Thematic Accuracy Consequences in Cadastre Land-cover Enrichment from a Pixel and from a Polygon Perspective

P. Serra, G. Moré, and X. Pons

Abstract

In this paper, cadastre agricultural cartography was enriched using crop raster maps obtained from remote sensing images. The work demonstrates the implications of applying two new terms: fidelity and purity. Per-pixel classifications and polygon enrichments were compared taking into account: (a) the consequences of using a more or less conservative strategy at the classification stage, using fidelity, and (b) the consequences of using modal thresholds at the enrichment stage when deciding which category each polygon is to be assigned to, using purity. More than 300,000 pixels and 2,800 polygons were used to measure the thematic accuracy of ten agricultural categories by means of confusion matrices. These were computed at pixel, polygon, and area level. Thematic accuracy was calculated in the classical way and without taking into account unclassified pixels as errors, as well as by paying special attention to the consequences for the classified area. The results show that polygon enrichment is a useful methodology, achieving thematic accuracies of 95.6 percent, when optimum parameters are used, while classifying 87.4 percent of the area.

Introduction and Objectives

Land-cover update of vector data is an essential requirement for a large number of applications. In many cases, such vector data correspond to cadastre information provided by a public administration and stored in a Geographic Information System (GIS) that incorporates parcel boundaries as minimum mapping units and, for this reason, is indivisible (Aplin *et al.*, 1999; Smith and Fuller, 2001). Furthermore, remote sensing data provide up-to-date land-cover information due to their synoptic perspective and temporal resolution being, in this case, the final product in raster format. Consequently, a methodology to combine vector data (i.e., cadastre) with raster data is needed (Lu and Weng, 2007).

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One possible solution can be vectorization followed by its integration with other vector data. However, this method may be problematic due to the presence of spurious or sliver polygons (Chrisman, 1992) as a consequence of geolocational mismatches or mixed edge pixels (Aspinall and Pearson, 1995), among other reasons.

A second methodology for integrating raster information into a vector cover consists in enriching the pre-existing vector cartography directly from the raster entity. The enrichment is based on calculating a number of statistics extracted from raster information inside each vector entity. In this case, the objective is to label all the fields or parcel polygons with the corresponding updated information from remote sensing. This objective can be achieved using two different approaches: by using a per-field classification or enriching vector data from a per-pixel classification. Per-field classifiers use vector data to subdivide the study area into parcels, and the classification is then based on those parcels, avoiding intra-class spectral variations (Lu and Weng, 2007). An alternative approach, when existing vector data are not required or not available, is to use an object-oriented classification, which consists of two steps: image segmentation and classification. The problems of the per-field classifiers are the relationship between the spectral and spatial properties of remotely sensed data, the size and shape of the fields, and the land-cover classes chosen (Janssen and Molenaar, 1995). According to Dean and Smith (2003) more problems may appear in those fields where multiple land-cover types occur or vector data do not correspond to management practices. Consequently, it is usually assumed that only one crop is cultivated in each field (Janssen and van Amsterdam, 1991). In such cases, a per-pixel classification may be more appropriate.

Therefore, the second approach consists in enriching vector data from a raster crop map obtained from a per-pixel classification, using a modal option, i.e., assigning to each polygon the crop with the highest presence inside its boundaries (Aplin *et al.*, 1999). The modal option may be modified using a relatively high threshold proportion, as in Martínez and Calera (2001) where a crop needed to occupy at least 80 percent of the total parcel surface. In this case, some of the problems mentioned in the first approach (per-field classification) may appear, but are easier to detect.

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Other advantages of this method are that the vector geometry is not modified (as in the per-field classification), and that the noise of per-pixel classification (salt and pepper effect or mixed edge pixels) is minimized.

In order to obtain a robust enrichment, an essential condition is to use a reliable classification, namely one with a high overall accuracy. Nevertheless, although a great deal of effort has been made to analyze thematic accuracy (TA), mainly using error matrices (Janssen and van der Wel, 1994; Foody, 2004), in most studies devoted to remote sensing classifications the consequences of making the classifier algorithm more or less conservative have scarcely been studied. In this regard, it is worth pointing out that in the majority of studies all the study area is classified despite the difficulty of applying suitable thresholds (Kershaw and Fuller, 1992). Consequently, there are few error matrices which include unclassified land, although there are some exceptions, such as Fuller *et al.* (1994) and Aplin *et al.* (1999).

Our selection of a hybrid classifier for this study is based on previous research that revealed that this method is very accurate for Mediterranean crop mapping (Serra *et al.*, 2005). Its suitability is due to the fact that it combines the statistical robustness of an unsupervised classifier (minimum intra-class variability and maximum inter-class distances) with the power of a statistically-based correspondence between statistical classes and thematic classes. This last assignation requires the introduction of two different parameters: fidelity, the most important parameter in our experience (Serra *et al.*, 2006), and representativity. In this paper, two crop maps were computed using two different fidelities, one of which was more conservative than the other.

As mentioned above, confusion or error matrices are the most common tool used to quantify TA (Foody, 2002). In the majority of studies, error matrices are quantified at the pixel scale at which classified pixels and test pixels are compared (Congalton *et al.*, 1998). Nevertheless, other less common options exist such as at parcel or field scale, where the spatial unit for TA assessment is the field instead of the pixel and the comparison is made using test fields. The option of obtaining TA per-field seems more appropriate than per-pixel because the minimum spatial unit stored in an agricultural GIS is the field (Dean and Smith, 2003; Wulder *et al.*, 2006). Two examples of an analysis of this kind are the studies performed by Smith and Fuller (2001) and Lloyd *et al.* (2004) where, after using per-field classifications, 113 and 2,361 test fields were used, respectively, to assess TA.

The last option for quantifying TA is to contrast areas rather than pixels or fields. The areas are extracted by pixel counting or from polygon areas (Congalton *et al.*, 1998; Martínez and Calera, 2001). This option may be an indicator of field fragmentation: some polygons may be misclassified, but their surface is small, and they are therefore less significant in the overall TA.

According to some authors, the evaluation of the TA of enriched polygons gives better results than the evaluation of simple pixel maps based on the same per-pixel classification. For example, Aplin *et al.* (1999) compare some polygon enrichments with per-pixel classifications and conclude that the enrichment may increase to 7.5 percent of the TA. In this study, each field was enriched using the class with the largest number of pixels (the modal land-cover class) without including a minimum threshold, in contrast to the work carried out by Martínez and Calera (2001) mentioned above. On the other hand, the work of Berberoglu *et al.* (2000) also evaluates this topic but reaches different conclusions depending on the classification method and is based on a study area which is relatively small (29,250 ha) and using only 600 test pixels. Finally, in Erol and Akdeniz (2005), the conclusions were also that the per-field classification based on a previous parcelization was better than the per-pixel classification when evaluating TA at pixel level in both cases (rasterizing polygons).

In order to improve the comparison between per-pixel evaluations, per-enriched polygon evaluations and per-area of enriched polygon evaluations, the objectives of this paper are twofold:

1. To understand the consequences for TA of being more or less restrictive at the classification stage (in our case, using two different fidelities in the hybrid classifier). This analysis is developed using two parameters: global accuracy and global accuracy of only classified pixels, both extracted from confusion matrices. The results are compared at pixel and polygon level and area. In the case of crop map accuracy, producers' accuracy is the parameter used to quantify accuracy of individual crops.
2. To analyze the consequences for TA of applying restrictions to polygon enrichment according to different percentages of modes; specifically, four different modal thresholds (or purities) are compared: 0 percent, 25 percent, 50 percent, and 75 percent. The results are compared at polygon level and area. In our opinion, this analysis is of particular interest because the consequences of the threshold proportion applied have hardly ever been studied and, as we will demonstrate, they have important implications.

Materials and Methods

Study Area and Remote Sensing Data

The study area is located in the center of Catalonia (North-East Spain), comprising 348,533 ha (including six counties) and more than 70,000 fields of agricultural land-use (Figure 1). It has a continental climate with cold winters and hot summers and between 350 and 450 mm of rainfall per year (Ninyerola *et al.*, 2000). It is a predominantly agricultural area dominated by irrigated herbaceous crops and dry permanent crops. The irrigation system is made up of different principal canals fed by the Segre and the Noguera Ribagorçana Rivers, which irrigate more than 120,000 ha.

In order to follow the temporal signatures of crops, a multitemporal approach was applied, including seven images from 2004. All the images used were acquired from a Landsat-5 Thematic Mapper annual subscription, corresponding to path 198 and row 031. The images were recorded on 16 May, 01 and 17 June, 19 July, 04 August, 23 October, and 08 November. According to some agricultural studies and our field experience (Serra *et al.*, 2003; Serra and Pons, 2008), the main herbaceous and permanent crops cultivated in the study area were: dry winter cereals, irrigated maize, irrigated alfalfa, irrigated rice, dry and irrigated fruit trees, fallow land, dry olive trees, dry vineyards, other dry and irrigated herbaceous crops, and pastures.

Figure 2 summarizes the methodology applied in this work. The first step was the geometric correction using the procedure developed by Palà and Pons (1995). During the geometric correction, all Landsat images were resampled using the nearest neighbor to preserve the original image radiometry. Georeferencing was carried out using a mean of 26 ground control points and 12 test points per image, giving an average RMS error of 18.5 m. The second step was the radiometric correction, through which digital numbers were converted into reflectance values using sensor calibration parameters and other factors such as atmospheric effects, solar incident angle accounting for relief, etc. (Pons and Solé-Sugrañes, 1994).

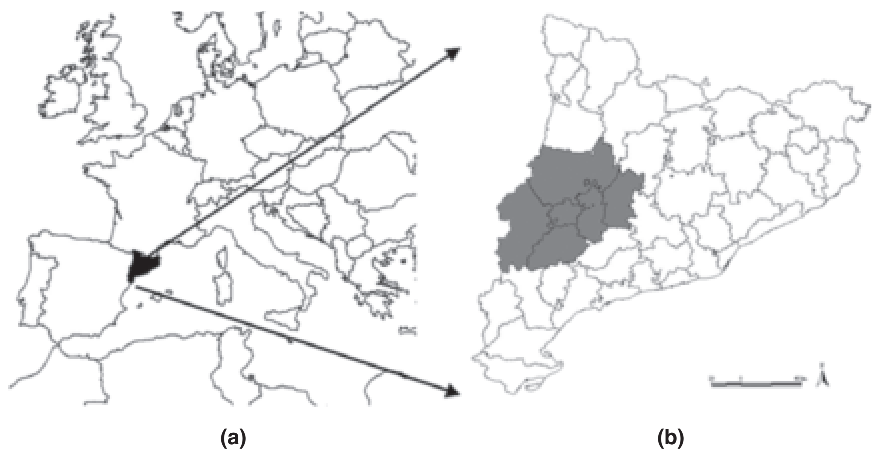

Figure 1. (a) the study area located in northeast Spain (Catalonia), and (b) the six counties situated in the center of Catalonia (in grey).

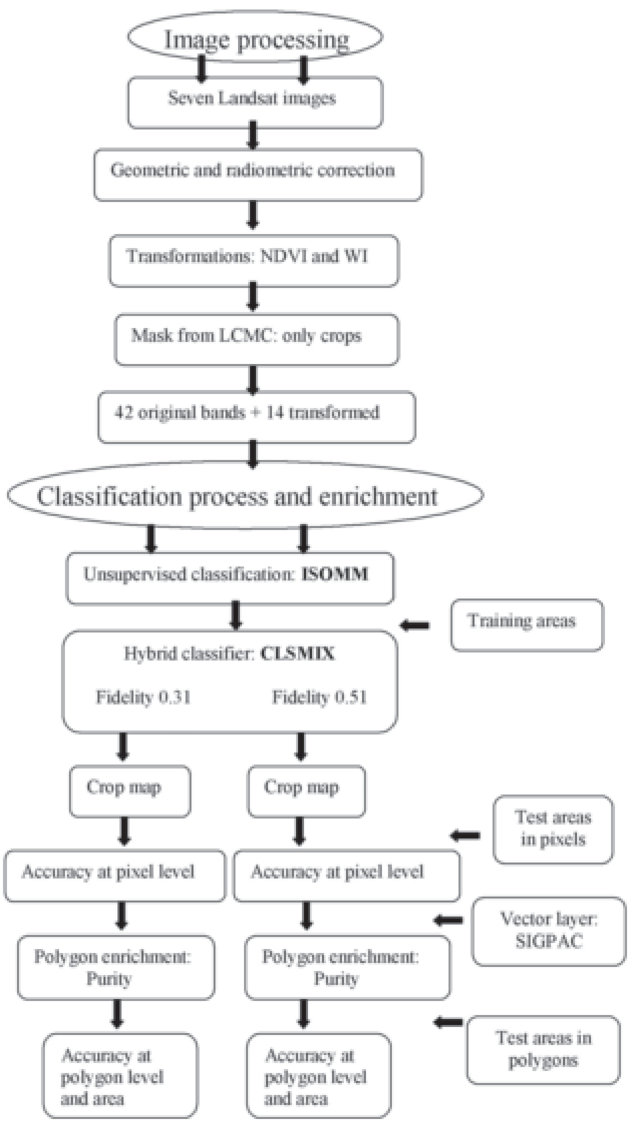

Figure 2. Diagram of the applied methodology.

Two transformations were subsequently included in the hybrid classifier for better crop discrimination: (a) the Normalized Difference Vegetation Index (NDVI), used as an estimate of chlorophyll activity (Lyon *et al.*, 2003; Thenkabail *et al.*, 1994), and (b) the Wetness Index (WI), extracted from a Tasseled Cap transformation, which is related to canopy and soil moisture (Crist *et al.*, 1986; Lillesand *et al.*, 2004).

In order to avoid spectral and radiometric confusion with other land-covers in the classification stage, a mask was applied selecting only agricultural covers and eliminating the rest (urban areas, etc.). The mask was obtained from the Mapa de Cobertes del Sòl (Land Cover Map of Catalonia; CREAF, 2006). This map is the result of photo interpretation of color orthophotos at scale 1:5 000 from 2002.

The vector layer to be enriched with remote sensing crop maps corresponded to the digital Sistema de Información Geográfica de Parcelas Agrícolas (SIGPAC) (Geographical Information System of Agricultural Fields). In Spain, SIGPAC is a public register for agricultural parcel identification, at scale 1:10 000, and is currently a mandatory reference for identifying an agricultural holding (MAPA, 2007) as well as acting as a de facto cadastre of agricultural usage. Parcels of SIGPAC have two different levels: one is the larger-parcel scale that corresponds to a piece of continuous land from one owner, and the second is the parcel scale that corresponds to a piece of continuous land with a unique crop inside a parcel. In this work the parcel scale was used.

Classification Process

Hybrid classifiers are especially valuable when cover types present complex variability in the spectral response. They are not new (Estes *et al.*, 1983), being usually the supervised process that leads or complements the unsupervised one (Lillesand *et al.*, 2004). In our case, the procedure works by starting with the unsupervised process to obtain many classes, while the supervised process is used to objectively assign these classes to the final categories.

Specifically, our hybrid classifier consists of two modules of MiraMon software (Pons, 2006): Isomm and Clsmix. In the Isomm module, an unsupervised classifier based on the IsoData algorithm, clusters are formed by iterative assignments of *n*-dimensional pixels. These assignments are based on the minimum Euclidean distance of a pixel from all current cluster centroids. One of the main features of Isomm is that it accepts hundreds of input variables. The main use of this property is to allow the use of high temporal resolution satellite series or other topographic and climatic variables (Moré *et al.*, 2006). But, as described before, in this study only multispectral and multitemporal remote sensing images were used, representing a total of 56 variables corresponding to the six TM bands (1, 2, 3, 4, 5, and 7; thermal bands were not included) of the seven dates mentioned above, plus the corresponding seven NDVIs and WIs.

In the second part of the classification process, Clsmix assigns each spectral class to a thematic class using two different parameters: fidelity and representativity. Fidelity is the threshold proportion at which a spectral class is accepted as being part of a thematic class in terms of the proportion of the spectral class that is inside the thematic class. For example, 0.9 means that if 90 percent or more of the spectral class inside the training areas is under a particular category, the spectral class will be assigned to this category (Table 1). On the other hand, representativity is the threshold proportion at which a spectral class is accepted as being part of a category in terms of the proportion of the category that is formed by a given spectral class. For example, 0.01 means that if 1 percent or more of the category is made up of a particular spectral class, the spectral class will be assigned to this category (Table 1). Conversely, a pixel will remain unclassified if no training area covers pixels in the same spectral class, or if given the input thresholds, no spectral class is adequate for it: either the pixel belongs to a class that is split too much among two or more categories or the pixel belongs to a class that is poorly representative of the total area of any category (the spectral class is noisy). In this work, a representativity of 0.01 has been used and two different fidelities tested: a fidelity of 0.31 (namely 31 percent or more of the spectral class inside the training areas is under a given thematic category) and another, which is much more restrictive, of 0.51.

Polygon Enrichment
Once the two crop maps were obtained, one for each fidelity threshold, the next step was to integrate this information into the SIGPAC. The methodology consisted in crossing crop maps and the digital rural cadastre vector map and assigning to each parcel the crop with the greatest presence inside its boundaries (this is the mode option).

In the polygon enrichment, an overlay of the raster classified image and of the vector cadastre was applied. The operation consists in calculating inside each polygon the total number of pixels, the modal class and its percentage from the total and entering them in the polygon database without modifying its geometry. Pixels with "Nodata" values (non-agricultural land) were appropriately excluded in the statistics computation. The point-in-polygon procedure (Laurini and Thompson, 1992) was used because it is a suitable criterion for deciding whether a pixel belonged to a polygon or not.

To accept a mode as representative of a polygon, a threshold value (in percentage) may be applied. Four purity percentages, which were more or less conservative, were considered: the first was without mode restrictions (purity >0 percent), namely, a polygon was classified according to its mode whatever the percentage. This option classified all polygons with a mode that was different from Nodata even if they displayed a high thematic pixel fragmentation (perhaps the mode was only a category of 15 percent). Another option was when the mode inside a polygon was at least 25 percent, in which case it was classified according to that mode, or otherwise remained unclassified. This option is somewhat conservative because only those polygons with poor modes (due to radiometric noise, border effect, etc.) will be left unclassified. For this reason two more restrictive options were included: purity ≥50 percent and purity ≥75 percent. With these more restrictive options, less pure polygons were left unclassified.

Table 1. Example of Fidelity and of Representativity. In the First Case, the Spectral Class Number 40 is Mainly Inside the Training Areas of Winter Cereals because 90.3 Percent of this Spectral Class Belongs to this Category. In the Second Case, the Objective is to Discriminate if the Spectral Classes are a not Insignificant Part of the Category Fruit Trees.

Spectral class # 40	Fidelity Number of pixels	%
Fruit trees	140	1.7
Other crops	193	2.4
Winter cereals	7279	90.3
Vineyards	95	1.2
Fallow land	350	4.3
Fruit trees	**Representativity Number of pixels**	**%**
Spectral class # 3	540	4.2
Spectral class # 4	4	0.03
Spectral class # 9	10	0.07
Spectral class # 11	130	1.0
. . .	. . .	. . .

Global Accuracy with Confusion Matrices
Error or confusion matrices are the most common methodology used to quantify TA (Foody, 2002). There are a variety of global accuracy measurements, but in this study, two of them have been used. The first corresponds to global accuracy (GA) and is calculated by dividing the number of well classified pixels by the total number of test pixels including unclassified pixels. Another measurement may take into account the GA, but only using the classified pixels (GA_CP). This second measurement corresponds to GA_CP and is calculated by dividing the number of well classified pixels by the total number of classified and tested pixels.

In the first stage of the hybrid classifier, Isomm found 174 clusters while in the second stage, Clsmix used the training areas, which were extracted from field work, covering an average of 6,517 pixels. The minimum number of pixels per class was 142 and 679, corresponding to rice and vineyards, respectively. Crop maps were validated through confusion matrices and using new, independent, test areas. These test areas were obtained from field work with the help of the Catalan Ministry of Agriculture. The next step was to label each parcel from SIGPAC with the corresponding true crop. These parcels were used to obtain confusion matrices at pixel and polygon level and area.

Results

Classified Area
After applying the methodology described above, final crop maps were obtained. According to the less restrictive fidelity (0.31) 344,195.2 ha were classified. Winter cereals occupied 34.6 percent of the total area, followed by fruit trees with 21.9 percent, fallow land with 16.5 percent and alfalfa and maize, with 7.9 percent and 7.5 percent, respectively. The rest of the crops made up the remaining 11.6 percent. When applying a more restrictive fidelity (0.51), 298,764.0 ha were classified. Winter cereals occupied 39.2 percent of the total area, followed by fruit trees with 21.4 percent, fallow land with 15.5 percent and maize and alfalfa, with 8.3 percent and 7.1 percent, respectively. The rest of the crops made up the remaining 8.5 percent.

Results When Evaluating at Pixel Level

Overall accuracies at pixel level were computed using the two global measurements mentioned above (GA and GA_CP). Table 2 shows that with a less restrictive fidelity (0.31) the hybrid classifier classifies 13.2 percent more pixels (8,604,879) compared with the more restrictive fidelity (7,469,101), and the number of successes is 4.7 percent higher (from 259,554 to 247,213). On the other hand, the difference between the number of pixels used to quantify TA including or excluding unclassified pixels is larger with a more restrictive fidelity: 11.1 percent (280,403 from 315,455 pixels) versus 2.3 percent (308,182 from 315,455). From the two overall accuracy measurements of crop maps (GA and GA_CP) only one showed an overall accuracy above 85 percent: when a more restrictive fidelity was applied and unclassified pixels ignored (GA_CP, 88.2 percent).

Results When Evaluating at Polygon Level

The second analysis was to use remote sensing crop maps to enrich the cadastre layer. The enriched area corresponded to the fields that were included in the SIGPAC database as described above. Two objectives were identified at this stage: to analyze the two fidelities in order to ascertain which of them was more effective in enriching vector data, and to understand how modal restrictions could affect the overall accuracies of polygons. To perform the accuracy test, a total of 2,819 polygons were used.

Table 3 shows the overall accuracies at polygon level according to fidelity 0.31 and fidelity 0.51. The total number of classified polygons was very similar in both cases (69,026 versus 68,506). In the case of no purity requirements (mode >0 percent), the total number of polygons used to quantify TA (test polygons) was also quite similar (2,819 versus 2,816). In other words, in the traditional modal land-cover class or per-field majority rule, the less restrictive fidelity showed that no polygon was left unclassified, whereas the more restrictive fidelity left three polygons unclassified. In the former case 2,529 polygons were well classified, corresponding to 89.7 percent of TA, while in the latter case 2,502 polygons were well classified, corresponding to 88.7 percent of TA. When the unclassified polygons are ignored, the TA is almost the same for both fidelities (89.7 percent and 88.8 percent) due to the absence of a purity requirement (Table 3 and Figure 3).

As described above, three different purity requirements were applied: 25 percent, 50 percent, and 75 percent. With a fidelity of 0.31 and a restrictive purity of 25 percent, only

TABLE 2. OVERALL ACCURACIES PER PIXEL. TA = THEMATIC ACCURACY; GA = GLOBAL ACCURACY; GA_CP = GLOBAL ACCURACY OF ONLY CLASSIFIED PIXELS (IGNORING UNCLASSIFIED PIXELS)

	Fidelity 0.31	**Fidelity 0.51**
Total number of classified pixels	8,604,879	7,469,101
Total number of pixels used to quantify TA, including unclassified pixels	315,455	315,455
Total number of pixels used to quantify TA, ignoring unclassified pixels	308,182	280,403
Unclassified pixels	7,273	35,052
Unclassified pixels (%)	2.3	11.1
Number of successes	259,554	247,213
GA (%)	82.3	78.4
GA_CP (%)	84.2	88.2

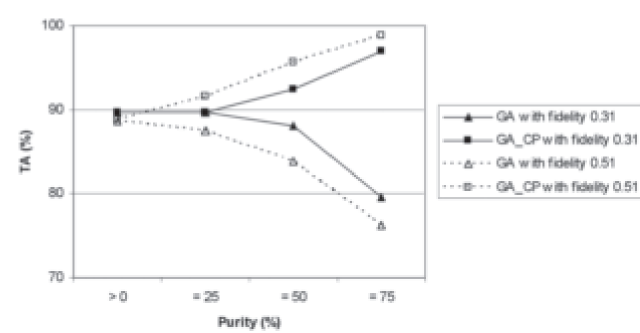

Figure 3. Overall thematic accuracies per polygon according to fidelity 0.31 and to fidelity 0.51 with different purities. TA = thematic accuracy.

TABLE 3. OVERALL THEMATIC ACCURACIES PER POLYGON. TA = THEMATIC ACCURACY

	Fidelity 0.31				Fidelity 0.51			
Total number of classified polygons	69,026				68,506			
Total number of test polygons	2,819							
Purity restrictions	**Mode > 0%**	**Mode ≥ 25%**	**Mode ≥ 50%**	**Mode ≥ 75%**	**Mode ≥ 0%**	**Mode ≥ 25%**	**Mode ≥ 50%**	**Mode ≥ 75%**
Total number of test polygons ignoring unclassified polygons	2,819	2,818	2,685	2,315	2,816	2,696	2,476	2,172
Unclassified polygons	0	1	134	504	3	123	343	647
Unclassified polygons (%)	0	0.03	4.7	17.9	0.1	4.4	12.2	22.9
Well classified polygons	2,529	2,529	2,483	2,245	2,502	2,467	2,366	2,148
TA including unclassified polygons (%) (GA)	89.7	89.7	88.1	79.6	88.7	87.5	83.9	76.2
TA ignoring unclassified polygons (%) (GA_CP)	89.7	89.7	92.5	97.0	88.8	91.5	95.6	98.9

one polygon was unclassified, giving a TA of 89.7 percent. This percentage is above the 87.5 percent that corresponds to a more restrictive fidelity and the same percentage of purity, but if unclassified polygons are ignored (123 in this case) the TA increases to 91.5 percent (Table 3 and Figure 3).

With a fidelity of 0.31 and a minimum purity of 50 percent, the number of unclassified polygons increases to 134, equivalent to 88.1 percent of TA if they are included as errors, or 92.5 percent if not. This more restricted purity combined with a fidelity of 0.51 gives a TA of 83.9 percent when unclassified polygons are included as errors, or 95.6 percent if not. In this case, the improvement between these TA is very large, but 343 polygons remain unclassified. Finally, the most restrictive purity, 75 percent and a fidelity of 0.31, results in a decrease of TA when unclassified polygons are included as errors, 79.6 percent; but, if not, the TA reaches 97.0 percent, with 504 polygons remaining unclassified. These results are more extreme when fidelity is 0.51 because the TA changes from 76.2 percent to 98.9 percent when unclassified polygons (647) are considered as errors or not (Table 3 and Figure 3). Therefore, TA seems to peak with this last option, improving it by more than 20 points, although resulting in 22.9 percent of unclassified polygons.

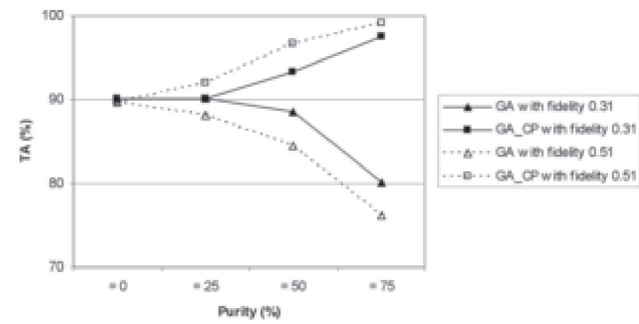

Figure 4. Overall thematic accuracies per area according to fidelity 0.31 and to fidelity 0.51 with different purities. TA = thematic accuracy.

Results When Evaluating the Area of the Enriched Polygons

In order to better understand the consequences of being more or less restrictive in fidelities and purities, a similar analysis, but per area of enriched polygons, was applied. The objective was to ascertain how many hectares were well classified and lost in the different options. Table 4 shows the overall accuracies per area according to fidelities of 0.31 and 0.51. The total area used to quantify TA was 12,625.4 ha. Without purity restrictions (mode >0), the total area used to quantify TA (from test polygons) was also quite similar (12,625.4 versus 12,624.6). As mentioned in the case of polygon level evaluation, the less restrictive fidelity shows that all the test area was classified, whereas the more restrictive fidelity left 0.8 hectares unclassified. In the former case 11,393.4 ha were well classified, corresponding to 90.2 of TA, while in the latter case 11,321.4 ha were well classified, corresponding to 89.7 percent of TA. When the unclassified area is ignored, the TA is the same for both fidelities (Table 4 and Figure 4).

As described above, three different purity requirements were applied: 25 percent, 50 percent, and 75 percent. With a fidelity of 0.31 and a restrictive purity of 25 percent, the unclassified area was only 2.2 ha, the TA remaining at 90.2 percent. This percentage is above the 88.1 percent that corresponds to a more restrictive fidelity and the same percentage of purity, but if the unclassified area is ignored (548.9 ha in this case), the TA increases to 92.1 percent (Table 4 and Figure 4).

With a fidelity of 0.31 and a minimum purity of 50 percent, the unclassified area increases to 644.4 ha, equivalent to 88.5 percent of TA if they are included as errors, or 93.3 percent if not. This more restricted purity combined with a fidelity of 0.51 produces 84.5 percent of TA when unclassified polygons are included as errors, or 96.6 percent if not. In this case, the improvement between these TA is very large, but 12.6 percent of the area remains unclassified. Finally, the more restrictive purity, 75 percent, and a fidelity of 0.31 results in a decrease of TA when the unclassified area is included as error, 80.1 percent; but, if not, the TA reaches 97.6 percent, remaining at 17.9 percent of the unclassified area. These results are more extreme when fidelity is 0.51 because the TA changes from 76.2 percent to 99.1 percent when the unclassified area (23.1 percent) is considered to be error or not (Table 4 and Figure 4). Therefore, as seen in the polygon level evaluation, TA seems to peak with this last option, improving it by more than 22 points, although causing 23.1 percent of the area to be unclassified.

Table 4. Overall Thematic Accuracies per Area. TA = Thematic Accuracy

	Fidelity 0.31				Fidelity 0.51			
Classified area (ha)	102,763.0				102,632.3			
Total area of test polygons (ha)	12,625.4							
Purity restrictions	**Mode > 0%**	**Mode ≥ 25%**	**Mode ≥ 50%**	**Mode ≥ 75%**	**Mode ≥ 0%**	**Mode ≥ 25%**	**Mode ≥ 50%**	**Mode ≥ 75%**
Total area used to quantify TA ignoring unclassified area (ha)	12,625.4	12,623.2	11,981.0	10,356.7	12,624.6	12,076.5	11,038.8	9,703.8
Unclassified area	0	2.2	644.4	2,268.7	0.8	548.9	1,586.5	2,921.6
Unclassified area (%)	0	0.01	5.1	17.9	0	4.3	12.6	23.1
Well classified area (ha)	11,393.4	11,393.4	11,180.0	10,113.4	11,321.4	11,137.1	10,666.5	9,615.9
TA including unclassified area (%) (GA)	90.2	90.2	88.5	80.1	89.7	88.1	84.5	76.2
TA ignoring unclassified area (%) (GA_CP)	90.2	90.2	93.3	97.6	89.7	92.1	96.6	99.1

Accuracy Results by Crop

Accuracy of individual crops includes producer's accuracy (PA) and user's accuracy (UA) (Congalton, 1991). In the former, the total number of correct pixels-polygons-area is divided by the total number of pixels-polygons-area of that crop according to the ground data. PA indicates the omission errors. In the case of the later, the total number of correct pixels-polygons-area in a category is divided by the total number of pixels-polygons that were classified in that category, measuring the commission errors. In our applied hybrid classifier, omission errors are more significant because commission errors are not affected by unclassified pixels (CP values). For this reason, and because differences between the two fidelities (0.31 and 0.51) are very weak, analysis of TA by crops is only analyzed in this work considering PA.

Crop accuracies at pixel level are shown in Figure 5. It depicts PA per pixel with fidelity 0.31 and 0.51, considering unclassified pixels as errors and without. In the case of PA with a fidelity of 0.31, the better PA corresponded to winter cereals (93 percent), maize (92.4 percent), rice (87.7 percent), and alfalfa (87.4 percent); whereas the PA of fruit trees, vineyards, fallow land, and pastures was below 80 percent, being the worst results in the case of other crops and olive trees, below 40 percent. On the other hand, PA when fidelity was 0.31 but unclassified pixels were not included as errors (PA_31_CP) produced better results in all crops and especially in rice because its PA increased until 97.1 percent. Finally, when fidelity was 0.51, the PA was smaller in all crops, but when the unclassified pixels were excluded (PA_51_CP), it was greater in all of them, with the exception of olive trees.

At polygon scale, alfalfa, rice, maize, and winter cereals presented analogous results than in the case of pixel level, showing high percentage of agreement and not being affected by different fidelities and purities because all the values were above 85 percent. A second situation was from fruit trees; in this case about 60 percent to 80 percent of TA was obtained with fidelities 0.31 and 0.51, and when unclassified pixels were not ignored, being the best results achieved with fidelity = 0.51 and purity = 75 percent when unclassified pixels were excluded (98.4 percent of TA). In the case of olive trees, any result showed a PA above 40 percent, demonstrating the impossibility of discriminating them with our hybrid classifier and these images. Finally, the fourth situation corresponded to vineyards, other crops, fallow land, and pastures. In these cases, results were very similar in purity 25 percent and 50 percent with a medium TA (between 40 percent and 60 percent) in both fidelities; whereas with a restrictive purity (75 percent), TA dropped below 40 percent, indicating a significant pixel fragmentation and, in consequence, more unclassified polygons. When these unclassified polygons were ignored and a restrictive purity applied, the TA increased until 90 percent.

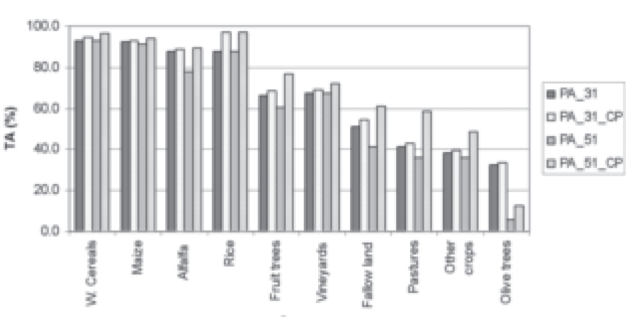

Figure 5. Producer's accuracy of crops according to fidelity 0.31 and 0.51 ignoring and without ignoring unclassified pixels as errors. TA = thematic accuracy. PA = Producer's accuracy. CP = only classified pixels.

Similar analysis than in pixels and polygons was performed by area. Results showed a high TA percentage (>90 percent) for alfalfa, rice, maize, and winter cereals, whatever the option chosen. The best results in the case of fruit trees (98 percent of TA) were obtained with a restrictive fidelity and purity (75 percent) and excluding unclassified area as error. This same option was the best for vineyards, other crops, and pastures; whereas for fallow land, the best option was when using a less restrictive fidelity and purity (50 percent) and excluding unclassified area as error.

Discussion and Conclusions

The first outcome provided by the results is that when evaluating at pixel level, a more restrictive fidelity (0.51) is always better than a less restrictive fidelity (0.31) if unclassified pixels are ignored. In view of this fact, the next question is: should an unclassified pixel be considered an error? Two answers are possible: "yes" because an unclassified pixel is not assigned to the right crop; "no" because an unclassified pixel is not assigned to a wrong crop. As shown above, the consequences of the answer may be remarkable: if TA is computed according to GA, the conclusion would be that a less restrictive fidelity is better, but it seems reasonable to believe the opposite, as shown by the results when TA is computed according to GA_CP.

Confusion matrices at polygon level give results that must be studied in detail. First, if no purity restrictions are applied, TA is better than in the pixel level case (at the polygon level, figures range from 88.7 percent to 89.7 percent while at pixel level, they range from 78.4 percent to 88.2 percent (Tables 2 and 3) except when a very restrictive purity (≥75 percent) is applied. Second, and again without purity restrictions, differences between computing TA on a GA or a GA_CP basis are quite similar. Third, when purity restrictions are applied, differences arise if unclassified polygons are considered as errors or not when computing TA. Indeed, when TA is computed according to GA, it seems that there is a decrease in TA when more purity is required (values from 89.7 percent to 79.6 percent in the case of fidelity 0.31, and from 88.7 percent and 76.2 percent in the case of fidelity 0.51). Nevertheless, if the reasonable approach of computing TA according to GA_CP is adopted, TA increases as more purity is required (values from 89.7 percent to 97.0 percent and from 88.8 percent to 98.9 percent for each fidelity), and TA figures are always clearly higher than in the GA case. When area results are examined (Table 4 and Figure 4) another conclusion arises: although the more restrictive fidelity and purity give better TA when GA_CP is considered, an important decrease in classified area may occur. Indeed, when purity restrictions are equal or less than 50 percent, the unclassified area ranges from 0 to 5.1 percent (fidelity 0.31) and from 0 to 12.6 percent (fidelity 0.51). Moreover, when purity is ≥75 percent, the unclassified area dramatically increases to 17.9 percent and 23.1 percent for each fidelity.

On the other hand, the crop analysis shows different situations. Some crops (alfalfa, rice, maize, and winter cereals) produced the high overall accuracy because they were very well classified by Clsmix (above 85 percent of TA) and for this reason they were not influenced by fidelities. Also, fruit trees had TA above 85 percent when purity restrictions were

50 percent or 75 percent and unclassified polygons or area were not considered as errors but whatever the fidelity. Olive tree results at pixel and polygon scale and area were unacceptable mainly due the scarce and heterogeneous disposition in the study area. Vineyards, fallow land, pastures, and other crops showed medium TA, being the best option to apply a restrictive fidelity and purity and not considering unclassified pixels-polygons-area as errors.

In conclusion, the results of this work are based on a large experiment, with a legend containing ten crops, and using more than 300,000 test pixels and 2,800 test polygons. In general, the per-polygon enrichment methodology gives better results than a simple per-pixel classification. Nevertheless, more factors have to be taken into account with regard to the consequences of applying more or less conservative parameters in the classification stage (fidelity) and in the enrichment stage (purity).

Indeed, the hybrid classifier makes it possible to be very conservative when a pixel is assigned to a category through the fidelity parameter. The more conservative the fidelity, the more TA increases. However, a greater number of unclassified pixels appear. This conclusion is also useful when the per-pixel classification is used in polygon enrichment. On the other hand, the best option in vector enrichment is to apply a modal threshold (purity) around 50 percent because this balances a very high TA (95.6 percent) with a moderate loss in classified polygons (12.2 percent) and area (12.6 percent).

Although the high accuracy obtained with the proposed methodology, it assumes that the cadastral data is accurate and widespread. We have to recognize that if no cadastre exists, or it is of poor quality in terms of geometric accuracy, it can be difficult or impossible to apply our methodology. Moreover, if a parcel has multiple crops, the enrichment will produce imperfect results, more problematic as more equal are the areas occupied by each one of the crops inside the parcel. We are currently working on heuristics methods to deal with such cases.

To summarize, and being aware of the comments of the last paragraph, polygon enrichment seems to be a very useful methodology that makes it possible to combine raster and cadastre data with a high degree of reliability, resulting in a product that matches the needs of public administrations (in terms of geometry and accuracy) more satisfactorily than other classical approaches.

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