PERFORMANCE OF TDVI IN URBAN LAND USE/COVER CLASSIFICATION FOR QUALITY OF PLACE MEASUREMENT

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ABSTRACT:

Measuring the Quality of Place (QOP) is a hard task since it involves both physical and socio-economic dimensions. Being one of the major land use categories, urban vegetation plays a significant role in one's judgment for QOP in a neighborhood. Both quantity and quality of the community parks and recreation areas are major determinants of neighborhood attraction. For these reasons, detection of urban vegetation cover has been one of the important implication areas of urban image classification techniques. Being one of the biophysical variable NDVI (a good measure of greenness), gives a useful way of QOP assessment of a place and it is a good indicator of the socio-economic conditions of the area. Due to the improvements in RS and GIS techniques, more recent vegetation indices yielding better results, post-classification and new spatial analysis techniques will serve for the increasing of the accuracy of these studies. In the last decade, over forty vegetation indices are introduced in the remote sensing literature, to measure the vegetation cover in different applications (Bannari *et al.*, 1995a). Since soil brightness, environmental effects, soil color, moisture and shadow are major complex mixture of vegetated areas; vegetation indices make an effort in minimizing the effect of those sources and enhance the vegetation response. A new vegetation index, "Transformed Difference Vegetation Index (TDVI) developed by Bannari et al. (2002), is tested in a previous work where the index has performed better than NDVI and SAVI. In that work, a comparative study between TDVI, SAVI and NDVI for estimating vegetation cover in urban environment from the Indian Remote Sensing Satellite (IRS-1D) imagery has been conducted. The validation of the obtained results according to the ground truth showed that the TDVI is an excellent tool for vegetation cover monitoring in urban environment. It does not saturate like NDVI or SAVI, it shows an excellent linearity as a function of the rate of vegetation cover. This paper adds on the previous work by analyzing the performance of TDVI in urban image classification. To make the comparison, same set of image data are used (IRS-1D) and a mixed approach of parallelepiped and maximum likelihood classification technique is applied in Montreal Island. Results indicate that, the performance of TDVI in urban image classification is better than NDVI and SAVI. The new index not only differentiates the urban vegetation cover better but also helps to minimize the error in classifying other unclassified pixels of urban categories. According to the Confusion Matrix results, the probability of the classification to accept or reject a pixel is computed as 95%. The results show that 97.80 % of the pixels are classified into the correct classes (overall accuracy). Kappa Coefficient is also calculated as 0.94 which is close to 1, hence this is also an indicator of a good classification.

1. INTRODUCTION

There is a high potential for the use of GIS and RS techniques on QOP measurements using spatial analysis techniques and land use information gathered from remotely sensed data. While the survey data provides the subjective opinions of people about the accessibility to public services, processing and analyzing the GIS and RS based information makes important contributions in understanding the objective dimension of the QOP such as the existence and proximity of the green spaces or the accessibility to health, emergency and transportation facilities.

This paper will focus on land use classification dimension of QOP which is obtained from remotely sensed data in RS environment. To improve the classification accuracy, a new vegetation index, Transformed Difference TDVI is tested in order to detect the urban vegetation better.

2. METHODOLOGY

Before the land use information extraction, the first step is atmospheric correction (absorption and scattering) and sensor radiometric calibration which is done by the Remote Sensing Laboratory of University of Ottawa. The second step is the geometric correction of the raw image data (IRS – 1D image of Montréal). The image of Montréal Island is rectified using "polynomial method". This method is chosen because, first, the inner city is generally a flat area (except the Plateau-Mont-Royal area); secondly, the main goal of this study is to obtain a land cover/use map which is thematic and will be integrated with other sources of data. The geometric correction is conducted with the help of GCPWorks module of the PCI Geomatica V9.0 software.The image is geocorrected using the "Universal Transverse Mercator" (UTM) projection, NAD 83 and GRS 80 are selected for the datum and for the ellipsoid types, respectively. Seven ground control points (GCPs) from the different areas of the image are selected. The success of the geometric correction is measured with an RMSE value of 0.06 pixels (smaller than 1.2 meters). After geocorrection, the next step is to extract the information about the greenness of the study area. To do that, different vegetation indices have been analyzed through the literature survey to find out which provides the best result in an urban environment. As a result, NDVI, SAVI and TDVI are applied to the study area and results are compared in the following section.

3. VEGETATION INDICES

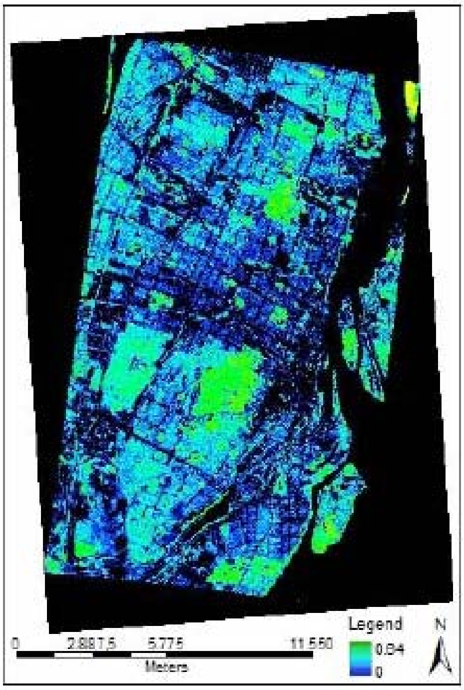

Figure 1: NDVI map of Montreal (Source: Bannari, Ozbakir and Langlois, 2006)

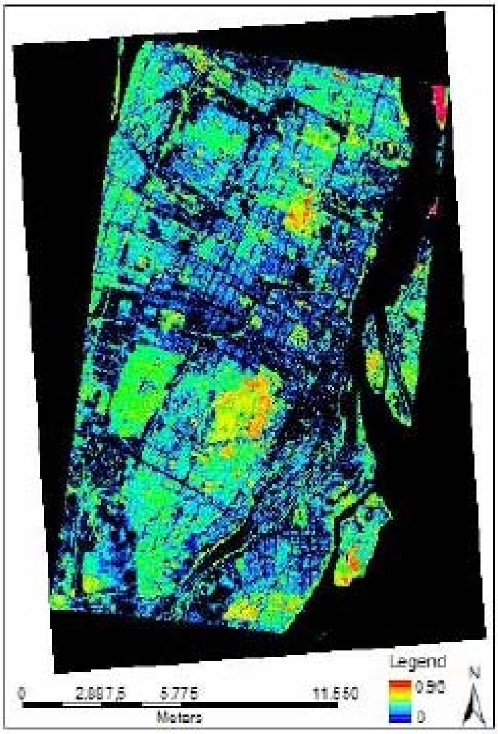

Figure 2: SAVI map of Montreal(Source: Bannari, Ozbakir and Langlois, 2006)

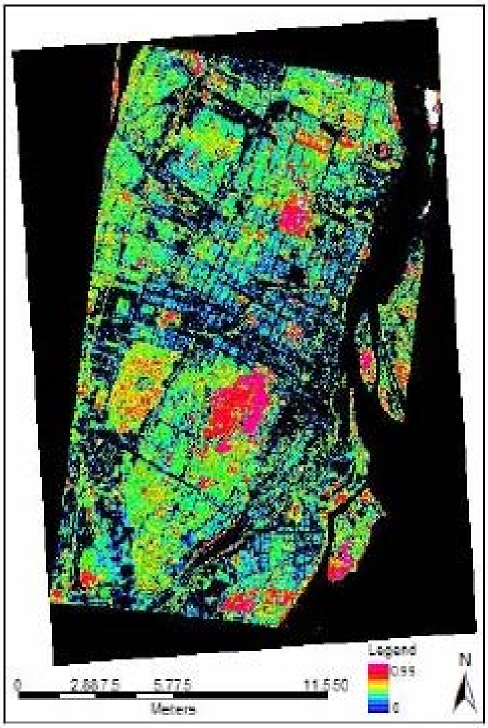

Figure 3: TDVI map of Montreal (Source: Bannari, Ozbakir and Langlois, 2006)

In the last decade, over forty vegetation indices are introduced in the remote sensing literature, to measure the vegetation cover in different applications (Bannari *et al.*, 1995a). Since soil brightness, environmental effects, soil color, moisture and shadow are major complex mixture of vegetated areas; vegetation indices make an effort in minimizing the effect of those sources and enhance the vegetation response. A new vegetation index, "Transformed Difference Vegetation Index (TDVI) developed by Bannari *et al.* (2002), is tested in a previous work where the index has performed better than NDVI and SAVI. In that study (Bannari, Ozbakir and Langlois, 2006), authors discuss a comparative study between TDVI, SAVI and NDVI for estimating vegetation cover in urban environment from the *Indian Remote Sensing Satellite* (IRS-1D) imagery has been conducted. The validation of the obtained results according to the ground truth showed that the TDVI is an excellent tool for vegetation cover monitoring in urban environment (Figures 1, 2 and 3). It does not saturate like NDVI or SAVI, it shows an excellent linearity as a function of the rate of vegetation cover.

4. IMAGE CLASSIFICATION

For this study, the supervised classification technique is applied to the IRS-1D image of Montréal that has been geocorrected and used to calculate the TDVI and Principal Component Analysis (PCA). the reason for selecting the "supervised classification technique" is that it enables the image analyst to decide on the classes and specify the training areas. For this research, the following eight land use classes are identified:

1. Urban with weak vegetation (which is an indicator of high dense urban areas),
2. Urban / vegetation (which is an indicator of medium dense urban areas),

3. Urban with dense vegetation (which is an indicator of low dense urban areas),
4. Parks and cemetery,
5. Urban forest,
6. Large surfaces (such as open areas or big shopping malls),
7. Water,
8. Clouds (although this is not a land use category, since an image correction to remove the effect of clouds is not applied, this is entered as a separate category and identified easily in the training area selection)

To this end, first step is the selection of training areas which the supervised classification will be based on. In the training area selection, the goal is to identify homogeneous samples of different surface cover types in the image. Samples are created by drawing colored layers over the parts of the image that are likely to be the information classes that the image analyst wishes to examine. Selecting appropriate training areas is based on the familiarity of the analyst with the geographical region and knowledge of the actual surface cover types shown in the image. For this purpose, to understand the study area better two trips are made to Montréal.

Once the training areas are selected, different methods are used for testing purposes such as histograms, signature separability, signature statistics and scatter plots. According to the results, the average separability is 1.99 while the minimum is 1.93 which shows an acceptable level of accuracy. The poorest separability occurs between the first three urban categories (the classes which usually show a mixed spectral signature in an urban area).

Moreover, especially the category for "urban with dense vegetation" is not very well separated from the parks and cemetery category. This was anticipated before the analysis since it is usually very difficult to differentiate the spectral signature of the neighbourhoods having trees in the backyards of the houses and the parks exist within that neighbourhood.

It is also important to underline the effect of TDVI for the separability of the classes that have vegetation cover. For example, not only "urban forest" is generally separated perfectly from other classes but also some classes that have mixed spectral signature (like urban with dense vegetation) show a good separability (1.99).

Having acceptable levels for the separability of the training areas, the next step is to conduct the classification process. There are mainly three methods of conduction of a supervised classification: minimum-distance-tomeans classifier, parallellpiped classifier and maximum likelihood classifier. Remote sensing software packages, such as PCI, construct bounding boxes, or parallelepipeds, around clusters of signatures collected from the training areas. The limits of these parallelepipeds represent each individual class in multispectral space.

In areas where parallelepipeds overlap or for pixels that fall outside parallelepiped limits, the maximum likelihood decision rule determines the classification. This rule calculates the statistical probability of a pixel belonging to a particular class, based on the variance and covariance of the spectral signatures. Therefore, the combination of the parallelepiped and maximum likelihood decision rules results in an output map in which no pixels are left unclassified.

Therefore, in the mixed urban environments this mixed approach is the most appropriate and used by researchers (Hill *et al.*, 2003; Pinard, 2004). For this study, since the study field is an urban area where the covariance is expected and it is very hard to differentiate the different categories, this mixed approach of the parallelepiped and maximum likelihood classifier technique is applied. The resulting image is shown in Figure 4.

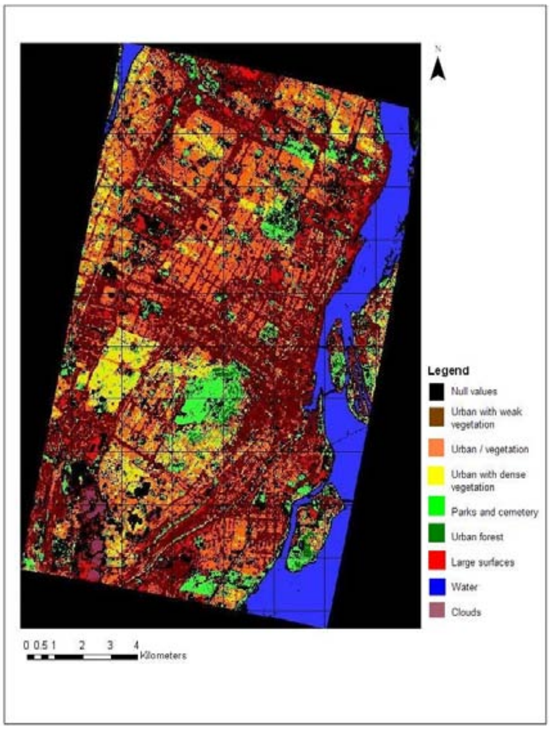

Figure 4: The resulting image of the mixed approach classification

The accuracy of the classification is tested using the "Confusion Matrix" to determine how well a classification has categorized a representative subset of pixels used in the training process of a supervised classification. According to this matrix, the probability of this classification to accept or reject a pixel was computed as 95%. The results show that 97.80 % of the pixels are classified into the correct classes (overall accuracy). This table also provides the information about "errors of commission" and "errors of omission". For example, 1.15 % of pixels have been assigned to the fourth class which is "Parks and cemetery", indicates the error of commission for the class "Parks and cemetery". However, it also indicates the error of omission since that percentage of pixel should normally have been assigned to the class "Urban Forest". Furthermore, the Kappa Coefficient is calculated as 0.94 (which is close to 1), which is also an indicator of a good classification.

5. CONCLUSION

As it was previously indicated, the differentiation among the green areas plays an important role in urban QOP studies. Since planning policies and urban management differ in forestry areas or parks and amusement areas, this study has provided promising results in separating the different categories successfully through the application of TDVI.

In this work, the performance of TDVI is tested in urban image classification. Results of the image classification using TDVI showed that a value of 0.94 was achieved for the Kappa Coefficient which is an indicator of good classification. With the help of these results, urban areas with vegetation cover were differentiated into three subcategories such as: 1) urban with dense vegetation 2) urban/vegetation 3) urban with weak vegetation. Green areas were also separated as: 1) parks and cemetery and 2) urban forest.

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