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Hyperspectral Reflectance as a Basis to Discriminate Olive Varieties—A Tool for Sustainable Crop Management

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Abstract: Worldwide sustainable development is threatened by current agricultural land change trends, particularly by the increasing rural farmland abandonment and agricultural intensification phenomena. In Mediterranean countries, these processes are affecting especially traditional olive groves with enormous socio-economic costs to rural areas, endangering environmental sustainability and biodiversity. Traditional olive groves abandonment and intensification are clearly related to the reduction of olive oil production income, leading to reduced economic viability. Most promising strategies to boost traditional groves competitiveness—such as olive oil differentiation through adoption of protected denomination of origin labels and development of value-added olive products—rely on knowledge of the olive varieties and its specific properties that confer their uniqueness and authenticity. Given the lack of information about olive varieties on traditional groves, a feasible and inexpensive method of variety identification is required. We analyzed leaf spectral information of ten Portuguese olive varieties with a powerful data-mining approach in order to verify the ability of satellite's hyperspectral sensors to provide an accurate olive variety identification. Our results show that these olive varieties are distinguishable by leaf reflectance information and suggest that even satellite open-source data could be used to map them. Additional advantages of olive varieties mapping were further discussed.

Keywords: traditional olive groves; olive cultivars; remote sensing; Sentinel 2; spectral reflectance; sustainable development; agricultural abandonment; agricultural intensification

1. Introduction

Sustainable development at a worldwide scale is crucially dependent on changes in land use structure [1], particularly with respect to the increasing global food demand and increasing land scarcity for agricultural production [2,3]. In terms of landscape dynamics, there have been three dominant agricultural land change processes with impact on biodiversity and nature values over the last half-century [4,5]: (1) In big cities surrounding areas, agricultural land was converted to urban use associated with rapid urbanization processes as a response to growing demographic demands [6]; (2) more economically productive areas have been intensified, incorporated into larger assemblages particularly within developed countries [7]; and (3) conversely, unproductive farm areas were increasingly abandoned, reforested, or included in rewilding for nature values with the creation of nature reserves or parks [8–10].

Agricultural land change phenomena—rural farmland abandonment and agricultural intensification—are ongoing processes all over the world and particularly in Europe, with potential important negative social and environmental impacts. Agricultural land abandonment has been an increasing problem, mostly in Southern Europe throughout the last decades [11], contrasting with Northern and Western Europe where agriculture intensification/expansion is the dominating land-use change process [12]. The extent of such landscape changes raises deep concerns in European authorities since they could entail significant negative impacts. Despite the potential positive role of abandoning areas on, for example, forest regrowth, natural regeneration, biodiversity and carbon sequestration, there is great concern on increased fire risk due to homogenization of woody vegetation [13–15]. Likewise, the loss of landscape heterogeneity, the decline in resource diversity and changes in disturbance regime associated with land abandonment may equally be responsible for significant biodiversity losses [16,17]. The integration of traditional agricultural lands into a more cost-efficient and intensive agricultural model capable of a higher food production also raises concerns as such practices often carry higher negative implications compromising ecosystem functioning, biodiversity, fresh water supply, preservation of the soil and natural restoration [16–19]. Additional concerns are raised regarding the loss of regional identities linked to the threat of cultural landscapes, essential for the sustainable development of specific communities [18,20–22].

In the Mediterranean agriculture scenario, both abandonment and intensification have been particularly relevant in traditional olive groves [23–26]. World olive growing occupies an area of 10.2 million hectares with more than 90% of the total area located in the Mediterranean Basin [27]. Traditional olive farming is a low-intensity farming system [28], associated with a low density of old olive trees, absence of irrigation, minimal pesticides and fungicides inputs and a low degree of mechanization. They are highly environmentally sustainable, supporting high levels of biodiversity and low rates of soil erosion [28], and play an important social-economic role in rural areas while providing income and employment [29]. Among other agro-economic systems, ancient traditional olive groves are recognized as Globally Important Agricultural Heritage Systems since they play a crucial role for agrobiodiversity conservation and livelihood [30]. The traditional olive groves may play an important role in building ecological and social resilience to climate change while maintaining ecological diversity, improving adaptability and putting into practice a sustainable model of land use which may go beyond business-as-usual logics [31,32]. In a food security realm, at a time when the actual intensification processes lead to the installation of monovarietal olive groves, preservation of traditional local adapted varieties plays an important role in environmental and climate change crop adaptation as well as aid in coping with genetic vulnerability issues by acting as diversity reservoirs [33–35]. The abandonment and the intensification of traditional olive groves entails environmental and social costs; it likely threatens the local economy, rural employment and agroecosystem’s resilience to climate change, as well as to other environmental disturbances, inherently affecting the food production ability in the future.

The abandonment of traditional olive farming practices is clearly linked with its economic trade-offs. The fragmented structure hampers farm competitiveness by escalating production costs [36], while intensive farming pulled down the overall market price making most olive traditional farms barely viable or even unviable [37–39]. Notwithstanding the complexity of current socio-economic dynamics, it is very likely that Mediterranean “traditional” olive farmers will continue following one of two main trajectories: (1) leaving the traditional farming practices and moving towards more profitable models, like intensive (200–400 plant/ha) or super-intensive (600–2000 plant/ha) olive farming, or even switching to a more promising and profitable crop, like almonds [23,25,26]; (2) searching for alternative economic opportunities outside the agricultural sector which consequently results in further abandonment of farmlands [40,41].

New approaches have been suggested to farmers in order to make traditional olive groves sustainable and viable again, in the context of the actual highly competitive international markets.

Strategies of income diversification recommended to traditional agricultural businesses [42] can equally be implemented to traditional olive farms, such as (1) olive oil differentiation (by shifting from traditional to organic management or by adoption of specific production process and/or quality requirements [39,43,44]), (2) crop diversity (promoting diversification of agricultural production [45,46]), (3) development of non-agricultural products (such as olive oil related agro-tourism activities [47]) and (4) development of new agricultural-related products (innovative value-added by-products [48,49]). For implementation of the promising diversification strategies based on olive oil differentiation or on the development of innovative value-added products, a high quality of palatable products is required; this in turn relies on the olive varieties used, as each variety produces olive fruits with distinct organoleptic proprieties and chemical compositions. It seems thus clear that the sustainability of traditional olive groves in the Mediterranean region is dependent on the knowledge of the olive varieties and its specific properties that confer their uniqueness and authenticity.

Bearing in mind that traditional production is based on centennial olives which were empirically selected by growers centuries ago, the identification of the varieties can no longer be guaranteed with certainty. In this context, an automatic, feasible, low-cost and accurate technique to determine olive varieties is highly valuable for both farmers and authorities (e.g., assisting in the decision-making process of the olive crop management system and of the best value-added product, enabling higher control of the composition of products, or the implementation of certification or labelling processes). At a national/European level, an olive variety identification technique that could be generally applied to a broad area with limited resources would allow for assessing the olive germplasm status and its geographical distribution, being an important tool in landscape management and sustainability.

Currently, as far as we know there is no prompt, effective and feasible technique that can determine olive varieties with reliable accuracy, independent of orchard dimension. Until recent years, variety identification has been based on olive morphological and agronomic traits, classically [50–54] (made difficult by morphological changes raising from the age of the trees, the phenological stage of the plants or even the specificities of the local environmental conditions) or aided by image analyses tools and a semi-automatic algorithm [55,56] (to accommodate variability issues). Pattern recognition through molecular methods has also been achieved [57]. Both approaches are promising in terms of olive variety discrimination, however, they are both not applicable to large olive grove areas as they rely on the collection of individual biological and visual data in the field (which is extremely costly, spatially limited and time-consuming).

Remarkable advances in recent years in satellites' remote sensors technology, particularly with the launch of satellites with hyperspectral sensors with very-high resolution [58], enable its use to small-scale applications like trees species identification (e.g., [59–61]). We hypothesized that the appropriate use of such remote technology could provide feasible and accurate olive variety identification on traditional olive groves. Our objective was to disclose the existence of different patterns in spectral reflectance signatures among olive varieties to support this hypothesis. Therefore, we carried out an intensive data mining classification approach using several machine learning classifiers and leaf spectral reflectance data. We further show that these spectral signatures can be used in a classification process that allows olive variety discrimination.

2. Materials and Methods

2.1. Olive Leaves Spectral Data

Leaf spectral reflectance data of ten representative Iberian olive varieties were collected using a handheld non-imaging spectroradiometer, the FieldSpec®3 (Analytical Spectral Devices (ASD), Inc., Boulder, CO, USA), coupled with both Plant Probe and Leaf Clip accessories. ASD FieldSpec®3 portable spectroradiometer consists of three detectors specifically designed to acquire different electromagnetic radiation. One covers the visible (VIS, 350 to 700 nm) and near-infrared (NIR, 701 to 1000 nm) regions of the electromagnetic spectrum with a spectral resolution of 3 nm. The other two cover the short-wave infrared (SWIR1, 1001 to 1830 nm; SWIR2,1831 to 2500 nm) spectral range with a spectral resolution of 10nm (ASD, 2007. FieldSpec® 3 user manual) The Leaf Clip is designed to minimize measurement errors associated with the stray light while using the Plant Probe accessory, which integrates a halogen bulb that emits radiation over the 350 to 2500 nm spectral range.

The measurements were carried out on October 2018 in the National Institute for Agricultural and Veterinary Research (INIAV) experimental station in Elvas, Portugal. One hundred fresh olive leaves were measured (10 random leaves per olive tree) for each of the following olive varieties: Arbequina, Azeiteira, Carrasquenha, Cobrançosa, Cordovil da Serra, Galega, Koroneiki, Picual, Redondil and Verdeal. The exception was Picual, for which only 85 leaves were measured. For each leaf, reflectance value was obtained for each 1 nm interval over 350–2500 nm wavelength range, which means we obtained 2150 reflectance values.

2.2. Machine Learning Classifier Algorithms

The discrimination task of olive leaf spectral information between distinct olive varieties relies on a data mining approach in which several classification supervised learning methods were tested in order to obtain an accurate classification model. Given the strengths and weaknesses of each algorithm and how well they fit both the dataset and classification problem, a set of six classification algorithms was selected for testing, among the most common ones: Classification And Regression Trees (CART) [62], Stochastic Gradient Boosting Machine (GBM) [63,64], Extreme Gradient Boost (XGBoost) [65,66], Random Forest (RF) [67], k-Nearest Neighbor (kNN) [68,69] and Support Vector Machine (SVM) [70,71].

Algorithms with distinct functional principles were included in our set. Decision Tree Algorithms, like CART, construct a model of decisions made based on actual values of attributes in the data. The decisions branch in tree structures until a prediction decision is made for a given record. Instance-based Algorithms, like kNN and SVM, typically build up a database of example data and compare new data to the database using a similarity measure to find the best match and make a prediction. GBM, RF and XGBoost algorithms are Ensemble Algorithms where final models composed of multiple weaker models that are independently trained are used and whose predictions are combined in some way to make the overall prediction. Those require an enormous effort on the selection of types of weak learners to combine and the ways in which to combine them.

The entire analysis was carried out using *mlr* package [72] implemented in R statistical software which provides an object-oriented and extensible framework for classification for the R language. For each tested algorithm, *mlr* package implements specific additional packages for the modelling process, namely *rpart* (CART) [73], *class* (kNN) [74], *e1071* (SVM) [75], *gbm* (GBM) [76], *randomForest* (RF) [77] and *xgboost* (XGBoost) [77].

2.3. Hyperparameters Optimization

Optimization of all classification models involves a hyperparameter-tuning process. For each classifier algorithm tested there is a different set of hyperparameters that should be tuned in order to maximise model predictive accuracy (Table 1).

Table 1. Hyperparameter's type and searching spaces used in the tuning process of each classifier algorithm tested.

Classifier algorithm	Hyperparameters			
	ID	Type	Search Space Limits	
			Lower	Upper
CART	cp	numeric	0	−6.6439
	maxdepth	integer	3	30
	minbucket	integer	5	50
	minsplit	integer	5	50
kNN	k	integer	1	∞
SVM	cost	numeric	0	∞
	gamma	numeric	0	∞
GBM	n.trees	integer	1	∞
	interaction depth	integer	1	∞
	shrinkage	numeric	0	∞
	n.minobsinnode	integer	1	∞
RF	nodesize	integer	1	∞
	mtry	integer	1	∞
XGBoost	nrounds	integer	1	∞
	maxdepth	integer	1	∞
	gamma	numeric	0	∞
	colsamples bytree	numeric	0	1
	min child weight	numeric	0	∞
	subsample	numeric	0	1

Hyperparameter-tuning is a truly hardware-demanding and time-consuming process when carried out with most common methods such as Grid Search or Random Search, especially with large parameters spaces. Those methods roam the full space of available parameter values in an isolated way without paying attention to past results. The search space grows exponentially with the number of tuned parameters, while for each hyperparameter combination a model needs to be trained, predictions must be generated in the validation data and the validation metric must be calculated. As a best combination between time consumption and suitability of results, we have chosen to tune the hyperparameters using a Sequential Model-Based Optimization, also known as Bayesian optimization, implemented in the mlrMBO package [78]. Bayesian Optimisation typically requires less iterations to get to the optimal set of hyperparameter values since it selects combinations in an "informed" way, considering past evaluations when choosing the hyperparameter set to evaluate next [79]. This limits the number of times a model is trained for validation since only those settings that are expected to generate a better validation score are passed through for evaluation. The upper and lower limits of search spaces used in mlrMBO for tuning each one of the hyperparameters are presented in Table 1.

2.4. Model Training and Validation

The full dataset is composed of 985 leaves reflectance percentage data for each one of the 2150 1nm intervals between 350–2500 nm,distributed by 10 olive variety classes. For the modelling, we randomly divided the dataset into training and validation sets, stratified by class, containing respectively 80% and 20% of the data. As the name says, the training set was used for training, i.e., to fit parameters of each classifier algorithm tested in order to produce a classification model. The validation set was then used to judge model performance by achieving their predictive accuracy in independent data. Confusion matrices resulting from the validation task were used to provide an estimation of the model's classification accuracy. Two predictive accuracy assessment measures were computed for each matrix: overall classification accuracy and Kappa coefficient [80].

2.5. Dimensionality Reduction and Performance Improvement

The hyper-dimensionality of our 2150 features dataset constitute a severe constraint to model training and validation processes, with high computational demands. Commonly, feature extraction and dimensional reduction approaches are implemented to lower computational needs and the time spent. Pre-processing a full dataset with principal components analysis (PCA), linear discriminant analysis (LDA), or a sequential combination of both (PCA+LDA) to obtain a set of "most relevant" features to feed machine learning classification algorithms has been showed to efficiently reduce time involved in model training and validation processes [81–83], without model accuracy costs. Interestingly, such approaches can even significantly increase the performance of the classification models.

Despite training and validating our models with a full feature dataset, we repeated the modelling process with distinct datasets resulting from the implementation of several dimensional reduction techniques over our original features to attempt enhancing the predictive ability of the classification algorithms. In the first and second cases we respectively used PCA and LDA resulting features. In the third case we used the final features dataset resulting from the PCA+LDA two steps approach, in which we get the linear discriminant features of our original dataset principal components. In addition to the previous and most common approaches, we also proposed and tested an alternative approach, a pairwise fashion dimensional reduction method we called Class-Paired LDA. Such a method implies that linear discriminant features are obtained for each pair of classes—in this case, olive varieties—and then the computation of coefficients was calculated for the entire dataset using those new features. Those final features were the ones used in the modelling procedure. Principal components and linear discriminant features were computed using *MASS* and *psych* packages respectively, both implemented with R statistical software. In our data mining approach, 30 final models were produced covering all the combinations of algorithms and dimensionality reduction strategies.

3. Results

The spectral reflectance signatures of the 10 olive varieties are presented in Figure 1. Despite following a similar profile, a careful visual inspection provides evidence for a relative separability of reflectance signatures in several wavelength ranges among most varieties, such as at 780–1300 nm, 1420–1870 nm and 2000–2400 nm (Figure 2). Those discrepancies between classes are likely incorporated in the different models produced by tested algorithms to achieve an accurate classification of olive reflectance.

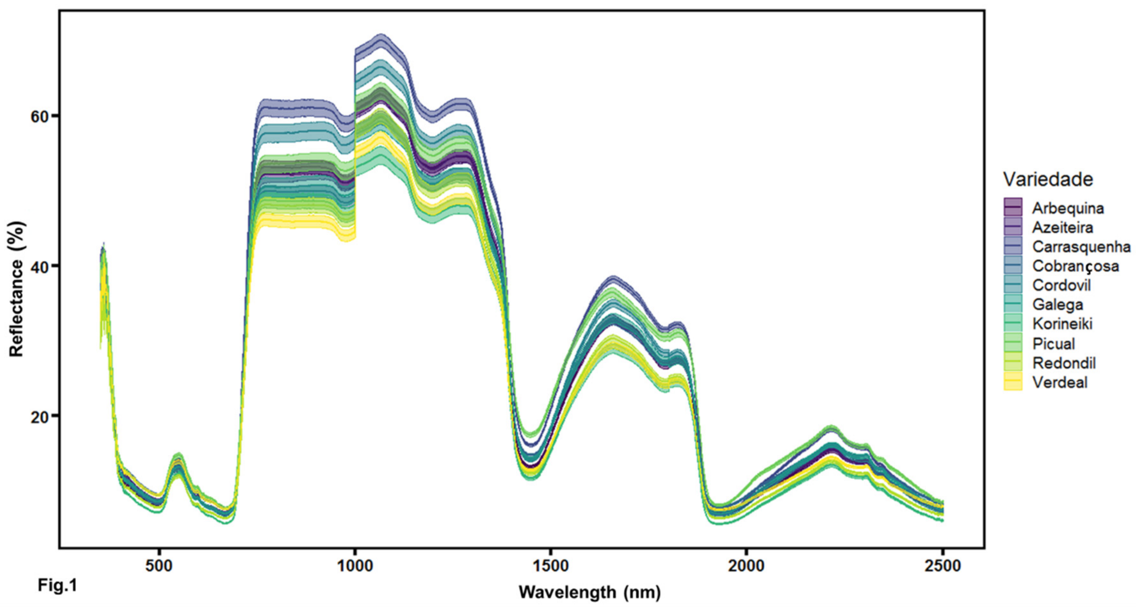


Figure 1. Leaf reflectance of olive varieties over 1nm intervals (n≈100). Band central lines represent average values by variety and shaded area represents the error envelope (Mean Standard Error).

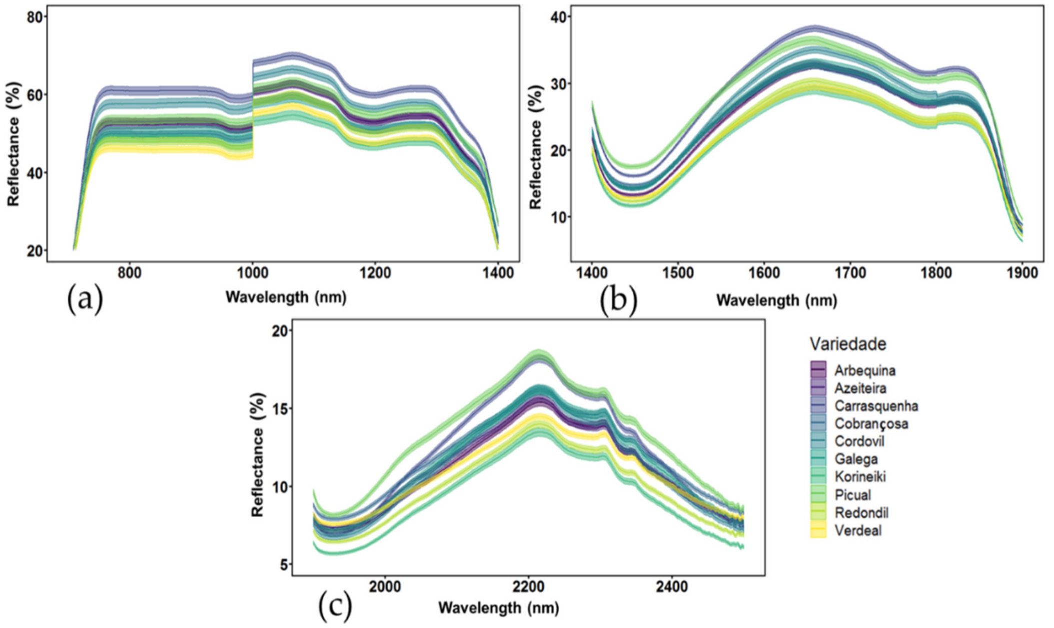


Figure 2. Separability of leaf reflectance signatures among olive varieties in three wavelength ranges of the electromagnetic spectrum, where the visual discrimination between classes are more evident: **(a)** 700nm-1400nm, **(b)** 1400nm-1900nm and **(c).** 1900nm-2500nm. Band central lines represent average values by variety and shaded area represents the error envelope (Mean Standard Error).

The hyperparameter optimization process preformed for the different algorithms and datasets resulted in the sequence of settings presented in Table 2.

Table 2. Hyperparameters selected for the final models in each algorithm for the different datasets.

Classifier Algorithm	Hyperparameter	Dimensional Reduction Approach				
		Original Features	**PCA**	**LDA**	**PCA-LDA**	**Class-paired LDA**
CART	cp	3.207201×10^{-3}	9.770812×10^{-4}	6.315712×10^{-2}	1.240644×10^{-3}	5.031421×10^{-3}
	maxdepth	24	13	12	25	27
	minbucket	5	5	34	5	5
	minsplit	5	8	21	14	22
kNN	k	5	9	1	9	
SVM	cost	32741.8	32743.65	108.0261	3.050549	1549.45
	gamma	3.058368×10^{-5}	1.492811×10^{-3}	3.053304×10^{-5}	4.249793×10^{-2}	4.102502×10^{-2}
GBM	n.trees	317	264	307	328	153
	interaction depth	8	5	9	10	3
	shrinkage	0.04550525	0.1688938	0.1347996	0.03450826	0.1730139
	n.minobsinnode	18	9	17	10	5
RF	nodesize	2	8	2	2	1
	mtry	252	10	5	2	7

XGBoost	nrounds	96	1097	2116	757	968
	maxdepth	6	8	0.2690774	4	6
	gamma	0.8234288	1.156659	9.357791	0.3196865	1.658614
	colsamples bytree	0.611975	0.6405206	0.5733329	0.5085781	0.4264549
	min child weight	3.864695	12.35923	0.3632626	2.421558	0.8988217
	subsample	0.7416891	0.8773087	0.374145	0.9138881	0.7521763

Of the 30 models generated in our data mining approach. ranges from models with lower predictive accuracy (like the worst performer produced by the kNN algorithm with principal components dataset (PCA) (overall accuracy= 0.2792; Kappa= 0.1983)) to the best performer model (produced by the SVM algorithm with Class-Paired linear discriminants (Class-Paired LDA) (overall accuracy= 0.8173; Kappa= 0.7970))(Table 3). In our olive leaf reflectance classification task with the present dataset. the SVM algorithm always produced the most accurate model regardless of the implementation of any dimensional reduction strategy (Table 3). Similarly. the use of Class-Paired LDA has shown to be the most effective dimensional reduction strategy in terms of improving the model's performance. since models produced using Class-Paired linear discriminants always achieved the higher overall accuracy regardless of the machine learning algorithm used in the classification task (Table 3).

Table 3. Preditive accuracy of the models generated in our data mining approach.

Classifier Algorithm	Dimensional Reduction Approach	Model Preditive Accuracy	
		Acuraccy	Kappa
CART	Original features	0.3553	0.2833
	PCA	0.3046	0.2267
	LDA	0.4518	0.3904
	PCA-LDA	0.5381	0.4864
	Class-paired LDA	0.6497	0.6109
kNN	Original features	0.3756	0.3058
	PCA	0.2792	0.1983
	LDA	0.7157	0.684
	PCA-LDA	0.6345	0.5936
	Class-paired LDA	0.7919	0.7686
SVM	Original features	0.7665	0.7403
	PCA	0.6904	0.6557
	LDA	0.6802	0.6445
	PCA-LDA	0.6802	0.6444
	Class-paired LDA **	0.8173	0.797
GBM	Original features	0.5736	0.526
	PCA	0.4822	0.4243
	LDA	0.533	0.4806
	PCA-LDA	0.6396	0.5993
	Class-paired LDA	0.7716	0.7461
RF	Original features	0.5482	0.4977
	PCA	0.4518	0.3902
	LDA	0.6345	0.5938
	PCA-LDA	0.6497	0.6105
	Class-paired LDA	0.7563	0.7292
XGBoost	Original features	0.5482	0.4978
	PCA	0.467	0.4074
	LDA	0.4721	0.4134
	PCA-LDA	0.6701	0.6331
	Class-paired LDA	0.7565	0.7292

** best performer model.

The best performer model was produced by the SVM algorithm with a dataset of 45 Class-Paired linear discriminants (Table 4) and configured with the following hyperparameter values: cost = 1549.45 and gamma = 4.10×10^{-2}. This model struggled specially with the classification of Azeiteira and Cordovil varieties. both with an accuracy of 70%. the lowest accuracy achieved. Azeiteira was misclassified mostly as Cobrançosa. The model handled the classification of Carrasquenha. Picual and Koroneiki extremely well. achieving respectively an accuracy of 95%. 94% and 90% (Table 5). The remaining classes were classified with an acceptable accuracy of 80% (Table 5).

Table 4. Relative importance of Class-Paired linear discriminants used with the SVM algorithm to produce the best performer model.

Linear Discriminant	Classes			Permutation Importance
LD45	Redondil	&	Verdeal	3.44×10^{-2}
LD11	Azeiteira	&	Cobrançosa	2.63×10^{-2}
LD34	Cordovil	&	Redondil	1.18×10^{-2}
LD6	Arbequina	&	Koroneiki	7.81×10^{-3}
LD42	Koroneiki	&	Verdeal	7.58×10^{-3}
LD31	Cordovil	&	Galega	6.77×10^{-3}
LD9	Arbequina	&	Verdeal	6.54×10^{-3}
LD12	Azeiteira	&	Cordovil	5.75×10^{-3}
LD15	Azeiteira	&	Picual	5.22×10^{-3}
LD17	Azeiteira	&	Verdeal	4.94×10^{-3}
LD35	Cordovil	&	Verdeal	4.16×10^{-3}
LD18	Carasquenha	&	Cobrançosa	4.03×10^{-3}
LD26	Cobrançosa	&	Galega	3.93×10^{-3}
LD36	Galega	&	Koroneiki	3.78×10^{-3}
LD19	Carasquenha	&	Cordovil	3.42×10^{-3}
LD27	Cobrançosa	&	Koroneiki	3.24×10^{-3}
LD8	Arbequina	&	Redondil	2.66×10^{-3}
LD16	Azeiteira	&	Redondil	2.66×10^{-3}
LD21	Carasquenha	&	Koroneiki	2.66×10^{-3}
LD2	Arbequina	&	Carasquenha	2.64×10^{-3}
LD4	Arbequina	&	Cordovil	2.59×10^{-3}
LD1	Arbequina	&	Azeiteira	2.56×10^{-3}
LD5	Arbequina	&	Galega	2.51×10^{-3}
LD38	Galega	&	Redondil	2.33×10^{-3}
LD29	Cobrançosa	&	Redondil	2.26×10^{-3}
LD7	Arbequina	&	Picual	2.18×10^{-3}
LD14	Azeiteira	&	Koroneiki	2.15×10^{-3}
LD3	Arbequina	&	Cobrançosa	2.13×10^{-3}
LD30	Cobrançosa	&	Verdeal	2.13×10^{-3}
LD43	Picual	&	Redondil	2.08×10^{-3}
LD25	Cobrançosa	&	Cordovil	1.67×10^{-3}
LD41	Koroneiki	&	Redondil	1.50×10^{-3}
LD13	Azeiteira	&	Galega	1.32×10^{-3}
LD28	Cobrançosa	&	Picual	1.09×10^{-3}
LD23	Carasquenha	&	Redondil	9.89×10^{-4}
LD10	Azeiteira	&	Carasquenha	6.59×10^{-4}
LD39	Galega	&	Verdeal	5.58×10^{-4}
LD20	Carasquenha	&	Galega	5.07×10^{-4}
LD40	Koroneiki	&	Picual	3.80×10^{-4}
LD24	Carasquenha	&	Verdeal	2.79×10^{-4}
LD37	Galega	&	Picual	2.53×10^{-4}
LD22	Carasquenha	&	Picual	1.01×10^{-4}
LD33	Cordovil	&	Picual	1.01×10^{-4}
LD32	Cordovil	&	Koroneiki	2.53×10^{-5}
LD44	Picual	&	Verdeal	0.00×10

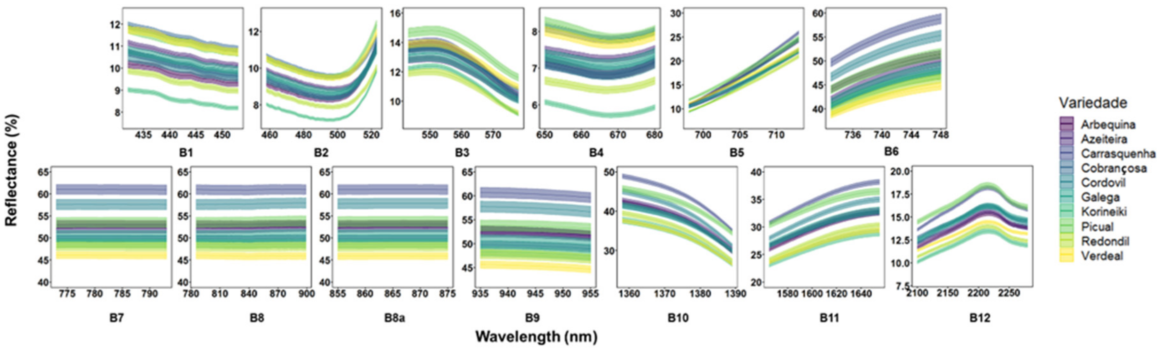
Table 5. Confusion matrix (in percentage) obtained with SVM algorithm applied to the Class-Paired linear discriminants dataset.

	Reference Data											
Classified Data	**Arbequina**	**Azeiteira**	**Carrasquenha**	**Cobrançosa**	**Cordovil**	**Galega**	**Koroneiki**	**Picual**	**Redondil**	**Verdeal**	**Total**	**User's Accuracy**
Arbequina	16	1	0	0	0	0	1	0	0	0	18	88.89
Azeiteira	0	14	0	0	1	1	0	0	2	2	20	70.00
Carrasquenha	0	0	19	0	1	0	0	0	0	0	20	95.00
Cobrançosa	0	4	0	16	0	1	0	1	0	0	22	72.73
Cordovil	0	1	0	0	14	1	0	0	0	1	17	82.35
Galega	1	0	0	1	1	16	1	0	0	0	20	80.00
Koroneiki	1	0	0	0	0	0	18	0	0	0	19	94.74
Picual	1	0	0	1	2	1	0	16	0	0	21	76.19
Redondil	1	0	1	2	0	0	0	0	16	1	21	76.19
Verdeal	0	0	0	0	1	0	0	0	2	16	19	84.21
Total	20	20	20	20	20	20	20	17	20	20	197	
Producer's accuracy	80.00	70.00	95.00	80.00	70.00	80.00	90.00	94.12	80.00	80.00		
Overall accuracy	81.73	**Kappa**	0.797									

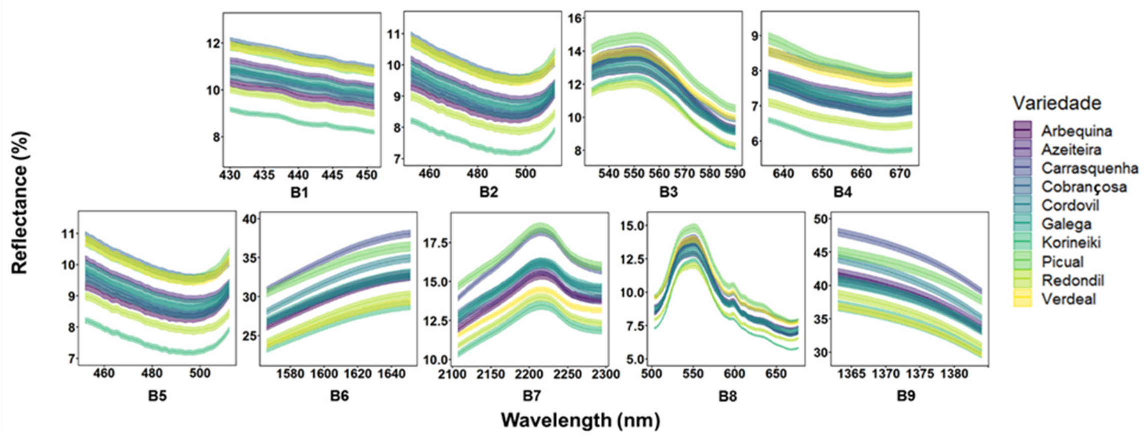
4. Discussion

The diversity of olive cultivars is very high. showing differences in the bioclimatic envelope and limiting factors [84]. and also in plant morphology. traits and phenology (e.g. Bacelar et al. [85]). Despite this. the distinction among olive varieties is not an easy task. The extraordinary accuracy achieved by our best performer model in the classification of most tested olive varieties is a clear substantiation that olive varieties yield distinguishable spectral reflectance patterns that can be used to identify them. Even an accuracy of 70%. the lowest achieved for individual variety classification (Azeiteira and Cordovil). is acceptable considering the challenging task of distinguishing leaf reflectance patterns among very closely related conspecifics originating from a recursive selection-hybridization process among domesticated and existing wild *Olea* forms [86]. Indeed. several authors have previously found differences between crop cultivars using non-destructive procedures based on spectral data. Gutierrez et al. [87] and Gizaw et al. [88] highlighted the potential of multispectral radiometers to detect differences between wheat genotypes. Silva Júnior et al. [89] used a non-imaging hyperspectral sensor to discriminate four soybean varieties through their spectral profile. Good results have been achieved for discriminating cultivars in permanent crops. A Fourier transform NIR spectrometer was used by Guo et al. [90] to distinguish four peach varieties commonly used in China. Suphamitmongkol et al. [91] also differentiated three varieties of Thai orange through the use of a short-wavelength spectrometer.

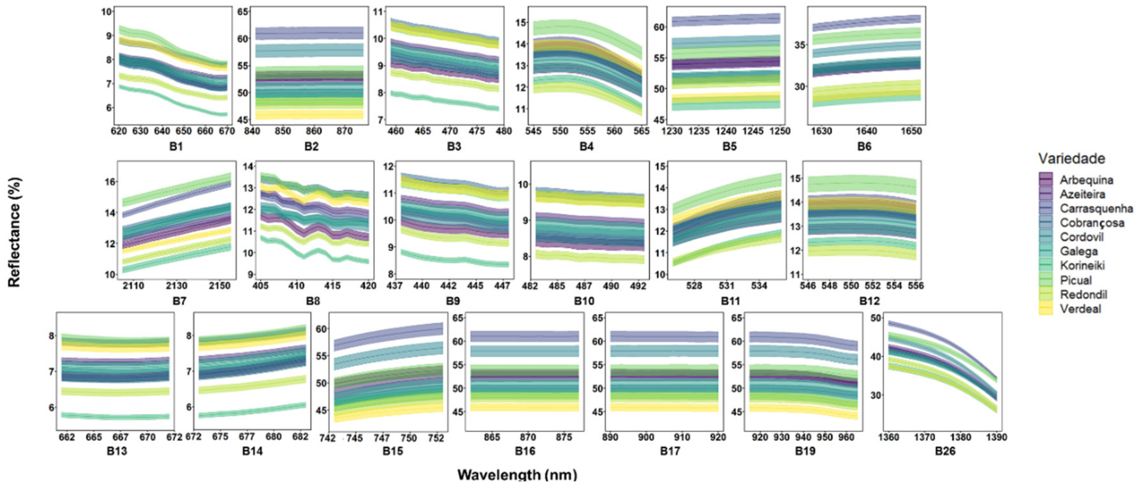
A careful analysis of olive leaf reflectance data in the spectral bands range of the satellites integrating three open-data earth observation projects. the Sentinel 2 (Figure 3a). Landsat 8 (Figure 3b) and MODIS - Moderate Resolution Imaging Spectroradiometer (Figure 3c). reveal the relative separability among all olive varieties' spectral reflectance. At least in one or two of the analyzed spectral bands there was no overlapping between the average standard error bands of each variety in relation to each other. a strong indicator that. in such ranges. varietal information is quite dissimilar. This clearly suggests. in turn. that data produced by these satellites provide the adequate spectral discrimination to support an olive variety identification process. The combination of multi-satellite and/or multi-temporal data obtained by different sensors may further increase the classification results obtained with snapshot single-satellite datasets. since it integrates additional spectral resolution and phenologic differences between olive varieties (in processes like flowering or fructification) that clearly temporarily affect the reflectance captured by satellites [92–94]. Concerning spatial resolution limitations. the monovarietal fashion of traditional olives groves and its typical patch size and distribution enable the use of such imagery for variety identification purposes. Particularly. Sentinel 2 data and Landsat 8 data. in which most band information has a spatial resolution that ranges from 10m to 30m. are strong candidates for the task. Even in lower tree density traditional groves. the olive canopy can easily fill the majority of the pixel area since in such orchards trees typically handle a much wider canopy than in higher density olive orchards. Additionally. the coarser spatial resolution information. like that obtained by the MODIS satellite. could be very helpful in increasing classification model accuracy by adding valuable additional information.



(a)



(b)



(c)

Figure 3. Separability of leaf reflectance signatures among olive varieties in the band range of the satellites Sentinel 2 **(a)** Landsat 8 **(b)** and MODIS—Moderate Resolution Imaging Spectroradiometer **(c)**. Reflectance band central lines represent average values by variety and the shaded area represents the error envelope (Mean Standard Error).

These findings support our hypothesis that remote sensing data could be used to identify olive cultivars. Unmanned aerial vehicle (UAV) imagery was used by Avola et al. [95] to distinguish two olive scions using vegetation indexes. Images obtained by UAV were also used by Kyratzis et al. [96] for durum wheat phenotyping in Mediterranean drylands. However. Matese et al. [97] showed that for precision viticulture. the advantage in using UAV is only cost-effective for areas under five hectares and above such threshold airborne and satellite provide better solutions. Thus. for large-scale areas. the solution may involve data provided by different sensors. particularly data from the Sentinel-2 mission with high temporal. spatial and spectral resolutions. and which have already been tested to discriminate and map small-scale crop types (e.g. Griffiths et al. [98]).

4.1. On the Importance of Olive Variety Discrimination

Mapping olive cultivars may be critical for the future of the southern European regions where natural resources are scarce. especially available water. and where large-scale negative impacts resulting from climate change are expected for olive yields [99]. Although the olive tree has stomatal regulation mechanisms to survive in drought conditions [100]. its eco-physiological response to irrigation is very high. particularly in critical moments of its vegetative cycle [101–107]. This allows for stabilization of the inter-annual variability in olive production which is a marked characteristic of olive trees. The results of Gómez-Rico et al. [106] for the cultivar *Olea europaea* L. cv. Cornicabra (for virgin olive oil) showed that the production in rain-fed conditions was 35% lower than the one obtained through different irrigation regimes. but that the results achieved based on regulated deficit irrigation were similar to the 100% restitution of the crop evapotranspiration (ETc). Patumi's et al. [107] findings. obtained in an intensive olive grove with *Olea europaea* L. cv. Kalamata (for olive oil and table olives). highlight that a restitution of 66% of ETc allows for achieving higher yields. and that the rate of ETc is a threshold above which yield increases were insignificant. The efficient. rational and sustained use of water is therefore mandatory. and deficit irrigation (application of water below the total crop needs defined by ETc) is a potential strategy to reduce excess consumption and to avoid severe and prolonged drought stress in plants. However. given the above-mentioned differences in the phenology of olive cultivars. the optimization of the irrigation scheme is also varietal dependent. highlighting the relevance in knowing the spatial distribution of the different cultivars.

The optimization of management practices resulting from knowledge of the spatial distribution of varieties goes well beyond irrigation issues. Given the differences between olive cultivars in flowering. fruiting and fruit ripening. and also in fruit retention and detachment forces. the spatial distribution of the varieties will enhance mechanical harvest efficiency. guaranteeing better quality fruits and reducing losses [108]. This is even more relevant since fruits ripen earlier in rainfed or poorly irrigated olive trees [109]. and in this way all the optimal adjustment of the irrigation and harvesting schemes depend on the integration of this information since the ripening stage has an important role in olive oil acidity and total phenol content [110]. In referring to pest and diseases. differences in susceptibility are attributed to tree varieties (e.g. [111–113]) with a high impact on crop management.

Moreover. the olive varieties also differ in the characteristics of the fruit that limit or enhance multiple uses [114] and in the quality of the olive oil. namely in its stability and chemical composition [115,116]. Since the quality of the final products are an added value for the sector. ensuring its authenticity is imperative. particularly for the extra virgin olive oils [117]. The spatial distribution of cultivars can be one of the phases of a hierarchical process of traceability and authenticity. in addition to genomic approaches [118]. whose usefulness may lie in the identification of fraudulent practices and for varietal and geographical certification.

4.2. Portugal as a Case Study

Olive trees are well adapted to the Mediterranean climate of southern Portugal and have been traditionally cultivated in dryland areas and managed as non-irrigated farming systems. In the mid-1980s the National Plan for Oliviculture was approved. with the aim of restructuring the olive sector by planting new areas and also densifying and/or converting existing ones. Under the reform of the Common Organization of the Market in Oils and Fats (Council Regulation (EC) n.º 1638/98 of 20 July 1998) was established as an incentive for the production of olive oil and. subsequently. the European Commission Decision 2000/406/CE of 9 June 2000 allowed Portugal to expand the area of olive groves by 30,000 hectares.

However. changes at the landscape scale only started to emerge after 2005 [119]. with an increase of 25,000 hectares in the area covered by olive groves between 2005 and 2008 [120]. According to data from the Portuguese Institute for Statistics. olive groves are the permanent crop with the largest area in mainland Portugal. covering 343,557 hectares of agricultural land (and a share of 48%) [121]. About 98% of the Portuguese olive groves are dedicated to the production of olive oil. and only 2% to the production of table olives [119]. The above-mentioned changes were reflected both in the production of olives and olive oil. Portugal is currently the fourth largest European producer of olive oil. with 1.0×10^6 hl in 2013 and 0.7×10^6 hl in 2014 [91]. In the period 2000–2007. the average annual production was 390,493.62 hl of olive oil and 252,247.50 ton of olives [121]. and between 2008 and 2014 these values substantially increased to 677,249.14 hl of olive oil and 421,386.42 ton of olives [121]. Most of the Portuguese production of olives and olive oil comes from the Alentejo region (69.58% and 68.55%. respectively; [121]).

This production growth was not only the result of increased area but also due to changes in management. which is presently much more intensive. The tree density range is between 30–173 trees ha^{-1} in traditional rainfed systems to 1700–3000 trees ha^{-1} in drip irrigated super-intensive olive orchards [122]. In Portugal. more than 46% of the total area covered by olive groves is irrigated. including 45,000 hectares occupied by intensive [123] and 4000 hectares covered by super-intensive olive groves [124].

However. not all olive cultivars can be managed under this high intensity. This is the reason behind the expansion of imported varieties in Portugal. such as *Olea europea* cv. Picual and *Olea europaea* cv. Arbequina. which are fast-growth and high-reach yields [125]. In this conversion process. we are losing varietal composition that contributes to the quality and singularity of the national product. its unique organoleptic characteristics and crop resilience.

Thus. changes are taking place very quickly. To counterbalance the tendency and mitigate the losses. spatial data is needed to discriminate traditionally managed crops making use of regional well-adapted cultivars. This information is critical for the sustainable management of olive groves in the future and for the guarantee of quality products with high market value.

5. Conclusions

We provided an approach based on distinguishable spectral reflectance patterns that allow low-cost. high-sensitivity identification of olive varieties. It supports the ability of satellite remote sensing that is being used to identify olive varieties in traditional and non-traditional groves in a cost-free fashion. enabling its mapping and monitoring across time. This approach. by identifying their olive tree patrimony and their inherent characteristics and uniqueness. can assist traditional olive farmers in decision-making processes both on crop management strategies and on the best value-added products to invest towards business viability and sustainability. This is a needed first step to counteract the abandonment of traditional olive farming practices and to promote their sustainability. paired with landscape diversification and ecosystem resilience. The optimization of management processes in areas that have undergone land use intensification and the valorization of products derived from endogenous varieties may contribute to a more rational use of the available resources to reduce the negative effects on ecological systems and related functions and services. and to decrease the conflicts between contrasting territorial policies.

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