ANALYSIS OF RAPID EYE’S RED EDGE BAND FOR IMAGE SEGMENTATION AND CLASSIFICATION

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ABSTRACT:
The objective of this study was to evaluate if a multi-resolution segmentation algorithm is sensitive to the RapidEye’s Red Edge band and its benefits for vegetation mapping using GEOBIA and machine learning. We used a high-resolution multi-spectral RapidEye image taken in June, 2010. This image was segmented with a multiresolution segmentation algorithm (MRIS) using a fine scale parameter (300) and thirteen different weights (from ‘0’ to ‘100’) were assigned to the Red Edge spectral band to evaluate its influence in the segmentation and classification process. Each weight generated a segmented image. Attributes related to spectral information, geometry and texture were calculated for each image segment using the eCognition Developer®. Visual interpretation was performed along with field data to select seven classes (Dense vegetation, Meadow, Mining area, Bare land, Rock outcrop, Urban area and Water). A sample of 800 objects described by its attributes was selected from each segmented image. A decision tree approach based on CART was applied to the samples to select the attributes that provides the best separation among the classes within the scene. An accuracy assessment for the classification using CART was performed to compare the different weights assigned to the Red edge spectral band. Results showed that the Red Edge channel had no significant influence on the segmentation process. The attributes importance rank showed that the index derived from Red Edge channel can be used as input for image classification.

1. INTRODUCTION
The use of remotely sensed images for mapping and monitoring land cover had fundamental importance in recent decades, in particular, due the development of new techniques and computer programs that enhanced the analysis and manipulation of these digital products.

Notable advances are being made in land cover mapping due the technological advancement of the recent and upcoming sensors. These advances rely mostly in the introduction of additional bands in multi-spectral sensors. In this study, the wavelength between red and near infrared (690 – 730 nm), called Red Edge band, is particularly focused on. Because of its sensitivity to the chlorophyll content of plants, this band is appropriate to vegetation studies. Many studies have been conducted in order to monitor biophysical parameters of vegetation to exploit the importance of the Red Edge for these purposes using spectroradiometry (Chang-Hua et al., 2010; Tian et al., 2011; Ren et al., 2011) and airborne imagery (Schlerf et al., 2009). In the context of spaceborne sensors, Delegido et al. (2011) conducted a study for monitoring green leaf area index and chlorophyll content using the Sentinel-2 Red Edge spectral bands. They have found that Red Edge improved significantly the accuracy of chlorophyll estimation.

RapidEye (Rapideye AG, 2011) represents a constellation of 5 multispectral satellites sensors which provide the Red Edge band. These satellites are equally spaced around a sun-synchronous orbit and have a spatial resolution of 5 meters (resampled). Recent studies in land cover mapping suggest that pixel-based approaches have disadvantages for such a high resolution imagery. One alternative to the pixel-based approach is the framework known as GEOBIA – Geographic Object-Based Image Analysis (Hay and Castilla, 2008). Previous studies have proved its advantages over the well-known pixel-based approach (Ait Belaid et al., 1992; Herrera et al., 2004; YU et al., 2006; Myint et al., 2011). The basic role of this new approach is to merge the adjacent pixels into spectrally homogeneous objects and lead the classification process as the objects being the minimum unit of analysis.

Characteristics within a scene such as spatial resolution and the number of bands can affect the segmentation results as well as the final classification. Consequently, many segmentation algorithms have been developed in recent years, all of them aiming at homogeneous image segments. The multi-resolution image segmentation (MRIS) implemented in eCognition Developer® software is a frequently used algorithm in Earth sciences (Blaschke, 2010). The MRIS offers the possibility to assign different weights to the spectral bands of the image. In this context, the evaluation of the influence of the spectral bands on the process of segmentation might be considered relevant in studies such vegetation mapping and land cover classification. Schuster et al. (2010) evaluated the influence of RapidEye Red Edge channel in the classification accuracy using a pixel-based approach and they have found that the Red Edge led to a slight improvement of the overall accuracy of the classification.

However, no studies exist to evaluate the influence of Red Edge channel in high-resolution multispectral satellites on the image segmentation process using the multiresolution segmentation algorithm in an object-based approach.

1.1 Aims
The objective of this study is to evaluate if multi-resolution segmentation is sensitive to the RapidEye Red Edge band and its benefits for vegetation mapping using an object-based
2. METODOLOGIA

2.1. Estudo de caso e dados

O Bioma Mata Atlântica é um dos mais importantes biomas do país, com estudos realizados pelo Centro de Pesquisas e Conservação da Floresta Atlântica (Brazil). No Brasil, o Bioma Mata Atlântica é considerado um hotspot de biodiversidade. A região é caracterizada por uma grande diversidade de ambientes e é ainda um grande destino turístico.

A área de estudo está localizada no centro da região de Minas Gerais, Brasil, dentro das áreas de Ouro Preto e Mariana (Figura 1). Esta região abriga os maiores remanescentes de Mata Atlântica dentro do estado de Minas Gerais e é considerada um importante biodiversidade hotspot. Esta região é caracterizada por uma grande diversidade de ambientes e é ainda um grande destino turístico.

O estudo de caso deve elucidar questões como:

1) Como a área de estudo impacta significativamente o algoritmo de segmentação e classificação?

2) O uso de uma técnica que incorpora Red Edge (Rayo Vermelho) para segmentação e classificação?

3) O uso da técnica de classificação que incorpora Red Edge (Rayo Vermelho) para segmentação e classificação?

2.2. Métodos

A rápida visão da proposta de método usada neste estudo pode ser vista na Figura 2.

2.2.1 Segmentation Image: o primeiro mapeamento de imagem incluiu segmentação na escala relativamente fina (300) usando o Cognition Developer® versão 8.0. Todos os outros parâmetros foram mantidos constantes (compactness 0.5 e shape 0.1) desde que o estudo focalizou exclusivamente na influência do Red Edge (Rayo Vermelho) na segmentação e classificação. Características como resolução espacial e número de bandas podem afetar as análises de segmentação. Muitos algoritmos de segmentação foram desenvolvidos nos últimos anos, todos eles tentando segmentar homogêneas imagens. O MRIS, software eCognition Developer® que foi usado neste estudo, permite a atribuição de pesos diferentes para cada banda da imagem. O MRIS oferece a possibilidade de atribuir pesos diferentes aos diferentes bandas da imagem. Para avaliar a sensibilidade do MRIS algoritmo para Red Edge, o conjunto de dados foi composto de diferentes segmentados de bandas derivadas de diferentes pesos. Inicialmente, todas as bandas (azul, verde, vermelho, Red Edge e infravermelho) foram igualmente ponderados. Em seguida, diferentes pesos foram atribuídos ao Red Edge para avaliar o impacto na segmentação e classificação. Os pesos foram gerados de diferentes formas: todas as bandas com peso 1 e não atribuído ao Red Edge (“No Red Edge”), não peso atribuído às outras bandas e Red Edge atribuído com 1 (“Only Red Edge”), todos as bandas de peso 1 e Red Edge com 2 (“w=2”) e assim por diante, criando assim 13 diferentes atributos de objetos baseados em segmentações de imagem de acordo com os pesos atribuídos ao Red Edge.

2.2.2 Image Objects Atributtes: Subsequente a segmentação da imagem, os atributos foram calculados para cada segmento da imagem usando o Cognition Developer® 8.0.

A nova index incorpora o espectro do Red Edge e foi calculado para estender o conjunto de entrada para o processo de classificação. Este novo index range from the classic NDVI index.
with the adaptation to the Red edge channel, according to the Equation 1.

\[
NDVI_{RedEdge} = \frac{Red \ Edge - Red}{Red \ Edge + Red}
\]  

(1)

where

Red Edge = reflectance value for the Red Edge channel

Red = reflectance value for the Red channel

Thus, fifty-two attributes were generated using the characteristics shown in Table 3.

<table>
<thead>
<tr>
<th>Spectral information</th>
<th>Band Ratio (RedEdge/NIR*, NDVI and NDVI Red Edge)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texture GLCM</td>
<td>Brightness</td>
</tr>
<tr>
<td></td>
<td>Homogeneity</td>
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<td></td>
<td>Standard deviation</td>
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<td>Compacity</td>
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<td></td>
<td>Boundary index/Shape</td>
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<td></td>
<td>Length/Width</td>
</tr>
</tbody>
</table>

Table 3. Attributes related to shape, pixel values and texture.

2.2.3 Data Mining and Variable Importance: A decision tree approach based on Classification and Regression Tree (Breiman et al., 1984) was used to select the attributes that provide the best separation among the classes within the RapidEye scene. Decision trees are strictly non-parametric and do not require any assumption regarding the data set distribution, presenting several advantages over traditional supervised classification such Maximum Likelihood classification (Friedl and Brodley, 1997).

The CART approach starts with a group of object samples described by a set of attributes – the training objects. This approach relies on splitting the data set into smaller homogeneous sub-sets according to the attributes in each split of the tree. For each weight applied to Red Edge spectral band, the segmentation generated a different number of objects. From these data sets, a sample of approximately 800 objects (from all land cover class) were input to de CART for data mining and classification to evaluate the effects of changing the weight of the Red Edge on the segmentation process and on vegetation mapping. The proportion of objects according to the occurrence of each class within the scene is shown in Table 4.

| Bare land            | 8%  |
| Dense Vegetation     | 40% |
| Meadow               | 20% |
| Mining area          | 10% |
| Rock outcrop         | 16% |
| Urban area           | 5%  |
| Water                | 1%  |

Table 4. Attributes related to shape and pixel values.

The CART approach was applied using the WEKA interface freely distributed on the internet and the results were evaluated using a ten-fold Cross-Validation. For further comparison between the weights, an accuracy assessment for the classification was performed using the Kappa statistic.

3. RESULTS AND DISCUSSION

3.1 Image Segmentation

Weights from 1 to 100 were input to the Red Edge band in the multiresolution segmentation algorithm. Segmentation results are shown in Figure 5.

![Figure 5](image_url)

Figure 5. Relationship between the weights assigned to the Red Edge and object count.

The segmentation process showed no significant influence of the Red Edge in the average object count. The differences within the weights assigned to the Red Edge rely mostly on the number of the objects. In particular, the weight “Only Red Edge” has over-segmented most of the land cover classes. Consequently, generating more objects within the classes as it is showed in Figure 6.

![Figure 6](image_url)

Figure 6. Shape and number of the objects generated by the weights “Only Red Edge” (A) and “No Red Edge” (B). The vegetation is showed in red and maroon due the color composition RGB 521.

3.2 Data Mining and Classification

The results for attribute importance and classification accuracy measures are summarized in Table 7 and 8. From the 52 attributes used in this study, data mining with decision trees indicated the attributes which provided the best class separation.

All the weights which include the Red Edge channel have presented the NDVI and NDVI Red Edge as the best attributes to provide separation among the seven classes. Although the weight ‘No Red Edge’ does not have any participation of the Red Edge channel in the segmentation process, it presented both NDVI and NDVI Red Edge values in the list of best attributes to separate the classes. The presence of NDVI and NDVI Red Edge as the most important attributes to provide separation within the classes can be explained by the fact that ‘Dense
Vegetation’ is the predominant land cover class within the area of study. It is known that attributes related to reflectance values in these regions of the electromagnetic spectrum is important to characterize vegetated areas rather than attributes related to shape of the objects, for example. As shown in the Table 7, the geometry attributes did not heavily participate on the classification process, as the Red Edge did not affect the shape and geometry of the objects.

![Table 7](attachment:image.png)

Table 7. Attributes importance for the weights assigned to the segmentation process.

![Table 8](attachment:image.png)

Table 8. Accuracy measures for the weights assigned to the segmentation process.
Cross validation, a measure of misclassification which represents the error rate of the tree, produced an average of 89.67% of overall correct classification for this model adjustment. The classes ‘Dense Vegetation’ and ‘Meadow’ showed the highest values of accuracy (Figure 9) due to their spectral characteristics, consequently, being easily separated from the other classes when using vegetation indices such as NDVI and its variation, NDVI Red Edge. However, the different weights did not show any influence on these classes, especially on the class ‘Dense Vegetation’, which was not affected by the weight ‘No Red Edge’.

The overall accuracy as well as the accuracy for each class did not show any significant increase or decrease trend (Figure 9). The weight ‘w=20’ presented the highest value of overall accuracy, which means that even higher weights had no influence on the segmentation and classification using CART.

4. CONCLUSIONS

Results indicated that the Red Edge band had little influence on the segmentation process, as well as on the class separability within the study area using an object-based approach. However, vegetation classes appear to be sensitive to the Red Edge channel and the derived index used in this study. The incorporation of the Red Edge channel presented no improvement on the overall accuracy of the classification.

REFERENCES


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Figure 9. Accuracy measurements for each class.


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