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COMPUTER SCIENCE

SPATIAL DECISION SUPPORT SYSTEMS

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The satellite image processing is an important tool for decision making in domains like agriculture, forestry, hydrology, for normal activity tracking but also in special situations caused by natural disasters. In this paper it is proposed a method for forestry surface evaluation in terms of occupied surface and also as number of trees. The segmentation method is based on watershed transform which offers good performances in case the objects to detect have connected borders. The method is applied for automatic multi-temporal analysis of forestry areas and represents a useful instrument for decision makers.

Keywords: Satellite images, watershed transform, segmentation, Geographic Information System.

1. INTRODUCTION

The decision process is the activity of choosing a future action between two or more alternatives. The action alternatives are defined after one or more objectives and requirements are analyzed and evaluated. The alternative for which the objectives are best met is the chosen decision. Decisions are taken by each person in everyday life, even if this process is in most cases not conscious. In case of organizations, the decision making process is more complex and usually a large number of possible choices have to be analyzed and evaluated. Geographic position is an important attribute of information used in decision making, especially for organizations. Most authors consider that about 80% of data used by managers and decision makers is geographically related [20, 24] and the amount of spatial information collected, managed, and analyzed has grown in the last years. In [27] is estimated that the mapping of data is essential for about 33% and important for other 56% of business intelligence activities. According to [13], the main chara-cterristics of Spatial Decision Problems (SDP) are: a large number of alternatives, spatial variability of the results, results are obtained using multiple criteria which may be qualitative or quantitative, more decision makers with different preferences are involved in evaluation and the most important, the decision process result is uncertain.

Because Geographic Information Systems (GIS) are complex applications in which the spatial position is the main information and all other data is related to it, it's difficult to use the GIS capabilities in other stand-alone applications. Usually the decision modules are embedded in GIS and are used as extensions of the main application. A strategy for integration of Multicriteria Analysis (MCA) in GIS is presented in [6]. In the first step different multicriteria evaluation functions are integrated in GIS and then, in the second step, the model for multicriteria aggregation procedure is defined. The separation of multicriteria evaluation functions allows the final decision support system to be more flexible. The complexity of spatial decision systems, problems encountered in GIS and Expert Systems integration are analyzed in [8]. The ability to model the real world is influenced by the inter-operability of these two components and once integrated the resulting tool is more powerful than any of its components.

In this paper, a method is proposed for multi-temporal analysis of forestry resources in inaccessible areas. The method is based on image processing techniques applied for multispectral remote sensing images. In most cases, remote sensing images are either optical images or radar images. Unlike optical images that are sensitive to light and cloud coverage of the studied area, radar sensors allow the acquisition of images in all lighting conditions.

The goal of satellite image processing is to turn them into images that can be more easily analyzed automatically or by a human user, to assess automatic or interactive objects or events depicted in the image. By analyzing satellite images it is possible to obtain useful information in various domains, such as agriculture, forestry, and hydrology. In agriculture, it is possible to determine the occupancy of the land, vegetation status or the areas affected by natural disasters. In forestry, the satellite images may be used to obtain information for deforested woodland tracking, forest road surveillance or areas affected by diseases or natural disasters. In terms of hydrology, flooded areas can be determined to assess the damages, identification of changed watercourses or water works supervision.

2. GIS AND DSS

A Geographic Information System (GIS) is an information system that allows the acquisition, storage, validation, integration, manipulation, analysis and visualization of data related to points on the earth surface [28]. A Geographic Information System was defined also as a system that integrates all the resources involved in geospatial data processing: applications, computers, information, people, rules and methods [20]. Geospatial data is the name used for all data describing earth surface features: objects and phenomena characterized by their geographical position. Geospatial data include two types of data: (1) *spatial data* which describe the location and geometry and (2) *attributes* of the earth surface features.

Usually, spatial data is organized in layers depending on what they represent (countries, counties, villages, cities, buildings, roads, railways, watercourses, and s.o.) as depicted in Figure 1. All the elements on the same layer are characterized by the same (or similar) attributes. The most used models for spatial data representation are: the *vector data model* and the *raster data model*. In *vector data models*, all spatial features are described by points, lines and polygons. The main advantages of the vector data model are: it offers a very compact description of the real world; the possibility to show or hide layers; fast rendering using different level of details. There are also disadvantages like: curve lines must be approximated by a large number of description points and textures can be represented only as graphical symbols. The *raster model* uses scanned maps and/or aerial or satellite images whose resolution limits the rendering quality and increases the memory requirements. The possibility of multiple layers usage is only simulated by image transparency. Mixed models, vector and raster are often encountered in practice.

The attributes are organized in databases which include a table for each layer of spatial data and each table contains a record for each element in the corresponding layer. Supplementary information which is not necessarily linked to specific geospatial elements but is used in GIS analysis may be included in external relational databases. Their format and content depend on the problem to solve or the analysis that must be done.

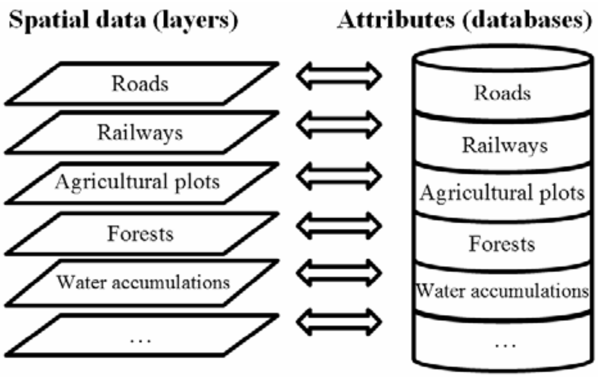


Fig. 1. Geospatial data organization as layers
in Geographic Information Systems.

As a conclusion, a geospatial database integrates a wide range of information from various sources having different forms of representation: raster and vector images, topographic measurements and relational databases. The association of information with the geographic position allows reducing the redundancy, interconnecting multiple databases and offers the possibility to analyze data and display the results at different levels of detail.

An example of a mixed model (raster and vector) is depicted in Figure 2.

a. Raster image of a forestry area (from [26])

b. Mixed model, raster and vector overlapped images

Fig. 2. Raster and vector models in GIS.

In Figure 2b it is shown a vector layer which describes the polygonal shapes of the forestry areas in the raster image (Fig. 2a). The corresponding attributes table includes for each polygonal element: identification information of the parcels, name, owner, total area, occupied area, number of trees, species, medium age, surface percent affected by diseases, surface percent affected by natural disasters. Results of periodical evaluations either by terrain observation or by automatic analysis of aerial or satellite images may be included in external databases.

In SDSS (Spatial Decision Support System) development, different models have been used. The most natural option is to include the spatial model into DSS, but this method is too difficult to implement while GIS are stand-alone applications oriented for maps manipulation. For these reason, in most cases, DSSs are implemented as modules in GIS applications [12].

A SDSS model to study the effects of industrial pollution on health is presented in [17]. The effects of water pollution, pesticide exposure and power lines location are studied in the proposed SDSS. A framework for land use analysis and change detection using a Geographic Resources Decision Support System and multispectral data is presented in [16]. SDSS are also used in administration for planning the urban infrastructures, as it is presented in [7]. The proposed model, based on spatial and temporal analysis is used for generating statistical spatial data and understanding the land ecosystem dynamics. More complex systems for the acquisition of plant data using vision systems, laser scanners and crop quality sensors with wireless data transmission are used to collect data used in a SDSS for irrigation to support farmers in efficient and sustainable management of orchards [15]. SDSS are used also for forest cover change detection, degradation prediction and monitoring [1, 5, 19, 23, 25].

3. REMOTE SENSING IMAGE ANALYSIS

Multi-temporal analysis of forestry areas requires to periodically evaluate the density of trees, the occupied area for each parcel. This evaluation can be performed by inspecting each area of interest or automatically using aerial or satellite images and image processing techniques. For automatic evaluation, segmentation techniques are used to detect the crown of trees if their boundaries are visible.

Image segmentation is the partitioning process of an image in disjoint homogenous regions representing background and foreground objects which are then used in classification, recognition or other evaluations. Properties of the image areas such as color intensity value or texture properties are used to find the border of detected objects [4, 10, 11]. In most cases the foreground objects are connected and supplementary geometric criteria must be used for single object detection. Segmentation result can be evaluated using objective criteria but usually they are compared to the human perception which is related to the purpose of the segmentation. More elaborated segmentation methods allow obtaining results closer to the semantic content of the image. In [21] and [22] a Gauss-Uniform Noise Mixed Models (GUN-MM) based segmentation method which is less sensitive to noise and computationally efficient is presented. Image fusion techniques are also used to combine the results of several segmentation methods in order to obtain more accurate results [3].

The procedure proposed in this section is applied for the segmentation of remote sensing images representing forestry areas. While the objects occurring in images have a similar texture and also are touching each other, the Watershed transform is used for precise boundary detection [18]. To avoid the problem of touching objects, in the segmentation procedure, the distance transform [9] is used to define the markers used in the watershed transform.

The idea of the watershed transform is to see the image as a digital elevation model of a terrain surface, placing sources of water in the local minimum positions and then filling the relief basins. When different basins have to be merged, barriers are built to avoid this situation. The filling process is stopped when the water level exceeds the highest position of the terrain surface [4, 10, 18]. Finally, the created barriers (watershed lines) specify the borders of the segmented regions. The watershed transform provides good results in case of noisy or irregularly textured images.

In the standard definition of watershed transform, for gray level images, the flooding starts from local minima values. In case of noisy or highly textured images this may lead to over-segmentation – objects of interest are segmented in more than one region. The same situation appears when there is no relation between regional minima and the objects in the image [10]. This situation can be avoided either by using markers in the watershed transform or by merging the over-segmentation resulted regions using clustering algorithms as in [10]. In our approach, the foreground markers – areas from which the flooding process starts –

are defined using the distance transform. It evaluates for each pixel in the image the minimum distance to a background (black) pixel. The distance transform is usually used to find boundaries of certain area and also for comparing binary images resulted from feature detection procedures [9].

The proposed segmentation procedure is described below (Fig. 3). In the first preliminary step, image enhancement techniques are applied: histogram equalization, noise removal and also image coordinates transform if required. Usually, the remote sensing images use the UTM (Universal Transverse Mercator) coordinates system. For future analysis and comparisons of the results to information included in local GIS databases, a conversion to the local coordinates system is required. For Romania, the local coordinates system is Stereo-70.

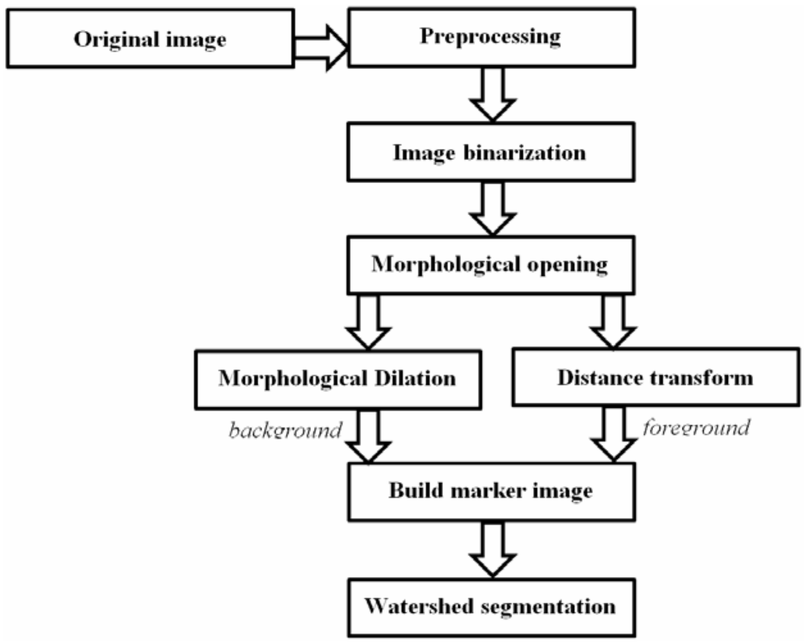
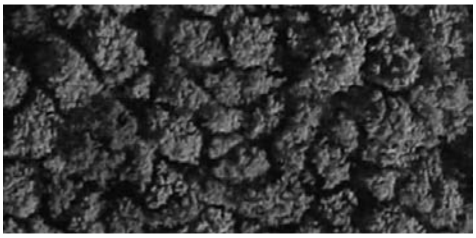


Fig. 3. Structure of the image analysis system.

Due the fact that images we intent to process are highly textured, a simple thresholding procedure is not enough to find the markers for the watershed transform. To apply the watershed transform, a supplementary filter in which image pixels are classified as *background*, *foreground* and *unknown* has to be applied.

To find the background of the scene, first a thresholding is applied to the *Green* band of the input RGB image (Fig. 4a). As it is depicted in Figure 4b the objects in the processed image are touching each other and also a lot of noise (vary small objects and small holes in large objects) is included. To remove this noise, morphological filters are applied: opening to remove small objects and dilation to remove the holes. The remaining black area is considered to be the background of the image.

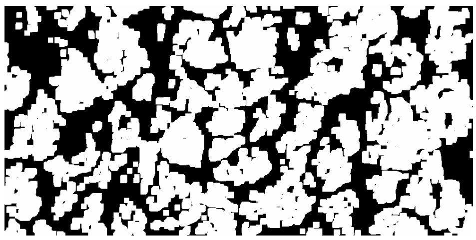
The final result depends on the first binarization step. While the input image depends on the acquisition conditions, two different adaptive binarization methods are used. The first one is the Otsu's method, which assumes that the image contains two classes of pixels (background and foreground) and then searches for a threshold that minimizes the variance within each class [14]. Considering that the images we process may contain different species of trees, with different ages or vegetation status, a multi-thresholding method based on the Particle Swarming Optimization Algorithm (PSO) is also applied. It finds a user defined number of thresholds by minimizing an error measure computed between the original and the segmented image [2]. In the experiments presented in this paper, the Root Mean Square Error (RMSE) was used as objective function for error minimization, but also the Structural Similarity Index (SSIM) is available in the current implementation to be used as objective function which must be maximized in the optimization process.



a. Original Image “test_1” (from [26])

b. Binarized image (Otsu method)

c. Result of morphological open operation

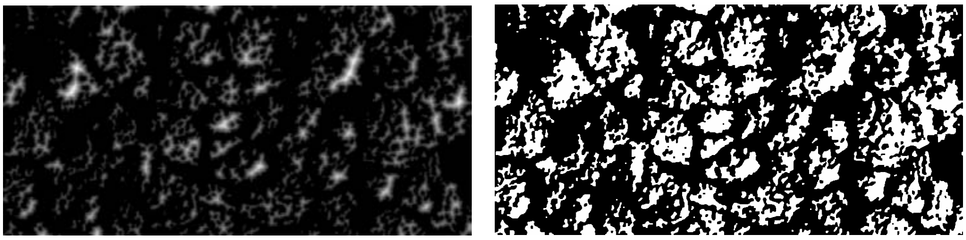


d. Result of morphological dilation operation (background)

Fig. 4. Background image detection.

After the background was determined (black pixels in Fig. 4d) the remaining foreground objects are still connected, almost all contours contain an area which includes more trees.

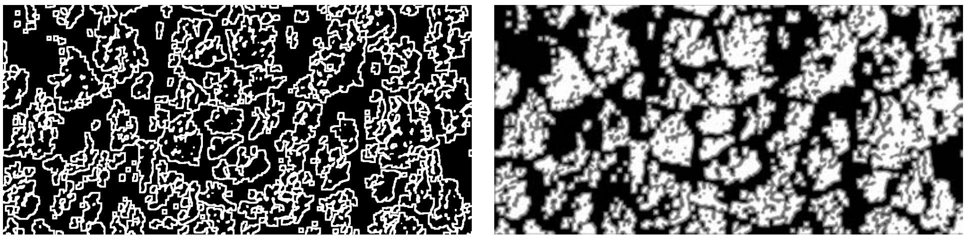
To find the foreground objects and disconnect them, the distance transform is applied to the morphological opening output and then the distance image is binarized. The binarization threshold is computed multiplying the maximum pixel value of the distance image by a threshold factor which is determined by experiments (Fig. 5b).



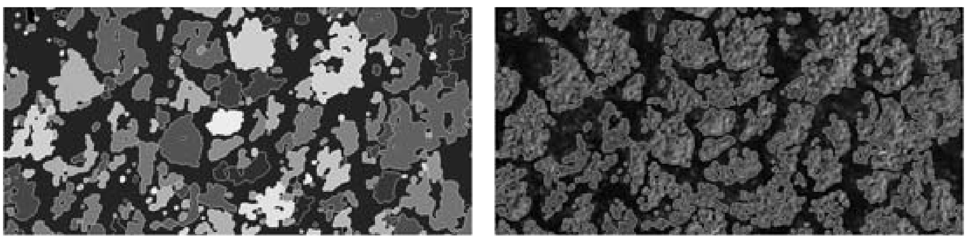
a. Result of distance transform b. Result of the distance transform image binarization (foreground)

Fig. 5. Foreground image determination.

The image areas that are not classified as background or foreground are denoted as *unknown*. It is obtained simply by computing the difference between background and foreground images (Fig. 6a). The unknown area is the subject of watershed segmentation and the object contours will be found in this area. The watershed markers image is built by setting to 0 the pixels corresponding to background area, to 1 the pixels corresponding to unknown area and other distinct values for each foreground object.



a. unknown area b. markers (white: foreground markers, black: background markers, gray: unknown)



c. detected objects d. final segmentation result

Fig. 6. Watershed segmentation results.

The following section describes the results of the segmentation procedure and the evaluation of the detected objects.

4. EXPERIMENTS

The proposed method was applied for color images downloaded from [26], with different resolutions. In this section the results obtained for two images (test_1 and test_2) are presented. The first image, test_1 has a resolution of 0.055 m/pixel (Fig. 4a) and the second image has a resolution of 0.217 m/pixel (Fig. 7a).

The intermediary images and segmentation results obtained for image "test_1" were presented in the previous section (Figs. 4, 5 and 6). The following tables show a comparison of results obtained by using the two binarization methods (Otsu and PSO) and also by varying the number of iterations in the morphological open and morphological dilation operations.

In Table 1 there are presented the results obtained for image "test_1" by applying the Otsu segmentation in the first binarization step. The table contains the following columns: number of iterations applied in the morphological open procedure, number of iterations applied in the dilation step, the threshold factor applied for distance transform image binarization, number of detected objects, the average area in m^2, area variance, the occupied area percent and the density computed as number of trees/ha.

Table 1

Results obtained for image "test_1" using Otsu binarization

Nr.	#open iterations	#dilation iterations	Thr. factor	# Objects	Average Area	Variance	Area %	Density
1	1	3	0.1	217	2.9	32.1	43.0	1485
2	1	4	0.1	240	2.9	34.0	47.7	1642
3	**2**	**3**	**0.1**	**230**	**2.5**	**21.2**	**40.0**	**1574**
4	2	4	0.1	259	2.5	22.1	44.5	1772
5	2	5	0.1	282	2.5	22.9	48.5	1930
6	3	5	0.1	254	2.3	16.0	40.8	1738

The visual analysis of the results reveals that in the first two cases many objects are connected, and in cases (4), (5) and (6) we obtained an over-segmentation of the objects. The best solution was obtained in the third case, when 2 open iterations and 3 dilation iterations were applied. In all experiments a threshold factor of 0.1 was applied for distance transform image binarization. If higher values are used some foreground objects are missed.

Because in the image the occupied area may have different color intensity, in the second experiment we applied the multiple threshold segmentation based on Particle Swarming Optimization. The second column of Table 2 shows the number of thresholds computed. Considering that always the background pixels have a lower color intensity, the first computed threshold was used for image binarization.

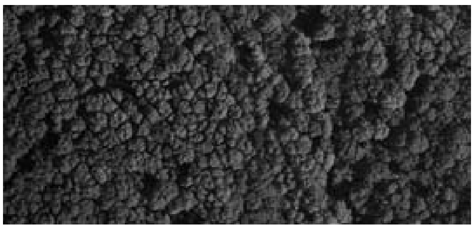
Table 2

Results obtained for image “test_1” using PSO based binarization

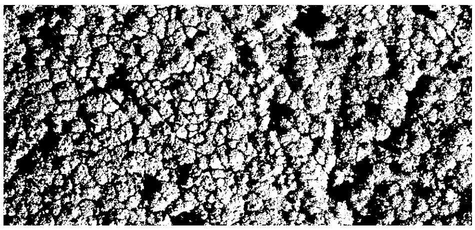
Nr.	**Thrs**	**#open iterations**	**#dilation iterations**	**Thr. factor**	**# Objects**	**Average Area**	**Variance**	**Area %**	**Density**
1	2	1	3	0.1	222	2.8	29.4	42.2	1519
2	**2**	**2**	**3**	**0.1**	**236**	**2.4**	**19.2**	**39.0**	**1614**
3	3	1	3	0.1	134	5.9	135.6	53.8	917
4	3	2	3	0.1	136	5.5	101.8	51.6	931

The best results were obtained in the second case, when 2 thresholds were determined. In the first case, many objects are not correctly segmented and others are connected. Similarly, in the last two cases many detected objects are connected.

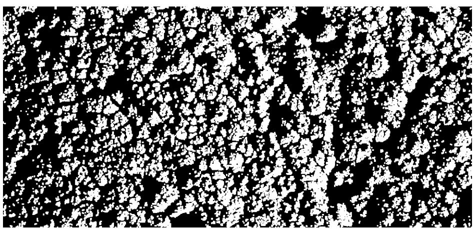
The second test image has a lower resolution of about 0.217 m/pixel. It’s obvious that in this case the background is less visible so that the situation of connected objects will be often encountered (Fig. 7). To avoid this situation, the number of morphological open iterations will be always 1.



a. Original Image “test_2” (from [26])

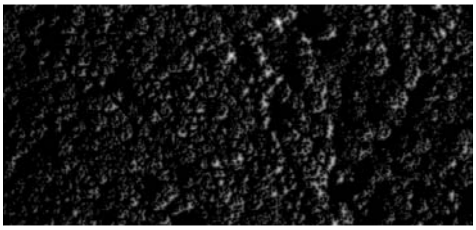


b. PSO based binarization result



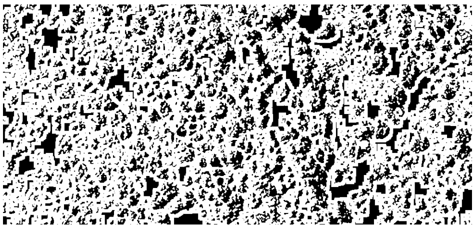
c. Result of morphological open operation

d. Result of morphological dilation

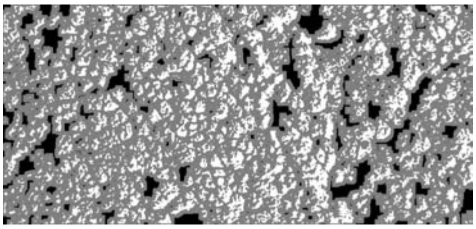


e. Result of distance transform

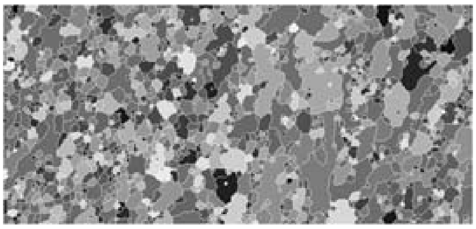
f. result of the distance transform image binarization



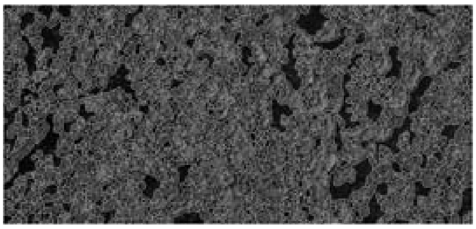
g. unknown area



h. markers (white: foreground markers, black: background markers, gray: unknown)



i. Detected objects



j. Final segmentation result

Fig. 7. Segmentation results steps in case of image “test_2”.

The following tables contain the results obtained by applying the two segmentation methods in the first binarization step.

Table 3

Results obtained for image “test_2” using Otsu binarization

Nr.	**#open iterations**	**#dilation iterations**	**Thr. factor**	**# Objects**	**Average Area**	**Variance**	**Area %**	**Density**
1	1	2	0.1	1469	5.2	106.4	36.3	698
2	1	3	0.1	1472	6.2	129.9	43.5	699
3	1	4	0.1	1472	7.2	152.3	50.1	699
4	**1**	**5**	**0.1**	**1473**	**8.0**	**170.5**	**56.1**	**700**

Table 4
Results obtained for image "test_2" using PSO based binarization

Nr.	Thrs	#open iterations	#dilation iterations	Thr. factor	# Objects	Average Area	Variance	Area %	Density
1	3	1	2	0.1	1391	6.8	322.9	45.2	661
2	**3**	**1**	**3**	**0.1**	**1392**	**8.1**	**394.0**	**53.6**	**661**
3	3	1	4	0.1	1392	9.2	452.4	61.1	661
4	3	1	5	0.1	1392	10.2	502.5	67.4	661
5	3	1	6	0.1	1392	11.0	540.9	72.6	661

For PSO based segmentation, the best results were obtained when 3 thresholds were determined. It must be noticed that in both cases, the number of detected objects and consequently the density of trees remain constant no matter the number of dilation iterations (the only varied parameter). As it was said before, many objects are connected, so the trees density and average area values obtained for this resolution of the input image are not relevant, but the percent of occupied area represents a good evaluation.

For images with lower resolution, as "test_2", some post-processing steps have to be applied to obtain more accurate values for number and density of trees. Considering that usually the shape of the trees crown is circular and in most cases the aspect ratio of the minimal bounding rectangle computed for connected detected objects have values greater than 2, supplementary segmentation steps may be applied in these areas.

In the following paragraphs it is presented how the extracted information may be used in spatial decisions systems. We consider a SDSS which contains information about forestry areas in layer "forest parcels". A simplified version of the attributes database is presented in Table 5. It includes information about its area which can't be changed and also the occupied area and the number of trees at the moment in which the records were added in the database. These values are based on ground observations, but in this experiment the data was randomly generated by the author.

Table 5
Structure of database with forest parcels (simplified)

ID	GIS_ID	NAME	Total area	Occupied	# Trees
101	100210	AAA	2000	1725	112
102	100211	BBB	125000	110200	8720
103	100214	CCC	25000	24500	1450
104	100321	DDD	35000	18500	1820

The results obtained using the automatic evaluation procedure is stored in an external database having the structure described in Table 6. For each processed image and for each parcel the database contain the occupied area and the number of detected trees.

Table 6

Structure of database with automatic evaluation results for parcel 101

Date	**01-07-10**	**21-05-11**	**12-09-11**	**21-08-12**	**12-05-13**	**24-08-13**	**06-06-14**	**22-08-14**
Area [m^2]	1725	1754	1756	1780	1740	820	851	854
# Trees	151	151	150	152	151	79	79	80

Some environmental changes, like deforestation, may be easily detected by decision makers by analyzing the charts generated using the information extracted from satellite images and stored in the external database. Figures 8 and 9 show some examples of such charts based on the detected number of trees and occupied area of the forestry parcels. Some small variations appear also because of the evaluations errors and different image acquisition conditions, but large variations indicate major changes in the forestry lots configuration.

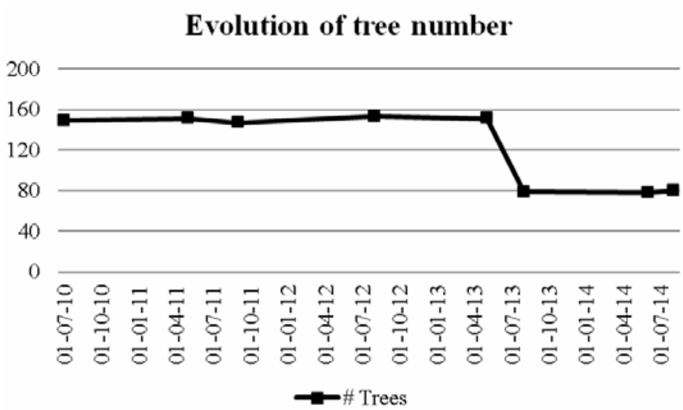


Fig. 8. Evolution of tree number (automatic detection).

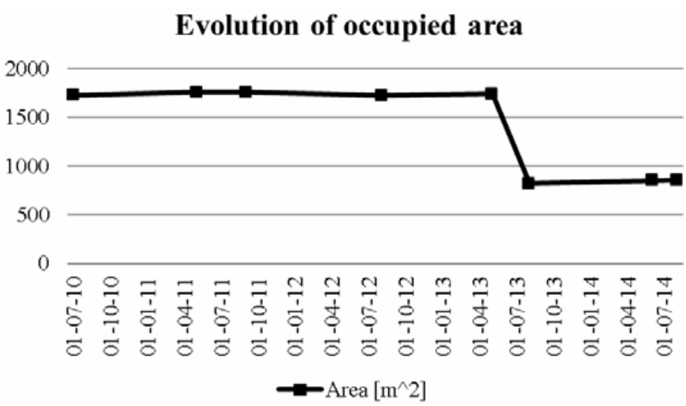


Fig. 9. Evolution of occupied area (automatic detection).

5. CONCLUSIONS

The proposed analysis method was tested on images containing only forestry areas. But this is not the real case, in which also other earth features may be visible in images (residential areas, water surfaces). In such situations, the proposed segmentation method may fail. The solution is to use the spatial information provided by the GIS infrastructure. The interest regions must be cropped from the input images and processed separately. In fact, the final evaluation results are associated in databases to individual elements in the "forest" layer. Another limitation is that for a more accurate analysis, high resolution images are required and some regions of interest may be partially visible. In this case, the solution is also offered by GIS. Partial regions are first cropped from images in which they are visible and then merged in a single image before processing.

The research will be continued by evaluating the measurement errors. It's obvious that some small occupied areas containing young trees with reduced height may be classified as background in automatic analysis. These background areas must be processed in an additional step to detect if the area is really free or it contains reduced height trees. For this step, some additional information obtained by ground observation may be required, facilitating some supervised classification procedures to be implemented. There is also the possibility to use texture classification techniques to obtain a more accurate evaluation of forestry areas.

The proposed instrument is useful for building a spatial decision support system for natural resources management and changes detection.

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