# PIXEL BASED CLASSIFICATION OF IMAGES

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***Abstract**: Nowadays, automation became a basic theme in all the fields of activity. Reducing the operator tasks from a workflow led to the need of research extensions in automation. In Photogrammetry we can start this process from the data collection and going to the final product generation. The main goal of this article is to facilitate the updating process of the National Geospatial Database and to ensure support for different products of our institution. The study was conducted on two types of coverage: extraurban and urban areas, both in Bihor County. The segmentation and classification process used the Single Feature Probability method, considering attributes like spectral signature, texture and shape. The results depend on the initial data, the workflow used and the samples collected.*

***Keywords:** segmentation, classification, nDSM, SFP,RGB image*

## 1. Introduction

Nowadays, the automation of every workflow is the main goal of the engineers. Every institution is using the human resources in this direction. The process of updating the geospatial datasets is very important in the work of a National Mapping Authority, like the National Center of Cartography.

For several years, researchers have tried to obtain the footprints of buildings in an automated manner. For this purpose, many methods have been proposed. Buildings can be extracted from aerial images, from airborne LiDAR data or from a combination of this two data acquisition methods.

When using remote sensing data, the process of image classification can be done more easily and man-made constructions, vegetation, etc. may be automatically mapped and analysed. The intensity value of the pixels in different bands of the multispectral images are used to differentiate objects. If the elevation information is used, besides intensity values, we can distinguish between ground and non-ground objects.

For remotely sensed imagery, the classification can be made by using machine learning, by one of the following methods: decision trees, random forest or support vector machines.  The classifier is trained over known areas, where the class is known. After the training, the image can be classified, obtaining the land cover map. Advanced methods can produce land cover maps with an overall accuracy of more than 80% (Zhang et al., 2015). This raster map is transformed into a vector map and the results are refined and generalized.

One way to generate urban land cover maps is to use as attributes the normalized height, obtained from the normalized digital surface model (nDSM) and the normalized difference vegetation index (NDVI). A research in this direction has been done by Joachim Höhle and Michael Höhle, in an article, from 2013, where they proposed the use of the statistical software environment R. The data consists of aerial images, in the workflow as input data will enter the point cloud generated from this images. The use of thresholds for the nDSM and NDVI values, offers the possibility to classify every point in the corresponding class. The classes used, in their work, are buildings, road and parking lot, trees, hedge and bush and wall and car ports (Höhle,2013).

In this paper, the focus will be in extracting building footprints from aerial RGB images, with the help of elevation data from the nDSM. Besides buildings, we will work on extracting parcel boundaries in extraurban areas based only on images. The steps for an image classification are determination of a classification system, selection of the training samples, image segmentation, feature extraction, post-classification processing and accuracy assesment.

The outline of this paper is the following: after the introduction (Chapter 1), we will focus on the description of the software used (Chapter 2). We will continue with two approaches for image classification, first we will focus on buildings extraction (Chapter 3) and secondly, we will compare the automated classification with the manual digitization for parcel boundaries in extraurban areas (Chapter 4). In the end we highlighted some conclusions about our work and about future opportunities (Chapter 5).

The input data comes from LAKI II Project (Land Administration Knowledge Improvement). This project started in 2017 and covers five counties in the western part of Romania. The project is divided in two: one photogrammetric flight (ground sample distance - 19 cm) to obtain orthophotos and one LiDAR flight (density – 8 points/square meter) for obtaining DTM and DSM.

## 2. Software used in the proposed workflow

### 2.1. IMAGINE Objective - for image classification

IMAGINE Objective is a framework in Erdas Imagine software and provides an automated process of extracting features from imagery. Salient visual image interpretation cues are quantified for a feature, machine learning components are trained with these cues, next these learned cues are applied to the imagery to derive features (Erdas Imagine Help).

After defining the classes, the workflow continues with the selection of training samples. The image is divided into: training set and testing set. From the training set, the software learns some properties of the image and then uses this learned properties to classify the entire image.

In pixel based classification, the classifier is trained on a set of pixels, and then the remainder of the pixels are attributed to one of the classes by the classifier. The number of training samples for every class is a very important aspect in the classification workflow. For a class, the number of training samples must be over 15, taking into account the tested area.

In this paper, the raster pixel processor method used was Single Feature Probability (SFP). This method computes the probability of every pixel from the input image, based on the pixel value and the training samples. The probability is a metric value and a higher value is assigned to those pixels whose values are similar to the ones of pixels in the non-background training samples. The next step is to perform the segmentation, this means to partition the raster image into segments based on pixel values and locations. The software gives two approaches for segmentation:

- standard segmentation (considers only the spectral information and represents an edge detection and region growing algorithm);
- lambda schedule segmentation (considers spectral, texture, size and shape for merging decisions).For the lambda schedule segmentation, the relative weights

control the merging functions. The spectral weight is measured as the mean of the digit number values of the pixels in the segments. The texture weight is measured as the standard deviation of the digit number values of the pixels in the segments. The size component corresponds to the number of pixels in the segment and the shape component is a measurement of the boundary complexity of the segment.

Based on the segmentation method used, there are some operators that can be applied to the segments. In the case of lambda schedule segmentation, the operators are eliminate, focal, probability filter, reclump (this operator renumbers the raster objects so that each raster object has a unique value) and size filter. The following step performed in Imagine Objective is the conversion from raster to vector. The workflow can continue in this framework but we concluded that for our research, the steps presented above are enough.

### 2.2. ArcGIS - for filtering and refinement of the data

A Geographic Information System (GIS) is an ensemble of personnel, equipment, software, methods and regulations, built with the purpose of capturing, storing, manipulating, analyzing, managing, and presenting all types of geographical data (Săvulescu, 1996). To be more precise, GIS is a computer based system with the goal to create maps and to **analyze data** (ESRI). An important aspect of a GIS is the way it organizes the data.

The data stored in a GIS is geographical referenced. Coupled with this data is usually tabular or attribute data. Attribute data can be generally defined as additional information about each of the spatial features (the attributes for a building could be the address, the number of storeys, the material of the roof, etc.). The two primary data types are raster and vector. Raster data is a way of representing images in the form of pixel arrays, while vector data are represented using geometric primitives, like points, lines or polygons. An object) is associated with a unique position in GIS that corresponds to the geographic position in the real world.

The fundamental purpose of geoprocessing is to provide tools and a framework for performing analysis and managing geographic data (ESRI, 2018). Geoprocessing functionality provides a large set of tools for performing GIS tasks, from simple selections to complex image classification. In the software ArcGIS, the selections can be made by location, by attribute or by graphics. This selections are an interactive method of viewing and highlighting the part of the data we need to analyze.

In the following, this software will be used for filtering and refinement of the data obtained from the supervised classification.

## 3. Case study for urban areas

For this paper, the chosen area is located in Oradea City, Bihor County, Romania. The input data consists of an orthophotoimage with a resolution of 20 centimeters, a digital terrain model (DTM) and a digital surface model (DSM), both models with 1 meter resolution. For our workflow we needed the nDSM, this was computed with a tool called *Image Difference*, the result is displayed in Figure 1. The information needed for this raster was transformed in vector format, using a *Spatial Modeler*. The polygons from the *nDSM.shp* were filtered and only the ones that represented buildings were kept.

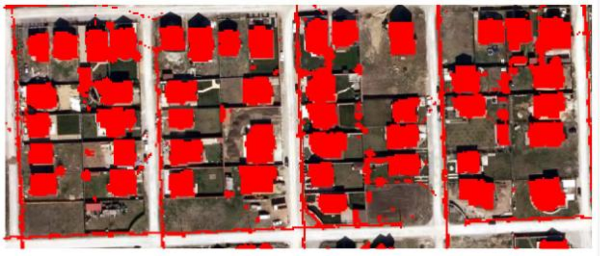

Fig. 1. nDSM

In *Imagine Objective*, we selected two different sets of training samples and used different weights for the segmentation algorithm. Our first approach, Test A, was to use four classes: vegetation, roads, buildings and shadow and to extract 45 training samples, this is shown in Figure 2. The other approach, Test B, used the following classes: vegetation, roads, buildings1 and buildings2 (this classes were separated based on colour) with 38 training samples.

Fig. 2. Training samples TEST A

For the lambda schedule segmentation, were used different combinations of values for the weights, the one used are displayed in Tabel 1. The result is a raster with all the segments obtained with the method described in Chapter 2.1 and it is displayed in Figure 3.

Fig. 3. Segmentation for Test A and for Test B

Tabel 1 – Relative weights used

| Weights | spectral | texture | size | shape |
|---|---|---|---|---|
| Test A | 0.8 | 0.7 | 0.5 | 0.6 |
| Test B | 0.8 | 0.8 | 0.7 | 0.3 |

The next step is to convert raster into vector, so we can say that the shapefile resulted is a primer land cover map. The number of polygons is 1910.

The workflow proposed, for buildings classification, is the one showed in Figure 4.

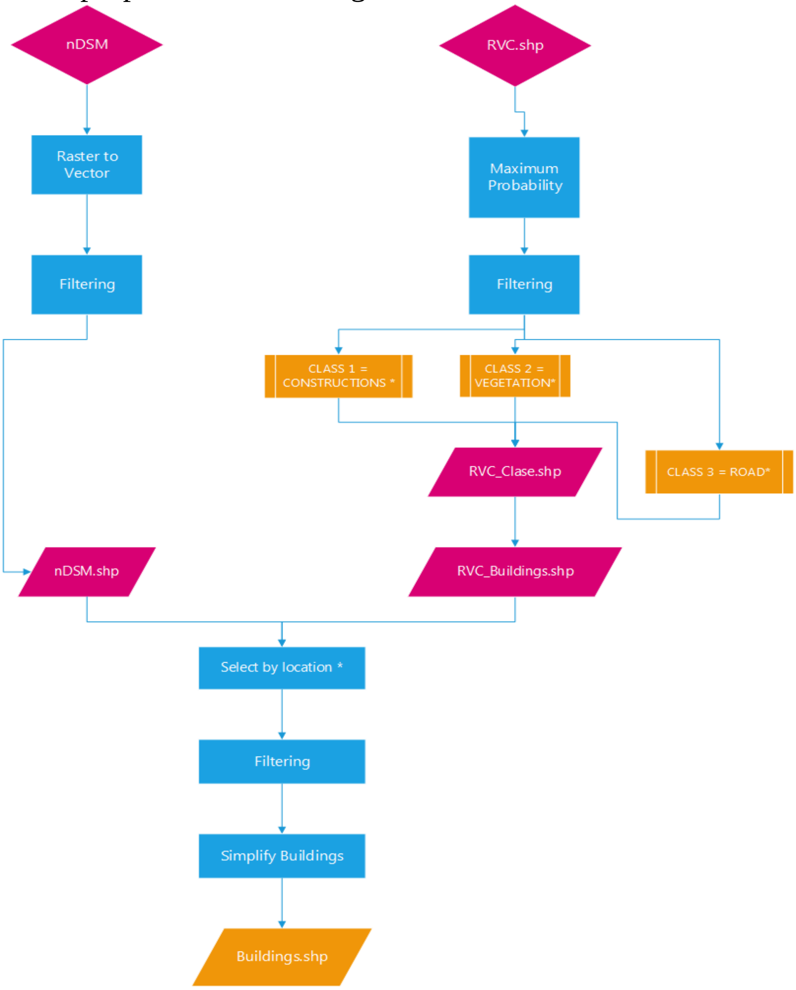


Fig. 4. Workflow

We computed the maximum probability for every polygon and then we assigned a class to every one of them. Because the image was acquired in March, the ground was not covered by grass, so the bare ground has the same spectral information as some of the roofs. Because of this situation, we filtered out, from the Buildings Class, the polygons that had a probability of being Vegetation higher than 0.5.

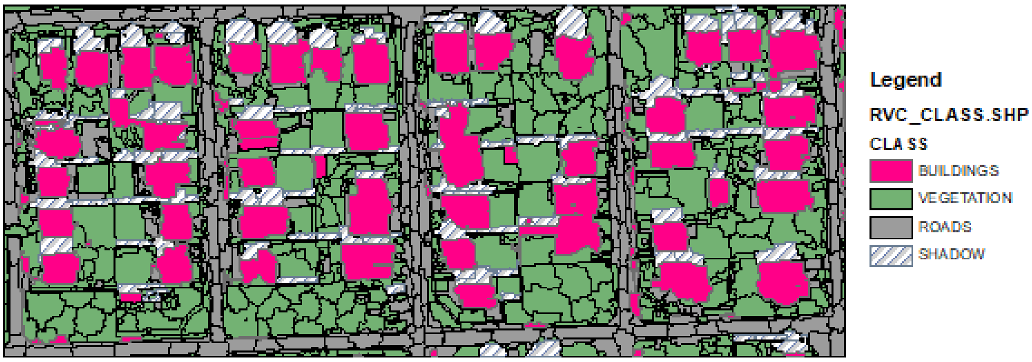


Fig. 5. Results of automated classification for TestA

We will focus our research on the Buildings Class, which was extracted separately for more filtering and refinement. First filter was based on buildings height, obtained from the nDSM. For this purpose, we used *Select by Location*, with the following statement "Select features from Buildings.shp that have their centroid in nDSM.shp". The polygons that did not fulfill this selection rule were deleted. The second filter was based on the area attribute, so we deleted all the polygons smaller than 50 square meters. To get the buildings in a more adequate form, we used the tool *Simplify Buildings.* Simplification of building boundaries is a type of generalization operation (Esri, 1996). Simplifying buildings means reducing details in the boundaries of buildings and maintaining the essential shape and size of the buildings. The results are shown in Figure6.

Fig. 6. Building polygons for Test A and Test B

The same area was digitized and the number of polygons obtained was 47. The result from the proposed workflow led to 42 building polygons. Even if this two values are not equal, the degree of completeness is 100%, we got, in the automated version, united buildings (the ones that are close in terms of location). This situation can be seen in Figure 7.

Fig. 7. Comparison between building polygons

## 4. Case study for extraurban areas

The area chosen for testing is the Administrative Territorial Unit Sânnicolau Român (7444 hectares), Bihor County, Romania. We used six classes and extracted 65 training samples. For the lambda schedule segmentation, were used different combinations of values for the weights, the one with the best results is shown in Figure 8.

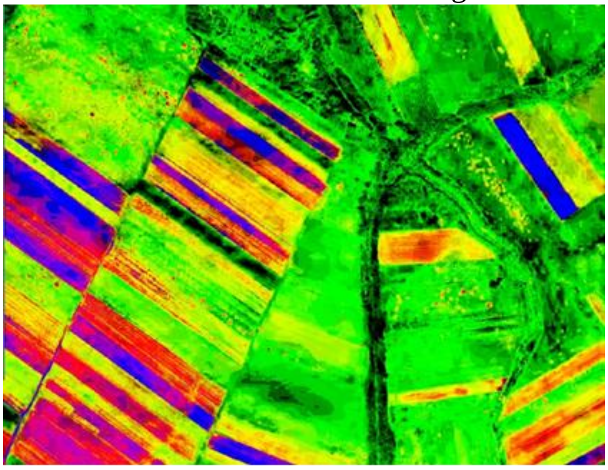

Fig. 8. Segmentation for Sânnnicolau Român
(0.5 spectral, 0.5 texture , 0.3 size and 0.3 shape)

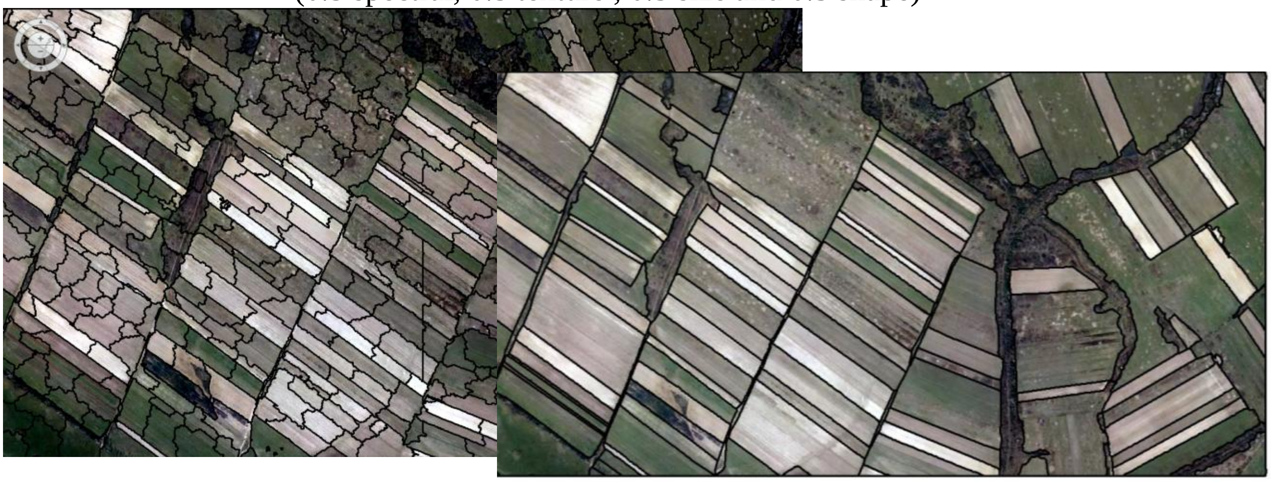

Fig. 9. Comparison between parcel boundaries (supervised classification vs. digitization)

One of the problems found is the delimitation between roads and parcels. The spectral values of the exploitation roads cannot be differentiated from the uncultivated agricultural land and this leads to confusions, that can be seen in Figure 10.

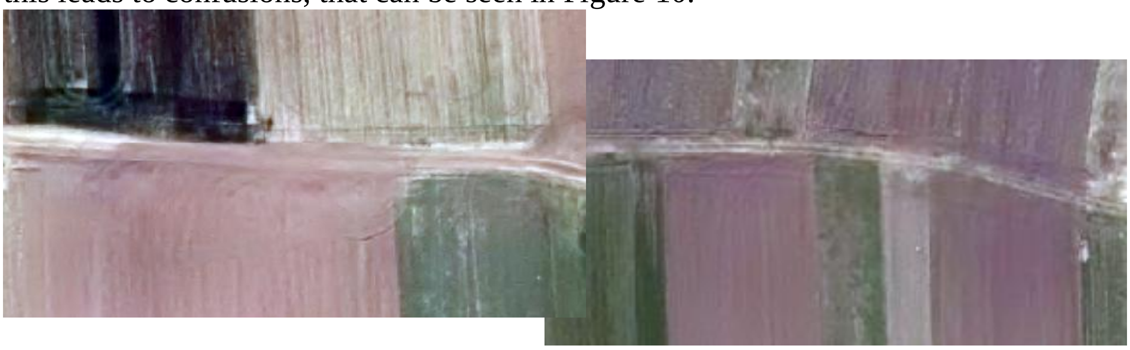

Fig. 10. Examples for exploitation roads

Another problem is that the time needed for reshaping the polygons resulted in an automated manner and obtaining a final product is longer than the time needed for digitization.

## 5. Conclusions

From the RGB image classification is very hard to obtain precise results, because the NDVI information is the key to start a good process of automated classification. The fact that the image acquisition period was in the early spring, the ground was not covered by grass, so the corresponding pixels have confusing information for the process.

Due to the low resolution of the digital models, the use of nDSM was not sufficient. For sure, a better resolution would have led to better results.

**The workflow presented can be used in a change detection process.** So, the polygons obtained can be compared to the polygons from the national geodatabase, TopRo5 (Topographic Reference Map of Romania, corresponding to 1:5000 scale), and we can detect the areas with changes that need updating.

In the future we will continue our research on this topic and will use multispectral images, that will be acquired in 2019-2020, for all the cities in Romania.

## 6. References

1. *J. Höhle & M. Höhle - Generation and assessment of urban land cover maps using high-resolution multispectral aerial cameras. International Journal on Advances in Software, vol, 6, no. 3&4, 2013;*
2. *J. Höhle - Generating Topographic Map Data from Classification Results, International Journal of Remote Sensing, DOI: 10.3390/rs9030224, 2017;*
3. *D. Lu & Q. Weng - A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, p. 823-870, DOI: 10.1080/01431160600746456, 2007;*
4. *C. Săvulescu - Sisteme informatice geografice, Note de curs, UTCB, 2000;*
5. *Q. Zhang, R. Qin, X. Huang, Y. Fang and L. Liu - Classification of Ultra-High Resolution Orthophotos Combined with DSM Using a Dual Morphological Top Hat Profile, Reomte Sensing 2015(7), p. 16422-16440, 2015;*
6. *Automation of Map Generation: The Cutting-Edge Technology. Source: https://downloads.esri.com/support/whitepapers/ao_/mapgen.pdf;*
7. *Release Guide Erdas Imagine, Hexagon Geospatial, 2018. Source: https://www.hexagongeospatial.com/technical-documents/release-guides-2018/erdas-imagine-2018-release-guide.*