Computers and Electronics in Agriculture 127 (2016) 158–167

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Delineation of site-specific management units for operational applications using the topographic position index in La Pampa, Argentina

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ARTICLE INFO

Article history:
Received 17 December 2015
Received in revised form 25 May 2016
Accepted 6 June 2016

Keywords:
Site specific management
Precision farming
Management unit
Topographic position index (TPI)
Autocorrelation function
Argentina

ABSTRACT

In this work we propose the use of the topographic position index (TPI), which takes into account the local topography for a given neighborhood, to delineate management units (MU) for site-specific systems. This study was performed in the province of La Pampa, in central Argentina, an area with sandy soils where the main limiting condition for crops is soil moisture. Usually, multi-annual yield maps are used for the delineation of MU. However, those are strongly influenced by issues that could be related to uncalibrated data and previous agronomical practices. Thus, there was a need for a methodology based on stable and unbiased parameters. The methodology was developed for a representative 100 ha field. The average size and orientation of the topographic structures were characterized applying the autocorrelation function on the topographic data, which was then used to determine an optimum neighborhood size for the TPI. TPI performed better than the topographic map to characterize the variability of the field. The correlation between yield and TPI was higher ($r = 0.74$) than that between yield and topography ($r = 0.54$). The resulting management units were delineated using an unsupervised classification approach on the TPI maps. From the confusion matrices, the overall accuracy was higher for the TPI derived maps than for the topography derived maps (62% against 47%) when compared to a yield map used as reference. We estimate that this methodology could be used for operational applications, the only requirement being topographic data for a given field, since it is simple, the algorithms used are unbiased and it could be performed using free software.

1. Introduction and background

In Argentina site-specific management, also known as Precision Farming, started to be developed around 1990, promoted by the National Agricultural Technology Institute (*Instituto Nacional de Tecnología Agropecuaria* (INTA)) (Bragachini et al., 2011). The number of yield monitors increased significantly from 2004 to 2010, with some 9600 units in 2014. Since 2007, variable rate technology (VRT) equipment has been rapidly increasing with approximately 2600 units in 2014 (Méndez et al., 2014). Some statistics show that 87% of all site specific management adopters use yield maps to some extent and 66% use satellite imagery. Most of them use yield data for visualization (83%) and some of them to delimit management zones (77%). The percentages are lower for the application of VRT for seeds and fertilizers (33% and 44% respectively). There is no statistical information regarding the use of topographical data or Geographic Information Systems (GIS) (Melchiori et al., 2013).

The province of La Pampa is situated in central Argentina between approximately 35° S and 39°11’ S, and 63°23’ W and 68°17’ W. Rainfed agriculture is one of the major economic activities of the province which is implemented in the northeastern part where the soil and climate conditions are appropriate (Fig. 1). The main crops are soybean (*Glycine max* L. Merr.), maize (*Zea mays* L.) and sunflower (*Helianthus annus*), with 1,000,000 hectares sown in the agricultural campaign 2014–2015 (MAGyP, 2015) mostly under no-till management.

The average precipitation is around 700 mm/year (APA, 2015) and the main constraint for crop development here is the low water retention capacity of the soil (INTA, 2004). Given these limiting conditions for crops, the adoption of site specific management strategies has a good potential to enhance crop yields by a better use of natural resources.

Site-specific management promotes the identification and management of areas, called management units (MU), within a given

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http://dx.doi.org/10.1016/j.compag.2016.06.005
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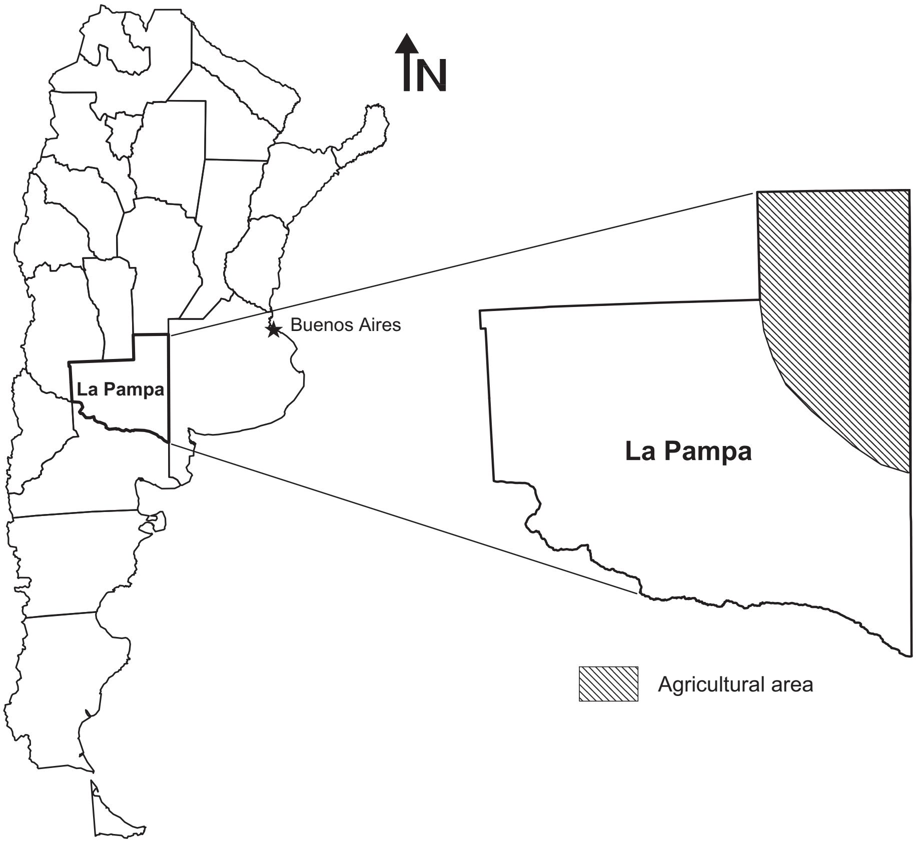


Fig. 1. Political map of Argentina showing the location of the province of La Pampa and Argentina Capital City (Buenos Aires). In the map of the province the agricultural area situated in the NE is indicated in diagonal pattern.

field, which represent subfield regions with homogeneous characteristics, such as texture, topography and nutrient levels (Moral et al., 2010). Each management unit is obtained by grouping the pixels of the layer used to characterize the spatial variability of the field (for example a yield map) applying some decision rule defined by the user. This process is usually known as classification or segmentation. Different types of layers can be used to generate the MU. Examples using yields maps can be found in Brock et al. (2005), Flowers et al. (2005), Jaynes et al. (2005) and Milne et al. (2012). Other types of layers used are topographic and electrical conductivity maps (Kweon, 2012; Fraisse et al., 2001), and soil fertility maps (Ortega and Santibáñez, 2007). Regarding the segmentation methods, various techniques have been proposed, for example Cordoba et al. (2013) used a methodology based on cluster analysis from spatial principal components and Zhang et al. (2016) developed a method for the delineation of rectangular management zones based on semivariograms. Other researchers used various clustering algorithms (Haghverdi et al., 2015; Brock et al., 2005; Fraisse et al., 2001; Li et al., 2007), segmentations based on image processing algorithms (Pedroso et al., 2010) and geostatistical techniques (Moral et al., 2011). In Argentina, some methodologies for the delineation of MU using yield maps can be found in (Justo et al., 2011). Peralta and Costa (2013) use the apparent electrical conductivity (ECa) as an estimator of the soil properties and for the delimitation of homogeneous areas in the province of Córdoba, Argentina. In La Pampa, much of the development was performed by farmers and private contractors that, probably due to its availability (Melchiori et al., 2013), use multi annual yield maps for the delineation of management units for VRT applications (personal communication). The situation observed in that case is that once variable rates of seeds and fertilizers are applied, the resulting yield is not only affected by the natural variation (i.e., the variation that would arise without VRT) but becomes entangled with the VRT strategy applied. Thus, there is a need to use some other variable, relatively invariant for the time scale of the agronomical practices, as estimator of the natural spatial variability of a field. One option is to use the topography, given its relationship with textural soil parameters and water availability. In the literature, some studies regarding the yield-topography relationship in Illinois and Indiana in the US can be found in Kravchenko and Bullock (2000); they show that elevation is the single most influential variable on yield. Also Marques da Silva and Silva (2008), for irrigated maize fields in Portugal, found that average yield presented a strong dependency on topography, as well as on derived parameters (slope and topographic indices) that reflect water availability (for example the wetness index and the distance to flow accumulation lines). Kweon (2012) used a fuzzy logic system using soil properties obtained from on-the-go electrical conductivity (EC), organic matter (OM) sensors and topographic attributes (slope and curvature). In Argentina, Franco et al. (2012) analyzed the relationship between topography and some primary as well as secondary characteristics and yields in the SE of the province of Buenos Aires. In the agricultural establishment where the present study was carried out, management units were generated by segmentation of the topographic maps for VRT applications of seeds and fertilizers since 2008 (Mieza et al., 2014). Also pilot studies regarding the optimum rates of seed and fertilizers for those management units have been performed (Ghironi et al., 2012).

From the analysis of yield maps on representative areas, it was observed that yield variability seems to correlate better with local minima and maxima topographic values rather than with the absolute values within a field. Taking this into consideration, the main objective of this work was to develop a simple and robust methodology for operational delineation of site specific management units based on the topographic position index (TPI), a topography derived index that takes into consideration the local topography for a given neighborhood (Weiss, 2001).

2. Materials and methods

2.1. Study area

The study area is situated in the northeastern part of the province, in the sub-region of sandy plains. The topography in this area shows NE–SW oriented sandy undulations with sandy plains between them. The soil is a sandy loam Entic Haplustoll carbonate-free up to 3 m. The methodology for this study was developed for one representative 100 ha plot that is in an agricultural establishment located10 km SE of General Pico city, within the Maracó Department. In Fig. 2, the sandy plains sub-region in the province, the location of the study site and a high resolution satellite image of the field are presented. The satellite image, with a spatial resolution of 4 m, was acquired by IKONOS satellite on the 1st of January 2010.

The crop at that time was maize with very low coverage. From the image it can be noticed the presence of the sandy undulations with NE–SW orientation. In the image are also indicated a transect (AA′) that was used to analyze the results and three points where soil tests were performed.

2.2. Methodology

An outline of the methodology proposed for the delineation of MU is presented in Fig. 3. The first step is to obtain or generate a digital elevation model (DEM) and a topographic map for the field. Next, by applying the autocorrelation function (ACF), the average size and orientation of the topographic structures are estimated. By thresholding the ACF image, a distinctive shape associated to the average topographic dimensions and orientation is obtained. Then, a local topographic map is generated applying the topographic position index (TPI) on the DEM with the resulting shape from the ACF as neighborhood. Finally, the MU are delineated using an unsupervised classification approach.

The results were validated using a yield map as an estimator of the natural variability of the field. We use the term "*natural variability*" to refer to the spatial variability of parameters at field level related mainly to soil composition, granulometry, fertility and position in the landscape that results in yield spatial variations. In the following subsections each step of the proposed methodology is further explained.

2.2.1. DEM and topographic map

A DEM and topographic map for the field were generated using a Trimble R3 DGPS mounted on an all terrain vehicle. The accuracy reported for this GPS (Trimble, 2005) is:

- $\pm(10\ \text{mm} + 1\ \text{ppm} * \text{distance to the base in mm.})^2 RMS$ (horizontal).
- $\pm(20\ \text{mm} + 1\ \text{ppm} * \text{distance to the base in mm.})^2 RMS$ (vertical).

In this case the maximum distance to the base was 2000 m, and then the calculated horizontal accuracy was ±12 mm and the vertical accuracy ±22 mm. The gps measurements were taken on a semi regular grid. The mean distance between measurements along track was 20 m while that across track was 50 m. Once collected, the data was differentially corrected by post-process and exported in tabular form. The Digital Elevation Model (DEM) and contour lines were generated using QGIS 2.8.2. QGIS is a multi-platform open source Geographic Information System (GIS) software licensed under the GNU General Public License. The latest version is QGIS 2.14 (QGIS Development Team, 2016). This software provides many functions to work with raster or vector data and it also includes plugins to access other free GIS-related software like GRASS (GRASS-PROJECT, 2016) and SAGA (Conrad et al., 2015) among others.

2.2.2. Characterization of the topographic structures

For the analysis of the topographic structures (average size, orientation, etc.) the autocorrelation function (ACF) was calculated on the DEM. The ACF describes how well a given image correlates with itself when it is displaced in all possible directions.

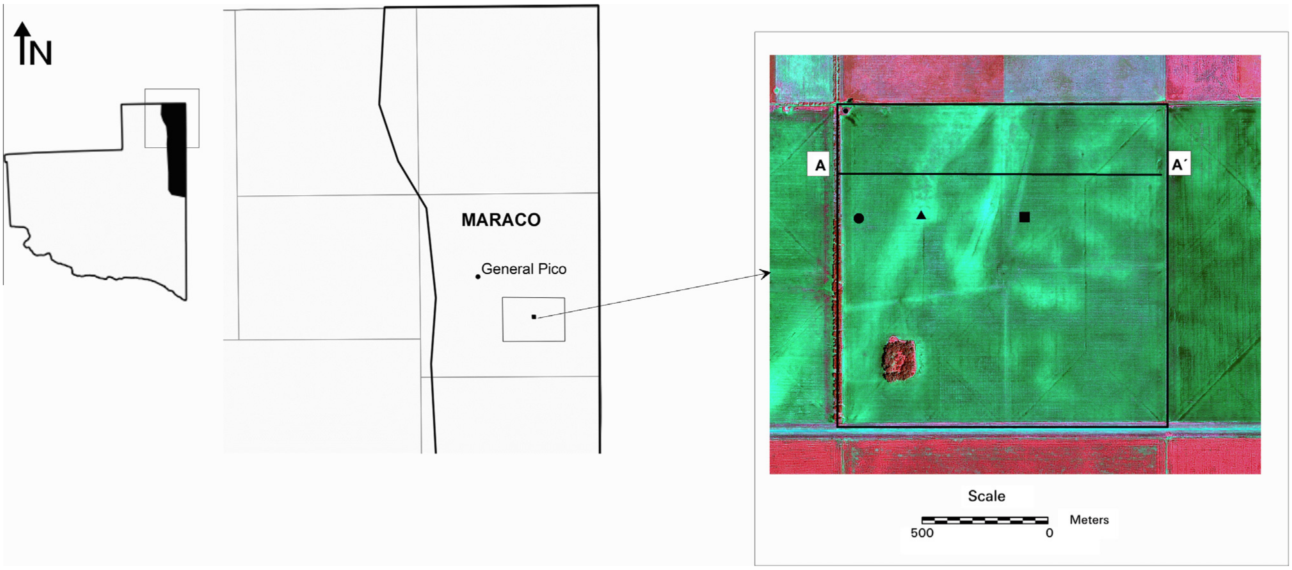


Fig. 2. In the image to the left is indicated the sub-region of sandy plains in the province of La Pampa. In the center the zoomed image showing the administrative units (departments), the limits of the agricultural establishment located in Maracó Department close to General Pico city and the location of the field under study. The bold line corresponds to the limits of the sandy plains sub-region. To the left an IKONOS satellite image of the field (ORBIMAGE Inc).

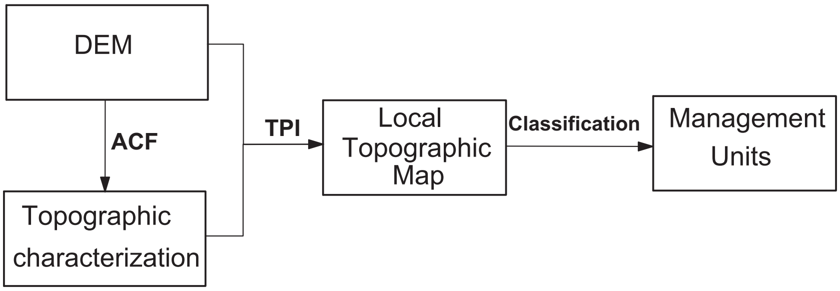


Fig. 3. Outline of the methodology proposed for the delineation of management units.

Heilbronner (1992) describes a method for shape analysis based on the relationship between the average geometric size and shape of grains in certain materials and the shape of its ACF using simulated and real halftone images. The ACF of a 2D image is also a two dimensional function of the same size. The center of the image yields the correlation when the displacement of the image with respect to itself is zero, and so the ACF always displays a maximum there. For isotropic patterns, the rate of decrease of the ACF values away from the origin is the same in all directions, thus the contour lines are circular. In cases where the fabric is anisotropic, the rate of decay of the ACF away from the center is not the same in all directions. As a result the contour lines of the ACF become elongated in the direction of maximum correlation. Using this methodology, structures sizes could be inferred from an ACF contour at a level between 0.39 and 0.5 of the total peak height. For this work the lower limit of 0.39 of peak height was selected in order to estimate the average size of the topographic structures based on the work of de Ronde et al. (2004), and also taking into consideration that is similar to the correlation length usually defined for one dimensional analysis, such as topographic profiles, that is the point at which the correlation drops to $1/e$ (0.3679) (Russ, 2002). When anisotropic formations are analyzed, the major radius (**b**), the minor radius (**a**) and the orientation of the resulting shape ϕ can be obtained from the radii and orientation measured on the ACF contours. We used this approach on the topographic map, in order to estimate the average size and shape of the topographic structures on the field, and use them to determine the neighborhood to calculate the TPI. For the sake of simplicity, here we chose to approximate the obtained shape by an ellipse, as the TPI neighborhood. Although, in principle, this is not necessary, it will be useful for comparison purposes, as described in the next section.

2.2.3. Local topographic map

In order to link topographic information to yield maps we propose to use the topographic position index (TPI), which is a local elevation index. TPI compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell. TPI is defined as the difference between the elevation of the central point z_0 and the average elevation around it $\bar{z}$ for a specified neighborhood (Weiss (2001), De Reu et al. (2013)):

$$TPI = z_0 - \bar{z}$$

Positive TPI values represent locations that are higher than the average of their surroundings, as defined by the neighborhood mask. Negative TPI values represent locations that are lower than their surroundings. TPI values near zero are either flat areas or areas of constant slope within the neighborhood used for its calculation. In the present work, a TPI using the previously defined elliptical mask was calculated for the DEM (implemented in FORTRAN) and, also, a circular mask with an area equal to that of the elliptical one (implemented both in FORTRAN and in QGIS software). The circular neighborhood was tested in order to compare the results with those using the elliptical shape since this type of neighborhood is already implemented in free software and it could be easier to put into practice with a view to operational uses of this methodology.

2.2.4. Management unit delineation

The delineation of management units was performed by means of an unsupervised classification of the elliptical TPI map. In order to compare the resultant MU, unsupervised classifications were also performed on the standardized yield map and the topographic map. Unsupervised classification is the identification of natural groups within multispectral data (Campbell, 1996). The inputs from the operator are usually the number of classes and some constraints, but the chance of obtaining a biased result due to the operator perceptions is highly reduced in this method. An unsupervised classification approach using ISODATA clustering (Tou and González, 1974) was implemented in Erdas Imagine 8.4. This approach was also used by Fraisse et al. (2001) for the classification of topographic attributes and soil electrical conductivity for management zones delineation. In this case the number of classes selected was three, taking into consideration agronomical and practical issues regarding the future application of variable rates of seeds and fertilizers in this unit. The result of each classification was a thematic map in raster format that can be converted into vector format, in order to generate maps for variable rate applications.

2.2.5. Analysis of the results

A yield map from the 2007–2008 agricultural campaign was used to validate the results. Care was taken to select a map that was complete, correctly calibrated and known not to have any particular management condition that could influence its natural variability. It is important to notice that there are not many yield maps available for the study area without VRT because the adoption of yield monitors and VRT technology occurred almost simultaneously. For the field under study, and since the 2008–2009 agricultural campaign, variable rates of seeds and fertilizers are applied on management units delineated using topographic maps and satellite images, so it should be assumed that yield maps since 2009 are influenced by that. Regarding the processing of the yield map, it was trimmed and cleaned-up using a methodology similar to the one proposed by Taylor et al. (2007). The data was trimmed to eliminate outliers and then harvesting artifacts were removed. Finally, a 15×15 m regular grid was generated from the yield map using krigging as the interpolation method and it was then standardized using the approach proposed by Blackmore (2000). The standardized yield (s_i) expressed as% is calculated as:

$$s_i = \left(\frac{y_i}{\bar{y}}\right) \times 100$$

y_i is the yield of each individual cell and $\bar{y}$ is the mean yield.

2.2.5.1. Statistical comparison of maps. In order to evaluate the relationships yield vs. topography and yield vs. TPI, correlograms were generated between the standardized yield map and the elliptical TPI, the circular TPI and the topographic maps. The Pearson correlation coefficient (r) and the 95% confidence interval for r ($[r_1, r_2]$) were calculated for the three correlations in order to determine if the variables under consideration were correlated and also to statistically compare the correlation coefficients pair wise.

2.2.5.2. Comparison of management units. The methodology applied for the comparison of the MU maps was the confusion matrix, a standard form for reporting accuracy of thematic maps as described by Campbell (1996), and the accuracy measures derived from it (overall, user's and producer's). The confusion matrix is an $n \times n$ array, n being the number of classes. The matrix shows the results of comparing the reference data against the classified data. Diagonal elements represent agreement between the reference and classified data. Off diagonal elements represent misclassified pixels. These misclassified pixels represent what are known as errors of omission and errors of commission. The most common measure of accuracy is the overall accuracy that represents the number of correctly classified pixels, usually expressed as a percentage. It is important to include as well producer's and user's accuracies, as explained by Story and Congalton (1986), because "a single value can be extremely misleading". User's accuracy represents the probability that a sample from the classified image actually represents that category on the ground, and producer's accuracy indicates the probability that a ground sample will be correctly classified. An extensive review of the topic can be found in the work of Foody (2002). Confusion matrices were generated in QGIS 2.8.2 using the classified yield map as reference to evaluate the accuracy of the thematic maps generated from the topographic map and the elliptical TPI map.

3. Results and discussion

3.1. Field measurements

The topographic map generated by means of the DGPS data collected in the field is presented in Fig. 4a. Elevation is expressed in meters above the mean sea level (MSL). In Fig. 4b, the standardized yield map for the agricultural campaign 2007–2008 is presented.

The crop planted was maize (*DK190*) under no-till rainfed management with uniform seeding rates of 65,000 seeds/ha and uniform N fertilization (72 kg/ha) applied at the time of planting.

Some climatic variables for the crop season under consideration, which goes from October 2007 to March 2008, are presented in Fig. 5. In the figure the potential evapotranspiration (PET) monthly averages, the mean temperature (Casagrande et al., 2012), and monthly precipitations (APA, 2015) are shown.

Some soil tests were performed for three representative sites within the field. These sites are also indicated in Fig. 4. The location **L**, called *loma*, corresponds to a high landscape position with coarser soil texture and lower water retention capacity. The other samples corresponds to intermediate **ML** (*media loma*) and low landscape positions **B** (*bajo*). In Table 1, soil relative proportions of sand, silt and clay, total organic matter (OM) content and the difference in elevation (Δh) between these sites are presented.

Soil moisture measurements, routinely performed in the establishment, were available for two of the sites (**L** and **B**), for three dates, during the agricultural season 2007–2008. Per site, 10 measurements from the surface up to a depth of 2 m, at 20 cm intervals were performed. The results are shown in Fig. 6. Soil moisture is expressed as the volumetric water content of each sample (m_v) (Gardner, 1986):

$$m_v = \delta_{ap} m_g$$

where $m_g = \frac{wet\ mass - dry\ mass}{dry\ mass}$ is the gravimetric moisture of the soil sample, and δ_{ap} is the apparent density of the soil in g/cm^3.

For all dates, soil moisture was higher for the *bajo* areas when compared to the *loma* areas, and it is important to notice that for the *loma*, soil moisture was consistently low up to a depth of two meters. On the other hand, in the *bajo* areas soil moisture increases with depth, this moisture could be extracted by crops (mainly sunflower and maize) because their rooting systems can reach those depths.

3.2. TPI

The methodology proposed for the characterization of the average shape and size of the topographic structures using the

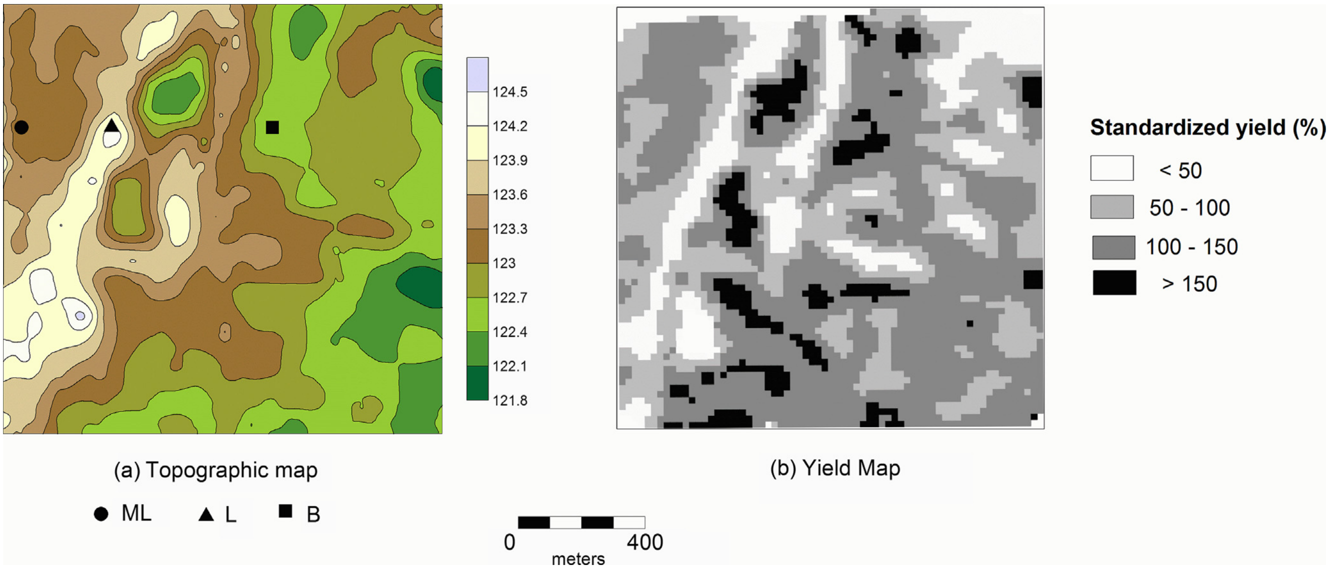


Fig. 4. (a) Topographic map of the field. Elevation measurements in meters above the mean sea level (MSL). Sites where soil tests were performed are indicated (filled circle, triangle and square). (b) Standardized yield map. Crop: maize. Agricultural season: 2007–2008. Raw data was provided by Ing. Agr. Daniel Martínez.

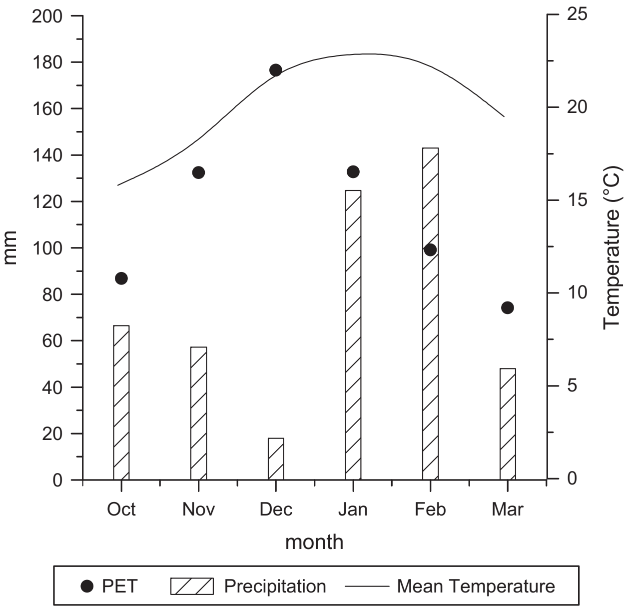


Fig. 5. Potential evapotranspiration monthly averages, precipitations and mean temperature from October 2007 to March 2008.

Table 1
Results of soil test for three representative sites within the field. The samples were taken from the topsoil (0–20 cm). *Source:* Ing. Agr. Daniel Martínez.

	L	ML	B
Clay (%)	2.72	2.72	4
Silt (%)	6	16	17
Sand (%)	91.28	81.28	79
OM (%)	0.76	1.01	1.16
Δh (m)[a]	1.5	0.6	0

[a] Relative.

autocorrelation function on the DEM was applied. From the analysis of the ACF, the resulting shape was approximated with an elliptical neighborhood that represents the characteristic shape, size and orientation of the topographic features for this field. The topographic contour lines, the ACF image and the elliptical shape with which it was approximated are shown in Fig. 7. In this case, the elliptical shape has a semi minor axis **a** = 256 m and semi major axis **b** = 350 m, with an orientation (ϕ) of 73° with respect to the horizontal axis. This shape represents the anisotropies in the topography with a preferred NE–SW orientation.

The equivalent radius, for an area equal to that of the ellipse, was calculated to be 277 m. TPI maps using both the elliptical and circular mask were calculated for the topographic map. In Fig. 8 the resulting maps for the elliptical and circular neighborhoods in vector format are presented; only minor differences can be observed between the two.

To evaluate the performance of the topographic map and the TPI maps to characterize within-field spatial variability, scatter plots were generated for the whole field. A negative linear correlation is observed between standardized yield and topography (Fig. 9a), implying that areas with higher elevation values (*lomas*) are associated with lower yield values and lower places presented higher yields. The same is observed when standardized yield is correlated with relative topographic position for each neighborhood evaluated through the TPI (Fig. 9b).

The Pearson correlation coefficient (r) and the 95% confidence interval for r ($[r_1,r_2]$) between the standardized yield maps and the elevation and the TPI maps for the elliptical and circular neighborhoods are presented in Table 2.

The highest absolute value for r was obtained for the elliptical neighborhood. The statistical comparison of the correlation coefficient pair wise, for all correlations, showed that there was no difference at the 95% confidence interval between r for the maps generated using the elliptical and equivalent radius. They were however statistically different when compared with the correlation coefficient between standardized yield and the topography. Thus, the TPI maps performed better at the 95% confidence interval than the topographic map to characterize the spatial variability of the field. In order to illustrate the results, in Fig. 10 the cross profiles AA′ were plotted for the standardized yield map, the topographic map and TPI map (elliptical neighborhood).

In the profiles, L1 is the highest absolute elevation and the yield, as expected, presented low values. However, although L2 is a local maximum, its yield value is as low as that of L1. A similar effect is observed with the local minimum B1.

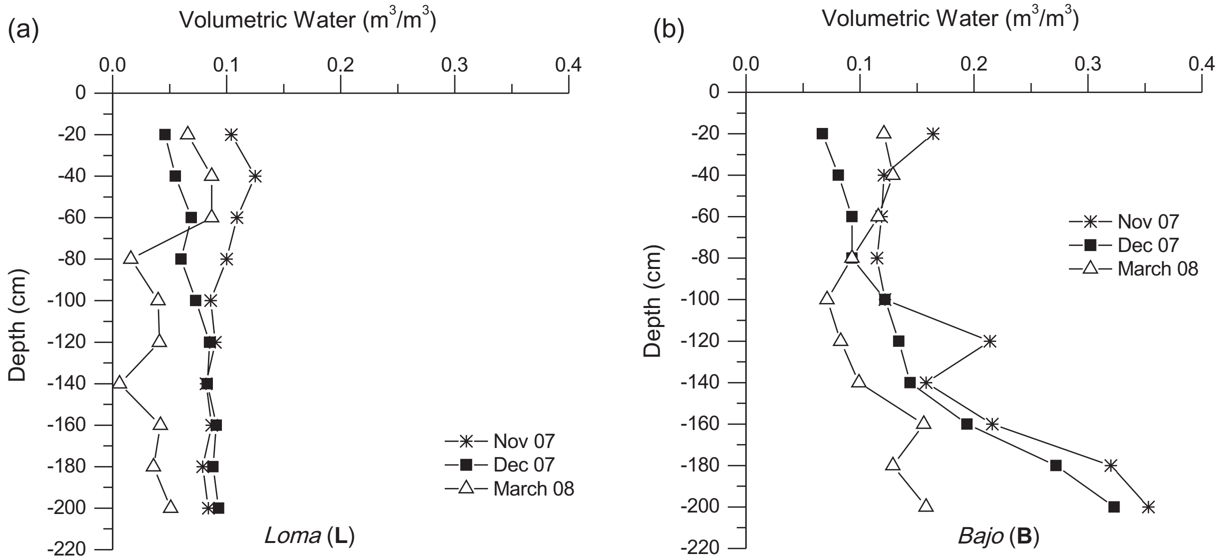


Fig. 6. Volumetric water content of the soil profile from the top up to 2 m, in two extreme landscape positions for three dates during the crop season 2007–2008. (a) Corresponds to *Loma* (L) y. (b) Corresponds to *Bajo* (B). The samples were taken at 20 cm intervals. *Source:* Ing. Agr. Daniel Martínez.

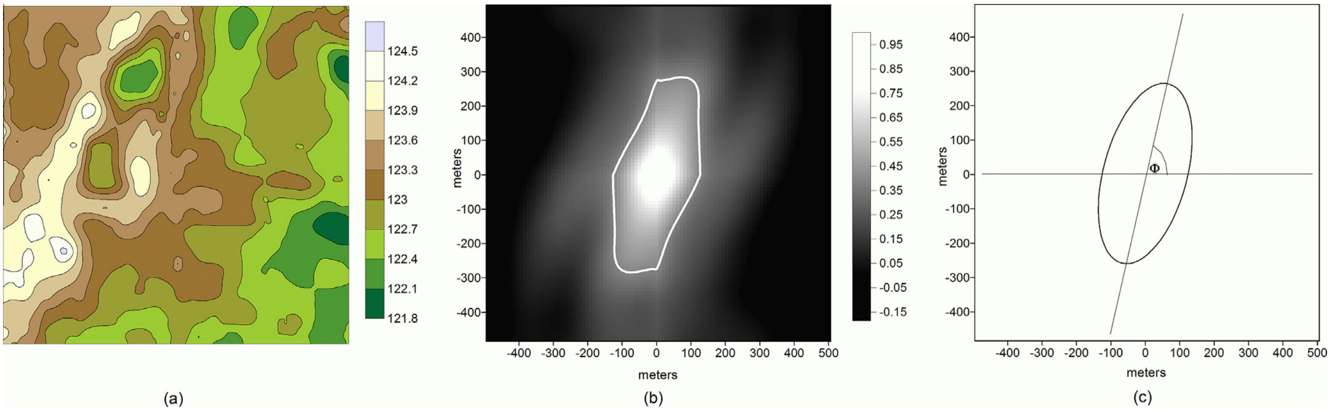


Fig. 7. (a) Topographic map. (b) ACF map and resulting shape to characterize the average size and orientation of the topographic structures. (c) Elliptical approximation of the characteristic shape in (b).

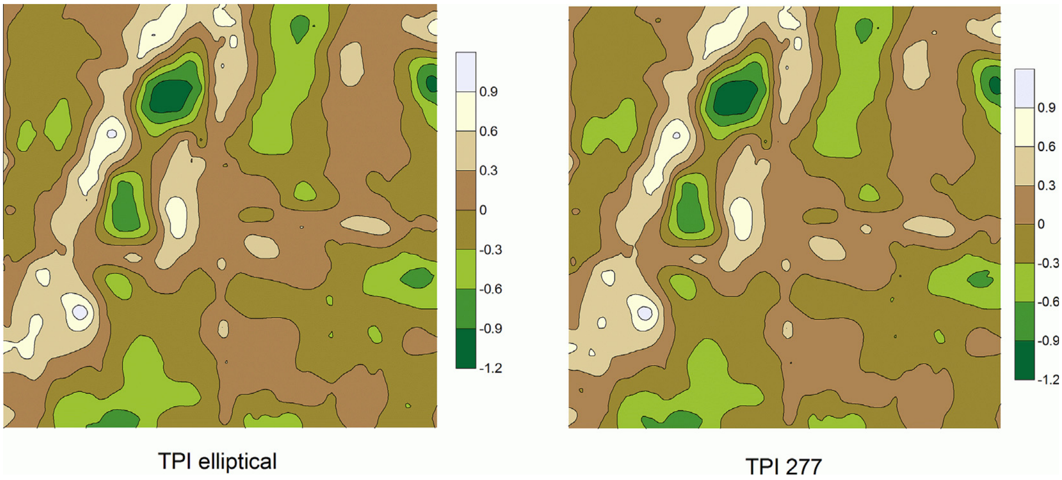


Fig. 8. TPI maps for the elliptical neighborhood estimated from the ACF analysis and TPI for an equivalent circular neighborhood (**R** = 277 m).

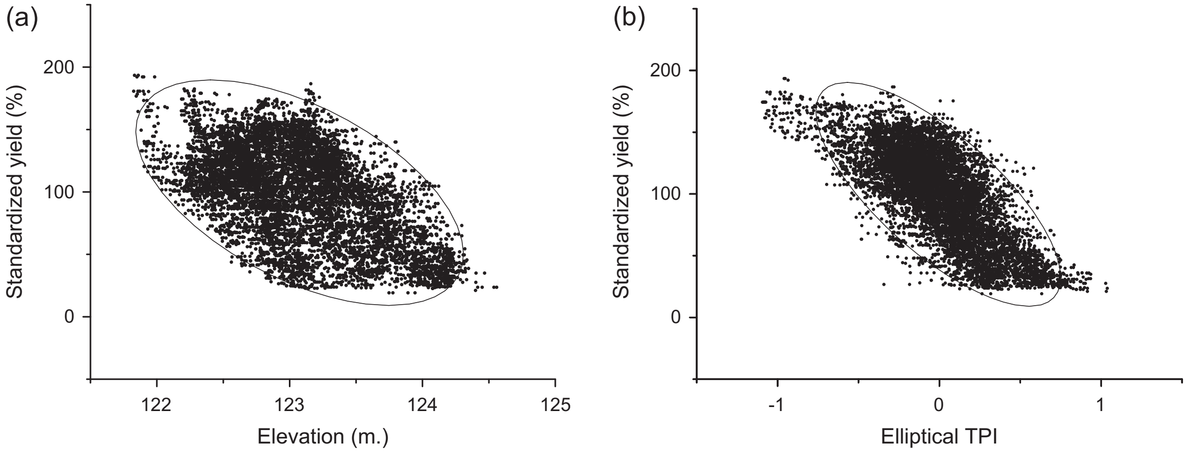


Fig. 9. Scatter plots for standardized yield versus elevation (a) and standardized yield versus Elliptical TPI (b).

3.3. Management unit delineation and accuracy assessment

The resulting thematic maps using the unsupervised classification approach for the yield map, the topographic map and the elliptical TPI map are presented in Fig. 11.

The thematic maps obtained using an unsupervised classifier is a map with *n* classes, *n* being the number of classes specified by the user. In our case, three classes were specified and the resulting post-classification classes were associated and renamed according to the classes in the ground (*loma*, *media loma* and *bajo*).

Table 2
Pearson correlation coefficient and the 95% confidence interval [r_1,r_2] between standardized yield and elliptical TPI, equivalent circular TPI and DEM.

Map	Person *r*	r_1	r_2
Elliptical TPI	0.742	0.729	0.748
TPI 277[a]	0.738	0.733	0.751
DEM	0.544	0.530	0.558

[a] Equivalent radius for elliptical TPI.

For the thematic map comparison, the classified yield map was used as reference to evaluate the thematic maps generated by classifying the topographic map and the elliptical TPI map. The confusion matrices, the overall, user's and producer's accuracy measures are shown in Table 3 for the yield map and the topographic map (tm), and in Table 4 for the yield map and the elliptical TPI map.

Comparing the two matrices, it can be seen that the overall accuracy using the elliptical TPI was significantly higher (62% against 47%). Also, all user's and producer's accuracy measures were higher for the elliptical TPI when compared with the topography. Based on the results obtained, segmentation based on the elliptical TPI map performed better than segmentation based on topographic maps, previously used for the delineation of management units in this field.

3.4. Discussion

The first experiences regarding the implementation of precision farming in La Pampa took place in 2008 at the agricultural establishment where this study was performed (Mieza and Martínez, 2008). Since then yield monitors are available but, in many cases, there are no representative yield maps available for a given field due to many factors, for example errors in the sensing equipment due to un-calibrated or missing data, previous management practices (e.g. different hybrids in the same field), extreme meteorological conditions, and induced spatial variability when VRT of seeds and fertilizers had been previously applied. The region is in the outskirts of the main agricultural area of Argentina (Pampean region), where soil and weather conditions are quite limiting for the development of crops. The soil presents high proportions of sand (it can reach up to more than 90%) and since crops are rainfed with average precipitation levels of 700 mm/year, water management is a key issue to develop agriculture. Because of that, no-till management has been adopted and only one crop per year is sown, usually oilseeds (soybeans, maize and sunflower). It is common knowledge among producers and agronomical engineers that those places with higher landscape positions are associated with higher proportion of sand and low water retention capacity and, consequently low crops yields. Due to this evidence, the first attempt to delineate management units involved the use of fields' topographic maps. From the yield maps, it was observed that yield correlated better with micro-topography, maybe due to flow accumulation areas. Then, we proposed a methodology using the topographic position index (TPI) which takes into account the local topography. Regarding the stability of the MU, as McBratney et al. (2005) pointed out, sometimes in the delineation of management zones there is insufficient recognition of temporal variation from year to year. Given that topography is a more stable parameter over time than yield, we estimate that the management units delineated using TPI could be applied for a wide range of conditions. For example some years this geographical area is affected by "El Niño" event, and then the precipitation levels are higher than the average. In those years, it is estimated that the same management units could be used but the agronomical prescriptions for them could differ (e.g. increasing the seed rates). We propose this methodology to be applied to similar areas where the main

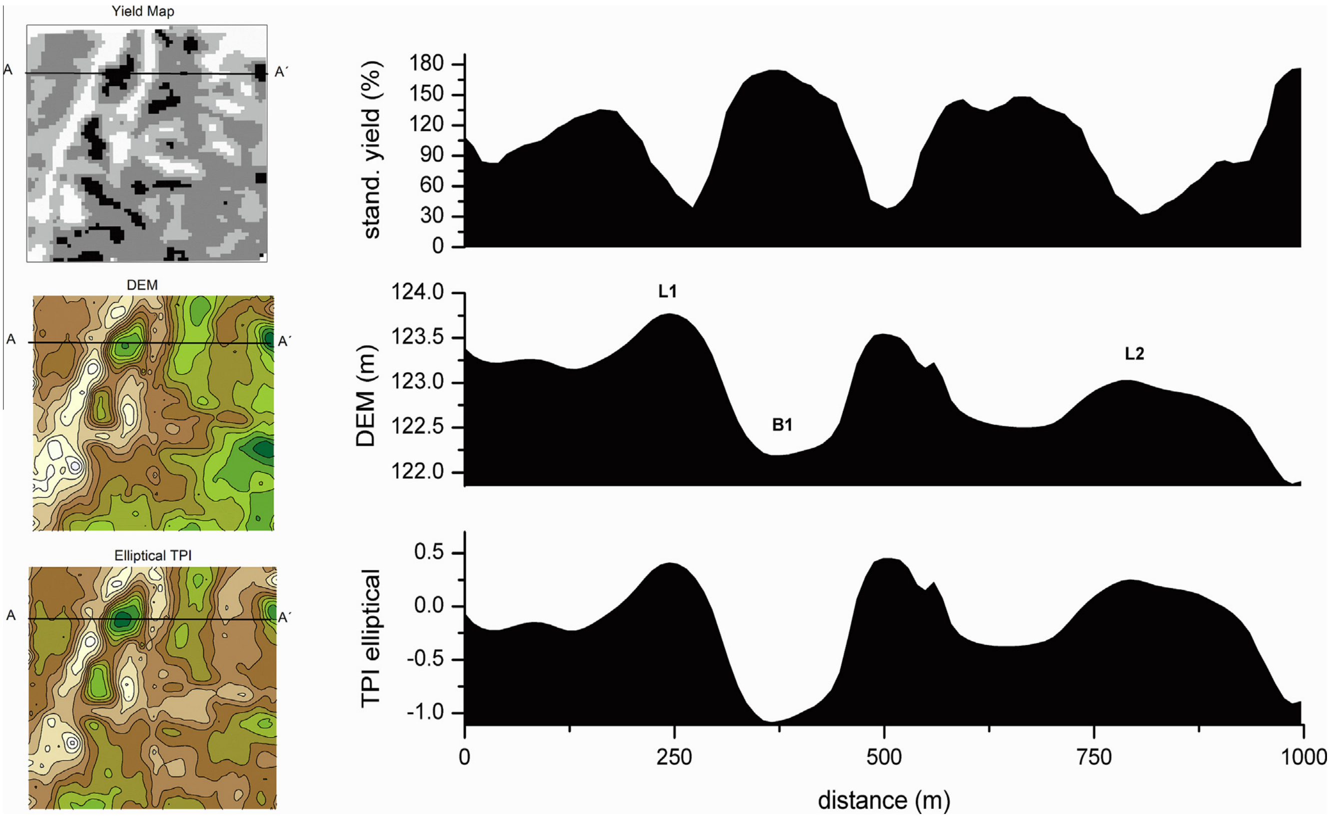
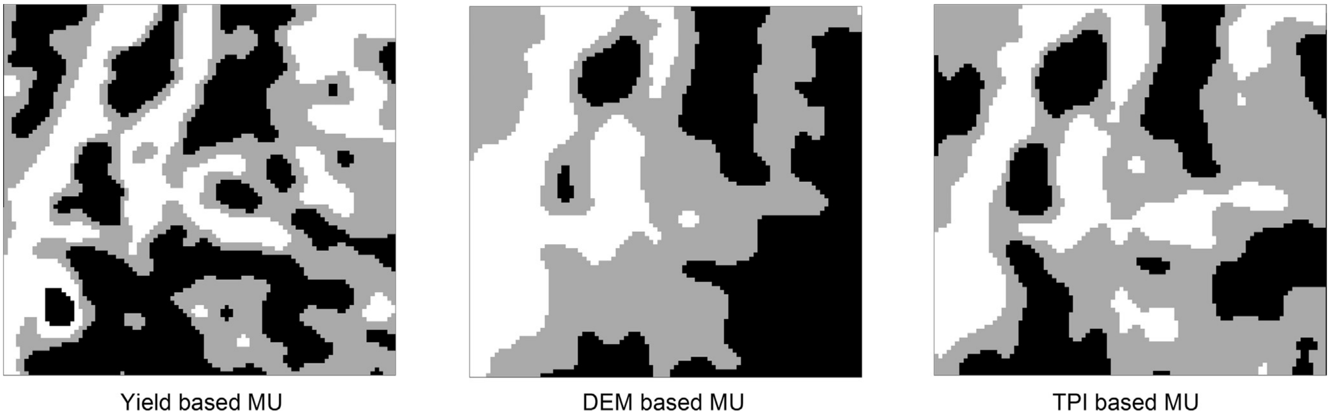


Fig. 10. Comparison of cross profiles AA′ in the standardized yield map, the DEM and the elliptical TPI map.



Yield based MU DEM based MU TPI based MU

Fig. 11. Management units delineated from the yield map, the topographic map and the elliptical TPI map.

Table 3
Confusion matrix for the MU based on the topographic map (tm) using the segmented yield map as reference.

Classified data (tm)	Reference data (yield map)				User's accuracy%
	Bajo	*M Loma*	*Loma*	Total	
Bajo	**1500**	1525	105	3130	48
M Loma	1232	**1249**	622	3103	40
Loma	182	807	**1184**	2173	54
Total	2914	3581	1911	**8406**	
Producer's accuracy %	51	35	62		Overall accuracy 47%

Bold values are indicated the number of pixels correctly classified for each class.

Table 4
Confusion matrix for the MU delineated from the elliptical TPI map using the segmented yield map as reference.

Classified data (TPI)	Reference data (yield map)				User's accuracy%
	Bajo	*M Loma*	*Loma*	Total	
Bajo	**1764**	1317	49	3130	56
M Loma	557	**1988**	558	3103	64
Loma	18	710	**1445**	2173	66
Total	2339	4015	2052	**8406**	
Producer's accuracy %	75	50	70		Overall accuracy 62%

Bold values are indicated the number of pixels correctly classified for each class.

limiting condition for agricultural crops is soil moisture that could associated to topography. In La Pampa alone, the extension of the area where this methodology could potentially be applied is around 750,000 ha s. Other aspects mentioned by McBratney et al. (2005) regarding the adoption of precision farming that this methodology could comply with, are the need of strategies flexible enough to operate in the practical world and the possibility to be applied on all fields in a farm.

4. Conclusions

In this work a simple and robust methodology for the delineation of management units for precision agriculture is presented. This methodology was designed for and tested in an area within the Province of La Pampa Argentina, with sandy soils and where the main limiting factor for crop production is water availability.

Multi annual yield maps are strongly influenced by issues that could be related to un-calibrated data, and previous agronomical practices. Instead, we propose the use of an index derived from topographic maps, the topographic position index (TPI), which takes into account the local topography. A methodology for the definition of an optimum elliptical TPI neighborhood was implemented based on the autocorrelation function on the topographic map. The results showed that the analysis of the autocorrelation function allowed the characterization of the size and preferred orientation of the topographic features. The elliptical TPI and an equivalent circular neighborhood have been tested and the resulting maps correlated with a standardized yield map.

TPI maps performed better at the 95% confidence interval than the topographic map to characterize the variability of the field.

The accuracy assessment of the management units delimited using the topography and TPI maps showed that all accuracy measures were higher for the TPI derived maps than for the DEM derived maps.

This methodology could be used for operational applications, the only requirement being the availability of topographic data for a given field, since it is simple, the algorithms used are unbiased and it could be performed using free software.

For future works, testing of the proposed methodology in other environments would be useful for assessing its range of validity.

Acknowledgments

We would like to dedicate this work to the memory of Daniel Enrique Martínez, an Agronomical Engineer who worked for many years in La Pampa and who shared with us his invaluable knowledge with generosity and passion, and also with whom some years ago we started developing applications for precision agriculture in La Pampa. Also we would like to thank all the farmers and technical advisors that provided data and also suggestions regarding our work.

This work was founded by the University of La Pampa (UNLPam), and is part of a project devoted to applied research for the regional development (POIRe 2013).

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