One of the most serious environmental problems, that planet Earth faces, is the deforestation. This study examines the deforestation, in one of planet’s most sensitive and important environmental area, Mato Grosso in Brazil. The study was conducted using satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS), over a period starting from 2001 until 2019. For this purpose, the method of Improved Change Vector Analysis was applied, while the processes of the calculation of vegetation indices were automated. From the first results it seems that, the deforestation rate has been increased.

**Key Words:** GIS, Brazilian Amazon, Deforestation, Vegetation Indices, Change Vector Analysis

**Introduction**

As hotspots of global biodiversity and carbon storage, tropical forests play an important role in biodiversity conservation, climate change mitigation and the provision of multiple other ecosystem services (Wang et al., 2019). Nearly two-thirds of the Amazon rainforest is located in Brazil, making it the biggest component in the region’s deforestation rate (Butler, 2016). In Brazilian Amazon (BA), forest areas have been significantly impacted by forest degradation due to different anthropogenic forest disturbance processes, such as selective logging, forest fires and forest fragmentation (Grecchi et al., 2017).

Among Brazilian states, Mato Grosso, is located in the Southern Amazon Forest. In Mato Grosso most of the seasonal forests, especially those that are evergreen or semideciduous, are concentrated in the central-north region of the state and constitute an area of ecological tension between Amazonian Forest and Cerrado biomes (Mews et al., 2012). They occur on relatively fertile and humid soils very attractive for agriculture (Mews et al., 2012). This region is also known as ‘the arc of deforestation’, with an important reduction of forests talking place (Nogueira et al., 2008; Mews et al., 2012).
Remote sensing change detection techniques can be used to verify changes in land use and land cover (LULC), like deforestation.

**Vegetation Indices**

In current research, four Vegetation Indices (VIs) were computed: the Normalized Difference Vegetation Index (NDVI), the Soil Adjusted Vegetation Index (SAVI), the Normalized Difference Moisture Index (NDMI) and the Enhanced Vegetation Index (EVI). These indices are used to estimate the correlation with Bare Soil Index (BI) (Diek et al., 2017) and are defined as follows:

\[
\text{NDVI} = \frac{(NIR - red)}{(NIR + red)}
\]

\[
\text{SAVI} = \left(\frac{(NIR - red)}{(NIR + red)}\right) \times (1 + L)
\]

\[
\text{EVI} = 2,5 \times \frac{(NIR - red)}{(NIR + C_1 \times red - C_2 \times BLUE + L)}
\]

\[
\text{NDMI} = \frac{(NIR - SWIR)}{(NIR + SWIR)}
\]

\[
\text{BI} = \frac{(SWIR2 + red) - (NIR + BLUE)}{(SWIR2 + red) + (NIR + BLUE)}
\]

**Change Vector Analysis**

Change vector analysis (CVA) is a radiometric technique, the primary utility of which is the detection of all changes presented in the input multispectral data (Malila 1980; Duy et al., 2012). It is flexible enough to be effective, when using diverse types of sensor data and radiometric change approaches, and capable of incorporating categorical information. CVA has been found to be useful under circumstances encountered in a variety of change detection applications (Johnsohn and Kosischke, 1998).

CVA algorithm produces two “channels” of output change information: (1) change vector direction; and (2) multispectral change magnitude (Duy et al., 2012; Chen et al., 2003).
\[
S = \sqrt{(VI_2 - VI_1)^2 + (Bl_2 - Bl_1)^2} = \sqrt{x_1^2 + x_2^2}
\]

\[
cos \theta_1 = \frac{x_1}{S}, \; cos \theta_2 = \frac{x_2}{S}, \ldots, \; cos \theta_n = \frac{x_n}{S}
\]

where \( S \) is the magnitude – intensity of change vector (Euclidean distance) and \( \theta \) is the direction of change vector in \( VI_1, VI_2, Bl_1, Bl_2 \) are Vegetation Indices and Bare Soil Indices at date 1 and date 2.

Figure 1: The concept of Change Vector Analysis in two spectral dimensions (Malila, 1980; Duy et al., 2012)

**Methodology**

**Data**

This study examines the deforestation in the central and south part of the Mato Grosso region and was conducted using satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS) from Terra satellite (MOD09A1 Version 6 product), over a period starting from 2001 until 2019. This product is a level-3 composite of 500 m resolution and provides observations during an 8-day period with high observation coverage, low view angle, absence of clouds or cloud shadow, and aerosol loading. Data are selected from the end of July for each year, when vegetation is typically at its peak and most part of the forest is visible, considering dry season. Geographic Information Systems (ArcGIS) and python programming languages have been used for the development of the whole process.

**Study Region**
Mato Grosso is the third largest by area of the states of Brazil and contains three main ecosystems: the Cerrado, the Pantanal and the Amazon rainforest. Neighboring states are Rondônia, Amazonas, Pará, Tocantins, Goiás and Mato Grosso de Sul.

In recent decades, Mato Grosso has become part of the Brazilian agricultural expansion front, so-called ‘agricultural frontier’, an important method to enhance agricultural and livestock production by converting previously unused areas of natural vegetation into new production zones (Mota et al., 2019). Therefore, Mato Grosso is a key state of the Brazilian Amazon, for investigations of forest cover changes, with very high deforestation rates and high occurrence of areas affected by forest disturbances (Butler, 2019).

Analysis

For this study, a user friendly approach, with the development of spatial models through ArcGIS, was designed. Selected data were atmospherically and geometrically corrected, with no influence over clouds, fog and other weather disturbances. The primary MODIS data format HDF (Hierarchical Data Format) was transformed in GeoTIFF and projected in WGS84, with a cell size of 0.005 degrees. Furthermore, the data were masked with the extent of the study region and VIs, along with BI, were calculated.

All the indices were normalized (0 – 1) and Pearson Correlation Coefficient, of each VI with the BI was estimated, with the use of python programming language. The VI, which gave the most suitable correlation coefficient, was selected for the calculation of the Change Vector Analysis.

In general, correlation coefficient ranges from (-1) until 1. If correlation is greater than 0.7 it is considered particularly high. Conversely, if it is close to 0.5, it is necessary to consider carefully the use or rejection of the markers, and the percentage of correlation they present, as they are likely to be contained in another parameter.
Moreover, spatial models for the calculation of Improved Change Vector Analysis, which provide the intensity (magnitude) and the direction of the vegetation changes, were developed. Finally, the CVA results only for forests were calculated.

**Results**

In this section, calculation of the four VIs and the BI, from 2001 until 2019, are presented. Based on these results, the VI, which gives the greatest inverse correlation, is selected for the calculation of the CVA. However, it is difficult to find the most appropriate threshold for every region. The change and no-change area cannot be distinguished by simply having a look on the distribution graph of one image (Duy et al., 2012). If the threshold value is low, the land cover change detection is low and vice versa (Baker et al., 2007).

In order to avoid these problems and find the appropriate threshold for the intensity changes, the improved NDVI-based method is selected (Tang, et al., 2015). Regions that seem to have no change according to the CVA method, between VIs and BI, range from 0 – 0.2. Low level changes range from 0.2 – 0.5, while high level changes are greater than 0.5.

With regard to forests, a decrease in land cover is observed, mainly due to the uncontrolled deforestation, illegal logging, as well as increases in the build-up areas (high urbanization rates).

**Vegetation Indices and Bare Soil Index**

VIs’ classification ranges from (-1) until 1. EVI and SAVI, which range from 0 – -1, don’t have values in the first class ((-1) – 0). Regions with lower VI values, seem to increase, and can be located mostly in southern parts of the study region.

Low NDVI values correspond to barren areas of rock, soil or water, while sparse vegetation tend to generate medium NDVI values (0 – 0.5). On the other hand, high NDVI values (0.6 – 0.8) correspond to dense vegetation, such as that found in tropical forests. Similar results can be observed also for the EVI and SAVI.

NDMI is sensitive to the water content of plants as well as bodies of water. Values for water bodies are larger than 0.5. Vegetation has much smaller values, which is observed in the southern part of the study region, with a range mainly from 0 – 0.1.

According to the BI, high values ranges from 0.8 until 1, correspond to bare soil areas and fallow lands, and are located in the southern part of the study region.
Correlation Coefficient Results

The VI with the best inverse correlation with BI is NDVI (-0.95). Therefore, this index has been selected for the calculation of the intensity and the direction of the land change.

Improved Change Vector Analysis

Intensity of CVA is classified into 3 levels (Figure 1a). First level (no change) ranges from 0 until 0.2, with green color. Respectively, second level (low level change) ranges from 0.2 till 0.5 (yellow), while the third level (high level change) can be observed with red, and corresponds to values greater than 0.5. When it comes to direction, it should be mentioned that changes mainly happen in two districts:
Direction II and Direction IV (Figure 1b). In Direction II the BI increases, while in Direction IV, the VI increases. BI increase could lead to the detection of the deforested areas.

<table>
<thead>
<tr>
<th>All Land Use Types</th>
<th>No Change (NC)</th>
<th>Low Level Change (LLC)</th>
<th>High Level Change (HLC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CVA (Total %)</td>
<td>79.49</td>
<td>16.35</td>
<td>4.16</td>
</tr>
<tr>
<td>Forest</td>
<td>Forest (with No Change)</td>
<td>Forest (LLC)</td>
<td>Forest (HLC)</td>
</tr>
<tr>
<td>CVA (Forest %)</td>
<td>17.10</td>
<td>10.15</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Table 1: CVA classification of the Intensity (%) of Total and Forest Land Changes, in Mato Grosso, Brazil (2001 – 2019).

In Table 1, all three levels of CVA classification (no change, low level change, high level change), for every land type and separately for the forests, are presented.

During 2001 – 2019, the no change intensity level (NC) occupied the largest area, from which 12.60% change in direction IV and 73.01% in direction II (reduced vegetation index and increased level of lighting). Low level changes (LLC), occupy the second larger area, with 16.35%, while 4.15% corresponds to high level changes (HLC).

Forests cover the 15.28% of the whole area. In the majority of the forest areas (17.10%) the first intensity level dominate, while 10.15% corresponds to low level changes. Moreover, 46.71% of the first and 9.66% of the second intensity level of forested areas, change in direction II (BI increase), which may lead to deforestation.
Figure 4: a) Intensity of the Change with the use of CVA, between NDMI and BI in Mato Grosso, Brazil, 2001 – 2019 (upper left); b) same as a) for the Direction of the Change (only areas with Low or High Level Change) (upper right); c) same as a) but for Forests (middle left); d) same as c) but for the Direction of the Change (middle right); e) Improved CVA, Intensity and Direction, of Forest Land Changes (%), in Mato Grosso, Brazil, 2001 – 2019.

Summary and Conclusions

In this study the deforestation, in one of planet’s most sensitive and important environmental area, Mato Grosso in Brazil is presented. For this purpose, a user-friendly fully automated process has been developed, in order the user to have the ability to run and calculate VIs and BI for any period and region he prefers.

Pearson Correlation Coefficient has been calculated, in order to find the VI, with the best correlation with BI. In current study this is NDVI. NDVI has been chosen for the calculation of the Improved Change Vector Analysis. Intensity, as well as direction of the change, between NDVI and BI is calculated. CVA Intensity is classified into 3 levels (no change, low level, change and high level change), while changes mainly happen in two districts (Direction II: BI Increase, Direction IV: VI Increase). The majority of the forests seem to decrease especially in first two CVA levels.
References


Online
