Evaluating vegetation indices for assessing productivity along a tropical rain forest chronosequence in Western Amazonia

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Honoring Anatoly Gitelson on the occasion of his 70th birthday

ABSTRACT

Tropical deforestation is leading not only to losses of biodiversity but also to regional losses of vegetation productivity. However, in many areas the deforestation process is usually accompanied by a fast forest regeneration that produces a mosaic of forest patches in different successional stages. These successional stages have different productivities owing primarily to differences in species composition and soil nutrients. In order to assess the long-term consequences of deforestation and forest regeneration on atmospheric carbon dynamics, it is imperative to analyze the spatio-temporal patterns of forest productivity along different successional stages. This study evaluates the suitability of five different vegetation indices for assessing productivity along a tropical rain forest chronosequence located in Western Amazonia. Among the indices tested, the Red Edge Chlorophyll Index (CI_{Red Edge}) and the Wide Dynamic Range Vegetation Index (WDRVI) proved to be the most suitable for this purpose. However, due to the current low availability of multi-spectral imagery acquired by spaceborne sensors with a band in the red edge region of the electromagnetic spectrum, the WDRVI serves as the most practical index. The dynamics of the regional productivity in the study area during the 2000s were assessed using the WDRVI and proved to be consistent with observed land cover dynamics.

Keywords: Chlorophyll indices, EVI, Hyperion, Landsat, NDVI, WDRVI

INTRODUCTION

With the current trends of change in the global climate induced by human modifications in the amount of greenhouse gases in the atmosphere (IPCC, 2007), it is critically important to analyze the spatio-temporal patterns of vegetation productivity from local to regional and global scales. This analysis requires developing techniques to delineate biomass accumulation and distribution at multiple scales (DeFries et al., 2007; Gibbs et al., 2007). Different methods have been developed for analyzing vegetation productivity, including field measurements derived from gas exchange towers (Suyker et al., 2004; Verma et al., 2005), simulation models (Ruimy et al., 1999), and analysis of greenness patterns derived from vegetation indices (Gitelson et al., 2006b; Garbulsky et al., 2008; Gitelson et al., 2008; Nakaji et al., 2008). Such procedures have been successfully applied in many vegetation types across the globe, including croplands, grasslands, and forests. However, the spatio-temporal dynamics of the productivity of tropical humid forests are little understood, partly attributed to their overall weak seasonality and high plant species diversity (Ewusie, 1992; Huete et al., 2008). This is unfortunate since tropical humid forests constitute around 56% of the forests worldwide, and are home to about 50% of all plant species on earth (Mayaux et al., 2005).
Tropical deforestation may not only lead to drastic regional decreases in precipitation (Walker et al., 2009) and overall changes in surface climate (McGuffie et al., 1995), but also to reductions in the productivity of vegetation at regional scales (Gibbs et al., 2007). However, forest regeneration in abandoned cropland and pastureland increases the aboveground primary productivity (Feldpausch et al., 2004), which may lead to overall increases in the amount of carbon sequestered by vegetation in deforested areas. Therefore, the changes in productivity due to tropical deforestation and subsequent forest regeneration are highly dynamic and need to be comprehensively and synoptically analyzed, in order to evaluate the overall effects of deforestation and forest regeneration on global carbon budgets.

The purpose of this study was to evaluate the suitability of vegetation indices developed by Professor Anatoly A. Gitelson and his colleagues (Gitelson et al., 2003a,c, 2005; Gitelson, 2004; Viña et al., 2004b; Viña and Gitelson, 2005) for assessing the changes in productivity along a chronosequence of successional stages of a tropical rain forest. These vegetation indices have been successfully used for evaluating the productivity of agroecosystems but their suitability for assessing changes in productivity in other ecosystems, particularly humid forests in tropical regions, has not been fully evaluated. Two widely used vegetation indices developed by other researchers were also included in the analysis, for comparison purposes.

METHODS

Study area

The study was performed in an area comprising 3,197.9 km² of the Amazon Basin (from 0°0′21″N to 0°27′25″N and 76°26′1″W to 76°59′56″W), with ca. 44% located in Colombia (Department of Putumayo) and ca. 56% in Ecuador (Province of Sucumbios). It includes parts of the San Miguel (international border), Putumayo, and Aguarico river basins (Fig. 1). Elevation ranges between 250 and 500 m. Mean annual rainfall and temperature are 3,528 mm and 25.3 °C, respectively (Puerto Asis weather station: 0°30′56″N, 76° 29′42″W, 260 m). While all months receive more than 200 mm of rainfall, two especially wet periods are distinguishable, one between April and June, and another in November. According to these temperature and precipitation regimes, the vegetation of the study area is classified as Lowland Tropical Rain Forest in the Holdridge life zone system (Holdridge, 1967).

Since the study area is located within the upper Amazon region, it is considered to have a high diversity of tree species (Gentry, 1992). It also exhibits the highest diversity in Colombia of monkey species, some of which are endemic to the region (Hernández-Camacho et al., 1992). However, the region has been subjected to a drastic deforestation, with an overall annual rate of forest loss between 1985 and 1996 of 1.72% (Viña et al., 2004a). Nevertheless, forest regeneration is also conspicuous, particularly due to the practice of shifting cultivation (i.e., abandonment of some cropland areas after a few years of cropping in order to allow soil nutrient recovery through natural forest regeneration), which is prevalent throughout the study region (Viña et al., 2004a). Therefore, deforestation and shifting cultivation have transformed a once completely forested landscape into a mosaic of agricultural lands (e.g., cropland and pasture for cattle ranching), built-up/barren lands, and forests in different successional stages, ranging from early (2–3 m of canopy height) to mature (more than 20 m of canopy height).

Forest cover dynamics

Changes in forest cover of the study region over time were evaluated using land cover maps of 1973, 1985, and 1996 developed from Landsat MSS and TM imagery in a previous study (Viña et al., 2004a). These maps were complemented with land cover maps of 2002 and 2008 developed in this study using Landsat ETM+ images acquired on October 14, 2002, September 12, 2008, and September 28, 2008 (obtained through the United States Geological Survey Global Visualization Viewer—http://glovis.usgs.gov). Several steps were performed to generate these maps. First, the level 1T digital number (DN) data of the reflective bands (1 to 5 and 7) of the Landsat ETM+ images were converted to at-sensor radiances and further to at-sensor reflectances following standard procedures (Chander et al., 2009). This procedure was also applied to the Landsat TM image of October 21, 1996 used in a previous study to generate a land cover map of 1996 (Viña et al., 2004a). Second, a linear regression technique was used to match the 2002 and 2008 ETM+ images (slaves) to the 1996 TM image (master). This regression technique was applied separately for each individual band. Third, due to the malfunction of the scan-line corrector in the ETM+ sensor on May 31, 2003, the ETM+ images of 2008 exhibited gaps of missing data. The lacunae in the September 12, 2008 image were filled using data from the September 28, 2008 image. Fourth, to classify the land cover in 2002 and 2008 without the need of ground-truth field data for calibration, the average spectral signatures of the different land cover types in the 1996 TM image were used to classify the 2002 and 2008 ETM+ images using a non-hierarchical supervised classification approach based on maximum likelihood decision rules.
Fig. 1. The study area covers 3197.9 km², occupying portions of the Department of Putumayo, Colombia (44% of the study area) and the province of Sucumbios, Ecuador (56% of the study area).
Since no ground-truth field data were available for validating these maps, overall accuracy (Congalton, 1991) was assessed using ca. 50 data points randomly located within high spatial resolution images acquired on January 19, 2004 and October 27, 2006, and accessed through Google Earth (http://www.google.com/earth/).

The pixels under forest cover in the 2002 land cover map were sorted into a chronosequence of four different forest successional stages. These successional stages were assigned based on whether the pixels classified as forest cover in the 2002 image were also present in (and since) the 1973 land cover map (i.e., >30 years old), present in (and since) the 1985 land cover map (i.e., 18–30 years old), present in (and since) the 1996 land cover map (i.e., 7–17 years old), or only appeared in the 2002 land cover map (i.e., <7 years old).

Comparison of the performance of vegetation indices along the forest chronosequence

Five different vegetation indices were used and compared for the assessment of productivity along the forest chronosequence (Table 1): the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), the Wide Dynamic Range Vegetation Index (WDRVI), and the Green and Red Edge Chlorophyll indices, \( CI_{\text{Green}} \) and \( CI_{\text{Red Edge}} \), respectively. The NDVI (Rouse et al., 1974, Tucker, 1979) has been by far the most widely used vegetation index for the analysis of vegetation dynamics. However, because the NDVI loses sensitivity under conditions of moderate to high green aboveground biomass (Myneni et al., 1997; Gitelson et al., 2003b,c; Gitelson, 2004), other vegetation indices have been developed, and their use has increased over the last few years. The EVI is a soil- and atmosphere-resistant index specifically designed for the MODIS system (Huete et al., 1996, 1997), and has been successfully used for evaluating vegetation dynamics in high biomass systems such as the tropical humid forests (Xiao et al., 2006). The WDRVI constitutes a non-linear transformation of the NDVI specifically designed to increase the sensitivity to changes in vegetation when the NDVI saturates (Gitelson, 2004; Viña et al., 2004b). This index exhibits a linear relationship with the fraction of photosynthetically active radiation absorbed by vegetation (Viña and Gitelson, 2005) and has been used for analyzing the spatio-temporal heterogeneity of tropical lowland forests (Aguilar-Amuchastegui and Henebry, 2006–2008). The \( CI_{\text{Green}} \) and the \( CI_{\text{Red Edge}} \) are semi-analytical surrogates of foliar (Gitelson et al., 2003a, 2006a) and canopy (Gitelson et al., 2005; Ciganda et al., 2008) chlorophyll content, and have been successfully related with green leaf area index (Gitelson et al., 2003c; Viña et al., 2011) and gross primary productivity (Gitelson et al., 2006b, 2008).

The NDVI, EVI, WDRVI, and \( CI_{\text{Green}} \) were calculated using the 2002 Landsat ETM+ at-sensor reflectance data (Table 1). However, since the \( CI_{\text{Red Edge}} \) requires a red edge band that is not available in the Landsat series, an image acquired on October 14, 2002 (i.e., same date as the 2002 Landsat ETM+ image acquisition) by the Hyperion system onboard the National Aeronautics and Space Administration’s EO-1 satellite was used for calculating the \( CI_{\text{Red Edge}} \). The Hyperion sensor collects data in 221 spectral bands (ca. 10 nm per band) within the range 356–2577 nm (Khurshid et al., 2006). The

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<th>Index</th>
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| Normalized Difference Vegetation Index | \[
\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}}} \]
|                                    | Rouse et al., 1974; Tucker, 1979                 |
| Enhanced Vegetation Index          | \[
\text{EVI} = 2.5 \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{1 + \rho_{\text{NIR}} + 6\rho_{\text{Red}} - 7.5\rho_{\text{Thick}}} = 7.5\rho_{\text{Thick}}
\]
|                                    | Huete et al., 1996, 1997                         |
| Wide-Dynamic Range Vegetation Index* | \[
\text{WDRVI} = \frac{\alpha \rho_{\text{NIR}} - \rho_{\text{Red}}}{\alpha \rho_{\text{NIR}} + \rho_{\text{Red}}}
\]
|                                    | Gitelson, 2004                                  |
| Green Chlorophyll Index            | \[
\text{CI}_{\text{Green}} = \frac{\rho_{\text{NIR}}}{\rho_{\text{Green}}} - 1
\]
|                                    | Gitelson et al., 2003a,c, 2005                   |
| Red Edge Chlorophyll Index         | \[
\text{CI}_{\text{Red Edge}} = \frac{\rho_{\text{NIR}}}{\rho_{\text{Red Edge}}} - 1
\]
|                                    | Gitelson et al., 2003a,c, 2005                   |

*The \( \alpha \) coefficient used in this study was 0.25. This was determined using a heuristic procedure (Henebry et al., 2004).
swath path of the Hyperion is very narrow (ca. 7.5 km) compared to the width of a Landsat TM/ETM+ scene, but the spatial resolution (ca. 30 m/pixel) is similar to that of the Landsat TM/ETM+ sensor systems. The Hyperion image was also obtained through the United States Geological Survey Global Visualization Viewer (http://glovis.usgs.gov) and was received geometrically rectified and with pixel values already calibrated to radiance (level 1GST). Narrow bands 34 to 36 were averaged to obtain a broad red edge band (ca. 690–720 nm), while bands 40 to 55 were averaged to simulate the near-infrared band of the Landsat ETM+ system (ca. 750–900 nm) (Chen and Henebry, 2010).

Values from the five vegetation indices (i.e., NDVI, EVI, WDRVI, CI\text{Green}, and CI\text{Red Edge}) were extracted from 3,000 pixels randomly distributed within the Hyperion image’s 7.5 km swath, which comprises about one-sixth of the study area. These values were used to assess the responses of different vegetation indices to forests in different successional stages, as well as to barren/built-up and agricultural areas. Pair-wise comparisons of vegetation index values among these different land cover types were performed using Bonferroni-corrected post-hoc Mann-Whitney U tests (SAS, 2004).

RESULTS AND DISCUSSION

Forest cover dynamics

The land cover maps of 2002 and 2008 (Fig. 2) derived from the Landsat ETM+ imagery had an overall accuracy of around 84%. Similar to the results obtained for the 1996 land cover map (Viña et al., 2004a) (Fig. 2), the agriculture class exhibited the lowest accuracies (ca. 72%), since it includes a wide array of land-cover categories, ranging from pastures to coffee plantations, with variable amounts of vegetative cover and different canopy architectures. In contrast, the forest cover class exhibited the highest classification accuracies (ca. 92%).

The annual rates of deforestation for the entire study area during the 1996–2002 period correspond to around 2.14% and reached a value of around 4.11% during the 2002–2008 period. Thus, deforestation rates during the 2000s were more than double those observed during the 1990s (Viña et al., 2004a). Consequently, the study region continues to exhibit a fast and dramatic loss of forest cover. However, forest regeneration is also conspicuous. Among the total forest area left in 2002 (ca. 1590 km²), ca. 13%, 7.5%, and 3% correspond to forests <7 years old, 7–17 years old, and 18–30 years old, respectively (Fig. 3). The rest corresponds to mature forests (>30 years old) that have been present since at least 1973 (Fig. 3) (Viña et al., 2004a). The larger amount of young secondary forest (<7 years old) present, compared to the older secondary stages (i.e., 7–17 and 18–30 years old) suggests that shifting cultivation is conspicuous and widespread across the entire study area, but secondary forests are seldom being allowed to reach maturity.

Analysis of productivity across the forest chronosequence

Relationships among the five different vegetation indices studied were obtained using the 3,000 random pixels selected along the 7.5 km swath of the Hyperion image (Fig. 3). The NDVI, the EVI, and the WDRVI exhibited a non-linear relationship with the CI\text{Red Edge}, while the CI\text{Green} exhibited an almost linear relationship (Fig. 4). These relationships show the saturation effect which indices like NDVI, EVI, and WDRVI experience at moderate-to-high green aboveground biomass values, as reported in several studies (Gitelson et al., 2003c, 2005, 2006b, 2008; Viña and Gitelson, 2005). However, the NDVI exhibited saturation at lower CI\text{Red Edge} values, followed by the EVI and the WDRVI (Fig. 4). In contrast, the almost linear relationship between the CI\text{Green} and the CI\text{Red Edge} suggests that both of these indices are equally sensitive to changes in green biomass. Nevertheless, the CI\text{Green} has been reported to be species-specific, while the CI\text{Red Edge} tends to be insensitive to different species (Gitelson et al., 2005, 2006b; Viña et al., 2011). Therefore, the CI\text{Red Edge} seems more appropriate for analyzing the changes in productivity among different successional stages of a forest chronosequence.

With the exception of the EVI, all vegetation indices evaluated exhibited a monotonic increase in their average values along the forest chronosequence (Figs. 5, 6). However, only the average values between the young (<7 years) and mature (>30 years) stages were significantly different. This pattern suggests that, with the exception of young vs. mature stages, forests in different successional stages have a wide variability in their productivities, deeming them difficult to isolate using vegetation indices alone. It has been reported that differences in productivity among forests of different ages and/or in different successional stages are primarily driven by differences in soil nutrients (Feldpausch et al., 2004). In addition, all indices exhibited no significant differences between agricultural land and young secondary forests (<7 years old), with the only exception being the EVI in which the agricultural land exhibited significantly higher values (Figs. 5, 6). Therefore, the productivity of agricultural land seems to be comparable to that of young secondary forests, and
Fig. 2. Panels on the left (A, C, E) correspond to false color composites of the satellite images used in the study. Band combinations (in the red, green, and blue color planes) correspond to bands 7, 4, 3 of the Landsat TM/ETM+ sensor systems, and bands 50 (around 850 nm), 33 (around 680 nm), and 20 (around 550 nm) of the Hyperion sensor system (i.e., image comprising a 7.5 km swath in panel C). Panels on the right (B, D, F) correspond to land cover classifications obtained from the Landsat TM/ETM+ images.
Fig. 3. Forest cover of the study area in 2002 sorted into four successional stages, from young (<7 years old) to mature (>30 years old). This forest chronosequence was obtained from land cover classifications of a Landsat MSS image acquired in 1973 (Viña et al., 2004a), Landsat TM imagery acquired in 1985 and 1996 (Viña et al., 2004a), and a Landsat ETM+ image acquired in 2002 (this study). The black dots along a 7.5 km swath correspond to 3,000 pixels randomly selected for analyzing vegetation index data obtained from the Landsat ETM+ and Hyperion images of 2002 (see Fig. 2C).

Fig. 4. Relationships among the vegetation indices evaluated in the study. Colored symbols correspond to the vegetation index values in the 3,000 pixels randomly selected (see Fig. 3). Black lines correspond to best-fit regression lines.
thus difficult to be isolated using the vegetation indices evaluated. However, the WDRVI and the CI_{Red\ Edge} were the only indices capable of distinguishing between agricultural land and intermediate successional stages of the forest (7–17 and 18–30 years old forests), as intermediate forests exhibited significantly higher values than agricultural areas (Figs. 5, 6). Thus, these two indices (among the five evaluated) seem to perform better for analyzing the changes in productivity along the tropical forest chronosequence. The WDRVI was also identified to be suitable for analyzing the productivity of crops using Landsat ETM+ data (Gitelson et al., 2008).

Due to its proven accuracy for assessing the spatio-temporal changes in vegetation productivity, as well as for being insensitive to different leaf structures and canopy architectures (characteristic of different species), the CI_{Red\ Edge} constitutes the index of choice for assessing vegetation productivity (Gitelson et al., 2006b). Preference for this index is also supported in this study,

Fig. 5. Average values of the (A) Normalized Difference Vegetation Index, NDVI, (B) Enhanced Vegetation Index, EVI, and (C) Wide Dynamic Range Vegetation Index, WDRVI, in different land cover types, derived from 3,000 randomly selected pixels (see Fig. 3) of the Landsat ETM+ image of 2002. Land cover types with different letters exhibit significantly ($p < 0.01$) different average vegetation index values, as determined by Bonferroni-corrected post-hoc Mann–Whitney U tests. Error bars correspond to 2 standard errors from the mean.

Fig. 6. Average values of the (A) Green Chlorophyll Index, CI_{Green}, and (B) Red Edge Chlorophyll Index, CI_{Red\ Edge}, in different land cover types, derived from 3,000 randomly selected pixels (see Fig. 3) of the Landsat ETM+ image of 2002 and the Hyperion image of 2002, respectively. Land cover types with different letters exhibit significantly ($p < 0.01$) different average vegetation index values, as determined by Bonferroni-corrected post-hoc Mann–Whitney U tests. Error bars correspond to 2 standard errors from the mean.
in which this index was suitable for assessing productivity across a tropical forest chronosequence. However, the CI\textsubscript{red edge} requires a red edge band that is not available in any current operational satellite sensor system, with the exception of the European Space Agency’s Medium Resolution Imaging Spectroradiometer (MERIS) and the EO-1 Hyperion. The MERIS system acquires data with a high temporal resolution and with an almost global coverage. However, the spatial resolution of MERIS data is relatively coarse (ca. 300 m/pixel over land). The Hyperion acquires data with a higher spatial resolution (ca. 30 m/pixel), but data acquisition is “on-demand”, thus has a very low temporal resolution and a low spatial coverage. Therefore, the WDRVI is the preferred index, since it can be obtained using all current operational satellite sensor systems, ranging from those with high spatial resolution but low temporal resolution and limited areal coverage (e.g., Ikonos and Quickbird), to those with high temporal resolution and global or near-global coverage but with coarse spatial resolutions (e.g., MODIS, MERIS, AVHRR, VIIRS).

**Application of the WDRVI to analyze regional changes in productivity**

As shown in Fig. 2, the study area exhibited a drastic conversion of forest cover to other land cover types during the 2000s. Thus, it was hypothesized that these losses of forest cover induced drastic changes in the regional productivity of the study area. The WDRVI was used to analyze these changes in productivity during the 2000s by using the Landsat TM image of 1996 and the Landsat ETM+ images of 2002 and 2008. A severe reduction in the WDRVI was observed between the 1996 and the 2002, which translates into drastic reductions in the regional productivity (Fig. 7). Nevertheless, the changes in WDRVI were not as drastic between 2002 and 2008, suggesting that the study area might be stabilizing in terms of vegetation productivity, despite continuous and drastic forest cover losses. Comparison of the dynamics of WDRVI values between 1996, 2002, and 2008 at pixel level reveals that, during the 1996–2002 period, the Colombian side of the study area exhibited wide-
spread reductions in WDRVI values (Fig. 8A). These reductions were mostly associated with the conversion of forest cover to barren lands (Fig. 2). In contrast, the Ecuadorian side exhibited overall increases in WDRVI values (Fig. 8A). However, during the 2002–2008 an opposite trend occurred in which the Ecuadorian side experienced mostly reductions in WDRVI values, while the Colombian side exhibited mostly gains (Fig. 8B). This inversion in the spatial dynamics of WDRVI is mainly associated with the conversion of barren land into agricultural land observed in the Colombian side, while the Ecuadorian side drastically increased its areas under built-up/barren (Fig. 2). Therefore, the dynamics of the regional productivity of the study area during the 2000s, assessed with the WDRVI, were consistent with observed land cover dynamics.

CONCLUDING REMARKS

This study evaluated the use of different vegetation indices for the analysis of the spatio-temporal changes in productivity of tropical rain forests exposed to drastic human-induced dynamics. Results showed that the WDRVI and the CI_{Red Edge}^* two vegetation indices previously identified as suitable for analyzing crop productivity, seem to also constitute the best indices for analyzing the productivity of tropical humid forests. However, due to issues of data availability, the WDRVI constitutes the most feasible to be used in an operational way, as it can be applied to a wide range of sensor systems, including the Landsat series.

While the study reports significant results, it is necessary to underline that it was based entirely on remotely sensed data. Therefore, further assessments are required to fully support the conclusions obtained, particularly using ground-level vegetation productivity measures.

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