DROUGHT MONITORING THROUGH SPACEBORNE HYPERSPECTRAL TIME-SERIES

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***Abstract*—The present study showcases the activities and first achievements of the European Commission funded Horizon project EXPERT in the development of a drought monitoring tool for agricultural applications. The work focusses on the creation of a temporally dense spaceborne hyperspectral time-series of PRISMA and EnMAP data over the Moara Domnească Didactic Farm, Bucharest, Romania. The study investigates how multitemporal hyperspectral images, combined with ancillary meteorological and vegetative phase data, can be beneficial for the investigation and identification of early signals of crop stress resulting from water deficits. The initial insights highlight that spectral anomalies can be detected and characterized versus a baseline understanding of the soil properties, as a needed foundation in order to identify signals due to drought impacts when a dense multi-temporal analysis is performed.**

***Index Terms*—Hyperspectral remote sensing, PRISMA, EnMAP, Drought, Agriculture.**

I. Introduction

Anthropogenic climate modifications are increasing the occurrence and intensity of climatic extreme events, alternating short, burst-like precipitations with prolonged periods of high temperatures and near-zero precipitation. These conditions pave the ground for two main phenomena that society is trying to defend from: floods and droughts. For the former, advanced forecasting and mapping models have been developed as a consequence of the immediate, undistinguished and devastating impact on the livelihood of the affected population. Droughts, on the other hand, despite threatening food production and overall survival of entire shares of population have long gone unnoticed, also as a consequence of the climatic regimes previously present in ”modern” countries. Periods of reduced precipitation coupled with elevated temperatures impact cultivations, causing high levels of evapotranspiration and, in turn, increasing the crop’s irrigation requirements. The increased occurrence of dry periods has raised attention to this matter, pushing the scientific community towards the development of more precise and physically-based models, coming to the aid of farmers and agricultural crop management.

The present work aims to showcase the case study developed for the Horizon Europe EXPERT project. The main goal of the project is building skills and knowledge in the utilization of hyperspectral data for the Romanian Space Agency (ROSA), with training modules provided by the Italian Space Agency (ASI) and the German Aerospace Center (DLR). In this context, the project aims at conceptualizing and developing a drought monitoring tool for agricultural crops in Romania.

Indeed, Romania is one of the biggest cereals producers in the EU [1]. In 2020-2024 Romania was the second European producer of grain maize, ranking after France [2]. In this time range, Romania produced circa 10 Megatonnes (Mt) of maize, that if combined with wheat, accounts for almost 87% of the total cereal production in the nation. According to a report issued by World Bank [3], the number of drought events, as well as their associated losses, have been increasing

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in severity in Romania in the past 50 years, accelerated by climate change. Hussain et al. [4] showed that droughts decrease the agricultural yield ranging between 30% to 90%, depending on the crop species. In 2022, Romania faced the impacts of the most severe drought in the past 500 years causing a 25-30% reduction in agricultural output. These insights are derived from the development of innovative modelling approaches enabled by the advancements of remote sensing technologies, offering new possibilities for regional scale monitoring of climatic and vegetation conditions. In this framework, the Monitoring Agricultural ResourceS (MARS) yield prediction model by the EC Joint Research Centre (JRC) [5] takes into account agroclimatic conditions such as crop growth models, meteorological inputs, soil characteristics, and remote sensing indicators for crop yield predictions. In relation to the aforementioned 2022 events and the general climatic conditions in Romania for the last years, the model forecasted a decrease in maize production greater than 10% for the 2020-2024 average yield, and the yield prediction for 2025 shows a 26% production decrease if compared to the last 5-year yield average [6]. In addition to the evidence provided by the MARS model, the European Drought Observatory (EDO) developed the Combined Drought Index (CDI), a tool capable of classifying drought severity stages according to a three-tier labelling. Similar to MARS, the index takes into account the deviation from the long-term trends for precipitation, soil moisture, and vegetation (FAPAR), the latter based on MODIS products with 500 m spatial resolution and 8-days temporal resolution. The presented information related to the model and index structure showcases the strong interdependency of meteorological variables with vegetation parameters. Nevertheless, vegetation response is taken into account only based on limited descriptors, such as the FAPAR index. For this reason, the aim of this research is to investigate how the numerous vegetation parameters that can be extracted from new-generation hyperspectral satellites such as PRISMA (PRecursore IperSpettrale della Missione Applicativa / Hyperspectral PRecursor of the Application Mission - Italian Space Agency) and EnMAP (Environmental Mapping and Analysis Program - German Space Agency) can benefit the assessment of drought impacts on crops and the detection of vegetation early stress signals.

With this goal in mind, ASI and DLR coordinated to collect hyperspectral satellite imagery at the highest temporal acquisition density over the area of study with PRISMA and EnMAP missions. Ancillary data from the Copernicus Sentinel-2 constellation and NASA MODIS are also used in the investigation of drought impacts on vegetation. In addition to the capacity building dimension of the project, the tool development aims at showcasing new possibilities deriving from recurrent hyperspectral acquisitions, a realistic scenario in view of the CHIME constellation by the European Space Agency (ESA) [7].

II. Materials and Methods

A. Study Area

The study site is located in Romania, 15 km north-east of Bucharest, at the Moara Domnească Didactic Farm managed by the University of Agronomic Sciences and Veterinary Medicine of Bucharest (44.4952°, 26.2530°, Fig. 1). The site presents a generally flat area with small elevation variations. Locally isolated and channel-like depressions manifest the past existence of lacustrine and creek environments, today smoothed and morphologically integrated with the flats. Such elements not only modified the landscape, but also deposited process-specific sediments such as clay and sand for lacustrine and creek environments [8] and a relevant component of aeolian transported glacial loess [9]. These environments and sediment typologies can create local heterogeneities in soil texture, grain size and permeability, therefore affecting crop health and productivity. For the period considered in the analysis and upon field observations in the first days of July 2025, the fields were cultivated mainly with maize and for a significantly smaller part with wheat. The field survey allowed to observe localized differential growing conditions in the field in correspondence of a local microtopographical circular depression where vegetation appeared to be less vigorous (see insert in Fig. 1, a condition that makes this plot more sensitive to the onset of drought related stress) [10]. Considering the illustrative potential of this plot in consideration of the overall field characteristics, the anomaly area was selected to investigate the impact of droughts on crops with different vigor.

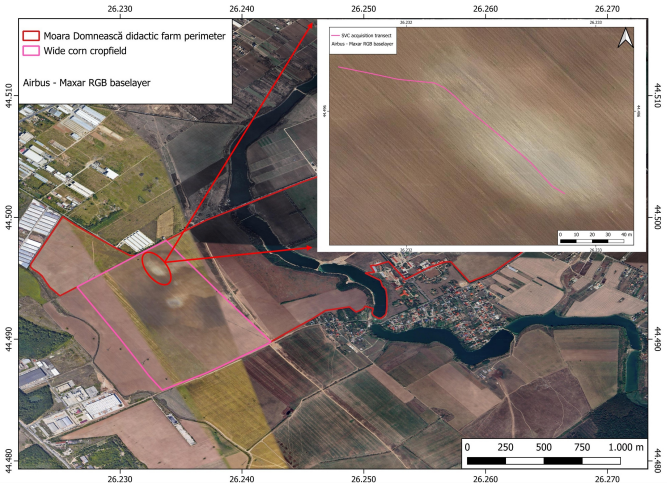


Fig. 1. Area of study within the Didactic Farm perimeter. The inset shows the portion of the field presenting vegetation with anomalous characteristics.

B. Imaging Spectroscopy

PRISMA and EnMAP acquisitions tasked over the area of study were geometrically and radiometrically corrected, and converted to reflectance values (PRISMA L2D and EnMAP L2A). ASI and DLR efforts ensured a monthly coverage of the area of interest (see Fig. 2). Image processing and data analysis

are carried out in a Python pipeline encompassing multiple tasks and steps. Firstly, using the AROSICS coregistration algorithm [11] hyperspectral images are co-registered with the closest matching cloud-free Sentinel-2 tile, to leverage Sentinel's unmatched geolocation accuracy [12]. Secondly, the data is prepared for the application of the Prospect and 4SAIL Radiative Transfer Models (RTMs) with the Pypro4sail python package [13]. Subsequently, a series of default vegetation primary variables are defined for the computation of Look-up Tables (LUTs). The application of such LUTs allows for the inversion of image-related spectra to obtain vegetation primary variables. In the future, this component of the pipeline will integrate additional representative vegetation features, directly derived from field and laboratory measurements to reduce the uncertainty related to the usage of default parameters in the LUT creation. In addition, error propagation will be assessed integrating the model with a Monte Carlo based global sensitivity analysis, allowing for the quantification of the uncertainty deriving from RTM inversion. The inversion process allows to obtain parameters such as leaf structure (N), chlorophyll *a* and *b*, carotenoid content, brown pigment content, water content, and Leaf Area Index (LAI). Working with high-dimensional data such as hyperspectral images poses a challenge related to data handling, especially when approaching the investigation from a multitemporal point of view. For this reason, the temporal stacking is performed on the RTM derived products, resulting in temporal trends of vegetation features and stressing variations related to the field conditions.

C. Ancillary Data

The analysis pipeline includes multiple ancillary datasets to represent the vegetation and meteorological field conditions. Among these, one of the vegetation features strongly influencing the response of crops to droughts is the cultivar's phenological phase at the time the water deficit impacts. Indeed, plant water stress causes severe changes in physiological processes, leading to a decrease or complete stop of growth, and posing a risk to the stability of crop production [14]. More specifically, wheat and maize are temperate crops suited to regions with seasonal rainfall [15], especially vulnerable to dryness during crucial growth phases like flowering and grain filling. Consequently, drought during these reproductive stages can severely reduce yields [16], [17]. Accordingly, to obtain phenological phases MODIS NDVI time-series [18] were extracted from Google Earth Engine for the area of interest during the maize growing season. The obtained reference NDVI evolution allows defining an NDVI threshold representing the change in the first and most sensitive phenological phases. More sophisticated models exist, such as the Derivative Dynamic Time Warping (DDTW) or shape model fitting (SMF-S) models [19], [20]; but can only be applied to the complete crop NDVI time-series. Additionally, the area of study is equipped with weather stations recording meteorological parameters. Therefore, the local potential evapotranspiration is computed according to the FAO 56 Penman-Monteith equation [21]. This value is then corrected by applying a crop factor specific for maize, resulting in a crop-calibrated evapotranspiration requirement. In view of extending the methodology to non-instrumented areas, the pipeline is designed to include the meteorological data extracted with the python package Meteostats [22].

D. Modelling Approach

The combination of results derived as specified above leads to the final and most relevant part of the processing and prediction algorithm. Here, the temporal variation of the vegetation traits, evapotranspiration requirements evolution and the phenological phases are combined using Machine Learning (ML), aiming at identifying patterns descriptive of drought stress onset. The regression algorithm currently adopted is a Random Forest, optimized with hyperparameter tuning. In the near future, additional algorithms will be tested for predictive accuracy and performance.

III. Results and Discussion

While the activity is still ongoing, some considerations can be made on the first results obtained. Inversion of vegetation traits with the application of RTMs shows the sensor's ability to capture subtle differences in field conditions. As previously stated in Section II-A, the investigated field exhibits localized anomalies, affecting the growth of vegetation therein. Fig. 3 shows the general LAI values in the EnMAP tile. Fig. 4 highlights how index correlates with the anomaly observed during field activities. This evidence can also be inferred from other inversion products. Considering that a singular image provides relevant information for intra-field heterogeneities, the adoption of a multitemporal approach will enable the identification of site specific dynamics, previously unobserved, and benefit the detection of vegetation stress responses. Despite the numerous acquisitions obtained over the area of study, the multitemporal hyperspectral analysis results, together with those deriving from MODIS phenological metrics and meteorological data, present challenges regarding the multimodal datasets integration and ML model development, which are currently being tackled.

IV. Conclusions

Overall, hyperspectral remote sensing has long proved its value and efficacy in multiple application fields. Nevertheless, with highly changing environments as croplands, shorter revisit time (similar to what is currently provided by multispectral missions and nanosatellite constellations) is needed. Therefore, this study showcases the relevance of international and inter-mission coordination efforts between ASI and DLR to achieve the highest possible temporal resolution over the area of study, with single-satellite missions. This allows investigating how adding temporal information can improve the detection of early vegetation stress signals related to drought impacts, by taking into account their dynamics. In addition, the integration of ancillary data from ground meteorological stations and multispectral missions allows to investigate correlations between droughts, vegetation response, and local

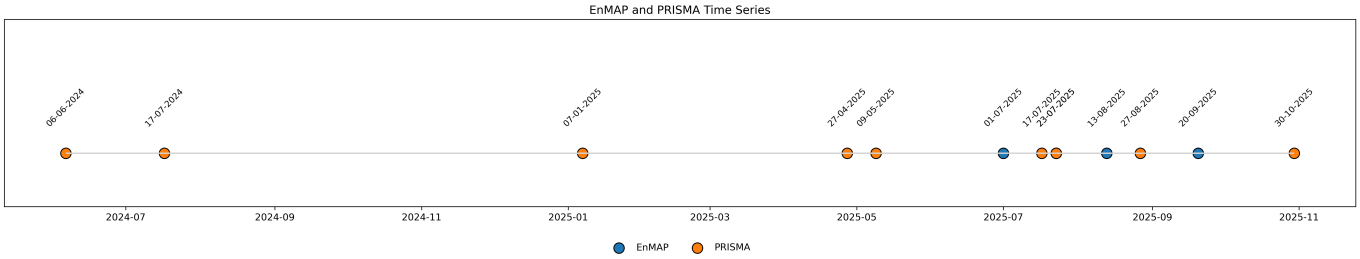


Fig. 2. Time-series of PRISMA and EnMAP acquisitions over the area of study.

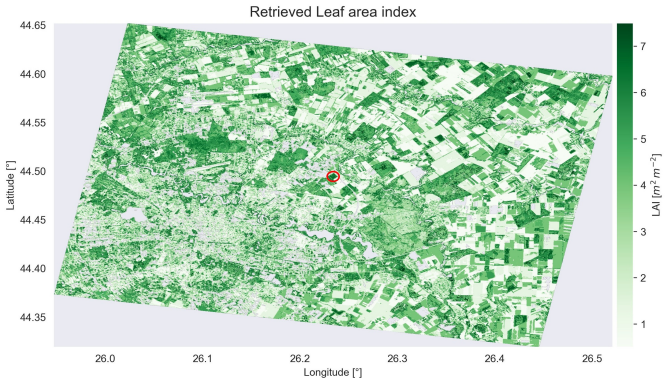


Fig. 3. Leaf Area Index (LAI) produced from the application of pypro4sail package to the 2025/07/01 EnMAP image. Red circle represents the position of the investigated field within the EnMAP tile.

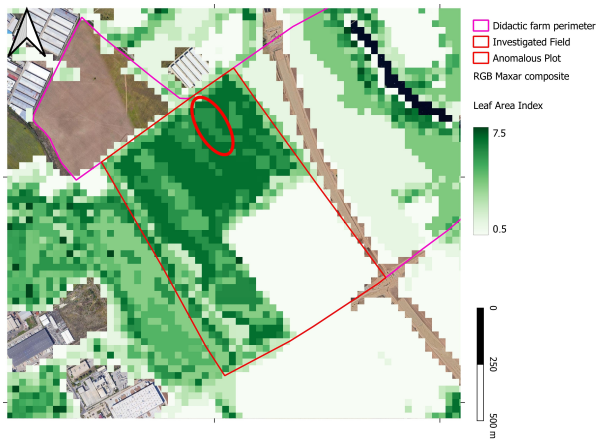


Fig. 4. Focus on the investigated field for the pypro4sail produced LAI computed on the 2025/07/01 EnMAP image. Red ellipse bounds the area identified with different vegetation characteristics (greenness, height) upon field survey.

conditions. The aim of this paper is not to demonstrate the full capabilities of the analysis pipeline, currently still under development, but to highlight how the prioritization of physically based inversion (RTM) achieved with standardized and sensor agnostic algorithms together with climate data, can serve as a methodological precursor for the operational use of the upcoming CHIME mission products.

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