REGION-BASED CLASSIFICATION POTENTIAL FOR LAND-COVER CLASSIFICATION WITH VERY HIGH SPATIAL RESOLUTION SATELLITE DATA

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ABSTRACT:

Since 1999, Very High spatial Resolution satellite data (Ikonos-2, QuickBird and OrbView-3) represent the surface of the Earth with more detail. However, information extraction by multispectral pixel-based classification proves to have become more complex owing to the internal variability increase in the land-cover units and to the weakness of spectral resolution.

Therefore, one possibility is to consider the internal spectral variability of land-cover classes as a valuable source of spatial information that can be used as an additional clue in characterizing and identifying land cover. Moreover, the spatial resolution gap that existed between satellite images and aerial photographs has strongly decreased, and the features used in visual interpretation transposed to digital analysis (texture, morphology and context) can be used as additional information on top of spectral features for the land cover classification. The difficulty of this approach is often to transpose the visual features to digital analysis.

To overcome this problem region-based classification could be used. Segmentation, before classification, produces regions that are more homogeneous in themselves than with nearby regions and represent discrete objects or areas in the image. Each region becomes then a unit analysis, which makes it possible to avoid much of the structural clutter and allows to measure and use a number of features on top of spectral features. These features can be the surface, the perimeter, the compactness, the degree and kind of texture. Segmentation is one of the only methods which ensures to measure the morphological features (surface, perimeter...) and the textural features on non-arbitrary neighbourhood.

In this context, our research focuses on the potential of land cover region-based classification of VHR satellite data through the study of the region feature relevance for classifying the land-cover classes in different kinds of Belgian landscapes; always keeping in mind the parallel with the visual interpretation which remains the reference.

1. INTRODUCTION

The very high spatial resolution satellite data are extraordinary from the point of view of the spatial resolution and increase the amount of information attainable on land cover at a local to national scales. In particular the minimum parcel size at which mapping takes place is considerably smaller than in contemporary surveys, and this will result in an increase in geometric detail and accuracy.

In spite of these advantages, the use of this kind of data involves some problems in the traditional per-pixel classification. With the spatial resolution refinement, the internal variability within homogenous land cover units increases (Woodcock and Strahler, 1987, Aplin et al., 1997, Thomas et al., 2003). The increased variability decreases the statistical separability of land cover classes in the spectral data space and this decreased separability tends to reduce per pixel classification accuracies. Another disadvantage with the very high spatial resolution satellite images is their relatively poor spectral resolution (Herold et al., 2003).

Different solutions were suggested in order to tackle the problem of reduced class separability in relation to the increased internal variability.

A first possibility is proposed by Cushnie (1987) and Marceau et al. (1990). It consists in applying a mathematical transformation to the original data so as to remove the excess spectral detail that is considered as noise (Cushnie, 1987). Some transformations are applied to the whole feature space (Principal Component Analysis …), while others are applied to individual bands through the process of spatial linear filtering. A common spatial linear filter is the mean-filter. It is a non-adaptive, low-pass filter where the intensity at each sample interval in the image is replaced by the mean of pixel values in a moving window surrounding the sample. These methods have, to some extent, led to an improvement in classification accuracy. However, they represent a reductionist approach, in the sense that they attempt to solve the problem of higher spectral confusion by eliminating part of the information that is present in the images.

A second possibility consists in taking advantage of the consequences of the increased resolution and to consider the internal spectral variability of classes as a valuable source of spatial information that can be used as an additional clue in characterizing and identifying land cover (Marceau et al., 1990, Shackelford et al., 2003). Moreover, this additional information could help overcome the poor spectral resolution problem (Guindon, 2000, Herold et al., 2002) and increase the classification accuracy for spectrally heterogeneous classes (Lillesand and Kiefer, 1994).

In fact, since the availability of the VHR satellite data, the spatial resolution gap that existed between satellite images and aerial photographs has strongly decreased, and the additional information that can be used on top of spectral features for the land cover classification, can be the features used in visual interpretation transposed to digital analysis. The increased resolution clarifies shapes, sharpens boundaries and alters the textural appearance of classes, and approaches that take advantage of these consequences to perform automated land cover classification are needed (Irons et al., 1985).

King (2002) calls for a return to land cover mapping principles, whereby expert knowledge on the part of the observer should contribute to the classification process. King (2002) asserts that the reliance of most current classification techniques on a single property, reflectance, to map land cover is a weakness, and that additional interpretation elements such as texture, context, size, shape and position should be included in the procedure. Haralick et al. (1973) said: "In a search for meaningful features for describing pictorial information, it is only natural to look toward the types of features which human beings use in interpreting pictorial information". The features used in visual interpretation (also called stimuli for image interpreatation) are: tone and color, size, shape, texture, pattern, shadows, site, and

association (Estes et al., 1983, Lillesand and Kiefer, 1994, Campbell, 1996).
Often, the difficulty of this approach is to transpose the visual features to digital analysis. To overcome these problems, a region based procedure can be used (De wit and Clevers, 2004, Carleer et al., 2005). The segmentation, before classification, produces regions which are more homogeneous in themselves than with nearby regions and represent discrete objects or areas in the image. Each image region then becomes a unit analysis and makes it possible to avoid much of the structural clutter.
The segmentation has other advantages; it allows measuring and using a number of features, on top of spectral features (Thomas et al., 2003, Herold et al., 2003). These features can be the surface, the perimeter, the compactness (area/perimeter²), the degree and kind of texture (Johnsson, 1994). The segmentation is one of the only method which ensures to measure the morphological features (surface, perimeter, shape…) (Segl and Kaufmann, 2001) which may be especially useful when very high spatial resolution data are available (Jensen and Cowen, 1999), and the textural features without taking into account nearby regions, unlike per-pixel methods for which a mobile window is used with an arbitrary neighborhood (Carleer and Wolff, 2004).
The features computed on the regions are then used in the classification process that becomes a region-based classification. The region-based classification provides a logical transition from the units of pixels to larger units in maps (Ryherd and Woodcock, 1996) by allowing an individual object to be classified and labeled as a single object rather than a collection of disparate pixels (Thomas et al., 2003). Moreover, the region-based classification provides a database containing classified land parcels in a format more closely aligned to the actual landscape structure and more suited to current GIS-based environmental applications (Smith and Fuller, 2001, Marçal et al.,2005, Weis et al., 2005). Unlike a conventional map, these data could be used as a storage framework and analysis tool for other datasets in later analyses (Smith ad Fuller, 2001). Because of the wealth of intra-object detail in the VHR satellite data, higher level image primitives (e.g. lines, regions, etc) will be more useful in interpretation than pixels (Guindon, 2000). The region-based classification might provide a further significant improvement of map accuracy and help to overcome spectral similarities between specific classes (Herold et al., 2003).
Then, this method makes it possible to approach visual interpretation which remains the reference.
In this context, the main objective of the study is to present the potential of the VHR satellite data region-based classification to identify the land-cover classes in different kind of Belgian landscape. The potential study was made through the study of region feature relevance to classify land-cover classes. The relevant features are then used in a land-cover region-based classification in order to assess their relevance, and in a more general context, to assess the potential of the VHR satellite data region-based classification for the land cover identification.

2. STUDY AREA, IMAGE AND FIELD DATA

The study areas are situated in Belgium. One is situated in the center of city of Ghent (urban area) and the other at 33 km in the south-east of Brussels and covers a large rural area principally characterized by croplands and pasture lands, but also by roads, isolated buildings, rivers, water bodies and villages.
The image data on the city of Ghent is an ortho-rectified QuickBird image acquired on August 23, 2002 with a spatial resolution of 0.63 m in the panchromatic band and 2.5 m in the multispectral bands.
The image data on the rural area are ortho-rectified SPOT and Ikonos images, acquired on March 17, 2004 and June 7, 2004, respectively. The data cover a surface of 74 km² and the spatial resolutions are 20 m for the MIR SPOT band, 10 m for the green, red and NIR SPOT bands, 4 m for the blue, green, red and NIR Ikonos bands and 1 m for the panchromatic Ikonos band. In this case, we used time series satellite data because in general, the use of time series satellite images is required for an accurate classification of most agricultural crops (Jewell, 1989, Murakami et al., 2001). This study will show also if the time series data are relevant compared to the features calculated after segmentation of the VHR data for the agricultural land-cover classification.
The Direction of Agriculture (Walloon Region, Belgium) provided the crop declarations of year 2004 and the crop field delineation for the study zone. These data were used to carry out the legend, the training and evaluation set for the rural classes.

3. METHOD

3.1. Segmentation

The segmentation technique used in this study is a "Region Growing" technique implemented in the eCognition software developed by Definiens Imaging (Definiens, 2005). The procedure starts at each point in the image with one-pixel objects and in numerous subsequent steps smaller image objects are merged into bigger ones, throughout a pair-wise clustering process. This segmentation technique makes it possible to segment the image on several levels. Each level is made up of the merger of the lower level regions. In this study, different levels were carried out on the basis of two different sets of VHR image bands (only PAN, and mustispectral bands + PAN). Only the VHR images were used, because we wanted to keep the maximum accuracy for the boundaries location.

3.2. Legend

The land-cover legend used in this study is a hierarchical legend with three main classes (Table 1). They subdivided into 17 land cover mainly based on land cover colors and vegetation types or crops (level 2). The three grey levels, the very reflective surface and the red surface are further divided according to intra-class land use (level 3): transportation area and building. For the

Table 1 Legend

Level 1		**Level 2**		**Level 3**
vegetation	1	shadow on vegetation	11	
		shrub and tree	12	
		grass (permanent meadow or pasture)	13	
		winter wheat	17	
		winter barley	18	
		textile flax	20	
non covered crop field	2	sugar beet	14	
		potato	15	
		ensilage maize	16	
		chicory	19	
non-vegetation	3	shadow on non-vegetation	21	
		water	22	
		red surface	23	transportation area **301**
		very reflective surface	24	
		light grey	25	building **302**
		medium grey	26	
		dark grey	27	

Table 2 Features calculated after segmentation

spectral features		textural features		morphological features	
mean of VHR bleu band	s1	St. Dev. of VHR bleu band	t1	Area excluding inner regions	m1
mean of VHR green band	s2	St. Dev. of VHR green band	t2	Lenght	m2
mean of VHR red band	s3	St. Dev. of VHR red band	t3	Width	m3
mean of VHR NIR band	s4	St. Dev. of VHR NIR band	t4	Length/Width	m4
mean of VHR pan. band	s5	St. Dev. of VHR pan. band	t5	Perimeter	m5
mean of VHR NDVI	s6	St. Dev. of VHR NDVI	t6	Compactness	m6
mean of SPOTgreen band	s7	St. Dev. of SPOT green band	t7		
mean of SPOT red band	s8	St. Dev. of SPOT red band	t8		
mean of SPOT NIR band	s9	St. Dev. of SPOT NIR band	t9		
mean of SPOT MIR band	s10	St. Dev. of SPOT MIR band	t10		
mean of SPOT NDVI	s11	St. Dev. of SPOT NDVI	t11		
ratio of VHR bleu band	s12	Homogeneity on VHR pan. band	t12		
ratio of VHR green band	s13	Homogeneity on VHR NIR band	t13		
ratio of VHR red band	s14	Homogeneity on SPOT NIR band	t14		
ratio of VHR NIR band	s15	Contrast on VHR pan. band	t15		
		Contrast on VHR NIR band	t16		
		Contrast on SPOT NIR band	t17		
		Dissimilarity on VHR pan. band	t18		
		Dissimilarity on VHR NIR band	t19		
		Dissimilarity on SPOT NIR band	t20		
		Entropy on VHR pan. band	t21		
		Entropy on VHR NIR band	t22		
		Entropy on SPOT NIR band	t23		
		Angular second moment on VHR pan. band	t24		
		Angular second moment on VHR NIR band	t25		
		Angular second moment on SPOT NIR band	t26		

study on the urban area, the main class "non-covered crop field" (level 1), the corresponding level 2 classes and the level 2 classes "winter wheat", "winter barley" and "textile flax" were not used.

3.3. Features

Forty-seven features were calculated on each region of each level for each class (Table 2). These features can be distributed in three categories: the spectral, textural and morphological features. The spectral features contain the mean of the 9 spectral bands, the mean of VHR image and SPOT NDVI, and 4 ratios of VHR image bands. The textural features contain the Standard Deviation of all spectral bands and NDVI, and five Haralick textural features calculated on the PAN and NIR VHR image band, and on the NIR SPOT band (Homogeneity, Contrast, Dissimilarity, Entropy and Angular Second Moment) (Haralick et al., 1973). The morphological features contain the area, length, width, length/width, perimeter and compactness of the regions.

3.4. Feature selection

In order to find the most suitable features for each class at each segmentation level, the public domain program "Multispec" was used. This program was designed for the analysis of multispectral and hyperspectral image data. The most suitable features are found by calculation of class separability based on the Bhattacharyya distance. The Bhattacharyya distance is defined as:

$$B=\frac{1}{8}[\mu_1-\mu_2]^T\left[\frac{\Sigma_1+\Sigma_2}{2}\right]^{-1}[\mu_1-\mu_2]+\frac{1}{2}\mathrm{Ln}\frac{\left|\frac{1}{2}[\Sigma_1+\Sigma_2]\right|}{\sqrt{|\Sigma_1||\Sigma_2|}}, \quad (1)$$

where μ_i and Σ_i are the mean vector and the covariance matrix of class i, respectively.

The Bhattacharyya distance is a sum where the first part represents the mean difference component and the second part the covariance difference component. A general problem results from having no defined thresholds in terms of class separability. However, this measure can be used to assess separability of land cover classes and to prioritize features that contribute most to discrimination among the land cover classes of interest (Herold t al., 2003). The Bhattacharyya distance provides a separability score between each land cover class for a given set of features. This information can be used to identify the features that contribute the largest amount of separation of these classes. The Bhattacharyya distance measure is derived from training areas selected in each level for each class. These training areas were selected by an expert on each segmentation level, as it is commonly done.

The top 5 feature combinations for best average separability are calculated for a combination of four features, for each level of the legend, on each level of the segmentation.

3.5. Classification

The relevant features and segmentation levels, found with the Bhattacharyya distance, are used in a land cover region-based classification, in order to see the practical advantage of their use. These classifications are performed in the eCognition software with a nearest neighbor classifier and the accuracy assessment of the classifications is calculated with random validation sets of points at each level of the legend. The use of points rather than polygons for the accuracy assessment ensures to provide statistically independent points (Herold et al., 2003). In order to do the comparison between the region-based and the pixel-based classification, a pixel-based classification is carried out with the same training set and accuracy is assessed with the same evaluation set. This pixel-based classification is performed with a maximum likelihood classifier.

4. FEATURE SELECTION RESULTS

4.1. Discrimination of the legend level 1 classes

In this test, the separability is calculated between the legend level 1 classes. The most relevant features are different for the rural and urban study area because of the different used classes (Table 3).

The only common feature is the "Mean of the VHR NDVI" and it is not surprising; NDVI is very often used for the identification of the vegetation compared with the non-vegetation.

Table 3 Four most relevant features for the discrimination of the legend level1 classes

Urban study area	Rural study area
Mean of VHR NDVI	Mean of VHR NDVI
Ratio of VHR red band	St. Dev. Of VHR NIR band
Ratio of VHR NIR band	St. Dev. Of VHR NDVI band
Angular Sd M on VHR Pan band	Angular Sd M on VHR NIR band

4.2. Discrimination of the vegetation classes (legend level 2)

In this test we calculated the separability between the vegetation legend level 2 classes. The most relevant features are different for the rural and urban study area because of the different used classes and different used features. Indeed, for the rural study area, there are also the features calculated on the SPOT data (Table 4).

Table 4 Four most relevant features for the discrimination of the vegetation classes

Urban study area	Rural study area
Mean of VHR green band	Mean of VHR NIR band
Homogeneity on the VHR Pan band	Mean of SPOT green band
Angular Sd M on VHR Pan band	Mean of SPOT NDVI
Angular Sd M on VHR NIR band	St. Dev. Of VHR NIR band

For the Urban study area, the majority of the relevant features are textural, which confirms the visual interpretation where textural features are very important in VHR data vegetation analysis.
On the other hand, for the rural area, the result shows that the multi-temporal spectral features are more effective than the spatial features, calculated thanks to the segmentation (textural and morphological features). The use of image taken on several dates during the growing cycle is very common and advisable for crop airphoto identification (Lillesand and Kiefer, 1994).

4.3. Discrimination of the non covered crop field classes (legend level 2, only for the rural study area)

In this test, the separability is calculated between the sugar beet, potato, ensilage maize and chicory classes. The most relevant features are the mean of VHR red, NIR and NDVI band, and the Angular second moment of the VHR NIR band.
There are almost only spectral features from only one date.

4.4. Discrimination of the non-vegetation classes (legend level 2)

In this test, the separability is calculated between the shadow on non-vegetation, water, red surface, very reflective surface, light grey, medium grey, dark grey classes. The same classes were used for the urban and rural study areas.
The most relevant features are very similar for the both study area (Table5).

Table 5 Four most relevant features for the discrimination of the non-vegetation classes

Urban study area	Rural study area
Mean of VHR green band	Mean of VHR red band
Mean of VHR red band	Ratio of VHR blue band
Ratio of VHR red band	Ratio of VHR red band
Ratio of VHR NIR band	Homogeneity on the VHR Pan band

There are almost only spectral features but it is not surprising because the classes are defined by their color. The separability is good for the majority of the classes, but some separabilities of class pair remains low. These class pairs are: water – shadow on non-vegetation, dark grey – shadow on non-vegetation, light grey – medium grey and medium grey – dark grey. For each problematic class pair, the best separabilities are calculated. The best separabilities for these problematic class pairs were obtained with spectral and textural features for the both study areas. Despite the color definition of the classes, the textural features play an important role to identify these classes.

4.5. Discrimination of the legend level 3

Also in this test, the used classes are the same for the both study areas. The separability is calculated between the transportation area and the building classes. The most relevant features are almost identical for the both study areas (Table 6).

Table 6 Four most relevant features for the discrimination of the legend level3 classes

Urban study area	Rural study area
length	Angular Sd M on SPOT NIR band
length / width	length
area excluding inner regions	length / width
compactness	compactness

There are almost only morphological features, and it is not surprising; the transportation area and building classes are land use classes and the relationship between spectral or textural features and land use is, in most instances, both complex and indirect (Barnsley and Barr, 1997). Despite this, many land use categories have a characteristic spatial expression (Barnsley and Barr, 1997) as showed in this test.

4.6. Relevant segmentation level

The previous tests showed that there is a parallel between the suitable features and the segmentation levels.
When the suitable features are only spectral features, the segmentation level has little importance. It does not influence the spectral information as so long as the objects are well defined. For example, the best separabilities for the legend level 2 vegetation classes for the rural study area are not significantly different between the different segmentation level, and were found with almost only spectral features (see 4.2).
On the other hand, it is on upper segmentation levels that the textural or morphological features are suitable. On these levels, the region shape or texture is better defined. At the lower levels, the regions are too small for a good textural or morphological identification. There is an over-segmentation, which happens when the segmentation process identifies too many boundaries. For the both study areas, the suitable segmentation levels do not exceed the fifth level. On the upper levels, all objects of the study zone are badly defined. There is probably under-segmentation.
The results show that the suitable segmentation level depends little on the legend level, as one could have expected it. These tests showed also the utility of multilevel segmentation in order to better define the classes.

5. CLASSIFICATION RESULTS

The relevant features, found with the Bhattacharyya distance, were used in a land cover region-based classification. The classification scheme and results are presented in the Table 7.
The results show an excellent classification of the legend level 1 classes (kappa = 0.99 and 0.91). The classes of the legend level 2 are well classified for the vegetation classes (kappa = 0.70 and 0.78) and for the non-vegetation classes (kappa = 0.78 and 0.82). It is not the case for the rural study area with the 'non covered crop field' classes; the classification results is bad (kappa = 0.48). This bad result is not surprising; visually, the identification of these four classes was already very difficult. The use of a third date, at the end of Augustus for example, when these fields are covered by crops, could improve this result.
The accuracy for the classification of 'building' and 'transportation area' classes is good for the rural study area (kappa = 0.73) and better than the results obtained in urban area

Table7 Region-based classification result

	kappa			kappa			kappa	
Level 1	**Urban**	**Rural**	**Level 2**	**Urban**	**Rural**	**Level 3**	**Urban**	**Rural**
vegetation	0,99	0,91	shadow on vegetation	0,7	0,78			
			shrub and tree					
			herb (permanent meadow or pasture)					
			winter wheat					
			winter barley					
			textile flax					
non covered crop field			sugar beet		0,48			
			potato					
			ensilage maize					
			chicory					
non-vegetation			shadow on non-vegetation	0,78	0,82			
			water					
			red surface			transportation area	0,51	0,73
			very reflective surface					
			light grey			building		
			medium grey					
			dark grey					

for the same classes (kappa = 0.51). In rural area, the buildings and the roads are better defined than in urban area. There is less occlusion of roads by the shadows or cars. The shape of the buildings is clearly defined because the houses are surrounded by vegetation and the houses are not adjoining, while the houses are smaller and adjoining in the urban area.
The pixel-based classification was performed with only the vegetation classes (legend level 2) for the rural stud area. The result is good (kappa = 0.73) but less good than the region-based classification result (kappa = 0.78). Visually, the region-based classifications show the almost disappearance of the salt and pepper effect visible in per pixel classification (Fig 4). This effect is badly represented in the kappa index, but is easily visually observable.

6. CONCLUSION

This study shows the potential of the region-based classification to identify the urban, rural and agricultural land cover and above all the crop types. This classification process overcome the problem of salt-and-pepper affect, very present in the per-pixel classifications, and makes easier the use of GIS.
This study shows also the utility of features calculated thanks to the segmentation. The morphological and textural features are very useful to classify many classes, principally the non-vegetation classes. These features overcome the poor spectral resolution of the VHR data. The study shows the segmentation utility in order to calculate the features on specific region without taking into account the nearby regions. The segmentation is one of the only methods which ensure to measure the morphological features (surface, perimeter, shape…) which are essential in the classification of the building and transportation area classes, when many studies used ancillary data (road buffer, D.E.M., existing maps …) to classify them.
However, these additional features are not useful in all cases. The results show that the time series spectral features are more effective than the spatial features, calculated thanks to the segmentation, for the discrimination of the vegetation classes in the rural study area and above all for the crop classes. That does not mean that the segmentation is useless, the segmentation allows to avoid the "salt-and- pepper" effect in the classification process for these classes.
In the previous tests, it is interesting to note that there is a parallel between the visual interpretation features and the features quantitatively selected. The visual interpretation features are used to interpret airphoto, but with the VHR satellite images the gap between the satellite images and the airphotos strongly decreased. The tests show that the visual interpretation could be a good mean to guide the choice of features but it does not allow to choose a specific feature because they are too much of it. Then, a quantitative selection, like Bhattacharyya distance, is essential to do the choice.
The study shows also the multi-level segmentation relevance to identify the rural land cover classes. However, contrary to what one might think, the suitable segmentation levels have a parallel with the suitable features, and not with the legend levels.
The relevance of the selected features and segmentation levels is confirmed by the good results of the region-based classifications. The region-based classification results show the potential of this technique to classify the land cover of the rural area with very high spatial satellite images.

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