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Use of UAV-borne multispectral data and vegetation indices for discriminating and mapping three indigenous vine varieties of the Greek Vineyard

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ABSTRACT

In line with precision viticulture, in recent years new methods of vineyard management have been introduced, so as to optimize vine cultivation and production of wine of the highest quality. Following on the methodologies developed for mapping other crop parameters, there is currently a growing research effort for the discrimination and mapping of vine varieties, as this information is useful for vineyard-scale management, local and regional inventory and planning purposes, application of EU Directives, and support of certification and production of high quality wines. This research focuses on developing a methodology, based on UAV-borne multispectral data, for discriminating and mapping three vine varieties in Attica, Greece, employing three non-parametric classifiers, namely Random Forest (RF), Support Vector Machines (SVM) and Spectral Angle Mapper (SAM), and selected vegetation indices (VIs). The suggested methodology uses easy to obtain and process, cost-effective images and relies mostly on free open-source software. Study conclusions suggest that although the multispectral images used did not result in the accurate discrimination of the vine varieties at pixel level, expressed by highest overall accuracy (OA) 61.6%, they nevertheless proved useful in mapping varieties at the plot level. Therefore, it is considered effective for applications that require such level mapping.

Keywords: classification, multispectral imagery, precision viticulture, UAV-borne imagery, vegetation indices, vine variety mapping

INTRODUCTION

As the viticulture/oenology industry has been historically very important for Europe, there is constant effort for more efficient vineyard management and oenological practices, which build upon the advantages of technological progress.

Even though it is common belief between winemakers that fine wine is the result of well grown grapes, rather than the following production processes within the winery, it is a fact that the use of technological advancements is more widespread in the winery than in the vineyard.

However, following the progress of precision agriculture, there is currently a tendency for shifting this ratio. In the recent years, there is an evident trend in employing proximal (Trought and Bramley, 2011; Baluja et al., 2012) and remote sensors (Hall et al., 2002; Matese et al., 2015) for acquiring accurate and up to date vineyard information. Studies from all over the world have proven that employing remote sensing, results to better management through better understanding of soil (Bramley and Hamilton, 2007), vine health (Mazzetto et al., 2010) and vine phenology (Lamb et al. 2004; Fraga et al., 2014).

One of current research pursuits is discriminating and mapping vine varieties, using non invasive remote sensing techniques. As Ferreiro-Arman et al. (2006) suggest, at the vineyard level, there is a need for vine variety discrimination as a useful tool for vine growers to detect misplantings and to manage inner field species variability, while at a regional level it can be used for planning and inventory purposes as well as for certification of wine growers.

However, varietal discrimination is not an easy task since the leaves of different varieties are structurally and biochemically similar (Lacar et al., 2001b) thus having very close spectral responses.

This has led research into addressing the problem using hyperspectral sensors, which provide a great number of spectral channels allowing subtle differences to be identified.

Lacar et al. (2001a) used CASI hyperspectral imagery in South Australia and Maximum Likelihood classifier to map two varieties (Cabernet Sauvignon and Shiraz). They found that the two vine varieties showed spectral differences primarily in the visible region (400-700nm) of the spectrum and more importantly between 530 and 570nm.

In another study, using hyperspectral proximal sensing, Lacar et al. (2001b) showed that between four varieties (Cabernet Sauvignon, Merlot, Semillon and Shiraz) Cabernet Sauvignon differed most from the other varieties, at approximately 512nm and 580nm, while 512nm, 580nm, 611nm, 649nm, 690nm and 763nm showed the greatest potential for discrimination between all four varieties.

Ferreiro-Arman et al. (2006) used CASI data and an assortment of classifiers to map six vine varieties (Cabernet Sauvignon, Merlot Noir, Petit Verdot, Cabernet Franc, Sauvignon and Semillon). They commented on the adequate spatial resolution of the imagery, highlighting that the alternating structure of vegetation and soil induces a strong influence on the discrimination of pixels. For this reason, they suggested that vine variety discrimination may be enhanced by considering higher level information on plots and parcels, as opposed to single pixels.

Ferreiro-Arman et al. (2007) assessed the capability of CASI imagery for the discrimination of three vine varieties (Cabernet Sauvignon, Cabernet France, Merlot Noir) both under constant and varying illumination conditions and showed that using illumination stratification increases classification accuracy.

However, hyperspectral imagery is more difficult to acquire and process, as also more expensive than multispectral (Adão et al. 2017). Therefore, studies that focus on mapping vine varieties based on multispectral imagery are also present in the literature.

Karakizi et al. (2015) in their study used in-situ hyperspectral, aerial hyperspectral and satellite multispectral data to discriminate vine varieties and found that they were all highly correlated. Analysis of in-situ reflectance indicated that certain vine varieties (Merlot, Sauvignon Blanc, Ksinomavro and Agiorgitiko) possess specific spectral properties and detectable behavior, which is in accordance with the findings of Lacar et al. (2001a) that different varieties pose varying discrimination possibilities.

Karakizi and Karantzalos (2015), also, used satellite multispectral imagery (World-View 2, Pleiades 1B) to map up to six vine varieties, within an object based scheme. They incorporated a row detection step in their methodology and found that classification accuracy greatly increased when reported for parcel level, as opposed to pixel level. They also found that Merlot and Sauvignon Blanc, achieved high completeness rates on all classifications they took part, indicating relatively distinct spectral behavior among the other varieties.

These were also confirmed by a similar study using multitemporal satellite multispectral data (WorldView-2), which also used textural features, as input to the classifiers (Karakizi et al. 2016).

The aim of this study is to assess the value of UAV-borne multispectral data, for discriminating and mapping three vine varieties in Attica, Greece. The objectives are:

- to develop a methodology, employing three non-parametric classifiers, namely Random Forest (RF), Support Vector Machines (SVM) and Spectral Angle Mapper (SAM), and selected vegetation indices (Vis), and
- to assess the accuracy of the resulted maps.

STUDY AREA

The study area (Figure 1) is a 1.3 ha vineyard located in Lavreotiki of the Keratea Community (close to Athens, Greece) that belongs to the wider Mediterranean wine-growing zone, a historic area prominent for its wine from ancient times of Socrates and Aristotle. It is located at an altitude of about 175 m, at the foot of Panios Mountains, embraced on both sides by sea, providing cultivation conditions of particular coolness. It differs from other parts of the Mediterranean region as its soils have a medium sandy loam texture with limestone background. Vines are planed 1,3m apart, in rows with 2m distance between them. The average vine height is of about 1 m and a bilateral Guyot training system is used.

Figure 1. Location of study area

The vineyard is planted with three indigenous varieties, namely Savvatiano, Assyrtiko and Malagouzia (Figure 2), which are used in the production of wines labeled "Protected Geographical Indication (PGI): Attica".

It is a non-irrigated vineyard, with relatively old age vines of 45-50 years, managed for low yield reaching a maximum of 4,000 kg per hectare.

DATA

An aerial survey took place at the end of July 2019, at the beginning of ripening (veraison), as this period (veraison) is considered appropriate for separating vine varieties based on literature. In the case of cooler regions, veraison takes place later, typically 40-60 days after fruit set (Tonietto and Carbonneau, 2004).

A Parrot Sequoia multi-spectral sensor (530 nm- 810 nm) was used, onboard a 3DR unmanned aerial vehicle (UAV). This sensor provides four individual bands, Red, Green, Red Edge, and NIR (as well as an RGB composite image) which are suitable for vegetation analysis. Prior to the flight, the sensor was calibrated using the appropriate calibration board. The flight parameters were defined to an altitude of 80m, which resulted in images with pixel size of less than 10 cm, along track image overlap was set at 85% and across track overlap at 80%. The flight took 5 minutes, during which 154 images were captured.

In addition, the vineyard boundary was measured with a GPS / GNSS Leica receiver, as well as internal boundaries of the three varieties parcels. Eight control points were also installed and measured with a GPS / GNSS geodetic receiver to allow precise geometric correction and orthorectification of the captured images.

Figure 2. Vine varieties of the study area

In parallel, reference data were collected at 25 locations in the vineyard, to be used for training the classifiers and assessing the accuracy of the final thematic maps.

METHODOLOGY

Figure 3 presents the consecutive steps followed during image analysis of this study. The collected images were initially pre-processed to be ready for further analysis. During the preprocessing, the four separate bands were aligned to eliminate the displacement that results from the positioning of the four lenses on the multi-spectral scanner. The images were then orthorectified using Agisoft's Metashape software, which initially creates a point cloud based on the estimated position of the sensor when capturing the images and subsequently creates a terrain elevation model, also using the control points collected in the field. They were afterwards merged into an orthomosaic.

To enhance the information contained in the resulting image, the following VIs (Table 1), which have proven useful in vine plant studies, were calculated and integrated into the image as additional bands to be taken into account during the classification phase.

The first of these indices, NDVI, was thresholded and used to mask out the non-vine pixels, so that further analysis could focus only on the pixels of interest.

Also, the reference dataset collected in the field was increased by digitizing 275 additional points on the multispectral image (Figure 4), in order to create adequate training and testing sets, for robust classification and accuracy assessment. This was feasible as it was verified that each vineyard parcel was planted with a single variety.

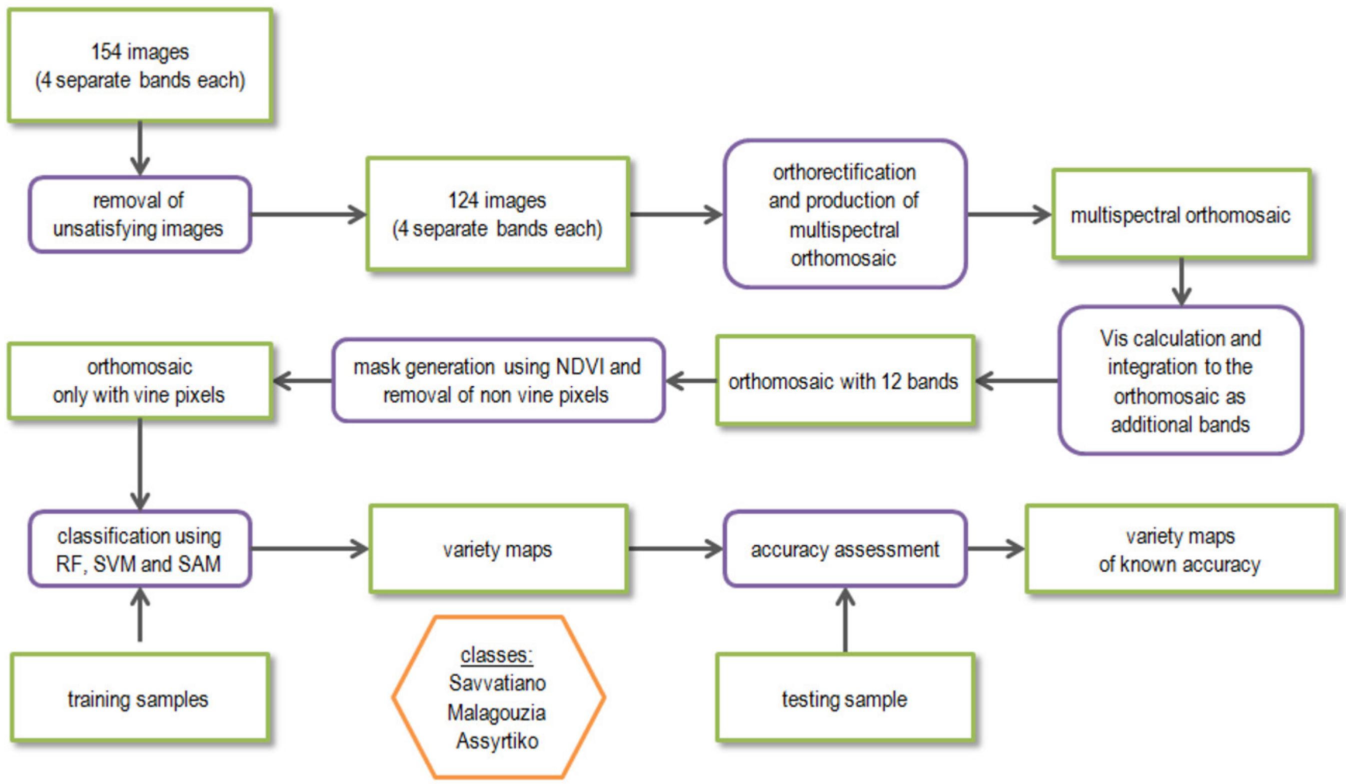

Figure 3. Methodology flowchart

Table 1. VIs integrated into the multispectral image

VI name	VI acronym	Expression	Description
Normalised Difference Vegetation Index	NDVI	$\frac{NIR-RED}{NIR+RED}$	Quantification of vegetation by measuring the difference between near infrared
Enhanced Vegetation Index 2	EVI2	$2.4\frac{NIR-RED}{NIR+RED+1}$	Optimized vegetation index, designed to enhance vegetation signal with improved sensitivity to areas with high biomass, and improved vegetation monitoring through decoupling of foliage signal and reduction of atmospheric effects
Chlorophyll Vegetation Index	CVI	$NIR\frac{RED}{GREEN^2}$	Index used to calculate the total leaf chlorophyll content.
Chlorophyll Index Green	CIgreen	$\frac{NIR}{GREEN}-1$	Index with values sensitive to small changes in chlorophyll content and are consistent with most species
Chlorophyll Index RedEdge	CIrededge	$\frac{NIR}{rededge}-1$	Index with values sensitive to small changes in chlorophyll content and are consistent with most species
Green/NIR Difference Vegetation Index	GDVI	$NIR-GREEN$	Indicator of the green or photosynthetic activity of living plants. It is particularly sensitive to changes in chlorophyll content in plants
Green-Red Normalised Difference Vegetation Index	GRNDVI	$\frac{NIR-(RED+GREEN)}{NIR+(RED+GREEN)}$	Index that highlights the amount of vegetation, the difference between vegetation and soil and reduces atmospheric effects
Normalized Difference Red/Green Redness Index	NDRGRI	$\frac{RED-GREEN}{RED+GREEN}$	Index with normalized red and green difference

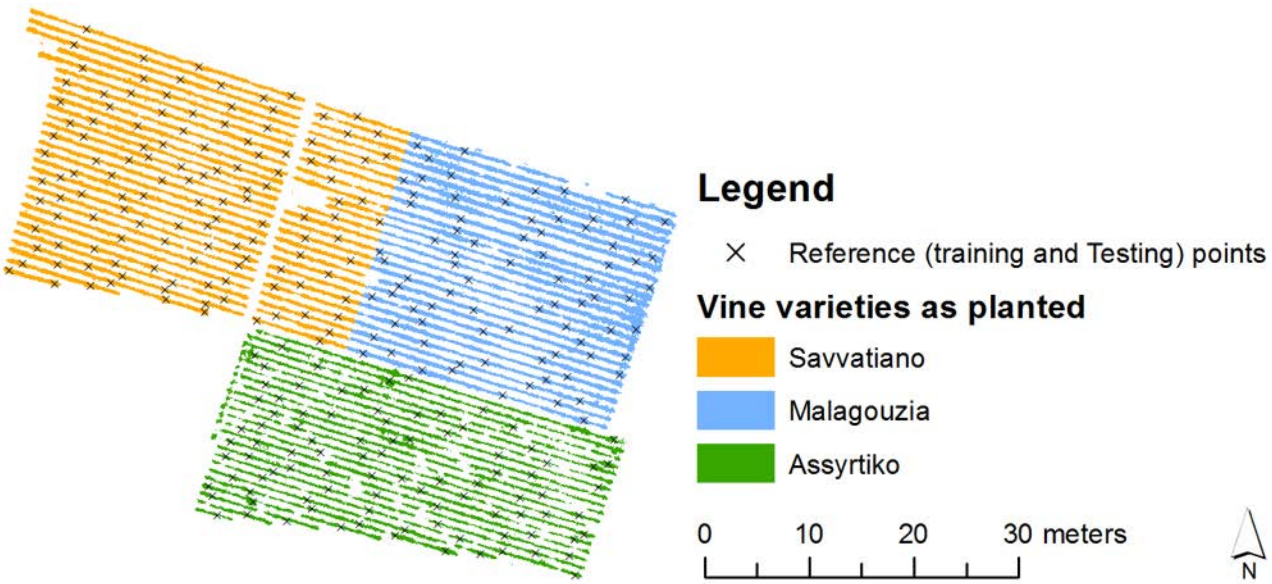

Figure 4. Reference dataset (training and testing)

The image and training data were then used in combination with the following classifiers in order to discriminate and map the three varieties present in the study area.

Random Forest is a non-parametric classifier that consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction (Pal, 2005).

Support Vector Machines (SVM) is an effective, distribution free classifier that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fitting to the data (Boser et al., 1992). The SVM seeks to find the optimal separating hyperplane between classes by focusing on the training cases that lie at the edge of the class distributions, the support vectors, with the other training cases effectively ignored (Brown et al., 2000; Belousov et al., 2002).

Spectral Angle Mapper (SAM) is a physically based classification algorithm that determines the spectral similarity between two spectra by calculating the angle between the two spectra, treating them as vectors in a space with dimensionality equal to the number of bands (Kruse et al., 1993). SAM compares the angle between the training spectra vectors of each class to the candidate pixel vectors of unknown class in n-dimensional space. It assigns to each candidate the class with the smallest angle.

The accuracy of the classification maps was assessed using a confusion matrix (Congalton and Green, 1999). This matrix cross-tabulates labels assigned to pixels by the classifier with labels assigned to the reference/testing sample, using geographic location as the key to cross-tabulation. Overall Accuracy (OA), the percentage of cases that are correctly classified, calculated along the confusion matrix diagonal, was calculated as well as user's and producer's accuracy (Story and Congalton, 1986).

RESULTS

The figures (Figures 5 and 6) show the vineyard as classified by the RF classifier, which achieved the highest OA (61.6%).

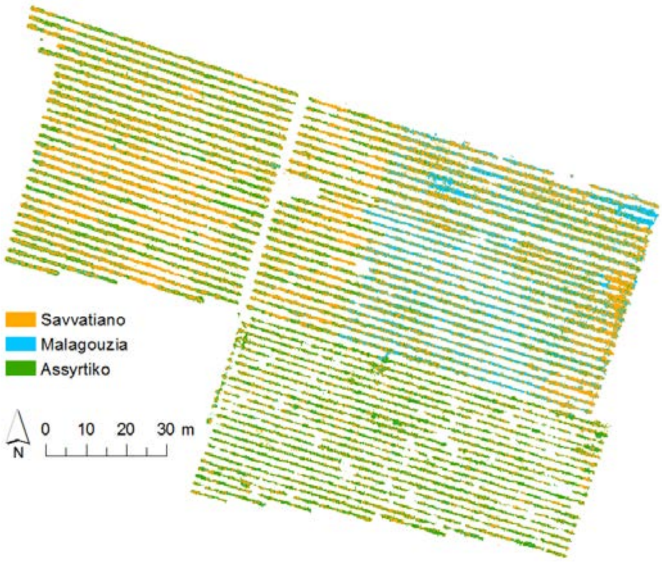

Figure 5. Map produced by RF classifier

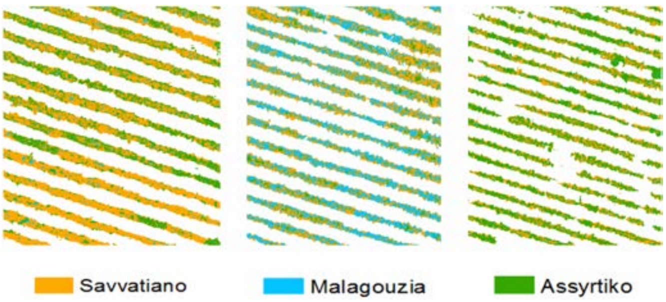

Figure 6. Focus on parts of the classified variety parcels

Tables 2 and 3 show the OA achieved by the three classifiers used, the confusion matrix that resulted from the RF classification, and the user's and producer's accuracy.

Table 2. OA achieved by the classifiers used

Classifier	OA
Random Forest	61.6%
Support Vector Machines	59.6%
Spectral Angle Mapper	58.6%

Table 3. Confusion matrix of RF classification

		Reference			
		Savvatiano	Malagouzia	Assyrtiko	Total
Classification	Savvatiano	79	30	30	139
	Malagouzia	46	48	5	99
	Assyrtiko	2	2	58	62
	Total	127	80	93	300

DISCUSSION

The results of this study show that multispectral data do not contain enough information to allow accurate discrimination and mapping of the three vine varieties that have been examined. Nevertheless, in each plot the majority of the pixels were correctly classified. Therefore, if post classification analysis is considered and results are aggregated at the plot level, plots are classified with 100% accuracy. This does not serve the purpose of identifying misplantings, but it does allow for the discrimination and mapping of single variety vineyard plots.

Further examination of the results shows that the variety pair that is more difficult to discriminate is Savvatiano and Assyrtiko. Looking at the resulting maps it is evident that a large number of pixels are falsely classified as Savvatiano while they belong to the other classes, thus this category has a large commission error. The exact opposite is the case with Malagouzia, where very few pixels of other categories have been assigned as such.

The following factors, aside the challenges imposed by VIs as described by Xue and Su (2017), are considered to have affected the results of the study and should be further addressed for potential increase of classification accuracy.

For this study, the aerial survey was held in July, during the veraison (vine ripening) in Greece, which based on existing literature is a favorable period for vine variety discrimination. During the course of the study, while gathering information from vine growers, it was suggested that another favorable period for discrimination is budding at the beginning of the growing season. This will be further explored to determine whether images taken at this stage of vine development are more suitable for the discrimination and mapping of vine varieties.

Also, the achieved accuracy would probably be different if mapping other varieties that have more diverse spectral response, as the literature suggests (Lacar et al., 2001b; Karakizi et al., 2015, Karakizi and Karantzalos, 2015). It is therefore considered to extend the study to other varieties of the Greek vineyard.

The methodology could be also extended to object-oriented analysis (GEOBIA) as opposed to the pixel-level analysis used in the present work. This would add value to the multispectral images by making advantage of their very high spatial resolution, which is very efficiently managed within GEOBIA (Chen et al., 2018)

It would also be of value to extend the research to include hyperspectral imagery, which provides richer spectral information, to examine whether this would lift the evident barrier of multispectral data.

CONCLUSIONS

Study conclusions suggest that although the multispectral images used did not result in the accurate discrimination of the vine varieties at pixel level, they nevertheless proved useful in mapping varieties at the plot level, which is requested in several stydies.

Given the fact that the methodology under consideration is based on easy to obtain and process, cost-effective images as well as that it relies mostly on free open source software, it is considered effective for applications that require plot level mapping.

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