Analysis of watercourses and land use based on automatic classification of satellite images.

Pedro França Araújo de Melo [a]

[a] School of Engineering, Federal University of Minas Gerais, Belo Horizonte, Minas Gerais, Brazil, pedrofmelo@ufmg.br

Abstract. Remote sensing technology has advanced significantly in recent decades, moving from aerial photographs taken from aircraft to high-resolution multi and hyperspectral images captured by orbital sensors. This progress has been supported by advancements in hardware and software, enabling sophisticated methods for image analysis in remote sensing research. Automatic classification of multispectral images is crucial for extracting information and identifying land cover patterns and other environmental characteristics of interest. In addition to spectral information, spatial information and context of neighboring pixels and objects are important in extracting meaningful information from remote sensing data. Region-based classifiers, which consider not only spectral information but also spatial relationships between pixels and their neighbors, are commonly used. This involves segmenting the image into contiguous pixels with relationships, which should be done prior to classification. In the study presented in this text, results of automatic classification of a Landsat image covering a portion of the municipality of Varginha/MG in Brazil are discussed. A supervised classification was performed using selected training samples. Although the accuracy rates were slightly below the desired level, according to the literature, this is not uncommon for automated classifications in regions with rugged terrain. To improve the quality of the maps, small corrections can be made using vector or raster editing operators available in GIS as a final adjustment procedure. This allows for a combination of automated classifiers and visual interpretation based on field observations to obtain reliable maps of watercourses, land use types, land occupation dynamics and other relevant environmental attributes in the region.

Keywords. Remote sensing, Image classification, Land use, Satellite Images, Landsat 8.

1. Introduction

Over the past few decades, remote sensing technology has undergone significant advancements, transitioning from aerial panchromatic photographs taken from aircraft to high-resolution multi and hyperspectral images captured by modern orbital sensors. This progress has been supported by the rapid development of hardware and software, enabling sophisticated methods for image analysis and digital processing in remote sensing research.

The sheer volume of remote sensing data generated daily would be of limited value in monitoring important natural resources and human activities on Earth if not for continuous scientific efforts to create new approaches and optimization methods for information extraction.

Automatic classification of multispectral images plays a crucial role in extracting information and identifying land cover patterns, as automatic classification of multispectral images categorizes the land cover, distinguishing the composition of different surface materials [1]. There are two main approaches:

- Supervised classification: relies on training samples for classifier training and requires field observations or photointerpretation knowledge, as a way of verifying the classes and respective pixels of the points raised [1];
- Unsupervised classification: uses statistical rule-based algorithms when representative training areas are not available, so that they are all defined by the software [1].

Automatic classifications aim to extract information from data collected by a sensor installed on a remote platform, determining a category for each pixel that is present on the surface, which is typically done using spectral attributes, such as the grayscale level in each spectral band [2].

In addition to spectral information, spatial information and the context of neighboring pixels and objects of interest are important in extracting meaningful information from remote sensing data. Thus, in a more comprehensive approach, algorithms commonly referred to as region-based classifiers use not only the spectral information of each pixel, but also the spatial information that involves the relationship between pixels and their neighbors. This process, of dividing the image into a set of contiguous pixels that have relationships with their neighbors is called segmentation and should be executed in the phase prior to classification.

In this study, results are presented for the automatic classification of a Landsat image covering a large portion of the municipality of Varginha/MG in Brazil. A supervised classification was performed using the selected training samples.

2. Methodology

As said before, the area chosen to be analyzed in relation to its land use and watercourses was the municipality of Varginha/MG - Brazil. Located in the southern region of Minas Gerais, the city has a territorial area of 395.396 km^2 (2022) according to data from the Brazilian Institute of Geography and Statistics (IBGE). The estimated population in 2021 was 137.608 people, with a population density of 311,29 inhabitants/km^2 (2010) and an HDI of 0,778 (2010). Additionally, the territory of Varginha is entirely composed of the Atlantic Forest biome and is located within the geomorphological domain of the Southwest Atlantic Plateau [3].

A Landsat image (from Landsat 8 satellite) taken on 04/10/2019, corresponding to orbit/point 219/75, was used. The image was obtained using the Semi-Automatic Classification Plugin (SCP) in QGIS software, where an automatic classification process was performed. The image was processed by cropping the scene and converting it to the desired coordinates (the original raster file had UTM coordinates for zone 23N and was reprojected to zone 23S).

The land use classes were defined through visual interpretation of the image, which served as a reference for evaluating the accuracy of automatic classifications. Several samples were collected for each class during the training phase of the classification algorithm, and the following classes were analyzed:

- Dense Vegetation;
- Rivers/Lakes;
- Exposed Soil;
- Urban Area;
- Pasture;
- Asphalt.

The training samples for the classifier were established by identifying characteristic patterns of each land use class within the image itself. The classifications were assessed for thematic errors, which refer to instances where objects were classified as belonging to a certain class, but in reality, they belonged to a different class.

Field truth data were obtained from visual interpretation of the same orbital image used for automatic classification techniques, in addition to the visual interpretation from Google Earth software images. A "confusion matrix" was constructed by cross-tabulating the mapping obtained from automatic classifications with the visual interpretation, which was considered as the reference for obtaining statistical accuracy coefficients. Due to the incorporation of more complex auxiliary parameters, visual interpretation allows for more realistic simulations compared to automatic classifications, and thus was considered as the truth [4].

3. Results and Discussion

After completing all the steps, Figure 1 displays the mapping obtained from automatic classification.

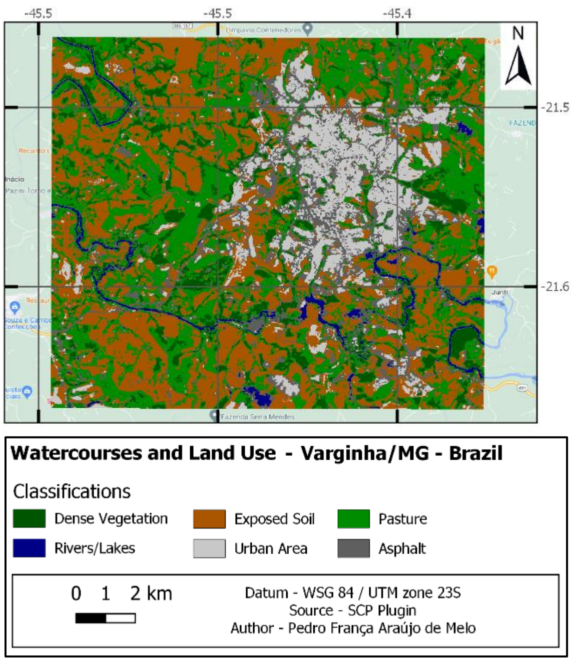

Fig. 1 - Map of land use and watercourses in the municipality of Varginha/MG - Brazil.

Therefore, after completing the automatic classification, it was possible to generate an “error matrix (confusion matrix)” for accuracy analysis. The six classes used in the classification were numbered as follows:

1 - Dense Vegetation;

2 - Rivers/Lakes;

3 - Exposed Soil;

4 - Urban Area;

5 - Pasture;

6 - Asphalt.

Thus, in Table 1, the “producer accuracy” for each of the classes used in the classification can be observed.

The matrix consists of rows and columns with the names of the classes, and each cell contains the number of pixels that were associated with each pair of classes. The columns represent the reference data, and the rows represent the classification product data. Finally, the elements on the diagonal represent the accuracy level for each class [5].

Tab. 1 – Error matrix (confusion matrix).

Classes	Dense Vegetation	Rivers/ Lakes	Exposed Soil
1	**37**	0	0
2	1	**5**	1
3	1	0	**123**
4	0	0	8
5	14	1	9
6	6	3	14
Total	59	9	155
Producer accuracy	62,7%	55,6%	79,4%

Classes	Urban Area	Pasture	Asphalt
1	0	2	0
2	0	0	0
3	1	7	1
4	**37**	0	0
5	0	**92**	0
6	11	12	**9**
Total	49	113	10
Producer accuracy	75,5%	81,4%	90,0%

Among the six classes used in the classification, the one with the highest accuracy (producer accuracy) was the "Asphalt" class, with 90%. On the other hand, the class with the lowest accuracy was the "Rivers/Lakes" class, with 55,6%. Despite being visually distinguishable, this class was sometimes confused during the automatic classification due to very dark pixels in some regions, resembling water regions, but actually belonging to other classes. The "Dense Vegetation" class also experienced similar confusion in certain points, resulting in an accuracy of 62,7%, while the other three classes had accuracies of 75,5% (Urban Area), 79,4% (Exposed Soil), and 81,4% (Pasture).

In addition to these, other matrices were also generated, such as the “error matrix of estimated area proportion”, the "quadratic error matrix of estimated area proportion", the "user's accuracy matrix of estimated area proportion" and the "producer's accuracy matrix of estimated area proportion”. By combining all of the previous matrices, the final "class area adjusted table" was generated, as shown in Table 2.

Tab. 2 – Class area adjusted table.

Classes	Area (km^2)	Error	Lower limit	Upper limit
1	30,89	2,44	26,10	35,67
2	4,82	1,25	2,37	7,27
3	80,42	3,13	74,29	86,58
4	25,51	2,13	21,33	29,69
5	58,81	3,18	52,57	65,06
6	5,23	1,54	2,21	8,25
Total	205,68			

4. Conclusion

For the studied region, despite the mapping generated by the automatic classification showing low accuracy rates for some classes, most of the classes exhibited accuracy ranging between 75% and 90%. However, the literature considers a minimum global accuracy index of 85% desirable [6]. In this case, the obtained classification fell below the desired level, which does not invalidate the results, as automated classifications in general tend to have moderate accuracy coefficients, especially in regions with rugged terrain, such as the municipality of Varginha/MG.

Thus, to achieve the desired quality for the mappings, small corrections made by vector or raster editing operators available in GIS can be included as a final adjustment procedure for the generated maps. This way, the efficiency of automated classifiers and the quality of visual interpretation based on field observations can be combined to obtain reliable maps of the spatial distribution of watercourses and different land use types, as well as the dynamics of land occupation in the region.

5. References

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