Development and evaluation of an automatic software for management zone delineation

Enrique M. Albornoz[a,b]; Alejandra C. Kemerer[c,d]; Romina Galarza[a]; M. Nicolas Mastaglia[a]; Ricardo Melchiori[c]; Cesar E. Martınez[a,e].

[a]Centro de Investigación en Señales, Sistemas e Inteligencia Computacional (SINC(i)), Fac. de Ingeniería y Cs. Hídricas, Univ. Nacional del Litoral, Santa Fe (Argentina)

[b]Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Argentina

[c]Grupo Recursos Naturales y Factores Abióticos. Instituto Nacional de Tecnología Agropecuaria (INTA). Estación Experimental Agropecuaria Paraná, Oro Verde, Entre Ríos (Argentina)

[d]Cátedras de SIG y Climatología Agrícola, Facultad de Ciencias Agropecuarias, Univ. Nacional de Entre Ríos, Oro Verde, Entre Ríos (Argentina)

[e]Laboratorio de Cibernética, Facultad de Ingeniería, Univ. Nacional de Entre Ríos, Oro Verde, Entre Ríos (Argentina)

Abstract

The availability of user-friendly and automatic software for management zone delineation is limiting the adoption of site-specific management practices. Several procedures for management zone delineation have been proposed, but they commonly require the use of different software, or advanced GIS and statistical skills of users, which limit their adoption. This study proposes a user-friendly and automatic software that would integrate all steps in order to delineate management zones and make prescription files. The software includes importation of different input data layers, re-projection and resizing data in a common grid size. An integrative index was proposed for the selection of the optimal number of zones after clustering analysis. Users are guided by graphical windows showing intermediate results. Also, additional automatic post-processing techniques to improve size, shape and fragmentation of delineated zones are available. The final step allows to generate the ESRI Shapefile required to make variable rate prescriptions by zone with minimal user intervention. The performance of our approach was evaluated for management zone delineation using single and multiple layers of data by comparing with MZA, and the improvement of our approach in the selection of the optimal number of zones and reducing zone-fragmentation was showed. The software design includes a simple graphical interface (GUI) and requires minimal user intervention in order to assist the end-user. The main contribution of this work was the successful development of this automatic user-friendly solution that includes all the necessary steps for management zone delineation and prescription file generation.

Keywords: Precision agriculture · Management zone · Clustering algorithms · Fuzzy C-means · Variable rate prescription

Introduction

Management zones are within-field areas of relatively homogeneous yield-limiting factors for which a single prescription rate of inputs may be adequate (Doerge 1999). The delineation of management zones for variable rate prescription includes several steps from pre-processing of data layers, clustering and selection of the number of zones, and finally the generation of a variable rate prescription file. Several reports deal with management zone delineation using different data layers such as soil properties (Mzuku et al. 2005), apparent soil electrical conductivity (Shaner et al. 2008), yield maps (Doberman et al. 2003; Jaynes et al. 2003), topographic attributes and soil electrical conductivity (Fraisse et al. 2001; Peralta et al. 2015), satellite imagery (Zhang et al. 2010) or a combination of several data layers (Fleming et al. 2000; Schepers et al. 2004; Hornung et al. 2006; Guastaferro et al. 2010).

The use of several data layers in a joint manner allows the integration of different factors related to crop productivity and contributes to a better delineation of management zones. However, the conditioning of data layers in the same spatial resolution requires advanced GIS expertise for interpolate data, as mentioned in Ping and Dobermann (2003), Fridgen et al. (2004), Taylor et al. (2007), and Guastaferro et al. (2010). The requirement of skills to deal with this task represents a common drawback for precision agriculture end-users.

Determination of the optimal number of zones for each field may be another controversial step in management zone delineation process. In MZA software (Fridgen et al. 2004), fuzziness performance index (FPI) and normalized classification entropy (NCE) are available to guide the selection of the optimal number of zones, but sometimes both indices show non-convergence at the same number of zones (Brock et al. 2005), hence the selection ends up being subjective. A recent report showed additional indices for the selection of the number of zones, but coincidence in the optimal number of zones was not obtained (Cordoba et al. 2016). To address this problem, Galarza et al. (2013) proposed using the Euclidean distance of three statistical indices to integrate the results in order to select a unique optimum number of zones.

Extensive work with different methods and degree of complexity have been reported for management zone delineation (Schepers et al. 2004; Frogbrook and Oliver 2007). The common clustering techniques may produce small fragments that could be removed by filtering to obtain more practical results (Ping and Dobermann 2003). The size and shape of delineated zones, as a limitation to farm machinery characteristics, had been considered only in few cases as in segmentation methods (Roudier et al. 2008; Pedroso et al. 2010; Guastaferro et al. 2010; Milne et al. 2012), or with the use of a rectangular shapes management zones (Cid-Garcia et al. 2013). Other alternative to improve shape and size of the zones consider the weighting of the spatial correlation of data (Cordoba et al. 2013). However, the use of all aforementioned methods require a thorough statistical knowledge that may condition their adoption.

A detailed step-by-step protocol for management zone delineation in order to assist precision agriculture end-users has been reported (Taylor et al. 2007). The integration of all these steps in a user-friendly software would facilitate the management zone delineation and their adoption (Zhang et al. 2002; Fridgen et al. 2004). Our work has aided in the generation of a tool for precision agriculture end-users, who commonly have no advanced GIS training, and for researchers who are focused on the comparisons of variable rates between zone input efficiency, but not in the evaluation of zone delineation methods.

The aims of this work were to develop an integrative tool that takes into account all the steps required for the management zone delineation, and to validate the performance of our approach with respect to MZA.

Materials and methods

A framework to delimit management zones and create prescription files was implemented as an automatic and easy-to-use software with a focus on end-users. The system was developed in the C++ programming language and the graphical user interface (GUI) was developed using the QT library[1]. The GUI provides information to assist the user at every step.

Data preparation

Zone delineation results depend on the quality of input data; hence, user files must be previously pre-processed in order to remove outliers. Vector and raster input data layer could be imported into the software. Vector data, such as apparent electrical conductivity, altimetry, and yield maps, are required as comma-delimited text files (.txt, .dat or .csv formats), where each row must contain the coordinate and the variable value. The raster data,

[1] http://qt-project.org/

such as satellite images or aerial photographs are required as GeoTiff. Each variable must be imported independently, and there are no restrictions on the number and size of input files.

The input data could have geographical or plane coordinates. In order to simplify the computation steps, the geographical coordinates are re-projected to plane coordinates. A routine was implemented to transform the latitude-longitude input coordinates into local plane coordinates based on the Gauss-Kruger projection (Bugayevskiy and Snyder 1995). All input variables are mapped to a common user-defined grid cell size which is interpolated by the Delaunay triangulation method (Torres 2005). The limits of the maps are automatically defined by the biggest coincident area for all variables. The implementation of this interpolation technique is provided by the CGAL library[2].

Clustering of variables

The clustering process groups N-dimensional data points using a measure of similarity. We selected FCM because it is a well-known clustering technique in pattern recognition (Dunn 1974; Bezdeck et al. 1984), implemented in similar applications such as MZA (Fridgen et al. 2004) and FuzME (Minasny and McBratney 2002). The user can set the minimum and maximum number of possible clusters, and additional parameters of the classification process such as fuzzy exponent, number of iterations, and convergence value.

In a fuzzy clustering each object may belong to one or more groups. The correspondences are based on the minimization of the following function

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \qquad 1 < m < \infty \qquad (1)$$

Where *m* is a fuzzy weighted index that determines the non-clarity of the groups, x_i is the *i-th* element in the set, u_{ij}^m is the membership degree of x_i to the *j* group, c_j is the center of the *d*-dimensional group, *N* the total number of objects, *C* the number of groups, and $\| . \|$ is some norm for measuring the similarity between objects and the centroid of the group.

The FCM process is performed by an iterative optimization of the objective function (1), updating the membership matrix u_{ij}^m and the centroids c_j.

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \qquad (2)$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \qquad (3)$$

The process is stopped when $max_{ij}\left\{ \left| u_{ij}^{k+1} - u_{ij}^{k} \right| \right\} <$ ε, where ε ∈ [0, 1] is a stopping criterion and *k* is the iteration. This procedure converges to a local minimum.

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[2] http://www.cgal.org

The result of the clustering process is evaluated by three indices, which are computed to each classification output from the minimum to maximum number of zones obtained.

The fuzzy performance index (FPI) (Odeh et al. 1992) and the normalized classification entropy (NCE) (Bezdeck et al. 1984) are calculated using only the membership matrix (U_{ij}), whereas the XB index (Xie and Beni 1991) is calculated using the membership matrix and the data set.

The FPI is defined as:

$$FPI = 1 - \frac{C}{C-1}\left[1 - \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^2\right] \qquad (4)$$

Then, when FPI → 0, the groups are more disjointed.

The NCE, is defined as:

$$NCE = \frac{1}{1-(C/N)}\left[-\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}\,.\log_a u_{ij}\right] \qquad (5)$$

Where the groups are more defined when NCE → 0.

Let $\sum \sigma_i$ be the total variation rate of the data set, where σ_i is the variance of the *i-th* set.

$$\sigma_i = \sum_{j=1}^{N} d_{ij}^2 \qquad (6)$$

Where d_{ij} is defined as $d_{ij} = \mu_{ij}\,\|x_j - c_i\|$,

Then, XB index is defined as (Xie and Beni, 1991)

$$XB = \frac{\pi}{(d_{min})^2} \qquad (7)$$

Where $d_{min} = min\|c_i - c_j\|$,

And $\pi = \frac{\sigma}{N}$ is the compactness of the data set. Here, the compact and well-disjointed groups will have small values for XB.

Clustering is optimal when the three indices reach their minimum value simultaneously. We additionally implemented the Euclidean distance of the indices $\sqrt{FPI^2 + NCE^2 + XB^2}$ as an integrative measure of quality to avoid subjectivity when the indices reach the minimum at a different number of zones (Galarza et al., 2013). As the indices have different ranges, a normalization procedure is required. Each index is normalized by the maximum value over all clustering, and then all indices are varied between 0 and 1. The optimum number of zones is indicated by the lowest Euclidean distance. The results of the classification from the minimum to the maximum number of clusters are displayed in visualization windows that show the clusters map and a table with the quality indices results. The user may visually evaluate the size and shape of the zones in relation to their machinery, in order to select the optimal number of classes to apply variable rate prescriptions.

Customization of the size and shape of the selected clustering

We proposed an automatic process that includes mathematical, morphological filters and a region-growing algorithm to remove isolated pixels, small or narrow areas in order to resolve some limitations of variable rate machinery, such as on the go delay to change rates, and path-width.

The mode filter is used to remove isolated pixels that are included within a bigger cluster. Each pixel is considered around a neighborhood, which is defined by the user among different mask sizes (3×3, 5×5 and 7×7 pixels). The value of the pixel defined as central is replaced by the most frequent value of the pixels in its neighborhood (Gonzalez and Woods 2008). The greater the mask size, the greater the smoothing effect.

After that, in order to remove narrow clusters, which are around or within others, erosion and dilation filters were included (Gonzalez and Woods 2008). In this context, erosion and dilation are morphological operators defined in the mathematical morphology theory for the analysis and processing of geometrical structures. Their operations are based on the comparison of a structuring element in a binary image (ss, binary mask with specific geometric structure) and the original image (I) using sliding window. The result is a new binary image that has 1s where ss fits the I, and 0s otherwise. Some applications of these filters in images are: eliminate noise, isolate individual components, join split components and find holes in an image, among others.

Customization process is completed by a region-growing algorithm, which groups small clusters into larger clusters, using criteria of adjacency and similarity. The process starts in pixels defined as seeds and the groups are formed by incorporating the neighbor pixels that satisfy the criteria (Gonzalez and Woods 2008).

Generation of shape file for management zones prescription

The final step of the software consists of procedures to automatically generate an ESRI Shapefile output, which includes the polygons of each management zone and the corresponding attribute table, where the user may customize the inputs rates to be assigned at each zone (i.e. seed density or fertilizer rates). Borders of the zones delineated are identified by the Moore algorithm (Gonzalez and Woods 2008) and used to create the polygon shape file with the Shapefile C Library (Warmerdam 1999). After that, the data base file (DBF file) is created using a specific function of the library and the polygon attributes.

Comparative zone delineation

The performance of our proposed software was evaluated and compared with MZA using data of two fields located in Entre Ríos province, Argentina. Site 1 was a 110-ha field (−32.204; −60.538) and Site 2 was a 9-ha field (−31.835; −60.545). Management zone delineation in Site 1 was performed based on NDVI calculated from CBERS 2B image, obtained around the wheat flowering period (September 16, 2008); maize yield map (season 2010); and an altimetry map obtained with a DGPS (Trimble R3, Trimble Navigation Limited, USA). Zone delineation in Site 2 was performed using a maize yield map (season 2010). The process included the importation of data, and the re-projection of yield map and altimetry from geographical coordinates (WGS84) to plane coordinates (using Gauss-Krüger method, zone 5). Yield map, altimetry and NDVI were interpolated to a common 10-m grid size. The same data set was processed at the similar spatial resolution by QGIS[3] in order to obtain a comma delimited file according to the input data requirements of MZA.

Management zone delineation with our software and MZA were performed by clustering analysis using a fuzzy exponent of 1.5; a convergence criterion of 0.0001; a maximum number of iterations of 300; minimum and maximum number of zones being 2 and 5, respectively, as in Fridgen et al. (2004).

An additional criterion applied to compare the performance of our software in relation to MZA was to determine the level of fragmentation of the zones by counting the number of patches classified by size. To this end, the sets of 8-connected pixels were obtained by means of the two-pass algorithm for finding connected components. In short, the binary image is scanned and a numerical label (starting from 1) is assigned for every pixel in accordance with that of its neighbors. In this way, unique labels are obtained for each object in the image, so that the number of patches correspond to the maximum label. Finally, the size (area) of each object is calculated as the number of pixels in the patch (Acharya and Ray 2005).

Results

Zone delineation based on NDVI, maize yield map and altimetry in Site 1, showed that fragmentation and zone limits (borders) were less clearly defined as the number of clusters increased from 2 to 5 (Fig. 1). The graphical interface of our software showed maps of the zones, table of validation indices, along with a graphical representation of the Euclidean distance for different number of zones, which indicate the optimal number of zones in the minimum value. The resulting clusters were not compact, with ill-defined boundaries and mixed inclusions due to the fact that the fuzzy C-means classification uses only the values of the variables, but it does not take into account the spatial localization. Clustering results showed small scattered areas and irregular borders in all cases, especially when 4 and 5 zones were delineated.

[3] http://www.qgis.org

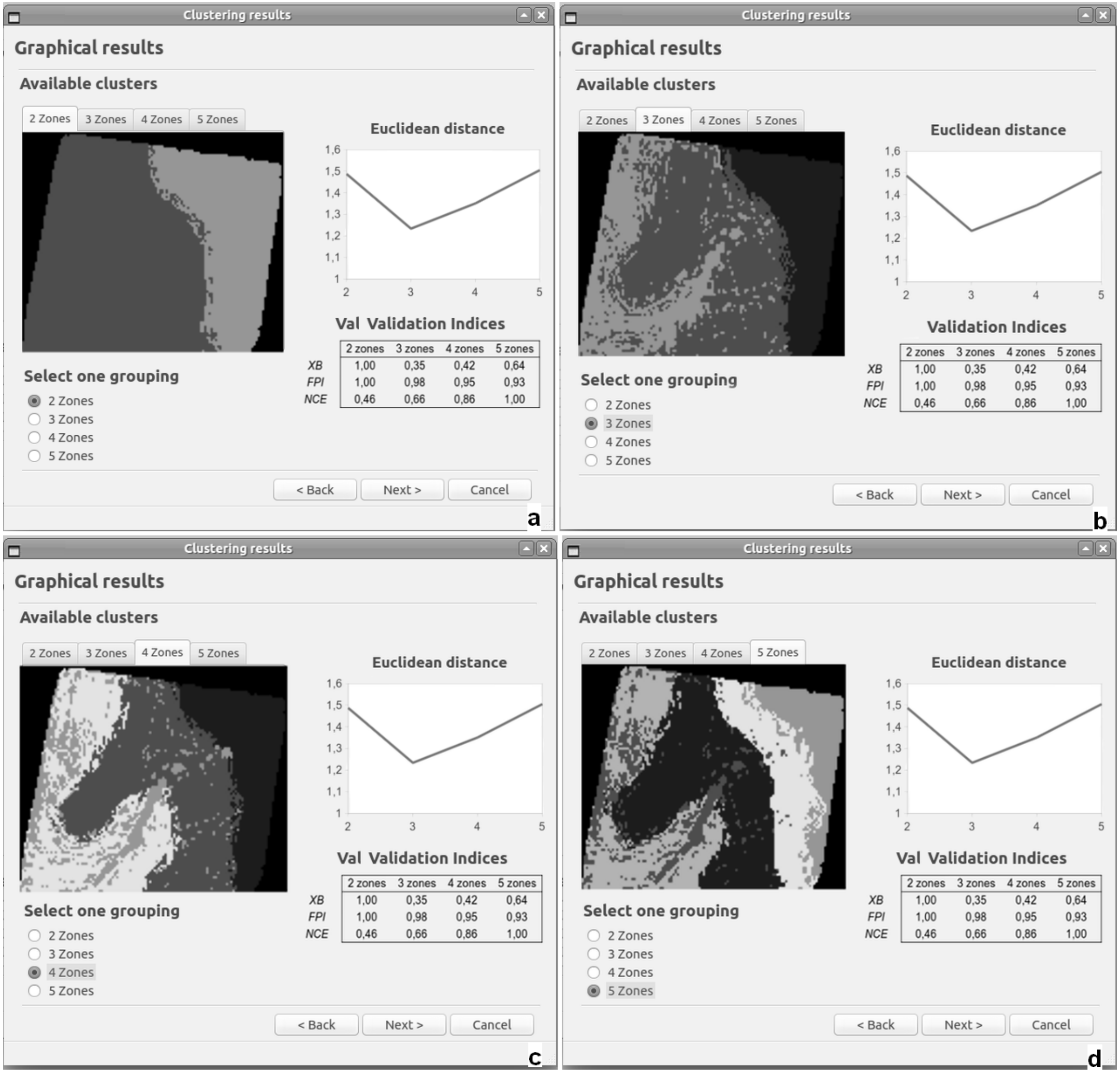

Fig. 1 Screen captures of the software showing different patterns of fragmentation and small mixed areas, for 2 (a), 3 (b), 4 (c) and 5 (d) zones delineated. The table of validation indices and graphic representing Euclidean distance for different number of zones, which indicate 3 zones as an optimum number to be delineated are also included.

When statistical criteria were applied to evaluate the performance of zone delineation (see table of indices in Fig. 1 a - d) the indices calculated reached the minimum value at a different number of zones. For NCE index the minimum value was obtained at 2 zones. The FPI index reached the minimum at 5 zones, while XB reached the minimum at 4 zones. The solution to this problem in our software is the use of the Euclidean distance as an integrative measure that reaches the minimum at 3 zones, which is the optimal number of zones chosen in order to continue to the next step.

The automatic post-processing methods to reduce the fragmentation performed by the use of a mode filter (with a 7 X 7 mask), erosion and dilation filter jointly with the fusion of areas smaller than 0.5, as was set, improve the border definition and compactness of the zones delineated (Fig. 3). The last step included in our software is a process for the generation of polygons for each zone delineated that allow to create an ESRI Shapefile were the user can introduce variable rate prescriptions. This automatic process was realized based on the Moore algorithm and the *Shapefile C Library* (Warmerdam 1999).

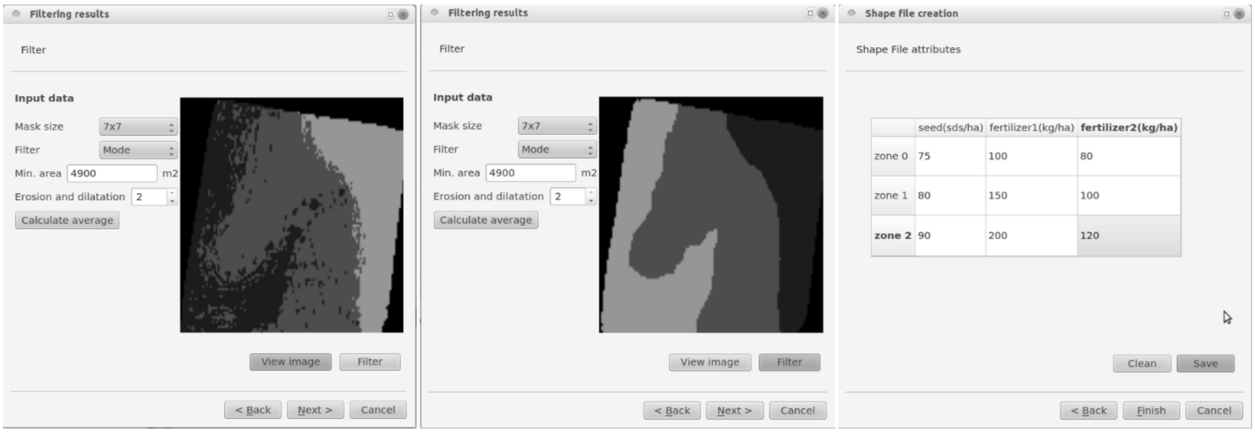

Fig. 2 Fragmentation for 3 management zones delineated in Site 1 before (left side), and after (center) the automatic filtering post-processing techniques for fusion of small areas, table of the shape file generated to assign variable rate prescriptions by zone (right side).

Zone delineation in Site 2 was performed by the same process using a maize yield map. The first screen capture (Fig. 3a) showed the result of clustering, table of indices and graphic with Euclidean distance indicating 2 as optimal number of zones to be delineated. Fig. 3b shows the improvement reached with automatic filtering post-processing techniques applied (mode, erosion and dilation filters, and labeling and growing region). ESRI Shapefile attribute table (DBF) created in the last step, as showed in the right side of Fig. 3, allow the user to introduce site-specific prescriptions.

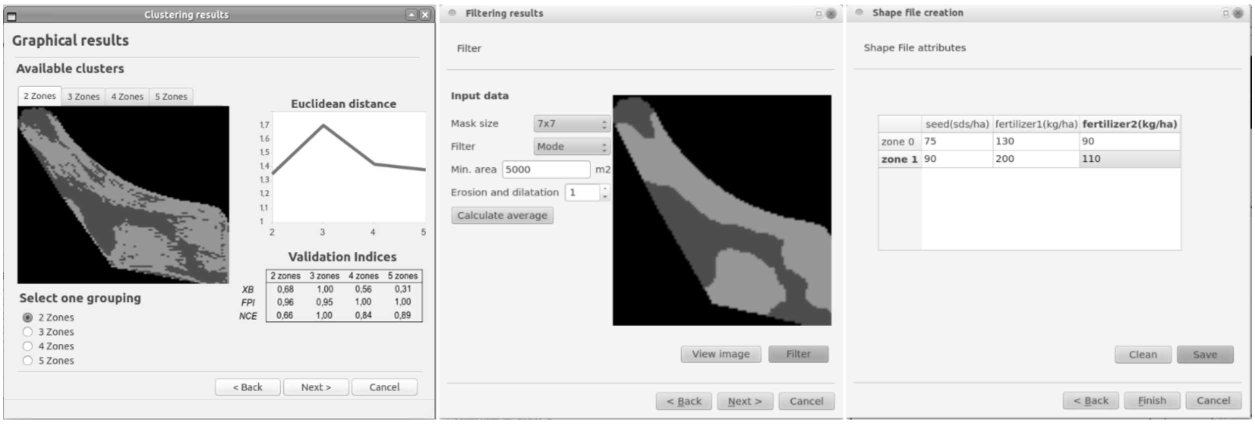

Fig. 3 Fragmentation for 2 management zones delineated in Site 2 before (left side), and after (center) the automatic filtering post-processing techniques for fusion of small areas, and table of the shape file generate to assign variable rate prescriptions by zone (right side).

The use of MZA to delineate zones showed three important differences. The first difference was that several steps were necessary for data pre-processing including interpolation and resizing of all data layers to a common grid, and conversion to a text file, which require specific GIS skills. The second difference was that the indices used to indicate the optimum number of zones do not reach a minimum in the same number. The results obtained in Site 1 showed that the index FPI reached a minimum with 5 zones, whereas NCE reached a minimum at 2 zones (Fig. 4a, b). At Site 2, the index FPI reached a minimum at 5 zones whereas NCE reached a minimum at 3 zones (Fig. 4c, d). This lack of coincidence in the number of zones does not suggest how to select the more convenient number of zones to be delineated. The third difference was that the cluster delineated showed many small fragments, inclusions and ill-defined borders. This problem requires refinements using additional software in order to improve the clustering results for a practical use in variable rate application.

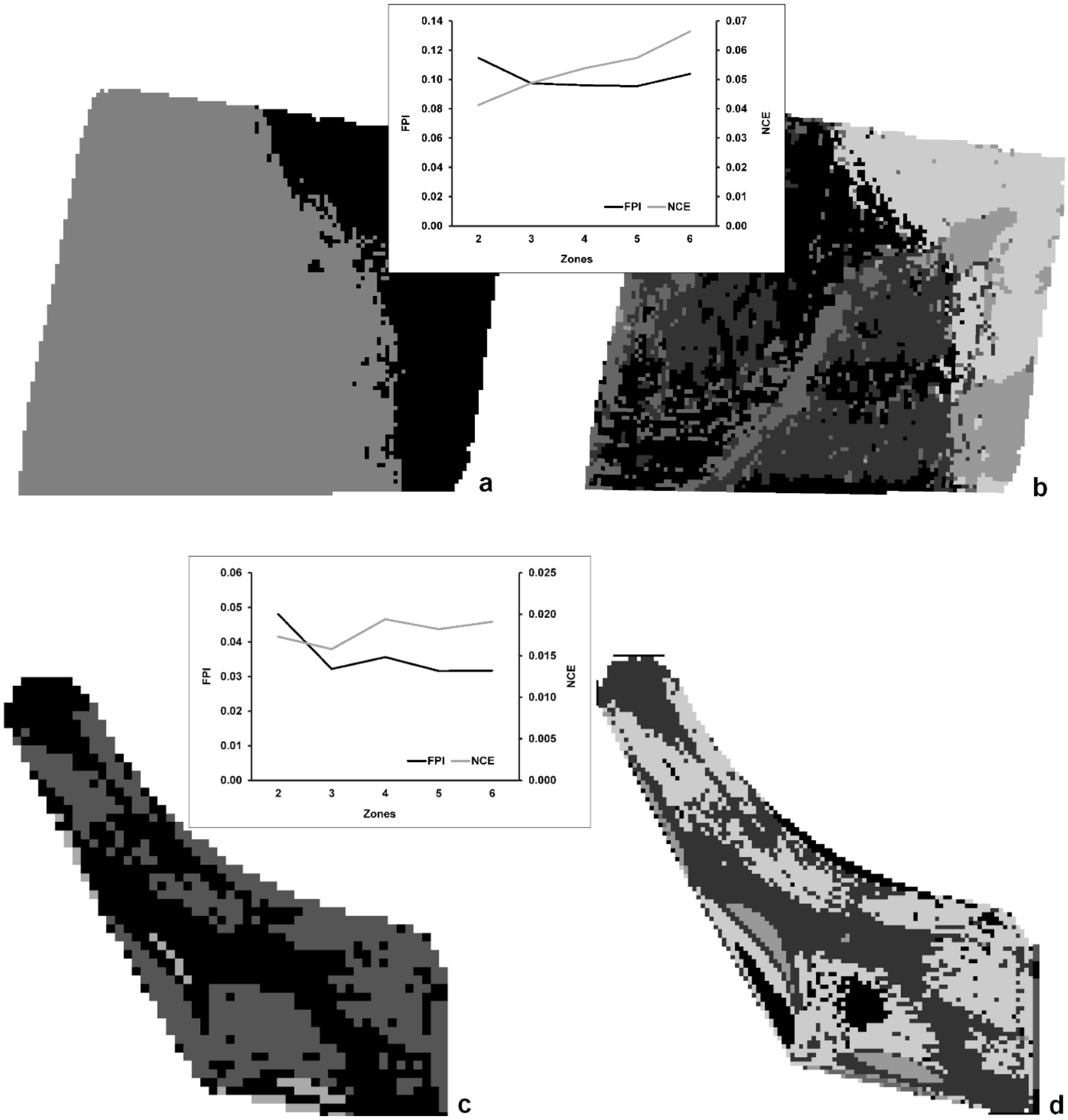

Fig. 4 Management zone analyst (MZA) results according to normalized classification entropy (NCE) (Site 1: a, Site 2: c) and indices from the fuzziness performance index (FPI) (Site 1: b, Site 2: d). Inserts show NCE and FPI indices for different numbers of zones for each site.

The fragmentation level of the delineated zones was determined as another measure to compare software performance. The number of patches that integrate each zone in different size classes was determined (Table 3). We observed that MZA divides the field area into zones of different size, some with areas smaller than 7 % of the field. A drawback observed in MZA results was that each zone was composed of patches of different size. Patches that were more abundant were those of small size (< 0.1 ha) within each zone, either for two or five zones in Site 1, and for three and five zones in Site 2 (Table 1), depending on the number of zones delimitated according to NCE and FPI indices of MZA.

Our software, which is focused on resolving the disadvantages previously described for MZA, allows to specify a minimum area to delineate zones and remove or aggregate small patches within each zone by automatic filtering techniques. The results of our software operation showed two and three zones composed by a unique and compact patch for Site 1 and Site 2, respectively. In Site 1, the size of zones delimited were of 49 and 51 % of the total area, and in Site 2, they varied from 23 to 45 % of total area.

Table 1 Analysis of the fragmentation determined by number and size of patches within two and five zones in Sites 1, and three and five zones delimited in Site 2 using MZA.

Site	Zones delimited	Total zone area	Number of patches for size classes		
			< 0.2 ha	0.2 – 2 ha	> 2 ha
1	1	72	7	0	1
	2	29	15	0	1
	1	18	13	1	1
	2	8	25	3	2
	3	15	180	5	2
	4	27	85	4	3
	5	34	55	0	4
2	1	0.4	11	0	0
	2	5.5	47	2	2
	3	6.5	37	2	1
	1	5.1	21	0	3
	2	0.6	21	2	0
	3	0.1	6	0	0
	4	5.5	58	1	1
	5	1.1	44	3	0

Discussion

The novelty of this work is the integration of different free libraries in order to develop a precision agriculture end-user software for management zone delineation. The developed software was oriented towards precision agriculture end-users without GIS-specific skills, a common characteristic of precision agriculture (PA) users (Taylor et al. 2007). Easy to use with minimum requirements of end-user intervention, as suggested by

McBratney et al. (2005), was considered in software design, jointly with the suitability to work with different types of data layer, robustness, and high computing efficiency.

One of the most noted pieces of software for management zone delineation, MZA (Fridgen et al. 2004), required the use of additional GIS tools to solve some specific steps in the zone delimitation process. In this sense, one advantage of our software with respect to MZA is the ease of importing and arranging data layers with different spatial resolution and projections such as soil sampling data, yield maps or satellite images.

The spatial variability of the data and the clustering method condition how homogeneous zones are delineated; while the optimal number of zones selected depends on the indices used to measure the performance of clustering (Fridgen et al. 2004). Sometimes, the indices available in MZA, suggest more than one possible optimal number of zones, which requires complementary evaluation in order to select the optimal classification. The solution to this problem was obtained introducing XB index (Xie and Beni, 1991), and using the Euclidean distance among NCE, PFI and XB indices. This procedure included in our software, always allows obtaining a unique optimal number of zones.

Another problem commonly observed in clustering methods results showed small, disjointed or irregularly shaped zones, which are not compatible with the size required by the machines, which is defined by the application width and delay to change rates. Some techniques to overcome zone fragmentation proposed in Doberman et al. (2003), and Córdoba et al. (2013), showed few advantages to obtain compactness; others techniques allow to impose restrictions in size or shape of the delineated zones (Roudier et al. 2011; Cid-Garcia et al. 2013), but are complex to use and require advanced statistical and GIS skills. Our approach has aided to resolve in a simple way these three aforementioned aspects: fragmentation, size, and shape of the delineated zones, with minimum size for the zones the only decision the user may make. The solution implemented was obtained by using mathematical and morphological filters in addition to labeling and growing region in a joint and automatic manner, which significantly reduce fragmentation and improve the aspects of shape and size of zones delimited.

A trial version of the software is available to check theirs functionalities joint with data sets in http://fich.unl.edu.ar/test/repo-agro/web/conversion. Continuous improvements, such as the resize of delineated zones up to field-borders, simple tools to remove outliers in imported data, and the inclusion of different projections systems to reproject coordinates, are been considered to be included in a cloud-based service.

Conclusions

The main contribution of this work is the development of a user-friendly software, focused on end-users without advanced GIS and statistic skills, including all the steps required for management zone delineation and also the generation of ESRI Shapefile required to make variable rate prescription.

The use of the Euclidean distance of the FPI, NCE and XB indices proposed, resolve the ambiguity in the selection of the optimal number of zones observed in MZA.

The automatic post-processing techniques implemented in this approach improved the zone compactness and reduce the fragmentation respect to MZA.

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Figure 1

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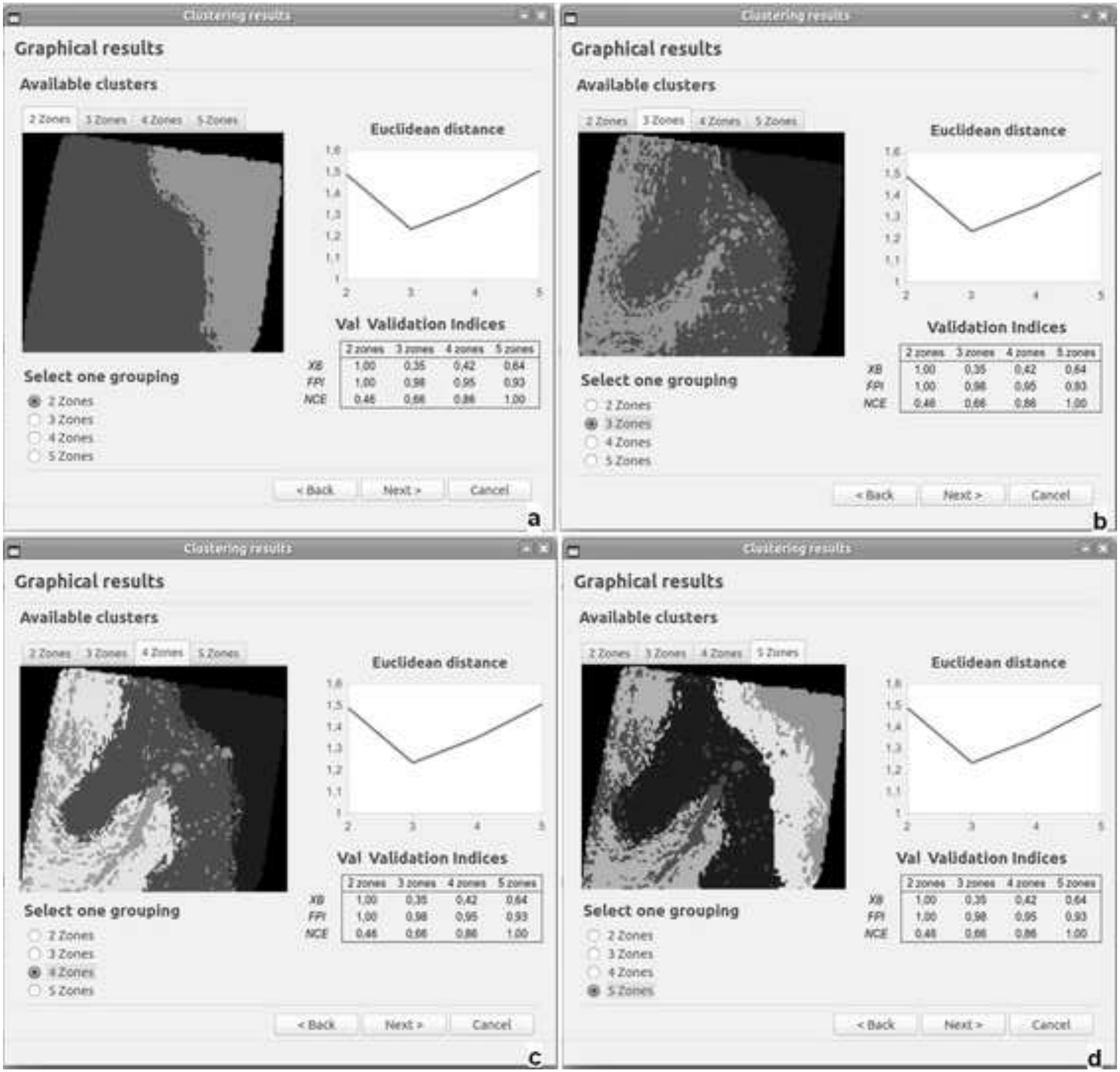

Figure 2

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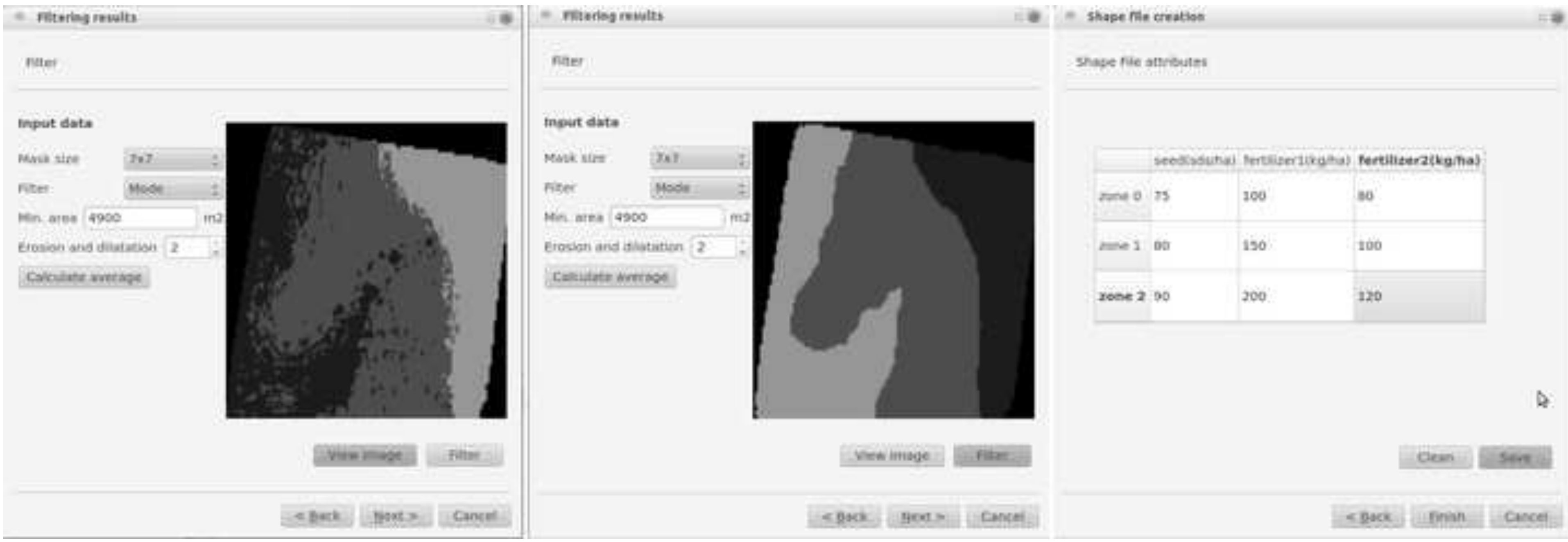
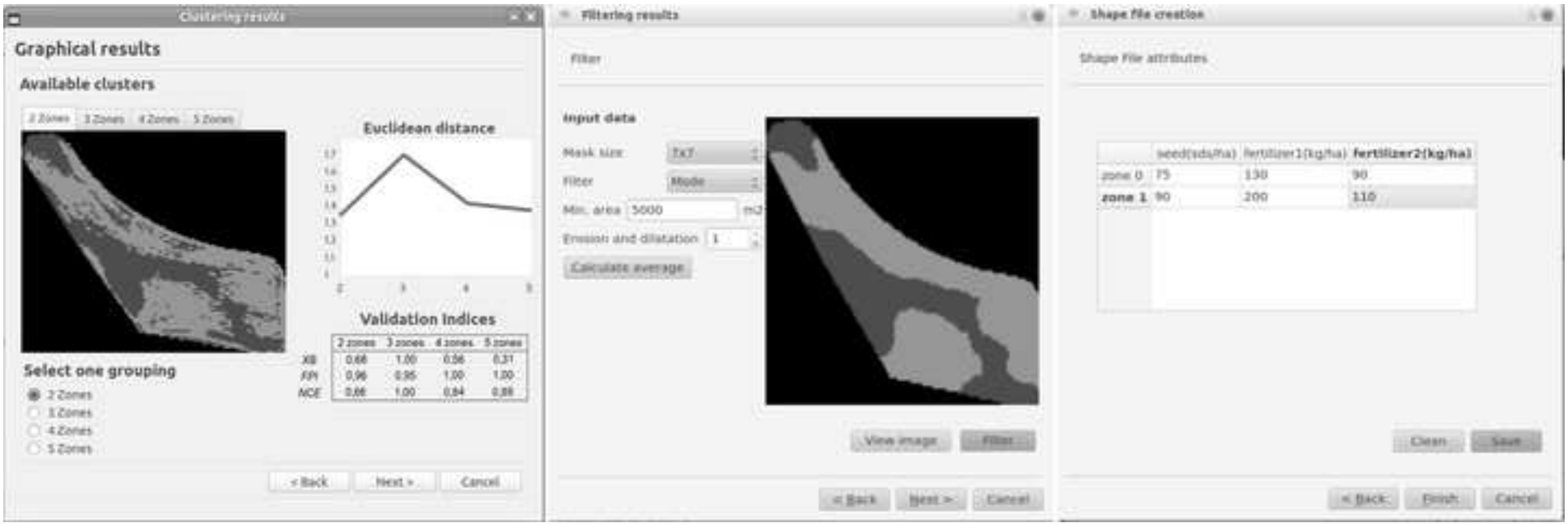


Figure 3


Clustering results
Graphical results
Available clusters
2 Zones
3 Zones
4 Zones
5 Zones
Euclidean distance
Validation indices
2 zones
3 zones
4 zones
5 zones
XB
FPI
NCE
Select one grouping
2 Zones
3 Zones
4 Zones
5 Zones
< Back
Next >
Cancel
Filtering results
Filter
Input data
Mask size
7x7
Filter
Mode
Min. area
5000
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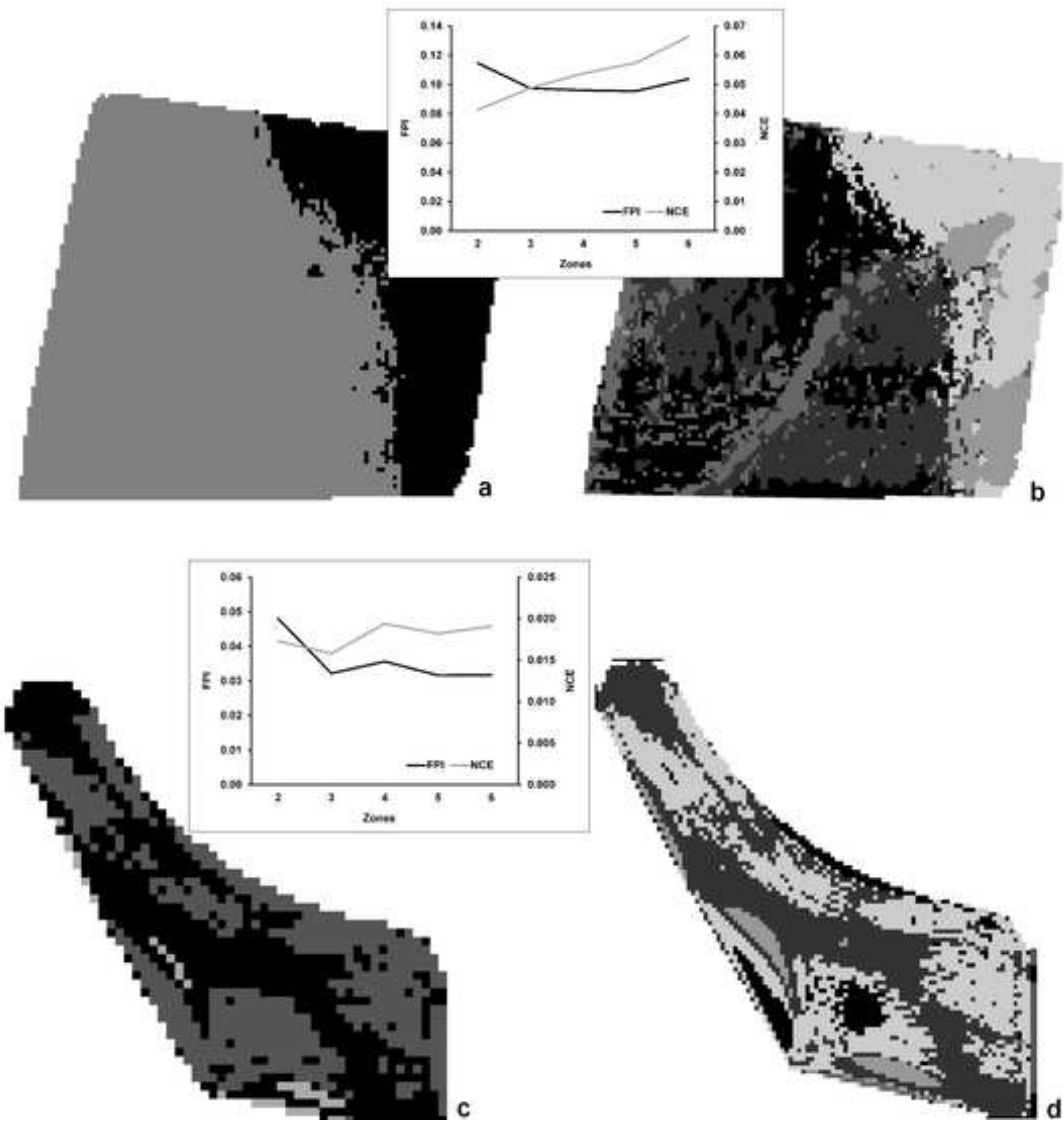
Erosion and dilatation
1
Calculate average
View image
Filter
< Back
Next >
Cancel
Shape file creation
Shape File attributes
seed(sds/ha)
fertilizer1(kg/ha)
fertilizer2(kg/ha)
zone 0
75
130
90
zone 1
90
200
110
Clean
Save
< Back
Finish
Cancel

Figure 4



Site	Zones delimited	Total zone area	Number of patches for size classes < 0.2 ha	0.2 – 2 ha	> 2 ha
1	1	72	7	0	1
	2	29	15	0	1
	1	18	13	1	1
	2	8	25	3	2
	3	15	180	5	2
	4	27	85	4	3
	5	34	55	0	4
2	1	0.4	11	0	0
	2	5.5	47	2	2
	3	6.5	37	2	1
	1	5.1	21	0	3
	2	0.6	21	2	0
	3	0.1	6	0	0
	4	5.5	58	1	1
	5	1.1	44	3	0