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Spatialization of classification accuracy using spatially constrained confusion matrixes and classification uncertainty

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Abstract

In this paper an approach is presented that enables the assessment of the spatial variability of the classification accuracy of a land cover map generated with soft classifiers, using the uncertainty information associated with the classification. Soft classifiers enable the computation of uncertainty measures for each pixel of the classified image. This information is used to identify regions with different levels of uncertainty. Two different approaches, based on the uncertainty information, were used to obtain the prior knowledge of whether it is likely to have different levels of accuracy. One consists in the aggregation of the pixels into regions corresponding to different uncertainty levels, choosing thresholds for the pixels uncertainty values, and the second includes a segmentation of the uncertainty image, computation of the mean uncertainty of the pixels within each object and the subsequent aggregation of objects using their mean uncertainty. The accuracy of these regions is then evaluated separately, building spatially constrained confusion matrixes and computing different accuracy indices for different regions, instead of a single confusion matrix and accuracy indices for the whole area. The identification of map regions with different levels of uncertainty enables to identify the spatial location of regions where different levels of accuracy are more likely to occur. The methodology is applied to a case study. The results showed that lower levels of accuracy are in general obtained for the regions with higher levels of uncertainty, and therefore the uncertainty information is a valuable indicator to assess the spatial variability of accuracy.

Keywords: land use/cover, accuracy assessment, uncertainty, spatial, soft classifiers

1. Introduction

The production of Land Cover Maps through the automatic classification of multispectral images is fundamental for many applications. However, since the process of classifying images into a set of classes is subject to error and uncertainty, the evaluation of the classification accuracy is also a key issue (*e.g.* Stehman & Czaplewski, 1998).

The accuracy assessment of land cover maps is usually performed building confusion matrixes using the classification results and reference data for a sample of points. From these matrices accuracy indices may be computed, such as the overall accuracy and the user's and producer's accuracy for each class (*e.g.* Story and Congalton, 1986; Stehman and Czaplewski, 1998). However, since usually one confusion matrix is built to the whole map, these indices apply to the whole area and, even though there may be different levels of accuracy in different regions of the map, this variability cannot be estimated with this methodology. To overcome this difficulty some approaches have been proposed. Steele *et al.* (1998) developed a method to map spatially based estimates of map accuracy using misclassification probabilities of points in the training sample, which are then used to estimate the misclassification probabilities in a lattice of points using interpolation. This method generates an error surface which is highly dependent on the spatial distribution of the training sample. Woodcock *et al.* (2001) computed separate accuracy matrixes for two strata, corresponding to error least likely and error most likely strata, but no spatial location was assigned to these two levels of error and therefore no spatialization of the classification accuracy was assessed. Van Oort *et al.* (2004) proposed a methodology to assess the spatial variability of classification accuracy using landscape indices and logistic regression models. This approach enables an estimation of which variables may be more relevant to estimate classification accuracy. Foody (2005) proposed the computation of geographically constrained confusion matrixes, derived for parts of the image, instead of only one confusion matrix to the whole image. To generate these confusion matrixes only sample points located in the vicinity of points of interest were used. Even though this methodology enables the construction of geographically constrained confusion matrixes, the question of which points to choose and which vicinity of those points to consider is left to the choice of the user. This methodology enables the estimation of the accuracy of a region, but no prior knowledge is used of whether it is likely to have fairly uniform levels of accuracy or if different levels of accuracy are likely to occur within its limits. The approach is useful to evaluate what happens in the vicinity of a point of interest; however it has limitations to assess the spatial variation of the classification accuracy, since the results are highly dependent on the points of interest chosen and the amplitude of the vicinity considered for the accuracy assessment. Comber *et al.* (2012) and Comber (2013) proposed the use of geographically weighted regression to estimate the spatial variation of accuracy. However, this approach considers that there is gradual variation of accuracy and does not have into consideration landscape fragmentation. Therefore, can hardly be used in regions where the considered classes present abrupt and frequent changes.

During the last decade soft classifiers have been used to assign to each pixel a degree of probability, possibility or membership to each of the classes under consideration, depending on the mathematical theory subjacent to the classification process. This additional information may be used to compute uncertainty measures, which translate the classifier's difficulty in assigning only one class to each pixel. Since an uncertainty value is obtained for each pixel, the spatial variation of uncertainty is available.

Several uncertainty measures may be used to assess the classification uncertainty (*e.g.* Gonçalves *et al.*, 2010; Pal and Bezdek, 2000; Yager, 1992). Some of these measures are only applicable when degrees of probability of assignment to a class are obtained, others when degrees of possibilities are obtained and others in any of these cases. Gonçalves *et al.* (2010) and Gonçalves *et al.* (2009) showed that uncertainty measures may be used as indicators of the classification accuracy. Based on these results some preliminary experiments were made by Fonte and Gonçalves (2011) to determine if correlation could be found between the levels of uncertainty and accuracy associated to specific regions. Confusion matrixes were computed for two individual regions with high levels of uncertainty and the results showed that the accuracy obtained for these regions was very different from the accuracy obtained for the global classification. Fonte *et al.* (2013) applied two different soft classifiers to two sets of multispectral images with different spatial resolutions. For each classifier and each set of images the classification uncertainty was evaluated and used to identify regions with different levels of uncertainty. The results showed that the overall accuracy of the regions with low, medium and high levels of uncertainty decreases with the increase of uncertainty. A similar trend is also observed for the user's and producer's accuracy per class.

The aim of the study herein presented is to use the uncertainty information to identify regions with different levels of accuracy using two different approaches to identify these regions and assess if the results obtained with both are consistent. The two approaches tested to separate the study area into regions with different levels of uncertainty were: 1) identification of regions through the segmentation of the uncertainty image and associate to each region the mean uncertainty of the pixels within the regions. The regions are then grouped into several levels of mean uncertainty, generating larger regions with different levels of uncertainty; 2) the pixels are grouped into different levels of uncertainty using the uncertainty value obtained for each pixel.

In both cases the accuracy assessment of the classification is then made independently for the regions corresponding to the different levels of uncertainty. Reference data sets are built for each approach, using independent reference samples for the regions with different levels of uncertainty and confusion matrixes are computed for each region obtained for each approach, enabling the construction of spatial constrained confusion matrixes and the computation of independent accuracy indices for the regions with different levels of uncertainty. The proposed methodology is applied to a case study.

2. Methodology and processes

2.1 Methodology workflow

The proposed methodology consists of the following steps: 1) multispectral image classification with a soft classifier; 2) Generation of a hard version of the classification produced in step 1; 3) Computation of the classification uncertainty using uncertainty measures; 4) Identification of regions with different levels of uncertainty; 5) Generation of confusion matrixes for each region obtained in the previous steps and for the global classification using reference data.

Two approaches are tested in this paper to identify the regions with different levels of uncertainty. The first approach, named SEGA, consists of: a) segment the uncertainty image obtained in step 3 above; b) compute the mean uncertainty for each object obtained in a); c) group the objects obtained in a) according to the mean uncertainty obtained in b), having in consideration the needs of the application (see Figure 1). The second approach, named AG, consists in aggregating the pixels of the uncertainty image into levels according to chosen thresholds.

The accuracy assessment of image classifications is usually made building confusion matrices (Story and Congalton, 1986) considering a sample of point for which reference data are collected. For the creation of spatially constrained confusion matrixes a sample of points has to be considered for each region where the accuracy is to be assessed. In this article the accuracy of the global classification is computed using a sample of points resulting from the aggregation of samples generated for the several uncertainty regions under consideration.

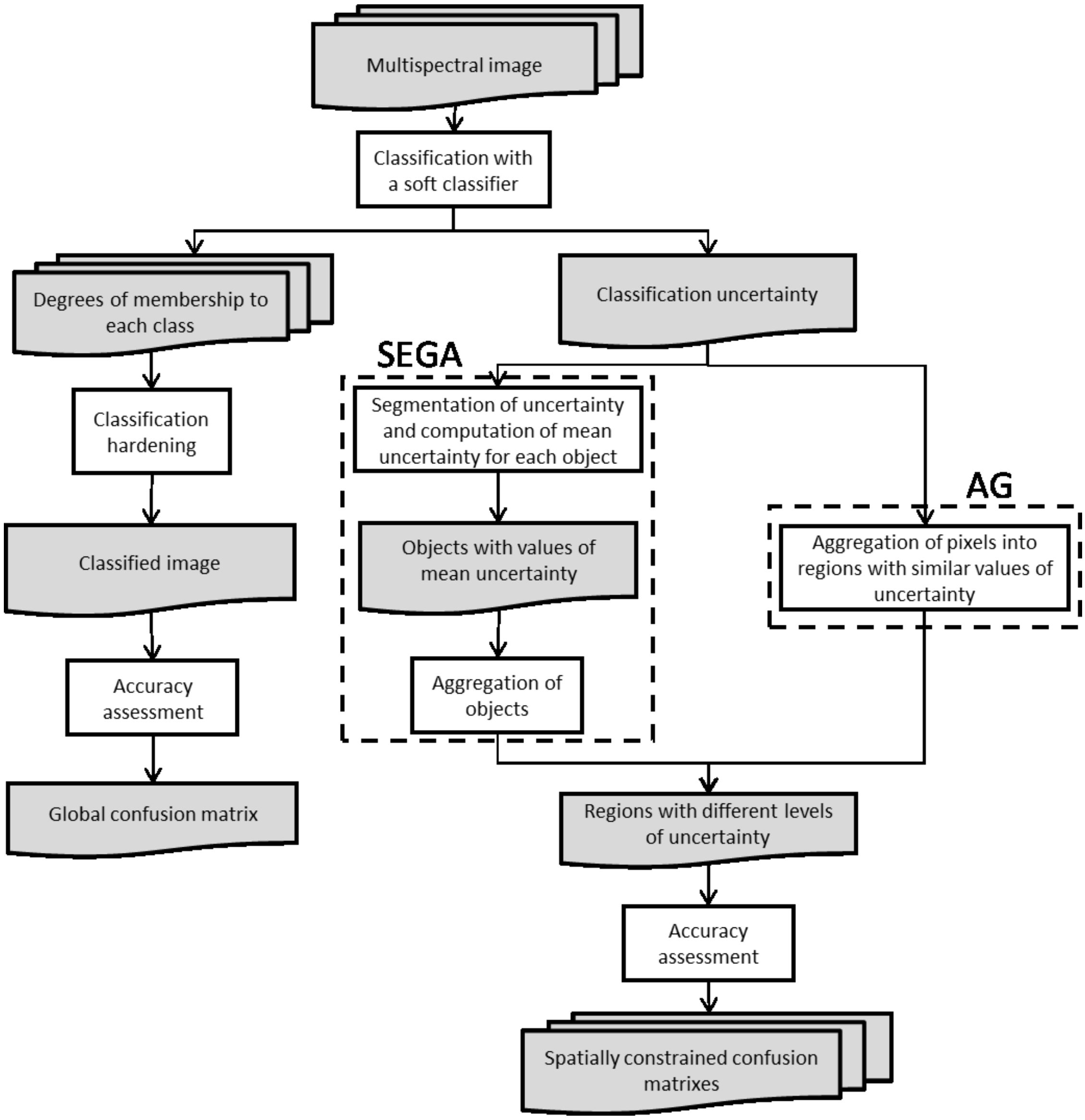

Figure 1 - Workflow of the methodology used.

2.2 Methodology rationale

The two approaches are tested to assess their influence on the obtained results. The easiest approach (AG) is a simple aggregation of pixels based on their uncertainty, without having into consideration the spatial location of the pixels. The SEGA approach has the aim of generating objects with spatial meaning based on the uncertainty of the classification. The computation of the mean uncertainty of the pixels included in each object generates objects with different levels of uncertainty, which may be analysed separately and confusion matrixes may be obtained for each (Fonte and Gonçalves, 2011). However, if small objects are obtained, it is highly inefficient or even impractical to generate a large number of confusion matrixes, which requires many reference data. To overcome this difficulty, the objects may be grouped into regions according to their mean uncertainty, reducing the number of individual zones to be analysed separately. The need to aggregate the objects is intimately related with the characteristics of the image, the nomenclature and the segmentation process, since different segmentation algorithms and different parameters for the same algorithms produce different results.

3. Case Study

3.1 Data

The image data used in this case study was a CARTERRA-Geo image (Jacobsen, 2002) obtained by the IKONOS-2 sensor, with a spatial resolution of 4m in the multispectral mode (XS) (Figure 2).

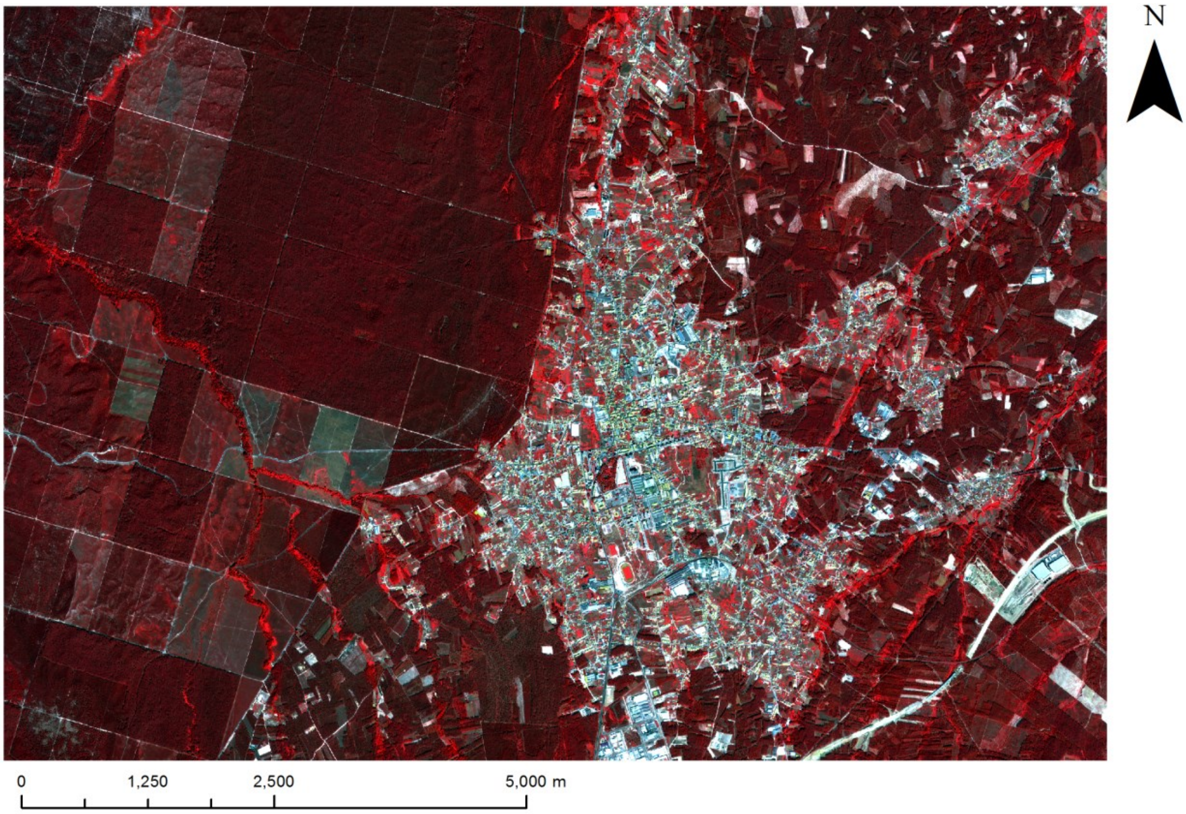

Figure 2 – False color composition (432) of the multispectral IKONOS image.

The image covers an area of 81.5 km2 located near the Portuguese coast, and includes regions with different characteristics, such as built up areas, agricultural fields and forest. The study was performed using the 4 multispectral bands.

3.2 Classification

The image classification needs to be done with a soft classifier. Several soft classifiers are available and may be used to this aim (*e.g.* Lein, 2011, Tso and Mather, 2001, Kuncheva, 2000, Foody *et al.*, 1992; Ibrahim *et al.*, 2005; Foody, 1996; Foody and Arora, 1997). The classifier used in this article is a Bayesian soft classifier which computes the posterior probabilities for each pixel associated to each class (Foody *et al.*, 1992). These posterior probabilities may be interpreted as representing the proportional cover of the classes in each pixel or as indicators of the uncertainty associated with the pixel allocation to the classes (Shi *et al.* 1999; Ibrahim *et al.* 2005). In this article, this second interpretation is considered, and the posterior probabilities are used to compute uncertainty measures.

Unlike traditional hard classifiers, the output obtained with a soft classifier is a set of images (one per class) that express, in this case, the probability that each pixel belongs to the class. A hard classification is obtained by assigning to each pixel the class corresponding to the higher probability value.

The classes used in this study are: Urban Areas (UA), Herbaceous Vegetation (HV), Shrub Lands (SL), Forest Areas (FA) and Barren Areas (BA). Figure 3 shows the hardened classification obtained for the multispectral image shown in Figure 2 and the image percentage occupied by each class.

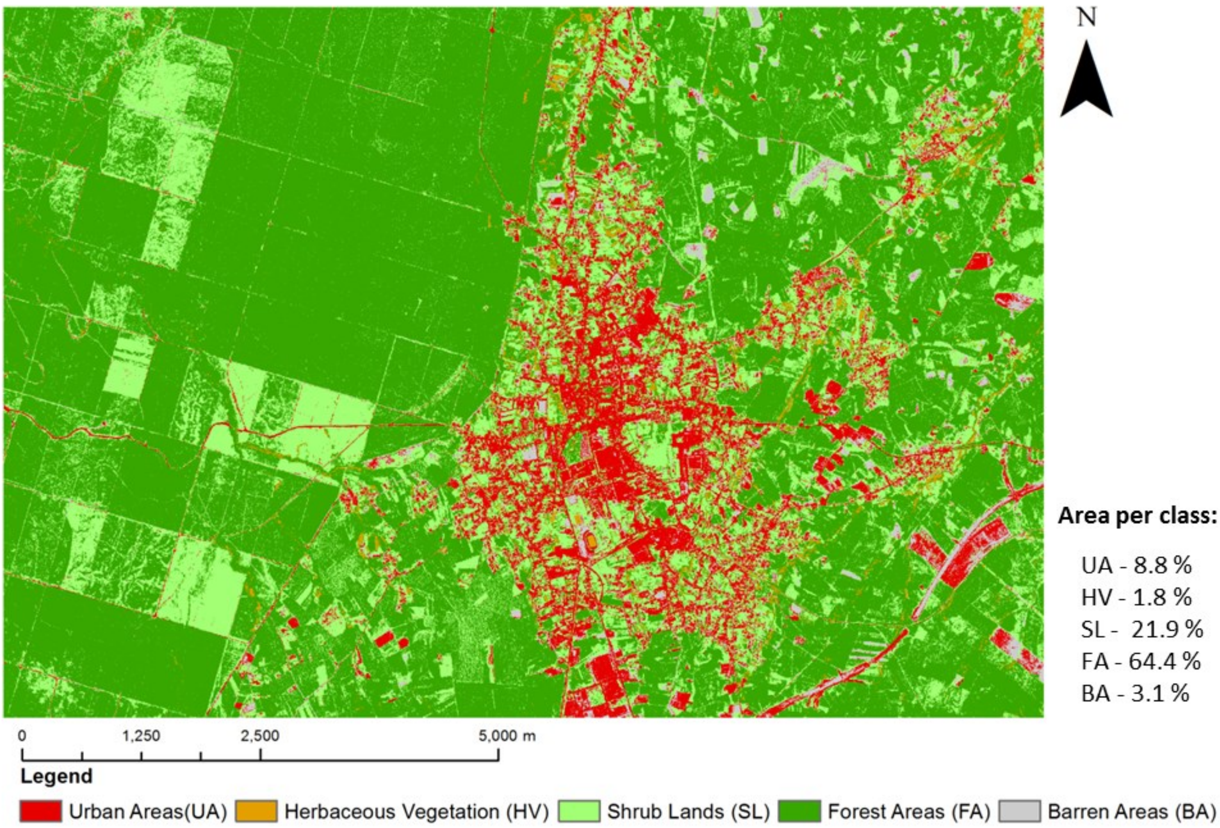

Figure 3 – Hardened classification of the multispectral image, obtained considering the class corresponding to the maximum probability at each pixel and respective area percentage.

3.3 Uncertainty computation

Several uncertainty measures may be used to evaluate the classifiers difficulty to assign only one class to each pixel (*e.g.* Gonçalves *et al.*, 2010a; Gonçalves *et al.*, 2010b, Foody, 1996). In this paper, the uncertainty associated with the soft classification is evaluated with the Relative Maximum Deviation Measure (RMD). The uncertainty is computed using equation (3), where *x* represents a pixel, $p_i(x)$ is the degree of probability associated to class *i* for pixel *x* and *n* is the number of classes.

$$RMD(x) = 1 - \frac{\max\limits_{i=1,..n}(p_i(x)) - \frac{\sum_{i=1}^{n} p_i(x)}{n}}{1 - \frac{1}{n}} \quad (3)$$

This uncertainty measure assumes values in the interval [0,1] and evaluates the degree of compatibility of the chosen class with a perfect match (corresponding to $p_i(x) = 1$). Figure 4 shows the spatial distribution of the uncertainty obtained for the case study and Table 1 the statistical information on the obtained uncertainty values.

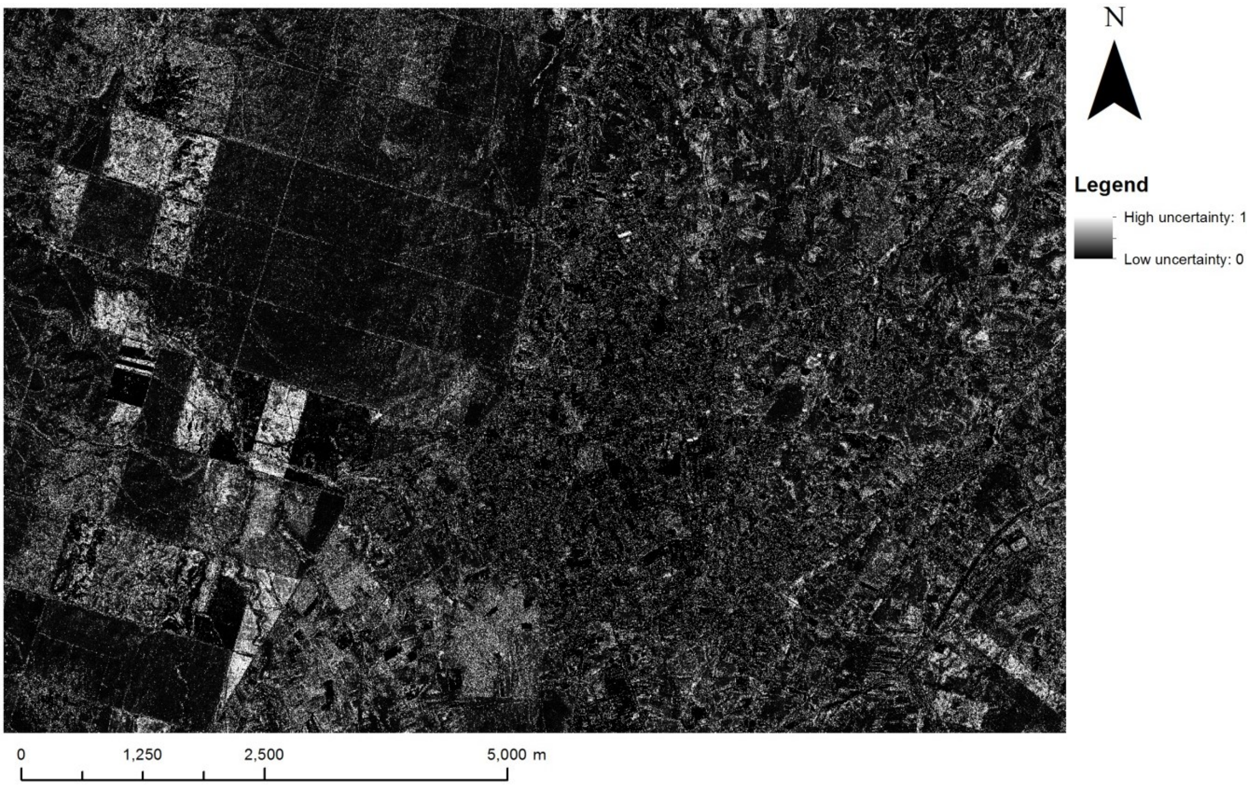

Figure 4 – Spatial distribution of the classification uncertainty.

Table 1 - Statistical information on the pixel uncertainty values obtained with the Relative Maximum Deviation Measure.

	Minimum	Maximum	Mean	Standard Deviation
Pixels uncertainty	0.00	0.81	0.06	0.12

It can be seen in Table 1 that the uncertainty values are in general very low (a mean value of 0.06 was obtained) with a standard deviation of 0.12. However, in some locations higher uncertainty values are observed, which achieve a maximum value of 0.81.

3.4 Identification of regions with different levels of uncertainty

3.4.1 Using image segmentation (SEGA)

Since the used uncertainty measure produce an uncertainty value for each spatial unit, varying between 0 and 1, where 0 corresponds to no uncertainty and 1 to the maximum uncertainty, an image is generated with the uncertainty values (Figure 4). Image segmentation techniques may therefore be used to identify objects with similar characteristics based on uncertainty.

Many segmentation algorithms are available, using techniques such as edge detection, clustering techniques, neural networks and fuzzy approaches (*e.g.* Russ, 2006; Ryherd and Woodcock 1996; Haralick and Shapiro, 1985; Pal and Pal, 1993). The segmentation results vary with the segmentation methods used, which may be more or less sensitive to noise and other characteristics of the image. For this particular type of use, the level of segmentation convenient for each application depends on the levels of uncertainty obtained and their spatial distribution as well as on the objectives of the study to be undertaken.

The segmentation of uncertainty was done in this study using an algorithm available in software IDRISI, which groups adjacent pixels into image segments according to their similarity. The variance of the input image is computed for each pixel using a moving window, whose size may be defined by the user. The values of the variance image are treated as elevation values in a digital elevation model and a watershed delineation process is used to group pixels into objects. An iterative process to merge adjacent objects is then used. Objects are merged if they satisfy simultaneously the following conditions: 1) the objects are adjacent; 2) they must be mutually most similar and 3) the similarity must be less than a user-specified threshold, referred to as similarity tolerance. The similarity is evaluated computing a difference between objects using the mean and standard deviation values of the segments as well as user defined weights for both the mean and the standard deviation. For the objects to be merged this difference must be less than the similarity tolerance, which may take values equal or larger than zero. For a value of zero no merging is done and the larger the value the larger the degree of generalization, resulting in larger objects (*e.g.* Gonzalez and Woods, 2008).

Several experiments were made to identify the parameters' values that enabled the identification of objects that corresponded to the patterns visually identified in the uncertainty image. The values used in the present example are a 3 pixels width moving window, mean and variance weights equal to 0.5 and a similarity tolerance of 50. Figure 5 shows the segmented uncertainty, where the shades of grey represent the mean uncertainty of the pixels belonging to each object.

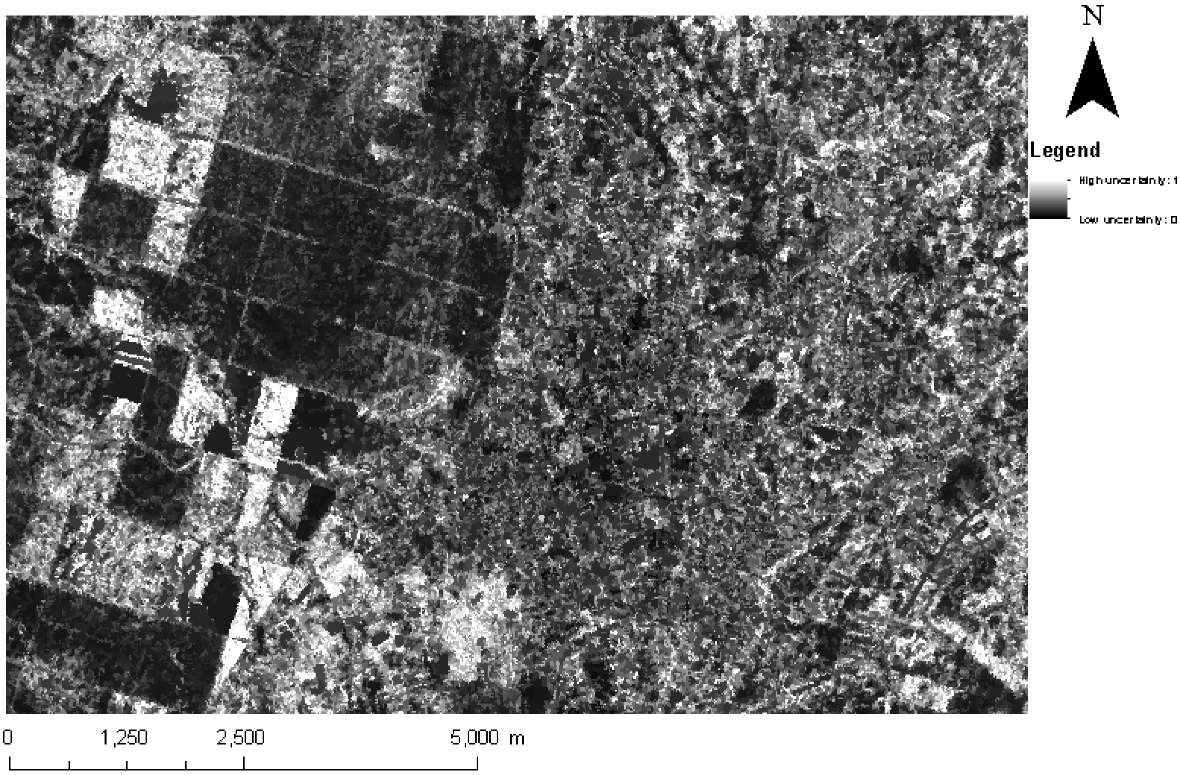

Figure 5 – Segmentation of the uncertainty. The shades of grey represent the mean uncertainty of the pixels belonging to each object.

Approximately 25,000 objects were generated with the segmentation. The statistical information on the mean uncertainty of the obtained objects is shown in Table 2. The results show only a decrease of 0.01 in the mean uncertainty; however the standard deviation decreased from 0.12 to 0.04 and the maximum uncertainty from 0.81 to 0.49.

Table 2 - Statistical information on the objects mean uncertainty.

	Minimum	Maximum	Mean	Standard Deviation
Objects' mean uncertainty	0.00	0.49	0.05	0.04

Since it is impractical to build confusion matrices for all objects obtained with this level of segmentation, the objects were grouped into three levels of mean uncertainty, namely low, medium and high uncertainty. Several threshold values were tested to delimit these levels of uncertainty. The separation was performed using a threshold value, based on the uncertainty information, which enabled to group the objects into regions with approximately equal areas. Figure 6 shows the threshold values considered for the three aggregated regions.

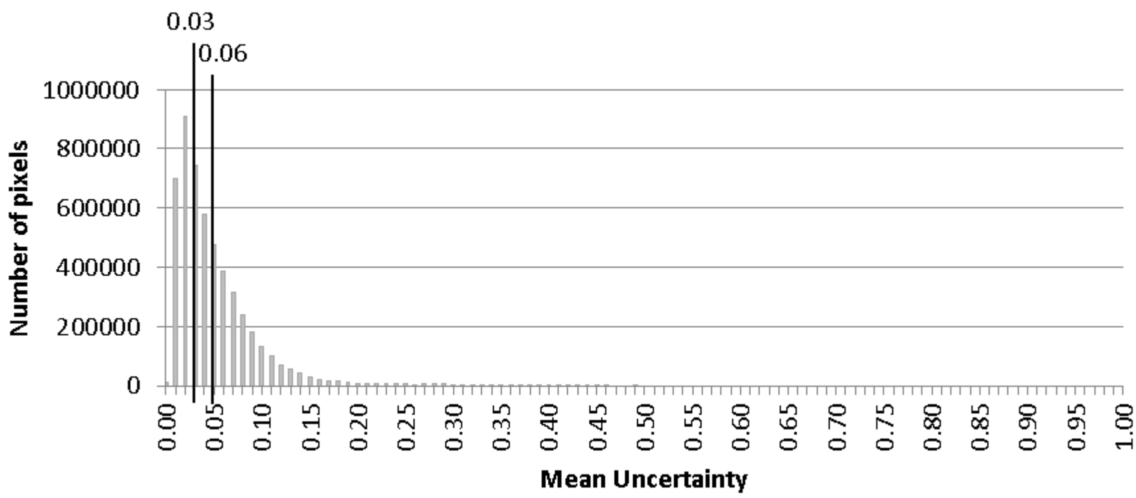

Figure 6 – Histogram showing the number of pixels as a function of the mean uncertainty, and the threshold values used to separate the three levels of uncertainty for SEGA.

Figure 7 a), b) and c) show the obtained regions for low, medium and high uncertainty, representing the classes assigned to each pixel considering the hardened classification.

3.4.2 Aggregating pixels (AG)

The second approach used in this study to identify regions with different levels of uncertainty was to aggregate pixels into three groups according to their uncertainty, corresponding to low, medium and high values of uncertainty. The adopted approach to separate these three levels was also to split the area into three regions with equal areas. Therefore, the separation was performed using a threshold value, based on the uncertainty information that enables to group the pixels into tree regions with the same number of pixels. Other approaches were also tested, such as equally spaced intervals and the Jenks Natural Breaks algorithm (Jenks, 1967). However, since most pixels have very low levels of uncertainty (Figure 4 and Table 1), the other tested approaches generated very unevenly distributed pixels by the three levels, including most pixels in the low uncertainty level. Figure 8 shows the limits considered for the three aggregated regions with AG. Figure 7 d), e) and f) show the obtained regions for respectively low, medium and high uncertainty, considering the classes assigned to the pixels with the hard classification.

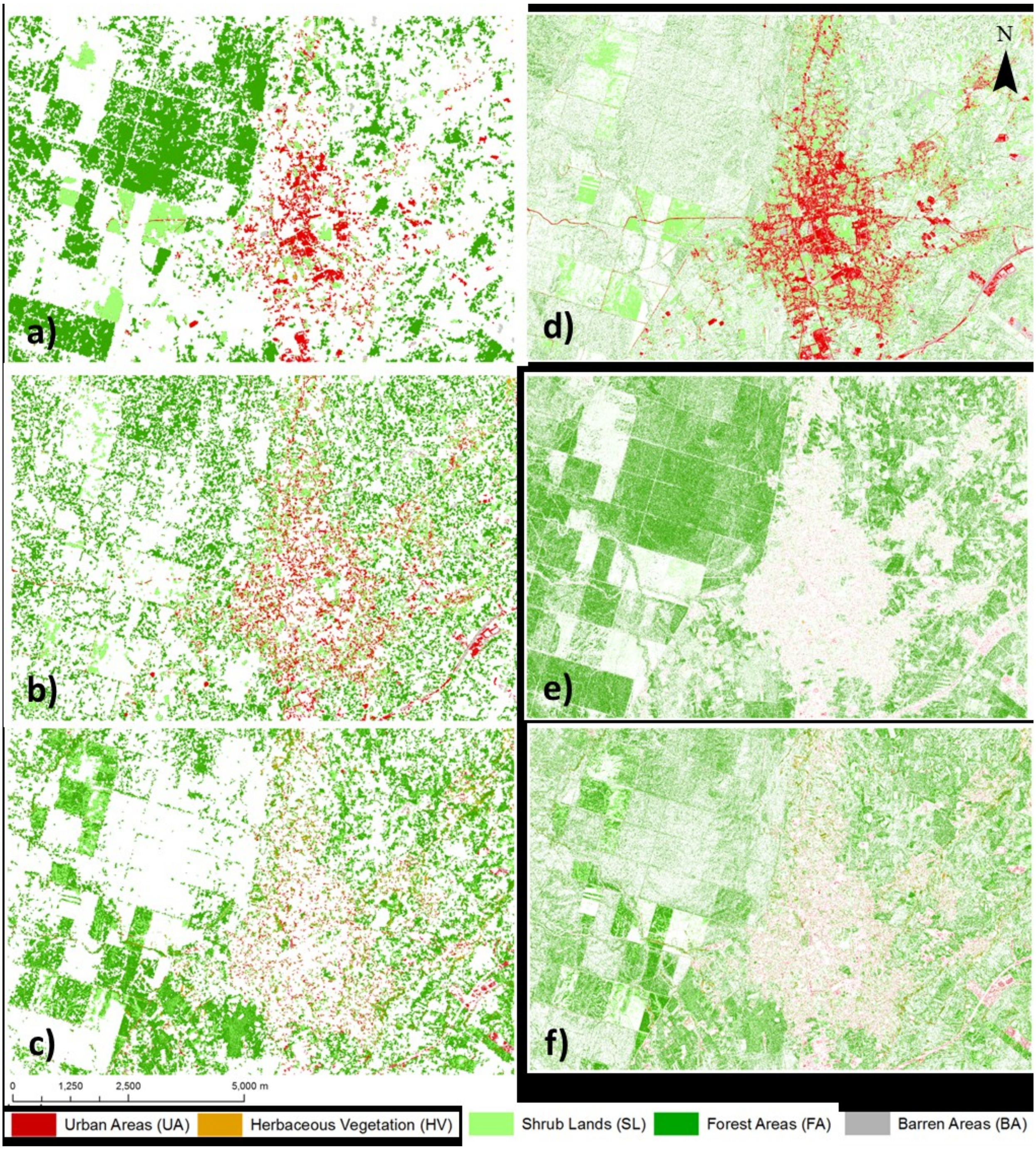

Figure 7 - Spatial distributions of the regions obtained for SEGA approach with low (a), medium (b) and high (c) uncertainty; and for AG approach with low (d), medium (e) and high (f) uncertainty, showing the classes assigned to each pixel with the hardened classification.

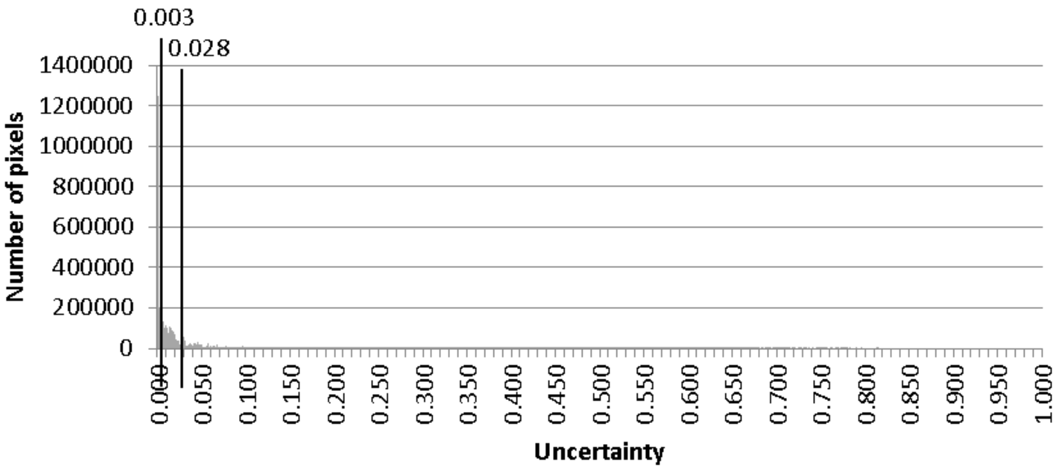

Figure 8 - Histogram showing the number of pixels as a function of the uncertainty, and the threshold values used to separate the three levels of uncertainty for AG.

3.5 Accuracy assessment

To assess the accuracy of the regions with different levels of uncertainty obtained with the two approaches a stratified random sample of points within each uncertainty region was used, considering the classes as strata for each region. A sample of 250 points was used per level of uncertainty, stratified by class. The accuracy of the hardened global classification was evaluated building a confusion matrix with all the points collected for the three levels of uncertainty in each approach, corresponding to a total of 750 points for each case. The overall accuracy as well as the user's and producer's accuracy obtained are shown respectively in Figures 9, 10 and 11.

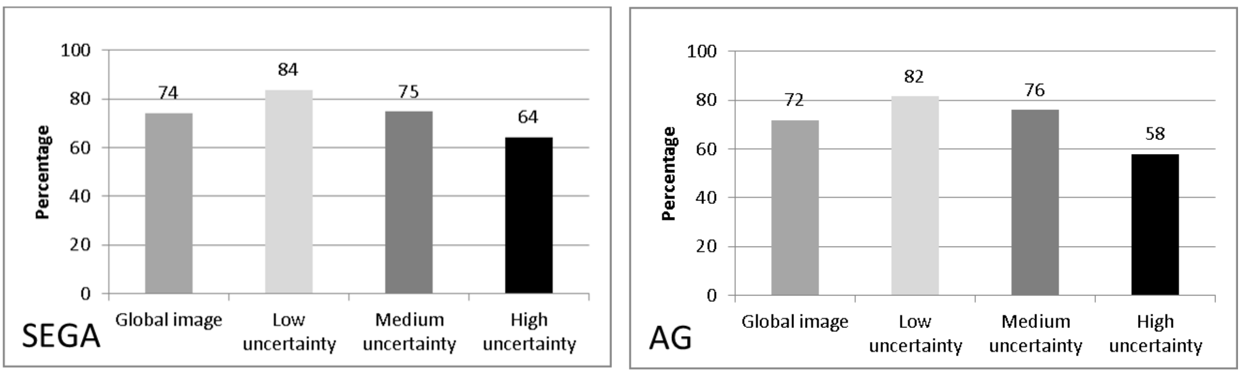

Figure 9 - Overall accuracy of the global image and the regions with low, medium and high uncertainty obtained: aggregating the objects generated using segmentation (SEGA) on the left, aggregating the pixels (AG) on the right.

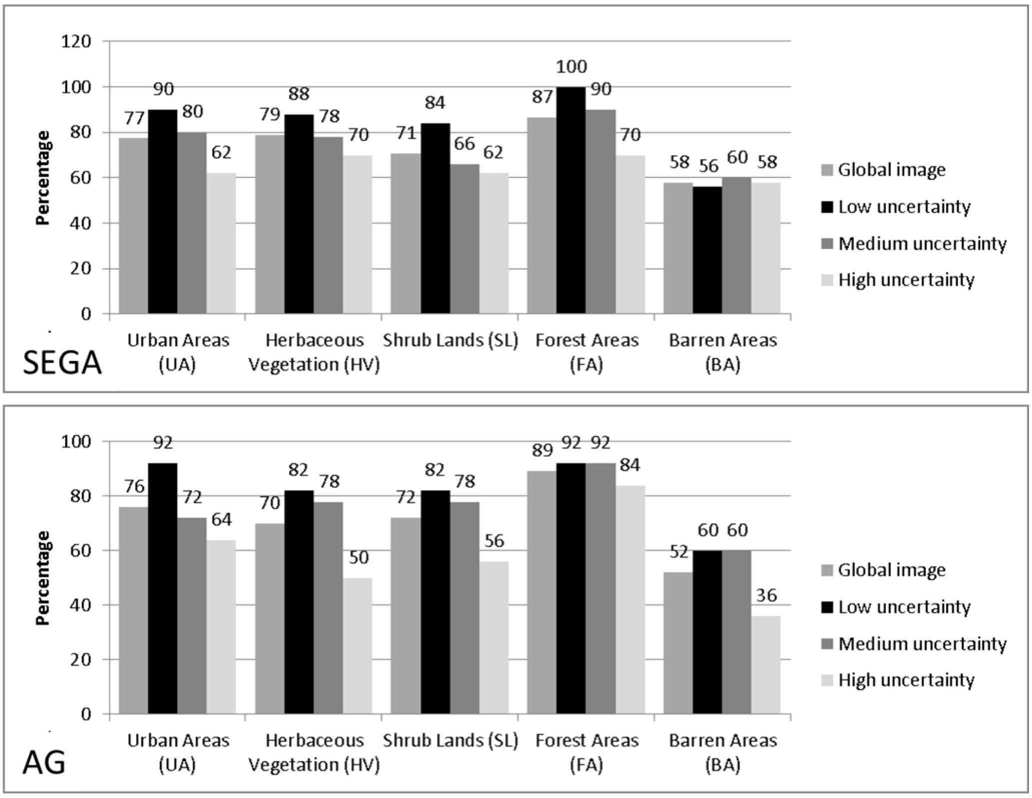

Figure 10 – User's accuracy per class of the global image and of the regions with low, medium and high uncertainty obtained: aggregating the objects generated using segmentation (SEGA) above, aggregating the pixels (AG) below.

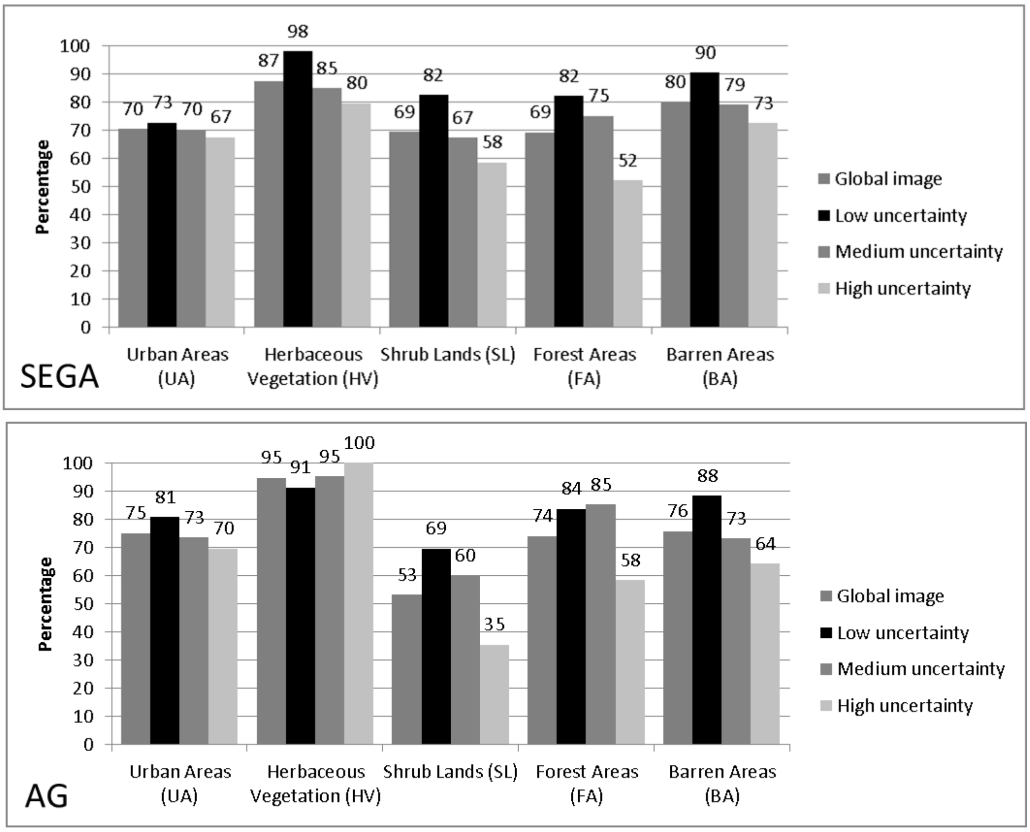

Figure 11 - Producer's accuracy per class of the global image and of the regions with low, medium and high uncertainty obtained: aggregating the objects generated using segmentation (SEGA) above, aggregating the pixels (AG) below.

3.6. Analysis of results

Analyzing the results of the overall accuracy obtained for the global image and the regions with low, medium and high uncertainty obtained with both approaches (SEGA and AG) it can be observed that the values obtained for both reference samples are similar, presenting a difference of 2% for the global image (Figure 9). In both cases the regions with low uncertainty have overall accuracy 10% larger than the overall accuracy of the global image, the overall accuracy of the regions with medium uncertainty is very similar to the overall accuracy of the global image (respectively 75% and 74% for SEGA and 76% and 72% for AG) and in both cases the overall accuracy of the regions with high uncertainty is inferior to the overall accuracy of the global image (respectively 64% versus 74% for SEGA and 58% versus 72% for AG).

Figure 10 shows the user's accuracy per class obtained for the global image and the regions corresponding to the three levels of uncertainty obtained with both approaches. Similar trends can be observed: higher values of accuracy are obtained for the regions with low uncertainty and lower accuracy values are obtained for the regions with higher uncertainty. An exception is found with the SEGA approach corresponding to the class Barren Areas, where very similar values were obtained for all regions. The users' accuracy of the regions with high uncertainty is equal to the accuracy of the global image and the accuracy of the regions with medium uncertainty is the largest, even though, only 4% larger than the value obtained for the region with low uncertainty.

With the AG approach the accuracy values obtained for the regions corresponding to the classes Forest Areas and Barren Areas with higher and medium uncertainty are equal and smaller for the region with high uncertainty. This means that, for these classes, the regions inserted into the low and medium levels of uncertainty show no considerable variation of accuracy, showing a decrease for the region with low uncertainty, especially for Barren Areas.

Figure 11 shows the producer's accuracy per class obtained for the global image and the regions corresponding to the three levels of uncertainty. The results are similar to the ones obtained for the user's accuracy, showing that in most cases the omission errors increase with the increase of uncertainty. However, in this example an exception is found, corresponding to the class Herbaceous Vegetation obtained with the AG approach. In this case, opposite to what would be expected, the accuracy value decreases with the decrease of uncertainty, even though the difference between the extreme values is only 9% and they are all larger than 90%.

Table 3 shows the percentage of area for each class included in each uncertainty level of each approach.

Table 3 - Percentage of area occupied by each class in the uncertainty regions obtained with SEGA and AG approach.

	Class in the uncertainty regions obtained with SEGA (%)			Class in the uncertainty regions obtained with AG (%)		
	Low	Medium	High	Low	Medium	High
Urban Areas (UA)	38	42	20	**77**	7	16
Herbaceous Vegetation (HV)	**7**	31	**62**	28	15	**57**
Shrub Lands (SL),	20	38	42	**58**	10	32
Forest Areas (FA)	37	31	32	17	**47**	36
Barren Areas (BA)	23	49	28	**66**	10	24

The distribution of the classes by the three levels of uncertainty is more even with the SEGA approach, except for the class Herbaceous Vegetation, where most of the class (62%) was included in the high level of uncertainty and only 7% in the low uncertainty. With the AG approach the medium level of uncertainty has less percentage of all classes except Forest Areas (47%). Most of the regions classified as Urban Areas are located in the low uncertainty region (77%) as well as the Barren Areas (66%) and Shrub Lands (58%). As with the SEGA approach, most of the Herbaceous Vegetation was included in the region with high uncertainty (57%).

A comparison can also be done on what is observed for the same class in the regions with different levels of uncertainty obtained with SEGA and AG approaches. Figure 12 shows the regions of Forest Areas obtained for the different approaches separated by the three levels of uncertainty, showing the different levels of user's accuracy. It can be seen that with the AG approach most of the pixels classified as forest belong to the middle level of uncertainty, opposed to the low uncertainty region for SEGA. A "salt and pepper" effect is clear for the AG results, which was eliminated with the SEGA approach. With both approaches regions with less accuracy were identified, which are spatially coincident in more than 50% of either.

Figure 13 and Figure 14 show a detail of regions classified as Urban Areas and Shrub Lands respectively with low, medium and high levels of uncertainty and also the spatial distribution of the initial uncertainty computed using the Relative Maximum Deviation Measure. Comparing what occurs in those regions confirms that the spatial distribution of the regions with different levels of uncertainty obtained with SEGA and AG approach are not always coincident.

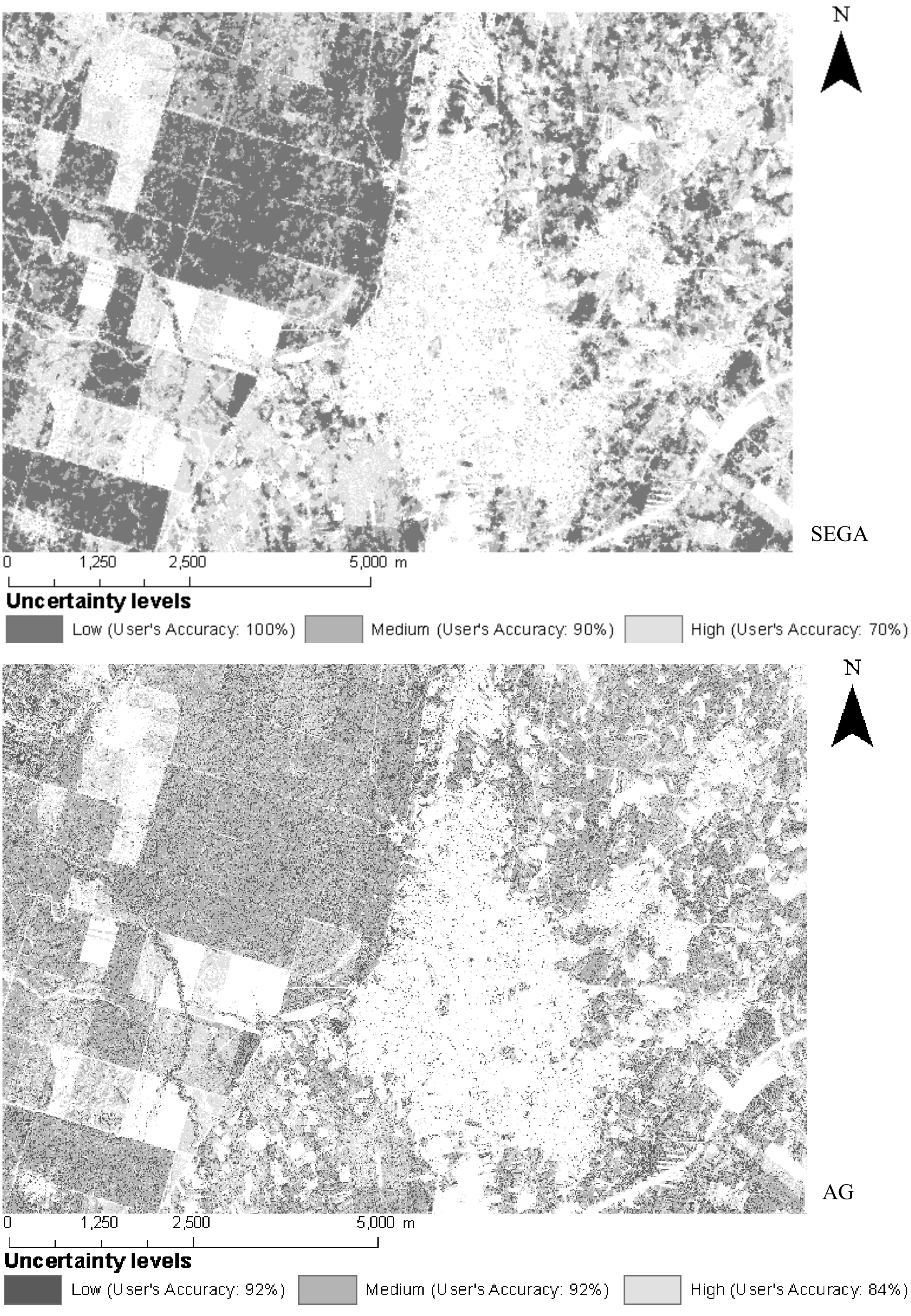

Figure 12 – Regions corresponding to the different levels of user's Accuracy for Forest Areas, above with SEGA approach and below with the AG approach.

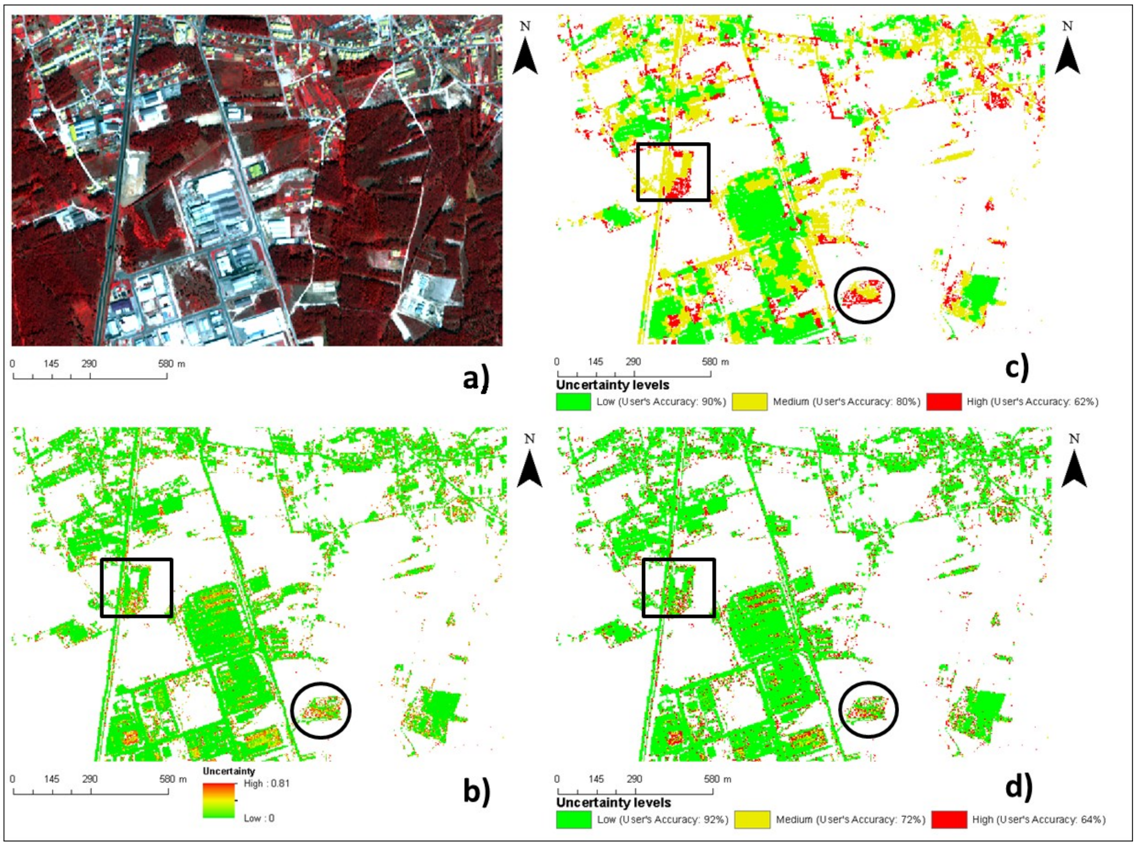

Figure 13 – Spatial distributions of uncertainty for Urban Areas: a) False color image, b) Classification uncertainty. Regions obtained with the SEGA (c), and AG approach (d).

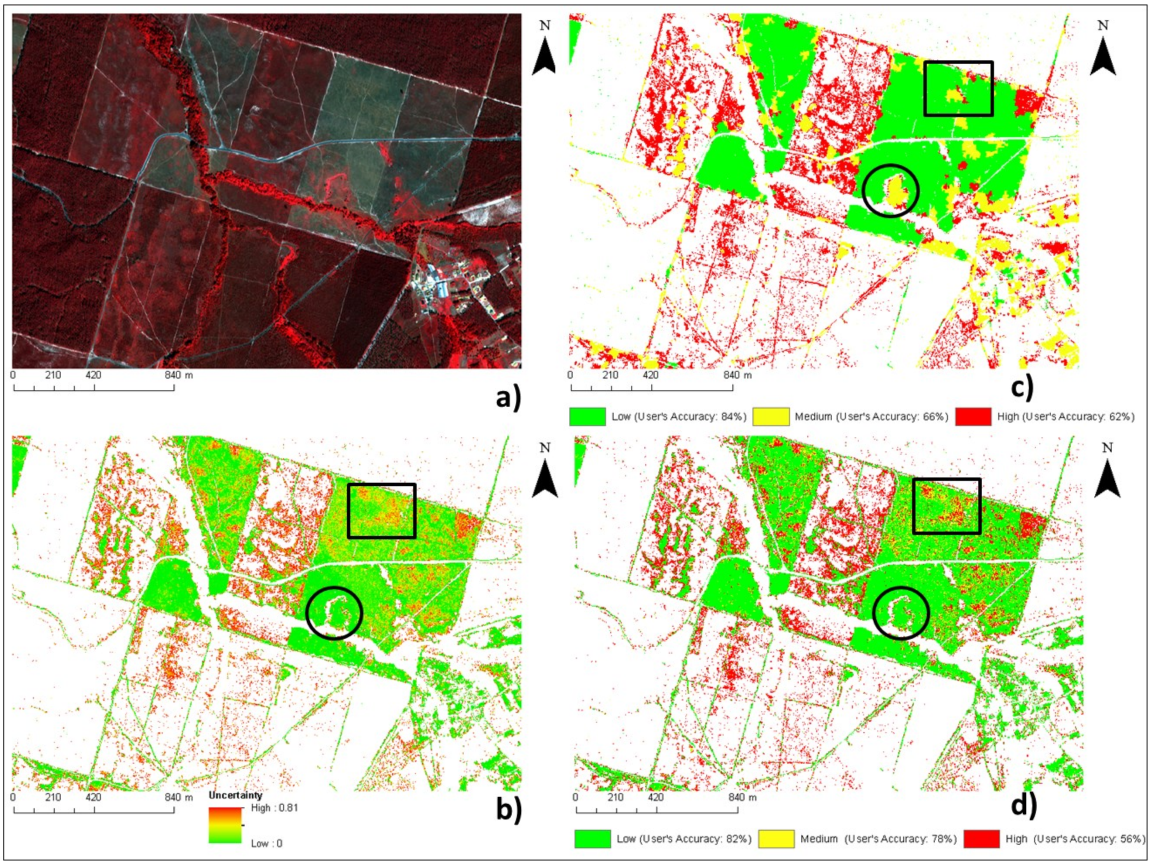

Figure 14 – Spatial distributions of uncertainty for Shrub Lands: a) False color image, b) Classification uncertainty. Regions obtained with the SEGA (c), and AG approach (d).

The regions with different levels of uncertainty obtained with SEGA approach were aggregated considering the mean uncertainty of the objects which leads that the spatial distribution is highly influenced by the mean values obtained. This was done to avoid the "salt and pepper" effect when the uncertainty has a lot of spatial variation within the same regions that can be visually identified. However, when the segmentation algorithm identifies regions where there is some diversity, the mean value is affected by the extreme values present in the region and different uncertainty patterns emerged, such as the ones highlighted by the circles and rectangles in Figures 13 and 14.

4. Discussion and conclusions

This article proposes a methodology to identify regions with different levels of accuracy using the classification uncertainty computed with the information provided by soft classifiers. The uncertainty expresses the classifiers difficulty in assigning each pixel to a class and it has been shown that it is more likely to have misclassifications in the regions with larger values of uncertainty (Gonçalves *et al.*, 2010, Gonçalves *et al.*, 2009). Therefore, the uncertainty may be used as an indicator of the classification accuracy. With the prior knowledge of where different levels of accuracy are expected, it is possible to establish geographically constrained confusion matrixes, which provide information on the spatial distribution of the classification accuracy.

Different approaches may be used to identify the regions to which the spatially constrained confusion matrixes will be associated. These may depend on the characteristics of the spatial distribution of uncertainty and also on the purpose of the application. The methodology proposed in this article requires: a classification with a soft classifier, the computation of the classification uncertainty and the identification of regions with different levels of uncertainty. In the case study presented two different approaches were used to identify the regions with different levels of uncertainty. One consists in the aggregation of the pixels into regions corresponding to different uncertainty levels, choosing thresholds for the pixels' uncertainty (AG approach). Three levels were considered, corresponding to low, medium and high uncertainty. The other approach includes a segmentation of the uncertainty image, computation of the mean uncertainty of the pixels within each object and the subsequent aggregation of objects using their mean uncertainty also in three regions (SEGA approach). In both cases the accuracy was then computed for the obtained regions separately.

The SEGA approach is more complex and the results are dependent on the segmentation algorithm and parameters used, as well as on the threshold values used for the objects aggregation. Besides that, the use of the mean uncertainty smooths the uncertainty values, which removes the “salt and pepper” effect present in some parts of the uncertainty image, but also contributes to the loss of information for the most and less problematic locations, and in some cases may create patterns of uncertainty variation that are not easily seen on the uncertainty image. Even though, besides all these difficulties, it can be seen that the results are consistent, corresponding in general to an increase of accuracy with a decrease of objects mean uncertainty.

The AG approach is very simple to implement and is only dependent on the threshold values used to define the chosen levels of uncertainty. The obtained patterns of uncertainty present a higher proximity to the uncertainty patterns obtained using the Relative Maximum Deviation Measure without any aggregation.

The accuracy results obtained for global image and the several regions with different levels of uncertainty with the two approaches showed that the three regions identified in each presented different levels of accuracy (enabling the spatialization of accuracy) and that the accuracy increased with the decrease of uncertainty. The proposed methodologies showed therefore to be promising to identify regions with different levels of accuracy of a hardened version of a classification performed with soft classifiers, providing information that may be quite useful, for example, for reporting the limitations of a land cover map, to identify regions with different characteristics within the same class, or for improving classification through the redefinition of the training samples. However, further investigations are still needed to improve the proposed methodologies.

A key issue that determines the outcomes of the approaches is the identification of the uncertainty values that define the regions. In this article these values were chosen using only the uncertainty values, regardless of the classes associated to the pixels. However, since the levels of uncertainty associated to the classes is in some cases very different, in future work methodologies should be tested that combine class and uncertainty information for the determination of the threshold values. Another point is the number of regions with different levels of uncertainty that are considered for the construction of spatially constrained confusion matrixes, which should be chosen depending on the aim of the application. The increase of number of regions enables the identification of more differences in the accuracy of the classification, but will result in additional time consuming work, since reference data are needed for each one. Therefore the strategy to identify and separate these levels is an important aspect that needs further analysis.

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