Precision Agriculture based on Machine Learning and Remote Sensing Techniques

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ABSTRACT

In today's rapidly evolving agricultural landscape, the integration of precision techniques and data-driven approaches has become essential, driven by technological innovations, such as the Internet of Things (IoT), Artificial Intelligence (AI), and cutting-edge aerial and satellite technologies. Precision agriculture aims to maximize productivity by closely monitoring soil health and employing advanced machine learning methods for precise data analysis. This study explores the evaluation of soil quality, placing particular emphasis on leveraging remote sensing technology to collect comprehensive data and imagery to analyze soil conditions related to olive cultivation. By harnessing cloud platforms integrated with satellite data, several analytical tools are made available, offering valuable insights for informed decision-making and operational efficiency across various sectors. Furthermore, this study introduces an AI-driven application tailored to predict the soil moisture levels. This application facilitates in-depth analysis, feature extraction, and the prediction of different vegetation indices using time-series satellite imagery. The study's findings highlight the exceptional accuracy achieved by the decision tree and extra tree regression models, with soil moisture estimation reaching approximately 91%, underscoring the importance and effectiveness of the proposed method in advancing agricultural practices.

Keywords-remote sensing; precision agriculture; artificial intelligence; soil moisture

I. INTRODUCTION

For decades, aircraft and satellites have been capturing the data and imagery of the Earth's surface, atmosphere, and oceans, which can be used for various applications that include urban and earth environmental observations. In 1972, Landsat, the first American civil satellite designed to monitor the ground surface, was launched and has contributed to the advancement of civil space-based remote sensing [1]. The technological progress based on sensing methods is considered a key to the success of precision agriculture. Remote sensing is used to improve productivity, reduce man labor, and ensure effective irrigation planning [2]. The main goal of precision agriculture is to support farmers in managing their production smartly and efficiently. The most important variable in any agricultural cultivation is soil moisture, which provides information about the water content and vegetation indices enployed in precision agriculture. Remote sensing offers the advantage of collecting vital information on a large temporal and spatial scale that cannot be achieved with traditional technologies.

Soil moisture plays an integral role in the proper growth of plants and crop yield production, since it not only serves as an agent of moisture restoration, but also as a temperature regulator for the plant. The need for different sources of moisture is explained through the process of thermoregulation. The plant evaporates up to 99 % of the water obtained and deploys between 0.2 and 0.5% of the remaining water to form a vegetative mass [3]. In 2010, the World Meteorological Organization [4] added soil moisture to the 50 Essential Climatic Variables (ECV) recommended for systematic observation. Soil moisture depends on various factors, which could be environmental, hydrogeological, and topological. Precise moisture measurements or predictions help to (1) make accurate plans for sowing dates, (2) monitoring the Soil Moisture Index (SMI), and (3) preventing financial losses for farmers. The use of vegetation indices in precision agriculture applications also provides many advantages to improve customer experience by saving costs [5].

The most accurate way to measure soil moisture is through the use of moisture sensors that are directly installed in the soil. There are four methods to measure soil moisture: (1) gravimeter, (2) watermark sensors, (3) capacitance sensors, and (4) tension meters. Unfortunately, directed measurements suffer from different issues depending on the sensor type. These issues are generally related to sensing area coverage, soil conditions, calibration requirements, and accessibility difficulties [5]. All these shortcomings encourage the development of remote sensing approaches, as they allow data acquisition for soil moisture measurements without physical contact with a sensor [6]. Applying remote sensing approaches to measure soil moisture can be further improved using Artificial Intelligence (AI) algorithms. Therefore, the accuracy of the received data depends on the performance of the AI algorithm [7].

The choice of using imagery to estimate moisture over traditional methods is multifaceted and has significant gains. Imagery, particularly from satellite sources, provides greater spatial coverage, allowing the monitoring of soil moisture levels in large agricultural areas cost-effectively and efficiently. Additionally, imagery-based approaches offer the ability to capture real-time or near-real-time data, enabling timely decision-making for agricultural practices such as irrigation management. Furthermore, remote sensing techniques can provide insights into soil moisture dynamics at various depths and spatial resolutions, providing a more comprehensive understanding of the soil moisture distribution compared to point measurements from traditional methods. This comprehensive spatial and temporal coverage improves the precision and accuracy of soil moisture estimates, thus facilitating optimized resource management and improved agricultural productivity.

Weather stations that capture information on soil moisture during a long period are publicly available and provide exact time series datasets, which can be employed to validate machine learning models. The International Soil Moisture Network is an international corporation that aims to validate and improve global satellite products on this topic [8]. This study introduces an innovative AI-powered solution to precisely estimate soil moisture, which is a crucial key parameter for successful agricultural production. The proposed approach integrates in situ measurements with advanced satellite imagery processing and machine learning algorithms, with the overarching goal of achieving precise soil moisture estimates in expansive spatial areas. The proposed solution can provide farmers with reliable data that may enable them to strategically design irrigation plans and optimize water usage to improve crop growth. This system also explores various vegetation indices, offering farmers valuable insights at every stage of their production cycle. This holistic approach can revolutionize agricultural practices, enabling farmers to make informed decisions and sustainably maximize their yields.

II. RELATED WORKS

Various methods have been proposed to extract valuable data for soil moisture information. Remote sensing techniques and instruments, such as satellites and radars, can be mainly divided into the following three categories of sensing methods.

1) Active Remote Sensing

This method captures soil moisture information using electromagnetic microwave radiation with wavelengths ranging between 0.5 and 100 cm [9]. The NASA SAR sensor is an active sensor that is the most widely deployed for soil moisture, as it can collect relevant information at a high resolution based on the spatial variation of the soil moisture in the ground [10]. Two parameters are included in the operation process: the sensor and the soil. The sensor parameter results in a variation in signal backscatter. The variation in soil surface characteristics represents the soil parameter. These methods calculate the attenuation of the signal backscatter through the canopy and volume of vegetation. The relationship between soil moisture and radar backscatter indicates that the lower the soil moisture content on the soil surface is, the stronger the radar backscatter [11] is considered. Many methods are adopted for active soil moisture sensors, but the most important ones are the backscattering models [12-14], statistical analysis techniques [15-16], and neural networks [17-18].

B. Passive Remote Sensing

Soil moisture information can also be modeled by utilizing passive sensors [19]. This approach defines the global distribution of soil moisture by capturing soil moisture information independently of the presence or absence of vegetation canopy. These sensors have the advantage of providing many important properties, such as the normalized difference vegetation index, research on the importance of these indices, and the relationship between them and many soil and environmental parameters. The universal triangular relationship method, the brightness model, and the statistical analysis technique are the most used approaches for this kind of sensing [20].

C. Combined Active and Passive Remote Sensing

With the increasing development of remote sensor instruments and space technologies, many methods integrate active and passive remote sensing approaches. The purpose is to mitigate their weaknesses and emphasize their strength. Active and passive remote sensing techniques aim to obtain a higher spatial resolution from active sensors and a higher temporal resolution with passive sensors to improve the accuracy of soil moisture estimation [20]. This approach is supported by the development of space applications that incorporate multisensory instruments and use their data in one system. In 2014, NASA launched the Soil Moisture Active, Passive (SMAP) mission [21], which is widely employed to obtain global soil moisture data with high temporal resolution and improved spatial resolutions that can even reach 3 km per pixel mark.

The most widely followed methods for this type of sensing are combined microwave algorithms, statistical analysis techniques, and neural networks. In [22], a satellite-derived system for soil properties was introduced to produce a preseason prediction. The prediction was based on the Normalized Difference Vegetation Index (NDVI). This is the most commonly utilized vegetation index in remote sensing, as it measures the photosynthetically active biomass in plants and provides a good idea of their health. In addition, it is implemented throughout the whole crop production season, and it also gives the most accurate insight in the middle of the season to monitor active crop growth. This system achieved valid results by exempting the need for high-resolution remote sensing data. In [23], a method was proposed to detect diseases in cotton through soil quality parameters using a support vector machine-based regression system. The model classified five cotton leaf diseases engaging a Raspberry Pi board with soil sensors, achieving a detection accuracy of about 83%. In [24], the role of intelligent agriculture was investigated by collecting information on productive crop management. A novel 3D drone mapping model was presented to address agriculture problems, using the wireless sensors based-IoT with AI intelligence algorithms to provide precision agriculture.

This study presents a smart precision agriculture system to detect soil moisture based on machine learning approaches. Satellite-captured soil quality data could replace traditional local soil moisture detection approaches, covering large areas and supporting high-precision agriculture.

III. PROPOSED MODEL

The proposed model employed the public dataset captured by the Landsat satellite. The Landsat program is a collaborative effort between the United States Geological Survey (USGS) and NASA and represents a long-standing initiative in satellite-based Earth observation. Its primary function involves providing detailed imagery of the Earth's surface, which holds significant value across a range of fields including agriculture, forestry, urban planning, and environmental surveillance. Operating along a specific orbital path, Landsat satellites capture comprehensive images of the planet's surface at regular intervals every 16 days. These images, referred to as multispectral data, encompass a wide spectrum of light wavelengths, thereby enabling researchers to conduct detailed analyses of the various earthly features and phenomena. Landsat data are publicly accessible, fostering widespread use and substantially contributing to the investigation of global environmental dynamics over extensive periods [1]. Figure 1 shows the training approach of the model, which consists of four steps.

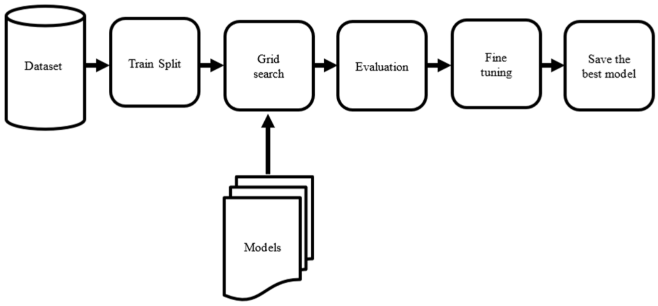

Fig. 1. Training model.

Train split is a technique for measuring the performance of a machine learning algorithm in any supervised learning problem and can be used for classification and regression tasks. Train split separates the dataset into two subsets. The first subset is the training set utilized to fit the model. The second set is the test set, which is not involved in the training of the model but instead serves the model with unknown inputs to make predictions and compare them to the actual values. Figure 2 briefly explains the training and test procedures for a dataset.

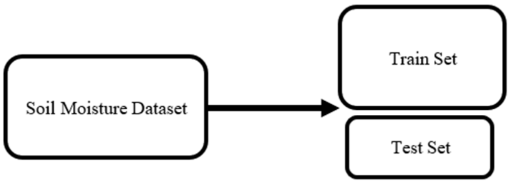

Fig. 2. Train-test split for soil moisture.

The size of the train and test sets is the most crucial parameter for the train test split configuration. The size of the training set depends on a few factors, including the computational cost in the training phase and the evaluation phase. In this case, the test and split methods were implemented using the scikit-learn library, particularly the train_test_split method with the following arguments:

x: Dataset containing the spectral indices after the feature selection procedure

y: Corresponding soil moisture values

Test_size: 0.2, meaning the dataset split is 80% for training and 20 % for testing

random_state: 0 to get the same training and testing set during different executions

After cleaning the data, only 69 samples were left out of the 80. The training set contained 80% of the dataset (55 samples) and the test set contained 14 samples. Every model is represented by a set of parameters. Training a machine learning model involves selecting the best hyperparameters for the learning algorithm to employ and learn to accurately map the input data (independent variables) to labels or targets (dependent variable). Due to the complexity of choosing the best hyperparameters for the proposed model, the grid search technique was adopted to automatically customize and optimize the proposed model. This technique was employed from the scikit-learn Python module for hyperparameter tuning. The first step is to define the search space, which can be illustrated as an n-dimensional volume. For each hyperparameter value, a point in the search space is a vector with a specific value. The optimization procedure aims to discover a vector that gives the model the best after-learning performance, such as maximum accuracy or least error. Some optimization algorithms are applied to achieve this task although the most well-known ones are random search and grid search. The latter is implemented by defining a search space as a grid of parameters and exhaustively evaluating every position on the grid.

The proposed model aims to estimate the soil moisture based on spectral indices. Then a set of predictors is defined. The main step is to choose the best model within the data. This is ensured by testing various models and comparing their results. During this step, many models, such as the regression models, are applied and evaluated according to scores based on the best hyperparameters, as illustrated in Figure 3.

IV. RESULTS AND EXPERIMENTATION

In the context of soil moisture prediction models, the physical meaning refers to how accurately the models reflect the actual moisture levels in the soil. This involves understanding how the predicted values align with the measured soil moisture data and how this information can be interpreted and used in practical applications. The training of the soil moisture dataset was implemented as a Python function. Then, the grid search optimization technique was applied to tune the hyperparameters of each model. The Python module responsible for this feature is called the sklearn model section, and the method followed is called GridSearchCV. Table I depicts a comparison of the results of this study with those of previous studies based on the accuracy score. This allows for a comprehensive evaluation of the effectiveness of the proposed approach compared to existing methods. This table also defines the best values for the chosen hyperparameters to which the grid search technique was applied.

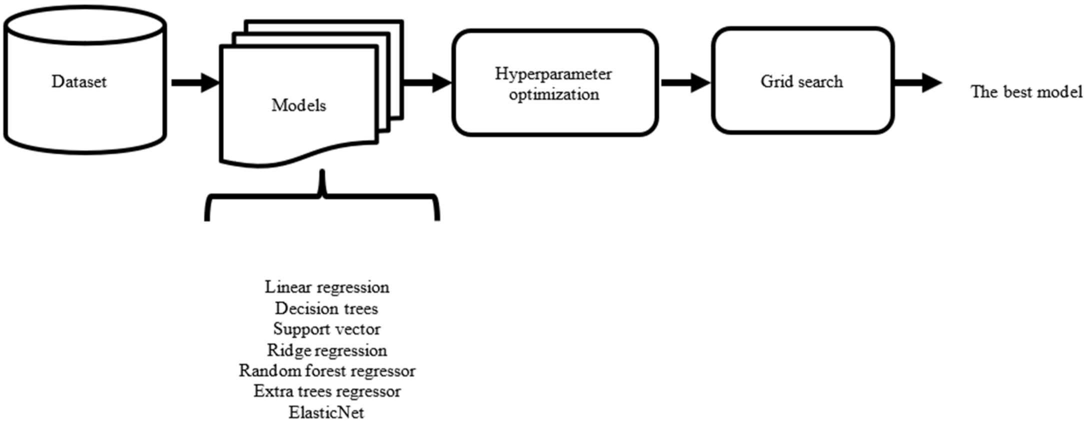

Fig. 3. Models' comparison procedure.

TABLE I. GRID SEARCH RESULTS

Model	Best score	Best parameters
Linear regression [25]	0.586132	{'copy_X': True, 'fit_intercept': True}
Decision tree [26]	0.909513	{'criterion': 'squared_error', 'splitter': 'best'}
Support vector regressor [27]	0.720655	{'C':10, 'epsilon':0.2, 'kernel': 'linear'}
Ridge regression [28]	0.684230	{'alpha':0.1, 'copy_X': True, 'fit_intercept':True}
Random forest regressor [29]	0.790572	{'criterion': 'squared_error', 'n_estimators': 10}
ElasticNet [30]	0.689741	{'alpha': 0.001, 'copy_X': True, 'fit_intercept': True}
Extra trees regressor (proposed model)	0.912985	{'criterion': 'squared_error', 'n_estimators': 100}

The linear regression model has poor accuracy, with a score of 58%, due to multicollinearity in the dataset. The technique of regularization was applied to the linear model to overcome this issue. Two models were deployed for the regularization of the linear regression model by implementing the L1 and L2 penalties, which are the ridge and ElasticNet models. The ridge model only uses the L2 penalty, while ElasticNet uses a combination of both penalties. As exhibited in the table above, both methods presented similar results with a score of around 70%, which is an impressive improvement compared to the linear regression model. The best parameters for ElasticNet included the alpha hyperparameter with a value of 0.001, which means that the model practically used only the L2 penalty, which explains the similar result. Therefore, the L1 penalty does not present any benefit to the prediction.

The support vector regressor exhibited slightly improved results compared to the ridge and ElasticNet models, scoring 72%. The search space for the C coefficient and epsilon hyperparameters was chosen based on the best practices for this problem. The linear kernel reached the best result. The poly and RBF kernels were utilized to explain the similarity in the score compared to the other linear models, including ridge and ElasticNet. The random forest regressor had even better results, scoring 79% accuracy. The most challenging task was to choose the correct number of estimators (10, 50, 100). The performance of the random forest model was improved when deploying a massive number of estimators, but its computational complexity constitutes a major drawback. The decision tree and extra trees regression models produced a decent score of around 91% with the criterion squared_error. These models performed the same way except for the splitting step, with the decision trees employing the bootstrap technique, while the extra trees regressor used a random search.

The results of the soil moisture prediction models reveal several noteworthy observations. Initially, the linear regression model demonstrated inadequate accuracy, attributed to the presence of multicollinearity in the dataset. However, significant improvements were observed when implementing the ridge and ElasticNet regularization models, both yielding comparable performance scores of approximately 70%. The ElasticNet model predominantly relied on the L2 penalty, indicating negligible benefits from the L1 penalty in terms of prediction accuracy. The support vector machine demonstrated a marginal enhancement over the regularization models, achieving a score of 72% due to meticulous hyperparameter selection via the grid search method, particularly favoring the linear kernel. The random forest regressor emerged as the best-performing model, scoring 79%, despite the persistent challenge of determining the optimal number of estimators. Finally, the decision tree and extra trees regression models exhibited the highest accuracy scores, hovering around 91%, underscoring their efficacy in predicting soil moisture levels. These results underscore the importance of leveraging diverse machine learning algorithms and optimization strategies to refine soil moisture predictions, thus fostering advancements in agricultural practices and environmental stewardship.

In summary, regularization techniques were applied to address the multicollinearity issues in the linear regression model, resulting in similar improvements in performance for both the ridge and ElasticNet models. The support vector machine exhibited a slight improvement over the regularization models, with its hyperparameters optimized by grid search. The random forest regression model outperformed the previous models, albeit with the challenge of selecting the optimal number of estimators. Lastly, the decision tree and extra trees regression models demonstrated robust performance, achieving a high accuracy score of around 91%, using different splitting techniques.

V. CONCLUSION

This study sheds light on the critical role of the soil moisture and vegetation indices in agricultural management. Given the limited availability of data, various machine-learning models were employed to accurately estimate soil moisture. In particular, the model based on the extra tree regressor excelled in predicting vegetation indices using satellite imagery. Both the decision tree and the extra tree regressor models demonstrated remarkable accuracy in estimating soil moisture, achieving an impressive accuracy rate of approximately 91%. Looking ahead, further improvement and testing of the proposed model can be achieved by increasing the sample size for soil moisture data. By expanding the dataset, the model's predictive capabilities can be enhanced, leading to more robust and reliable results. Additionally, ongoing advances in remote sensing technology offer promising opportunities to refine the model's performance and amplify its applications in precision agriculture.

REFERENCES

[1] J. R. Irons, J. L. Dwyer, and J. A. Barsi, "The next Landsat satellite: The Landsat Data Continuity Mission," *Remote Sensing of Environment*, vol. 122, pp. 11–21, Jul. 2012, https://doi.org/10.1016/j.rse.2011.08.026.

[2] A. Massaoudi, A. Berguiga, A. Harchay, M. Ben Ayed, and H. Belmabrouk, "Spectral and Energy Efficiency Trade-Off in UAV-Based Olive Irrigation Systems," *Applied Sciences*, vol. 13, no. 19, Jan. 2023, Art. no. 10739, https://doi.org/10.3390/app131910739.

[3] L. Yang *et al.*, "Effects of Superabsorbent Polymers on Infiltration and Evaporation of Soil Moisture Under Point Source Drip Irrigation," *Irrigation and Drainage*, vol. 64, no. 2, pp. 275–282, 2015, https://doi.org/10.1002/ird.1883.

[4] W. Dorigo *et al.*, "A New International Network for in Situ Soil Moisture Data," *Eos, Transactions American Geophysical Union*, vol. 92, no. 17, pp. 141–142, 2011, https://doi.org/10.1029/2011EO170001.

[5] M. N. Navidi, J. Seyedmohammadi, and S. A. Seyed Jalali, "Predicting soil water content using support vector machines improved by meta-heuristic algorithms and remotely sensed data," *Geomechanics and Geoengineering*, vol. 17, no. 3, pp. 712–726, May 2022, https://doi.org/10.1080/17486025.2020.1864032.

[6] S. A. B. Anas, R. S. S. Singh, and N. A. B. Kamarudin, "Designing an IoT Agriculture Monitoring System for Improving Farmer's Acceptance of Using IoT Technology," *Engineering, Technology & Applied Science Research*, vol. 12, no. 1, pp. 8157–8163, Feb. 2022, https://doi.org/10.48084/etasr.4667.

[7] J. Guo, Q. Bai, W. Guo, Z. Bu, and W. Zhang, "Soil moisture content estimation in winter wheat planting area for multi-source sensing data using CNNR," *Computers and Electronics in Agriculture*, vol. 193, p. 106670, Feb. 2022, https://doi.org/10.1016/j.compag.2021.106670.

[8] Y. A, G. Wang, P. Hu, X. Lai, B. Xue, and Q. Fang, "Root-zone soil moisture estimation based on remote sensing data and deep learning," *Environmental Research*, vol. 212, Sep. 2022, Art. no. 113278, https://doi.org/10.1016/j.envres.2022.113278.

[9] N. C. Eli-Chukwu, "Applications of Artificial Intelligence in Agriculture: A Review," *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, pp. 4377–4383, Aug. 2019, https://doi.org/10.48084/etasr.2756.

[10] S. Adeli, B. Salehi, M. Mahdianpari, L. J. Quackenbush, and B. Chapman, "Moving Toward L-Band NASA-ISRO SAR Mission (NISAR) Dense Time Series: Multipolarization Object-Based Classification of Wetlands Using Two Machine Learning Algorithms," *Earth and Space Science*, vol. 8, no. 11, 2021, Art. no. e2021EA001742, https://doi.org/10.1029/2021EA001742.

[11] N. C. Kundur and P. B. Mallikarjuna, "Deep Convolutional Neural Network Architecture for Plant Seedling Classification," *Engineering, Technology & Applied Science Research*, vol. 12, no. 6, pp. 9464–9470, Dec. 2022, https://doi.org/10.48084/etasr.5282.

[12] M. Xing, L. Chen, J. Wang, J. Shang, and X. Huang, "Soil Moisture Retrieval Using SAR Backscattering Ratio Method during the Crop Growing Season," *Remote Sensing*, vol. 14, no. 13, 2022, https://doi.org/10.3390/rs14133210.

[13] S. Chatterjee, J. Huang, and A. E. Hartemink, "Establishing an Empirical Model for Surface Soil Moisture Retrieval at the U.S. Climate Reference Network Using Sentinel-1 Backscatter and Ancillary Data," *Remote Sensing*, vol. 12, no. 8, 2020, https://doi.org/10.3390/rs12081242.

[14] J. Ezzahar *et al.*, "Evaluation of Backscattering Models and Support Vector Machine for the Retrieval of Bare Soil Moisture from Sentinel-1 Data," *Remote Sensing*, vol. 12, no. 1, 2020, https://doi.org/10.3390/rs12010072.

[15] Y. Wang, J. Yang, Y. Chen, P. De Maeyer, Z. Li, and W. Duan, "Detecting the Causal Effect of Soil Moisture on Precipitation Using Convergent Cross Mapping," *Scientific Reports*, vol. 8, no. 1, Art. no. 12171, Aug. 2018, https://doi.org/10.1038/s41598-018-30669-2.

[16] S. K. Dash and R. Sinha, "Spatiotemporal dynamics and interrelationship between soil moisture and groundwater over the Critical Zone Observatory in the Central Ganga plain, North India," *Hydrology and Earth System Sciences Discussions*, pp. 1–32, Feb. 2022, https://doi.org/10.5194/hess-2022-47.

[17] O. Eroglu, M. Kurum, D. Boyd, and A. C. Gurbuz, "High Spatio-Temporal Resolution CYGNSS Soil Moisture Estimates Using Artificial Neural Networks," *Remote Sensing*, vol. 11, no. 19, Jan. 2019, Art. no. 2272, https://doi.org/10.3390/rs11192272.

[18] Q. Yuan, H. Xu, T. Li, H. Shen, and L. Zhang, "Estimating surface soil moisture from satellite observations using a generalized regression neural network trained on sparse ground-based measurements in the continental U.S," *Journal of Hydrology*, vol. 580, Jan. 2020, Art. no. 124351, https://doi.org/10.1016/j.jhydrol.2019.124351.

[19] A. Sure and O. Dikshit, "Estimation of root zone soil moisture using passive microwave remote sensing: A case study for rice and wheat crops for three states in the Indo-Gangetic basin," *Journal of Environmental Management*, vol. 234, pp. 75–89, Mar. 2019, https://doi.org/10.1016/j.jenvman.2018.12.109.

[20] K. Edokossi, A. Calabia, S. Jin, and I. Molina, "GNSS-Reflectometry and Remote Sensing of Soil Moisture: A Review of Measurement Techniques, Methods, and Applications," *Remote Sensing*, vol. 12, no. 4, Jan. 2020, Art. no. 614, https://doi.org/10.3390/rs12040614.

[21] N. Ye *et al.*, "The Soil Moisture Active Passive Experiments: Validation of the SMAP Products in Australia," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 4, pp. 2922–2939, Jul. 2021, https://doi.org/10.1109/TGRS.2020.3007371.

[22] R. L. F. Cunha, B. Silva, and M. A. S. Netto, "A Scalable Machine Learning System for Pre-Season Agriculture Yield Forecast," in *2018 IEEE 14th International Conference on e-Science (e-Science)*, Amsterdam, Netherlands, Nov. 2018, pp. 423–430, https://doi.org/10.1109/eScience.2018.00131.

[23] A. A. Sarangdhar and V. R. Pawar, "Machine learning regression technique for cotton leaf disease detection and controlling using IoT," in *2017 International conference of Electronics, Communication and*

Aerospace Technology (ICECA), Coimbatore, India, Apr. 2017, vol. 2, pp. 449–454, https://doi.org/10.1109/ICECA.2017.8212855.

[24] P. K. Dutta and S. Mitra, "Application of Agricultural Drones and IoT to Understand Food Supply Chain During Post COVID-19," in *Agricultural Informatics*, John Wiley & Sons, Ltd, 2021, pp. 67–87.

[25] G. Ruß and R. Kruse, "Regression Models for Spatial Data: An Example from Precision Agriculture," in *Advances in Data Mining. Applications and Theoretical Aspects*, Berlin, Germany, 2010, pp. 450–463, https://doi.org/10.1007/978-3-642-14400-4_35.

[26] T. Waheed, R. B. Bonnell, S. O. Prasher, and E. Paulet, "Measuring performance in precision agriculture: CART-A decision tree approach," *Agricultural Water Management*, vol. 84, no. 1, pp. 173–185, Jul. 2006, https://doi.org/10.1016/j.agwat.2005.12.003.

[27] V. Sirisha and G. Sahitya, "Smart irrigation system for the reinforcement of Precision agriculture using prediction algorithm: SVR based smart irrigation," in *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, Jan. 2021, pp. 1059–1066, https://doi.org/10.1109/ICICT50816.2021.9358524.

[28] M. K. Sudha, M. Manorama, and T. Aditi, Eds., "Smart Agricultural Decision Support Systems for Predicting Soil Nutrition Value Using IoT and Ridge Regression," *AGRIS on-line Papers in Economics and Informatics*, vol. XIV, no. 1, pp. 95–106, 2022, https://doi.org/10.22004/ag.econ.320342.

[29] María Fernanda Restrepo Suescún, "Machine learning approaches for tomato crop yield prediction in precision agriculture," NOVA Information Management School, Lisbon, Portugal, Aug. 2021.

[30] Z. Chen and P. de Boves Harrington, "Self-Optimizing Support Vector Elastic Net," *Analytical Chemistry*, vol. 92, no. 23, pp. 15306–15316, Dec. 2020, https://doi.org/10.1021/acs.analchem.0c01506.

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