Harvesting Intelligence: A Conceptual AI Framework for Precision Irrigation

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Abstract: Efficient water resource management is paramount for sustainable agriculture amidst increasing global population and climate variability. This paper establishes a novel theoretical framework for an AI-driven Decision Support System (DSS) specifically designed to enhance precision irrigation practices. The primary aim of this investigation is to leverage this framework to develop a deep learning AI model capable of accurately predicting and precisely detecting water stress sections within crops of interest, thereby enabling highly targeted and efficient water applications. The proposed framework integrates multiple heterogeneous data sources to construct a comprehensive spatio-temporal understanding of crop water status. It includes Earth Observation (EO) data from Sentinel-2 B satellites, specifically utilizing vegetation indices such as Normalized Difference Vegetation Index (NDVI) for assessing vegetation health and Normalized Difference Moisture Index (NDMI) for soil water content. Complementing this, high-resolution in-situ measurements are collected by IoT sensors (e.g., IoT-NPK for soil moisture, NPK levels, temperature, and pH) mounted on mobile robot platforms like PlatypOUs, providing essential ground truth validation. Furthermore, meteorological data, i.e., precipitation, air, and soil humidity, is integrated to provide crucial environmental context and predictive insights. This paper outlines a methodology for developing a Recurrent Neural Network (RNN) architecture based on a U-Net topology that will effectively encode features from these integrated data streams. The model incorporates multiple convolution layers for efficient spatial feature extraction, Long Short-Term Memory (LSTM) layers to capture temporal dependencies, and attention layers to focus on the most critical features for prediction. The ultimate output is a newly generated image representing the predicted spatial distribution of water stress across the field of interest, allowing pixel-based classification for targeted irrigation recommendations. This foundational investigation, including initial data analysis and feature engineering, paves the way towards optimized water use, significantly improving agricultural productivity and enhancing resource conservation.

Future research will focus on this advanced AI model's rigorous development, training, and validation.

Index Terms: Water sustainability, Precision Farming, Artificial Intelligence, Human operator support, Mobile Robot Platforms, IoT.

1 Introduction

The increasing global population and changing climate patterns place unprecedented demands on water resources, particularly in the agricultural sector, which accounts for a significant portion of freshwater consumption [1]. Thus, efficient management of water resources is crucial to ensure sustainable agricultural productivity and global food security [2]. Traditional irrigation practices often lead to water wastage due to inefficient distribution and a lack of precise information on crop water requirements [3]. Therefore, there is a growing need for innovative approaches to optimize water use, improve crop yields, and minimize environmental impact.

The health and productivity of crops are intricately linked to the availability of essential nutrients, including nitrates (N), phosphates (P), and potassium (K) [4]. These macro-nutrients play vital roles in various physiological processes such as photosynthesis, nutrient transport, and root development [5]. Monitoring their levels in the soil is crucial to optimize fertilization and irrigation strategies [6]. In addition, Earth Observation (EO) systems provide valuable data for land cover classification [7], [8], which is essential to understand the spatial distribution of different types of vegetation and their water requirements. Classifying land cover makes it possible to identify areas with similar hydrological characteristics and tailor irrigation management accordingly.

Satellite sensors offer a powerful means to assess vegetation conditions and water stress [9]. The Normalized Difference Vegetation Index (NDVI) is a widely used index that measures the greenness of vegetation and is related to photosynthetic activity and biomass [10]. On the other hand, the Normalized Difference Moisture Index (NDMI) is sensitive to the water content of vegetation and soil [7]. These indices, derived from multi-spectral imagery acquired by satellites, i.e., Sentinel-2 A/B, provide valuable information on crop water status's spatial and temporal variability [8], [11].

Although EO provides a broad overview, in situ data collection is essential to capture variations at higher resolution and validate satellite-based information [9]. For this reason, mobile robot platforms equipped with environmental sensors offer a flexible and efficient solution to collect real-time data on soil conditions [12], [13]. These robots can measure crucial parameters, e.g., soil moisture and temperature, at specific locations within the field to be studied [14], providing valuable data to calibrate and validate models of water stress.

This paper is part of the Water Resource Efficiency Network (WREN) project, which aims to enhance the spatial and temporal resolution of drought monitoring and improve site-specific management support for optimal irrigation and crop yield, combining remote sensing and local data, leveraging EO methods and AI techniques [8]. This paper proposes a conceptual framework for an AI-driven decision support system (DSS), which integrates EO data, in-situ measurements from IoT sensors and mobile robot platforms, and advanced machine learning techniques to predict crop water stress and optimize irrigation scheduling. Based on the U-Net model, the proposed system will leverage a Recurrent Neural Network (RNN) architecture to effectively encode relevant features from satellite images and in-situ data. This approach aims to provide accurate, site-specific irrigation recommendations, enhance water use efficiency, improve crop health, and promote sustainable farming practices.

2 Background and Related Work

2.1 Earth Observation and Precision Farming

Earth Observation (EO) has become an indispensable tool in modern agriculture, offering a wide range of applications for precision farming ,[3], [9]. EO data from satellite and aerial platforms provide valuable information on various crop and environmental parameters, enabling farmers to make informed decisions and optimize their management practices.

The research of Ferreira et. al. [15] suggested that the combination of Earth observation and machine learning was successfully applied in several different fields across the world. The implications of EO in precision farming are not excluded, as this data can be used for multiple purposes e.g., crop monitoring, water management, nutrient management, pest and disease management, yield prediction, estimating crop yields before harvest; and land cover classification [7], [3], [11].

Consequently, by providing timely and accurate information, EO helps farmers to improve input use efficiency, reduce environmental impact, and enhance crop productivity [16].

Vegetation indices (VIs) are quantitative measures derived from EO data that provide information about the biophysical properties of a field to be studied, as they are widely used to assess crop health, monitor growth, and detect stress [17]. The Normalized Difference Vegetation Index (NDVI) is used to measure the difference between near-infrared (NIR) and red light reflected by vegetation, as healthy vegetation reflects more NIR light and absorbs more red light, resulting in high NDVI values, while low NDVI values indicate sparse or stressed vegetation [18].

On the other hand, the Normalized Difference Moisture Index (NDMI) is another important VI sensitive to vegetation water content. It uses the difference between NIR and shortwave infrared (SWIR) reflectance. SWIR is sensitive to water in plant canopies, so NDMI can help estimate crop water status and detect water stress [7].

Other VIs, such as the Enhanced Vegetation Index (EVI) and the Soil-Adjusted Vegetation Index (SAVI), are also used in agriculture to account for atmospheric effects and soil background, respectively, making them a good option to extract relevant characteristics to estimate crop water content [17].

Previous research has demonstrated the potential of EO and Artificial Intelligence (AI) to improve agricultural water management. For instance, [7] found a correlation above 90% between soil moisture values estimated from satellite images (using NDMI) and ground-truth moisture lectures based on the OPTRAM model, highlighting the effectiveness of EO in capturing soil moisture variations.

2.2 Mobile Robot Platforms in Precision Farming

In addition to EO data, real-time information on soil conditions is crucial for precision farming [8]. Soil parameters such as N, P, K levels, temperature, moisture, and pH can vary significantly within a field, affecting crop growth and yield [6], [4].

Sensors with ion-selective electrodes (ISEs) are devices that measure the activity of specific ions in a solution [19]. For this reason, this method can be used to determine the concentration of N, P, and K ions in the soil, providing a direct measure of nutrient availability to plants [20]. These electrodes are designed to selectively respond to their target ions, generating a potential difference proportional to the ion activity, which can then be converted into a measurable concentration using the Nernst equation 1 [19].

$$E = E^0 + \frac{RT}{nF} \ln(a_i) \tag{1}$$

where:

E is the measured potential, E^0 is the standard electrode potential, R is the ideal gas constant, T is the absolute temperature, n is the charge of the ion, F is the Faraday constant, a_i is the activity of the ion.

These sensors can be incorporated into Unmanned Vehicles (UV) as they can collect relevant soil information [13], providing a comprehensive understanding of its conditions throughout the field of study to optimize and validate water distribution models, fertilizer usage, irrigation scheduling, and other management practices.

Mobile robot platforms are increasingly being adopted in precision farming for various tasks, including in situ data collection [14]. As UVs can navigate through the field, this technology can significantly reduce the workload of farmers or researchers in several ways, being one of the motivations of this research.

2.2.1 The PlatypOUs Robot Platform.

The PlatypOUs robot (shown in Figure 1) is a differential drive mobile platform with two wheels on the front and a caster wheel on the back. Created by the Special College of Robotics of Obuda University [21]. The control system is based on the open-source ROS robotics middleware. The version used is Noetic [22], where a node has been created to receive a velocity input in a twist format to control the robot's position.

The robot has environmental sensors, including an IoT-NPK sensor, which measures soil moisture, NPK levels, temperature, and pH. Mobile robots like PlatypOUS streamlines the data collection process, improving the efficiency and accuracy of in situ measurements, which are crucial to generate accurate land cover maps, calibrate EO data, and train AI models to predict crop water stress.

2.3 AI in Precision Farming

AI is rapidly transforming the agricultural sector [2], with significant advances in water stress estimation and precision farming [3]. Machine learning algorithms, including deep learning techniques, are increasingly used to analyze complex agricultural data from various sources, including EO imagery, meteorological data, and in situ sensor measurements [5].

In water stress estimation, AI models are being developed to predict crop water requirements and detect drought conditions [23]. These models can identify patterns and relationships between different variables, such as vegetation indices, soil moisture, and weather parameters, to provide accurate and timely information on crop water status [24].

Artificial intelligence plays a crucial role in precision farming, allowing the development of site-specific management strategies [25]. Machine learning algorithms can be used to analyze data on soil properties, crop health, and environmental conditions to optimize the application of inputs such as water, fertilizers, and pesticides [23]. It increases efficiency, reduces costs, and minimizes environmental impact [16].

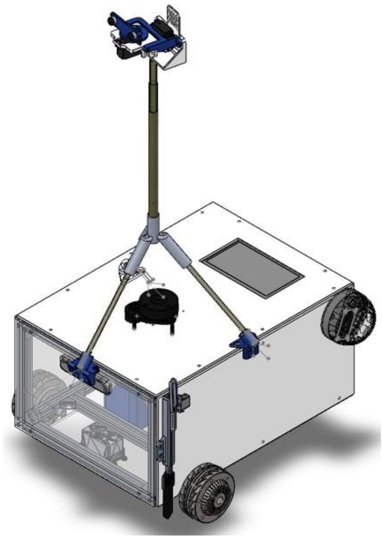

Figure 1
CAD representation of the PlatypOUs mobile robot platform

3 Methodology

The proposed methodology aims to analyze and integrate information from multiple data sources i.e. EO data (e.g. NDMI, NDVI), in-situ soil features' measurements, and weather stations information to train an AI in order to take part in a Decision Support System (DSS) for precision irrigation.

3.1 Field of Study

The land selected to be the subject of analysis is located in the region of Esztergom - Hungary (Csolnok), as shown in Figure 2.

3.2 Dataset acquisition and Pre-processing

3.2.1. Earth Observation Data. Multi-spectral images will be acquired from Sentinel-2 A/B satellites between January 2022 and May 2025. These images will be pre-selected based on the cloud cover percentage, where a threshold of 20% was set to discriminate relevant images considering the location of the field to be analyzed. Furthermore, vegetation indices, i.e. NDMI and NDVI will be calculated using equations 2 and 3, respectively, based on the frequencies Near Infrared (NIR), Short Wave Infrared (SWIR), and Red (RED) captured by the satellite sensors.

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \tag{2}$$

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{3}$$

Figure 2
Field of Study

As stated in section 2, Wojtaszek et. al. found a correlation above 90% between soil moisture values estimated from satellite images (using NDMI) and ground-truth moisture data [10]. These results strongly suggest that satellite imagery, more specifically, the NDMI and NDVI indexes, are ideal for providing relevant features to a deep learning model capable of predicting the state of water stress of the crop of interest [5], [14].

On the other hand, a shape based on the land geometry and location will be applied as a mask to create fix-sized images that contain only the information of the Field of Interest (FoI) to reduce noise and limit the amount of information that the deep learning model will process, therefore reducing the processing time [11], [15].

3.2.2 In-situ Data

Real-time data on soil conditions will be collected using IoT sensors mounted on a mobile robot platform. For research and development purposes, the PlatypOUS platform has been used to test the system integration, as the robot is equipped with an IoT-NPK sensor (see Figure 3) to measure soil moisture, NPK levels, temperature, and pH.

Once the data has been collected, an Inverse Distance Weight interpolation method will be applied to estimate the soil's moisture content across the entire FOI, to be used during the training and validation process of the deep learning model development [26].

3.2.3 Meteorological data

Weather data (i.e. precipitation, air and soil temperature, relative humidity, and soil moisture at different depths) will be collected from 121 available meteorological stations distributed throughout the country, as can be noticed in red dots inside the map of Figure 4.

The mentioned information is collected and stored in a csv file where each row contains the daily average of each variable sorted by station ID, opening the possibility of training a Random Forest Regressor model to predict future values on each one of the available stations.

The resultant dataset will be divided into two sub-sets: features (X) and targets (y). Both include all four selected variables, with the aim of predicting all variables based on their interdependence.

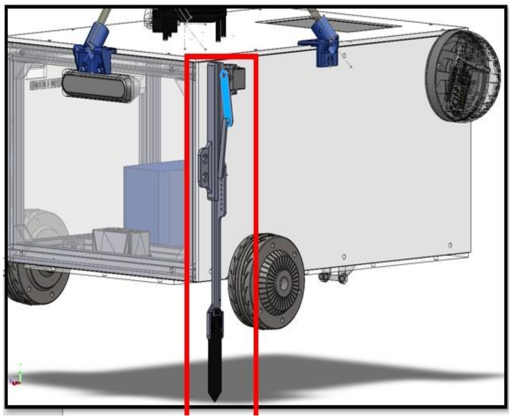

Figure 3

N-P-K Sensor

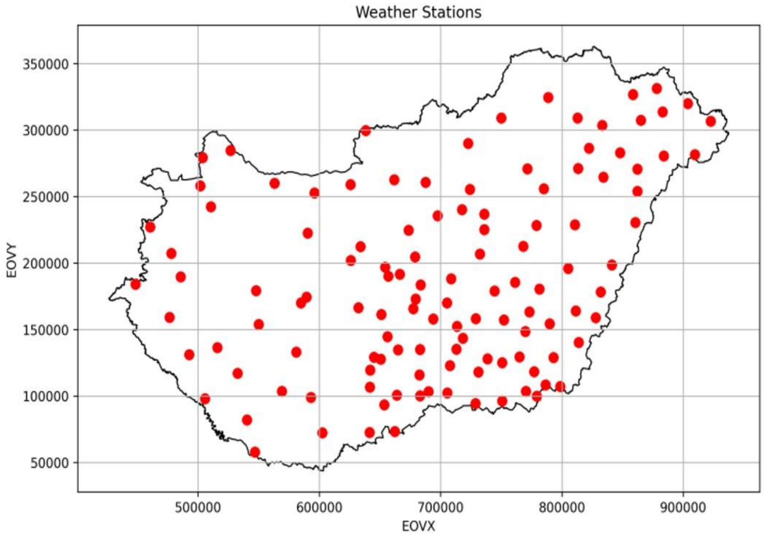

Figure 4
Spatial distribution of the available weather station across Hungary

Furthermore, the datasets will be normalized using the library *StandardScaler* [27] to normalize all features and target values between -1 and 1, ensuring they are on comparable scales to improve the model's performance.

The results of the Random Forest model predictions will be evaluated by comparing them with actual weather data, where metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) will assess the model accuracy [28].

3.3 Feature Engineering and Variable Selection

Random forests are known for their robustness and ability to handle large datasets with numerous variables. In this methodology, the model is hyper-parameterized using the library *GridSearchCV* to optimize performance, ensuring accurate predictions [29].

A set of four variables, i.e. *air temperature, soil temperature, soil moisture, and relative humidity,* was selected to be part of the prediction validation process; selection that was performed based on the author's considerations.

On the other hand, one of the features that Random Forest models offer is applied in this study where apart of a forecasting regression process, a relevance analysis will be performed to

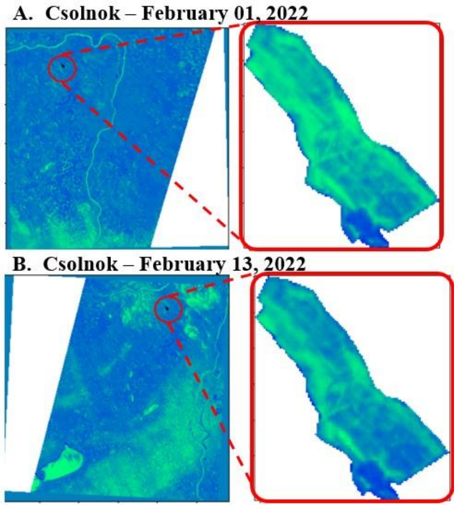

Figure 5
Satellite image pre-processing result

determine which of the preselected variables is the most relevant in weather forecasting [30], to be included as features in the proposed deep learning model.

4 Results

4.1 EO - Satellite images

Figure 5 shows two instances of the satellite image pre-processing, where A and B are the NDMI calculated per pixel before the region of interest is cut out while maintaining the geographic coordinates, and the respective normalized value, where the regions colored blue are the sections presenting more water stress.

4.2 Forecasted Variables

After training the Random Forest model based on the found hyper-parameters, it was used to predict the four selected variables for the test dataset (y). Predictions were scaled back to their original units using the inverse transform of the library StandardScaler [27]. The results were evaluated for each target variable, and the root mean square error (RMSE) was calculated as a measure of the accuracy of the prediction using equation 4.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

where y_i and $\hat{y}_i$ are the real and the predicted values, respectively, and n is the total number of trials.

RMSE Results	
Variable Name	RMSE (%)
Air Temperature	1.25
Relative humidity	3.45
Soil Temperature	1.75
Soil Moisture	4.02

Table 1
Calculated rmse for the selected variables

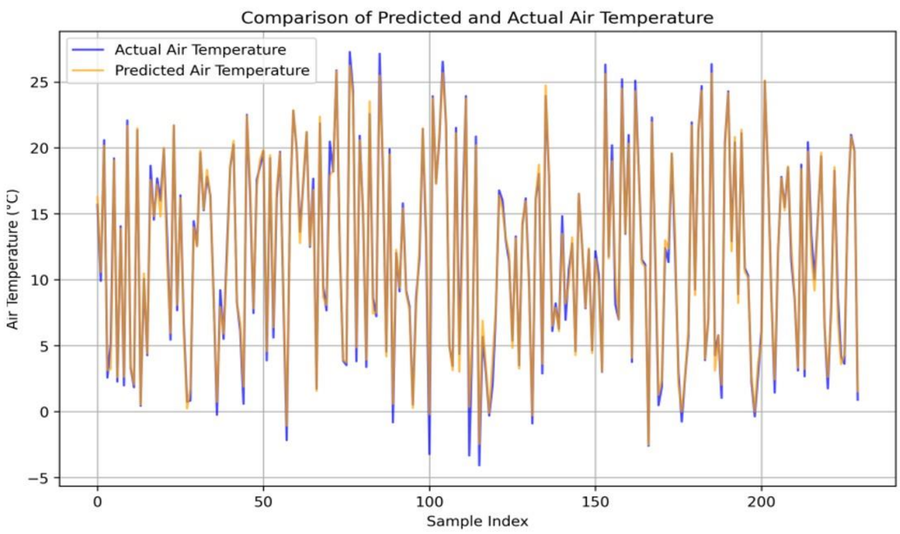

Figure 6
Predicted vs. Real values of one of the selected variables (Air Temperature)

Table 1 displays the resultant RMSE for each of the analyzed variables. In contrast, figure 6 compares the predicted and real data for the variable Air Temperature.

4.3 Variable Relevance Analysis

As section 3 mentioned, a Random Forest model was implemented to analyze the relevance of the available variables in terms of weather forecasting. As a result of the feature relevance analysis, it was identified that air and soil temperature were the most significant while predicting weather patterns from the selected dataset, as shown in Figure 7, underscoring their importance in agricultural modeling and suggesting that these variables should be included as features for the proposed AI model.

4.4 Discussion

The presented paper proposes a system framework to develop a DSS based on deep learning methods. It is RNNs that include convolution layers to encode relevant information, LSTM layers to retain time-relevant features into account to generate a prediction based on the

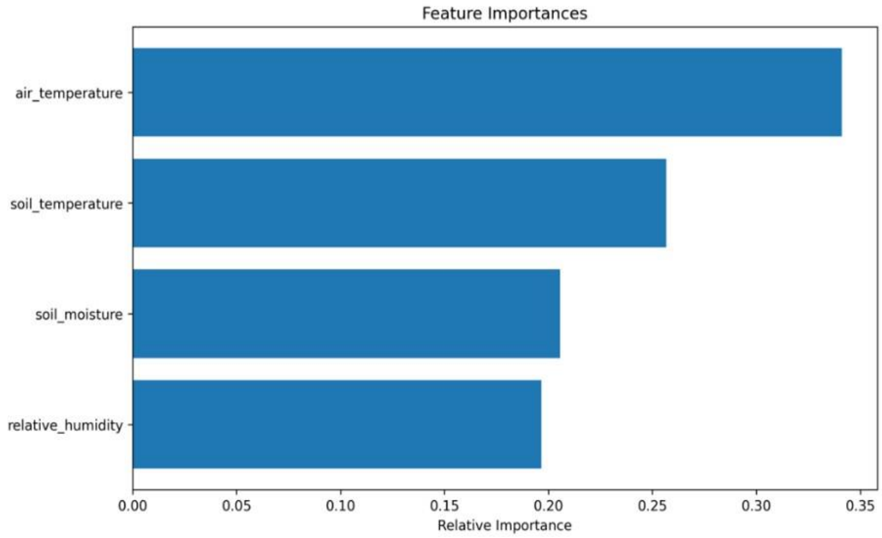

Figure 7

Results of the feature Relevance analysis

output of an attention layer before it is decoded to obtain a generated image representing the predicted state of the water stress distribution on the field of interest to be studied, providing the availability to suggest irrigation in the location where it is required, reducing the waste of the water resource during the irrigation process as it will be delimited to the area where it is required to prevent drought.

Although this proposal includes multiple relevant features from different data sources, it is notable that there is more information that should be considered in the DSS, as underground water deposits and elevation levels, land cover maps, in order to obtain a water flow approximation that could prevent drought in crops.

5 Further Developments

5.1 AI Model Development and Validation

A Recurrent Neural Network (RNN) model will be developed to predict crop water stress based on the extracted features. The model will be trained using historical data and validated using independent data sets. The following Figure 8 shows a representation of the topology of the proposed model, Where can be notable the intention to use multiple convolution layers to encode the features presented in the post-processed satellite images while including the most relevant variables from the weather stations to posteriorly integrate a Long Short Term Memory layer (LSTM) to capture the relevance of the encoded data, to continue with an Attention layer to highlight the relevance of the most important features to be considered before a set of inverse convolutions are decoding the predicted information into a newly generated image based on the predicted values.

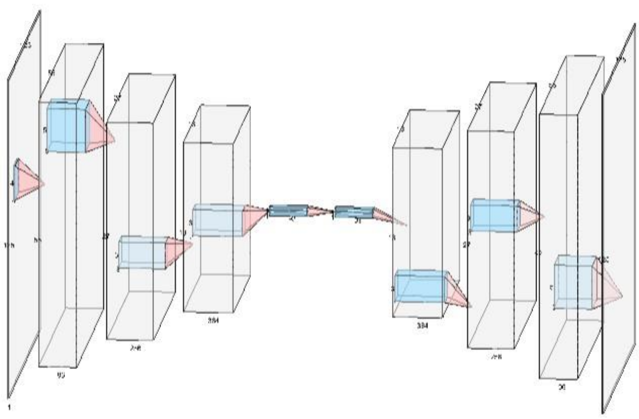

Figure 8.
Topological representation of the proposed Deep learning model

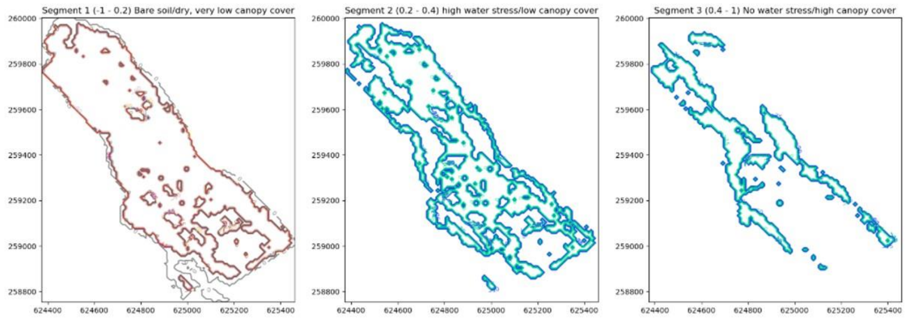

Figure 9
Example of the pixel-based classification

5.2 Decision Support System Development

A decision support system (DSS) will be developed to provide irrigation recommendations based on the model predictions.

The DSS will integrate data visualization tools and a user-friendly interface where the farmer will be notified where irrigation is required after applying a pixel-based classification, as the example in Figure 9 shows, where the range to determine the water-stressed sections was selected for demonstration purposes.

Conclusion

This paper successfully establishes a robust theoretical framework for an AI-driven Decision Support System (DSS) aimed at highly precise water stress detection and optimized irrigation management in agricultural settings. The feasibility and potential of this framework are underpinned by several key findings derived from the investigation.

Firstly, the research demonstrates the efficacy of integrating diverse, multi-modal data streams for a holistic understanding of crop water status. It This includes Earth Observation (EO) data, specifically the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) derived from Sentinel-2 A/B satellites, which provide crucial insights into vegetation health and soil water content. Secondly, integrating high-resolution in-situ measurements collected by IoT-NPK sensors on mobile robot platforms like PlatypOUs, provides essential ground truth for soil moisture, NPK levels, temperature, and pH. Complementing these, comprehensive meteorological data from a network of weather stations offers critical environmental context and predictive insights. The successful preliminary analysis, including the validation of meteorological data forecasting with low RMSE values (e.g., 1.25% for air temperature, 1.75% for soil temperature) suggests that variables such as air and soil temperature and humidity should be considered as features to take into account while training a deep learning model. On the other hand, satellite images can provide important information related to vegetation's health and soil water content by calculating the indexes NDVI and NDMI, respectively. The proposed deep learning topology includes convolution layers to encode information, an LSTM and Attention layer to perform a prediction, and inverse convolutions to generate an image based on the predicted features.

References

[1] S. N. Ngigi, Climate change adaptation strategies: water resources management options for smallholder farming systems in sub-Saharan Africa. New York, NY: The Earth Institute at Columbia University, 2009.

[2] A. L. Srivastav, R. Dhyani, M. Ranjan, S. Madhav, and M. Sillanpa¨a, "Climate-resilient strategies for sustainable¨ management of water resources and agriculture," Environmental Science and Pollution Research, vol. 28, no. 31, pp. 41576–41595, 2021.

[3] N. S. Grigg, Water Resources Management: Principles, Methods, and Tools. John Wiley & Sons, 2023.

[4] K. Misbah, A. Laamrani, K. Khechba, D. Dhiba, and A. Chehbouni, "Multi-sensors remote sensing applications for assessing, monitoring, and mapping npk content in soil and crops in african agricultural land," Remote Sensing, vol. 14, no. 1, p. 81, 2021.

[5] D. Gosai, C. Raval, R. Nayak, H. Jayswal, and A. Patel, "Crop recommendation system using machine learning," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 7, no. 3, pp. 558–569, 2021.

[6] A. Andualem, T. Wato, A. Asfaw, and G. Urgi, "Improving primary nutrients (npk) use efficiency for the sustainable production and productivity of cereal crops: A compressive review," Journal of Agriculture Sustainability and Environment ISSN, vol. 2997, p. 271X, 2024.

[7] M. W. Veron˝ e, V. Szab´ o, J. Kauser, A. Kocsis, and L. Lippmann, "55. mapping of soil moisture variability within´ a field by the optram model," in Precision agriculture'21. Wageningen Academic, 2021, pp. 459–466.

[8] M. G. B. V. P. A. N. G. K. J. N. E. B. A. E. G. Veron˝ e, M Wojtaszek () and G. Gy, "Water resources in´ efficient networks (wren) project overview and presentation of the research results carried out during the first year." International Symposium on Applied Informatics and Related Areas, vol. 18, 2023.

[9] Q. Zhao, L. Yu, Z. Du, D. Peng, P. Hao, Y. Zhang, and P. Gong, “An overview of the applications of earth observation satellite data: impacts and future trends,” Remote Sensing, vol. 14, no. 8, p. 1863, 2022.

[10] M. Wojtaszek and I. Abdurahmanov, “Crop water condition mapping by optical remote sensing.” International Journal of Geoinformatics, vol. 17, no. 1, 2021.

[11] H. Zhao, L. Di, Z. Sun, P. Hao, E. Yu, C. Zhang, and L. Lin, “Impacts of soil moisture on crop health: A remote sensing perspective,” in 2021 9th International Conference on Agro-Geoinformatics (Agro-Geoinformatics). IEEE, 2021, pp. 1–4.

[12] A. Vasudevan, D. A. Kumar, and N. Bhuvaneswari, “Precision farming using unmanned aerial and ground vehicles,” in 2016 IEEE technological innovations in ICT for agriculture and rural development (TIAR). IEEE, 2016, pp. 146–150.

[13] M. Padhiary, R. Kumar, and L. N. Sethi, “Navigating the future of agriculture: A comprehensive review of automatic all-terrain vehicles in precision farming,” Journal of The Institution of Engineers (India): Series A, vol. 105, no. 3, pp. 767–782, 2024.

[14] A. Farella, F. Paciolla, T. Quartarella, and S. Pascuzzi, “Agricultural unmanned ground vehicle (ugv): a brief overview,” in International Symposium on Farm Machinery and Processes Management in Sustainable Agriculture. Springer, 2024, pp. 137–146.

[15] B. Ferreira, R. G. Silva, and M. Iten, “Earth observation satellite imagery information based decision support using machine learning,” Remote Sensing, vol. 14, no. 15, p. 3776, 2022.

[16] R. Wilkinson, M. Mleczko, R. Brewin, K. Gaston, M. Mueller, J. Shutler, X. Yan, and K. Anderson, “Environmental impacts of earth observation data in the constellation and cloud computing era,” Science of The Total Environment, vol. 909, p. 168584, 2024.

[17] G. Camps-Valls, M. Campos-Taberner, A. Moreno-Mart´ ´ınez, S. Walther, G. Duveiller, A. Cescatti, M. D. Mahecha, J. Munoz-Mar˜ ´ı, F. J. Garc´ıa-Haro, L. Guanter et al., “A unified vegetation index for quantifying the terrestrial biosphere,” Science Advances, vol. 7, no. 9, p. eabc7447, 2021.

[18] S. Li, L. Xu, Y. Jing, H. Yin, X. Li, and X. Guan, “High-quality vegetation index product generation: A review of ndvi time series reconstruction techniques,” International Journal of Applied Earth Observation and Geoinformation, vol. 105, p. 102640, 2021.

[19] C. R. Rousseau and P. Buhlmann, “Calibration-free potentiometric sensing with solid-contact ion-selective¨ electrodes,” TrAC Trends in Analytical Chemistry, vol. 140, p. 116277, 2021.

[20] A. Kumari, P. Mishra, S. K. Chaulya, G. M. Prasad, M. Nadeem, V. Kisku, V. Kumar, and A. Chowdhury, “Estimation of soil nutrients and fertilizer dosage

using ion-selective electrodes for efficient soil management," Communications in soil science and plant analysis, vol. 55, no. 13, pp. 1920–1941, 2024.

[21] E. Noboa, M. Racz, L. Sz´ ucs, P. Galambos, G. M˝ arton, and G. Eigner, "Development of an emg based svm´ supported control solution for the platypous education mobile robot using mindrove headset," IFAC-PapersOnLine, vol. 54, no. 15, pp. 304–309, 2021.

[22] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Ng, "ROS: an open-source Robot Operating System," vol. 3, Jan. 2009, journal Abbreviation: ICRA Workshop on Open Source Software Publication Title: ICRA Workshop on Open Source Software.

[23] N. S. Chandel, S. K. Chakraborty, A. K. Chandel, K. Dubey, D. Jat, Y. A. Rajwade et al., "State-of-the-art aienabled mobile device for real-time water stress detection of field crops," Engineering Applications of Artificial Intelligence, vol. 131, p. 107863, 2024.

[24] I. A. Lakhiar, H. Yan, C. Zhang, G. Wang, B. He, B. Hao, Y. Han, B. Wang, R. Bao, T. N. Syed et al., "A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints," Agriculture, vol. 14, no. 7, p. 1141, 2024.

[25] I. Malashin, V. Tynchenko, A. Gantimurov, V. Nelyub, A. Borodulin, and Y. Tynchenko, "Predicting sustainable crop yields: Deep learning and explainable ai tools," Sustainability, vol. 16, no. 21, p. 9437, 2024.

[26] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," Electronic markets, vol. 31, no. 3, pp. 685–695, 2021.

[27] A. Majumder, S. Gupta, D. Singh, and S. Majumder, "An advanced model to predict heart disease applying random forest classifier and whale optimization algorithm," Indian Journal of Science and Technology, vol. 16, no. 43, pp. 3679–3690, 2023.

[28] R. Meenal, P. A. Michael, D. Pamela, and E. Rajasekaran, "Weather prediction using random forest machine learning model," Indonesian Journal of Electrical Engineering and Computer Science, vol. 22, no. 2, pp. 1208– 1215, 2021.

[29] T. Hidayat, D. Manongga, Y. Nataliani, S. Wijono, S. Y. Prasetyo, E. Maria, U. Raharja, I. Sembiring et al., "Performance prediction using cross validation (gridsearchcv) for stunting prevalence," in 2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS). IEEE, 2024, pp. 1–6.

[30] A. Mizumoto, "Calculating the relative importance of multiple regression predictor variables using dominance analysis and random forests," Language Learning, vol. 73, no. 1, pp. 161–196, 2023.