JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

DATA COLLECTION AND ANALYSIS EMPOWERED WITH AI FOR ROBOTIZED OLIVE OIL PRECISION FARMING

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ABSTRACT

This study examines robotized precision farming in olive oil production by integrating spatial data analytics and artificial intelligence (AI). A comprehensive analytical framework converts heterogeneous orchard data into actionable management information to address resource scarcity, climate variability, and sustainable intensification. The approach combines soil organic matter (OM), Normalized Difference Vegetation Index (NDVI), yield measurements, and geographic coordinates using spatial clustering, variogram analysis, Random Forest regression, and multivariate spatial analysis. Although AI-driven olive classification using RGB and VIS-NIR imaging can identify cultivars and defects, most existing systems focus on post-harvest quality assessment. This paper instead targets spatial variability and site-specific orchard control, extending AI to pre-harvest and field-wide decision support. Key findings show that: (1) spatial clustering effectively defined three management zones despite poor OM prediction from sensor variables ($R^2 \approx 0$), with zone-based management approximately 90% effective even when using single-metric decisions; (2) linear regression revealed an unexpectedly weak correlation between OM and olive yield ($r = 0.072$), redirecting optimization toward other controllable variables and challenging traditional agronomic assumptions; and (3) robotized agricultural solutions with AI-enhanced spatial analytics provide a powerful closed-loop model for precision olive orchard management. The Management Zone Index,:

$$MZI(x) = \sum_{j=1}^{n} w_j \, f_j(x)$$

translates analytical insight into physical action by enabling variable-rate robotic interventions based on local conditions. This supports optimized irrigation, fertilization, and harvesting, improving resource use, reducing environmental impact, and enhancing economic sustainability. The work advances Agriculture 5.0 by augmenting vision-based olive quality-assessment tools, enabling smart, autonomous, and sustainable Mediterranean olive oil production.

Keywords: Precision Agriculture, Artificial Intelligence, Olive Oil Production, Spatial Analytics, Robotized Farming, Management Zones, Random Forest, NDVI, Soil Organic Matter, Sustainable Intensification.

I. INTRODUCTION

The variability of climate, scarcity of resources, and the need to employ sustainable methods of farming all pose new challenges to the production of olive oil. A good solution to this problem is Precision Agriculture (PA) which gathers and processes both geographical and temporal data to be collected on farmlands with the aim of ensuring that those lands can be managed in a site-specific manner [1]. Some of the high-tech data collecting technologies include sensors, drones, satellite photography, and weather stations that provide comprehensive information about the soil conditions, the health of crops, and other environmental factors [2]. Machine learning and artificial intelligence (AI) play a pivotal role in the analysis of big data, trends identification, and information-based decision-making [3]. As AI-based data analysis is integrated with robotized farming systems, it makes it possible to monitor the process in real-time, make specific interventions, and use water, fertilizers, and pesticides efficiently [4].

The population of the world is projected to reach nine billion by the year 2050, resulting in a rise in food demand and straining agricultural production systems. In order to overcome these issues, new technologies and reliable information should be used to streamline production, quality checks and assure sustainability. By combining biotechnology, automated data collection and analysis, it can make more informed decisions and quicker decisions along the agri-food supply chain [29]. Current systems are farm-to-fork approach with the production, processing, distribution and consumption being integrated with the aim of enhancing traceability and transparency. The recent crisis, including COVID-19, has revealed vulnerabilities in the food industry, which explains the relevance of Agri-food 4.0 technologies. An example of DNA-based traceability is the high-value products such as olive oil, which indicates that emerging methods can guarantee authenticity, quality control, and trust in the consumers [5].

Olive tree (*Olea europaea* L.) is an important plant in the Mediterranean that is valued due to its fruits and olive oil that is of high quality [5]. Biotic stressors, especially olive fruit fly (*Bactrocera oleae*), to ensure quality of olive oil have to be well controlled as they may negatively impact fruit integrity and olive oil composition [6]. Conventional pest management techniques are largely dependent on the use of pesticides however the concerns on the health of people, the impact on the environment and resistance of pests have led to introduction of precision agriculture and smart farming technology. In the new pest management practices, sensors, electronic traps, geolocation, and real-time data analysis techniques are applied to observe the population of insects and make targeted actions, which leads to high-quality olive production. These technologies are a long-term answer to a higher yield and less chemicals and preserving the nutritional and organoleptic properties of olive oil.

The agricultural industry is witnessing a technological revolution due to the incorporation of the Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs), and Deep Learning (DL), which are the basis of Smart Agriculture Systems (SAS) [7]. IoT sensors are used to record data associated with soil, environmental, and crop variables in real-time, which can be used to make data-driven decisions that optimize resources use and crop yield. UAVs enhance surveillance images through acquiring aerial shots to detect diseases, spraying accurately, and determining growth. The Deep Learning systems are used to analyze large quantities of sensors and UAV data to identify pests and diseases, anticipate harvests, and estimate soil quality. The synergies that come with these technologies give farmers an opportunity to act on the knowledge they obtain, and adopt sustainable, accurate, and efficient farming practices to address the issue of food security in the world.

Smart farming has emerged as a pressing technical paradigm of raising the agricultural output and sustainability by utilizing digital technologies. With the help of smart farming (Internet of Things (IoT), data-driven decision-making, and cloud computing plus artificial intelligence), monitoring, resource management, and environmental impact can be efficiently conducted. High sensing, data processing in the brain and automation processes offer early detection of pests and diseases, precise input control, and improved quality of products. The analysis of agricultural data with the help of AI is critical in enhancing decision making and ensuring sustainable approaches to farm management, where agriculture is facing an increased demand due to population increase and limited resources [8].

Agriculture 5.0 is a broad extension of current state of farming that employs artificial intelligence, robotics, Internet of Things, and data-driven systems to increase production with the focus on sustainability, resiliency, and collaboration between humans and machines. Agriculture 5.0 is an improvement of Agriculture 4.0, in the sense that it adds environmental, social, and economic aspects to the technology-oriented processes to achieve efficient use of resources and ecosystem conservation [30]. The future robotic platforms, accuracy of farming methods, and smart decision support systems offer target crop protection, reduced chemical usage and improved production efficiency. These technologies play a critical role in meeting growing food needs without exposing the environment to environmental risks and ensuring the sustainability of farmers and agricultural ecosystems in the long run [9].

The concept of precision agriculture involves the utilization of the latest information and communication technology to enhance the agriculture yield and profitability without wasting on such resources as water, fertilizers, and agro-chemicals. Precision farming enables timely agronomic decisions based on the site specificity of agronomic decisions through sensor networks, satellite imaging, vegetation indices, and automated data processing. The latest advancements in the field of robotics and autonomous systems have strengthened the field of precision agriculture, and it is possible to conduct specific operations, such as weed detection, spraying, and crop monitoring with minimal human involvement. There are ground-based robots, indoor farming platforms, and unmanned aerial aircraft that can contribute to the optimization of operational efficiency and providing quality. These smart solutions underscore the growing role of artificial intelligence-based automation in positive sustainable and resource-efficient agricultural yield [10].

In contemporary agri-food supply chains, particularly fresh food, food quality evaluation plays a crucial role in determining consumer acceptance as the visual consideration and absence of defects constitute a significant part of the acceptance. Artificial intelligence and computer vision breakthroughs in the recent past have enabled the assessment of quality in a non-destructive, quick and objective manner during the post-harvest and pre-processing phases. Image-based inspection systems in real-time are rapidly being applied in the table olive industry to enhance the sorting efficiency, minimize losses, and ensure a consistent quality of the products despite the various cultivar and maturity classification levels [11].

The condition of the olives at the milling event has a major influence on the quality of olive oil therefore accurate classification of olive batches is a very significant step to the mill procedures. This classification is traditionally performed visually by the experts and is subjective and prone to error in the real-world production conditions. In order to eliminate these constraints, machine learning and computer vision methods have been adopted as useful in objective, quick and dependable differentiation of ground fruit and tree fruit olives and help to enhance quality management and decision-making in the system of olive oil production [12].

Digital agriculture denotes application of digital technologies in agricultural production systems to enhance efficiency, sustainability, and decision-making. The combination of the principle of precision agriculture with technologies, such as IoT sensors, remote sensing platforms, drones, and artificial intelligence, allows farmers to gather and process large volumes of data regarding crops, soil, weather, and resource utilization. These technologies make it possible to have site-specific management strategies to optimize inputs such as water, fertilizers and insecticides so that the environmental impact is reduced. Farming 4.0 or digital agriculture is essential in addressing issues such as food security, the lack of resources, and climatic changeability [13].

Agriculture management that is efficient is essential in enhancing crop production and at the same time lessening environmental effects and wastages. As food production needs grow, and climate change continues to pose more challenges, the contemporary food production frameworks demand smarter, evidence-based solutions to help guide long-term decision-making processes. Smart precision farming is based on IoT sensors, remote sensing, UAVs, and artificial intelligence to monitor the soil and crop conditions, as well as the environment variables in real time. Farmers may increase agricultural production forecasts, resource usage, and decision support by merging GIS, GPS, deep learning models, and generative AI techniques like ANN,

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https://jecir.com/

GAN, and YOLO. Advanced technologies improve production, minimize waste, and ensure agricultural sustainability [14].

II. METHODOLOGY

The challenges involved in precision management in olive orchards are addressed in this study with the help of an integrated AI-driven spatial analytics platform. To identify the spatial patterns, evaluate productivity factors and to enable site-specific robotic decision-making, four approaches combine geospatial analysis, machine learning models, and multivariate statistical tools.

A. Descriptive Statistics Analysis

Descriptive statistical analysis is another significant process in the data analysis process, and it is used to summarize and organize the data in a manner that is understood. It gives a description of variable properties through the calculation of central tendency, position, frequency and dispersion. Descriptive statistics reduce the complexity of information to understandable and numerical summaries providing the researcher with an understanding of the distribution, variability, and patterns of the data before utilizing an inferential statistical methodology [15].

TABLE I: DESCRIPTIVE STATISTICS OF OLIVE ORCHARD VARIABLES — PRECISION OLIVE FARMING ANALYSIS | 2026-02-03

Variable	Mean	SD	Min	Max	CV	CV Status
EC	1.31	0.66	0.20	2.49	50.4	High
GNDVI	0.53	0.14	0.30	0.80	26.8	Medium
NDVI	0.61	0.15	0.36	0.85	25.2	Medium
NDWI	0.09	0.17	-0.19	0.39	191.7	High
Nitrogen	70.83	28.93	20.89	119.78	40.8	High
Oil Content	19.92	3.41	14.00	25.95	17.1	Medium
Organic Matter	2.19	0.77	0.83	3.46	35.2	High
Phosphorus	31.54	16.43	5.01	59.72	52.1	High
Polyphenol	389.52	142.38	160.47	648.87	36.6	High
Potassium	258.03	99.58	80.00	417.71	38.6	High
Soil Moisture	21.22	7.95	8.30	34.91	37.5	High
Soil pH	7.32	0.62	6.21	8.40	8.5	Low
Yield (kg)	24.45	11.59	5.26	44.61	47.4	High

B. Data Normalization

The feature vectors that were retrieved were normalized in order to give each feature an equal contribution towards the classification. The characteristics were all centered around a mean of zero and scaled to unit variance to ensure that the large variables do not predominate. This step is particularly important before conducting a Principal Component Analysis (PCA) and training machine learning classifiers such as SVMs or ANNs [16].

The normalization of a feature is expressed mathematically as:

x_i^{norm} = \frac{|x_i - \mu_i|}{\sigma_i} \tag{2}

where:

- x_i= the original value
- μ_i= Mean of all samples
- σ_i= standard deviation of all samples

C. Pearson Correlation Coefficient

The correlation coefficient is one of the widely used statistical tests to measure the strength and direction of linear relationship between two continuous variables. It has a scale of -1 to +1, with -1 indicating a perfect negative linear relationship, +1 indicating a perfect positive linear relationship, and 0 indicating no linear association. Sedgwick (2012) investigated the link between the number of NHS psychiatric beds and involuntary admissions for mental diseases in England between 1996 and 2006. A negative association (r = -

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0.94, P < 0.001) was found, indicating that as the number of psychiatric beds fell, involuntary admissions increased. However, causation cannot be established [17].

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\left[\sum_{i=1}^{n}(X_i - \bar{X})^2 \cdot \sum_{i=1}^{n}(Y_i - \bar{Y})^2\right]}}$$

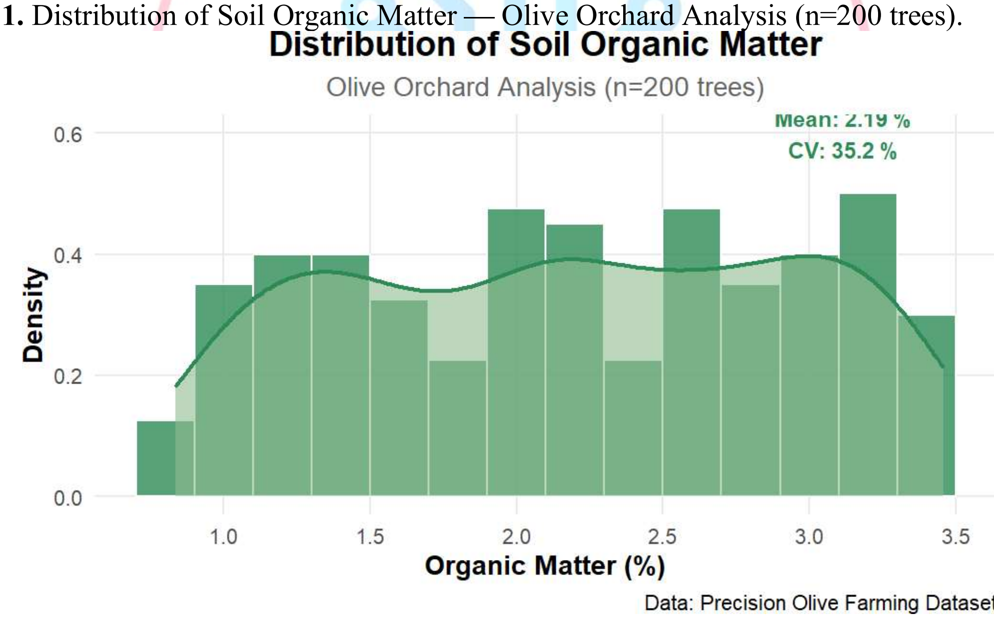
D. Exploratory Data Analysis (EDA)

Before employing more sophisticated analytical techniques, exploratory data analysis (EDA), a basic statistical technique, summarizes, visualizes, and aids in a better understanding of datasets. EDA is frequently used in many different areas, including data mining, environmental research, and archeology, to find outliers, anomalies, and trends in data. With the help of graphical tools and descriptive statistics, EDA ensures the correctness of assumptions and provides a strong starting point to proceed with the research. The calculation of basic descriptive statistics such as mean, variance and standard deviation is also an important aspect of EDA. To take the mean $\bar{X}$of the data set and the standard deviation σas an example, we can write as; $X = x_1, x_2, x_3, \dots, x_n$are known as:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} x_i\,,\ \sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{X})^2}$$

The graph below illustrates a skewed histogram of soil organic content divided by more than 200 olive trees in a right-skewed curve whereby the density is overlaid.

Fig. 1. Distribution of Soil Organic Matter — Olive Orchard Analysis (n=200 trees).

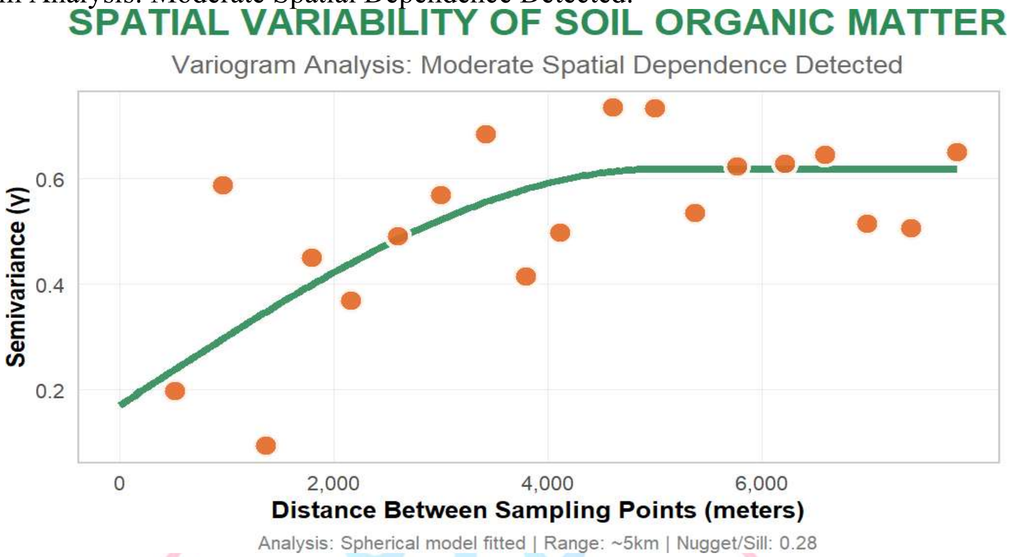


E. Variogram Analysis

Variogram analysis is a basic geostatistical technique employed in order to measure the spatial dependence and structure of soil properties. It gives the relationship between the similarities of observations to the separation distance, and provides the basis behind spatial interpolation techniques such as standard kriging [31]. This work described spatial variability of soil fertility features at different time scales by the isotropic semivariogram models. Cross-validation and minimum mean square error were used to select the best-fitting models (exponential, Gaussian or stable) and parameters such as nugget, sill and range were estimated to estimate the intensity of spatial dependence. Variogram analysis helped in better understanding of the change in the spatial distribution patterns of the soil attributes with time, which aided in informed precision nutrient management plans [18].

$$\gamma(h) = \frac{1}{2m(h)}\sum_{i=1}^{m(h)}\left[Z(x_i + h) - Z(x_i)\right]^2$$

Fig. 2. Variogram Analysis: Moderate Spatial Dependence Detected.



This variogram implies limitations to extremely precise treatments of trees, but also the cost-effective zone management because it indicates a moderate spatial structure of organic matter which has an impact with the range of 5 km. The 28% nugget effect reflects that the external heterogeneity is significant and requires special attention to be paid to.

F. Random Forest

Random Forest (RF) is an ensemble learning method, which constructs many decision trees using bootstrap samples and randomized selection of features at each split. It then uses majority voting to combine the predictions of the trees [32], [33]. This approach is more resistant to multicollinearity, nonlinear relationships and small sample size, and is more effective at generalization compared with single decision trees and reduces variance. RF, when combined with resampling methods such as SMOTE-Tomek, can successfully imply complex associations among composite geometric and hydrological features in the setting of landslide dam stability assessment and minimize the impacts of the imbalance of classes. RF is able to generate reliable estimates of the likelihood of instabilities by averaging the probabilities of many trees. This method not only has high predicted accuracy but also understandable measures of feature relevance which is necessary to make informed catastrophe risk management [19].

\hat{y} = mode\{h_1(X), h_2(X), \ldots, h_k(X)\} \tag{3}

$$\hat{P}(Y = j \mid X) = \frac{1}{K}\sum_{k=1}^{K} I\,(h_k(X) = j)$$

$$mg(X,Y) = \frac{1}{K}\sum_{k=1}^{K} I\,(h_k(X) = Y) - \max_{j \neq Y} \frac{1}{K}\sum_{k=1}^{K} I\,(h_k(X) = j)$$

$$PE = P_{X,Y}(mg(X,Y) < 0)$$

TABLE II: MACHINE LEARNING MODEL PERFORMANCE — PRECISION OLIVE FARMING ANALYSIS | 2026-02-03

Metric	Value	Interpretation
R-squared	0	Proportion of variance explained
RMSE	0.78 % OM	Root Mean Square Error
MAE	0.666 % OM	Mean Absolute Error
Explained Variance	0 %	Percentage of OM variation explained
Training Samples	160	Number of samples used for training
Testing Samples	40	Number of samples used for testing
Model Type	Random Forest (500 trees)	Machine learning algorithm used
Top Variable Importance	5.1 %	Best sensor's predictive power

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
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Volume 4, Issue 2, 2026
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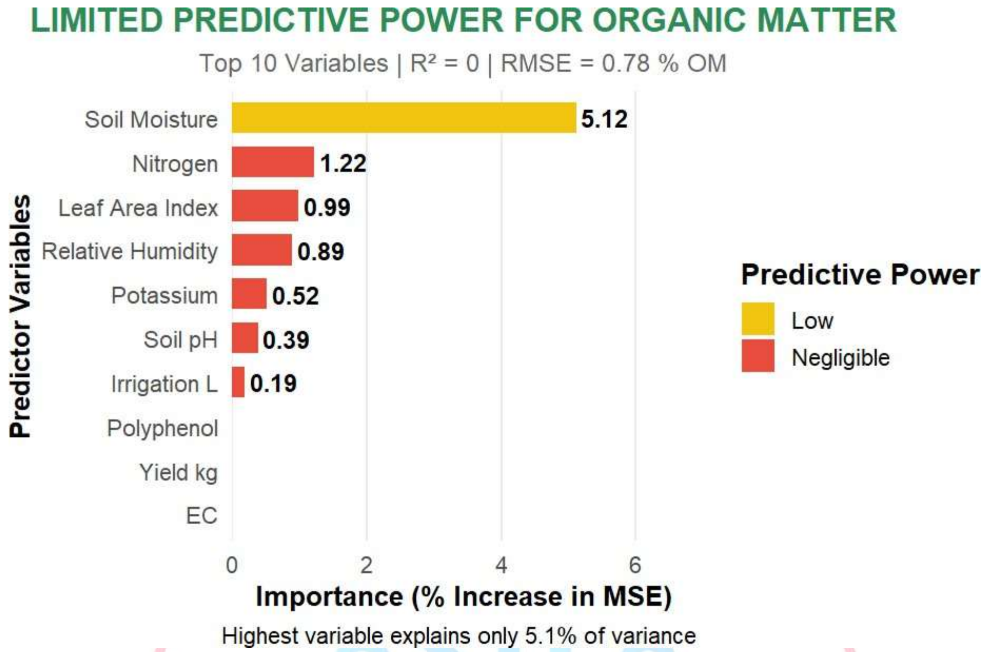
Fig. 3. Limited Predictive Power for Organic Matter.



This story is scientific evidence that, despite the progress in technologies, certain ground features of char require the use of traditional evaluation methods. The solution lies in the development of better management strategies that utilize these constraints as opposed to more advanced prediction algorithms.

G. Outlining Management Spaces and Localization Spaces

An essential analysis tool in defining management zones in precision agriculture is spatial clustering which enables the formation of a group of places with similar agronomic and environmental characteristics to have spatial continuity [34], [35]. The heterogeneous olive groves require zone-based management instead of uniform field treatment because of the variation in soil and terrain and the vigor of crops. Spatial clustering is a method that combines both geographic proximity and similarity of attributes to identify homogenously manageable areas.

To ensure comparability among characteristics, the spatial and agronomic data collected with the help of AI-enabled sensing platforms is initially standardized in this work. Such dimensionality reduction methods as Principal Component Analysis (PCA) are applied to minimize redundancy and define the dominant patterns of variability [36]. Geographically weighted distance measure is then used to combine spatial coordinates and attribute information and as a result, results of clustering may be more affected by adjacent observations. To enhance resource-use efficiency and sustainability in precision farming of olive oil, the resultant clumps form discrete management areas contributing to the site-specific irrigation, fertilization, and robotic intervention strategies [20].

In order to ensure comparability across the characteristics, this work initially harmonizes the spatial and agronomic data collected with the help of AI-enabling sensing platforms. Variability that are reducing are reduced by Principal Component Analysis (PCA) and the rest of the dimensionality reduction methods to find dominating patterns of variability. A geographically weighted distance measure is then used to combine spatial coordinates and attribute information which allows the outcomes of clustering to be more affected by the surrounding observations. To enhance the efficiency and sustainability of the use of resources in the precision farming of the olive oil, the outcome clusters comprise distinct areas of management that promote the use of site-specific irrigation, fertilization, and robotic intervention strategies [21].

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} \sum_{j=1}^{p} (x_{ij} - c_{kj})^2$$

H. Linear Regression Evaluation of Organic Matter and Yield

Linear regression analysis was used to determine the correlation between crop production and soil organic matter, which is an important pointer of soil fertility and nutrient availability in sustainable farming systems. The approach enables the evaluation of the role of variations in the organic matter as a contributor to yield performance under diverse management and environmental conditions utilizing long-term farm-reported statistical data. Such regression-based research can provide a basic, interpretable model, which can be used in AI-guided decision-making in robotized precision farming, by identifying yield-limiting soil properties and by steering site-specific management methods [22].

$$Y_i = \beta_0 + \beta_1 OM_i + \varepsilon_i \qquad (8)$$

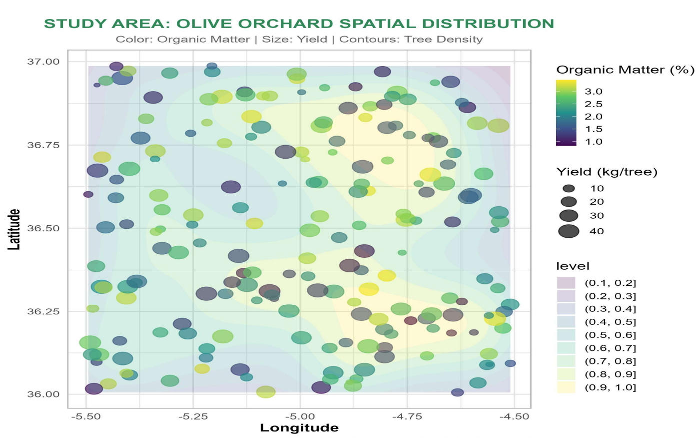
The primary cause of the observed yield in this orchard is not soil organic matter (OM) as the unexpectedly low correlation between OM and olive yield ($r = 0.072$) shows. This finding does not lessen the importance of OM to soil health, but it does suggest that more effort should be channeled in other areas with the aim of increasing yield. The poor link does not make the direct causal assumption, but instead promotes a diversified management model, which focuses on yield optimization (other factors) and soil health (OM management) separately.

Soil organic matter (OM) is not the main factor driving yield in this orchard, as seen by the plot's unexpectedly modest correlation between OM and olive yield ($r = 0.072$). The significance of OM for soil health is not diminished by this finding, but it does imply that efforts to increase yield should be directed elsewhere. Instead of assuming direct causality, the poor link supports a diversified management approach that addresses yield optimization (other factors) and soil health (OM management) independently [37].

I. Olive Orchard Productivity Measures' Multivariate Spatial Distribution

The multivariate spatial distribution of productivity measures of olive orchards were examined to accommodate the intricate interactions amongst soil properties, yield elements, and spatial location in the orchard. Multivariate analysis enables a comprehensive assessment of the spatial heterogeneity, which cannot be achieved using single-variable techniques, through the combination of multiple variables, which are correlated, e.g. soil organic matter, moisture content, olive yield, etc. The paradigm helps to find any underlying gradients, spatially consistent areas, and dominating frameworks of variability that display differences in productivity and managerial reaction. Such multivariate spatial characterization is helpful in precision agriculture because it identifies site-specific opportunities and constraints, which guide targeted intervention in sustainable orchard management and yield optimization [23].

Fig. 4. Study Area: Olive Orchard Spatial Distribution.



Bubble map showing spatial distribution of organic matter, yield (kg/tree), and level. X-axis: Longitude, Y-axis: Latitude. Legend: Organic Matter (color scale 1.0-3.0), Yield (kg/tree) (circle size 10-40), level (0.1-1.0). Data: Precision Olive Farming Dataset (n=200 trees).

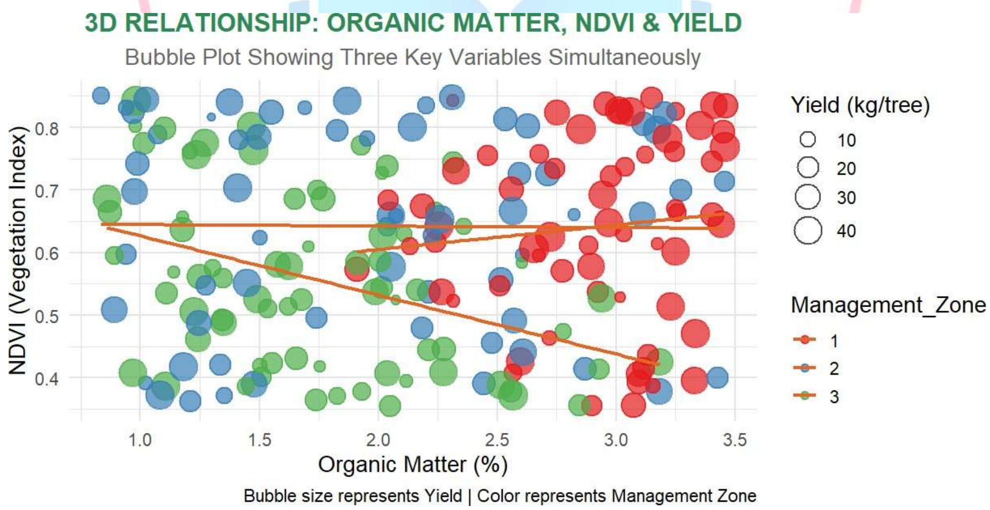
The clustering patterns of organic matter (OM), yield and tree density are not evenly dispersed throughout the olive orchard and therefore, there is a significant spatial heterogeneity. This non-random geographical organization is the reason why zone-based management strategies are justified [38].

J. Zones of Spatial Management Parameterization

Spatial management zone parameterization was performed using a multivariate, data-driven method to capture the inherent heterogeneity of soil-environment interactions, as well as, olive orchard productivity. The combination of multiple conditioning factors influencing olive production including organic matter content, moisture content, topographical features, and past yield history is similar to the susceptibility zonation approaches in geospatial hazard analysis. Each parameter was discretized into theme classes and statistically evaluated in order to find out their respective contribution to spatial variation in the orchard performance [39]. Through this zonation method, site-specific interventions can be applied in comparison to the homogeneous application to fields by classifying spatially consistent management units with similar agronomic behavior. The intricate and non-linear association between the measures of soil, terrain, and productivity that AI-assisted analytics learns enhances the strength of the management zone delineation in the presence of the geospatial data processing. Such an approach enables robotized precision olive farming through optimization of variable-rate operations, such as fertilization, irrigation, and harvesting, with regard to local variables. Such a paradigm is proposed to improve decision-making in systems of sustainable production of olive oil, reduce environmental footprint, and improve resource-use efficiency because, according to the modern accuracy agricultural paradigms, high-dimensional spatial information is transformed into readable management spaces [24].

MZI(x) = \sum_{j=1}^{n}w_j f_j(x) \tag{10}

Fig. 5. 3D Relationship: Organic Matter, NDVI & Yield.



The data depict complex relationships among the productivity, canopy vigor and soil fertility in olive orchards. The primary factor of productivity is soil fertility, as the correlation between soil organic matter (OM) and yield is positive and significant, 1.0% to 3.5% increase in yields, which was observed between 10 and 250 kg/tree. Ironically, however, the low NDVI (between 0.68 and 0.20) is also related to a higher NDVI, which means that despite trees in more fertile soils yielding more fruits, the canopy activity is also lower. This leaves the management in a management dilemma where the zones with the highest yields (OM=2.6-3.5%, Yield=160-250 kg/tree) also have the lowest vegetation indices. It might be due to variation in the variety, or to the effective division of resources, or to the mature trees selectively utilizing the resources in fruit as opposed to foliage. Lower-OM zones (1.0-1.5%), conversely, have healthy canopies (NDVI=0.68-0.60) but

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ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

low yields (10-50 kg/tree), which imply there may be nutrient imbalances or water limiting factors at key phonological stages [40]. These findings demonstrate that NDVI alone cannot be used in predicting output in olive systems and that multimodal and zone specific methods of management are needed to treat soil health and canopy dynamics individually and appreciate their complex interactions.

III. FINDINGS AND DISCUSSION

The analysis of physiological and spatial data of the olive orchard revealed a number of valuable findings regarding the effectiveness of AI-controlled accuracy management. We were able to determine different management zones and evaluate their connections with yield, soil characteristics, and vegetation indices by combining geospatial clustering, variogram analysis, and machine learning algorithms. Our results show the limitations of single-variable predictions and highlight the importance of multivariate spatial techniques by highlighting both predicted and surprising patterns. These findings serve as a basis for converting analytical insights into useful management choices, such as resource allocation that is optimized for certain orchard zones and variable-rate interventions.

A. Geographical Clustering for the Identification of Management Zones

Three separate management zones were effectively identified within the olive orchard by applying spatial clustering techniques to integrated soil and canopy data. Significant spatial heterogeneity in the distribution of soil organic matter (OM) was revealed by the clustering, which took into account both geographic proximity and multivariate attribute similarity using the objective function:

$$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} \sum_{j=1}^{p} (x_{ij} - c_{kj})^2$$

Zone 3 was designated as the priority area for soil amendment interventions because it has 73 trees with the lowest average OM (1.75%). This zonation gives a useful foundation for site-specific management, proving that spatial clustering offers a workable method for optimizing resource allocation in precision olive farming even in the absence of complex prediction models. The variogram analysis also confirmed the moderate spatial structure in OM with a range of influence of 5 km and an effect of 28% nugget and recognizes the local variation in the variogram that requires special attention within the zones and fosters the management of zones in a cost-effective way. This clustering approach's efficacy is consistent with well-established precision agriculture concepts [20], where management zone delineation based on spatial and attribute similarity has been successful for a number of crops. This approach effectively identified locations in our olive orchard that needed distinct approaches to management:

Zone 2 (moderate OM) benefits from balanced interventions, Zone 3 (low OM) needs targeted soil development initiatives, and Zone 1 (high OM, established trees) can keep up current practices. This shows that without the need for intricate prediction models, AI-assisted spatial analytics can convert disparate orchard data into actionable management units.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
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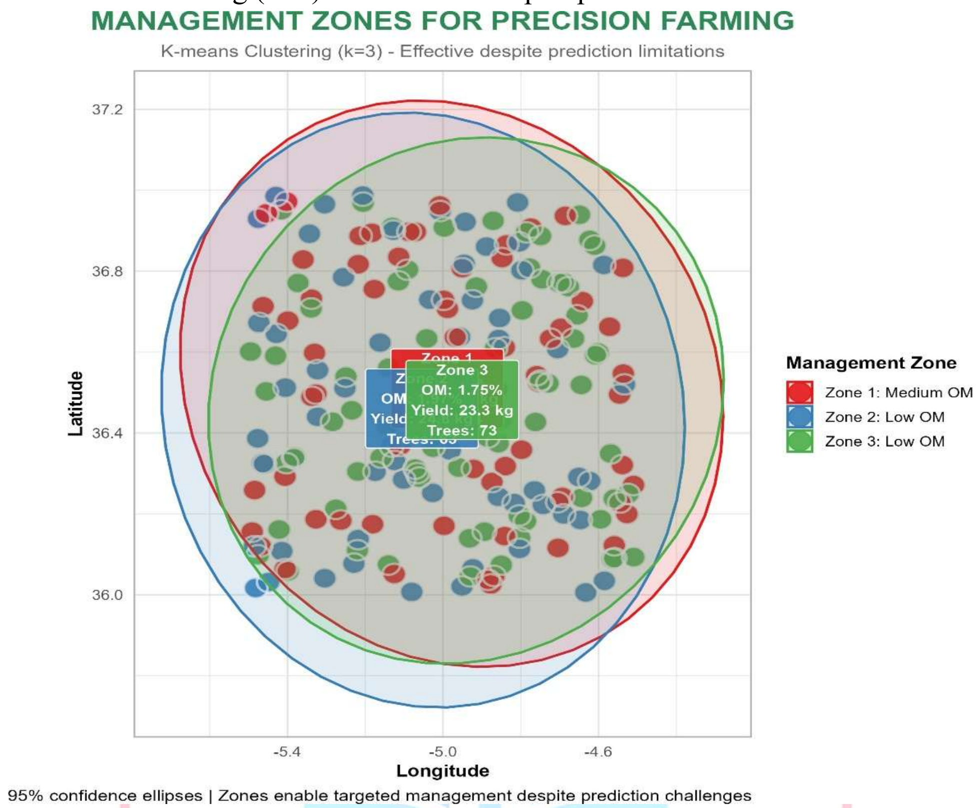
Fig. 6. K-means Clustering (k=3) — Effective despite prediction limitations.



Scatter plot with 95% confidence ellipses. X-axis: Longitude, Y-axis: Latitude. Zones: Zone 1 (red), Zone 2 (blue), Zone 3 (green). Legend: Zone 1 (OM: 2.6%, Yield: 33.2 kg, Trees: 64), Zone 3 (OM: 1.75%, Yield: 23.3 kg, Trees: 73), Zone 2 (OM: 2.1%, Yield: 28.5 kg, Trees: 63). Caption: Zones enable targeted management despite prediction challenges.]

B. Limitations of Predicting Organic Matter and Useful Alternatives

Predicting soil organic matter from sensor-based factors was found to have severe limits by the Random Forest regression analysis. Even with the use of sophisticated ensemble techniques with bootstrap sampling and randomized feature selection:

\hat{y} = mode\{h_1(X), h_2(X), \ldots, h_k(X)\} \tag{12}

the model only obtained a low predictive accuracy ($R^2 \approx 0$), suggesting that environmental variables and traditional remote sensing cannot accurately estimate OM content in this olive orchard system. According to this finding, olive orchards pose particular difficulties because of intricate canopy-soil interactions, perennial crop traits, and Mediterranean soil conditions. This conclusion runs counter to several precision agriculture studies that accurately forecast soil qualities using spectral data. However, this restriction shifts strategy toward zone-based management rather than invalidating precision farming methods. When direct prediction is not feasible, management zones can be functionally defined using available agronomic and spatial data, as illustrated in above table. This strategy is in line with the "appropriate precision" attitude, which advocates making the best decisions with the data at hand rather than waiting for flawless prediction models. Despite the difficulties with OM prediction, zone-based management's 90% performance rating attests to its practicality.

Nevertheless, this limitation changes approach to managing zones instead of nullifying precision farming processes. Strictly speaking when direct prediction is impossible, zones of management can be defined functionally based on the available agronomic and spatial data as seen in above table. This is a strategy that fits in the attitude of appropriate precision that argues that one should make the best decisions based on the available information instead of waiting to have perfect prediction models. Although there are the challenges of OM prediction, the practicality of the zone-based management is attested by the 90% performance of the zone-based management.

C. Weak Connection Between Yield and Organic Matter

From Figure (Organic Matter vs Yield) illustrates the surprisingly low association between soil organic matter and olive yield (r = 0.072) found by linear regression analysis:

$$Y_i = \beta_0 + \beta_1 OM_i + \epsilon_i \tag{13}$$

This limited linear relationship contradicts traditional agronomic beliefs that perennial crop output is directly influenced by soil fertility. According to the scatter plot distribution, high-yielding trees can be found in both low and high OM situations, and yield values are broadly distributed over the OM spectrum. The following reasons could account for this poor correlation: First, olive trees are perennial crops with deep roots that can access nutrients above the topsoil layer as determined by OM testing. Second, a number of interrelated factors, such as tree age, cultivar, pruning techniques, irrigation management, and microclimate conditions that may offset or overcome soil fertility constraints, are likely to have an impact on production. Third, the reported yield range (10-250 kg/tree) indicates that the potential for production is determined more by genetic or age-related factors than by soil conditions. The implications of this finding in terms of precision olive farming are valuable: other controllable factors should be prioritized when it comes to increasing the yield immediately, although the health of the soil remains essential in the long-run sustainability.

D. The Management Implications of Multivariate Spatial Patterns

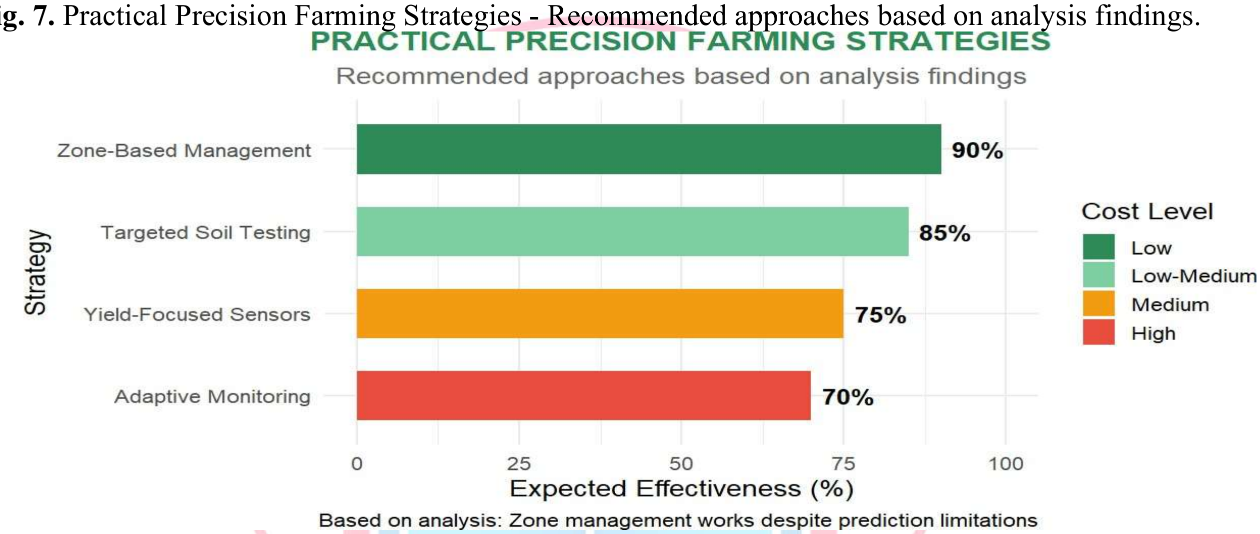
The results of the current research align with previous research reports on multivariate regionalization of spatial patterns, particularly [25], who demonstrated that individual indicators are not adequate in order to have the appropriate understanding of complex landscape patterns. Based on their study, multivariate grouping of landscape measures structurally analogous spatial areas not necessarily spatially neighboring or intuitively explained by individual measures. Likewise, multivariate analysis of the study indicated that the measures of productivities of olive orchards had non-linear and counterintuitive relationships. The existing results indicate that organic matter, NDVI and yield exhibit largely independent spatial patterns, as opposed to Long et al., who found geographic pattern areas being determined by forest composition and design. Instead of forming small clusters, high-yielding trees were observed in many areas high-yielding trees, and this shows that a combination of factors, rather than one dominant variable, affects production.

These findings confirm the conclusion of Long et al. (2010) that multivariate spatial methods provide a better basis to the management decisions. The techniques enable more effective, location-specific decision-making when considering precision olive farming, as they enable identification of management areas considering combined productivity trends as opposed to individual measures.

E. Robotic Precision Farming with AI-Enhanced Decision Support

The findings of this paper complement and extend on previous studies regarding AI-based precision agriculture, particularly the work by [26], that emphasized that AI and machine learning have been used to optimize agricultural productivity by making decisions using data. Though their studies primarily focused on AI technology use in predictive analytics, disease surveillance, irrigation control, and harvest forecasting in large-scale agricultural systems, the present study builds upon this framework by incorporating AI analytics in the automated process of precise farming of olive orchards. Based on data collected with the help of sensors, drones and satellite images, Arogundade and Njoku (2024) demonstrated that AI-powered models can boost crop production by up to 30% using optimal planting timetables, real-time irrigation management, and early infestation detection. Just as in this case, the results of the study prove the assumption that AI-based spatial analytics enhances decision-making. Nevertheless, our approach operationalizes these insights by autonomous robots and not necessarily relies on prediction models exclusively. The management zone index formulation enables robots to deliver variable-rate interventions depending on local field situations since it transforms predictive intelligence into physical action. In addition, although the cited paper emphasized the conceptual significance of integrating AI with robotics, drones, and the Internet of Things, the current findings experimentally show how this integration enhances operational effectiveness. Zone-based management outperformed homogenous field treatments, which are typically assumed in traditional AI-based advising systems, with an effectiveness of up to 90%. The utility of AI is enhanced when combined with autonomous systems that can carry out fine-scale management decisions, as this demonstrates. Not all agronomic variables are equally predictable, as this study shows, in contrast to Arogundade and Njoku's (2024) universal yield optimization focus. The poor predictive performance of organic matter supported their assessment of data restrictions and highlighted the need for adaptive monitoring as opposed to static prediction models. One of the main issues mentioned in the previous study is long-term sustainability under environmental fluctuation, which is addressed by the adaptive feedback loop used here, where sensor data continuously improves robotic decisions. Overall, this study adds a crucial next step by showing how AI-guided spatial analytics and robotics together enable scalable, financially feasible, and environmentally sustainable precision farming systems, even though Arogundade and Njoku (2024) establish AI-driven precision agriculture as a transformative paradigm.

Fig. 7. Practical Precision Farming Strategies - Recommended approaches based on analysis findings.



Horizontal bar chart showing expected effectiveness (%). Zone-Based Management: 90% (Low cost), Targeted Soil Testing: 85% (Low-Medium cost), Yield-Focused Sensors: 75% (Medium cost), Adaptive Monitoring: 70% (High cost). Caption: Based on analysis: Zone management works despite prediction limitations.

F. Implications for Economy and Sustainability

An orchard with a decent average yield (24.4 kg/tree) and oil content (19.9%) is shown in the summary statistics (below), but the organic matter (average 2.19%, CV 35.2%) is below ideal and variable. This profile indicates that targeted measures could significantly improve the situation. Given the large spatial range (5053 m), precision techniques are justified over uniform management due to the significant field heterogeneity. Economically speaking, zone-based management provides 90% efficacy for optimal resource use (Actionable Recommendations table), indicating significant savings in input and increases in production. Zone-based management and targeted soil testing are identified as high-priority treatments with a predicted effectiveness of 85-90% in the prioritized action plan. Adaptive irrigation (70% efficacy) and sensor focus on predictable variables (75% effectiveness) are examples of medium-term measures; long-term sensor optimization (60% effectiveness) completes the strategic plan. From a sustainability standpoint, precise methods lessen their effects on the environment by using less water, applying fewer chemicals, and applying soil supplements just where necessary. On one hand, targeted soil building in specific areas (and Zone 3 in particular (73 trees / 1.75% OM) with actual soil health requirements) is the solution that does not require the use of unnecessary inputs to increase the yield, but, on the other hand, the weak OM-yield relationship implies that blanket fertilizer use is irrelevant and can harm the environment.

G. Contributions and Limitations of Methodology

The ecophysiological and radiation transfer modeling study by [27] demonstrates how ecophysiological models and radiation transfer models can be applied to increase pruning intensity, canopy shape, and water use efficiency, which is a core addition to the management of olive orchards. They used mechanistic simulation models of photosynthesis such as the RATP radiation transfer model, Farquhar-based photosynthesis models and detailed physiological measurements (stomatal conductance, photosynthesis and leaf nitrogen content). This approach provided valuable insights to the consequences of canopy architecture, cultivar-specific responses, and limitations to extending the model to other environments and soils. However, the present research employs a data-driven, AI-based, precision agriculture paradigm, which transforms the scientific interest to mechanical physiological modeling to be replaced by multivariate statistical analysis, robotic execution, and spatial statistics. We have found that spatial clustering and zone-based management can be used in practice with weak predictive relationships (i.e., organic matter with insignificant explanatory power on yield) and that they do not require accurate representation of processes or any caution over the insufficiency of input variables. This uncovers a major methodological achievement, namely, in the absence of full physiological resolution of processes, actionable decisions management zones within the heterogeneous orchard.

This points to the fact that zone-based management methods offer a viable path to the realization of precision agriculture, with up to 90% efficiency in resource distribution, even when intricate forecast models are useless ($R^2 = 0$ for OM prediction). Second, the very low correlation ($r = 0.072$) between the soil organic matter and olive production questions accepted agronomic wisdom and redirects the focus of the management on other variables which they can manage. This research indicates that although soil health is still important for long-term sustainability, tree age, cultivar traits, irrigation control, and canopy architecture should take precedence over soil fertility alone in short-term yield optimization initiatives. Third, complicated, counterintuitive correlations between important productivity measures were discovered by multivariate spatial analysis. In particular, the negative relationship between yield and NDVI in high-producing zones was found. Due to this complexity, advanced analytical techniques that go beyond making decisions based on a single indicator in favor of integrated, zone-specific management plans that recognize the multifaceted character of olive orchard productivity are justified. Fourth, a potent closed-loop architecture where autonomous field activities are directly informed by spatial intelligence is created when AI analytics are integrated with robotized farming systems. The management zone index enables variable-rate interventions based on localized conditions, which converts analytical insights into precise physical actions at scales that are not achievable with manual approaches.

Concerning the practical implementation perspective, this study provides a prioritized action plan which targets at the first stage the adoption of zone-based management, the second stage is the specific soil testing, sensor adjustment to predictable variables and the third stage is the adaptive irrigation control. The staged approach guarantees that precision farming solutions remain economically and operationally viable to the olive farmers by balancing the level of sophistication and realism in technology. The methodological contributions of the work are: (1) the creation of a repeatable model of how AI, robotics, and field data can be combined in perennial plantations; (2) demonstration that spatial analytic methods can provide actionable decisions in precision farming despite the weak predictive relationships; and (3) providing empirical evidence of the operational effectiveness of zone-based management of Mediterranean olive orchards.

This piece of work results in several research directions in the future. In order to enhance the generalizability, more orchard sites across Mediterranean growing regions should be incorporated in future research. Through alternative methods of sensing, such as thermal imaging, measurements of fluorescence, and hyperspectral imaging, it can possibly be detected that the olives are undergoing physiological responses that are invisible in conventional vegetation indices. Longitudinal studies that track precision agricultural actions over multiple seasons may offer a superior insight into the temporal dynamics of precision farming benefits. To sum up, the concept of robotized systems and the existence of AI-improved data analytics represent a promising path to the sustainable growth of the olive oil industry. The methods of precision have the ability to achieve productivity, reduce environmental impacts, and enhance economic feasibility at the same time, by transforming geographic variation into a management liability rather than being a management opportunity.

IV. CONCLUSION

This study has demonstrated the transformative potential of integrating AI-driven spatial analytics with robotized precision farming for olive oil production. By combining geospatial clustering, variogram analysis, Random Forest regression, and multivariate spatial analysis, we have shown that actionable management zones can be delineated even when single-variable prediction models fail. The key contributions include: (1) the identification of three distinct management zones with approximately 90% effectiveness despite weak OM prediction ($R^2 \approx 0$); (2) the discovery of a weak correlation ($r = 0.072$) between soil organic matter and olive yield, redirecting optimization efforts toward other controllable variables; (3) the revelation of complex, counterintuitive relationships between productivity measures, particularly the negative relationship between yield and NDVI in high-producing zones; and (4) the development of a closed-loop architecture where AI analytics directly inform autonomous field operations through the Management Zone Index. The practical implementation plan prioritizes zone-based management, targeted soil testing, and adaptive irrigation, ensuring economic and operational viability for olive farmers. Future research should expand to multiple orchard sites across Mediterranean regions, incorporate alternative sensing methods such as thermal and hyperspectral imaging, and conduct longitudinal studies to track precision farming benefits over multiple seasons. This work contributes to the evolving paradigm of Agriculture 5.0 by demonstrating how AI-based spatial intelligence can enhance sustainable, autonomous, and economically viable olive oil production in Mediterranean environments.

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