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Using Soil and Landscape Properties to Delineate Management Zones in Vines

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Abstract: Precision Agriculture aims at managing agricultural fields in sub-field scale according to the real needs of each part of the field. Precision Viticulture is defined as the application of Precision Agriculture in vines. The current study was focused on delineating management zones using soil and topography properties. Variation of soil properties across the field were initially measured using electrical conductivity sensor EM-38. RTK-GPS was utilised to define field topography (elevation map). Topography is important when delineating management zones because it affects soil properties like movement of water and elements, soil erosion causing different depth and texture. ECa and elevation zones produced. Initially, soil sampling was carried out as targeted soil sampling based on zones formed by EM38. In 2010 samples were taken from grid of 10X20 m. Soil texture analysis was carried out. Soil depth was also measured in the grid points. Elevation, electrical conductivity soil depth and soil texture showed high spatial variability. Principle component analysis was used to define the parameters that affected mostly the variability. Management zones were defined using fuzzy clustering algorithms (MZA software). ArcGIS software package was additionally used for the data analysis and map creation. Initially six management zones were delineated giving the best results but finally only three zones were delineated as the size of the field was too small for six zones.
Key words: Precision viticulture, EM-38, management zones, fuzzy clustering

INTRODUCTION

Precision Viticulture (PV) is the application of Precision Agriculture (PA), in vineyards. It was first applied in the USA (Wample) and Australia (Bramley) in the 1999 by performing yield mapping (Bramley, 2001; Arno et al., 2009). In recent years, many PA companies and agricultural institutions have been working with PV. Development and adoption of PV was enhanced after commercial yield monitors for grape harvesters were made available. In Montpellier (France), a yield and grape quality sensor was developed (Tisseyre et al., 2001). Spatial variability of grape yield and quality has also been studied in Chile since 2001 (Ortega et al., 2003). In Spain yield mapping has been performed since 2002 (Arnó et al., 2005). In Greece (Thessaly), yield and quality mapping of grapevines was carried out in 2006 (Tagarakis et al., 2006).

PV, as most PA applications, is a continuous cyclical process (Bramley et al., 2003) including data collection, data analysis and management zones delineation, management decisions and evaluation of the applied practices. Within management zones, the effect of soil and other abiotic factors on the vine parameters (yield, vigour, quality attributes) is similar (Kitchen et al., 2005).

Management zones can be formed using a variety of data. More stable over time zones are formed using soil based measurements. Soil electrical conductivity (ECa) mapping has been extensively used to delineate management zones (Kitchen et al., 2005; Molin and Castro, 2008; Moral et al., 2010). ECa measurements are suitable to analyze spatial variability for static soil properties like salinity, texture (Editorial, 2005) and organic matter (Shaner et al., 2008). Molin and Castro (2008) found that ECa measurements at two depths were highly correlated with texture (r = 0.75 for shallow ECa readings and 0.66 for deep ECa readings with soil clay content). On the contrary, Kuhn et al., (2008) concluded that soil organic matter CaCO3 were more important in relation to ECa_{25} (apparent electrical conductivity corrected to 25^{o}C) than clay. In recent works, ECa data were used to perform soil drainage mapping (Liu et al., 2008).

Kitchen et al.. (2005) used soil electrical conductivity (ECa) and elevation data to delineate productivity zones. They used unsupervised fuzzy *c*-means clustering in for zone delineation.

In Brazil, fuzzy clustering techniques were applied to establish management zones in a field cultivated with arable crops (Molin and Castro, 2008). The authors concluded that principal component analysis and fuzzy logic application on ECa and soil data may lead to the delineation of reliable soil management zones.

Principal component analysis was also used by Fraisse et al., (2001). They analyzed topographic attributes and soil electrical conductivity in order to identify management zones. The analysis indicated that the most important attributes to include when performing unsupervised classification were the elevation and soil ECa. Slope and Compound Topographic Index (an index which represents the spatial distribution of water accumulation areas in the landscape) were less important but may also be included in the analysis.

The aim of the present study was to collect and analyze field data of soil properties and to investigate possible correlations among the measured parameters in order to delineate management zones in a commercial vineyard.

MATERIALS and METHODS

The study was conducted in a commercial vineyard (one hectare area) at Mikrothives, Central Greece (Latitude: 39.26^{o}, Longitude: 22.73^{o}). The vineyard was planted with *Vitis vinifera* cv. Agiorgitiko, a Greek variety producing high quality red wine, grafted onto 1103P rootstock. Vines were trained to a bilateral cordon and were spaced 1.0×2.6 m. The vineyard was located on a steep slope. The upper part had poorer soil (light, stony, shallow) compared to the lower part where the soil was deeper and more fertile, the result of long time erosion.

An elevation map of the field was prepared using RTK-GPS (Ag-GPS 252, Trimble Ltd., USA). The GPS was mounted on a tractor that moved across the field between the rows at 4 m apart.

The elevation data were processed by the ArcGIS software (ESRI, Inc., USA) to calculate the grade of the slope of the vineyard in two ways. Slope in degrees and slope percentage.

Apparent electrical conductivity (ECa) measurements gave a first assessment of soil variability. ECa mapping took place in autumn 2009 using an EM-38 probe (EM38 RT, Geonics LTD, Ontario Canada). Vertical dipole mode was used. The measurement was performed by walking across the field between the rows at 4 m apart. A D-GPS (Differential-GPS 106, Trimble Ltd., USA) was used to record the position of each measurement. The data logger (Allegro CX, Jupiner Systems Inc., Logan Utah, USA) was set to record a value every second.

Soil depth was estimated by digging holes across the vineyard at georefferenced points using the soil sampler.

Two soil sampling methods were used. In 2009 was targeted soil sampling. The samples were taken according to the ECa and elevation zones produced. Nine soil samples were taken from one depth 0-40 cm and analyzed. The second soil sampling took place in 2010 on grid of 10X20 m. The vineyard was sectioned in 48 parts each one sized 10x20 m. Samples were taken from two soil depths: 0-15 cm and 15-40 cm.

Data analysis

Soil sampling grid was the largest grid (10×20 m) among all the measurements taken. Therefore all the measurement data was transformed on the 48 section grid. A GIS software (ArcGIS, ESRI, Inc., USA) was utilized to calculate the mean values for each measurement in each section.

Descriptive statistics were produced using the SPSS statistical software. Principal component analysis was then performed to check the significance of the factors that were measured.

The Kaiser Meyer Olkin measure of sampling adequacy (KMO) was calculated. It indicates whether the sampling size of the data gives reliable factor analysis. It varies between 0 and 1. As the KMO value reaches 1 patterns of correlations are more compact providing distinct and reliable factors (Field, 2009). According to literature KMO values below 0.5 are not acceptable, values between 0.5 and 0.7 are mediocre, between 0.7 and 0.8 the values are good, 0.8 to 0.9 they are great and finally values between 0.9 and 1 are superb (Hutcheson and Sofroniou, 1999).

RESULTS and DISCUSSION

Initially descriptive statistics were exported giving a first statistical assessment of the data variables. The results from the descriptive statistics are presented in Table 1.

Soil depth, ECa, slope degree, slope percent and sand content showed high spatial variability.

Principal component analysis was performed. All the soil and landscape variables were used in the initial data set. The initial analysis gave poor results. When the silt variable was removed from the data set the results were better. Therefore the silt parameter was excluded from the analysis.

Principal component analysis calculates a Pearson's correlation matrix (Table 2). The variables which are not correlated with any of the other variables were excluded from the further analysis. Furthermore, principal component analysis calculates the proportion of variance explained from each component (parameter).

As mentioned above the Kaiser Meyer Olkin measure of sampling adequacy (KMO) indicates whether the sampling size of the data gives reliable factor analysis. For the current research dataset the KMO value was 0.736 which indicate that the data are appropriate for performing factor analysis.

In theory, there are three types of variance that occur in each variable. Some of the variance is common with other variables known as common variance, some is the variance which is specific to that measure known as unique variance and finally there is some variance which occurs by the error (Field, 2009). Performing Principal component analysis to a dataset with several variables, linear transformation occurs compressing the original data into a smaller set of non-correlated variables, the components (Molin and Castro, 2008). The components represent most of the information contained in the original data set (Afifi and Clark, 1996). As the components are formed, each variable has different participation (loading) on each component.

Table 3 shows the percentage of the total data set variance that could be explained by each principal component in the analysis. The first three components explain 90.4% of the total data set variance. Over half of the variance is explained by the first component. Table 4 contains the loadings of each variable onto each component.

As seen on Tables 3 and 4 the loadings of the soil texture variables (clay and sand content for the two sampling depths) onto the first component which explains over 50% of the total variability are very high. The other variables except 'soil depth' showed quite high values as well. However 'soil depth' showed very high loading onto the second component which explains 27.6% of the total variance.

Table 1. Descriptive statistics for the variable data

Descriptive Statistics							
Variable	**N**	**Mean**	**Std. Dev.**	**Variance**	**C.V.**	**Skewness**	**Kurtosis**
SoilDepth	48	58.07	21.09	444.79	36.32	1.46	1.11
Eca	48	53.07	16.90	285.49	31.84	0.12	-0.75
elevation	48	104.52	5.84	34.11	5.59	-0.21	-1.30
slope degree	48	7.68	1.91	3.65	24.87	0.25	-0.44
slope percent	48	13.57	3.43	11.75	25.26	0.10	-0.72
CLAY_0_15	48	44.18	2.77	7.69	6.28	-0.55	0.13
CLAY_15_40	48	44.02	3.61	13.04	8.20	-0.14	0.35
SAND_0_15	48	32.11	3.89	15.15	12.12	0.35	-0.55
SAND_15_40	48	27.94	4.28	18.33	15.33	0.29	-0.12
SILT_0_15	48	23.72	2.34	5.48	9.87	-0.15	-0.25
SILT_15_40	48	28.04	1.29	1.67	4.61	-0.11	-0.59

Table 2. Pearson's correlation matrix

Variable	Soil Depth	ECa	Elevation	Slope degree	Slope percent	Clay 0_15	Clay 15_40	Sand 0_15	Sand 15_40
SoilDepth	1.000	.721**	-.754**	-.348*	-.345*	.026	.187	.114	-.167
ECa	.721**	1.000	-.810**	.077	.073	.395*	.462**	-.311*	-.457**
Elevation	-.754**	-.810**	1.000	-.255*	-.267*	-.465**	-.487**	.293*	.459**
Slope degree	-.348*	.077	-.255*	1.000	.986**	.559**	.297*	-.505**	-.311*
Slope percent	-.345*	.073	-.267*	.986**	1.000	.591**	.333*	-.539**	-.336*
CLAY_0_15	.026	.395*	-.465**	.559**	.591**	1.000	.743**	-.804**	-.675**
CLAY_15_40	.187	.462**	-.487**	.297*	.333*	.743**	1.000	-.688**	-.961**
SAND_0_15	.114	-.311*	.293*	-.505**	-.539**	-.804**	-.688**	1.000	.656**
SAND_15_40	-.167	-.457**	.459**	-.311*	-.336*	-.675**	-.961**	.656**	1.000

**significant at p<0.001
*significant at p<0.05

Table 3. Total variance explained for each of the components

Total Variance Explained			
Component	Total	% of Variance	Cumulative %
1	4.564	50.712	50.712
2	2.483	27.588	78.300
3	1.087	12.079	90.379
4	.396	4.402	94.780
5	.226	2.507	97.288
6	.153	1.695	98.983
7	.050	.553	99.535
8	.030	.336	99.872
9	.012	.128	100.000

Extraction Method: Principal Component Analysis.

Table 4. Component matrix for the Principal Component Analysis

Component Matrix[a]			
Variable	Component		
	1	2	3
CLAY_0_15	.883	.167	-.101
CLAY_15_40	.862	-.093	-.430
SAND_15_40	-.840	.081	.424
SAND_0_15	-.808	-.266	.247
elevation	-.684	.567	-.396
slope percent	.643	.613	.437
slope degree	.617	.613	.468
SoilDepth	.211	-.932	.193
ECa	.613	-.655	.218

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Consequently, the Principal Component Analysis indicated that in the zone delineation should be used all the measured variables except the 'silt content'. Fuzzy clustering algorithms were used for management zones delineation. These algorithms are classifying data into homogenous zones. MZA software (ARS, University of Missouri) was utilised. The software performs fuzzy clustering c-means analysis. Mahalanobis Measure of Similarity was used. Previous studies concluded that Mahalanobis Measure of Similarity is ideal for soil and landscape data classification. Euclidean measure of similarity should be used only for statistically independent variables demonstrating equal variances (Fridgen et al, 2004).

The proper number of zones was defined by two indices, FPI (Fuzziness Performance Index) and NCE (Normalized Classification Entropy). As these indices approach 0, classes became more distinct, with less membership sharing. The optimum number of clusters was achieved when both factors had minimal values. The best combination was achieved when classified in 6 classes (Figure 1).

Even though the best index combination was achieved for 6 zones, this delineation is non manageable for the experimental vineyard as seem on the map (Figure 3). Additionally the difference between three and six zones is not very large. The area size (1 hectare) is quite small to divide it in more than 3 zones. The indices values for the two zone delineation are quite high. Therefore the vineyard was divided in three management zones.

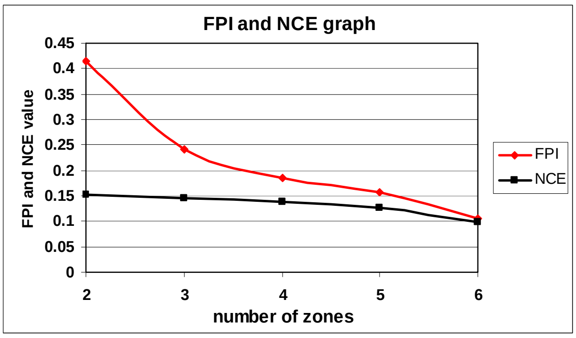

Figure 1. FPI and NCE index graph

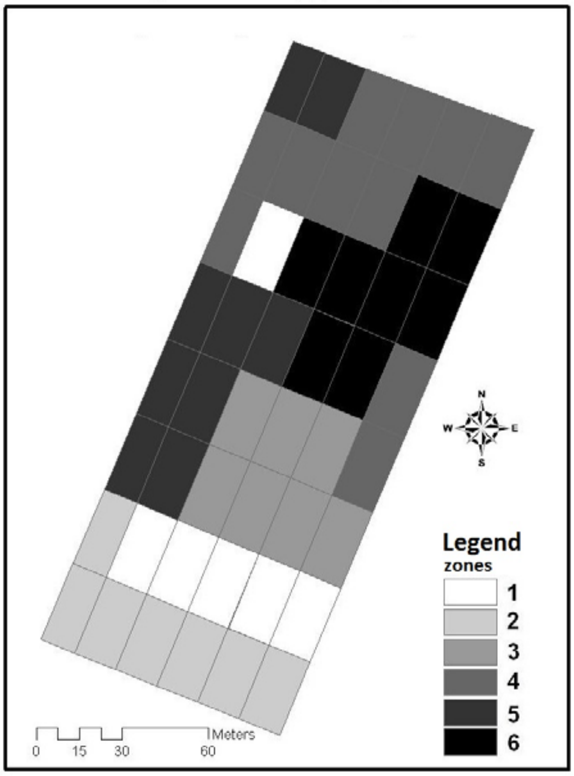

Figure 2. Management zone map. Delineation in six zones

According to the final management zone map (Figure 3), the bottom part of the vineyard (approximately 0.25 ha area) represent the first management zone. This zone demonstrates low altitude, high ECa values, low slope grade, high clay content and intermediate sand content.

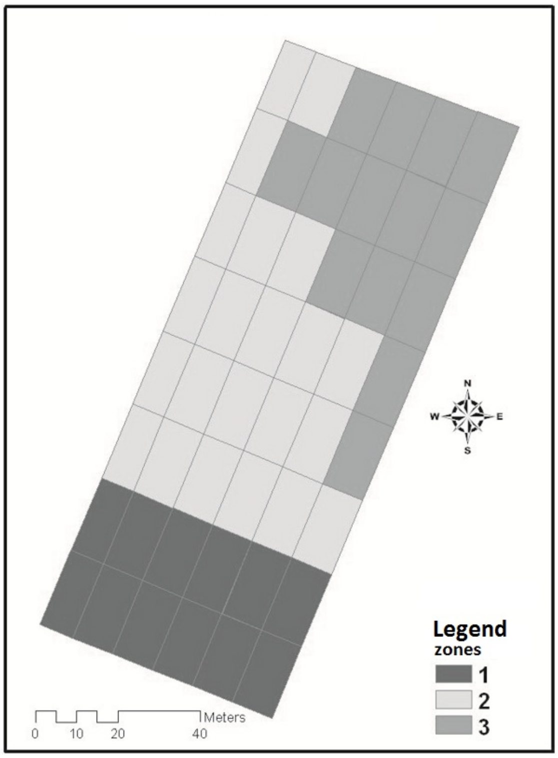

Figure 3. Management zone map. Delineation in three zones

The second zone is located at the center and left part of the field (approximately 0.45 ha area). It shows intermediate altitude, low ECa values high slope grade, intermediate clay content and low sand content.

The third zone is at the upper right part of the field with the highest altitude (0.3 ha). The zone properties are: intermediate ECa values, low slope grade, low clay content and high sand content.

It should be noted that these zones agree with the observations of the famrer.

CONCLUSIONS

From the presented results it can be concluded that:

1. Soil variables showed high spatial variability despite the small size of the experimental vineyard. Particularly the Coefficient of Variation was high for the variables: Soil depth (C.V.=36.32%), ECa (C.V.=31.84%), slope degree (C.V.=24.87%), slope percent (C.V.=25.28%), sand 0-15cm (C.V.=12.12%) and sand 15-40cm (C.V.= 15.33%).
2. Soil based measurements are considered time stable variables. Data processing of ground based measurements may lead to more stable over time management zones.
3. ECa was negatively correlated to elevation ($r=-0.81$ significant at $p<0.001$) and sand content ($r=-0.457$ significant at $p<0.001$) and positively correlated to soil depth ($r=0.721$ significant at $p<0.001$) and clay content ($r=0.462$ at $p<0.01$). On the other hand, soil depth was negatively correlated to elevation ($r=-0.754$ at $p<0.001$) while clay content was significantly correlated to slope degree and slope percent ($r=0.559$ and $r=0.591$ respectively at $p<0.001$). Sand content was significantly negatively correlated to slope degree and slope percent ($r=-0.505$ and $r=-0.539$ respectively at $p<0.001$).
4. Principal component analysis can be considered as a useful statistical tool to analyze soil data. It is a statistically safe method for analyzing the relationship between the measured parameters and the effect that each parameter shows on the data set. Consequently it can become a useful tool for management zone delineation, assisting the researcher on the selection of the variables.

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