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Deep Learning for Automatic Outlining Agricultural Parcels: Exploiting the Land Parcel Identification System

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ABSTRACT Accurate and up-to-date information on the spatial and geographical characteristics of agricultural areas is an indispensable value for the various activities related to agriculture and research. Most agricultural studies and policies are carried out at the field level, for which precise boundaries are required. Today, high-resolution remote sensing images provide useful spatial information for plot delineation; however, manual processing is time-consuming and prone to human error. The objective of this paper is to explore the potential of deep learning (DL) approach, in particular a convolutional neural network (CNN) model, for the automatic outlining of agricultural plot boundaries from orthophotos over large areas with a heterogeneous landscape. Since DL approaches require a large amount of labeled data to learn, we have exploited the open data from the Land Parcel Identification System (LPIS) from the Chartered Community of Navarre, Spain. The boundaries of the agricultural plots obtained from our methodology were compared with those obtained using a state-of-the-art methodology known as gPb-UCM (global probability of boundary followed by ultrametric contour map) through an error measurement called the boundary displacement error index (BDE). In BDE terms, the results obtained by our method outperform those obtained from the gPb-UCM method. In this regard, CNN models trained with LPIS data are a useful and powerful tool that would reduce intensive manual labor in outlining agricultural plots.

INDEX TERMS Convolutional neural network, deep learning, edge extraction, land parcel identification system, parcels delineation.

I. INTRODUCTION

World food production needs to grow by 70% in developing countries to meet food demands of 9 billion people by 2050 [1]. Hence, the agricultural sector faces a critical global challenge: ensuring access to safe, healthy, and

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nutritious food for a growing world population; and, at the same time using natural resources more sustainably while making an effective contribution to climate change adaptation and mitigation [2]. For agriculture to be sustainable, agricultural practices must take full advantage of technology, research and development and adapt to local requirements. Adequate statistics, geo-spatial information, maps and qualitative knowledge are needed for the planning and

management of the agricultural sector [3]. On the other hand, a symbiosis between technical and investment-oriented organizations is also necessary.

At the European level, the Common Agricultural Policy (CAP) fosters green and sustainable agriculture¹ by offering compensation payments to farmers. The geographical location and size of the agricultural parcel play a key role in determining which payment entitlements may be eligible and for which payment may be claimed for [4]. In this regard, the Land Parcel Identification System (LPIS), a GIS inventory similar to cadastre, has been created as a control mechanism to verify the eligibility of subsidies, and monitoring of plots with respect to selected environmental rules and rural development programs [4], [5]. The European Union (EU) Member States have their own LPIS which follows common guidelines. In addition to its original purpose, LPIS information has proven useful for studying various aspects of agricultural activity [6], such as the effect of land fragmentation and carbon dioxide emissions.

The dynamic nature of agricultural activities (e.g., crop rotation, subdivision or consolidation of fields, temporary fallow) generally makes agricultural plots unstable both in boundaries and land use [4]. Therefore, in order to reduce the risk of paying sanctions due to the improper identification of agricultural lands [7], the LPIS should be updated regularly (i.e. once a year). In general, the creation and updating of each LPIS is mainly done by photo-interpretation using very high resolution orthophotos [7], which makes it a laborious process which is susceptible to human error [8]. In this respect, efforts should focus on the automation of workflows for the outlining parcels in cadastral maps [9]. In the literature on remote sensing, automatic and semi-automatic methods have been proposed to outline the boundaries of agricultural plots. Most of them are based on image segmentation, edge detection algorithms and classification models, or combinations of these techniques.

Crommelinck *et al.* [10] proposed a workflow, based on an ultrametric contour map (UCM) generated from the gPb (globalized probability of boundary based contour detection), known as gPb-UCM [11], for the automatic delineation of objects, in particular cadastral boundaries, using RGB images acquired through an unmanned aerial vehicle (UAV) platform. The results showed that a gPb-UCM based approach is best suited for areas in which object contours are clearly visible and coincide with cadastral boundaries, obtaining correctness rates of up to 80%. The authors concluded that this approach is of limited usability as an independent approach to cadastral mapping, and can be used for an initial location of the boundaries of candidate objects, which need to be verified and located exactly by integrating additional workflow steps. In a later work [12], Crommelinck *et al.* proposed a workflow for the interactive outlining of cadastral boundaries from UAV data. The components of this boundary delineation

methodology were: gPb contour detection, SLIC (simple linear iterative clustering) superpixels and random forest classifier. The main results reported were that, compared to manual delineation, the number of clicks per 100 million was reduced by up to 86%. However, as the authors state, this methodology was not applied to real-world cadastral mapping scenarios, so it requires more research and development to be used in cadastral mapping workflows.

In the work of García-Pedrero *et al.* [13], a new methodology based on a consensus of superpixel segmentations for delineating agricultural farm boundaries was presented. The most important contributions of this work have been to combine segmentation at different scales using superpixels and to incorporate information of the vegetative stage by means of images taken on different dates in order to obtain a single segmentation of the agricultural plots. Ghaffarian and Turker [14] proposed a segmentation method based on active contour models for the automatic extraction of sub-boundaries (boundaries between different types of crops) within permanent agricultural fields. Active contour models used the results of both automatic fuzzy c-means clustering and edge detection to calculate an improved gradient vector flow [15]. This methodology is a promising solution for outlining sub-boundaries on agricultural plots with high intra-plot variability. However, to establish the geometry of agricultural fields, the authors used a reliable parcel database. In [16], Xu *et al.* addressed the problem of outlining agricultural parcels using a stratified extraction method based on objects from RGB satellite imagery. According to the authors, the estimation of the segmentation scale based on spatial statistics can avoid sub-segmentation and over-segmentation to a certain degree. However, the accuracy of the segmentation and its subsequent analysis was limited in regions with complex objects.

The aforementioned approaches have several drawbacks: they are sensitive to intra-plot variability, which can produce more segments than desired; and most of these methods rely heavily on a correct selection of parameters (e.g., the similarity measure used to group the pixels of the image), which requires prior knowledge of the scene or trial-and-error tuning. In order to overcome these drawbacks, García-Pedrero *et al.* [17] proposed a methodology for delineating agricultural plots using a machine learning method known as RUSboost classifier [18]. This methodology used superpixels as minimum processing units, and a superpixel agglomeration process where the decision to join two superpixels is taken by the classifier resulting in a segmentation where agricultural plots are distinguished. A disadvantage is the amount of time taken to select the most suitable features to get a good performance from a machine learning classifier [19]. In addition, the variability in plot sizes and shapes means that certain configuration parameters do not allow for the proper delineation and classification of all agricultural plots in a scene [20].

Considering that deep learning (DL) techniques have proven useful as a tool in understanding agricultural

¹https://ec.europa.eu/agriculture/sites/agriculture/files/events/2012/rio-side-event/brochure_en.pdf

processes [21], [22], DL methodologies for outlining agricultural plots seem to be a solution to overcome the drawbacks of the aforementioned approaches.

DL techniques, and in particular convolutional neural networks (CNNs) are capable of exploiting the unknown structure in the input data distribution to discover good representations, often at multiple levels, with higher-level features defined in terms of lower-level features; reducing large and complex data sets to a predictive output [23], [24]. This provides greater learning capacity and therefore higher performance and accuracy compared to traditional methods. Two types of CNNs are generally used in remote sensing applications [25]: patch-based convolutional networks and fully convolutional networks. In the first approach, a typical CNN model receives fixed-size patches centered on each image pixel as input and, consequently, the network's response (prediction) to every single pixel is represented by the image region corresponding to that particular patch [26]. These models work particularly well in sparse annotated data sets; however, when dense predictions are required (i.e., one for each pixel of the image) they require a lot of computational power [27]. Although there are approaches to reduce these resources such as the use of superpixels instead of pixels [28], they present problems such as inaccuracies at the edges of the objects in the image. On the other hand, fully convolutional networks are built solely from locally connected layers, such as convolution, pooling, and upsampling [29]. Unlike patch-based architectures, they can offer dense predictions because they do not contain fully connected layers with fixed dimensions, depending only on the size of the input image. Thus, a fully convolutional network tries to learn representations and make decisions based on local spatial information [30]. These features make them more efficient than patch-based approach [25].

As far as the authors know, there is little literature available dealing with the automatic/semi-automatic delineation of agricultural plots using CNNs. Xia *et al.* [31] proposed a workflow for the extraction of deep edges of crop plots from very high spatial resolution images. The workflow combined RCF [32] and U-Net [33] models respectively to detect soft edges (rivers and roads) and to detect regions such as hard edges and types of farmland. To evaluate the methodology they used a pansharpened image from the GF-2 satellite [34] with a coverage area of 1808 km², which is equivalent to a square image of 1680 by 1680 pixels (spatial resolution of 0.8 m). While the work is difficult to replicate due to the lack of information provided in the methodology, the results showed a promising future for DL-based techniques. In [35], the authors proposed a strategy to detect field boundaries using a fully convolutional network (FCN) in combination with a grouping algorithm. Field boundary detection was defined as a supervised pixel classification problem, using the SegNet architecture [36] to distinguish boundary from non-boundary pixels. The detected boundaries were used to extract a hierarchy of closed segments using gPb-UCM. The final segmentation was obtained by applying the

single-scale combinatorial grouping algorithm [37]. The methodology was applied in two areas of study, using images from WorldView-2 and 3. Although the results showed that the methodology is promising, the size and number of images used in this work do not appear to be sufficient to avoid over-adjustment of the models. This issue was not addressed in this research. These approaches are an important contribution to the development of tools based on DL for boundary cadastral of agricultural plots. However, in both cases, the experiments have been carried out using very limited training areas. This restricts the capacity of the generalization of the results, tending to over-fit the obtained models. Although the importance of DL is increasing, there are significant challenges that have to be tackled to develop robust models. One of the most important drawbacks and barriers to the use of DL methodologies in agriculture is the lack of large labeled data sets needed for modeling [38]. Because of this, it is possible to say that DL-based strategies for the generation of agricultural cadastres present a gap between laboratory-scale developments and their application in the real world.

In order to reduce the gap described above, in this paper we explored the use of a DL methodology for the automated mapping of agricultural plot boundaries over a large area with a heterogeneous landscape. In particular, we performed an experimental analysis using the LPIS open-data of an extensive region of Spain. The proposed approach opens up the possibility to create a framework to support human operator task, as a complementary tool for the systematic updating of agricultural cadastral boundaries on a large scale.

The rest of the manuscript is organized as follows: Section II describes the data set used as well as its geographical location. Section III describes each stage of the proposed methodology. The results obtained as well as their discussion are presented in Section IV. Finally, the conclusions and problems to be addressed in future efforts are presented in Section V.

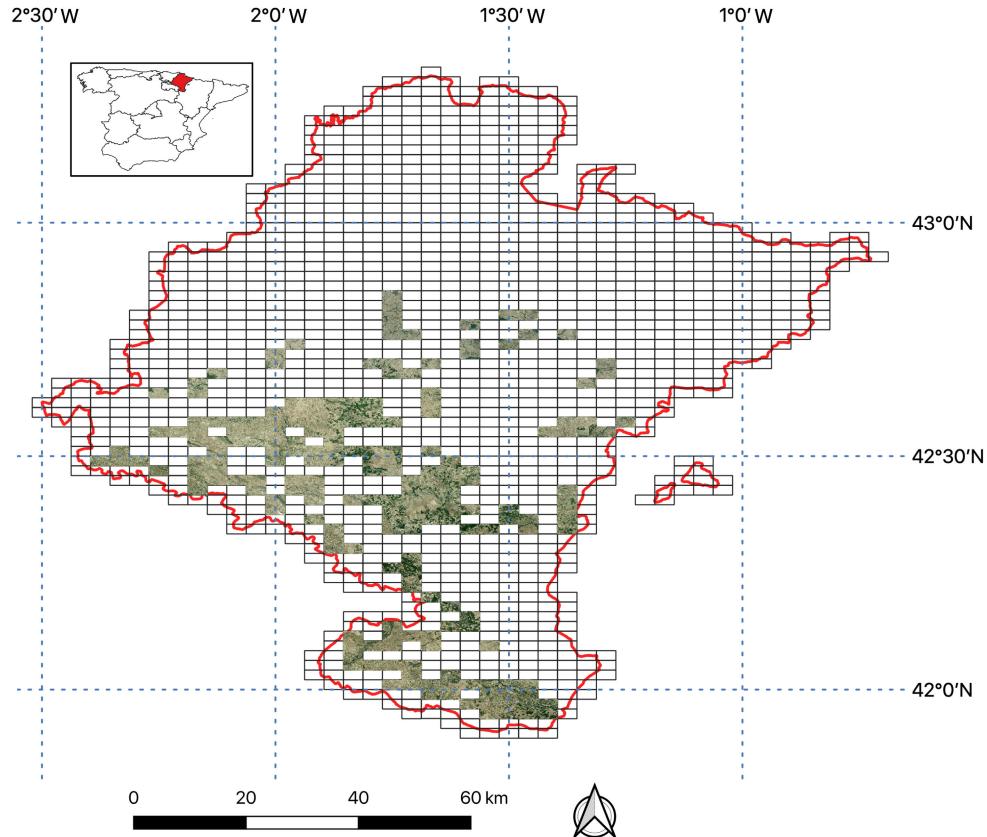
II. STUDY AREA AND MATERIAL

In Spain, the implementation of LPIS, called SIGPAC, is supported by the Ministry of Agriculture, Food and Environment of the Government of Spain. SIGPAC is a public data source that allows the geographical identification (e.g., land use and boundaries) of parcels declared by farmers and stockbreeders throughout the Spanish territory. All SIGPAC data² has been generated from digital orthophotos (RGB images), cadastral information and on-site field visits.

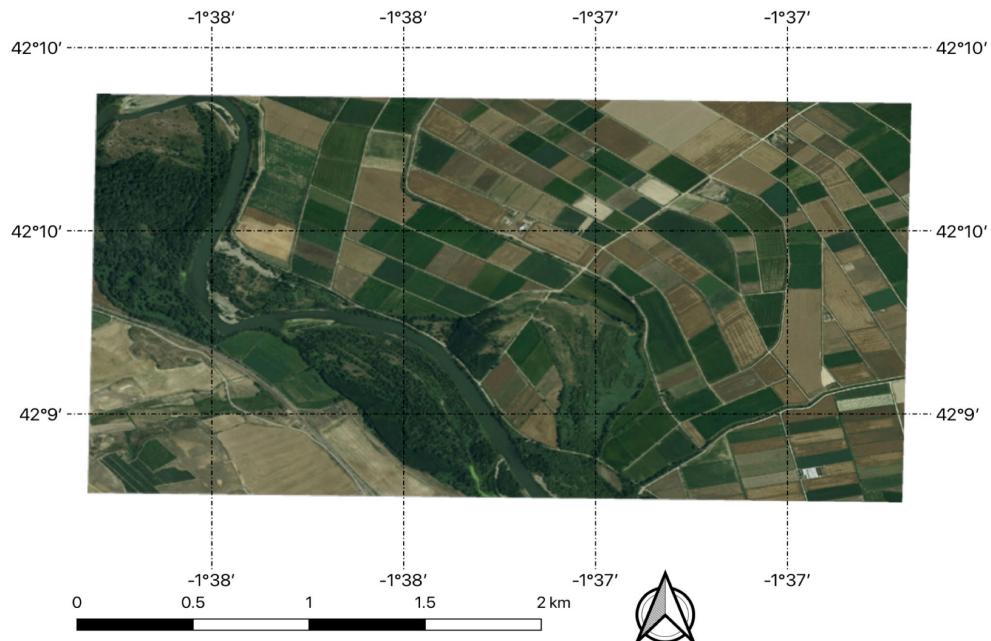
In this work the data set corresponding to the last revision (2019) of the SIGPAC of the Chartered Community of Navarre³ was used. From this, 207 raster tiles were selected, each corresponding to an RGB image of 9,384 × 13,688 pixels and 25 cm spatial resolution. The location of the study site as well as the coverage of the raster tiles used are shown in Figure 1. In addition, the boundaries of agricultural

²<https://www.fega.es/es/node/48564>. Last accessed April 2019.

³<https://sigpac.tracasa.es>. Last accessed on February 2019.



a Location of the Chartered Community of Navarre, Spain.



b An example of SIGPAC's tile.

FIGURE 1. Study site.

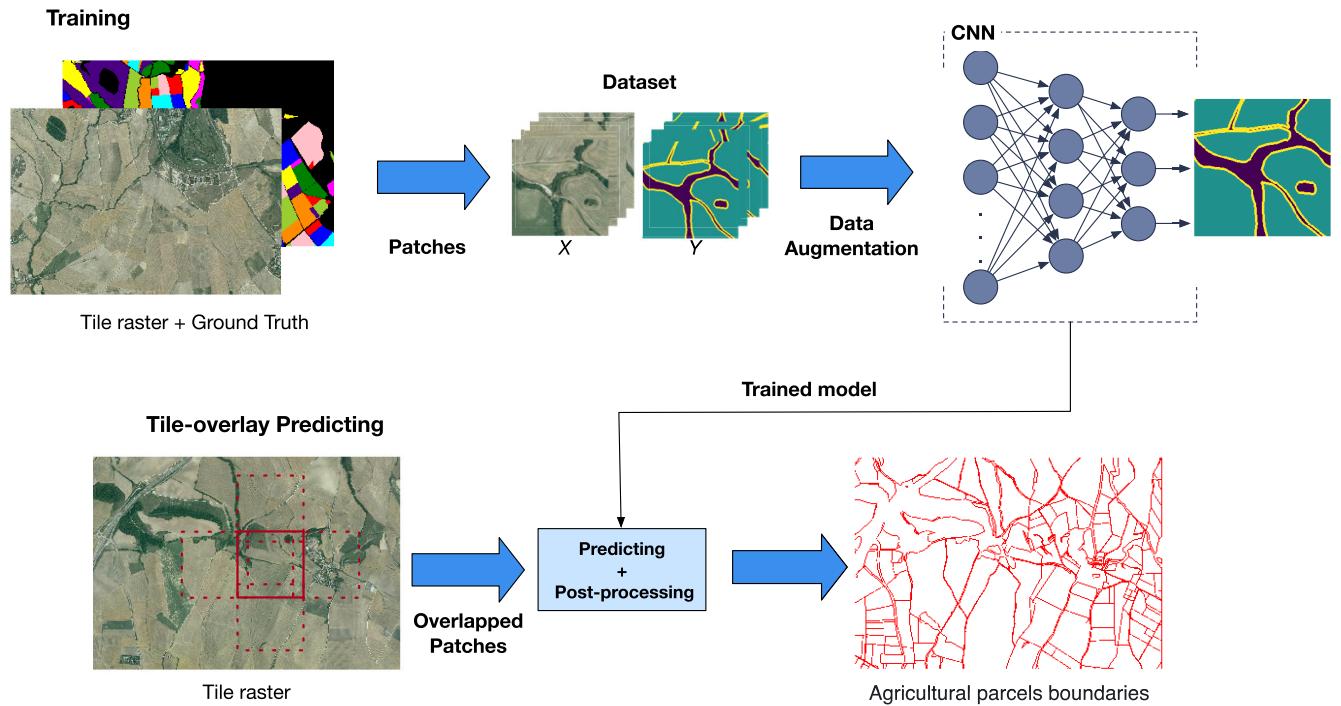


FIGURE 2. Workflow to train the models and predicting agricultural plots boundaries.

plots in the same area are available in Shapefile format, covering most of the tiles. Since SIGPAC contains information not exclusively on agricultural plots (e.g., water bodies and cities), from the available information only those parcels corresponding to the following land cover were selected: fruit trees, nuts, olive groves, orchards, arable land and vineyards. This information was used as ground truth (GT).

III. METHODS

The proposed methodology (Figure 2) is based on a CNN model, known as U-Net, to outline agricultural plots boundaries automatically. To overcome the lack of labeled data sets needed to train the model, in this work, open-access LPIS data was used. The main steps of the proposed methodology are detailed below.

A. PRE-PROCESSING

To reduce the time and computational requirements of the training process, the spatial resolution of the data set was reduced by 1/8 by the nearest neighbor algorithm, obtaining images of 2 m resolution and size of 1,173 by 1,711 pixels. Although it is known that more contextual information helps to better identify objects in an image [39], hardware limitations impose the maximum image size with which it is possible to work. In this regard, the downsizing of the images allows computing costs to be reduced as well as extending the contextual information.

GT (shapefile) was rasterized to this same resolution. From the polygons (agricultural plots) of the GT, three classes were

generated corresponding to the background, the plot and a buffer around the boundaries of the agricultural plots. The latter represents the transition between the background and the agricultural plot and is used to reduce possible errors caused by the inaccuracy of the manual outlining carried out by manual operators. To train the models, the raster tiles and the GT were clipped into overlapping patches of 224 by 224 pixels, with a 50% overlap. The area covered by each patch is equivalent to 20 hectares, which provides a good representation of the context of the agricultural plots. Because the GT does not completely cover the tiles (i.e., not all of the plots have been delineated), only those patches with a GT coverage greater than or equal to 50% were used. Considering that the training data set must contain as many different examples as possible to avoid over-fit of the model generated, data augmentation was applied by means of a random Dihedral transformation of the *Dih4* group [40]. In addition, with a probability of 0.5, a random rotation was performed with those degrees in the range of 45° to -45°. Based on the work of [41], the patches were normalized, subtracting the mean RGB value of ImageNet data set ($R = 103.939$, $G = 116.779$, $B = 123.680$) from each channel.

B. TRAINING CNNS MODEL

We used the U-Net architecture [33] (Figure 3), a cutting-edge neural network model to segment images, to delineate agricultural plots. The U-Net architecture can be described in general terms as a model of multi-scale encoders-decoders with skip connections. The coding part extracts the

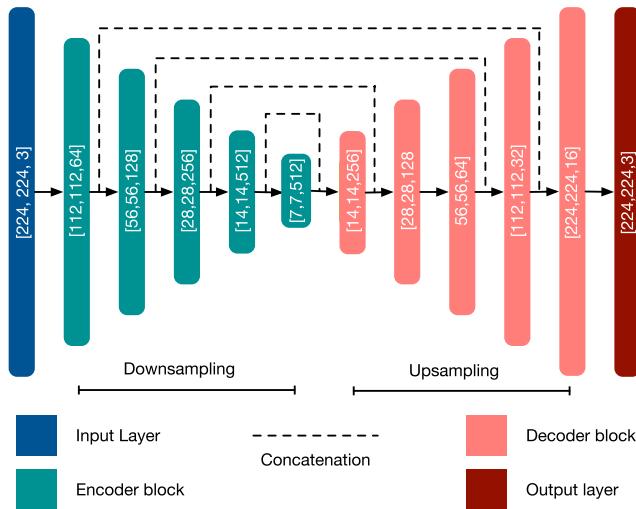


FIGURE 3. Unet model. Block outputs are shown in parentheses in the format [height, width, number of channels].

characteristics of the data while reducing the width and height of the input data. The decoder part shows the feature maps and halves the number of feature channels. Skip connections alleviate the problem of the vanishing gradient improving the learning process [42]. Finally, the output layer uses a 1×1 convolution along with an activation function to map the feature vector to an output matrix with the width and height of the input image. In this work, we used a softmax function as the activation function. Based on the work of [43], the encoders and decoders of the network were built using a VGG-16 [41] encoder pre-trained on ImageNet. As can be seen in (Figure 4), an encoder block includes three 3×3 convolutional layers with a stride of 1 and the same number of output channels. The last layer of this block is a maximum pooling layer that reduces input by calculating the maximum value for non-overlapping windows (2×2). On the other hand, a decoder block consists of an upsampling layer, two 3×3 convolutional layers, two batch normalization layers, and two ReLU activation layers arranged as shown in Figure 4. The upsampling layer replicates the rows and columns of the input data by doubling their size. The batch normalization layer applies a data standardization (mean zero and standard deviation close to one) to the input batch. The ReLU activation layer rectifies the input data by replacing values below zero with zeros.

The use of trained weights on ImageNet data was preferred over training from scratch because it usually accelerates convergence and helps reduce over-fitting in small data sets [44]. The network was retrained using the Adam optimizer [45] with a learning rate of 0.0001 and a batch size of 16. As the loss function, a combination of Jaccard distance [46] and categorical cross-entropy [47] proposed by Rakhlin *et al.* [48] was used. The proposed model was trained for a period of 200 epochs.

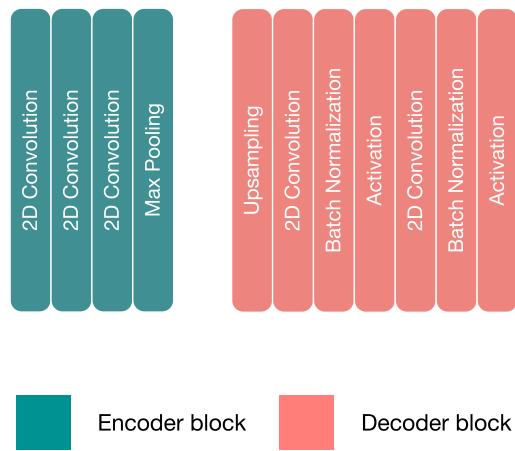


FIGURE 4. Encoder and decoder blocks.

C. POSTPROCESSING

In order to obtain the boundaries of the agricultural plots of a complete tile, the following post-processing strategy is followed. First, a padded version of the tile obtained through a mirror padding strategy is divided into several overlapping patches, from which the U-net model performed the segmentation. During the prediction phase, random transformations are applied to the test patches. In this way instead of showing the regular images only once to the trained model the various versions of the images are shown several times improving the chances of identifying the target and predicting it accordingly [49]. In this work, we used the eight transformations of the *Dih4* group. Once the model provides the segmented images, the inverse transformation is performed on them, in such a way that all the pixels agree. The final segmentation of a tile is given by a soft voting that returns the final class label \bar{y}_i as arg max of the sum of predicted probabilities:

$$\bar{y}_i = \arg \max_c \sum_m w_c \hat{y}_{i,c}^m \quad c \in \{0, 1, 2\} \quad (1)$$

where $\hat{y}_{i,c}^m$ is the probability of the i^{th} pixel belonging to the $c - th$ class given the prediction m , w_c is the weight, and M is the total number of predictions over the i^{th} pixel. As can be intuited, M depends on the number of overlaps and the number of *Dih4* transformations. In this work, the weights (w_c) were defined as $1/C$, this allows all classes to have the same weight during the final prediction, however, other weights can be explored to favor a particular class, for example in favor of agricultural plots in environments with a mostly urban cover. To reduce distortions due to the border effects of the sliding window, the probabilities of each window are weighted by a Gaussian function with $\sigma = 1$ and $\mu = 0$. After obtaining the prediction of a complete tile, the corresponding edges of segments corresponding to the parcel class are obtained. This last step provides the final delineation of the agricultural plots.

D. ASSESSMENT OF ACCURACY

In order to evaluate the results an error measurement centered on the boundaries of the image objects, known as boundary displacement error index (BDE), was chosen. The BDE index, proposed in [50], measures the difference between two segmented images by averaging the displacement of their corresponding segment border pixels. Specifically, the distance (d_E) between a boundary pixel (b_s) in the obtained boundary image (B_s) and the closest pixel (b_{gt}) in the ground-truth boundary image (B_{gt}) is used to define the disagreement (error) of each boundary pixel. The BDE index can be defined mathematically as follows:

$$BDE = \frac{1}{2} \left(\frac{1}{|B_s|} \sum_{b_s \in B_s} \sum_{b_{gt} \in B_{gt}} \min\{d_E(b_s, b_{gt})\} + \frac{1}{|B_{gt}|} \sum_{b_{gt} \in B_{gt}} \sum_{b_s \in B_s} \min\{d_E(b_{gt}, b_s)\} \right) \quad (2)$$

A more detailed description of the BDE index can be found in [50].

E. PERFORMANCE EVALUATION

To measure the performance of our method, the results obtained were compared with the gPb-UCM method used by [10]. The gPb-UCM workflow consists of three phases: (1) contour detection using gPb, (2) segmentation using Oriented Watershed Transformation (OWT), which forms the initial contours of the regions, and (3) construction of an ultra-metric map (UCM), which defines a hierarchical segmentation according to a th threshold within a range of [0, 1]. Increasing the threshold is equivalent to eliminating contours and merging separate regions. A more detailed description of the gPb-UCM method can be found at [11].⁴ In this paper, an empirical analysis gave us $th = 0.05$ as an appropriate value. This value is similar to that reported in the work of [10].

From the 207 available tiles, 186 were randomly selected for training and 21 for testing. As well as for the training and prediction of the proposed methodology, in the case of gPb-UCM the spatial resolution of the data set was reduced by 1/8 by the nearest neighbor algorithm, obtaining images of 2 m resolution. Tiles used for training were subjected to the pre-processing process described in Section III-A, generating 150k patches used for training and 15k for calibrating (validation set) the model. Since the LPIS may contain errors, as established by [51], another external set of two manually delineated tiles was created to evaluate the proposed method. On the other hand, the other two sets (testing and external sets) were subjected to the post-process described in the Section III-C, which provides the delineation of the agricultural plots by tile.

⁴Codes used are available at <https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html>. Last accessed on July 2019.

TABLE 1. Normalized confusion matrix.

	background	parcel	buffer
background	0.89	0.05	0.06
parcel	0.01	0.96	0.04
buffer	0.07	0.24	0.69

All of the experiments have been carried out using an NVIDIA Titan Xp GPU with 3840 CUDA cores and 12 GB of memory. The codes were developed in Python using the Keras [52] framework.

IV. RESULTS AND DISCUSSION

The results obtained from the classification for the three classes (background, parcel, and buffer) of the 21 test tiles are shown in the confusion matrix of Table 1. The inaccuracy of the edges of the LPIS plots caused the pixels belonging to the buffer class to be confused with the other classes, particularly the parcel class. On the other hand, the background and parcel classes showed a success rate of more than 89%. Since the transitions between what is an agricultural plot and what is background, represented by the buffer class, is not so clear, it is not possible to obtain a good representation of the boundaries of agricultural plots considering only a classification of a single class i.e. the agricultural plot boundary. It is important to point out that although the precision obtained in the buffer class is not excellent (69%), this is not a disadvantage to the aim of this work, because agricultural plot boundaries are obtained from the parcel class.

Visual examples of buffer classification problems are shown in the Figure 5. As can be seen, in some cases the model has problems in identifying the different classes which results in missing sections of plots or the lack of separation between them (buffer). It should be noted that in some cases it is even difficult to visually distinguish the separations between them. Discrepancies can also be observed between what we would visually consider to be the boundaries of a plot and what is reported by SIGPAC. This highlights the importance of having automatic/semi-automatic methods to update the boundaries of agricultural parcels for operational use.

As mentioned previously, the boundaries are extracted from the segments belonging to the class parcel, which in this work provide the boundaries of the agricultural plots and whose accuracy is discussed below.

The results of the evaluation using the BDE index that compares the boundaries obtained using the proposed methodology and gPb-UCM with those of SIGPAC for each of the 21 tiles in the test set are shown in the Figure 6. As can be seen, for all tiles, the value of the BDE index is lower for the boundaries generated by the proposed methodology than for those obtained using the gPb-UCM method. The greatest difference between the two methods with respect to the GT is observed in tile number 4, with BDE values of 14.64 for gPb-UCM and 5.53 for our approach; while tile

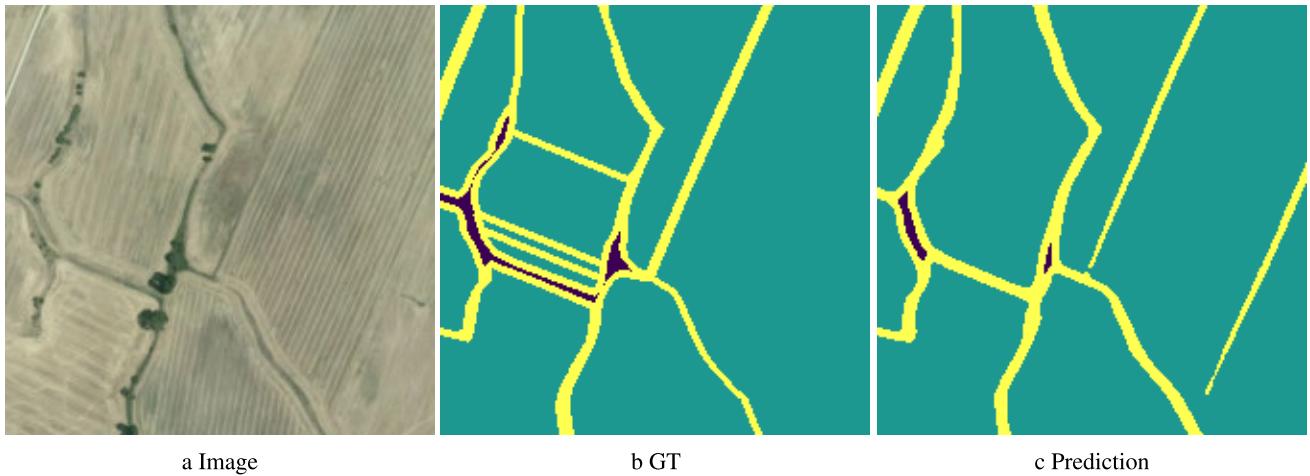


FIGURE 5. Comparison between SIGPAC ground-truth and convolutional neural network output. As can be seen there are some discrepancies between the image and the classes obtained from SIGPAC. In addition, some inaccuracies in the predictions of the neural network can be appreciated. The background, parcel and buffer classes are shown in navy blue, green and yellow, respectively.

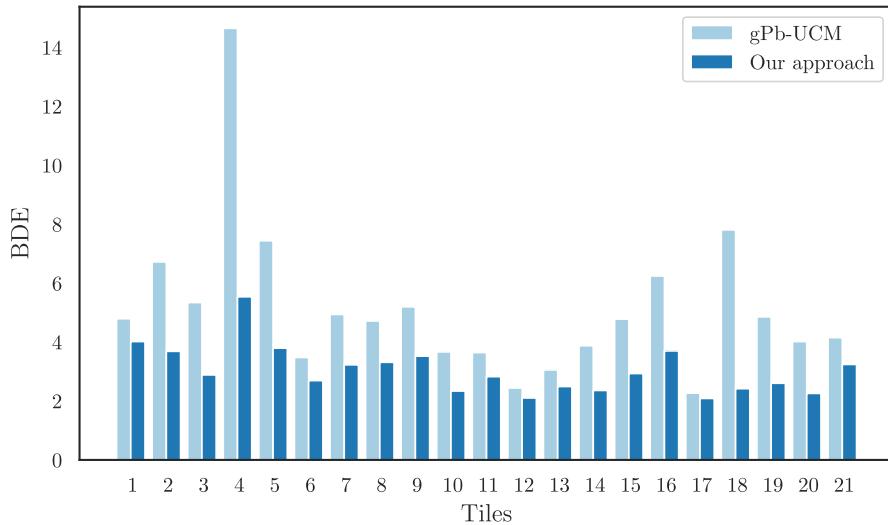


FIGURE 6. BDE index values of the results obtained by our approach and the gPb-UCM method for the 21 test tiles.

number 17 shows the smallest difference between them with BDE values of 2.26 for gPb-UCM and 2.08 for our approach.

In order to understand these differences between the two aforementioned methods, tiles 4 and 17 are shown in Figure 7. At first glance, there are differences between the types of plots that appear in each of the tiles, while tile 4 (Figure 7a) mainly includes large, well-defined plots as well as an urban area, tile 17 (Figure 7b) contains small plots. These differences are reflected in the GT, where many more boundaries are observed in tile 17 (Figure 7d) than in tile 4 (Figure 7c). In the case of tile 4, it can be seen that while the results produced by our approach (Figure 7e) are more in line with the GT, the gPb-UCM method (Figure 7g) not only generates the edges corresponding to the boundaries of agricultural plots, but also edges within urban areas. In this regard, it is important to highlight that gPb-UCM is an unsupervised method,

therefore, a further step (e.g., classification) is necessary to eliminate areas that are not of interest. In the case of the proposed approach this step is not necessary as classification is implicitly included. The less clear the natural boundaries of the agricultural plots, the greater the possibility of discrepancy, resulting in a higher BDE index value. This usually occurs on large farmlands, which are generally divided for operational reasons (e.g. different crops or other uses). On the other hand, the results obtained from the two methods in tile 17 (Figure 7f and 7h) are better because the boundaries of the plots are clearer due to over-fragmentation of the land.

These results are shown in much more detail in Figure 8. The boundaries obtained by the proposed approach (Figure 8c and 8d) fit the GT boundaries better (Figure 8a and 8b) than those generated by the gPb-UCM method (Figure 8e and 8f). It should be noted that the boundary transitions of our

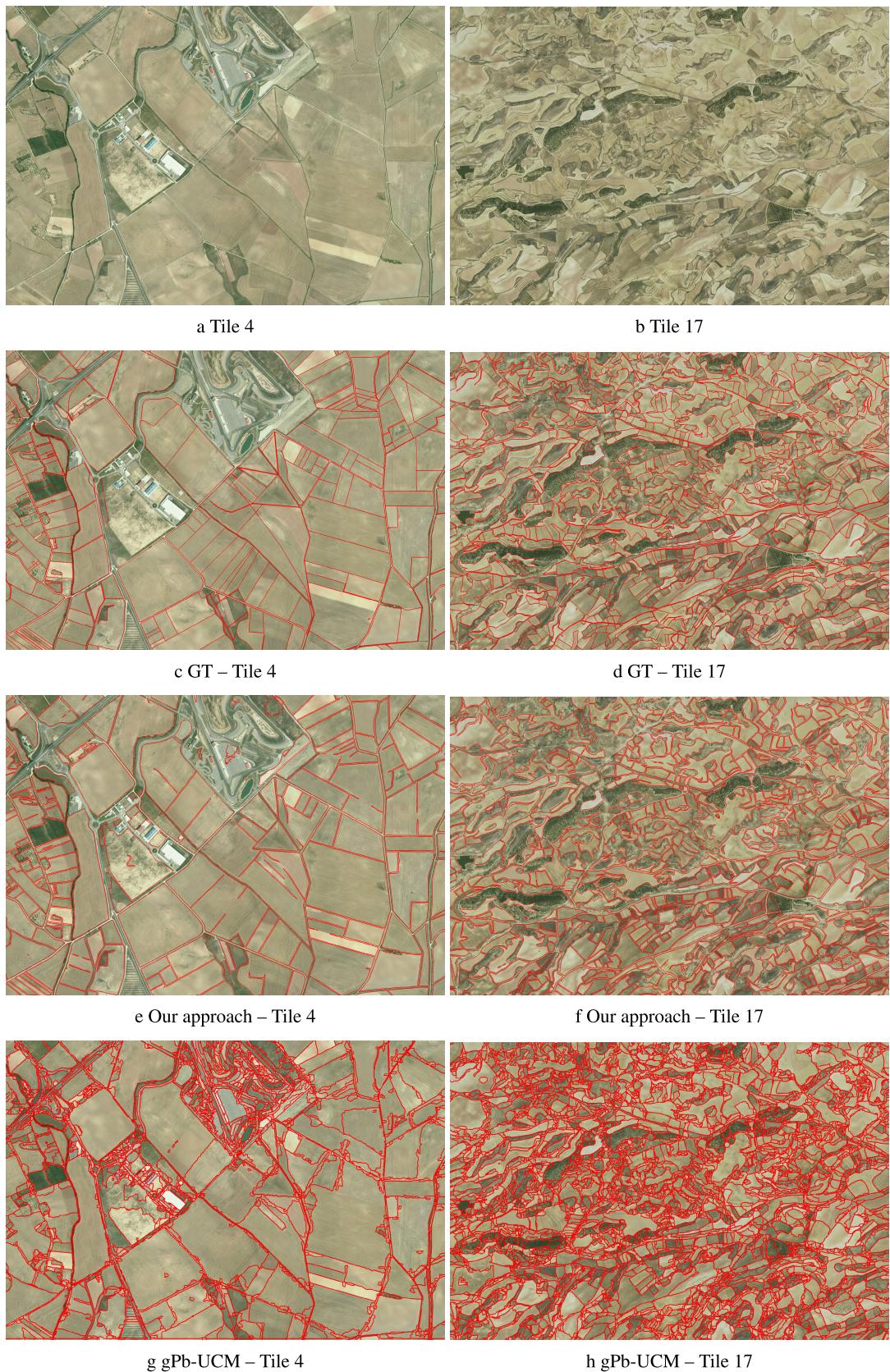


FIGURE 7. Results of the delineation of agricultural parcels. The proposed model and the gPb-UCM methodology obtained the worst BDE value in tile 4 while the results for tile 17 were the best.

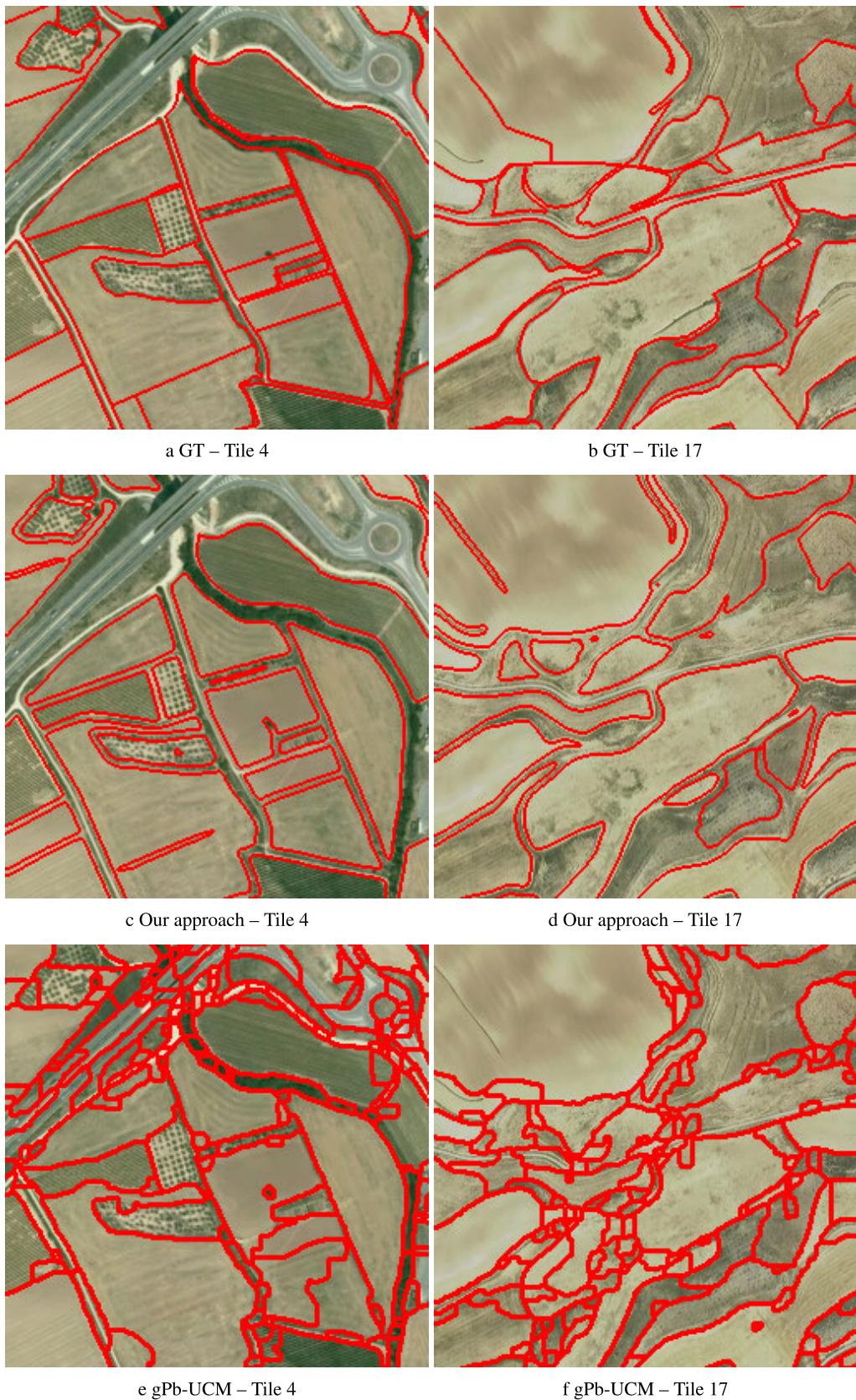


FIGURE 8. Examples of enlarged random regions for better visualization. The regions correspond to the results shown in Figure 7.



FIGURE 9. Results obtained in two hand-delineated tiles are different from those used in the training and test sets.

approach are also smoother than the edges obtained by gPb-UCM. In addition those obtained by gPb-UCM present oversegmentation.

At this point, and for a better interpretation of the results, it is important to noted that the available GT does not fully cover the 21 tiles, which could be a handicap for the correct evaluation of the performance of the methods compared.

To show the generalization capability of the proposed approach, two tiles (Figure 9a and 9b) corresponding to a geographical location different from that of the tiles used the training and testing (i.e., external set) were evaluated. The boundaries of the agricultural plots of these tiles were drawn by hand using GIS software. Despite the operator's knowledge of the study area and the digitization process, drawing the boundaries of the agricultural plots was a major, error-prone and time-consuming challenge.

In the Figure 9 it can be observed that in these tiles the proposed model also provides a much greater precision than gPb-UCM for the identification of the agricultural plots, demonstrating their capacity for generalization. Specifically, the BDE values obtained by gPb-UCM for case 1 and case 2 were 12.45 and 10.45, respectively, whereas for the proposed approach the errors were 3.93 and 4.86. In addition, the proposed methodology, based on CNN models, successfully distinguishes between those areas with urban cover and those areas with agricultural cover, without postprocessing requirements. (Fig. 9(e)).

From authors point of view, the outstanding results obtained have been achieved thanks to the combination of the DL model, which has provided really good results in different image processing tasks, with a large amount of annotated training data set, it being another strength of our work. The use of SIGPAC public data has provided a large volume of training data, which has been increased with the application of augmented techniques. The final result has been a DL model with a high generalization performance as has been showed in the delineation results of data with a different geographical localization that the tiles used in the training and test phases.

However, the computational management of this large amount of data has required a reduction in the spatial resolution of the original data. This has made it possible to feed the network with images covering an area of about 20 ha, which provides contextual information on the environment of the agricultural plots which, with the original resolution and current means of calculation, is difficult to approximate.

Moreover, since our approach is based on a machine learning process, even though discrepancies between images and SIGPAC information are present in some parcels, the generated DL model has the ability of detecting the borders of a parcel not included in SIGPAC. These results confirm the capability of working with out-of-date cadastres for updating them.

As regards the comparison with methods that do not require annotated data, such as the gPb-UCM method,

which has been used as a reference in this work, it has been shown that the reference method presents oversegmentation in some areas, and that the boundaries obtained by the proposed approach fit the SIGPAC boundaries better than those generated by the gPb-UCM method and which are also finer, reducing uncertainty in the label assignation.

Although the proposed method provides great precision to find the visible edges of the plots automatically, a successful update of the agricultural cadastre still requires the participation of owners, surveyors and other actors with spatial knowledge of the sites to be analyzed [53], [54], allowing the inclusion of non-visible edges (e.g. those that depend on legal aspects). However, starting from the edges obtained by our method would undoubtedly improve the efficiency of the updating process.

V. CONCLUSION

The main contribution of this research is the development of an automatic DL tool for the automatic tracing of agricultural parcels, using a public data source such as LPIS, which opens up the possibility of a systematic updating of agricultural cadastral boundaries. The use of LPIS data reduces the main drawback of DL, the availability of annotated data sets to carry out the training of CNN models.

Considering the state-of-the-art and the results obtained in this work, the methodologies for the automated outlining of agricultural plot boundaries should be considered as a complementary tool for the expert operator. One of the main limitations for the complete automation of the delineation process lies in the discrepancy between what is seen in the images and what is generally recorded as a plot, which can be influenced by issues such as land ownership (i.e., cadastral register) and the agricultural practices developed on the land (e.g., mixed crops).

Finally, this research could play an important role in agricultural decision-making by converting remote sensing data into timely and accurate information, contributing to the development of sustainable agriculture and reducing the gap between information technologies and users.

Future work should focus on: (1) evaluating the generalization capacity of CNN models to be used in other agricultural land cover, and (2) developing an automatic DL tool for spatial-temporal characterization of agricultural land uses, allowing a sustainable agricultural management, and (3) develop semi-supervised DL approaches (expert-in-the-loop approach) to update agricultural parcel boundaries in order to reduce labor-intensive use of labor for this task.

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REFERENCES

- [1] G. C. Nelson, M. W. Rosegrant, A. Palazzo, I. Gray, C. Ingersoll, R. Robertson, S. Tokgoz, T. Zhu, T. B. Sulser, C. Ringler, S. Msangi, and L. You, *Food Security, Farming, and Climate Change to 2050: Challenges to 2050 and Beyond*. Washington, DC, USA: International Food Policy Research Institute, 2010.
- [2] *OECD-FAO Agricultural Outlook 2017-2026*, OECD/FAO, Paris, France, 2017.
- [3] G. Scott and A. Rajabifard, "Sustainable development and geospatial information: A strategic framework for integrating a global policy agenda into national geospatial capabilities," *Geo-Spatial Inf. Sci.*, vol. 20, no. 2, pp. 59–76, 2017.
- [4] K. Kocur-Bera, "Data compatibility between the land and building cadaster (LBC) and the land parcel identification system (LPIS) in the context of area-based payments: A case study in the polish region of Warmia and Mazury," *Land Policy*, vol. 80, pp. 370–379, Jan. 2019.
- [5] O. Leo and G. Lemoine, "Land parcel identification systems in the frame of regulation (EC) 1593/2000 version 1.4," *Inst. Environ. Sustainab.*, Ispra, Italia, Discuss. Paper, 2001.
- [6] F. Levavasseur, P. Martin, C. Bouty, A. Barbottin, V. Bretagnolle, O. Théron, O. Scheurer, and N. Piskiewicz, "RPG explorer: A new tool to ease the analysis of agricultural landscape dynamics with the land parcel identification system," *Comput. Electron. Agricult.*, vol. 127, pp. 541–552, Sep. 2016.
- [7] K. Taşdemir and C. Wirnhardt, "Neural network-based clustering for agriculture management," *EURASIP J. Adv. Signal Process.*, vol. 2012, no. 1, p. 200, Sep. 2012.
- [8] L. Matikainen, K. Karila, P. Litkey, E. Ahokas, A. Munck, M. Karjalainen, and J. Hyppä, "The challenge of automated change detection: Developing a method for the updating of land parcels," *ISPRS Ann. Photogramm., Remote Sens. Spatial Inf. Sci.*, vols. 1–4, pp. 239–244, Aug./Sep. 2012.
- [9] S. Crommelinck, R. Bennett, M. Gerke, F. Nex, M. Y. Yang, and G. Vosselman, "Review of automatic feature extraction from high-resolution optical sensor data for UAV-based cadastral mapping," *Remote Sens.*, vol. 8, no. 8, p. 689, 2016.
- [10] S. Crommelinck, R. Bennett, M. Gerke, M. Y. Yang, and G. Vosselman, "Contour detection for UAV-based cadastral mapping," *Remote Sens.*, vol. 9, no. 2, p. 171, 2017.
- [11] P. Arbeláez, M. Maire, C. Fowlkes, and J. Malik, "Contour detection and hierarchical image segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 5, pp. 898–916, May 2011.
- [12] S. Crommelinck, B. Höfle, M. N. Koeva, M. Y. Yang, and G. Vosselman, "Interactive cadastral boundary delineation from UAV data," *ISPRS Ann. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 4, no. 2, pp. 81–88, 2018.
- [13] A. García-Pedrero, C. Gonzalo-Martín, M. Lillo-Saavedra, and D. Rodríguez-Esparragón, "The outlining of agricultural plots based on spatiotemporal consensus segmentation," *Remote Sens.*, vol. 10, no. 12, p. 1991, 2018.
- [14] S. Ghaffarian and M. Turker, "An improved cluster-based snake model for automatic agricultural field boundary extraction from high spatial resolution imagery," *Int. J. Remote Sens.*, vol. 40, no. 4, pp. 1217–1247, 2019.
- [15] S. Zhu and R. Gao, "A novel generalized gradient vector flow snake model using minimal surface and component-normalized method for medical image segmentation," *Biomed. Signal Process. Control*, vol. 26, pp. 1–10, Apr. 2016.
- [16] L. Xu, D. Ming, W. Zhou, H. Bao, Y. Chen, and X. Ling, "Farmland extraction from high spatial resolution remote sensing images based on stratified scale pre-estimation," *Remote Sens.*, vol. 11, no. 2, p. 108, 2019.
- [17] A. García-Pedrero, C. Gonzalo-Martín, and M. Lillo-Saavedra, "A machine learning approach for agricultural parcel delineation through agglomerative segmentation," *Int. J. Remote Sens.*, vol. 38, no. 7, pp. 1809–1819, 2017.
- [18] C. Seiffert, T. M. Khoshgoftaar, J. Van Hulse, and A. Napolitano, "RUSBoost: A hybrid approach to alleviating class imbalance," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 40, no. 1, pp. 185–197, Jan. 2010.
- [19] S. Georganos, T. Grippo, S. Vanhuysse, M. Lennert, M. Shimoni, S. Kalogiou, and E. Wolff, "Less is more: Optimizing classification performance through feature selection in a very-high-resolution remote sensing object-based urban application," *GISci. Remote Sens.*, vol. 55, no. 2, pp. 221–242, Nov. 2018.
- [20] J. Im, L. J. Quackenbush, M. Li, and F. Fang, *Optimum Scale in Object-Based Image Analysis*. Hoboken, NJ, USA: Wiley, 2014, ch. 10, pp. 197–214.
- [21] A. Kamilaris and F. X. Prenafeta-Boldú, "A review of the use of convolutional neural networks in agriculture," *J. Agricult. Sci.*, vol. 156, no. 3, pp. 312–322, 2018.
- [22] C. Zhang, I. Sargent, X. Pan, H. Li, A. Gardiner, J. Hare, and P. M. Atkinson, "Joint deep learning for land cover and land use classification," *Remote Sens. Environ.*, vol. 221, pp. 173–187, Feb. 2019.
- [23] W. G. Hatcher and W. Yu, "A survey of deep learning: Platforms, applications and emerging research trends," *IEEE Access*, vol. 6, pp. 24411–24432, 2018.
- [24] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, p. 436, 2015.
- [25] F. Mohammadimanesh, B. Salehi, M. Mahdianpari, E. Gill, and M. Molinier, "A new fully convolutional neural network for semantic segmentation of polarimetric sar imagery in complex land cover ecosystem," *ISPRS J. Photogramm. Remote Sens.*, vol. 151, pp. 223–236, May 2019.
- [26] M. Mahdianpari, B. Salehi, M. Rezaee, F. Mohammadimanesh, and Y. Zhang, "Very deep convolutional neural networks for complex land cover mapping using multispectral remote sensing imagery," *Remote Sens.*, vol. 10, no. 7, p. 1119, 2018.
- [27] M. Papadomanolaki, M. Vakalopoulou, and K. Karantzalos, "A novel object-based deep learning framework for semantic segmentation of very high-resolution remote sensing data: Comparison with convolutional and fully convolutional networks," *Remote Sens.*, vol. 11, no. 6, p. 684, 2019.
- [28] C. Gonzalo-Martín, A. García-Pedrero, M. Lillo-Saavedra, and E. Menasalvas, "Deep learning for superpixel-based classification of remote sensing images," in *GEOBIA 2016: Solutions and Synergies*, N. Kerle, M. Gerke, and S. Lefevre, Eds. Enschede, The Netherlands: Univ. of Twente Faculty of Geo-Information and Earth Observation (ITC), 2016, pp. 1–6.
- [29] S. Srinivas, R. K. Sarvadevabhatla, K. R. Mopuri, N. Prabhu, S. S. S. Kruthiventi, and R. V. Babu, "An introduction to deep convolutional neural nets for computer vision," in *Deep Learning for Medical Image Analysis*, S. K. Zhou, H. Greenspan, and D. Shen, Eds. New York, NY, USA: Academic, 2017, pp. 25–52.
- [30] E. Maggiori, Y. Tarabalka, G. Charpiat, and P. Alliez, "Convolutional neural networks for large-scale remote-sensing image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 2, pp. 645–657, Feb. 2017.
- [31] L. Xia, J. Luo, Y. Sun, and H. Yang, "Deep extraction of cropland parcels from very high-resolution remotely sensed imagery," in *Proc. 7th Int. Conf. Agro-Geoinform. (Agro-Geoinform.)*, Aug. 2018, pp. 1–5.
- [32] Y. Liu, M.-M. Cheng, X. Hu, K. Wang, and X. Bai, "Richer convolutional features for edge detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 5872–5881.
- [33] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Cham, Switzerland: Springer, 2015, pp. 234–241.
- [34] G. Xingfa and T. Xudong, "Overview of China earth observation satellite programs [space agencies]," *IEEE Geosci. Remote Sens. Mag.*, vol. 3, no. 3, pp. 113–129, Sep. 2015.
- [35] C. Persello, V. A. Tolpekin, J. R. Bergado, and R. A. de By, "Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping," *Remote Sens. Environ.*, vol. 231, Sep. 2019, Art. no. 111253.
- [36] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A deep convolutional encoder-decoder architecture for image segmentation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 12, pp. 2481–2495, Dec. 2017.
- [37] J. Pont-Tuset, P. Arbeláez, J. T. Barron, F. Marques, and J. Malik, "Multi-scale combinatorial grouping for image segmentation and object proposal generation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 1, pp. 128–140, Jan. 2017.
- [38] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Aug. 2018.
- [39] Z. Zhang and Y. Wang, "JointNet: A common neural network for road and building extraction," *Remote Sens.*, vol. 11, no. 6, p. 696, 2019.
- [40] V. Iglovikov, S. Mushinskiy, and V. Osin, "Satellite imagery feature detection using deep convolutional neural network: A Kaggle competition," Jun. 2017, *arXiv:1706.06169*. [Online]. Available: <https://arxiv.org/abs/1706.06169>

- [41] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," Sep. 2014, *arXiv:1409.1556*. [Online]. Available: <https://arxiv.org/abs/1409.1556>
- [42] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2016, pp. 770–778.
- [43] V. Iglovikov and A. Shvets, "TernausNet: U-net with VGG11 encoder pre-trained on ImageNet for image segmentation," Jan. 2018, *arXiv:1801.05746*. [Online]. Available: <https://arxiv.org/abs/1801.05746>
- [44] K. He, R. Girshick, and P. Dollár, "Rethinking ImageNet pre-training," Nov. 2018, *arXiv:1811.08883*. [Online]. Available: <https://arxiv.org/abs/1811.08883>
- [45] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," Dec. 2014, *arXiv:1412.6980*. [Online]. Available: <https://arxiv.org/abs/1412.6980>
- [46] M. A. Rahman and Y. Wang, "Optimizing intersection-over-union in deep neural networks for image segmentation," in *Proc. Int. Symp. Vis. Comput.* Cham, Switzerland: Springer, 2016, pp. 234–244.
- [47] J. Moolayil, *Learn Keras for Deep Neural Networks: A Fast-Track Approach to Modern Deep Learning With Python*, 1st ed. New York, NY, USA: Apress, 2018.
- [48] A. Rakhlilin, A. Davydow, and S. Nikolenko, "Land cover classification from satellite imagery with U-net and Lovász-Softmax loss," in *Proc. CVPR Workshops*, 2018, pp. 262–266.
- [49] I. den Bakker, *Python Deep Learning Cookbook: Over 75 Practical Recipes on Neural Network Modeling, Reinforcement Learning, and Transfer Learning Using Python*. Birmingham, U.K.: Packt, 2017.
- [50] J. Freixenet, X. Muñoz, D. Raba, J. Martí, and X. Cufí, "Yet another survey on image segmentation: Region and boundary information integration," in *Proc. Eur. Conf. Comput. Vis.* Berlin, Germany: Springer, 2002, pp. 408–422.
- [51] M. Zygmunt, M. Siejka, M. Ślusarski, Z. Siejka, I. Piech, and S. Bacior, "Database inconsistency errors correction, on example of LPIS databases in Poland," *Surv. Rev.*, vol. 47, no. 343, pp. 256–264, 2015.
- [52] F. Chollet. (2015). *Keras*. [Online]. Available: <https://keras.io>
- [53] E. Nyandwi, M. Koeva, D. Kohli, and R. Bennett, "Comparing human versus machine-driven cadastral boundary feature extraction," *Remote Sens.*, vol. 11, no. 14, p. 1662, 2019.
- [54] X. Xia, C. Persello, and M. Koeva, "Deep fully convolutional networks for cadastral boundary detection from UAV images," *Remote Sens.*, vol. 11, no. 14, p. 1725, 2019.



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