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**EXTRACTING AND CLASSIFYING BARE SOIL EROSION RISK AREAS IN A URBAN BASIN USING OBJECT-ORIENTED TECHNOLOGIES, HIGH RESOLUTION IMAGERY AND ELEVATION DATA**

R. A. A. Nobrega, C. G. O'Hara, V. Vijayaraj, G. Olson, S. Kim  
J. A. Quintanilha\* and M. T. L. Barros\*

**ABSTRACT:** Investigating urban basin characteristics is of extreme importance for planning and managing the environment. In areas of moderate to rugged terrain, uncontrolled terrace building and soil removal are considered harmful to drainage basins and in-stream water quality. Identifying and classifying areas with potential for erosive soil can help prevent environmental damages. However, detecting and measuring these activities within irregular settlements on the outskirts of large cities are difficult tasks, especially in developing countries. This paper presents a study area near the urbanized extent of Sao Paulo City-Brazil, characterized by recent and unplanned occupation, where dense urbanization is found intermixed with preserved nature areas in the upstream part of the basin. In this tropical location, areas are normally affected by storms and seasonal high-water events. The impact of soil erosion on in-stream flow has enlarged areas subject to flood inundation. The methodology presented employs high resolution imagery to depict irregular settlements, vegetation coverage, and bare soils. Although easily visualized on images, classifying bare soils according to the potential risk for erosion and producing relative risk maps is problematic. The large amount of data requires automated procedures of image classification. However, the high internal variance of these images causes incompatibility with most traditional classifiers. To overcome this shortcoming of traditional approaches, image classification for this effort utilizes object-oriented technologies. First, the image is segmented and the objects are detected through spectral, spatial and topological characteristics. Relationships among objects are used for final fuzzy classification. The accuracy of 81.3% shows the potential of the methodology. Later, pre-classified objects are analyzed considering information from a digital terrain model. The classification provides information about the relative susceptibility to erosion for areas with bare soils.

**KEY TERMS:** object-based classification, high resolution image, erosion, urban basin, water.

### INTRODUCTION

Recent developments on digital sensors and have stimulated new methodologies for land cover/land use classification. The newer generation of satellite sensors, increased in radiometry as well as spectral and spatial resolutions, should be considered as a new paradigm to be explored. Concerning the spatial resolution, Neubert & Meinel (2005) reports the improvement on urban object discriminations and the reduction of spectral mixing of pixels. Tso & Mather (2001) and Repaka et al (2004) agree that the efficiency of traditional per-pixel classification is reduced for high resolution images. However, investigations on classification from high resolution images have shown significant increases in accuracy when object-based approaches were used. The growing need for precise geoinformation for the GIS community generates the necessity for new research and new applications.

The object-based classification proposed in this methodology aims the precise extraction of bare soils from a study area located in an urban region of Sao Paulo city – Brazil. The region is characterized by recent and unplanned occupation, where dense urbanization is found intermixed with preserved natural areas in the upstream part of the basin. Some tropical storms and seasonal high-water events that affect this area, composed by moderate to rugged terrain, have caused impact of soil erosion on in-stream flow and have enlarged areas subject to flood inundation.

The present work reports a methodology that extracts polygons of bare soil areas with high accuracy through segmentation and classification according to the slope map by using GIS analysis. The goal is to create a methodology that provides precise geoinformation to support hydrologic and land management works.

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\*Respectively, Research Associate, Associate Professor, Research Associate, Research Associate, Research Associate, Associate Professor, Associate Professor. GeoResources Institute, Mississippi State University, Mississippi State-MS 39759, Phone: (662) 325-5114, Fax: (662) 325-7692. Escola Politecnica da Universidade de Sao Paulo, Sao Paulo, Brazil. E-Mail: rodrigo@gri.msstate.edu

## Data Sets and Study Area

A multi-spectral Ikonos image, recorded in 2002 over the north region of town was used for this research. The study area covers 2.75 x 1.5 Km located in the upstream part of the Cabucu de Baixo River basin, between the latitudes 23°26'26"SS and 23°27'16"SS and longitudes 46°40'14"W and 46°41'28"W.

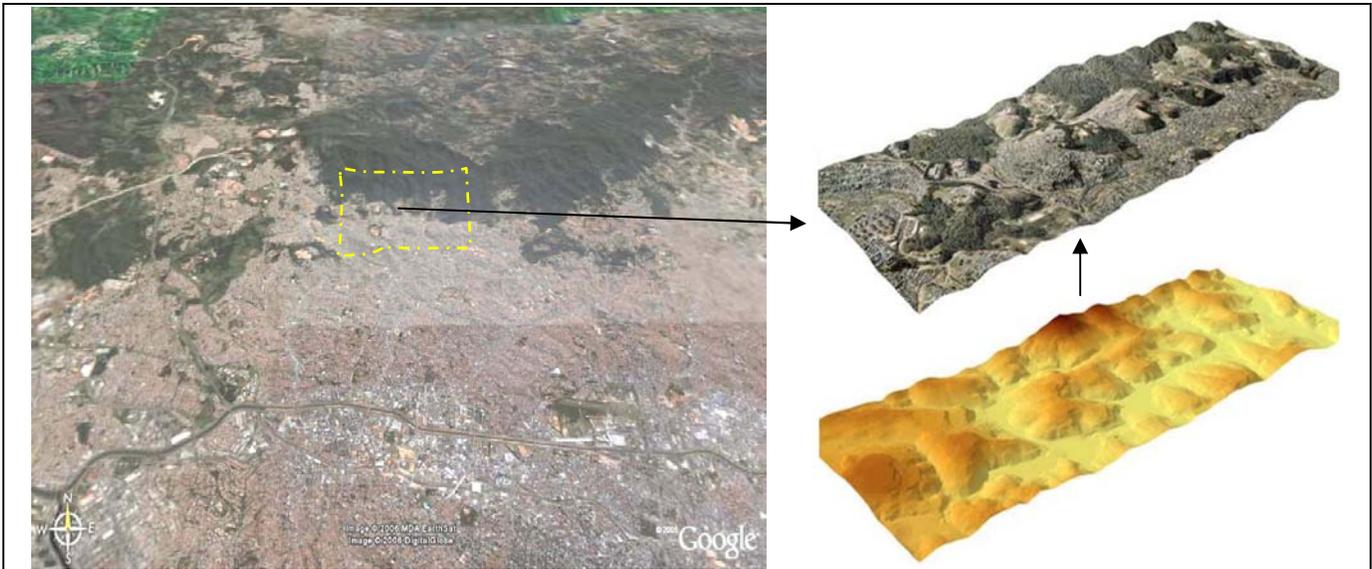


Figure 1. General visualization of north region of Sao Paulo (extracted from Google Earth) and the detailed study area.

Originally, the imagery was composed of NIR, Red, Green and Blue bands with 11 bits, orthorectified and resampled to 1 meter spatial resolution. However, the Principal Components (PC) were previously calculated and inserted on the project on behalf of providing a large range of separability among objects in the scene.

The methodology also required a slope map generated from a precise digital terrain model. This data was prepared in 2004 covering the full basin and previously used on the Decision Support System. In this research, the slope map was subset according to the limits of study area. The Definiens eCognition was utilized to extract bare soil polygons and slope analysis was performed using ESRI ArcGIS.

### OBJECT-BASED CLASSIFICATION OF THE BARE SOIL AREAS

Object-based classification uses a different approach to assign classes to the objects. After creating the objects a large amount of characteristics can be extracted, regarding spectral, geometric and topological domains. The classification rules can be constructed supported by the object characteristics.

#### Segmentation

Due to the importance of properties of the objects, the segmentation required extensive analyses to fit the desired urban objects relative to the segments. Variations of scale parameter, bands, degree of shape and compactness homogeneity were tested. The best result was a combination of all original bands, scale parameter of 30, shape homogeneity of 0.9 and compactness of 0.1.

An important observation can be considered for the shape homogeneity criterion. The larger the value, the lower the consideration for color on the generation of the segments. It was necessary to detect small ceramic roofs.

#### Customized Features

Three customized features were implemented and used to classify the land cover. The Normalized Difference Vegetation Index (NDVI) was employed to detect vegetation covered areas. According to Jensen (1996), NDVI has been used extensively to measure vegetation amount on a worldwide basis. Originally developed in 1973, the NDVI computes the

normalized difference of brightness values from NIR and Red rationing and its use is disseminated today. Indeed, the vegetation areas have higher values than others.

$$NDVI = \left( \frac{\mu NIR - \mu RED}{\mu NIR + RED} \right)$$

The second customized feature was created to point out shadows and other extremely dark areas in the remaining image. The Shadow General Indicator uses a difference of brightness values between Blue band and the PC-1. Analyzing these two images independently, the difference of brightness values for shadow and other similar objects are low in comparison with the remaining objects of the image. However in different ranges, the subtraction of PC-1 values from Blue ones produces a new map where the values are negatives. For the result image, the bright areas indicate the shadow objects that will be detected and masked out latter.

$$Shadow\_General\_Indicator = \mu Blue - \mu PC1$$

Another feature was customized by using the combination of PC-3 and Blue toward the detection of bare soil areas. Despite the PC-3 could discriminate the bare soil objects well, the excessive heterogeneity of the unplanned settlement makes more difficult to analyse where the bare soil areas are mixed with the buildings and the streets. To improve the power of discrimination, the Blue band was introduced because due to the low brightness for bare soil areas as well as the low variance in comparison with other bands. Also, the equation uses a large and negative value on denominator just to produce small values.

$$Bare\_General\_Indicator = \left( \frac{\mu PC3 * \mu Blue}{-100000} \right)$$

#### Classification

Three main classes were previously defined: Vegetation General, Shadow General and Bare General. However, the extraction of bare soil areas began from the classification of vegetation areas by using the NDVI feature. Objects with NDVI value that are higher then the threshold of 0.2 were considered as vegetation. Likewise, the shadow areas were detected for the rest of the scene by using the Shadow General Indicator feature, with threshold of -425. These values were introduced to each class definition to compose the fuzzy-soft scheme. Each object was classified according to the degree of pertinence of the class. These two initial steps were necessary due to the complexity of the scene. Vegetation areas as well as shadow areas were masked out from the remaining classification scheme to increase of detection of bare soil objects.



Figure 2. Combination of Red, Green and Blue bands of Ikonos image and the respective final classification.

Concerning the detection of the bare soil areas, two new classes were introduced -Ceramic Roof and Bare Soil- as child-classes of the Bare General class. The spectral patterns of ceramic roofs and bare soil areas are very similar. The introduction of geometric and topological properties increased the power of the classification. Basically, the bare general objects were analyzed according to the area, rectangular fitting and relative border to the Shadow General class. Objects in accordance

with the three conditions had higher potential to be classified as Ceramic Roofs. Otherwise, they were classified as Bare Soils.

Table 1. Relative areas per class

CLASS	AREA (m <sup>2</sup> )	%
Vegetation General	1,982,186	63.56
Urbanized	827,189	26.52
Bare Soil	175,224	5.62
Shadow General	115,080	3.69
Ceramic Roof	19,046	0.61
<b>TOTAL AREA</b>	<b>3,118,725</b>	<b>100</b>

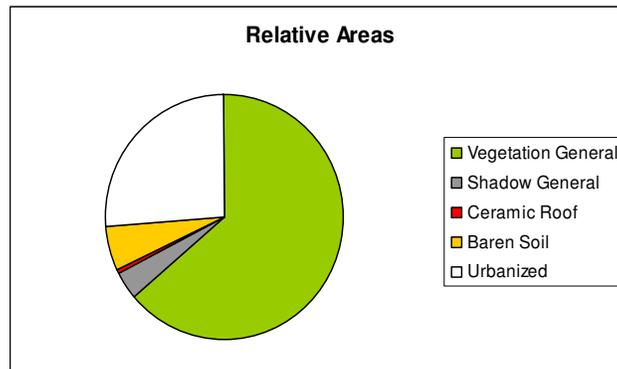


Figure 3. Relative area per class.

Certain steps were considered to validate the methodology regarding the accuracy of automatic procedure for bare soil detection. First, all areas of bare soil compatible with the visualization scale of 1:2000 were digitalized on screen using an appropriated combination of bands Red, Green and Blue. The digitized polygons were considered error-free. Then, a comparison between these two sets of bare soil polygons was done. The accuracy of the automatic approach was 81.3 %. Omission error of 18.7 % was partially generated by the cartographic generalization due to the resolution of the image. The commission error of 28.7 % was generated due to very high similarity between the proprieties of ceramic roofs and some bare soil polygons, especially inside the urbanized areas.

Table 2. Analysis of the of the classification for bare soil areas

METHOD	AREA (m <sup>2</sup> )
Manual (visual interpretation)	159,254.4
Automatic (object-based classification)	175,224.0
Correct classification (area of intersection)	129,479.4

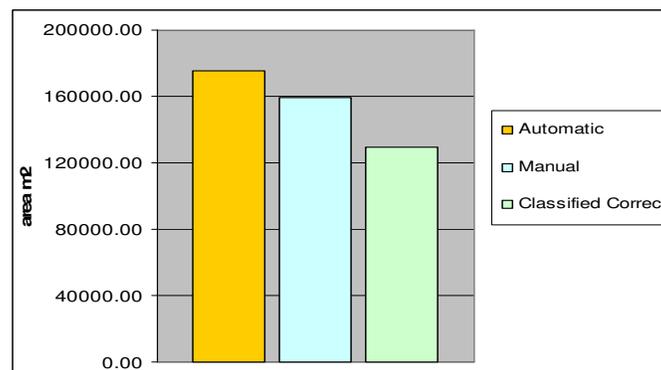


Figure 4. Comparison between manual and automatic results for the classification of bare soil areas

SLOPE CLASSIFICATION

After the extraction of the bare soil areas, the polygons were submitted to a new classification, according to the slope map. This processing required the conversion of the polygons to a raster data to compute the intersection of both slope map and bare soil images. During this processing, some cautions must be taken to preserve the compatibility between the spatial resolutions of both sources. The less the pixel size, the precise the measuring of the areas over the new classified bare soil image. The spatial resolution of the raster elevation data was one meter.

A new raster data was generated including 5 classes of information. The majority of bare soil polygons are located on areas with low degree of slope, almost 86 %, represented in yellow on Figure 5. Almost 13% are composed by areas moderated to rugged terrain. Only less than 1% is composed by very high slope, but their potential to surface erosion can produce significant environmental damages. Figure 6 illustrates a superimposition between the digital terrain model, the orthophoto and the detected bare soil polygons.

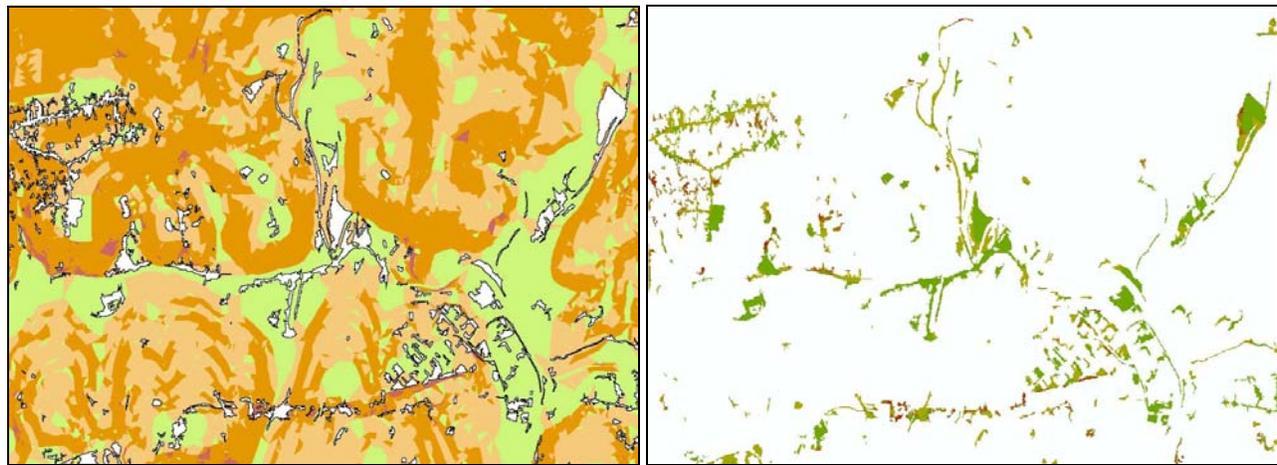


Figure 5. Superimposition of classified areas and slope map. Fragmentation of bare soil polygons according to the slope map.

Table 3. Classification of new bare soil polygons according to the slope map

Object_ID	Slope %	Area (m <sup>2</sup> )	relative area %	potential for superficial erosion
0	0 – 10	87,360	49.86	very low
1	10 – 25	63,408	36.19	low
2	25 – 50	18,478	10.54	medium
3	50 – 100	4,569	2.61	high
4	100 or more	1,409	0.80	very high

However some of these areas do not look very sensitive to surface erosion, most of them are located in flooding regions, low and flat land alongside of watercourse. To do a decisive analysis of the potential for surface erosion the geological characteristics of these areas must be considered.

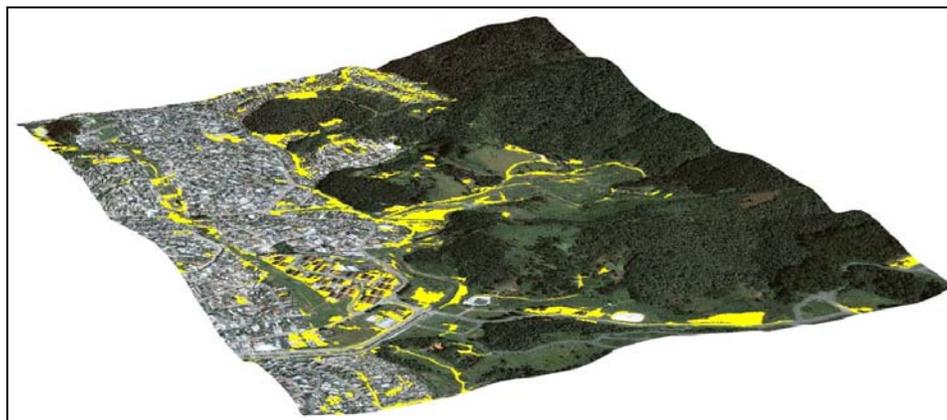


Figure 6. Three-dimensional visualization of extracted bare soil polygons over the Ikonos orthorectified image.

## DISCUSSION AND CONCLUSION

However the first experimentation of object-based classification to extract specific information of an unplanned settlement from high resolution satellite imagery, the results show the high potential of this technology. In comparison to visual interpretation, the accuracy of 81,3 % reports how precise the classification process can be, considering the extreme heterogeneity of the spectral and spatial characteristics of the land cover.

Otherwise, nowadays, remote sensing and GIS are more integrated than never. The recent developments interfacing remote sensing and GIS have obtained positive results, especially for high resolution images. In accordance to the set of these new geo-applications, this paper presents a methodology to support information of the amount and location of bare soil areas. The accuracy of the processing shows that the final mapping can provide good technical information to urban land/water management. Based on the promising results, futures studies could be developed.

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