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Identifying soil management strategies in olive groves through satellite imagery using conventional and machine learning approaches

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Introduction

The agricultural landscape in Southern Spain, particularly in the Córdoba countryside, is in an on-going transformation due to the expansion of woody crops, like olives orchards [1], which has implications for the erosion risk in the area. In this sense, the use of remote sensing to determine actual soil management strategies is a useful approach to calibrate erosion factors, e.g. the cover and management factor in RUSLE [2].

This communication explores the performance of several algorithms for the identification of soil management strategies in olive orchards. For this, it were considered 3 classes, as depicted in Fig.1. i) Bare soil (**BS**), with any combination of herbicide application and/or tillage; ii) Partial soil cover of the lane (alternate lanes of bare soil and cover crops, or narrow cover crop strips, less than 1 m wide, in all the lanes) by temporary cover crops (**TCC**), defined as those grown during the rainy season (autumn and winter) which are controlled in early spring); and iii) Full ground cover along all the lanes covering the entire inter-row (**FCC**), also controlled as temporary cover crops.

Fig.1 - Commercial olive orchards each of which employs one of the soil management strategies under study, as indicated in the lower left corner of each photograph.

Materials and Methods

A total of thirty-four olive farms, Fig.2, with a known soil management strategy were selected within the study area, located in the countryside of Cordoba (Southern Spain); more details in [1]. Fifty-percent of the farms were used for training, 25% for calibration and 25% for validation, balancing among treatments.

For each of the selected olive groves, a rectangular buffer of 50 x 100 meters was delineated at the centroid of the plot. The longest side of the buffer was aligned with the crop rows to ensure consistent spectral extraction. These buffers were then used to extract spectral bands from the Sentinel satellite constellation.

Fig. 2 - Spatial distribution of the studied olive farms (left) overlaid on a Sentinel true color composition image (10 meters resolution) from the 21st of February 2019. Red, purple, and light green dots and lines represent olive groves managed under BS, TCC, and FCC strategies. respectively.

The dataset used in this study included eight vegetation indices - ARVI, AVI, EVI, GNDVI, MBI, MCARI, NDVI, and SAVI - as detailed in Table 1, and ten individual spectral bands. After exploratory analysis, the temporal variation of both vegetation indexes and spectral reflectance values was evaluated by comparing summer (July 18th, 2018) and winter (February 21st, 2019) acquisitions.

Table 1 - Spectral vegetation indices used in the study, with their corresponding equations and consulted reference.

Name	Formula
ARVI	$(B8-(2\cdot B4-B2)/(B8+\ 2\cdot B4-B2)$
AVI	$(B8\cdot(1\ -B4)\ \cdot(B8-B4))^{1/3}$
EVI	$2.5\cdot(B8-B4)/(B8+6\cdot B4\ -7.5\cdot B2+1)$
GNDVI	$(B8\ -B3/B8+B3)$
MBI	$\left(\sqrt{(B11^2-B12^2)}\right)/B8$
MCARI	$\big((B5-B4)-0.2\cdot(B5-B3)\big)/(B5/B4)$
NDVI	$(B8\ -B4/B8+B4)$
SAVI	$((B8-B4)\cdot 1.5)/(B8+B4+1.5)$

A comparison of five different techniques, Fig.3, using the same Sentinel satellite imagery was performed. The techniques were: 1- Support Vector Machines (SVM); 2- Linear Discriminant Analysis (LDA); 3- Random Forest (RF); 4- Boosted Regression Trees (BRT); 5-Dense Neural Networks (DNN).

In order to ensure robust performance assessment, a two-stage random sampling strategy was applied. First, 50 random iterations were performed to extract the validation set, representing 25% of the total dataset in each iteration. The remaining 75% of the data was then randomly split into training (two-thirds) and calibration (one-third) subsets, also repeated across 50 iterations. The procedure resulted in a total of 2,500 simulations, which were performed for each evaluated technique and each type of classification, reaching a total of 25,000 simulations.) .

Dataset partitioning and pre-processing were carried out using the pandas library in Python. Complementary tools included NumPy for efficient numerical computations, and scikit-learn for implementing the random splitting strategy and managing data pipelines. This workflow ensured reproducibility and consistency across all simulations.

The conventional classification techniques were implemented using scikit-learn, a widely used machine learning library that provides efficient tools for data preprocessing, model selection and evaluation. A feedforward dense neural network was implemented in TensorFlow/Keras, with an input layer, three hidden layers (ReLU), and a SoftMax output layer. L2 regularization, Adam optimizer, and early stopping were used to reduce overfitting.

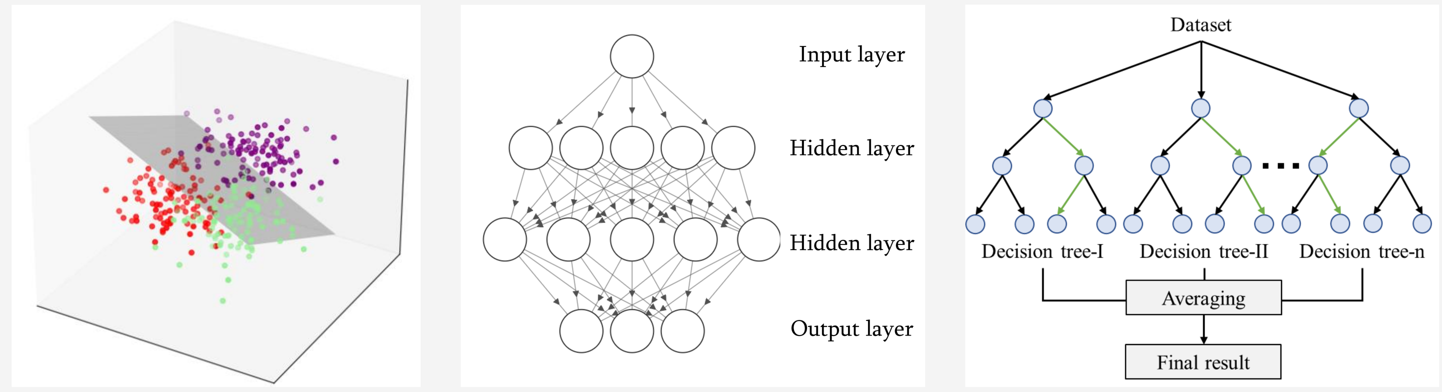

Fig. 3 - Schematic overview of three classification algorithms (SVM. DNN. and RF, from left to right) employed in techniques for soil management strategy detection in olive groves.

In addition, the entire methodological framework was independently applied to datasets derived from spectral indices and spectral wavelengths, allowing a comparative analysis of their predictive capabilities. To comprehensively assess techniques performance, several evaluation metrics were calculated for the training, calibration and validation subsets. These included accuracy, to quantify overall classification performance; sensitivity, to measure the techniques' ability to correctly identify positive cases; and specificity, to assess its effectiveness in distinguishing negative cases. This multi-metric evaluation provided a more nuanced understanding of the strengths and limitations of each classification approach.

Results

The results confirm that vegetation indexes outperform wavelength combinations in classification accuracy across all five techniques, as depicted in Fig.4. For the binary classification (BS vs. TCC&FCC), LDA and SVM were the best-performing techniques, reaching 99% accuracy with F1-score and Cohen's Kappa values of 0.99 and 1.00, respectively. These results, obtained from the validation set for the vegetation index dataset, indicate a high accuracy classification capability.

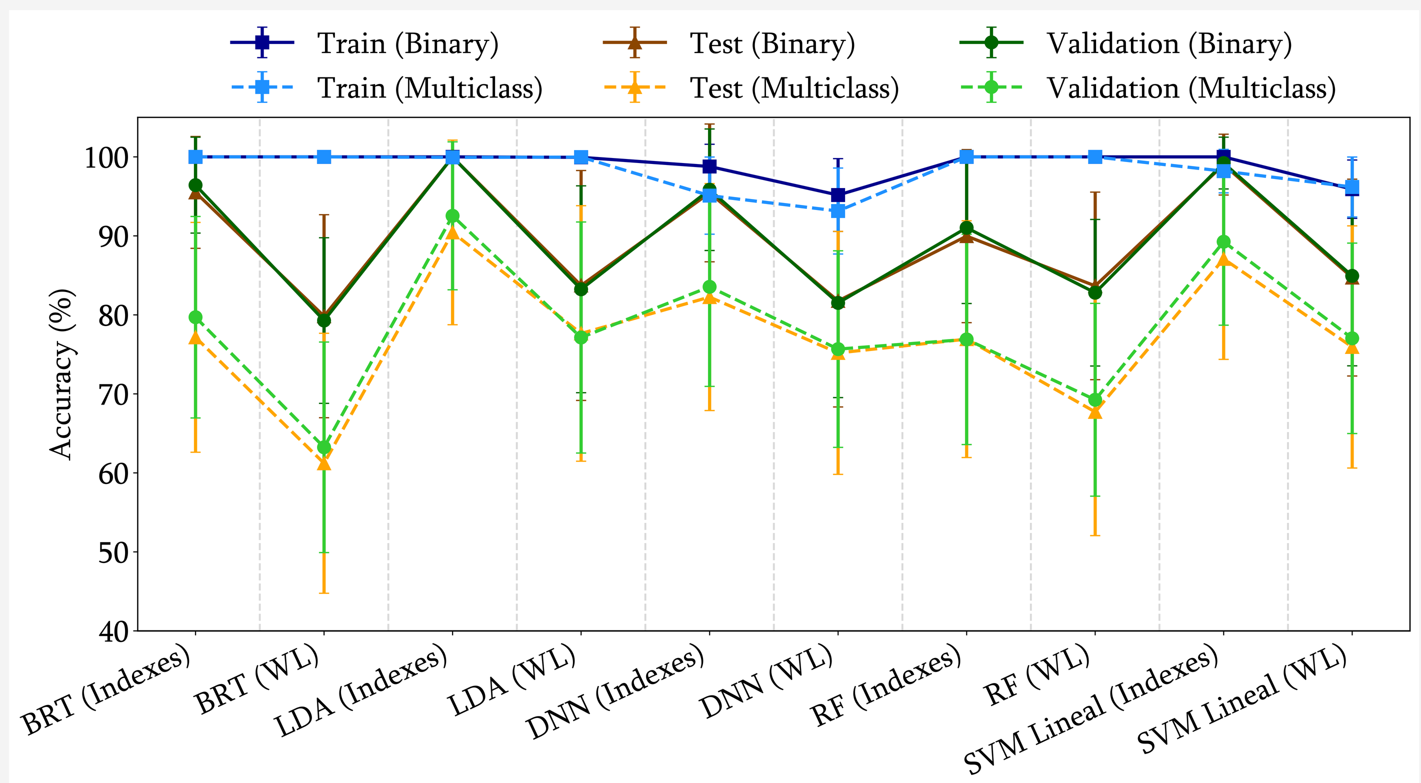

Fig.4 - Performance assessment of classification techniques across training, calibration, and validation subsets: Binary Classification (solid lines) vs. multiclass Classification (dashed lines).

In the multiclass classification (BS-TCC-FCC), performance declined across all models. LDA remained the best (92% accuracy, Kappa = 0.88), also followed by SVM (89% accuracy, Kappa = 0.83). The remaining models showed a more pronounced accuracy drop, with Random Forest reaching only 76% and BRT dropping to 79%.

Despite the increased complexity of the multiclass classification, vegetation indexes consistently yielded better results than wavelength combinations, highlighting their effectiveness in spectral-based classification tasks. Given the model's persistently superior performance in binary and multiclass classification tasks, LDA was selected for further analysis.

In order to enhance comprehension of the model's behavior and the contribution of each spectral index, the variable importance and the weight of the coefficient of each vegetation index were extracted for both classification schemes, Fig.5. The aim of this analysis was to identify which indices played the most important role in discriminating soil management strategies. Among the eight indices considered, ARVI, EVI, NDVI, and SAVI consistently demonstrated the highest weights, indicating a stronger influence in distinguishing soil management strategies across both binary and multiclass classifications. It is noteworthy that ARVI was identified as the most informative index in both cases. Subsequent to these findings, the classification processes were repeated, this time using Linear Discriminant Analysis (LDA) exclusively.

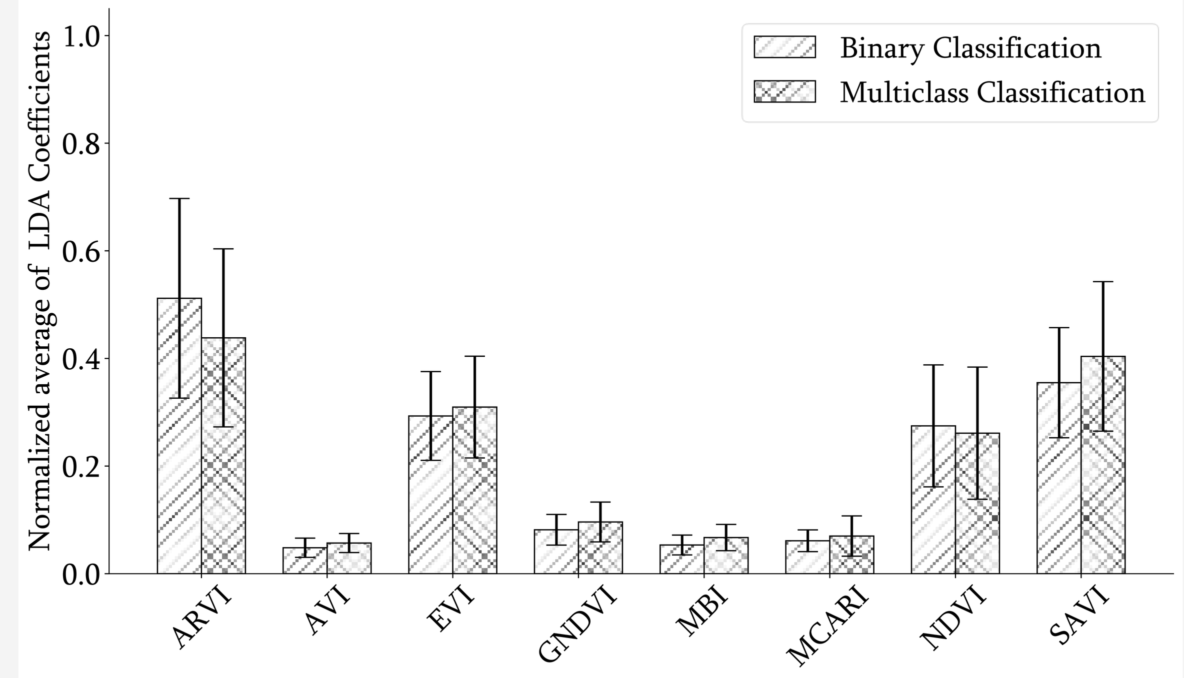

Fig. 5 - Normalized importance of vegetation indexes using LDA for binary and multiclass classification. Error bars represent the standard deviation.

Fig.6 presents the classification performance obtained using the LDA classifier across three dataset configurations: i) a comprehensive dataset including all vegetation indices, ii) a reduced dataset composed of the four most informative indices (ARVI, EVI, NDVI, and SAVI), and iii) ARVI used individually to evaluate its standalone discriminatory capability.

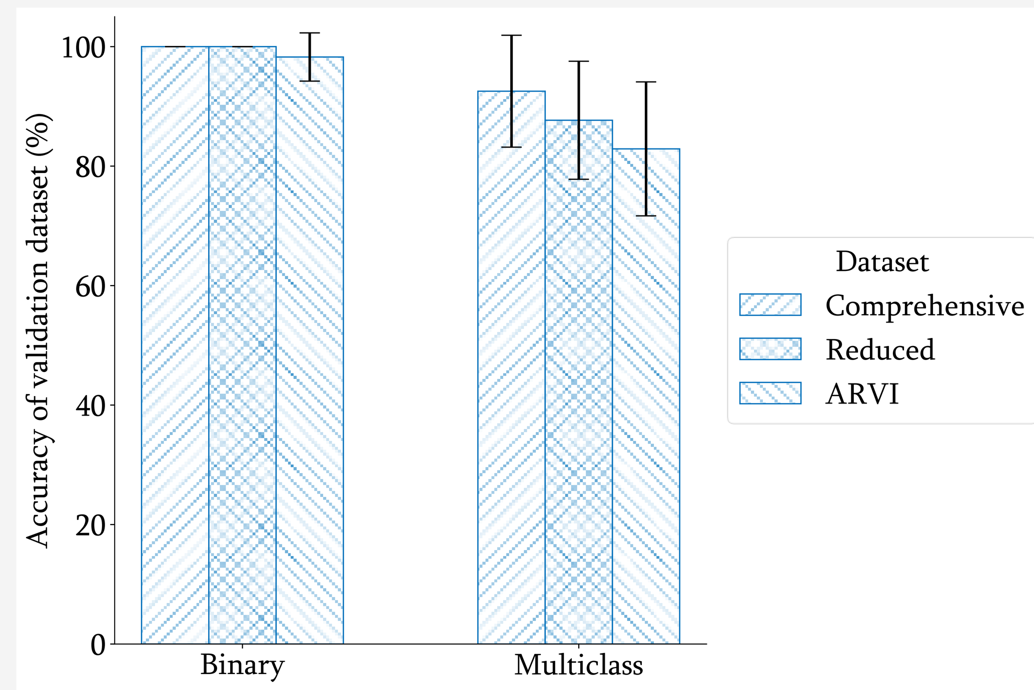

Fig. 6 - Accuracy of the validation dataset for binary and multiclass classification using the Linear Discriminant Analysis (LDA) classifier across three datasets: Comprehensive, Reduced, and ARVI. Error bars represent the standard deviation.

The comparative analysis reveals clear patterns. The comprehensive dataset consistently achieved the highest validation accuracy in both binary and multiclass classification, highlighting the benefits of incorporating the full set of indices. The reduced dataset performed similarly in the binary case but showed a moderate decline under multiclass conditions, suggesting that variable reduction may compromise performance when dealing with more complex classification tasks. Despite using only one variable, the ARVI index yielded competitive results in binary classification, confirming its relevance as a standalone variable. However, its effectiveness decreased in the multiclass scenario, indicating limitations when used in isolation for multiclass classification tasks.

F1 score and Cohen's Kappa were computed using the LDA classifier to further assess classification performance. It was found that both the comprehensive and reduced datasets achieved optimal results in the binary setting (F1 = 1.00; Kappa = 1.00), confirming their reliability with sufficient input information. The ARVI-only dataset also yielded substantial results in binary classification ($F1 = 0.98 \pm 0.03$; Kappa $= 0.97 \pm 0.1$, where ± indicates the standard deviation), thereby validating its utility as a standalone index. However, its performance was reduced in the multi-class scenario ($F1 = 0.83 \pm 0.1$; Kappa $= 0.74 \pm 0.2$), suggesting that reducing the input features to a single index may limit the model's ability to discriminate between more complex soil management strategies.

Conclusions

1- Vegetation indices, particularly those selected for their relevance (ARVI, EVI, NDVI, and SAVI) proved to be a reliable and efficient tool for identifying cover crop and bare soil based management practices in olives, supporting large-scale erosion risk assessments. Further validation under diverse Mediterranean conditions and alternative management strategies is needed to confirm the method's generalisability.

2- Future research will extend this approach to other woody crops, such as almond orchards and vineyards. Which been deciduous tree might require methodological adaptations.

References

[1] Guzmán et al.. 2022. Expansion of olive orchards and their impact on the cultivation and landscape through a case study in the countryside of Cordoba (Spain). Land Use Policy. 116. 106065.

[2] Renard et al.. 1997. Agricultural Handbook 703. USDA-ARS. Washington. DC.

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