# A Fully Segment-Based Method
# for the Classification of Satellite Images

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**Abstract.** This paper presents a novel implementation of the *thematic classification of data obtained via remote sensing.* The identification of land cover categories on images is particularly important in the agricultural applications of remote sensing. Better results can be achieved in the analysis of satellite images than in the case of pixel-based classification generally applied for digital images, if the similarity between the neighbouring pixels of land cover is utilised. To achieve this, one possible solution is the segment-based approach. The segment-based classification method introduced in the authors' previous article ([7]) has been improved. The possibility of joining the adjacent homogeneous image objects has been made more flexible. Furthermore, the whole procedure has consequently been made segment-based: the units of both clustering and class assingment have become segments instead of pixels. Besides, the human expert knowledge needed earlier at specific points of the classification has essentially been built into the program.

## 1 Introduction

Remote sensing (RS) has a continuously increasing role in survey, observation and control activities related to agriculture. In the past years, several monitoring tasks were supported by remote sensing in Hungary. Crop mapping and yield forecasting, flood, waterlog and drought monitoring, applications related to area-based subsidies and ragweed (ambrosia) control and exemption can be mentioned, among others. Remote sensing provides a sophisticated and cost-effective technology to monitoring activities, but the research and methodology that support the applications are also crucial points of the successful solution.

## 2 A Brief Overview of Remote Sensing

Earth observation satellites (e.g. Landsat and NOAA series) gather information from the Earth's surface. The reflected electromagnetic radiation is detected in several wavelength intervals, and the result is stored in a *remotely sensed*

*image*, a kind of digital image. A definite part of the whole electromagnetic spectrum, called optical band, has dominant importance in RS. The radiation of the surface is measured by sensors, each capturing a given subinterval of the spectrum. A multispectral image can be regarded as a matrix, the elements of which correspond to a given spot (approximately a square-shaped area) of the surface. The elements of image matrix, called *pixels*, are themselves vectors of the intensity values recorded by the different sensors.

RS images are categorised by four principal parameters. (1) *Pixel size* is the area of the surface spot belonging to one pixel, that is, the smallest distinguishable area. Most images in our practice — the high resolution (HR) images — have a pixel size in the $25\,\text{m} \times 25\,\text{m}$ magnitude. (2) The available *spectral bands* and the respective wavelength intervals determine the possible thematic applications. (3) *Radiometric resolution* refers to the number of distinguishable intensity levels. The intensity values are usually the integer values of the interval 0–255 in the case of HR images. (4) *Period of acquisition* (e.g. 16 days) is the time between the passes of a given satellite over the same area.

Before starting the analysis of images, some *preprocessing steps* are carried out. Geometric and radiometric corrections transform the raw images into a uniform spatial and spectral system. The effects disturbing detection and data transfer can be decreased by atmospheric correction and noise filtering. In the case of several images, preprocessing steps make it possible to use them simultaneously in thematic mapping applications.
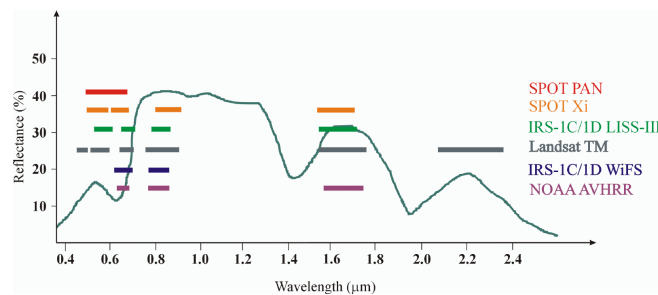


**Fig. 1.** A typical reflectance function of vegetation and the spectral bands of some satellite sensors

The ratio of reflected and incident radiation, the so-called *reflectance* heavily depends on the land cover and the wavelength. The *reflectance function* of a given land cover gives the reflectance along the optical band. Every land cover category has its own characteristic reflectance function, which depends on the phenological phase and the maturity of vegetation. This fact can be used to make distinction between land covers, which is a fundamental requirement of RS. Figure 1 shows the reflectance function of a typical cultivated crop. Horizontal

lines in the figure show a few examples of the spectral bands covered by some satellite sensors.

Practical applications of determining land covers include *vegetation mapping* as well as flood, waterlog and drought monitoring. Remote sensing minimizes the need for "traditional" survey in the field. It yields immediate, coherent and accurate results even for large areas at a relatively low unit cost. Richards [1] and McCloy [2] give detailed introduction to the topic of remote sensing and its applications.

## 3  The Traditional Pixel-Based Classification

The task of thematic classification is to produce a digital thematic map of a certain area. The pixels of a thematic image usually refer to categories of land cover (classes) — this is an important difference from satellite images, where pixel values contain radiation intensities in spectral bands. The set of categories can be rather varying among the different applications: they can not only represent crop species, but they can show the severity of drought, and they can make distinction between the areas affected by waterlog.

The input of classification methods consists of one or several satellite images. They usually use a set of known thematic data (reference data), stored as thematic maps describing the parts of examined area that are known in advance. They are divided into two parts: training reference data (training areas) are used to determine the distributions describing land cover categories, while test reference data are the basis of accuracy assessment. The complex procedure of classification is usually not completely automatic; it is often improved by the interaction of a human expert.

Throughout this article, a *vegetation mapping* (crop mapping) application is taken as an example, where the task is to determine the crop species on agricultural areas with $25\,\mathrm{m} \times 25\,\mathrm{m}$ spatial resolution (see Csornai et al., [3]).

The vegetation period and the progress of development of different crops can be rather varying throughout the year, but their reflectance often coincides in a given period. This is why images from multiple dates are necessary to create an adequate classification. Figure 2 shows a satellite image series of three dates, taken of the same area. The simplest way to involve multi-temporal data into the classification is when several images of the target area, having different acquisition dates, are "stacked together" to compose a multi-layer image.

It is a known observation in remote sensing that a large amount of pixels representing the same crop species show nearly normal distribution, or can be approximated with several normal distributions. The following assumption is made as the principle of traditional classification task: each thematic category (e.g. wheat) can be described with the composition of appropriate *spectral subclasses*, each subclass having multivariate normal distribution in the multi-dimensional intensity space.

The pixel-based classification method described in [7] has been significantly modified. As a consequence, deep analogy can be observed between the pixel-
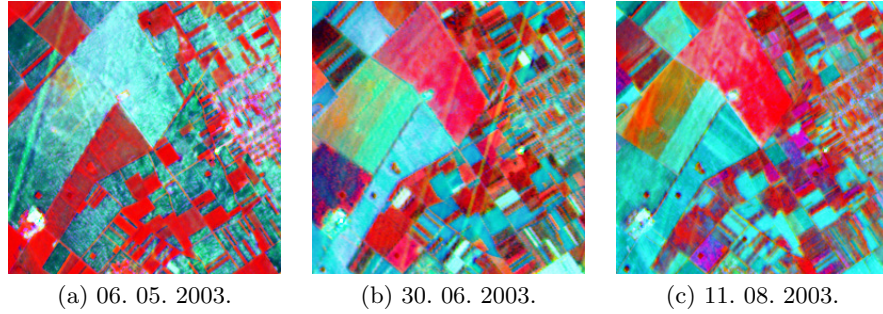
|                     |                     |                     |
| ------------------- | ------------------- | ------------------- |
| (a) 06. 05. 2003.   | (b) 30. 06. 2003.   | (c) 11. 08. 2003.   |

**Fig. 2.** A satellite image series of the sample area

based and segment-based classification. Together with accuracy assesment, the classification procedure consists of four major parts.

1. The first step in determining classes is *clustering*. This is an unsupervised procedure, in which no preliminary information (reference data) is used from the target area. Clusters are compact groups of the intensity space that characterise land cover categories. During this procedure, in each iteration the cluster map shows the assignment of cluster identifiers to pixels. In the procedure, the pixels of clusters with few elements and ones being far from every cluster are not classified. At the end of procedure the mean vectors and covariance matrices (together: the signatures) of the clusters are calculated. Clusters determine the initial values of the spectral subclasses of land covers.
2. In the second step, in the *training phase* the aim is to assign a land cover category to each spectral subclass.
   In this step, the spectral subclasses that build up the distribution of pixels belonging to crops, as introduced above, are formed, starting from the clusters evolved in the first step. The input of this step is the original image, the map of training reference data and the cluster map. Its output is the signature set of spectral subclasses together with the assugnment between them and land cover categories.
   Firstly, the pixels of image are assigned again to the clusters. This yields a new "cluster map" instead of the original one. The assignment is done with the maximum-likelihood method. Every $x$ pixel is classified to the cluster $\omega_k$ for which the following probability is maximum:

$$p(x|\omega_k) = (2\pi)^{-N/2}|\Sigma_k|^{-1/2}e^{-(x-\mu_k)^\mathrm{T}\Sigma_k^{-1}(x-\mu_k)/2} \tag{1}$$

   However, if even the maximum probability is small (i.e., according to the $\chi^2$ test of hypothesis, the point does not fit into the cluster with a probability of 99%), then it is not classified.
   Next, the correspondence between clusters and reference areas is examined. For each cluster, the intersection of the points belonging to it and the ref-

erence categories is determined. The next procedure assigns a label to every cluster:

If there is not enough reference area compared to the cluster size
Then
    If the cluster is large
    Then the cluster is *to be reclassified*
    Else the cluster is *to be abandoned*
Else
    We search for the crop that intersects the most with the cluster
    If this crop does not intersect sufficiently
    Then the cluster is *to be reclassified*
    Else
        We search for all the relevant crops
        If there is only one relevant crop
        Then the cluster is *classified*
        Else the cluster is *to be cut*

After the decision made within this procedure, we remember the only relevant crop for the *classified* clusters, and all the relevant crops for the clusters *to be cut*.

3. In the *classification phase* the pixels belonging to the labelled clusters are classified into land cover categories.
Firstly, the pixels of clusters *to be reclassified* are classified with maximum-likelihood decision into one of the clusters that are *classified* or *to be cut*. The points not fitting into any cluster are abandoned.
Next, the signatures of the reference pixels belonging to the relevant crops within clusters *to be cut* are determined. The parameters of distributions assumed to be normal are estimated on the basis of the intersection of the cluster and the reference areas of relevant crops. Then the points belonging to the cluster are classified into one of these "subclusters" with maximum-likelihood decision, but at this point, the pixels not fitting into the subcluster are not abandoned.
Finally, the pixels of *classified* clusters are assigned to the class of the only relevant crop.
In the resulting image, the majority of pixels are assigned with a class. The pixels abandoned in the initial clustering, the ones of the clusters *to be abandoned* and the ones abandoned during the reclassification fall into the unknown category, that is, they have not been classified.

4. Finally, an *accuracy assessment* is carried out with the usage of the test reference areas. In the case of high error rate, some of the previous steps are executed again with a modified parameter setting. (See the details in [8].)

It has to be noted that this "pixelwise" classification method completely ignores the identity or similarity of the neighbouring pixels in homogeneous areas (i.e., falling into the same agricultural parcel), as it uses only the intensity of pixels.

Figure 3 illustrates the result of the clustering (a) and the classification (b) for a known area.
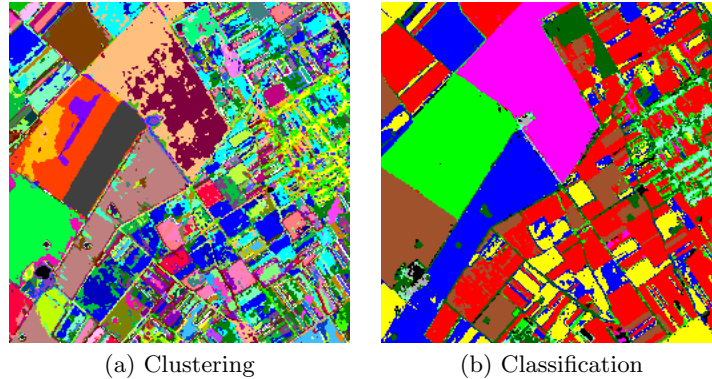


(a) Clustering (b) Classification

**Fig. 3.** The result of pixel-based processing

## 4 The Method of Segment-Based Classification

A possible improvement of the traditional pixel-based classification method is to group certain pixels into so-called textitsegments and to apply further classification steps to segments. The segmentation procedure described here is based on the method given by Kettig and Landgrebe [5], which was enhanced at several points (see, for example, Fekete and Farkasfalvy [6], László et al. [7]). Several further segmentation procedures are known, Schoenmakers [4] has written a a detailed overview on them. The algorithm of segmentation is described in details in the next section.

In the variant of segment-based classification described in [7] the so-called textitsegment-based filtering was applied after segmentation. This means that the value of each pixel was replaced by the average intensity value of the segment containing the pixel. It was followed by pixel-based clustering and classification, during which the pixels belonging to the same segment remained together. However, the information on deviation of the segments has been lost, which makes it hard to differentiate between segments that belong to different land cover categories, but have similar mean intensity.

In the method chosen in this paper, segments "pass through" the whole clustering and classification. The segments themselves are clustered and classified instead of tracing back the procedure to a pixel-based one. Due to this choice, less information is lost. This solution conforms to the model in which the distribution of intensity values within a segment can be approximated with a normal distribution. The mean ($\mu$) and the covariance matrix ($\Sigma$) describing the distribution can be calculated from original intensity values.

The segment-based classification procedure has been improved at one further point. The classification of segments instead of pixels helps in the preservation of the homogeneities present in images, which stem from the properties of nature. However, this approach is not adequate enough to categorise the border points and heterogeneous areas necessarily present in images. This is why the classification method is finished with a step in which the categorisation of every point is revised. The automatic procedure for the assignment between clusters (or spectral subclasses) and thematic categories, presented in Sect. 3 (Step 2 and 3), is applied also in the segment-based approach.

## 5  The Segmentation of Images

In [7] a method was presented to take into account the position of pixels — in this case, information derived from the adjacency — in the classification procedure. To achieve this, a segmentation procedure was applied before the "classical" clustering and classification. A *segment* is a contiguous set of adjacent, spectrally similar pixels. The result of segmentation is a thematic map, called the *segment map*, which contains the number of the respective segment for each point.

Several significant improvements have been made on the method described in [7]. Firstly, the dependence upon the processing order was reduced. Secondly, the borders of segments can be more refined, which results in segments better conforming to the real status of the surface. The aim of the algorithm is to delineate spatially contiguous and statistically homogeneous areas. Adjacent pixels that probably belong to the same land cover — according to an appropriate similarity criteria — are grouped into the same segment.

In the first step of the segmentation algorithm, the image is subdivided into cells with $2 \times 2$ size. Then a decision is made on each cell whether it can be considered homogeneous. A cell is homogeneous if the following inequality holds in every band (where $n$ is the number of pixels in a cell; in this case, $n = 4$):

$$\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{(n-1)\bar{x}^2} \leq C_H \tag{2}$$

The condition means that in every band, the deviation remains under a certain limit compared to the average intensity. The pixels of inhomogeneous cells are not categorised into segments, and a region-growing algorithm is run on the homogeneous cells.

The algorithm passes through the rows of cells from up to down, and cells are taken from left to right within a row. For each cell, a test is made whether it can be connected to an existing cell, based on a contraction rule. Due to the order in the examination of cells, in Fig. 4 cells 1, 2, 4, 6 are already the members of some cell (it is possible that they are forming a segment in themselves). In the following, a decision is made to which of them cell 0 can be connected. First all the possibilities are examined, then one or more of the possible connections are chosen.
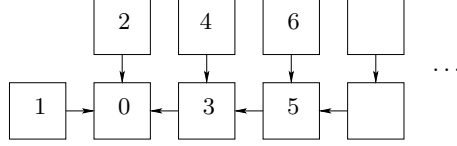
**Fig. 4.** The order of the contraction of cells

Firstly, it is examined whether cell 0 can be connected to cell 1 or 2, as shown in the figure.

Next, a decision is made whether cell 3 can be connected to the segment containing cell 4, and if so, whether cell 0 can be connected to this new segment (3 plus the segment of 4).

$6-5$, $6-5-3$ and $6-5-3-0$ connections are examined similarly (assuming the preceding consitions are met). Looking ahead to the right can be arbitrarily extended (depending on a runtime parameter), as is illustrated in the figure.

Among the connection possibilities examined the one with the smallest distance between the segment and the cell is chosen. If intermediate cells are parts of a connection, then during the consecutive contracions, the maximum segment-cell distance is taken into account. If neither of the above connections is possible, then a new segment is initiated with the current cell.

The decision on the possible contractions is made on the basis of ANOVA-like criteria determined by the means and standard deviations of segments. Let $x$ and $y$ denote a sample (segment) with $m$ and $n$ elements (points), respectively, and let $z$ mean the distribution resulted from the contraction of $x$ and $y$. The following quantites are calculated in each band:

$$A_x = \sum_{i=1}^{m}(x_i - \bar{x})^2 \qquad A_y = \sum_{i=1}^{n}(y_i - \bar{y})^2 \qquad A = A_x + A_y \tag{3}$$

$$B_x = \sum_{i=1}^{m}(x_i - \bar{z})^2 \qquad B_y = \sum_{i=1}^{n}(y_i - \bar{z})^2 \qquad B = B_x + B_y \tag{4}$$

Segment contraction is allowed with respect to a certain band if both the following inequalities are met for given $C_1$ and $C_2$ values:

$$(A/B)^{(m+n)/2} \geq C_1 \tag{5}$$

$$\left( \frac{(A_x/m)^{m-1}(A_y/n)^{n-1}}{(A/(m+n))^{m+n-2}} \right)^{1/2} \geq C_2 \tag{6}$$

Two segments are allowed to be contracted if inequalities (5) and (6) are met in every band.

As a result of an appropriately parametrized decision procedure, a segment map is obtained where the connected parts expectedly belong to the same land

cover category. On the other hand, one land cover category can be composed of several segments — either lying far from each other or adjacent ones. A segment map of the previously introduced sample area is shown in Fig. 5, together with a satellite image so that they can be easily compared.
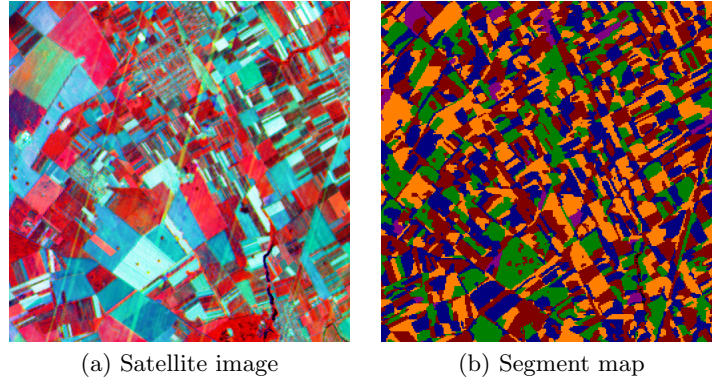


(a) Satellite image          (b) Segment map

**Fig. 5.** The result of segmentation

## 6    Segment-Based Clustering

In an earlier phase of the work (see [7]) segment-based classification was traced back with an appropriate substitution to the application of pixelwise clustering and pixelwise classification, as was mentioned in Sect. 4. Since then, a segment-based clustering procedure has been developed, which categorises segments instead of pixels.

The Isodata clustering algorithm has been modified so that it deals with segments. The general scheme of the algorithm consists of the following steps:

**Step 1** Initial cluster centres are chosen
**Step 2** Segments are assigned to the nearest cluster centre
**Step 3** Small clusters are abandoned
**Step 4** Clusters near to each other are contracted
**Step 5** Large clusters are subdivided
**Step 6** If the stopping criterion is not met, then the algorithm is continued from Step 2 with new cluster centres derived from the current clusters

In the algorithm there are several possibilities in the choice of applied methods, distance functions and parameters.

In Step 1, initial cluster centres are chosen randomly, according to a normal distribution that approximates the best all the intensity values present in the

image. Such a random point is obtained if you add to the empirical mean vector an independent vector of standard normal distribution multiplied with the Cholesky-decomposition of the empirical covariance matrix.

In Step 2, segments are assigned to the centre with the minimum Euclidean distance from the points of segment (using quadratic mean). However, if even the minimum distance is higher than a certain threshold, the segment is not assigned to any cluster. The mean Euclidean distance between centre $x$ and segment $\omega$ is

$$d(\omega, x) = \sqrt{\sum_k \mu_k^2 - 2\mu_k x_k + x_k^2 + \sigma_{kk}} \ . \tag{7}$$

In Step 3, clusters with number of elements less than a given threshold are abandoned.

In Step 4, clusters with similar intensities are contracted. To achieve this, the separability of the empirical distributions determined by the clusters is examined (distances are meant in the intensity space). To measure this between clusters $\omega_i$ and $\omega_j$, the Bhattacharya distance is used:

$$d(\omega_i, \omega_j) = \frac{(\mu_i - \mu_j)^{\mathrm{T}} \left( \frac{\Sigma_i + \Sigma_j}{2} \right)^{-1} (\mu_i - \mu_j)}{8} + \frac{1}{2} \ln \frac{\left| \frac{\Sigma_i + \Sigma_j}{2} \right|}{\sqrt{|\Sigma_i||\Sigma_j|}} \tag{8}$$

In the current algorithm, the subdivision in Step 5 is not applied. With the choice of appropriately many initial cluster centres, the occurence of clusters having significant intersection with several land cover categories can be minimised or eliminated.

The algorithm stops after a pre-defined number of iterations. Another stopping criterion, the movement of centres, could be applied: the algorithm would stop if the movement of cluster centres, using an appropriate norm, is small within two consecutive iterations.

The normal distributions in spectral space, determined by the algorithm, are considered the result of clustering. They are described with the mean vectors and covariance matrices (see the first step of the classification algorithm in Sect. 3). Certain pixels do not take part in the formation of signatures: first, the points that were out of scope of segmentation (that is, the points that fell into inhomogeneous cells), second, the points of segments far from all clusters. An illustration for the result of segment-based clustering is shown in Fig. 6.

## 7   The Thematic Classification of Segments

The aim of segment-based classification is the determination of the distributions constituting the land cover categories. As mentioned, several distributions may belong to a thematic category, and this is why the term "spectral subclass" is used. In the first step the segments of image are again assigned to the evolved clusters. The assignment is done with the maximum-likelihood method, as in the case of the pixel-based approach.
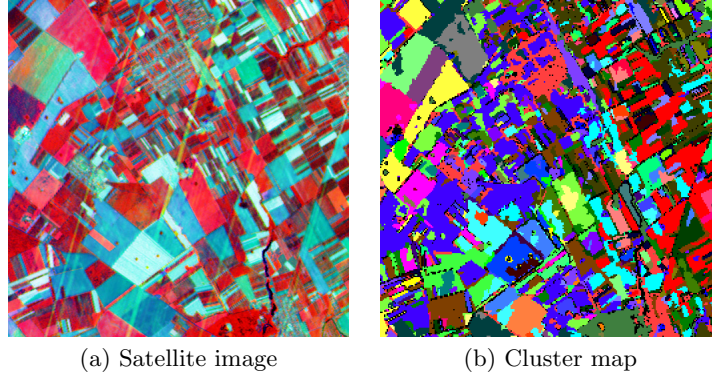
(a) Satellite image      (b) Cluster map

**Fig. 6.** The result of segment-based clustering

The logarithmic average of probabilities over the pixels of segment is used as discriminant function in the maximum-likelihood decision:

$$\mathrm{E}(\log P(\omega_s|\omega_k)) = \tag{9}$$

$$= \frac{\sum_{x\in\omega_s} -\frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma_k| - (x-\mu_k)^\mathrm{T}\Sigma_k^{-1}(x-\mu_k)/2}{n_s} =$$

$$= -\frac{N\log(2\pi) + \log|\Sigma_k| + \mathrm{tr}(\Sigma_k^{-1}(\Sigma_s + \mu_s\mu_s^\mathrm{T})) - 2\mu_k^\mathrm{T}\Sigma_k^{-1}\mu_s + \mu_k^\mathrm{T}\Sigma_k^{-1}\mu_k}{2}$$

The average of $\chi^2$ values over the pixels is used in the $\chi^2$ decision:

$$\mathrm{tr}(\Sigma_k^{-1}(\Sigma_s + \mu_s\mu_s^\mathrm{T})) - 2\mu_k^\mathrm{T}\Sigma_k^{-1}\mu_s + \mu_k^\mathrm{T}\Sigma_k^{-1}\mu_k \tag{10}$$

The algorithm assigns all the segments to a cluster, except the ones not belonging to any cluster with 99% probability, according to the $\chi^2$ test. This yields a new "cluster map" instead of the original one.

Next, the intersection of reference areas and the cluster map is calculated. Each cluster is assigned by a label with the same procedure used in the pixelwise case (see Sect. 3, second step). The label of clusters can be *to be abandoned*, *classified*, *to be reclassified* and *to be cut*. The processing of clusters, depending on labels, is formally the same as in the pixelwise case. It has to be noted that during the assignment between segments of clusters *to be cut* and intersections of clusters and reference data categories, the logarithmic discriminant function introduced above is used again.

After these steps the primary classification of image has evolved. Its result is that almost all the segments are assigned to one of the land cover categories. It may happen that a segment draws in a pixel not fitting to its category. Another possible drawback is that the grouping of pixels into cells makes the handling of border points coarser. Because of this, the primary classification is revised by a

pixelwise $\chi^2$ test of hypothesis at a level of 99%, implicitly applying the test for the subclusters of clusters *to be cut*.

Finally, the so-called pointwise correction follows: the pixels fallen out during the revision of segmentation, clustering and classification are assigned with maximum-likelihood method to a cluster that is *classified* or *to be cut* (or into one of its subclusters), and through this mapping, into a thematic category. However, the $\chi^2$ test at a level of 99% is also applied for this categorisation.

After these steps, for all the pixels categorised at the end of procedure, the assignment of the thematic category is reasonable. The test reference areas are used in accuracy assessment, as in the case of the pixel-based case. Figure 7 illustrates the result of the segment-based classification for the sample area introduced earlier.
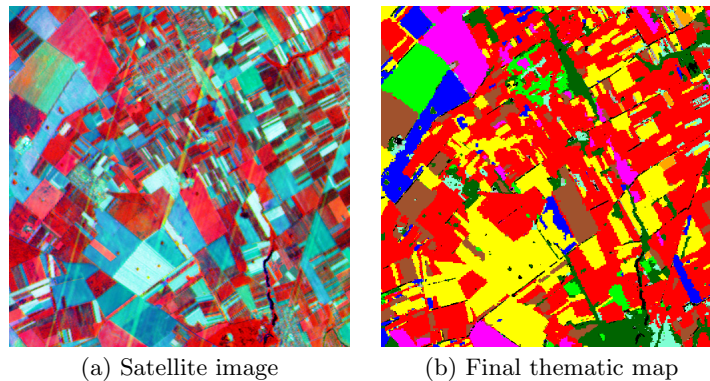


(a) Satellite image          (b) Final thematic map

**Fig. 7.** The result of segment-based classification

## 8    Conclusions and research perspectives

This article has presented possible developments for several steps of thematic classification, improving the final result both qualitatively and quantitatively.

Compared to the method described in [7], within the algorithm of segmentation the conditions of joining different segments were made more flexible and symmetrical. Owing to this, the result is more realistic and is less dependent on the processing order of cells, while the efficiency has been kept. Besides, the algorithm has become less sensitive to the parameters (for example, $C_1$ and $C_2$ in (5) and (6)).

The most conspicuous result of applying clustering for segments instead of pixels is the increase of speed: the number of objects to be clustered decreases by several orders of magnitude. Furthermore, while the deviation of segments was ignored because of the segment-based filtering, now this kind of information is also utilised.

The authors have implemented a version of Isodata clustering, which is more robust if spectrally isolated points are present.

As a quantitative evaluation of classification, it can be stated that the thematic accuracy is usually higher when using segment-based methods. With appropriately chosen parameters the global accuracy can be increased by about 2-3% on average. In the following, a typical confusion matrix is presented in the pixel-based (Table 1) and in the segment-based (Table 2) case.

The result of classification is also improved by the possibility of allowing the separated processing of pixels not fitting to their neighbourhood or to the majority of the image, which might otherwise distort the result.

**Table 1.** The confusion matrix of a pixel-based classification

|  | C0 | C1 | C3 | C4 | C10 | C12 | C13 | C14 | C22 | C27 | C40 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | 392 | 9394 | 128 | 93 | 0 | 0 | 0 | 0 | 0 | 22 | 0 |
| C3 | 14 | 1681 | 522 | 0 | 0 | 0 | 0 | 0 | 2 | 7 | 0 |
| C4 | 51 | 325 | 0 | 207 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| C10 | 227 | 218 | 0 | 0 | 3650 | 1 | 19 | 0 | 73 | 5 | 0 |
| C12 | 19 | 0 | 0 | 0 | 2 | 5702 | 0 | 0 | 0 | 4 | 6 |
| C13 | 26 | 0 | 0 | 0 | 72 | 43 | 11476 | 0 | 3 | 0 | 0 |
| C14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 981 | 0 | 0 | 0 |
| C22 | 0 | 3 | 0 | 0 | 20 | 0 | 2 | 0 | 2551 | 17 | 8 |
| C27 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 484 | 0 |
| C40 | 3 | 1 | 30 | 0 | 32 | 0 | 0 | 0 | 13 | 0 | 5381 |

Overall accuracy          91.8%

**Table 2.** The confusion matrix of a segment-based classification

|  | C0 | C1 | C3 | C4 | C10 | C12 | C13 | C14 | C22 | C27 | C40 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| C1 | 121 | 9352 | 513 | 32 | 0 | 0 | 0 | 1 | 3 | 7 | 0 |
| C3 | 16 | 57 | 2142 | 1 | 0 | 0 | 0 | 0 | 6 | 4 | 0 |
| C4 | 20 | 323 | 0 | 238 | 0 | 0 | 0 | 0 | 2 | 0 | 0 |
| C10 | 190 | 10 | 2 | 0 | 3816 | 84 | 10 | 0 | 59 | 22 | 0 |
| C12 | 7 | 0 | 7 | 0 | 1 | 5701 | 0 | 0 | 0 | 8 | 9 |
| C13 | 25 | 0 | 0 | 0 | 6 | 73 | 11436 | 0 | 75 | 0 | 5 |
| C14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 981 | 0 | 0 | 0 |
| C22 | 2 | 2 | 1 | 0 | 5 | 7 | 0 | 0 | 2582 | 1 | 1 |
| C27 | 1 | 4 | 0 | 0 | 0 | 2 | 0 | 0 | 10 | 470 | 0 |
| C40 | 1 | 0 | 83 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5376 |

Overall accuracy          95.9%

In agricultural applications, the advantages of segmentation are best seen in the distinction between spectrally similar arable land crops. This is why this method utilises the regularity of parcels resulted by the cultivation structure. For example, making distinction between maize and sunflower based solely on their spectral characteristics is rather difficult: in the case of common pixel-based classification, it might happen that an area belonging to one parcel contains both pixels classified as maize and ones classified as sunflower, in irregular arrangement. However, within a heterogeneously developed parcel, segmentation can better "keep together" the pixels with different intensities — see Fig. 8. Therefore, more realistic classification result is obtained locally, in the interior of the parcels. Nevertheless, at the border of different land covers it may happen that the result of pixel-based classification is more appropriate. In summary, due to the dominance of interior pixels, using the segment-based method usually increases the global accuracy.
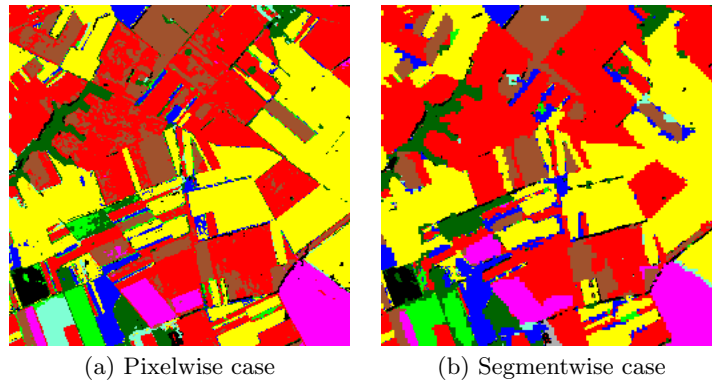


(a) Pixelwise case          (b) Segmentwise case

**Fig. 8.** The decrease in confusion as the result of segmentation

In this article, a crop mapping application was taken as an example. Indeed, during the development and the explanation of the methods the properties of agricultural areas were taken into account. However, segmentation can also be used in other thematic classification applications, for example forest mapping, waterlog monitoring and general mapping of land cover categories (not restricted to agricultural areas).

The method was developed to work with optical satellite images with similar parameters, especially, with identical spatial resolution. However, it can also take other kinds of remote sensing data as input (e.g. aerial photos, radar images), if identical pixel size is provided, possibly with the resampling of input data. Furthermore, with some modifications, prior resampling can be avoided, and the handling of different resolutions can be integrated into the program.

In the classification phase reference data — used in the form of thematic raster maps — is usually derived from a vector layer resulted from e.g. GPS

survey. Other vector layers can be similarly integrated, which may increase the classification accuracy.

In its present state, the segmentation procedure uses solely the input raster images themselves to delineate segments, but it is possible to involve other prior knowledge to improve the results. With a method similar to the one used in the classification phase, even vector layers can be used. The use of cadastral data seems to be promising in agricultural and other land cover mapping applications, but it can lead to errors if the borders of official administrative cadastral parcels do not match the actual cultivation structure. In countries using physical or farmer blocks as the reference units of Land Parcel Identification System (the reference system of agricultural subsidies), the layer of block boundaries may effectively complement the input satellite images. If recent topographical maps are available in vector form, certain layers of them can also be used as an aid in segmentation. Basically, these kinds of vector data are appropriate to give "hints" to the program about the location of segment boundaries. They can improve the accuracy, and, as they usually limit the looking ahead in the procedure (see Section 5), and in general, the size of segments, the method can be also made more efficient with their usage.

Thorough testing of the possibilities and advantages of introducing preliminary geographical data into the classification is the subject of further research.

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