THE ASSESSMENT OF VEGETATION SEASONAL DYNAMICS USING MULTITEMPORAL NDVI AND EVI IMAGES DERIVED FROM MODIS

Eduarda Martiniano de Oliveira Silveira[1], Luis Marcelo Tavares de Carvalho[2], Fausto Weimar Acerbi-Júnior[2], José Marcio de Mello[2]

(received: may 16, 2007; accepted: april 30, 2008)

ABSTRACT: The objectives of this work were to characterize seasonal dynamics of cerrado, deciduous and semideciduous forests in the north of Minas Gerais, Brazil. Time series of NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index) derived from MODIS sensor, were compared by analyzing temporal profiles and image classification results. The results showed that: (1) there is an agreement between vegetation indexes and the monthly precipitation pattern; (2) deciduous forest showed the lowest values and the highest variation; (3) cerrado and the semideciduous forest presented higher values and lower variation; (4) based on the classification accuracies the best vegetation index for mapping the vegetation classes in the study area was the NDVI, however both indexes might be used to assess the vegetation seasonal dynamic; and (5) further research need to be carried out exploring the use of feature extractions algorithms to improve classification accuracy of cerrado, semideciduous and deciduos forests in Minas Gerais, Brazil.

Key words: Remote sensing, time series, vegetation indies.

CARACTERIZAÇÃO DA DINÂMICA SAZONAL DA VEGETAÇÃO USANDO IMAGENS MULTITEMPORAIS NDVI E EVI DERIVADAS DO SENSOR MODIS

RESUMO: *O objetivo deste trabalho foi caracterizar a dinâmica sazonal do cerrado, floresta estacional semidecidual e decidual no norte do estado de Minas Gerais, Brasil. Séries multitemporais dos índices de vegetação NDVI (índice de vegetação da diferença normalizada) e EVI (índice de vegetação melhorado) derivados do sensor MODIS, foram comparadas analisando o perfil temporal e os resultados de classificação das imagens. Os resultados mostraram que: (1) Os índices de vegetação estudados refletiram o padrão sazonal das fisionomias, diferenciando os períodos chuvosos e os períodos de seca; (2) a fisionomia floresta estacional decidual apresentou menores valores dos índices e maior variação; (3) as fisionomias cerrado e floresta estacional semidecidual apresentaram alto valores dos índices e baixa variação; (4) de acordo com os resultados das classificações o melhor índice para o mapeamento das fisionomias na área de estudo foi o NDVI, porém ambos podem ser usados para avaliar a dinâmica sazonal da vegetação; e (5) estudos precisam ser realizados explorando algoritmos de extração de feições para melhorar a acuracidade do mapeamento das fisionomias cerrado, floresta decídua e semidecidua na área de estudo.*

Palavras-chave: Sensoriamento remoto, série multitemporal, índices de vegetação.

1 INTRODUCTION

Maps of the distribution and status of the Earth's vegetation and land cover are critical for parameterization of global climate and ecosystem process models as well as characterization of the distribution and status of major land surface types for environmental, ecological and natural resource applications at global and regional scales (MUCHONEY et al., 2000).

The seasonal behavior of vegetation is a fundamental component of successful image interpretation (LILLESAND & KIEFER, 1987). For land cover assessment, the timing of image acquisition can be critical. Knowledge of crop calendars and phenology is often a crucial element in vegetation interpretation. Since the 1970s, researches have recognized the potential of multitemporal satellite observations to provide information about the phenological development of natural vegetation and crops (REED et al., 1994) moreover the combination of vegetation indexes with multitemporal imagery that captures phenology has produced successful vegetation classifications (SADER et al., 1990).

Because of the synoptic coverage and repeated temporal sampling that satellite observations afford, remotely sensed data possess significant potential for monitoring vegetation dynamics (MYNENI et al., 1997). Satellite vegetation index (VI) data such as the Normalized Difference Vegetation Index (NDVI) are correlated with

[1]Federal University of Lavras/UFLA – P.O. Box 3037 – 37200-000 – Lavras, MG – Brazil – dudalavras@hotmail.com
[2]Federal University of Lavras/UFLA – P.O. Box 3037 – 37200-000 – Lavras, MG – Brazil – passarinho@ufla.br, fausto@ufla.br, jmmello@ufla.br

green leaf area index (LAI), green biomass, and percent green vegetation cover (ASRAR et al., 1989; BARET & GUYOT, 1991).

The radiometric and geometric properties of the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra spacecraft, in combination with improved atmospheric correction and cloud screening, provide a substantially improved basis for studies of this nature (ZHANG et al., 2002). The MODIS instrument has 36 spectral bands that range from 250 m to 1 km where seven spectral bands are specifically designed for land applications (JUSTICE et al., 1997).

The MODIS VI products provide consistent, spatial and temporal comparisons of global vegetation conditions which are used to monitor the Earth's terrestrial photosynthetic vegetation activity in support of phenologic, change detection, and biophysical interpretations. Two VI algorithms were produced. One is the NDVI, which is referred to as the continuity index to the existing NOAA-AVHRR derived NDVI. The other is an enhanced vegetation index (EVI) with improved sensitivity into high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences. This two VIs complement each other in global vegetation studies and improve upon the extraction of canopy biophysical parameters (HUETE et al., 1997).

Thus, this study was motivated by the following research questions: (1) Are MODIS vegetation indexes (NDVI and EVI) able to depict the seasonal dynamics of cerrado, deciduous and semideciduous forest? (2) What is the best vegetation index (VI) to map different land cover types in the study area?

The general objectives of this study were: (1) To characterize the seasonal vegetation dynamics captured by NDVI and EVI; (2) To compare the performance of NDVI and EVI temporal profiles for image classification.

2 MATERIAL AND METHODS

The study area (Figure 1) is located in the state of Minas Gerais, Brazil and is delimited by the coordinates S 14º 47' 25'' - S 15º 53' 16" and W 43º 52' 52'' - W 45º 6' 17''. The area is cover by three major land cover types: deciduous forest, semideciduous forest and cerrado (Brazilian savannas).

Figure 2 shows the seasonal patterns in monthly precipitation for the year 2003, 2004 and 2005 as well as the historical data for the last 31 years.

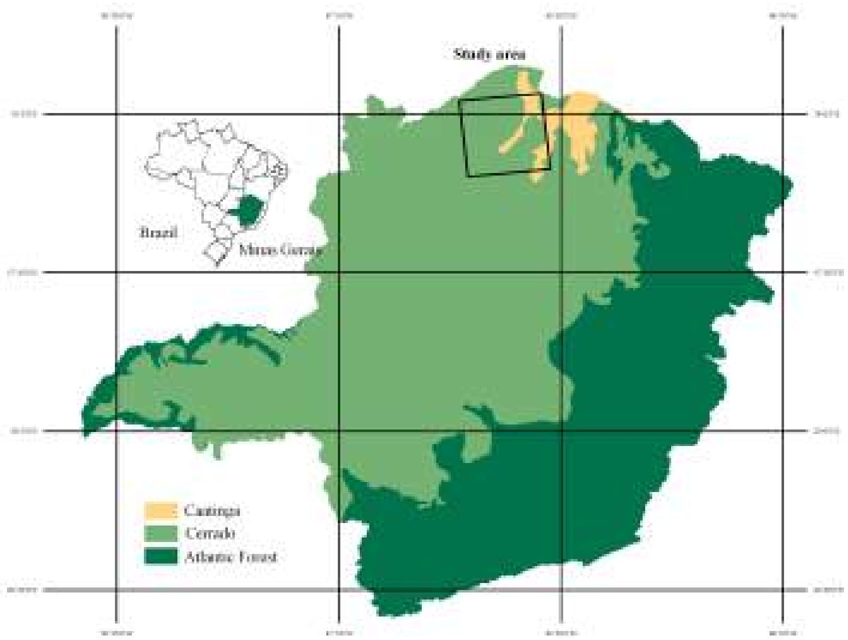

Figure 1 – Study area.
Figure 1 – *Área de estudo*.

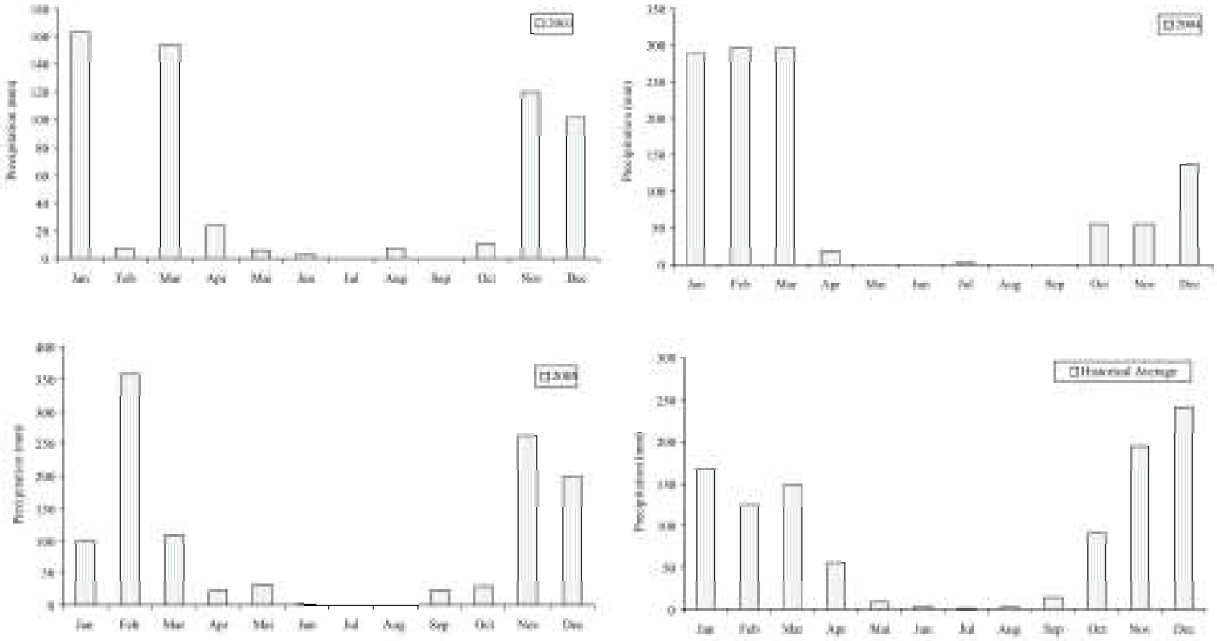

Figure 2 – Monthly precipitation pattern.

***Figura 2 –** Precipitação média mensal.*

MODIS 16-day vegetation indexes composite with 250 m of spatial resolution from TERRA satellite, were used to derive three years (2003, 2004 and 2005) NDVI and EVI temporal profiles. The images were resampled to Albers Conic Equal Area projection.

Along with the image data, there exists a map that associates a quality assurance number (QA) with each pixel of the image. The QA is a 16 bit coded integer. The various groups of this 16 bit long binary code describe different properties of the pixel. One can set thresholds or specific values for these different groups to check the 'quality' of the pixel and then label it either good or bad depending upon the application.

The quality assessment (QA) was carried out through MODIS metadata in order to ensure that the images were generated without errors or artifacts. Quality assessment bits from each data indicted data of good quality.

The NDVI is a normalized transform of the near infrared (NIR) to red reflectance ratio, ρ nir/ ρ red , designed to standardize VI values between –1 and +1 formulated as:

$$NDVI = \left[\frac{\rho nir - \rho red}{\rho nir + \rho red}\right] \qquad (1)$$

In spite of the intensive use of the NDVI and its variety of applications, several limitations of the index are known. Among these are the sensitivity for soil (especially dark and/ or wet) background (HUETE et al., 1991), saturation of the index values in case of dense and multilayered canopy (LILLESAETER, 1982), and sensitivity for atmospheric influence (HOLBEN, 1986) since aerosol increases the apparent reflectance in the red band by scattering sunlight directly to the sensor and decreases to a lesser degree the reflectance in the NIR by absorption of sunlight (FRASER & KAUFMAN, 1985).

Liu & Huete (1995) developed a feedback based approach to correct for the interactive canopy background and atmospheric influences, incorporating both background adjustment and atmospheric resistance concepts. This enhanced, soil and atmosphere resistant vegetation index (EVI) was simplified to:

$$EVI = 2.5\frac{(\rho_{nir} - \rho_{red})}{(L + \rho_{nir} + C_1\rho_{red} + C_2\rho_{blue})} \qquad (2)$$

Where ρ is 'apparent' (top-of-the-atmosphere) or 'surface' directional reflectances, L is a canopy background adjustment term, and C_1 and C_2 weigh the use of the blue channel in aerosol correction of the red channel (HUETE et al., 1994). The blue band is sensitive to atmospheric conditions and is often used for atmospheric correction. EVI directly adjusts the reflectance in the red bands as a function of the reflectance in the blue band (HUETE el al., 2002).

A set of 200 homogeneous pixels distributed over the area were randomly selected from each land cover type in order to generate the NDVI and EVI temporal profiles and characterize seasonal dynamics of the vegetation. The selection was based on field campaigns, as well as on a vegetation map produced at the Federal University of Lavras - UFLA (SCOLFORO & CARVALHO, 2006).

Additionally, the NDVI and EVI multitemporal images were classified using a decision tree (DT) algorithm (Figure 3). A DT is defined as a classification procedure that recursively partitions a data set into more uniform subdivisions based on tests defined at each node in the tree (QUINLAN, 1993). A DT is composed of a root node, a set of internal nodes and a set of terminal nodes. Each internal node has one parent node and two or more descendant nodes.

A data set is classified according to the decision surfaces defined by the tree, and class labels are assigned to each observation according to the leaf node into which the observation falls. Decisions trees share advantages compared with traditional probabilistic algorithms because they are strictly nonparametric, free from distribution assumptions, able to deal with nonlinear relations, insensitive to missing values and capable of handling numerical and categorical inputs (CARVALHO, 2001).

The classifier was trained with a set of sampled pixels (1500) distributed over seven main land cover types: cerrado, semideciduous and deciduous forest, water and others (eucalyptus, cultures and pasture).

To compare the classified images an accuracy assessment using an independent validation set of 1500 pixels was carried out based on the overall and per class accuracy as well as on the kappa coefficient. The validation set was based on field campaigns.

Error matrices are very effective representations of map accuracy because the individual accuracies of each map category with both the errors of inclusion and errors of exclusion (CONGALTON, 1999).

3 RESULTS AND DISCUSSION

The results showed agreement between the vegetation indexes and the monthly precipitation pattern. The seasonal behavior of the vegetation, which is mainly driven by precipitation, is clearly seen in the NDVI and EVI temporal profiles during the three years (Figure 4).

High NDVI and EVI values, indicative of high photosynthetic activity and biomass accumulation were found in the rainy months, while the lowest values in the dry period.

Similar results were found by Espig et al. (2006) using NDVI and EVI images for the year 2003 and 2004 working in a semiarid region of Brazil. They studied the seasonal variation of six areas and reported that the highest values of NDVI and EVI occurred in the months of higher precipitation.

Xiao et al. (2006) conducted a regional scale analysis of tropical evergreen forests in South America using time series of EVI from MODIS in 2002 and the results showed a large dynamic range and spatial variations of annual maximum EVI The maximum EVI in 2002 typically occurs during the late dry season to early wet season. This suggest that leaf phenology in tropical evergreen forests is not determined by the seasonality of precipitation.

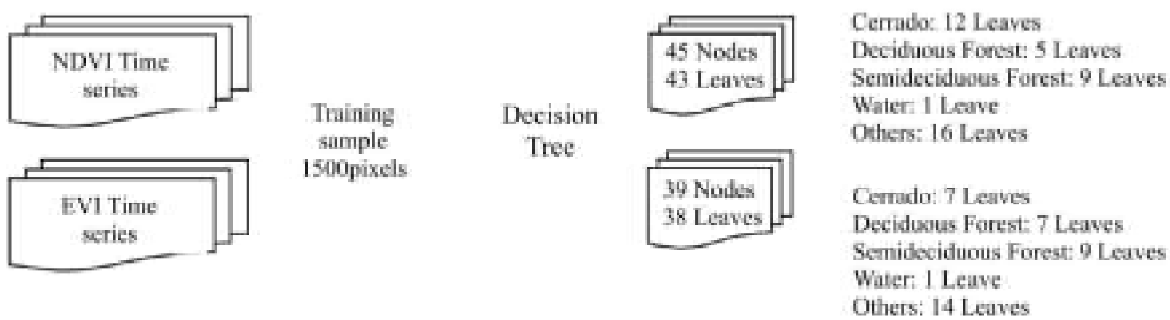

Figure 3 – Decision Tree.

Figura 3 – *Árvore de Decisão.*

Among the vegetation types the deciduous forest showed the lowest VI values and the highest variation. This is because more than 50% of the leaves are lost during the dry season. These characteristics are consistent and distinct in comparison with other land cover types, and may provide valuable information that could potentially be used when classifying land cover types.

Compared to the deciduous forest the cerrado and the semideciduous forest presented higher VI values and lower variation. This is because most of the species in the cerrado are evergreen or semideciduous. Thus, leaf fall proceeds simultaneously with the development of new leaves and the total green biomass may decrease during the dry period, but the trees never remain entirely leafless.

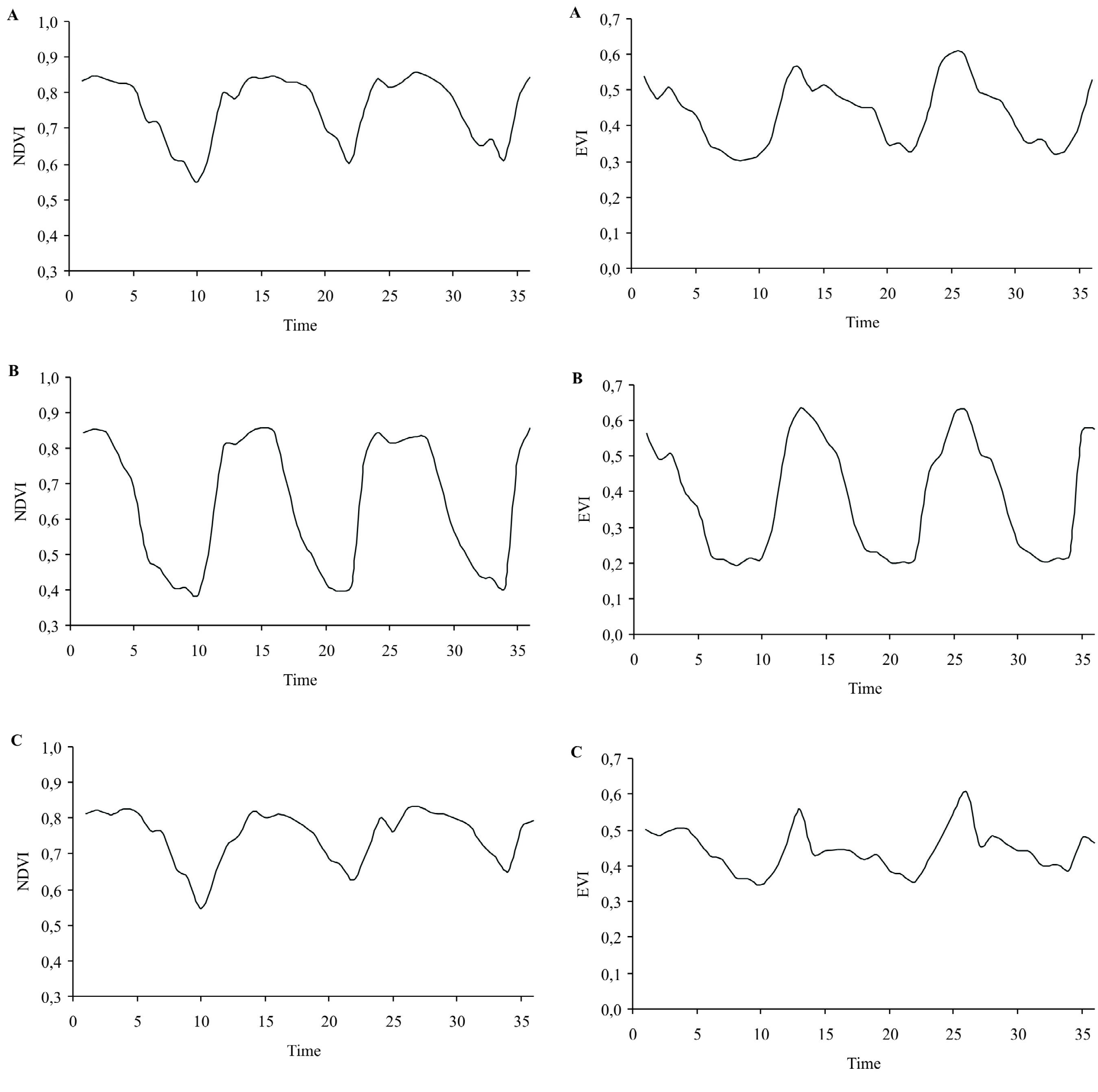

Figure 4 – NDVI and EVI temporal profiles for (A) cerrado, (B) deciduous forest and (C) semideciduous forest.

***Figura 4** – Perfil temporal dos índices NDVI e EVI para (A) cerrado, (B) floresta estacional decidual, (C) floresta estacional semidecidual.*

According to Ferreira et al. (2004) there is a low overall range in VI values among the physiognomies, and this can be readily attributed to the narrow radiometric variations associated with the different land cover types. Near infrared variation among the physiognomies were low and thus, the EVI, which by design tends to be more sensitive to NIR reflectances (HUETE et al., 1997), yielded lower responses and variations.

The NDVI showed higher values than the EVI. This occurred because the EVI is sensitive to shadows and may be responding to the higher amount of shadows in the land cover types. The NDVI, by contrast, tends to be higher with shaded backgrounds (FERREIRA et al., 2004).

Considering the classified images, in terms of overall accuracy and kappa coefficient the values were 89.9% and 0.86 for maps produced from NDVI images (Table 1), and 87.8% and 0.82 for maps produced from EVI images (Table 2). Based on these values the best vegetation index for mapping the vegetation classes in the study area was obtained using the NDVI images.

Analysing the error matrix 90.2 % of the cerrado class areas have been correctly identified as cerrado and 90.6 % of the areas called cerrado on the map are actually cerrado on the ground.

Considering the deciduous class, 89.6 % of this class was correctly identified and 98.9% of the areas on the map are deciduous forest on the ground. For semideciduous class, 75.0% of this class area has been correctly identified and 78.9 % of the areas called semideciduous are actually semideciduous on the ground.

Thus, considering the NDVI time series for classification, the user accuracy show higher values than the producer accuracy for all classes. As a result the classes areas were more excluded from the category to which they actually belong than included in an incorrect category.

Considering the EVI time series for classification, the user accuracy show higher values than the producer accuracy only for the deciduous class. Thus considering the cerrado and semideciduous classes, the areas were more included incorrectly than excluded from the classes to which they belong. The inverse occurred with the deciduous class.

In both classifications, the higher commission error values were encountered for semideciduous class. The higher omission error values were encountered for

Table 1 – Accuracy measures for maps produced from NDVI.

***Tabela 1** – Medidas de acuracidade da classificação obtida através do NDVI.*

Mapped class	Cerrado	Semideciduous	Deciduous	Commission error	User accuracy
Cerrado	90.2	22.0	3.3	9.4%	90.6 %
Semideciduous	6.6	75.0	0.0	21.0 %	78.9 %
Deciduous	0.0	0.0	89.6	1.1 %	98.9 %
Omission error	9.8 %	25.0 %	10.3 %		
Producer accuracy	90.2 %	75.0 %	89.7 %		
Overall accuracy	89.9 %	Kappa coefficient = 0.86			

Table 2 – Accuracy measures for maps produced from EVI .

***Tabela 2** – Medidas de acuracidade da classificação obtida através do EVI.*

Mapped class	Cerrado	Semideciduous	Deciduous	Commission error	User accuracy
Cerrado	92.0	12.5	9.7	10.4 %	89.6 %
Semideciduous	7.8	85.0	0.0	26.1 %	73.9 %
Deciduous	0.0	0.0	80.0	5.9 %	94.1 %
Omission error	8.0 %	15.0 %	20.0 %		
Producer accuracy	92.0 %	85.0 %	80.0 %		
Overall accuracy	87.8 %	Kappa coefficient = 0.82			

semideciduous class for NDVI (25.0%) and deciduous class (20.0%) for EVI.

The classified NDVI and EVI images are shown in Figure 5. Comparing the classified images, the shape and spatial location of the classes were well defined in both images. The highest misclassification value occurred between semideciduous and cerrado class.

4 CONCLUSIONS

We evaluated the seasonal dynamics of cerrado, deciduous and semideciduous forest in the north of Minas Gerais, Brazil, using time series of NDVI and EVI derived from MODIS.

As a conclusion the vegetation indexestemporal profiles were efficient to depict the seasonal dynamics of vegetation showing an agreement with the monthly precipitation pattern. The best index for mapping cerrado, deciduous and semideciduos forest in the study area is the NDVI. However both indexes might be used to assess the vegetation seasonal dynamic.

After these promising results, further research need to be carried out exploring the use of feature extractions algorithms to improve classification accuracy of cerrado, semideciduous and deciduos forests in Minas Gerais, Brazil.

5 BIBLIOGRAPHICAL REFERENCES

ASRAR, G., MYNENI, R. B., KANEMASU, E. T. Estimation of plant canopy attributes from spectral reflectance measurements. In: ASRAR, G. **Theory and applications of optical remote sensing**. New York: WILEY, 1989. p. 252–296.

BARET, F., GUYOT, G. Potentials and limits of vegetation indexesfor LAI and APAR assessment. **Remote Sensing of Environment**, n. 35, p. 161– 173, 1991.

CARVALHO, L.M.T. **Mapping and monitoring forest remnants: A multiscale analysis of spatio-temporal data.** 2001. 138 p. Thesis – Wageningen University.

CONGALTON, R.G.; G. GREEN, K. **Assessing the accuracy of remotely sensed data:** principles and practices. New york: Lewis publishers, 1999. 137 p.

ESPIG, S.A., SOARES, J. V., SANTOS, J. R. Variações sazonais do EVI e NDVI em áreas do semi-árido brasileiro. IN: VII SEMINÁRIO EM ATUALIZAÇÃO EM SENSORIAMENTO REMOTO E SISTEMAS DE INFORMAÇÕES GEOGRÁFICAS APLICADOS À ENGENHARIA FLORESTAL, 2006, Curitiba. **Anais:** São José dos Campos: INPE, 2006. p. 219 – 223.

FERREIRA, L.G. YOSHIOKA, H., HUETE, A., SANO, E.E. Optical characterization of the Brazilian savanna phisiognomies for improved land cover monitoring of the cerrado biome: preliminary assessments from an airbo rne campaign over an LBA core site. **Journal of Arid Environments,** vol. 56, p. 425 – 447, 2004.

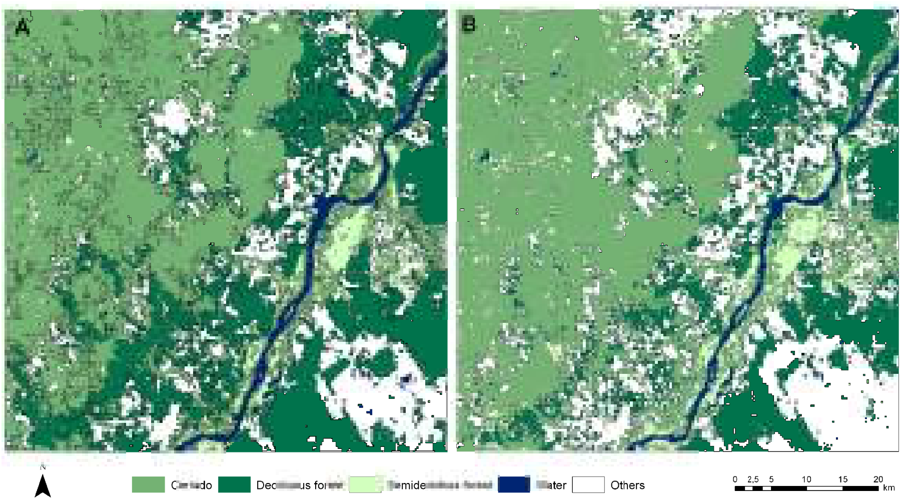

Figure 5 – Classified images – (A) NDVI (B) EVI.

Figura 5 *– Imagens classificadas - (A) NDVI (B) EVI.*

FRASER, R. S., KAUFMAN, Y. J. The relative importance of aerosol scattering and absorption in remote sensing. **IEEE Transactions on Geoscience and Remote Sensing**, n. 23, p. 625- 633, 1985.

HOLBEN, B. N. Characterization of maximum value composites from temporal AVHRR data. **International Journal of Remote Sensing,** USA, vol. 7, p. 1417-1434, 1986.

HUETE, A., DIDAN, K., MIURA, T., RODRIGUEZ, E. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. **Remote Sensing of Environment**, v. 83, p. 195– 213, 2002.

HUETE, A.R., LIU, H.Q., BATCHILY, K., VAN LEEUWEN, W. A comparison of vegetation indexesover a global set of TM images for EOS-MODIS. **Remote Sensing of Environment,** n. 59, p.440 - 451, 1997.

HUETE, A., JUSTICE, C. AND LIU, H. Development of vegetation and soil indexesfor MODIS-EOS, **Remote Sensing of Environment**. n.49, p. 224 – 234, 1994.

HUETE, A.R., JUSTICE, C.O., VAN LEEUWEN, W. **MODIS Vegetation Index (MOD 13), EOS MODIS Algorithm-Theoretical Basis Document, NASA Goddard Space Flight Center.** Greenbelt, Maryland, 1991.131p.

JUSTICE, C. O., VERMOTE, E., TOWNSHEND, J. R. G., DEFRIES, R., ROY, D. P., HALL, D. K., SALOMONSON, V. V., PRIVETTE, J. L., RIGGS, G., STRAHLER, A., LUCHT, W., MYNENI, R. B., KNYAZIKHIN, Y., RUNNING, S. W., NEMANI, R. R., WAN, Z. M., HUETE, A. R., VAN LEEUWEN, W., WOLFE, R. E., GIGLIO, L., MULLER, J. P., LEWIS, P., & BARNSLEY, M. J. The moderate resolution imaging spectroradiometer (MODIS): land remote sensing for global change research. **IEEE Transactions on Geoscience and Remote Sensing**, n. 36, p. 1228– 1249, 1997.

LILLESAND, T.M., KIEFER, R.W. **Remote sensing and image interpretation.** New York: Wiley. 1987. 724p.

LILLESAETER, O. Spectral reflectance of partly transmitting leaves: laboratory measurements and mathematical modeling. **Remote Sensing of the Environment**, n. 12, p. 247– 254, 1982.

LIU, H. Q., HUETE, A. R. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise, **IEEE Transactions on Geoscience and Remote Sensing**, vol. 33, p. 457-465, 1995.

MYNENI, R. B., KEELING, C. D., TUCKER, C. J., ASRAR, G., NEMANI, R. R. Increased plant growth in the northern high latitudes from 1981– 1991. **Nature,** vol 386, p. 698 – 702, 1997.

MUCHONEY, D., BORAK, J., CHI, H., FRIEDL, M., GOPAL, S., HODGES, J., MORROW, N., STRAHLER, A. Application of the MODIS global supervised classi. cation model to vegetation and land cover mapping of Central America. **International Journal of Remote Sensing,** USA, vol. 21, n. 6 & 7, p. 1115 – 1138, 2000.

QUINLAN, J. R., Programs for Machine Learning, Morgan Kaufmann Publishers, Amsterdam, 1993. 328p.

REED, B.C., BROWN, J.F., VANDERZEE, D., LOVELAND, T.R., MERCHANT, J.W, OHLEN, D.O. Measuring phenological variability from satellite imagery. **Journal of Vegetation Science,** vol. 5, p. 703 – 714, 1994.

SADER, S. A., STONE, T. A., JOYCE, A. T. Remote sensing of tropical forests: an overview of research and applications using no photographic sensors. **Photogrammetric Engineering and Remote Sensing**, vol 56, p. 1343–1351, 1990.

SCOLFORO, J.R., CARVALHO, L.M.T. **Mapeamento e inventário da flora nativa e dos reflorestamentos de Minas Gerais.** UFLA, 2006. 288 p.

XIAO, X., HAGEN, S., ZHANG, Q., KELLER, M., MOORE, B. Detecting leaf phenology o seasonally moist tropical forests in south America with multi-temporal MODIS images. **Remote Sensing of Environment,** n. 103**,** p.465 – 473**,** 2006.

ZHANG, X., SOHLBERG, R. A., TOWNSHEND, J. R. G., DIMICELI, C., CARROLL, M. L., EASTMAN, J. C. Detection of land cover changes using MODIS 250 m data. **Remote Sensing of Environment**, n. 83, p. 336– 350, 2002.