URBAN LAND COVER CLASSIFICATION WITH WORLDVIEW-2 IMAGES USING DATA MINING AND OBJECT-BASED IMAGE ANALYSIS

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ABSTRACT:

The products available from new satellite sensor systems with high spatial resolution present a considerable potential for applications in urban areas. These datasets open new perspectives for the automatic extraction of information for environmental planning and management. However in order to get efficiently the information required, innovative concepts are necessary at both working phases: segmentation and discrimination of objects within the image. The objective of this study is to develop a methodology using OBIA and Data mining techniques to map land cover with WorldView-2 images in a western district of São Paulo municipality (Brazil). The Data mining techniques used were decision trees at algorithm C4.5 from the free software package WEKA, known as "J48". It allows the system user to configure different functionalities which intervene at the final Data mining result, such as MinNumObj: the minimum number of instances (objects) by sheet. Through this functionality it is possible to control the size and complexity of the tree generated. In this study the performance of image classification obtained from two decision trees was evaluated, considering different MinNumObj. The statistical assessment indicated a good precision for both maps, with *Kappa* Indices of 0.7876 (MinNumObj: 25) and 0.8383 (MinNumObj: 2).

1. INTRODUCTION

Urban areas occupy relatively small areas of the Earth surface, but its extension, distribution and evolution have a considerable impact on the environment and on social-economic dynamics worldwide (SMALL, 2005).

In these areas where most human activities are developed, significant changes of natural resources occur. There are significant changes from the natural resources and of the characteristics from the ecosystems within and surrounding such places (POWELL et al., 2007).

Presently there are over twelve operational very high resolution satellites orbiting Earth. However, until very recently the increase of spatial resolution was not concomitant to the increase of spectral resolution at these sensor systems. This hampered the discrimination of several urban targets with similar spectral behavior in the visible spectrum such as asphalt paved streets and buildings covered by dark asbestos roofs (PINHO, 2005). With the launch of WorldView-2 satellite, 8 multispectral bands became available (2.00 m spatial resolution) besides the panchromatic band (0.50 m spatial resolution) allowing further discrimination of urban targets.

Due to the high resolution and the large amount of data available from satellite systems such as WorldView-2, traditional pixel-by-pixel classification schemes were inadequate (EHLERS, 2007) and new computational tools and concepts for image analysis were developed (MAKTAV, 2005).

In this context Blaschke (2010) reports that the OBIA (Object-based Image Analysis) paradigm allows the simulation of visual interpretation by knowledge modeling. In order to do that, normally semantic networks are built, based on attributes such as form, spectral information, texture, morphology, and context, among others.

Data mining tools can increase the potential of the analysis from remote sensing data (KORTING et. al., 2008). Methods of attribute selection became very attractive for remote sensing studies because hundreds of spectral, texture and geometric attributes can be used in OBIA classification routines (NOVACK et al., 2011).

In this frame the motivation for this study is the great potential of satellite images with high spatial and spectral resolution for detailed mapping of the urban space, of interest for urban and regional planning agencies.

The objective of this study is to develop a methodology using OBIA and Data mining techniques to map land cover with WorldView-2 images in a western district of São Paulo municipality, Brazil (Figure 1).

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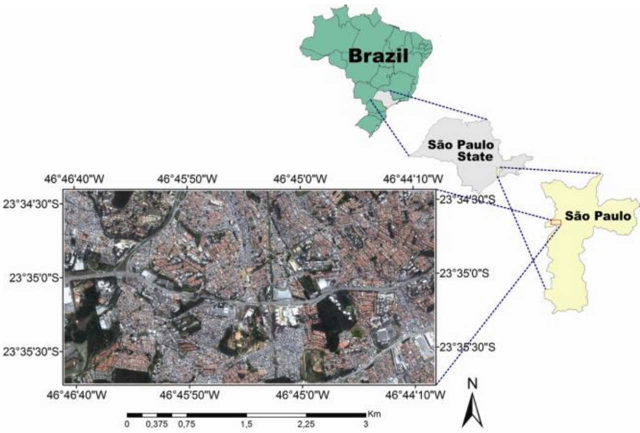

Figure 1 - Geographic localization of the study area.

2. MATERIALS

1. WorldView-2 scene, OR Standard 2A including a panchromatic image with 0.50 m spatial resolution and 8 multispectral bands: (Coastal Blue, Blue, Green, Yellow, Red, Red Edge, Near-Infrared-1 e Near-Infrared-2), with 2.00 m spatial resolution and 16 bits radiometric resolution were used. This image data take was in Oct. 24th 2010, with an incidence angle of 8.99°.

2. Software Definiens Developer 7.0 was used for attribute selection, multi-resolution segmentation, generation of class hierarchy and WV-2 image classification.

3. For the selection of attributes, ideal thresholds as well as decision trees, the free software WEKA (Waikato Environment for Knowledge Analysis), version 3.6.5 was used.

3. METHODOLOGY

The methodology included the following procedures: data pre-processing, definition and characterization of land cover classes, preparation of training sets and Data mining evaluation, considering two experiments: 1st Selection of parameters by the analyst and 2nd Automatic selection of parameters.

3.1 Data pre-processing

Initially a hybrid WV-2 image was generated by the PCA - Principal Components Analysis method (SCHOWENGERDT, 2007).

Afterwards, the WV-2 images were ortho-rectified by a Rational Function Model (RFM), using RPCs, a digital elevation model (DEM) and Ground Control Points (GCPs). According to PEC, the Brazilian Accuracy Standard (Brasil, 1984), a product compatible to scale 1:2,500 was obtained.

3.2 Definition and characterization of land cover classes

It consisted on the visual analysis of land cover classes from the hybrid WV-2 scene, supported by field survey and high resolution Google Earth images. The land cover classes were: Swimming pool, Bare soil, Arboreal vegetation, Grass vegetation, Shadow, Ceramic roof, Metallic roof, Medium-concrete cover, Dark-concrete cover, Clear-concrete cover (high brightness), River, Asphalt, Natural rock floor, Polyethylene cover and Bare rock.

3.3 Preparation of training sets and Data mining evaluation

After image segmentation and land cover class definition and characterization, samples of these classes were collected to prepare data banks related to training sets and evaluation for Data mining. Totally 120 samples were collected for each class, except for "River", "Natural rock floor", "Polyethylene cover" and "Bare soil" which are very inexpressive in the area under study. The 120 samples were divided into 2 groups: 70% for training and 30% for testing. So the option was for the test set available for the generation of decision trees by the J48 classifier of WEKA. The sample collection at WV-2 image was performed after a detailed interpretation of the scene, aiming to cover the entire internal variability of classes referring to color, tone, form, texture and brightness.

3.4 Experiment I – Selection of parameters for mining by the analyst

Using the J48 algorithm, 12 decision trees were generated, and the parameter referring to the minimum number of objects (MinNumObj) was modified. It controls the size and complexity of the tree generated. In order to repeat the choice of the final tree within the Definiens Developer environment for land cover classification, the following four criteria were considered: 1st number of nodes, 2nd number of leaves, 3rd number of attributes without repetition, 4th *Kappa* Index. Table 1 presents the results of analysis for the model selection.

Trees		Criteria			
ID	Min Num Obj	Number of nodes	Number of leaves	Attributes without repetition	*Kappa* Index
01	2	55	57	42	0.8765
02	10	25	27	22	0.8207
03	15	19	21	17	0.8168
04	20	17	19	15	0.8129
05	25	16	18	15	0.8119
06	30	16	18	15	0.8010
07	35	16	18	15	0.7901
08	40	15	17	14	0.7882
09	45	15	17	14	0.7429
10	50	14	16	14	0.7168
11	55	13	15	14	0.6896
12	60	13	15	13	0.6386

Table 1 – Results of the analysis for model selection

So for instance tree number 5 was selected, which presents 25 objects as the minimum number of instances per sheet. It has a higher *Kappa* Index than trees 6 and 7, although it has the same amount of nodes and leaves.

3.5 Experiment II – Automatic selection of mining parameters

At this experiment, unlike at the first one, there was no intervention from the interpreter during the decision tree generation. In other words, the tree was elaborated with 2 minimum numbers of instances per leaf (standard configuration of WEKA). So J48 elaborated a tree with 55 nodes, 57 leaves and a *Kappa* Index of 0.8765, calculated at WEKA by cross tabulation.

4. RESULTS AND DISCUSSION

At tree number 5, from the first experiment, the Data mining algorithm chose the following attributes as the best ones to discriminate among land cover classes: HSI Transformation Saturation (R=Red G=Green B=Blue); Max. pixel value Coastal; Ratio Yellow; Min. pixel value Blue; Rel. area to super-object; Standard deviation Coastal; Ratio Yellow by Red Edge; Min. pixel value Green; Ratio Blue by Green; Min. pixel value NIR2; Ratio NIR1 by Red Edge; Ratio Red Edge by Green; Ratio to super-object Red; Ratio Yellow by Green; Ratio Red by NIR1.

Figure 2 shows the Decision Tree and Semantic Network generated at Experiment I. One denotes here that classes "Bare soil", "Ceramic roof" and "Bare rock" appear at more than one node at the tree. "Ceramic roof" is lonely at the first node, being classified by the spectral attribute Min. pixel value Blue. At a lower node this class is found together with "Bare soil", separated at this level by the spectral attribute Min. pixel value Green. At another node, class "Ceramic roof" is shown together with class "Natural rock floor". They are separated by the spectral attribute Standard Deviation Coastal.

At another branch of the tree, classes "Dark-concrete cover" and "Bare rock" are found at the same node. They are separated by the spectral attribute Ratio of Red Edge by Green (customized by the analyst in Definiens Developer system). At a little farther on node, "Bare rock" is together with "Shadow". Both are separated by the attribute Ratio to super-object Red.

At experiment II, the J48 algorithm elected the best attributes for land cover class separation as follows: HSI Transformation Saturation(R=Red G=Green B=Blue); Ratio Yellow; Ratio Green; Min. pixel value Blue; Mean Yellow; Roundness; Mean diff. to super-object Yellow; Standard deviation Red Edge; Mean of outer border Yellow; Min. pixel value Green; Mean diff. to scene Blue; Mean Diff. to neighbors Yellow; Ratio Red; Standard deviation Coastal; StdDev diff. to super-object Yellow; Mean NIR2; Ratio to super-object Coastal; Ratio of Yellow by Green; Standard deviation Red Edge; NDVI; Standard deviation Yellow; Max. pixel value Red Edge; Ratio Yellow by Red Edge; Min. pixel value Red; Min. pixel value Coastal; Mean diff. to scene NIR2; Max. pixel value Yellow; Ratio Blue by Green; Min. pixel value NIR2; Ratio NIR1 by Red Edge; Ratio to scene Coastal; Ratio Blue; Standard deviation Green; Mean of inner border Coastal; Ratio Red; Mean Diff. to neighbors Red Edge; Brightness; Max. pixel value Coastal; Ratio Yellow by Red; Ratio Red by NIR1; Max. pixel value Blue.

In this study, the Conditional *Kappa* Index was calculated to evaluate the accuracy of each experiment for the distinction of each land cover class. The *Kappa* values for both experiments, considered good, are presented at Figure 3.

Figure 4 presents the thematic maps originated from WV-2 image classifications. Arboreal and grass vegetation are easily distinguishable due to high NDVI values, in spite of confusion among them. The classification of high brightness objects (Clear-concrete cover) presented good results in both experiments. The highest confusion within this class occurs at Metallic roofs. In the area under study several Metallic roofs presented different levels of aging and material oxidation, deposition of pollution substances, etc. which might explain the low performance at the experiments.

At both experiments class Bare soil was well discriminated. It is noteworthy that for the classification of urban areas, the correct classification of this target is a difficult task because its confusion with Ceramic roofs, which have approximately the same chemical composition.

Both experiments present a low performance for classes Bare Rock and River. This might be due to the small number of samples from these classes, of low extension in the area under study.

Classes Medium-concrete and dark-concrete cover were created to group objects such as fibro-cement roofs with and without asbestos, pigmented cement roofs, flat slab dark cover, as well as concrete paving. According to the confusion matrix the class Medium-concrete cover confounds mostly with a high brightness class, whereas class Dark-concrete cover confounds frequently with Shadow. This is due to the fact that this class includes urban targets composed mainly by concrete with less brightness than objects of cover classes with medium-concrete cover and high brightness.

Class Shadow presented good results at both experiments. At the second one shadows on the crown of trees were very well classified, which is not usual in high spatial resolution images.

Class Swimming pool presented a similar performance at both experiments. The targets it confused most frequently were Metallic cover and Shadow. Pinho (2005) reports the same observation during the classification of a Quickbird-2 scene.

Class Natural rock floor confused a little with Ceramic roofs. However experiment II presented the best results.

In general, good results were obtained with class Asphalt.

Class Polyethylene Cover (at the parking lot of a supermarket) presented the best results at Experiment II, confusing with class Shadow.

5. CONCLUSION

With the availability of new spectral bands at the WorldView-2 sensor system, the task to discover attributes, thresholds and to structure the network became more difficult. So the use of Data mining by decision trees became a fast and efficient procedure to fulfill this task, and consequently for the classification process.

The statistical assessment indicated a good precision for both maps, with *Kappa* Indices of 0.7876 (MinNumObj: 25) and 0.8383 (MinNumObj: 2).

In this work we used the Yellow band to discriminate class Ceramic roof and Bare soil. According to literature these two classes do not present a good separability in land cover classifications using images of former high resolution satellite systems.

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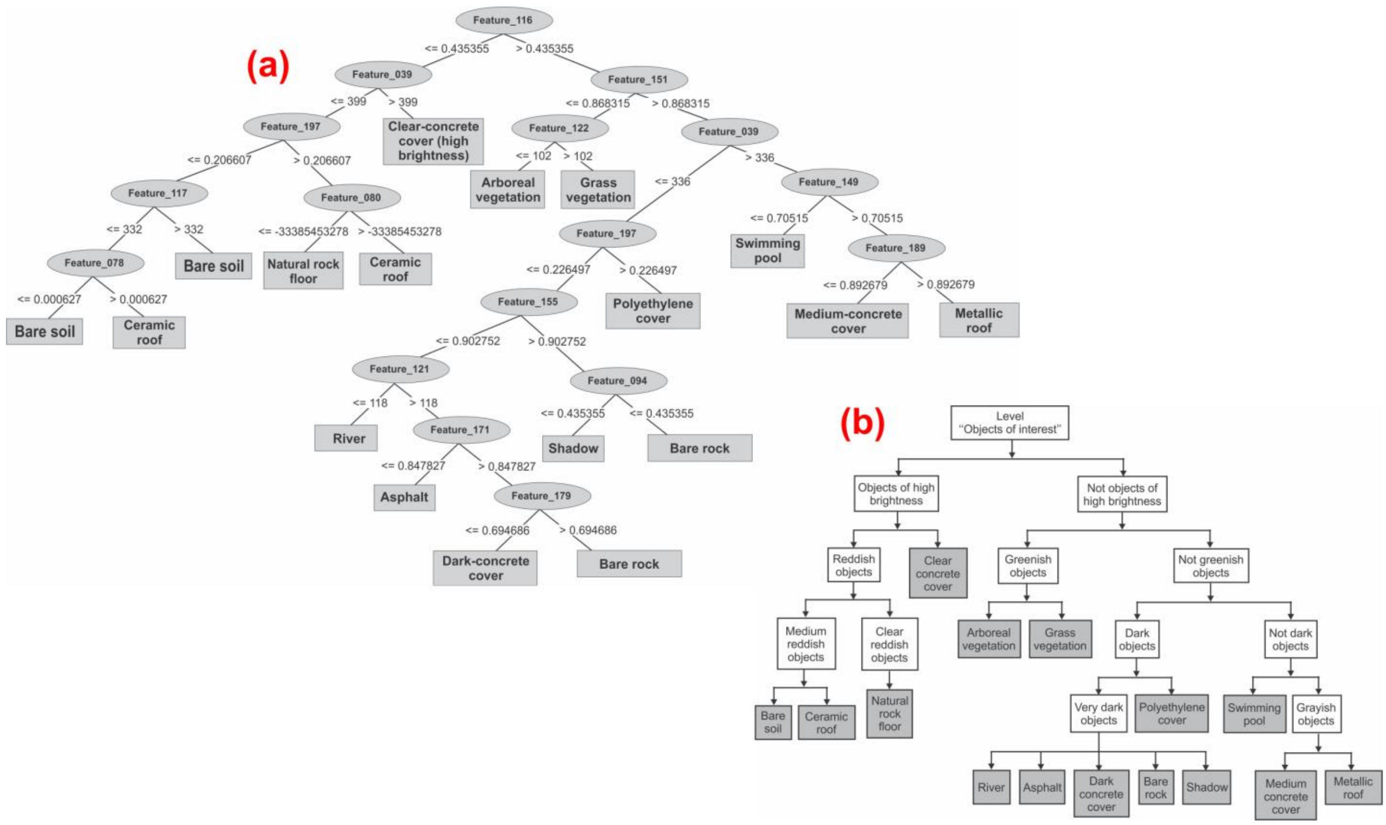

Figure 2 - (a) Decision tree generated by J48 algorithm with MinNumObj: 25 and respective (b) Semantic Network (Experiment I).

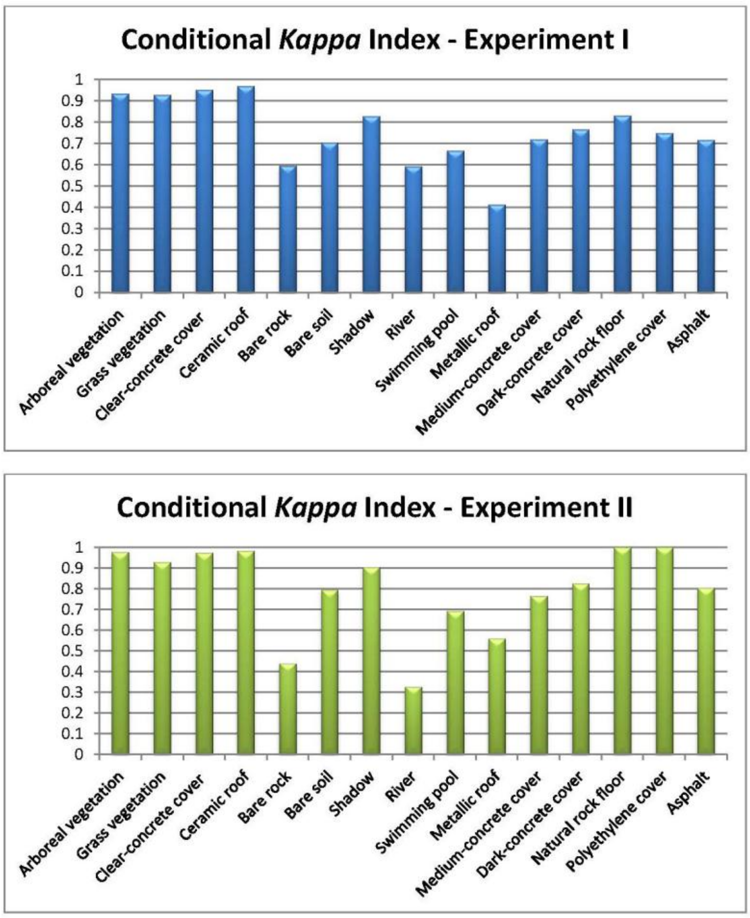

Figure 3 - *Kappa* Index values per class (Conditional *Kappa* Index) for the Experiments I and II.

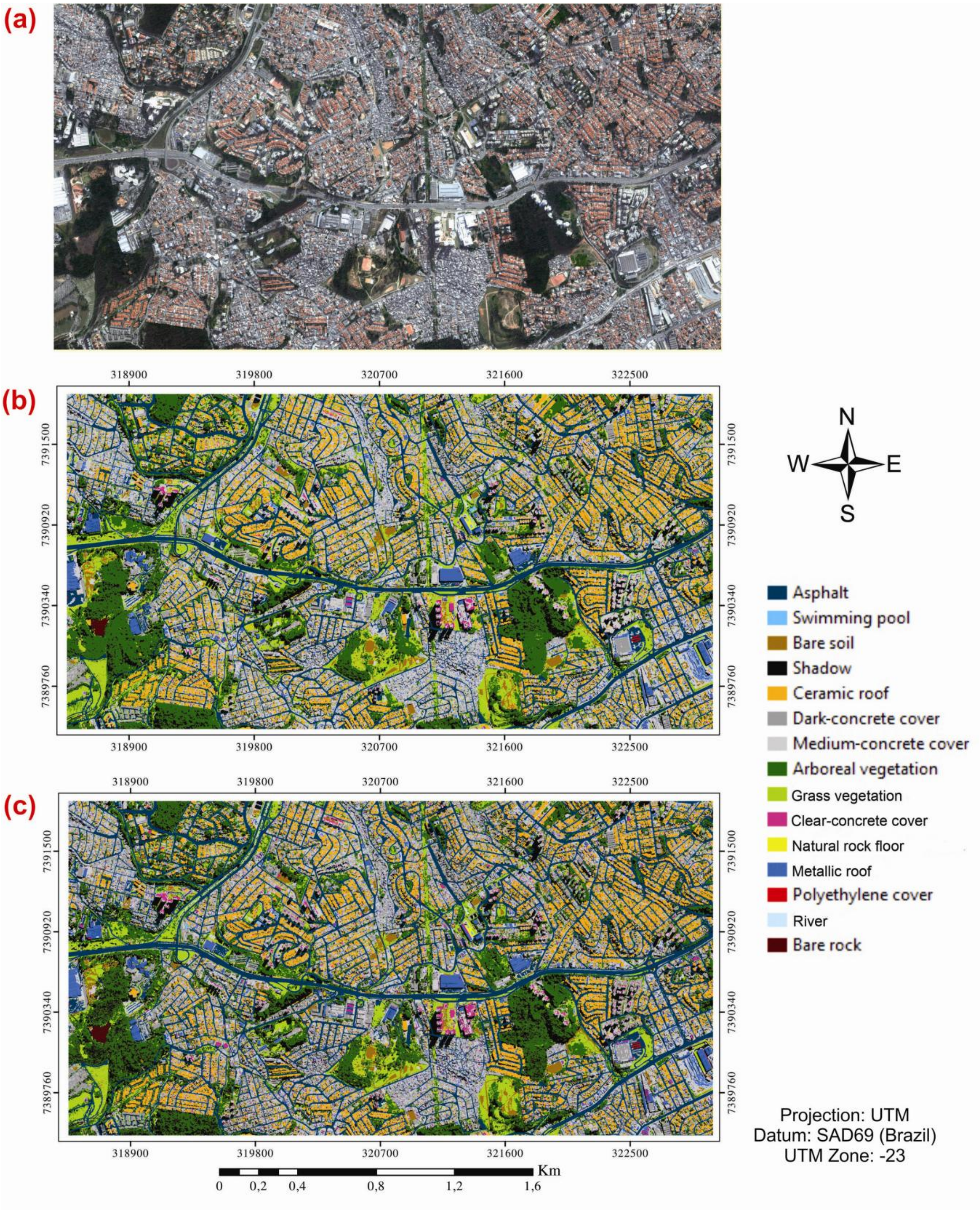

Figure 4 - (a) WorldView-2 image (RGB532), (b) Thematic map generated in Experiment I and (c) Thematic map generated in Experiment II.