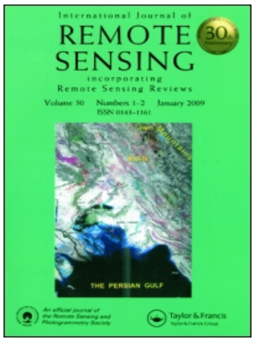

International Journal of Remote Sensing

ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: http://www.tandfonline.com/loi/tres20

A machine learning approach for agricultural parcel delineation through agglomerative segmentation

A. García-Pedrero, C. Gonzalo-Martín & M. Lillo-Saavedra

To cite this article: A. García-Pedrero, C. Gonzalo-Martín & M. Lillo-Saavedra (2017) A machine learning approach for agricultural parcel delineation through agglomerative segmentation, International Journal of Remote Sensing, 38:7, 1809-1819, DOI: 10.1080/01431161.2016.1278312

To link to this article: http://dx.doi.org/10.1080/01431161.2016.1278312

Published online: 31 Jan 2017.

INTERNATIONAL JOURNAL OF REMOTE SENSING, 2017
VOL. 38, NO. 7, 1809–1819
http://dx.doi.org/10.1080/01431161.2016.1278312

A machine learning approach for agricultural parcel delineation through agglomerative segmentation

A. García-Pedrero [a,b], C. Gonzalo-Martín [a,b] and M. Lillo-Saavedra [c,d]

[a]Center for Biomedical Technology, Universidad Politécnica de Madrid, Pozuelo de Alarcón, Spain; [b]Escuela Técnica Superior de Ingenieros Informáticos, Universidad Politécnica de Madrid, Boadilla del Monte, Spain; [c]Faculty of Agricultural Engineering, University of Concepción, Chillán, Chile; [d]Water Research Center for Agriculture and Mining, CRHIAM, University of Concepción, Chillán, Chile

ABSTRACT
A correct delineation of agricultural parcels is a primary requirement for any parcel-based application such as the estimate of agricultural subsidies. Currently, high-resolution remote-sensing images provide useful spatial information to delineate parcels; however, their manual processing is highly time consuming. Thus, it is necessary to create methods which allow performing this task automatically. In this work, the use of a machine-learning algorithm to delineate agricultural parcels is explored through a novel methodology. The proposed methodology combines superpixels and supervised classification in order to determine which adjacent superpixels should be merged, transforming the segmentation issue into a machine learning matter. A visual evaluation of results obtained by the methodology applied to two areas of a high-resolution satellite image of fragmented agricultural landscape points out that the use of machine-learning algorithm for this task is promising.

ARTICLE HISTORY
Received 15 October 2015
Accepted 23 December 2016

1. Introduction

Accurate and up-to-date information about status, acreage, and the type of agricultural lands is assumed to be a valuable element for diverse agricultural-related agencies. This information allows stakeholders among other things to establish agricultural policies (Mirón Pérez 2005; van Der Molen 2002) to reduce greenhouse gas emissions, regulate water rights, and estimate subsidies. In this regard, it is important to consider that about 75% of the world's agricultural lands are small (less than 2 ha) and family operated (Lowder, Skoet, and Raney 2016). This implies highly fragmented agricultural landscapes with a high spatial heterogeneity produced by the diversity in sizes, shapes, and crops of the different agricultural parcels. Therefore, in order to generate precise information about these agricultural lands, a primary requirement is to have a correct delineation at parcel level.

The delineation of agricultural lands has been addressed with different initiatives around the world for a long time. In 1980, the National Research Council published

CONTACT A. García-Pedrero angel.garcia@ctb.upm.es Center for Biomedical Technology, Universidad Politécnica de Madrid, Pozuelo de Alarcón 28233, Spain

the report *Need for a Multipurpose Cadastre* (NRC 1980) which has been updated by the study *National Land Parcel Data: A Vision for the Future* that examines the status of land-parcel data in the USA and provides a set of recommendations that would foster a national system for land parcel (NRC 2007). In the European scenario, it can be mentioned the land parcel identification systems promoted by the European Union in order to represent the activities of farmers on their lands (Leo and Lemoine 2001). These initiatives commonly use very high-resolution remotely sensed imagery to perform a manual delineation of agricultural parcel boundaries. However, a non-trivial issue is how to process a huge data volume maintaining the accuracy and time requirements. Even though the manual delineation can be very precise, it suffers from the subjectivity of operator and is highly time consuming. Moreover, the repeatability of the delineation is not insured even when the same operator performs it at two different times.

To address these problems, automatic and semiautomatic methods have been proposed in the remote-sensing literature. Most of these methods are based on image segmentation. Mueller, Segl, and Kaufmann (2004) proposed an object-based approach for extracting large human-made objects, especially agricultural fields, from high-resolution imagery. This approach combined edge detection models with region-based segmentation to extract regularly shaped objects. In the work of Da Costa et al. (2007), an algorithm to automatically delineate vine parcels from very high resolution images based on their textural properties was developed. From texture attributes, they applied a thresholding method to discriminate between vine and non-vine pixels. Tiwari et al. (2009) proposed a semi-automatic methodology for extracting field boundaries from data captured by the sensor linear imaging self-scanning sensor-IV on-board ResourceSat-1 (IRS-P6) satellite. A segmentation using tonal and textural gradients was performed and the generated regions were classified to derive preliminary field boundaries. Finally, Snakes Algorithm was used to refine the geometry of these field boundaries. Turker and Kok (2013) used perceptual grouping for automatic extraction of dynamic sub-boundaries within existing agricultural fields from remote-sensing imagery. To perform field-based analysis, the approach integrated field boundary data and satellite imagery. Canny edge detector was used to detect the edge pixels. In general, approaches based on segmentation methods have the following drawbacks: (1) they are sensitive to intra-parcel variability which can produce more segments than desired, (2) most of these methods are highly dependent on a correct parameter selection (e.g. the similarity measured used to group image pixels) that requires a prior knowledge about the scene or tuning by trial error. Moreover, variability in sizes and shapes of the plots which causes a certain configuration parameters do not allow properly delineate all parcels.

Recently in computer vision field, approaches intending to imitate the delineation made by an expert through supervised classification methods have been successfully applied to natural image segmentation (Nunez-Iglesias et al. 2013). Therefore, it is assumed that a similar approach could be useful for agricultural parcels delineation. The objective of this work is to establish whether approaches based on machine learning are able to correctly learn how to delineate agricultural parcels in high-resolution images.

In this work, a novel methodology to delineate agricultural parcels following a supervised classification approach is presented. The proposed methodology uses superpixels as minimum processing units, whereas a process of agglomeration of superpixels is used to obtain a final segmentation where the parcels (objects of interest) are distinguished. Superpixels are a form of image segmentation; however, the focus lies more on a controlled over-segmentation. Thus, the image is divided into several homogeneous regions with a determined number of pixels. Superpixels can then be agglomerated for obtaining larger regions. In this regard, a classification method is trained using part of a segmented scene under study, to take the determination whether two adjacent superpixels should be merged. The structure of the article is the following: the data used in this study as well as the proposed methodology are described in the next Section. The obtained results are presented and discussed in Section 3. Finally, main conclusions are given in Section 4.

2. Data and methods

2.1. *Study site and dataset*

The study area corresponds to a Chilean central valley (70°40′7″W, 32°48′11″S) mostly characterized by small agricultural parcels with crops of full canopy coverage and orchards. A WorldView-2 (WV-2) satellite image, acquired on 3 December 2011, was used in this study. The WV-2 image has a spatial resolution of 2.4 m and four spectral bands which properties are described in Table 1. To evaluate the proposed approach, two regions of 522 × 522 pixels each were clipped from the WV-2 scene (Figure 1). Figure 1(a,b) correspond to the areas under analysis, from here on called Image A and Image B, respectively. Agricultural parcels in both images have been manually delineated obtaining reference parcel maps.

2.2. *Methodology*

To delineate agricultural parcels, the proposed methodology combines superpixel processing and a classification method, which provide the basis to decide when two adjacent superpixels should be merged. An overall overview of the proposed methodology is shown in Figure 2.

The methodology starts with an over-segmentation of the image obtained through a superpixel algorithm (see Section 2.2.1). Then, from the generated superpixel representation, a dataset is created by extracting segment features of each pair of superpixels. Instances in dataset are labelled in two classes depending on if they belong to the same object (parcel) or not; this information is given by a previously generated reference

Table 1. Spectral properties of the WV-2 images.

Band	Spectral range (nm)
Blue	450–510
Green	510–580
Red	630–690
Near infrared	770–895

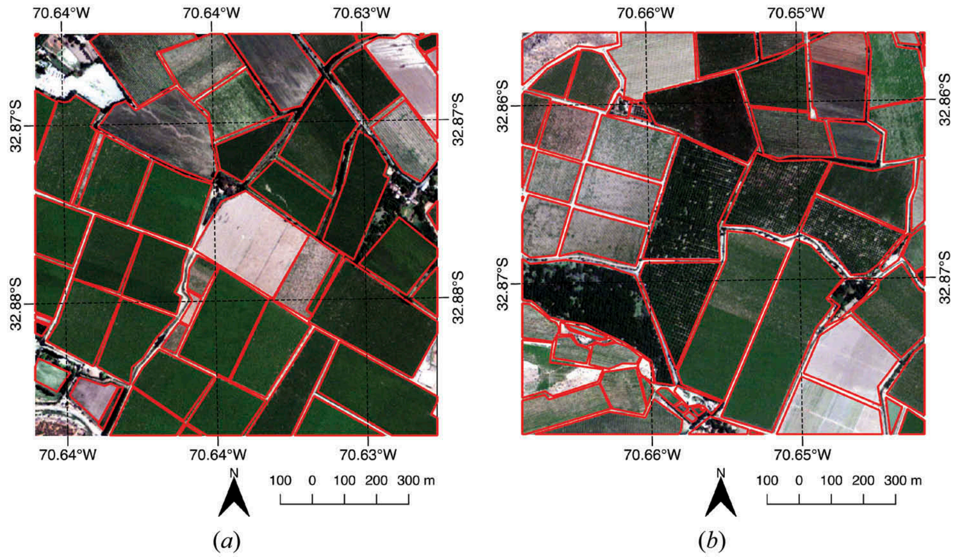

Figure 1. Study areas are shown in a real colour composition. Borders of each parcel are displayed in red. (a) and (b) Correspond to Images A and B, respectively.

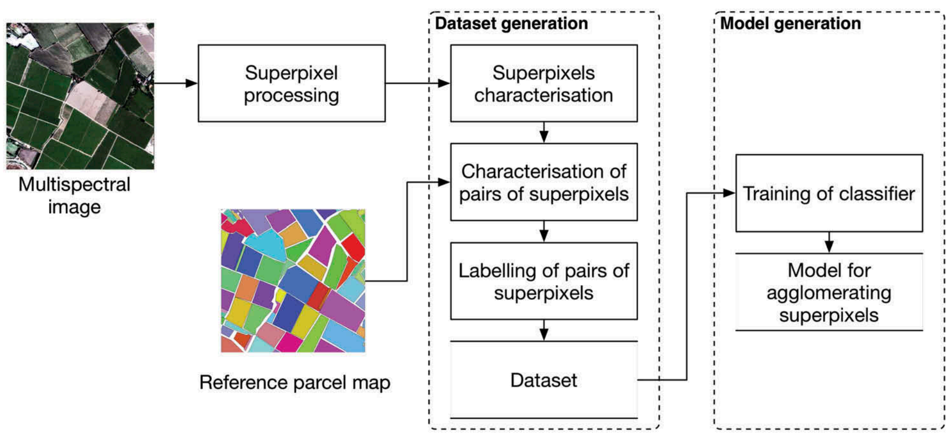

Figure 2. Overall overview of the proposed methodology.

parcel map. Dataset generation is described in detail in Section 2.2.2. Finally, dataset is used to generate a machine learning model, through training a classification method (Section 2.2.3). This model is later used to determine from dataset features whether two superpixels should be merged.

All processes, used in this methodology, are carried out using in-house developed codes and run on the MATLAB® platform.

2.2.1. *Superpixel processing*

A superpixel is a small, local, and coherent cluster which contains a statistically homogeneous image region according to certain criteria such as colour, texture, among others

(Ren and Malik 2003). Superpixels are a form of image segmentation, but the focus lies more on an image over-segmentation, not on segmenting meaningful objects (Schick and Stiefelhagen 2011). In this regard, superpixel processing is not seen as an end in itself but rather a preprocessing step in order to solve a major problem, in this case the efficient analysis of a scene. Superpixel techniques enhance image analysis, e.g. reducing the influence of noise and intra-class spectral variability, preserving most edges of images, and improving the computational speed of later steps such as the segmentation of meaningful objects (Achanta et al. 2012).

Superpixel processing is carried out by a modified version of the segmentation method called simple linear iterative clustering (SLIC) (Achanta et al. 2012), which is in turn based on the well-known k-means method, to group image pixels into superpixels. The original SLIC algorithm works in the RGB colour space (defined by only the Red, Green, and Blue spectral bands) and considers two parameters: k, the desired number of superpixels, and c, the compactness factor. A larger value of c emphasizes the importance of the spatial proximity resulting in more compact superpixels. The SLIC version used in this work corresponds to the implemented by Gonzalo Martín et al. (2015), which extends the method to work with multispectral images.

2.2.2. *Creation of dataset*

All available spectral bands (i.e. four bands, from blue to near infrared) as well as three spectral indices commonly used in remote-sensing image analysis are used for feature extraction. The spectral indices (defined in Equation (1)–(3)) used in this study are normalized difference vegetation index (Rouse et al. 1974), normalized difference water index (Gao 1996), and spectral shape index (Chen et al. 2009).

$$\mathrm{NDVI} = \frac{B_{\mathrm{NIR}} - B_{\mathrm{R}}}{B_{\mathrm{NIR}} + B_{\mathrm{R}}} \tag{1}$$

$$\mathrm{NDWI} = \frac{B_{\mathrm{G}} - B_{\mathrm{NIR}}}{B_{\mathrm{G}} + B_{\mathrm{NIR}}} \tag{2}$$

$$\mathrm{SSI} = |B_{\mathrm{R}} + B_{\mathrm{B}} + 2B_{\mathrm{G}}| \tag{3}$$

where B_{R}, B_{B}, B_{G}, and B_{NIR} represent the red, blue, green, and near-infrared spectral bands, respectively. In addition, a set of texture-based features is computed using local entropy (Equation (4)) from the above features, varying the size of the neighbourhood (N) in which entropy is measured. The local entropy is calculated as follows (Gonzalez, Woods, and Eddins 2004)

$$H = -\sum_{i=0}^{l-1} p(z_i)\log_2 p(z_i) \tag{4}$$

where z_i is a random variable indicating intensity, $p(z)$ is the histogram of the intensity levels in N, and l is the number of possible intensity levels.

Thus, using aforementioned features (e.g. spectral indices, and texture), each superpixel is characterized by a feature vector (**f**), whose components are defined by the average value of the pixel feature values that are part of it. Finally, the dataset **F**, used in the classification process, is created by characterizing each pair of superpixels (i and j), using their corresponding feature vectors, as follows

$$F_{ij} = \left|\mathbf{f}_i - \mathbf{f}_j\right| \quad \forall i \neq j \tag{5}$$

where $\mathbf{f}_i$ is the feature vector of the ith superpixel, and $|\cdot|$ represents the absolute value. The main idea is to create a multidimensional feature space, in which a machine-learning (classifier) method learns a function able to predict when a pair of superpixels belong to the same object. In this work, an absolute difference is used; however, pairs of superpixels can be characterized in diverse ways (e.g. by applying different distance measures or by concatenating both feature vectors); in this regard, the feature vector representing the relationship between those superpixels must be a vector with some properties such as symmetry (i.e. $\mathbf{F}_{ij} = \mathbf{F}_{ji}$), and it cannot be negative.

Since the aim of this work is to agglomerate superpixels, only those that are adjacent are considered. A label set $\mathbf{L}$ (target labels) is created using the information about the adjacency of superpixels and the available reference parcel map (ground-truth data). Thus, each instance of dataset $\mathbf{F}$ is labelled according to Equation (6).

$$\mathbf{L}_{ij} = \begin{cases} +1, & \text{if } i \text{ and } j \text{ belong to the same parcel and } i \neq j; \\ -1, & \text{otherwise} \end{cases} \tag{6}$$

where i corresponds to the ith superpixel and $\mathbf{L}_{ij}$ represents the label of the instance $\mathbf{F}_{ij}$. Here, a positive label for $\mathbf{L}_{ij}$ indicates that superpixels i and j should be merged, whereas a negative one means that both superpixels belong to different objects; hence, they should not be merged.

2.2.3. *Classification process*

Due to the characteristics of the landscape under analysis, target labels are imbalanced (i.e. there are more positive labels than negative, or in other words, more pairs of superpixels belong to the same object). Therefore, a classifier that considers this distribution of the classes is needed in order to obtain satisfactory results. For this reason, the RUSBoost algorithm is used as classifier.

RUSBoost is a hybrid boosting/sampling method proposed by Seiffert et al. (2010), which is a state-of-the-art method for learning from imbalanced datasets. RUSBoost improves boosting algorithm by resampling training data in order to balance the class distribution. Unlike other ensemble methods, RUSBoost applies an under-sampling strategy to randomly remove samples from the majority class, before the training of each weak learner algorithm that is part of the ensemble. It combines many weak classifiers g_t into a strong classifier G by linear combination. The final classifier is constructed as

$$G(x) = \arg\max_{y \in Y} \sum_t g_t(\mathbf{x}, y) \log \frac{1}{a_t} \tag{7}$$

where $g_t(\mathbf{x}, y)$ represents the output of classifier g_t, expressed as the posterior probability for the class $y \in Y$ given the feature vector $\mathbf{x}$.

The resulting class y of RUSBoost method, given the input feature vector $\mathbf{x}$, is the one that gets the maximum value. The weak learners are added incrementally to $G(\mathbf{x})$. In each iteration t, RUSBoost randomly subsamples the majority class in training set X until a subset X'_t with a desired class distribution is reached. For example, if the desired class ratio r is 50:50, then the majority class examples are randomly removed until the numbers of majority and minority class examples are equal. Hence, a weight α_t is assigned to the weak learner according to the relation

$$\alpha_t = \frac{\varepsilon_t}{1 - \varepsilon_t} \tag{8}$$

where ε_t represents the pseudo loss based on the original training set X and it is calculated as

$$\varepsilon_t = \sum_{(i,y):y_i \neq y} D_t(i)(1 - g_t(x_i, y_i) + g_t(x_i, y)) \tag{9}$$

where $g_t(x_i, y_i)$ expresses the posterior probability of the classifier g_t for a class y_i that is different from the real class. $\mathbf{D}$ is a weight distribution for all examples in X, which weights (D_t) are updated after each iteration as follows

$$D_{t+1}(i) = D_t(i)\alpha_t^{\frac{1}{2}(1+h_t(x_i,y_i)-h_t(x_i,y:y\neq y_i))} \tag{10}$$

and then, D_{t+1} is normalized to 1. Initially, the weight of each example $D_1(i)$ is set to $1/n$, where n is the number of examples in the training set (X).

During classification process, dataset $\mathbf{F}$ and label set $\mathbf{L}$ provide the feature vectors and their corresponding classes in the form of the patterns $(\mathbf{F}_{ij}, L_{ij})$ that the classifier must learn in order to delineate agricultural parcels.

3. Results

To prove the potential of the proposed approach, two experiments have been carried out. The first one uses the image A to generate the classification model which is subsequently tested on image B. The second experiment is similar to previous one but interchanging the images used to generate and test the model.

From each image, a total of 5450 superpixels were automatically generated through modified SLIC method (i.e. extended to multispectral images), where each superpixel is composed of 50 pixels on average. The number of pixels that constitutes each superpixel was chosen experimentally to agree with the size of most of the treetops present in the images under analysis. They represent 2% of observations to analyse respect to the entire number of pixels under analysis per image. Due to visualization issues, only enlarged regions containing a set of generated superpixels are shown in Figure 3. As can be observed, superpixels adhere well to the boundaries of spectrally homogeneous regions, in particular, borders of parcels are well delineated.

The number of instances generated for scenes A and B is 12,691 (77.44% positive and 22.56% negative) and 12,994 (78.75% positive and 21.24% negative), respectively. Each instance was characterized by a vector of 28 features: seven corresponding to the four bands and the spectral indexes, and the remaining 21 to the local entropy computed on neighbourhoods of three different sizes (9, 17, 33) over the seven first features. These

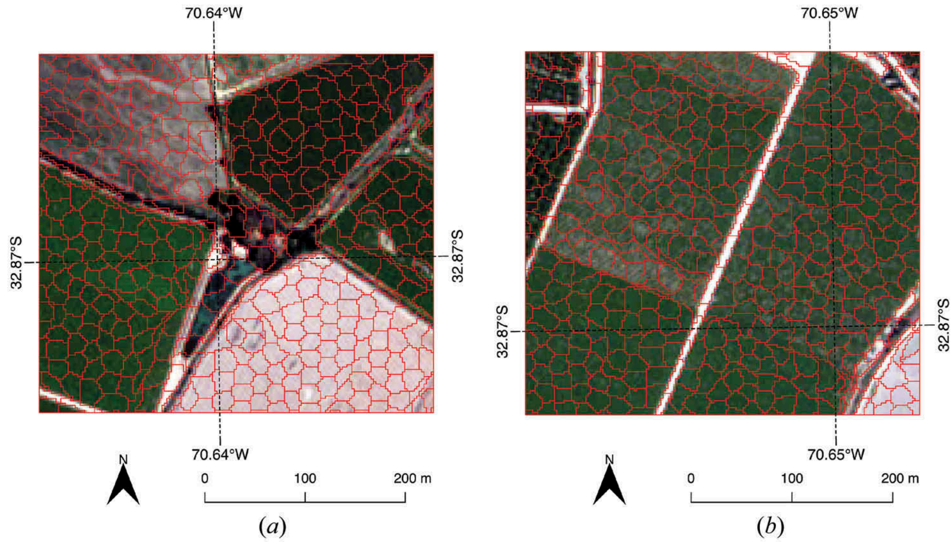

Figure 3. Superpixel segmentation of two small areas. Borders of each superpixel are shown in red. (a) and (b) Correspond to Images A and B, respectively.

instances were used to create two datasets, one for each image. During the classification step, a total of 1000 decision trees were used as weak classifiers to build a single RUSBoost classifier using a ratio of sampling of 50:50.

To evaluate the results obtained by the classifier, a 10-fold cross validation was performed separately using both datasets. During each fold, non-overlapping testing and validation sets (which correspond to seen data) were generated by randomly selecting positive and negative instances maintaining their original class distribution. The obtained results showed mean accuracies (user and producer) greater than 89% with a small standard deviation (lower than 1.09 on average) for positive instances (merge), whereas user and producer accuracies lie between 73% and 78% in the case of negative instances. This may occur because there are few negative (do not merge) instances for training the classifier, requiring more negative instances to improve these results. The assessment of classification using the test set is displayed in Table 2. The low variability of the accuracies in 10 folds points out that the method is stable; therefore, similar results are expected during the validation process.

To test our approach, the classifier of the fold with the best overall accuracy in the validation set was used to determine which superpixels should be merged in the test image. Thus, overall accuracies of 83.53% and 85.58% were obtained using as input the test images (unseen data) A and B, respectively. The results of applying these models to validation and test data are shown in Figure 4, as seen the results in validation set fit better with the ground truth than the results

Table 2. Accuracy assessment of the classification (validation set).

Image	Class	User's accuracy (%)	Producer's accuracy (%)
A	+ (merge)	94.01 ± 1.09	92.85 ± 0.84
	− (do not merge)	75.13 ± 3.32	78.63 ± 2.85
B	+ (merge)	89.58 ± 0.87	92.97 ± 0.71
	− (do not merge)	73.66 ± 2.95	76.57 ± 2.99

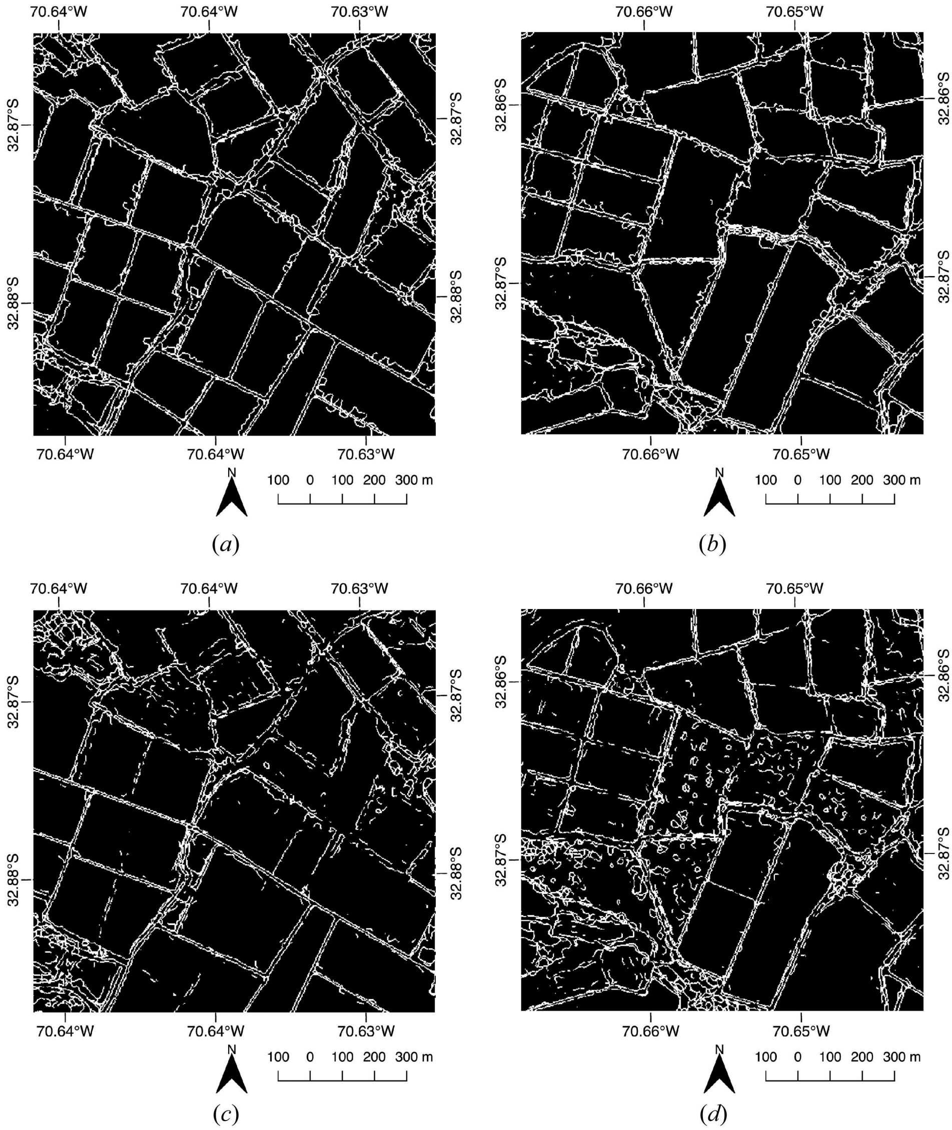

Figure 4. First row shows the results obtained by the best models in the seen data for Images A (a) and B (b), as well as the results of the same model applied to unseen data (second row) for Images A (c) and B (d). For visualization purposes, only it is shown that white borders of superpixels should be separated.

obtained in test set. However, in both cases, most of the superpixels were correctly merged, indicating that better results can be obtained by improving the methodology.

4. Conclusions

This article has presented a methodology for the automatic delineation of agricultural parcels in high-resolution images (WV-2). The proposed methodology uses an extended version of SLIC algorithm for over-segmentating the image to generate superpixels and a supervised classification method to determine when adjacent superpixels should be merged. The results showed that it is possible to train a machine learning to delineate agricultural parcels. In this regard, learning from data, how agricultural parcel is delineated poses an alternative to traditional segmentation algorithms, which could be exploited to imitate the labour of a human operator. Two main aspects will be improved in future research: (1) determining the optimal features to train the methodology, (2) exploring different ways to measure the similarity of adjacent superpixels (e.g. testing diverse distances), and (3) extending the process to different interest objects and scales.

Acknowledgements

A. García-Pedrero (Grant Number 216146) acknowledges the support for the realization of his doctoral thesis to the Mexican National Council of Science and Technology (CONACyT). This work has been funded by the Fondo de Fomento al Desarrollo Científico y Tecnológico (FONDEF IT13I20002) through the project entitled 'AQUASAT: Un servicio integrado para el manejo sitio-específico del agua de riego' and by the Centro de Recursos Hídricos para la Agricultura y la Minería (CONICYT/FONDAP/1513001) and by the Universidad Politécnica de Madrid (AL-16-PID-07). The authors would like to thank the Editors and the anonymous reviewers for their helpful and constructive comments that greatly contributed to improving this manuscript. They would also like to thank Dr. Rodolfo Guzman Huerta for his comments and suggestions for improving this manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

A. García-Pedrero acknowledges the support for the realization of his doctoral thesis to the Mexican National Council of Science and Technology (CONACyT) [Grant Number 216146]. This work has been funded by the Fondo de Fomento al Desarrollo Científico y Tecnológico (FONDEF IT13I20002) through the project entitled 'AQUASAT: Un servicio integrado para el manejo sitio-específico del agua de riego' and by the Centro de Recursos Hídricos para la Agricultura y la Minería (CONICYT/FONDAP/1513001) and by the Universidad Politécnica de Madrid (AL-16-PID-07)

ORCID

A. García-Pedrero http://orcid.org/0000-0002-6848-481X
C. Gonzalo-Martín http://orcid.org/0000-0002-0804-9293

References

Achanta, R., A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Süsstrunk. 2012. "SLIC Superpixels Compared to State-Of-The-Art Superpixel Methods." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 34 (11): 2274–2282. doi:10.1109/TPAMI.2012.120.

Chen, Y., W. Su, J. Li, and Z. Sun. 2009. "Hierarchical Object Oriented Classification Using Very High Resolution Imagery And Lidar Data Over Urban Areas." *Advances In Space Research* 43 (7): 1101–1110. doi:10.1016/j.asr.2008.11.008.

Da Costa, J. P., F. Michelet, C. Germain, O. Lavialle, and G. Grenier. 2007. "Delineation of Vine Parcels by Segmentation of High Resolution Remote Sensed Images." *Precision Agriculture* 8 (1–2): 95–110. doi:10.1007/s11119-007-9031-3.

Gao, B.-C. 1996. "NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space." *Remote Sensing of Environment* 58 (3): 257–266. doi:10.1016/S0034-4257(96)00067-3.

Gonzalez, R. C., R. E. Woods, and S. L. Eddins. 2004. *Digital Image Processing Using MATLAB*. Upper Saddle River, New Jersey: Pearson Education India.

Gonzalo Martín, C., E. Menasalvas, M. Lillo Saavedra, D. Fonseca-Luengo, A. Garcia-Pedrero, and R. Costumero. 2015. "Local Optimal Scale in a Hierarchical Segmentation Method for Satellite Images." *Journal of Intelligent Information Systems* 46(3): 517-529.

Leo, O., and G. Lemoine. 2001. "Land Parcel Identification Systems in the Frame of Regulaton (EC) 1593/2000 Version 1.4." Tech. rep. Ispra, Italia: Institute for Environment and Sustainability.

Lowder, S. K., J. Skoet, and T. Raney. 2016. "The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide." *World Development*. 87: 16-29.

Mirón Pérez, J. 2005. "Cadastre and the Reform of European Union's Common Agricultural Policy. Implementation of the SIGPAC." http://www.catastro.meh.es/documentos/publicaciones/ct/ct54/01-catastro_54_ing.pdf

Mueller, M., K. Segl, and H. Kaufmann. 2004. "Edge-and Region-Based Segmentation Technique for the Extraction of Large, Man-Made Objects in High-Resolution Satellite Imagery." *Pattern Recognition* 37 (8): 1619–1628. doi:10.1016/j.patcog.2004.03.001.

National Research Council. 1980. *Need for a Multipurpose Cadastre*. Washington, DC: National Academy Press.

National Research Council. 2007. *National Land Parcel Data: A Vision for the Future*. Washington, DC: The National Academies Press.

Nunez-Iglesias, J., R. Kennedy, T. Parag, J. Shi, and D. B. Chklovskii. 2013. "Machine Learning of Hierarchical Clustering to Segment 2D and 3D Images." *PLoS One* 8: 1–11. doi:10.1371/journal.pone.0071715.

Ren, X., and J. Malik. 2003. "Learning a Classification Model for Segmentation." In *Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on*, October10–17, edited by Bob Werner, Vol. 1. Los Alamitos, California: IEEE.

Rouse, J. _. W. Jr, R. H. Haas, J. A. Schell, and D. W. Deering. 1974. "Monitoring Vegetation Systems in the Great Plains with ERTS." *NASA Special Publication* 351: 309.

Schick, A., and R. Stiefelhagen. 2011. "Evaluating Image Segments by Applying the Description Length to Sets of Superpixels." In *Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*, 1394–1401. IEEE.

Seiffert, C., T. M. Khoshgoftaar, J. Van Hulse, and A. Napolitano. 2010. "Rusboost: A Hybrid Approach to Alleviating Class Imbalance." *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 40 (1): 185–197. doi:10.1109/TSMCA.2009.2029559.

Tiwari, P. S., H. Pande, M. Kumar, and V. K. Dadhwal. 2009. "Potential of IRS P-6 LISS IV for Agriculture Field Boundary Delineation." *Journal of Applied Remote Sensing* 3 (1): 033528–033528. doi:10.1117/1.3133306.

Turker, M., and E. H. Kok. 2013. "Field-Based Sub-Boundary Extraction from Remote Sensing Imagery Using Perceptual Grouping." *ISPRS Journal of Photogrammetry and Remote Sensing* 79: 106–121. doi:10.1016/j.isprsjprs.2013.02.009.

van Der Molen, P. 2002. "The use of the Cadastre among the Members States: Property rights, land registration and Cadastre in the European Union." http://www.catastro.meh.es/documentos/publicaciones/ct/ct45/02ingles.pdf