′′N, 11°58′48′′), Ferrara, Italy is an agri-food business with one of the largest agricultural holdings in Italy (Figure 12). It has 3850 ha of arable land, the majority of which is made up of clay and silty soils. Mostly climate is warm and moderate. The farm grows seven major crops i.e., wheat, barley, corn, rice, soybeans, potatoes, and other crops for horticulture and medicine. Typically, these crops are produced in succession over several years in rotation. Winter wheat, which is susceptible to severe lodging, is seeded from the end of October to the beginning of November and harvested by the end of June. Several wheat cultivars were grown in 2018, including PR22D66, Marco Aurelio, Claudio, Monastir Massimo Meridio, Rebelde, Odisseo, Giorgione and Senatore Capelli. The cultivation area of wheat in 2023 was 664.24 ha, the wheat field sizes varied between 2.38 and 84.86 ha.
In May 2023, an extensive field campaign was carried out in which several in situ biophysical parameters including crop height, plant density, LAI, biomass, tiller number, shoot numbers, cover percentage, fresh biomass, flower weight etc. as well as stress related parameters such as slant height, vertical lodged height, lodged area %, point of line failure, crop angle inclination, and lodging score) were measured. Further, wheat samples were destructively harvested and carried to laboratory for subsequent measurements of lab-based biochemical measurements (dry biomass, dry matter content, water content, nitrogen content, carbon content). Field sampling in lodged and healthy fields was carried out using a stratified random sampling approach at three levels: 1) (ESU) Plot – (90 m X 90 m); 2) Subplot – (15 m X 15 m); 3) Microplot – (1.5 m X 1.5 m). In each ESU/plot, five subplots and in each subplot three microplots were considered for measurements of physiological parameters. In total 65 (ESU) plots have been sampled of which 33 were lodged and 32 were healthy plots. In the measured ESUs, a total of 322 subplots (165 lodged and 157 healthy subplots) and 968 microplots (498 lodged and 470 healthy microplots) were measured.

The project aims to use both in-situ and lab measurements of physiological parameters to detect lodging and assess its severity in wheat fields in combination with satellite imagery from Sentinel 2, simulated Chime, DESIS and EnMap. The detection and mapping of lodging can be advanced through utilization of narrowband indices, machine learning algorithms and inversion of PROSAIL-PRO radiative transfer modeling while considering multiple factors like crop angle of inclination, leaf area index (LAI), spectral characteristics, and absorption features. This test site can assist in identifying specific spectral regions sensitive to lodging and predict key agricultural variables such as leaf inclination angle, LAI, nitrogen, chlorophyll, and water content, which are crucial indicators for lodging in wheat.

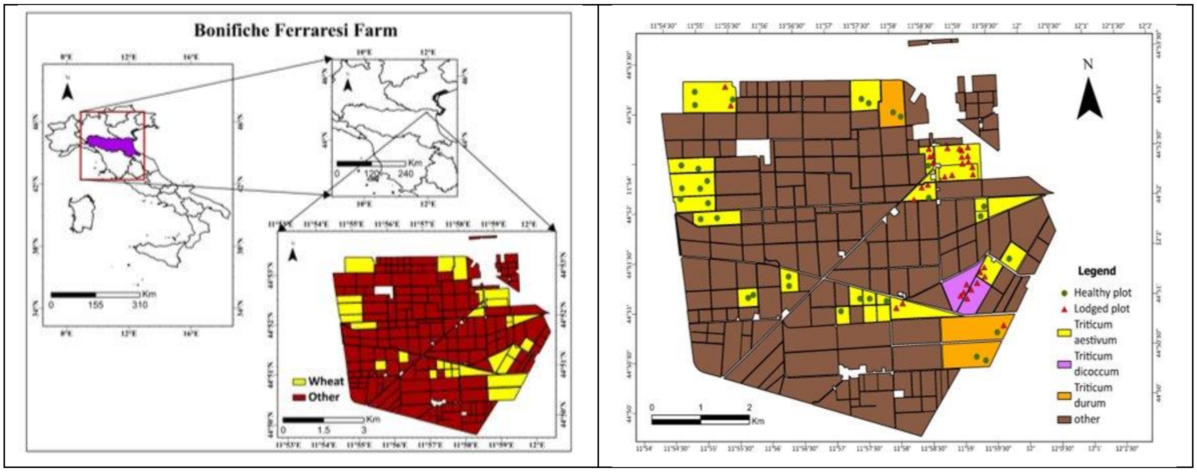

Figure 12. Location of the study area and distribution of sampled plots during field campaign 2023 in Jolanda di Savoia, Ferrara, Italy.

6. BEST APPROACHES FOR VALIDATING EO BASED CROP PRODUCTS

This section deciphers a suitable approach to validate stress maps derived from remote sensing data if developed algorithms are effectively representing the actual stress conditions of the field. For systematic validation, we need a feedback loop between satellite-based monitoring and field observations to continuously improve the accuracy of crop stress maps. For which algorithms will be tested on different crop types at different growth stages, as stress responses can vary significantly among crops. Certain validation metrics can be used in this process for instance correlation coefficients, RMSE, Bias, accuracy assessment, time series, regression plots, variance, and phase differences etc. while comparing results with ground-based information. For hybrid model's performance evaluation, suitable metrics could be on accuracy, precision, recall, F1-score, or area under the receiver operating characteristic curve (AUC-ROC). It can explain the uncertainties in the derived products, besides that, some simple measures like visual inspections, collecting data from multiple locations within satellite image area and yield assessment could also be useful. The project will consider various points while developing a final product, according to figure 13.

- Using installed ground-based instruments, such as spectroradiometers and thermal cameras, at some validation sites other than test areas to directly measure crop properties and compare them with intermediatory subject to availability i.e., satellite or airborne data. Dividing pilot areas into training and validation datasets for different spatial zones and temporal periods to assess algorithms performances in stress detection.

- Soil moisture sensors data at various depths can be used to validate remotely sensed water stress products. Similarly leaf-level measurements, such as chlorophyll content, leaf water potential, and stomatal conductance, to validate remote sensing-based indicators of crop stress.
- Direct comparison and validation of spectral indices from high-resolution, in-situ spectral data that closely matches the spectral bands of the remote sensing.
- Use of validation transects within fields to capture spatial variations in crop stress. These transects can serve as reference areas for remote sensing validation. Besides that, simultaneous data collection with remote sensing data acquisition will minimize temporal discrepancies that could affect validation accuracy.
- Analyzing temporal trends in both remote sensing and ground truth data will assist in understanding the dynamics of crop stress over time.
- Engaging agronomists and field experts for insights into specific stressors affecting the crop
- Experimental data from other sites on mobile ground platforms (e.g., tractor-mounted sensors) taken at different growth stages and across larger areas can be used.
- Use of Monte Carlo simulations or bootstrapping methods for estimating uncertainty associated with remote sensing-based crop stress products.

The project will use bottom-up approach to validate regional to global crop stressors products derived from remote sensing data (i.e., from local field-level measurement to global comparison with satellite-derived single or multiple stressor products) (Figure 14). In validation process, we will be considering.

- Methods and instruments used to collect the field stress conditions at each site.
- Measurement extent and sampling scheme at each site.
- Integration of field data with high-resolution imagery (EnMap, DESIS, Sentinel 2, PRISMA) at 30 m resolution.
- Algorithms used in deriving crop traits as stress indicators.
- Methods to compare high-resolution product with moderate-resolution product (CCI Soil Moisture product, MODIS Evapotranspiration products, LSA-SAF ET product, MOD17GPP product, newly developed Sen4GPP product by UoS and Gross Dry Matter Product (GDMP) by Copernicus Global Land Service.
- Network of sites available for field validation (Fluxnet, AgMerra, PhenoCam, EnMap validation sites).

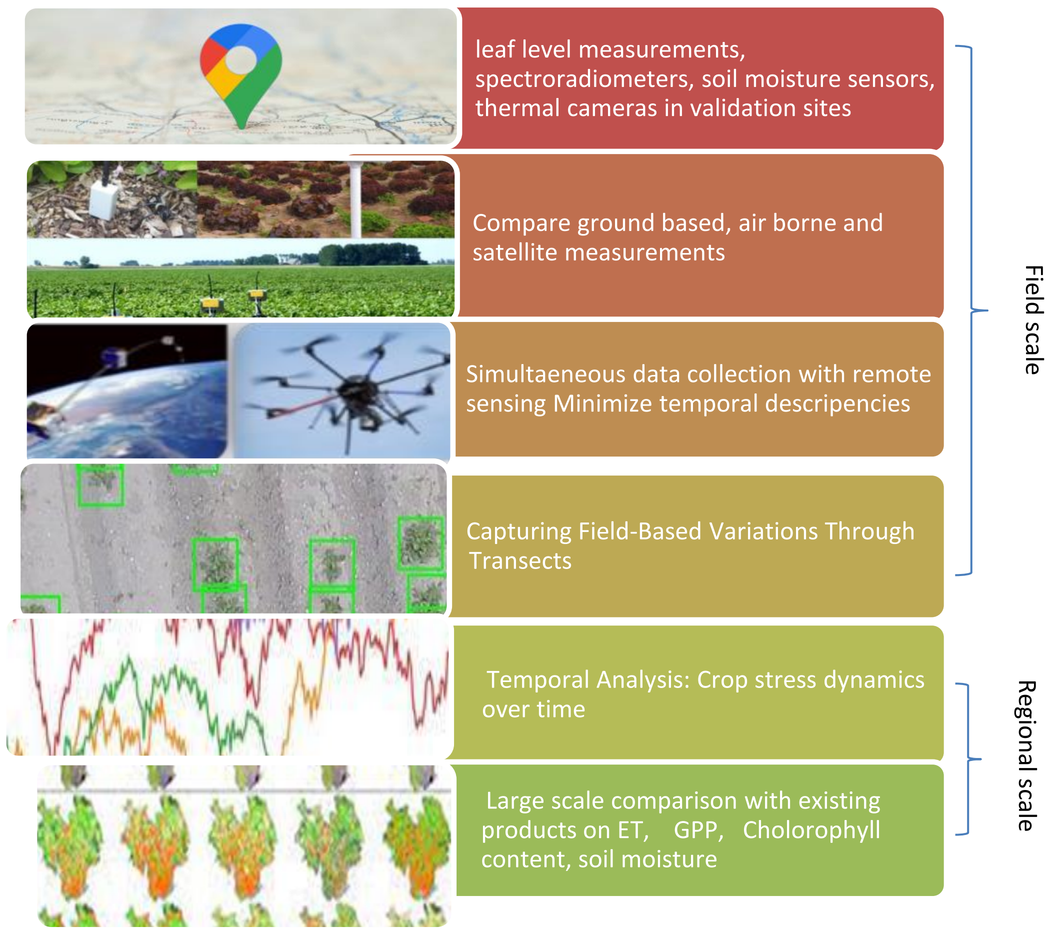

Figure 13. Flowchart displaying different stages of comparison for crop stressor product mapping.

In our test sites, local field measurements are taken on elementary sampling units (ESU), sub plots and microplots following field specific sampling strategy to capture the variability across the corresponding site extent. The measurements are repeated within the ESU specially to capture the variability within the high spatial resolution imagery (30 m). The number of ESUs is varied by extent of the site, field variability and the extent of the ESUs themselves. This field data from ESUs will be linked to the spectral features from aerial and satellite base images through various up scaling approaches (RTMs and machine learning) which will establish the relationship between the field-based crop stress estimates and high-resolution imagery i.e., EnMap, Sentinel 2, PRISMA. Final step would be large scale validation through the comparison between the aggregated high-resolution crop stressor maps and the corresponding satellite products over Europe and Canada such as Sen4GPP, Evaporative Stress Index – EcoStress as well as an ensemble of sites from sources mentioned in section 3.3.

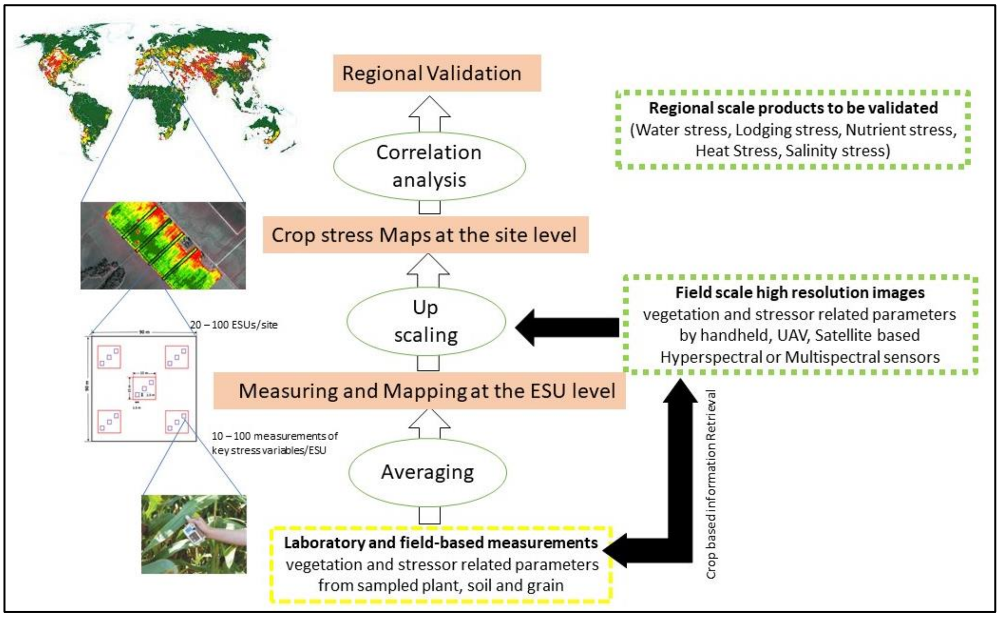

Figure 14. Validation framework for high resolution Crop stressor products and their deriving methodologies.

All these validation activities are essential to check the accuracy of our product and to guide refinement of algorithms used. This evaluation will show the degree of coherence between the products of the experimental dataset with respect to the current range of stress indicators determined using i) all independent products (comparison of global/regional mean values, mean regional/local seasonal cycles, interannual variability) ii) identify the reasons for the differences, if any, between the experimental dataset products iii) to assess, for regions where the Lodging/salinity/drought products would be coherent, the weaknesses of the approaches relying on radiative transfer modelling or machine learning approaches pointing possibly to some process weaknesses and drawing conclusion on how to improve the stress monitoring methodologies.

7. EUROPEAN AND INTERNATIONAL INITIATIVES ON CROP STRESS EVALUATION

Integrating of EO4Cereal Stress into other European and international initiatives that are already focused on monitoring the impacts of multiple stressors on crops can enhance collaboration, data sharing, and the overall effectiveness of our research efforts. Collaboration at both the European and international levels can lead to more comprehensive and globally relevant findings. Here are some notable initiatives and organizations that could be considered for integration:

7.1. European Initiatives

1. **Copernicus Program**: The Copernicus program, led by the European Space Agency (ESA) and the European Commission, provides a wealth of Earth Observation data and services. Sentinel mission datasets will be deployed in the experimental dataset generation.

   Weblink: https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Europe_s_Copernicus_programme

2. **JRC - Joint Research Centre**: The JRC, the European Commission's science and knowledge service, is actively involved in research related to agriculture, land use, and environmental monitoring. Partnering with JRC can provide valuable insights and resources.

   Weblink:

   https://joint-research-centre.ec.europa.eu/scientific-activities-z/agricultural-monitoring_en

3. **EC JPI FACCE** (Joint Programming Initiative on Agriculture, Food Security, and Climate Change): focuses on addressing the challenges of food security and agriculture in the context of climate change. Integration with JPI FACCE can facilitate access to research networks and knowledge sharing.

   Weblink:

   https://www.faccejpi.net/en/faccejpi/about.htm

4. **EU-funded Research Projects**: Many EU-funded research projects and consortia listed below are dedicated to agricultural monitoring and sustainability. Joining or collaborating with these projects can provide access to shared resources and expertise. Their list with briefings is given in table 10.

Table 10. List of European funded projects with point of contact and duration of the projects.

Project	Objective	Coordinator	Period
MEF4CAP - EU's Horizon 2020 research and innovation programme **https://mef4cap.eu/**	bringing monitoring and technology expertise together to investigate the possibilities and limitations of satellite and sensor data and the increased digitalisation within the agricultural sector.	Stichting Wageningen Research, Netherlands	1 Oct 2020 – 31 January 2024
INVITE - EU's Horizon 2020 research and innovation programme **https://www.h2020-invite.eu/**	to improve both efficiency of variety testing and the information available to stakeholders on variety performance under a range of production conditions and biotic and abiotic stresses.	Acta les instituts techniques agricoles, France	5 Years

DROPSA https://www.eppo.int/RESOURCES/special_projects/dropsa	Provide strategies to develop effective, innovative, and practical approaches to protect major European fruit crops from pests and pathogens	University of Padova, Italy	January 2014 to February 2018
AgriLink - Connecting farmers, advisers and researchers for productive and sustainable agriculture https://www.agrilink2020.eu/	6 Living Labs to develop and test new advisory methods and tools (including information and communication technologies - ICT supported) to better link research and practice.	James Hutton Institute, Scotland	2017 to 2021
Horizon Europe ScaleAgData https://scaleagdata.eu/en	to bridge the data gap of observations at the local level by unlocking, integrating and upscaling the data from in-situ sensors on farms. To develop the data technology (from data streaming, data analytics and AI (Artificial Intelligence) applications)	VITO Remote sensing, Belgium	December 2022 - December 2026
DIONE https://dione-project.eu/	developing a direct payment controlling toolbox for paying agencies to abide by the modernised CAP (Common Agricultural Policy) regulations, involving novel techniques that will improve the capabilities of satellite technology while integrating various data sources (drones, soil sensors and mobile applications). At the same time a system developed on a regional or national scale will evaluate the monitored parameters to form evidence-based conclusions regarding eventual environmental impacts on an entire region.	Institute of Communication and Computer Systems, Greece	January 2020 to October 2022
CIRCASA https://www.circasa-project.eu/	to develop international synergies concerning research and knowledge exchange in the field of carbon sequestration in agricultural soils at European Union and global levels, with the active engagement of all relevant stakeholders.	Institut national de recherche pour l'agriculture, l'alimentation et l'environnement, France	Nov 2017 to Feb 2021

5. **EOS**- Agro platform is a web-based commercial agriculture monitoring system designed to offer various services to farmers, agricultural cooperatives, and agribusiness firms. These services typically include early detection of crop risks, cost reduction strategies, farm performance monitoring, and customized solutions using AI-driven satellite-based data and analysis. https://eos.com/products/crop-monitoring/

6. Agricultural Drought Monitoring System (ADMS) in Poland – is based on meteorological data and soil-agricultural maps to present the spatial heterogeneity of water retention in different soil drought vulnerability categories. The functionality of the ADMS has been modified by using NDVI and NDWI

from S-1 and S-2 images, which are promising water shortage indicators for crops. https://susza.iung.pulawy.pl/en/

7.2. International Initiatives

Some international programs are;

1. **Water Stress and Climate Indices for Africa' (WaSCIA) -** aims to deliver high-quality Water Stress and Climate Indices through an easy-to-use web interface to help the management of drought and water stress in Africa, operated by TELESPAZIO VEGA UK LIMITED (GB). The goal of the WaSCIA service is to provide crucial information to help detect early onsets of water stress related to drought conditions, its severity and spatial extent all over Senegal. Its methodology framework is shown in figure 15 deciphering fusion of Sentinel 2 and 3 products and indices for Evapotranspiration and Soil moisture mapping used for water stress detection. https://eo4society.esa.int/projects/wascia

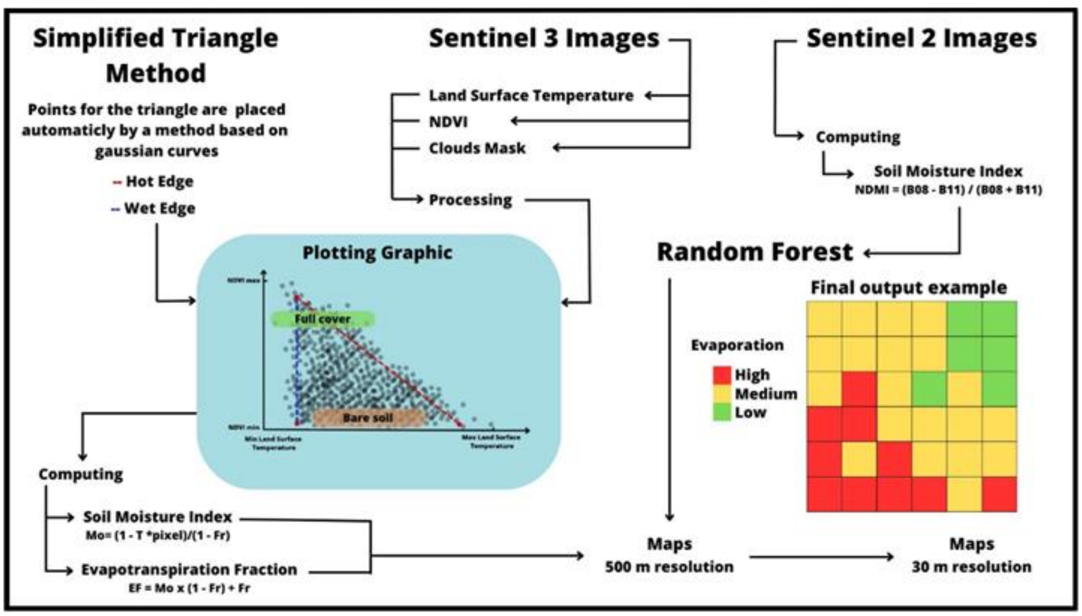

Figure 15. explains methodology framework of WaSCIA project.

2. **GEOGLAM** (Group on Earth Observations Global Agricultural Monitoring): is an international initiative aimed at improving global agricultural monitoring using EO data. EO4CerealStress could align with GEOGLAM to contribute to global food security efforts. https://earthobservations.org/geoglam.php.

3. **FAO - Food and Agriculture Organization of the United Nations**: has various programs and data portals related to crop monitoring and agricultural sustainability like GAEZ, WAPOR etc. Collaborating with FAO can help disseminate our project's findings and contribute to global policy recommendations. FAO report on Crop yield response to Water, Irrigation and Drainage paper 66 by

Pasquale Steduto (FAO, Land and Water Division) could be a useful baseline material for studying water stress mitigations in crops (Carr, 2013).

i. Agro-Ecological Zones (AEZ) modelling framework and databases, **GAEZ**: https://gaez.fao.org/

ii. The FAO portal to monitor Water Productivity through Open access of Remotely sensed derived data, **WAPOR:** https://wapor.apps.fao.org/home/WAPOR_2/1

4. **CGIAR** (Consultative Group for International Agricultural Research): CGIAR is a global research partnership dedicated to reducing poverty, enhancing food security, and improving natural resource management. Collaborating with CGIAR centers can provide useful insights in agricultural research. One connection could be Stress Tolerant Maize for Africa (STMA) project implemented to improve maize varieties with resistance and tolerance to drought, low soil fertility, heat, diseases such as Maize Lethal Necrosis and pests affecting maize production areas in the region. Project closed in March 2020. Link is here: https://www.cimmyt.org/projects/stress-tolerant-maize-for-africa-stma/

5. **AfricaRice (2014 – 2019)** and its team developed and deployed rice varieties with a high yield and better tolerance to drought, submergence, salinity, iron toxicity and low temperature, as part of a joint AfricaRice/IRRI project. National agricultural research systems (NARS) scientists (particularly breeders) and rest of the partners were involved in the selection process to obtain the best cultivars for their own farmers and consumers. Details are in https://www.africarice.org/arica

6. **Drought Watch Program** (Canada) is a national monitoring program using earth observation, climate data and models to evaluate crop stress related to extreme weather. Data sets include crop condition, satellite soil moisture (SMOS), satellite evapotranspiration (ALEXI-MODIS) and integrated products like the Vegetation Drought Response Index (using MODIS), the Canadian Drought Monitor (integrating many data sets include groundwater estimates from GRACE) and yield forecasts. Details are at: https://agriculture.canada.ca/en/agricultural-production/weather and an interactive tool is available here: https://agriculture.canada.ca/atlas/apps/metrics/index-en.html?appid=ccm-epc

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