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Delineating management zones to apply site-specific irrigation in the Venice lagoon watershed

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Abstract

The aim of this work was to develop a protocol to identify management zones (MZs) to apply variable rate irrigation (VRI) in the Venice Lagoon Watershed. In a 12.5-ha field cultivated with sugarbeet, sparse soil analysis, electromagnetic induction (EMI) scans and a multispectral radiometer (MSR) system were applied to gather information on spatial variability. To identify the MZs, unsupervised fuzzy *c*-means clustering was applied to 7 different combinations of thematic maps. Preliminary results suggest that the combination of EMI and MSR could be an efficient and cost-effective method for delineating MZs to apply site-specific irrigation.

Keywords: variable rate irrigation, vegetation indices, electromagnetic inductions scans, fuzzy *c*-means clustering

Introduction

Venice Lagoon Watershed is an area with a unique landscape and natural elements. Water pollution by nitrates is a serious problem in the Venice Lagoon Watershed with concentrations in the groundwater that can exceed the drinking water limits more than once a year. Inefficient agricultural water management could contribute to surface water runoff or leaching of pollutants. Variable Rate Irrigation (VRI) has been proposed as a new technology to improve water use efficiency and thus reduce agricultural pollution. Application of VRI requires management zones (MZs) to be delineated within the field with homogeneous water requirements. Various techniques for delineating MZs are currently being investigated (e.g. Taylor *et al.*, 2003 ; Mzuku *et al.*, 2005). Soil sampling at a few randomly selected positions has been the traditional way to obtain information about the soil and state of the crop, even if it is generally time-consuming, labour-intensive and costly. The potential use of intensively-recorded ancillary data, such as electro-magnetic induction scans (EMI) or multispectral remote sensing data, has been examined in recent years, because they are relatively easy and inexpensive to collect (Blackmer *et al.*, 1995). If the sparse and more intensive data are spatially correlated, then the additional information from the ancillary data can be used to improve the estimation precision of the sparsely sampled primary variable (Kitchen *et al.*, 2005; Castrignanò *et al.*, 2000). The use of multispectral data is also useful for site-specific irrigation as it gives an estimate of the variability of crop biomass and indirectly of water requirements (Basnyat *et al.*, 2005). Appropriate statistical methods, such as cluster analysis (Fridgen *et al.*, 2004) or factorial kriging analysis (Castriganò *et al.*,

2006), are then required to integrate the information provided by the different thematic maps to delineate the MZs.
The aim of this work was to develop a protocol to identify management zones for applying VRI in the Venice Lagoon Watershed.

Material and methods

The study was conducted in 2005. The site was a 12.5-ha field cultivated with sugarbeet (*Beta vulgaris* L.), located in the Venice Lagoon Watershed. A mixed-sampling scheme was followed of the top soil layer: 40 samples were collected at the nodes of a 60-m grid and 80 additional points where collected at the nodes of 10 transects. The transects were set in the north and east axis at 1, 5, 15, 30 metres from 10 randomly chosen nodes of the grid. Each soil sample was analysed for bulk density, water content, texture, pH, electrical conductivity (1:2), soil organic matter (SOM), TKN and phosphorus Olsen.
Multispectral reflectance (MSR) readings were collecetd with a hand-held passive spectroradiometer (Model MSR187, CropScan, Inc., Rochester, MN) with 8 narrowband wavelengths (460-810mm). The radiometer sensor was positioned 2 m above the crop row to measure the reflectance of a surface of almost 1 m^2. Readings were collected on four different dates (20/6, 4/7, 15/7 and 28/7) between the phenological phase of 20% interow coverage and harvest. Three ratio vegetative indices (VIs) were calculated from the percentage reflectance (*R*): Normalized Difference Vegetation Index ($NDVI = R_{nir}\text{-}R_{red}/R_{nir}+R_{red}$), Ratio Vegetation Index ($RVI = R_{red}/R_{nir}$) and Modified Chlorophyll Adsorption Index (MCARI = $(R_{nir}\text{-}N_{red})\text{-}0.2\ (R_{nir}\text{-}R_{green})(N_{nir}/R_{red})$). Apparent soil electrical conductivity (EC_a) was measured by an EMI sensor (Geonics EM38DD). The EM38DD was operated in both horizontal and vertical orientations. The instrument provided a weighted depth reading to approximately 0.5 m in the horizontal orientation and 1.5 m in the vertical orientation. EMI measurements were collected in November 2005, carried out in the field with associated DGPS antenna. At harvest (4/8/2005) the sugarbeet storage roots were collected from 1-m^2 sampling areas centred in the 120 nodes of the grid/transects. These roots were analysed for dry weight and sugar content. Thematic maps were created from the soil and reflectance data using the geostatistical kriging technique (GS+7.0, Gamma Design Software). Leave-one-out cross-validation was performed to evaluate the goodness of the inferred maps.
To identify the MZs, unsupervised fuzzy *c*-means clustering (Management Zone Analyst 1.0 , Fridgen *et al*., 2004) was applied to the following combinations of maps: C1) ECa; C2) soil parameters (sand+clay+ SOM + P Olsen); C3) soil parameters + shallow ECa; C4) VIs from the last date (RVI+ MCARI); C5) soil parameters + RVI; C6) ECa+RVI; C7) ECa+RVI + soil parameters. Unlike conventional set theory, which allows an individual to belong to just one set, fuzzy set theory allows individuals to exhibit partial membership in each of a number of sets, and to consequently better represent the continuous variability in natural phenomena (Fridgen *et al*., 2004).
In the cluster process it was necessary to define a priori the number of clusters i.e. MZs. To select the best number of clusters a) we clustered data by different combinations of parameters and number of clusters (from 2 to 8) and b) evaluated the results with the Fuzziness Performance Index (FPI). The FPI is a measure of the degree of separation (i.e. fuzziness) between fuzzy *c*-partitions and the data classified through the cluster analysis (Fridgen *et al*., 2004). It is defined as:

$$FPI = 1 - \frac{c}{(c-1)}\left[1 - \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^2 / n\right]$$

where c = cluster centroids, u_{ik} = values for each k observation and cluster i. Values of FPI may range from 0 to 1. Values approaching 0 indicate distinct classes with little membership sharing while values near 1 indicate non-distinct classes with a large degree of membership sharing.

Crop yield data were not sufficiently representative to verify the results by comparing the within-zone productivity with the MZs maps. A preliminary evaluation of the protocol was carried out a) assuming that the most representative MZs maps were obtained by integrating all the available information (C7) and b) by comparing these maps with those obtained with a lower levels of information (C1 to C6).

Results and Discussion

Significant correlations were found between NDVI and RVI and the main soil parameters (tab. 1). The coefficient of correlation varied according to the soil parameters and date of reading: the highest values were observed with the sand, on the first three dates. On the contrary, MCARI presented a significant correlation, even if low, only with the sand and clay at the end of July. No correlation was found between soil parameters and shallow and deep EC_a. Correlation of the VIs with crop yield was in general poor and significant only on the two final dates for NDVI and RVI, and on 20/6 for MCARI, whereas a poor correlation was found with sugar content on 15/7. Shallow EC_a was correlated ($p<0.05$) with both sugar content ($r = 0.33$) and crop yield ($r = -0.31$). Correlation coefficients were also for this parameter very low.

Table 1: Correlation between the soil parameters and EMI and VIs; bold type correlations are significant at the 5 % level.

	Sand	*Clay*	*SOM*	*TKN*	*P Olsen*	*Yield*	*Sugar*
EC Shallow	0.035	-0.024	0.138	0.007	-0.044	**-0.313**	**0.333**
EC Deep	-0.016	0.001	-0.021	-0.033	0.139	-0.134	0.086
NDVI(20/6)	**-0.512**	**0.424**	**0.321**	**0.302**	**0.217**	0.174	-0.168
NDVI(4/7)	**-0.482**	**0.318**	**0.317**	**0.289**	0.109	0.122	-0.106
NDVI(15/7)	**-0.516**	**0.388**	**0.288**	**0.264**	0.072	**0.265**	**-0.236**
NDVI(28/7)	**-0.339**	**0.197**	**0.207**	0.169	-0.006	**0.208**	-0.134
RVI(20/6)	**-0.512**	**0.424**	**0.321**	**0.302**	**0.217**	0.174	-0.168
RVI(4/7)	**-0.482**	**0.318**	**0.317**	**0.289**	0.109	0.122	-0.106
RVI(15/7)	**-0.516**	**0.388**	**0.288**	0.264	0.072	**0.265**	**-0.236**
RVI(28/7)	**-0.339**	**0.197**	**0.207**	0.169	-0.006	**0.208**	-0.134
MCARI(20/6)	0.151	-0.077	-0.162	-0.120	-0.097	**-0.246**	0.112
MCARI(4/7)	-0.040	0.102	0.016	-0.065	-0.087	0.032	0.031
MCARI(15/7)	0.201	-0.143	-0.015	0.010	0.000	-0.181	**0.200**
MCARI(28/7)	**-0.240**	**0.209**	0.130	0.076	0.014	-0.124	-0.067

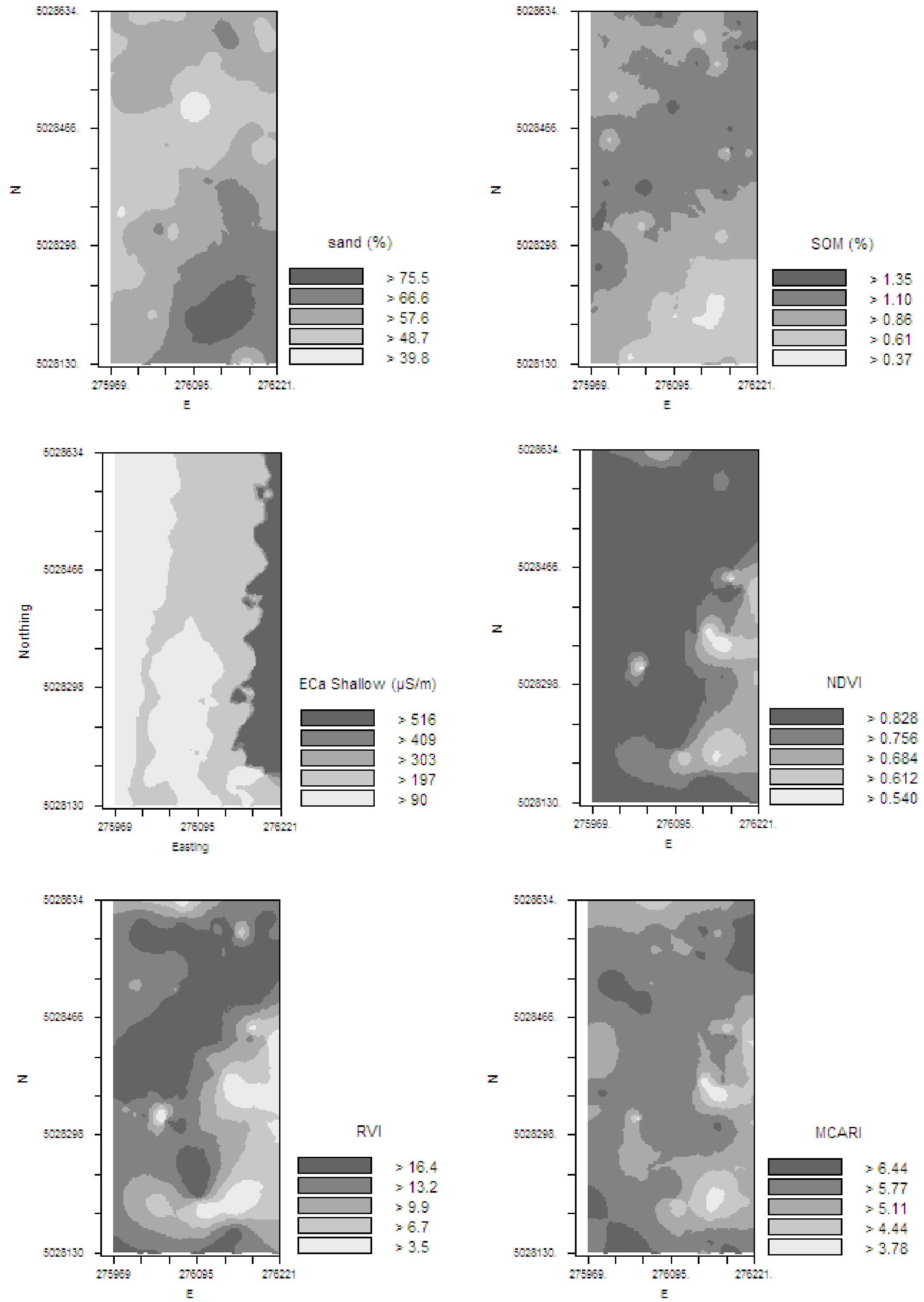

Figure 1: Thematic maps: sand, soil organic matter (SOM), shallow EC_a and VIs (NDVI, RVI and MCARI; 28/7)

The soil thematic maps (e.g. sand and SOM) showed a variability and distribution similar to the VIs maps (fig. 1). The south-eastern zone was characterized by coarse texture and low SOM (< 1%) whereas the central-northern zone had the highest content of clay and SOM (up to 2%). Soil fertility limited crop growth in the south-eastern zone, as also confirmed by the lower values of NDVI and RVI. The map of the shallow ECa (fig. 1) presented a different spatial structure to the previous maps, evidencing a strong gradient in the WE direction: in the eastern part the ECa increased abruptly from 200 to 600 mS m^{-1} within a few metres. Most likely the intrusion of salty water from an open canal marking the eastern boundary of the field affected the ECa.

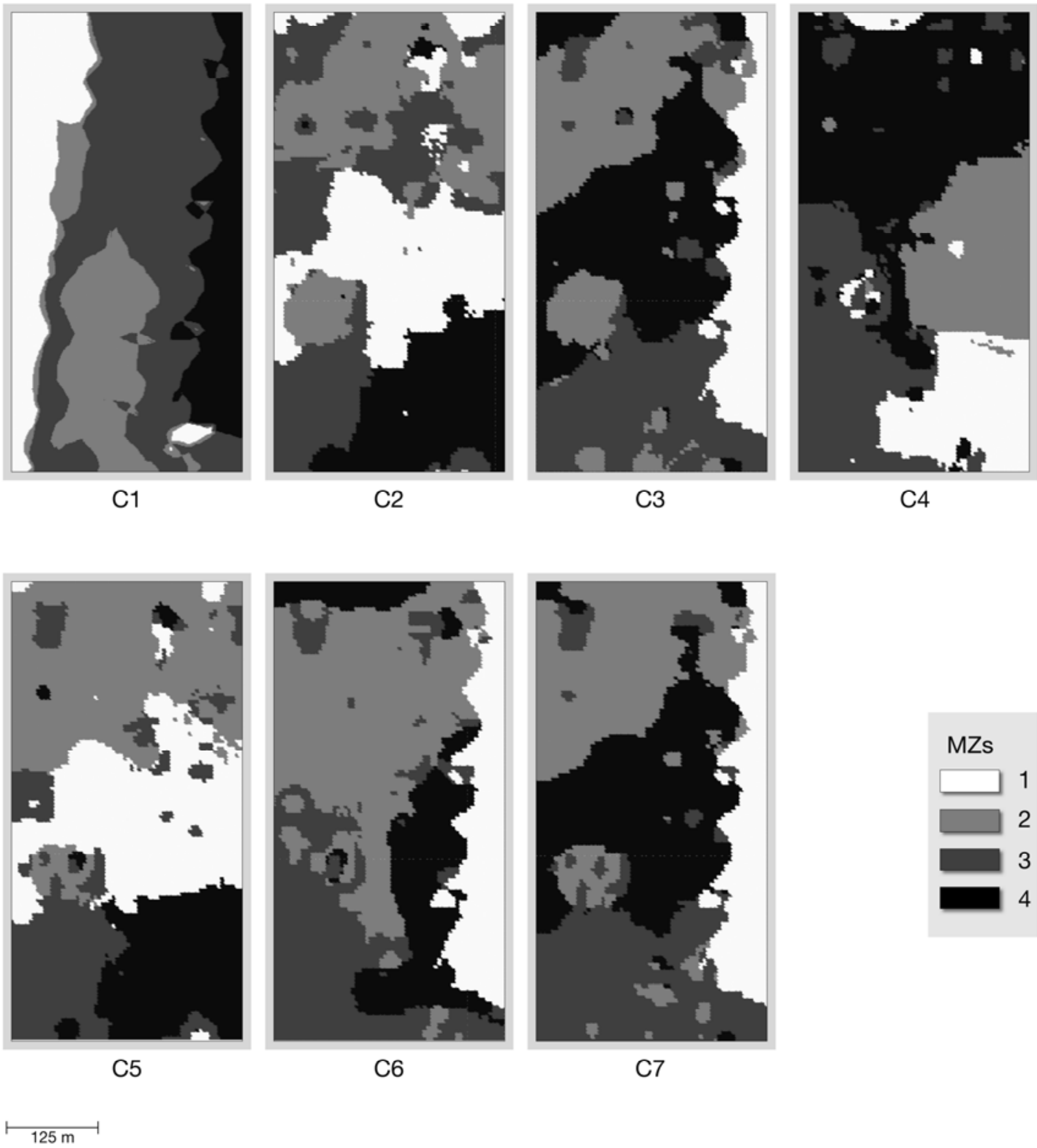

Figure 2: Management Zones maps obtained for the different combinations of parameters using 4 clusters. The meanings of the abbreviations are reported in the text

MZs maps showed a different pattern according to the various combinations of parameters and number of clusters (fig. 2). We observed no significant improvement of the FPI with a cluster number higher than 4. Only the combinations obtained processing the vegetation index data (C4) enhanced the degree of separation increasing the number of clusters (fig. 3). As expected, the FPI values increased with the number of clustering parameters and, consequently, the data variability also increased.
In general, cluster analyses using only 4 clusters achieved a good separation between classes and produced MZs maps with a practical significance. Indeed MZs maps obtained with a higher number of clusters, even if representative of the natural variability within the field, had the highest degree of fragmentation and number of small-sized (< 10 m^2) zones. From a practical point of view this is a serious constraint, especially when the minimal size of the MZs doesn't match the resolution of the variable rate system. For the same reason, the MZs maps obtained using 3 clusters (fig. 4) could also represent an acceptable compromise between classification accuracy and practical use of the map.

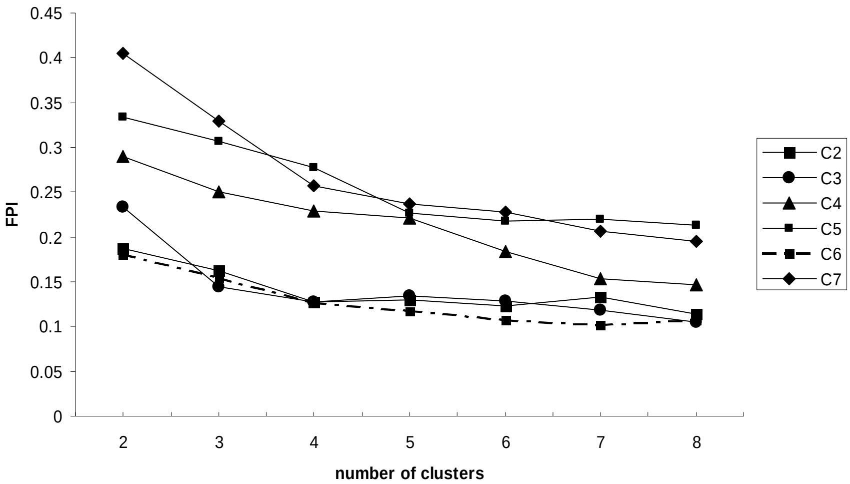

Figure 3: Fuzziness performance index (FPI) as calculated by MZA for the different combinations.

MZs maps obtained reducing the number of clustered parameters, i.e. excluding RVI or soil parameters (fig. 2), presented a pattern similar to the best theoretical MZs map with 4 clusters, with a loss of information that, according to this preliminary analysis and considering the cost of the information, appears to have no practical significance.

Conclusions

These preliminary results suggest that the combination of EMI and MSR could be an efficient and cost-effective method for delineating management zones to apply site-specific irrigations in the Venice Lagoon Watershed. From a practical point of view it is expedient to select the combination of parameters that allow MZs maps to be built with a satisfactory ratio between accuracy and cost. The application of unsupervised fuzzy *c*-means clustering was a valuable way to integrate the information and assess which variables were most important for creating MZs. Multiyear productivity data are necessary to verify the results, by comparing the within-zone productivity with the MZs maps.

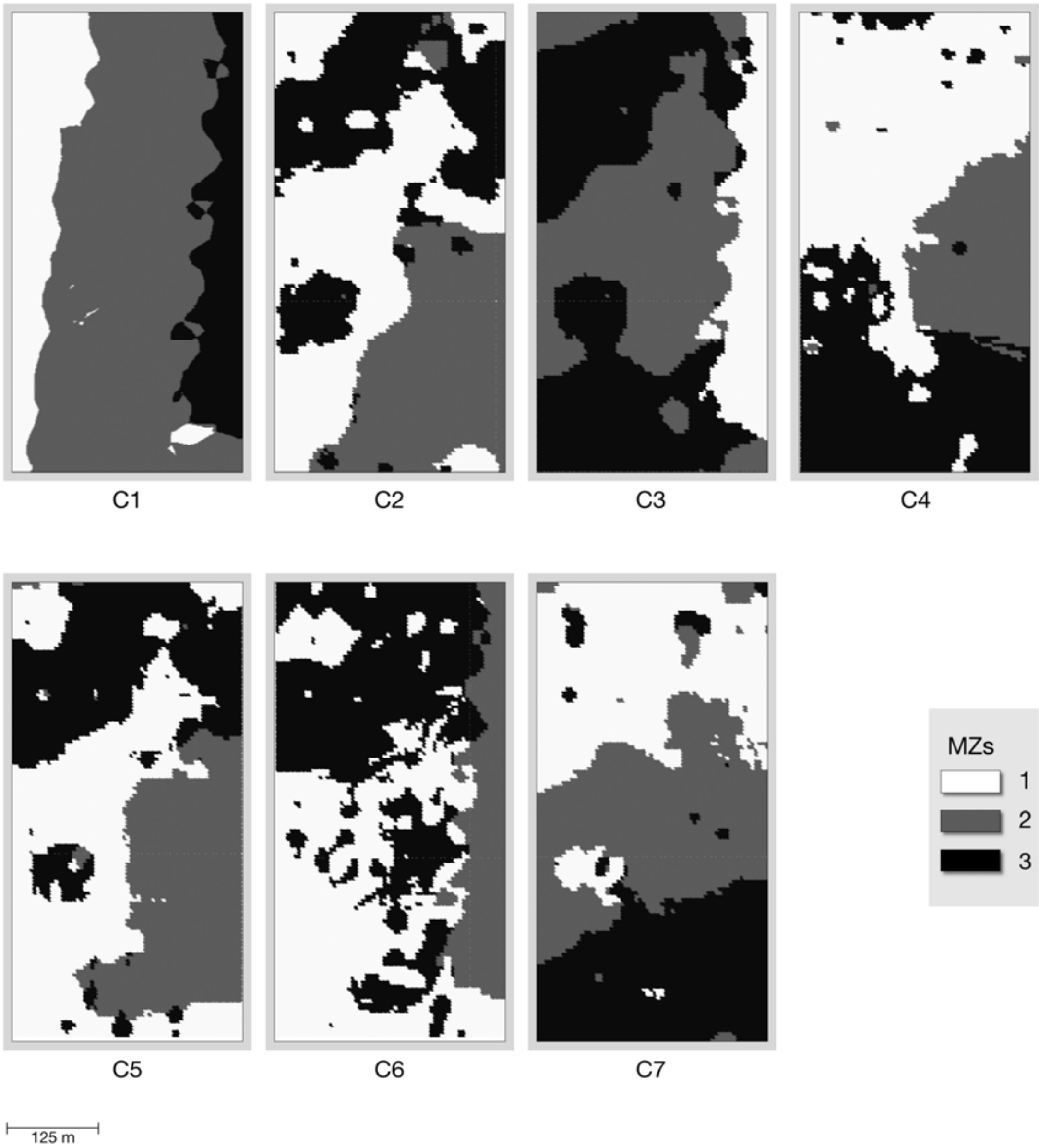

Figure 4: Management Zones maps obtained for the different combinations of parameters using 3 clusters. The meanings of the abbreviations are reported in the text.

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