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On the measurability of change in Amazon vegetation from MODIS

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ABSTRACT

The Amazon rainforest is a critical hotspot for bio-diversity, and plays an essential role in global carbon, water and energy fluxes and the earth's climate. Our ability to project the role of vegetation carbon feedbacks on future climate critically depends upon our understanding of this tropical ecosystem, its tolerance to climate extremes and tipping points of ecosystem collapse. Satellite remote sensing is the only practical approach to obtain observational evidence of trends and changes across large regions of the Amazon forest; however, inferring these trends in the presence of high cloud cover fraction and aerosol concentrations has led to widely varying conclusions. Our study provides a simple and direct statistical analysis of a measurable change in daily and composite surface reflectance obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) based on the noise level of data and the number of available observations. Depending on time frame and data product chosen for analysis, changes in leaf area need to exceed up to 2 units leaf area per unit ground area (expressed as $m^2\ m^{-2}$) across much of the basin before these changes can be detected at a 95% confidence level with conventional approaches, roughly corresponding to a change in NDVI and EVI of about 25%. A potential way forward may be provided by advanced multi-angular techniques, such as the Multi-Angle Implementation of Atmospheric Correction Algorithm (MAIAC), which allowed detection of changes of about 0.6–0.8 units in leaf area (2–6% change in NDVI) at the same confidence level. In our analysis, the use of the Enhanced Vegetation Index (EVI) did not improve accuracy of detectable change in leaf area but added a complicating sensitivity to the bi-directional reflectance, or view geometry effects.

1. Introduction

The importance of tropical vegetation for the earth system is undisputed (Atkinson, Dash, & Jeganathan, 2011; Malhi et al., 2008; Phillips et al., 2009), however, responses of tropical forests to changes in climate are only poorly understood (Samanta et al., 2010). Spaceborne remote sensing is often the only practical way to observe such changes at useful spatial and temporal scales (Shukla, Nobre, & Sellers, 1990), but the scientific community has been struggling to interpret existing satellite data in the presence of large cloud cover fraction and aerosol concentrations, which led to conflicting evidence over sensitivity for instance to prolonged drought events and thresholds of forest dieback. As a prominent example, the severe Amazon drought in 2005 provided an opportunity to investigate vegetation response to extreme events, but inferences based on remote sensing observations were inconsistent with those based on field studies. Using observations from 55 long-term monitoring plots, Phillips et al. (2009) concluded that the Amazon basin lost an estimated 1.2–1.6 Pg of carbon as a result of this drought. In contrast, Saleska, Didan, Huete, and da Rocha (2007) reported greening of the Amazon forest, suggesting increased photosynthetic activity based on the Enhanced Vegetation Index (EVI) from the 16-days MODIS surface reflectance (SR) MOD13 product.

In addition to inter-annual changes, seasonal variability of tropical vegetation has also been actively debated. A substantial body of literature (Asner, Nepstad, Cardinot, & Ray, 2004; Brando et al., 2010; Graham, Mulkey, Kitajima, Phillips, & Wright, 2003; Huete et al., 2006; Hutyra et al., 2007; Myneni et al., 2007; Nemani et al., 2003; Restrepo-Coupe et al., 2013; Samanta et al., 2012b) supports the view that photosynthetic activity initially increases during the dry season in response to an increase in incident PAR while water supply is maintained through deep root systems (Nepstad et al., 1994). In contrast, Morton et al. (2014) argued that MOD09-derived observations of seasonal greening of tropical vegetation are an artifact of the sun-sensor geometry, concluding that tropical forests maintain consistent greenness and structure throughout dry and wet seasons.

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Since its launch in 2000, MODIS has been the workhorse of Amazon remote sensing due to its superior data quality when compared to AVHRR (Huete et al., 2002). Surface reflectance is routinely derived from top of atmosphere measurements, using pixel-based atmospheric correction and cloud screening (Vermote & Kotchenova, 2008). However, errors in the estimation of atmospheric aerosol loadings (Grogan & Fensholt, 2013; Samanta, Ganguly, Vermote, Nemani, & Myneni, 2012a; Samanta et al., 2010) and deficiencies in cloud screening (Hilker et al., 2012) can introduce variability in estimated surface parameters unrelated to actual changes in vegetation (Zelazowski, Sayer, Thomas, & Grainger, 2011) which may lead to incorrect inferences of vegetation trends (Samanta et al., 2012a). Alternative processing techniques, such as the recently developed Multi-Angle Implementation of Atmospheric Correction Algorithm (MAIAC) (Lyapustin et al., 2011) hold promise to overcome some of these limitations by providing more accuracy in cloud screening, atmospheric correction and accounting for BRDF effects (Hilker et al., 2012). However, statistical analysis of quantifiable change is currently missing. Such analysis will be needed if we are to reconcile remote sensing observations with field studies and in order to determine potentials and limitations for using satellite derived evidence for change over tropical forests.

Detectable change in surface reflectance depends on noise and sampling frequency. Independent estimates of measurement noise are difficult across vast areas such as the Amazon basin, however, a first approximation may be obtained from high frequency changes in observed surface reflectance, when assuming little change in vegetation over short periods of time. While this simple approach has limitations, high frequency changes in surface reflectance mostly characterize processing errors from clouds and aerosols as a pixel, unless disturbed by logging or fire, would not be expected to change from one day to the next (Hilker et al., 2012). Common approaches to mitigate noise include compositing of best available pixels, these techniques however, significantly reduce the number of observations.

The objective of this paper is to evaluate detectable changes in vegetation greenness given statistical properties of noise driven by cloud cover, aerosol loading and other effects including bi-directionality of surface reflectance. The tradeoffs of using daily vs. composited surface reflectance are being discussed and detectable changes are quantified. We also evaluated the usefulness of Aqua vs. Terra observations, a question related to the diurnal cycle of early afternoon cloud development. Our hope is to provide a sounder statistical basis for the recent discussion on seasonal and inter-annual changes in Amazon vegetation.

2. Methods

2.1. MODIS MOD09/MYD09 observations

Our study encompasses 12 MODIS tiles (h10v08 and h13v10), a land area of 12.25 million km^2, spanning 10°N to 20°S in latitude and 80°W to 42°W in longitude. We used MODIS data from the Terra and Aqua satellite platforms acquired between 2000/02/24 and 2012/12/31 (Terra) and between 2002/07/04 and 2012/12/31 (Aqua). Collection 5 data of the MOD09GA/MYD09GA 1 km daily surface reflectance product were obtained from the reverb data gateway of NASA's Goddard Space Flight Center (reverb.echo.nasa.gov) as well as 1 km vegetation index (VI) composites from MOD/MYD13A2. Clouds were masked by means of the 'state_1km' scientific dataset (SDS) included in the MYD09GA product, which is based on two cloud detection algorithms, the MOD/MYD35 cloud mask (Frey et al., 2008) and an additional, internal cloud screening (Vermote & Kotchenova, 2008). In addition to cloud masking, all conventional MODIS data were quality filtered using the MODIS quality (Q_A) and pixel reliability flags and only cloud free pixels with the highest data quality were passed and used for all subsequent analyses. An overview of the quality and cloud flags set is provided in Table 1.

Table 1
Quality/cloud flags of the MYD09GA product used in this study. Flags that are not mentioned were not used (Hilker et al., 2012).

Product	SDS name	Flag	Accepted values
MYD09GA	QC 500 m	MODLAND QA bits	00 (ideal quality — all bands)
		Band 1 data quality	0000 (highest quality)
		Band 2 data quality	0000 (highest quality)
		Atm. corr. performed	1 (yes)
	State 1 km	Cloud state	00 (clear)
		Cloud shadow	0 (no)
		Aerosol quantity	00/01 (climatology/low)
		Cirrus detected	00 (none)
		Internal cloud flag	0 (no cloud)
		Fire flag	0 (no fire)
		Pixel adjacent to cloud	0 (no)
MYD13A2	VI quality	MODLAND QA Bits	00 (VI produced with good quality)
		VI usefulness	0000 (Highest quality) 0001/0010/0100/1000 (Lower quality)
		Aerosol quantity	00/01 (climatology/low)
		Adjacent cloud	0 (no)
		Mixed cloud	0 (no)
		Possible shadow	0 (no)
	Pixel reliability	Rank key	0 (good data — use with confidence)

2.2. MAIAC observations

In addition to conventionally processed daily MODIS data, we also obtained MODIS observations processed with the MAIAC algorithm. MAIAC is a new generation cloud screening and atmospheric correction technique that uses an adaptive time series analysis and processing of groups of pixels to derive atmospheric aerosol concentration and surface reflectance without typical empirical assumptions. In previous work (Hilker et al., 2012), we have demonstrated a 3–10 fold reduction in noise of MAIAC SR, while the algorithm at the same time yields 2–5 times more observations as a result of a more accurate, less conservative cloud mask. Both these properties should make it more suitable to detect changes in the Amazon basin. MAIAC data were obtained for the identical 12 MODIS tiles and time period from NASA's Level 1 and Atmosphere Archive and Distribution System (LAADS Web) ftp://ladsweb.nascom.nasa.gov/MAIAC. Recently, also a composited VI product has been provided. Detailed descriptions of MAIAC and quality testing are provided elsewhere (Lyapustin, Wang, Laszlo, & Hilker, 2011, 2012; Lyapustin et al., 2011).

2.3. Approach

Our ability to observe trends and changes in tropical vegetation depends on the number of available clear sky observations and measurement noise. In tropical latitudes, this noise results largely from undetected clouds and cloud shadows (particularly during the wet season) and high aerosol levels during the biomass burning (dry) season (Aragão et al., 2008; Hilker et al., 2012). Typical techniques to overcome high noise levels include best pixel compositing, which effectively increases the data quality at the cost of a reduced number of observations. Analysis of seasonal changes from composited data products is therefore often pursued by combining observations over multiple years (such as averaging multi-year observations acquired during June and comparing them to multi-year observations acquired during October), assuming a regular onset of dry and wet seasons.

We pursued two different approaches for change analysis, one based on daily satellite observations and another based on multi-year averages of VI composites. Composited data are most commonly used for determining change in tropical vegetation, however daily observations would be desirable to better understand changes for instance during extreme events or dieback that happens up to several years after the extreme event occurred (Doughty et al., 2015). Also, the quality of composite data still depends on the quality of the original daily observations.

Different techniques may be utilized to infer the status of terrestrial vegetation; here we used the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), as the two most commonly applied remote sensing metrics. We computed both NDVI and EVI from daily MOD/MYD09 and MAIAC reflectance, for the composited data, the indices were already provided. NDVI is defined as (Tucker et al., 1979)

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

where ρ_{nir} and ρ_{red} is the atmospherically corrected surface reflectance in the near infrared and red bands, respectively, and EVI is defined as

$$EVI = G \times \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L} \tag{2}$$

where L is the canopy background adjustment (1.0); C_1 (6.0) and C_2 (7.5) are the coefficients of the aerosol resistance term; and G (2.5) is a scaling factor (Huete, Justice, & Liu, 1994).

Statistical significance of seasonal changes in vegetation was assessed using a two sided t-test with unequal numbers of observation and variances (Satterthwaite, 1946; Welch, 1947), as both data quality (i.e., variance) and number of observations varies between the dry and wet seasons due to variations in cloud cover and aerosol loading:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}} \tag{3}$$

where $\overline{X}_i$, s_i and N_i are the ith sample mean, sample variance and sample size, respectively.

3. Results

Fig. 1 shows an overview of the number of cloud free daily observations available per month across Amazonia. The percentage of cloud free data was lowest during November and April and peaked during June and August, the dry season across the southern basin.

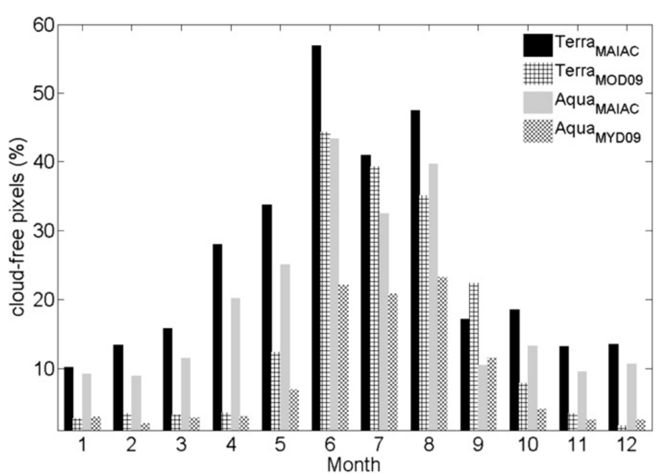

Fig. 1. Percentage of high quality observations available from different MODIS products for the example of the year 2007. Observations processed with MAIAC are shown as black (Terra) and gray (Aqua) bars, the corresponding observations processed with the conventional product are shown as horizontal and diagonal hatches (for MOD/MYD09 pixels quality was defined by the quality flags shown in Table 1).

The conventional product yielded between 2 and 45% of cloud free, high quality observations from MODIS on Terra (MOD09); the percentage of pixels observed from MODIS on Aqua (MYD09) ranged between 1 and 21%. MAIAC yielded between 10% and 60% clear sky observations from MODIS on Terra and between 8% and 42% of cloud free data from MODIS on Aqua. Relative improvement was largest during wet season suggesting that MAIAC was particularly successful in detecting small cloud-free areas in regions with extensive cloud cover. The spatial distribution of available observations varied notably between rain season (Fig. 2 shows the example of March 2007) and dry season (Fig. 3 shows the example of August 2007). The less conservative cloud mask implemented in MAIAC resulted in a more complete coverage of the Amazon basin particularly during the wet season, owing to observations from both the Terra and Aqua platform (here shown for the example of 2007, Fig. 2). In contrast, MOD09/MYD09 covered only about half of the study area (Fig. 3C); contributions from MODIS on Aqua were relatively minor. During the dry season, the numbers of observations were more similar; with MAIAC acquiring about 20% more observations. When using the best pixel composites (Fig. 4) both MAIAC and MOD/MYD13 were able to provide data across most of the basin during beginning and end of the dry season, differences in the number of available cloud free pixels were, however, still pronounced particularly during the end of the dry season.

Figs. 5 and 6 show the coefficient of variation in daily observations over the period of one month, for wet and dry seasons. The results in both Figs. 5 and 6 are based on daily surface reflectance that has not been normalized for the BRDF effects. The variation of Terra and Aqua NDVI (Fig. 5) was assessed as coefficient of variation rather than simple σ to allow a better comparison to EVI (Fig. 6). For NDVI, the coefficients of variation ranged between 0.15 and 0.20 across most of the basin for MOD09/MYD09, whereas MAIAC estimates were in the order of about 0.05 throughout the study area. Compared to NDVI, EVI showed a notably higher variability during both the dry and wet seasons and for both data products. The coefficient of variation for EVI ranged between 0.1 and 0.2 for most of the study area for both MAIAC and MOD09/MYD09. It can be seen from the results presented in Fig. 7 that this increased variability in EVI compared to NDVI may largely be attributed to BRDF effects, or in other words, to changes in the view geometry. The figure shows daily observations from MAIAC, but normalized to a common sun-observer geometry (BRF_n) ($\theta_s = 45°$ solar zenith angle and nadir view). The objective was to assess the contribution of angular effects to noise in vegetation indices, in comparison to the non-normalized MAIAC product. Only MAIAC results are shown here, as no BRDF-normalized daily product is available from MOD/MYD09. In Fig. 7, improvements in NDVI (compare to Fig. 5) were relatively smaller, indicating a weaker dependence of NDVI on view and illumination angles. Improvements for EVI on the other hand were notable, suggesting a much stronger dependence of EVI on view and sun-angle variations (compare Figs. 6 and 7c, d). After BRDF-normalization, variations in EVI were more comparable to those obtained from MAIAC NDVI product, though still somewhat larger in some regions. Over vegetation, the BRDF effect results in increase of reflectance in the backscattering direction (less shadowing) compared to the forward scattering direction (more shadowing). By virtue of its mathematical form, this difference is somewhat mitigated in NDVI, but it has a larger effect on EVI due to constant factors in the denominator providing different weights to the reflective bands in the nominator and denominator. A simple exercise shows that a 5% difference in the directional scattering of the red and NIR bands leads to about 2% change in NDVI vs about 8% change in EVI. For this reason, a high variability between monthly averaged EVI is expected. This variability was present in both the MOD09/MYD09 and MAIAC data as the changes in EVI due to sun-sensor geometry exceeded the noise resulting from the aerosol and cloud effects.

Figs. 8 and 9 show the corresponding coefficients of variation for MOD/MYD13 and MAIAC composites, again separately for NDVI and EVI. The composited results yielded notably less variability for NDVI

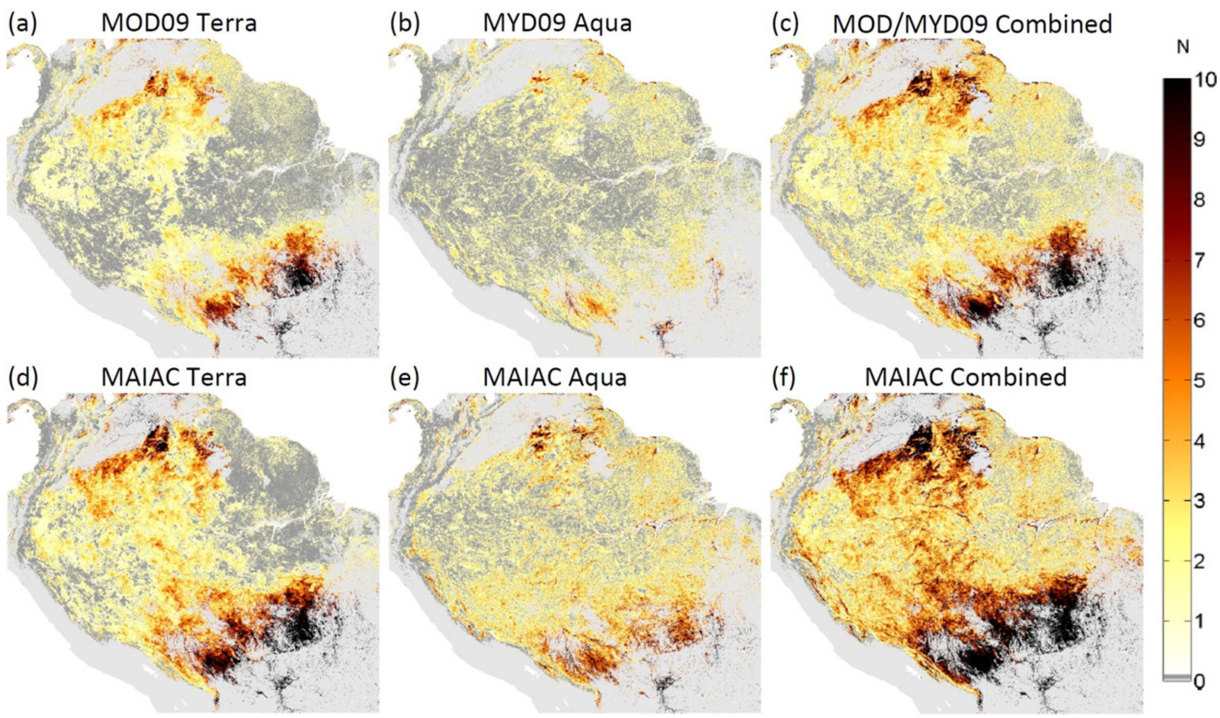

Fig. 2. Number of cloud free observations available during the month of March 2007 from the conventional product (top row) and MAIAC (bottom row). The left and center columns show number of observations acquired from Terra and Aqua, respectively, the right column shows the combined data.

for both the MOD/MYD13 and MAIAC products, with conventional composite estimates ranging between 0.04 and 0.08 during June and October, whereas MAIAC composites yielded coefficients of variations largely between 0.02 and 0.05. Compared to NDVI, composited results for EVI were notably higher, particularly for the conventional MOD/MYD13 product with values ranging between 0.08 and 0.18, whereas MAIAC results ranged between 0.05 and 0.1 (with a few exceptions in the north eastern part of the basin). Note that MAIAC composites are by default normalized to a fixed sun sensor geometry.

Based on the number of observations (n) and σ, we calculated the ability to predict a hypothetical 10% change in vegetation greenness between June and October (10% roughly represents the expected inter-

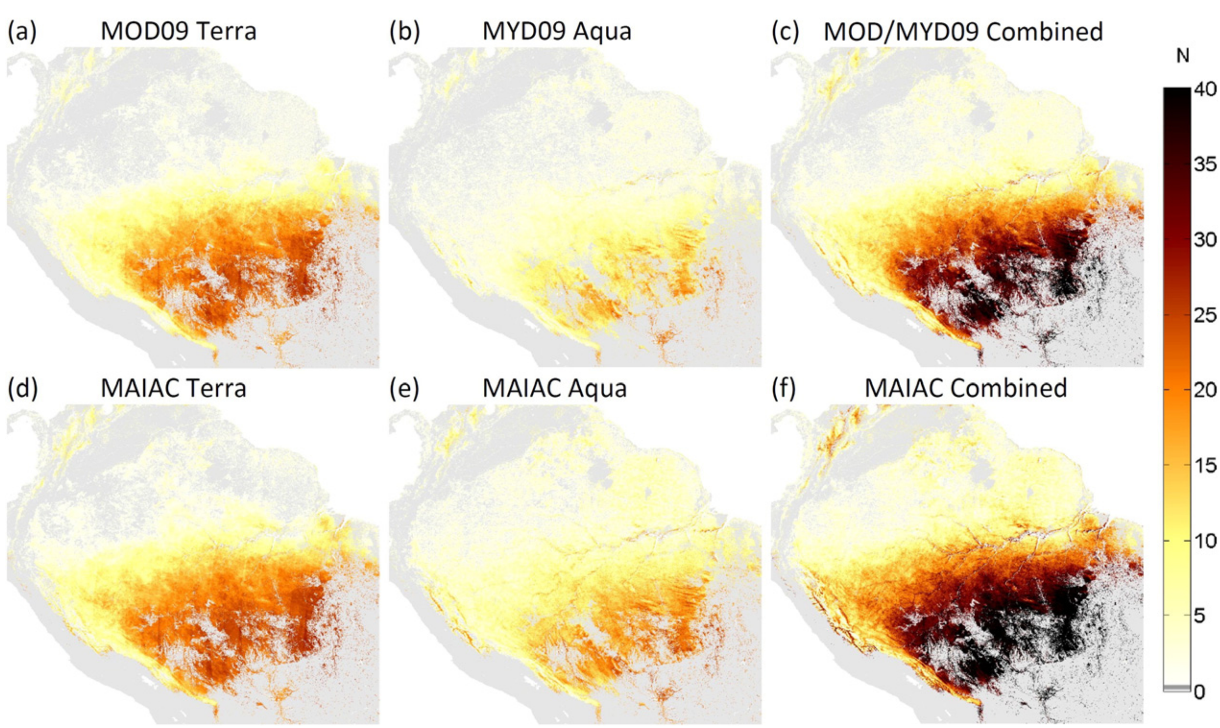

Fig. 3. Number of cloud free observations available during the month of August 2007 from the conventional product (top row) and MAIAC (bottom row). The left and center columns show number of observations acquired from Terra and Aqua, respectively, the right column shows the combined data.

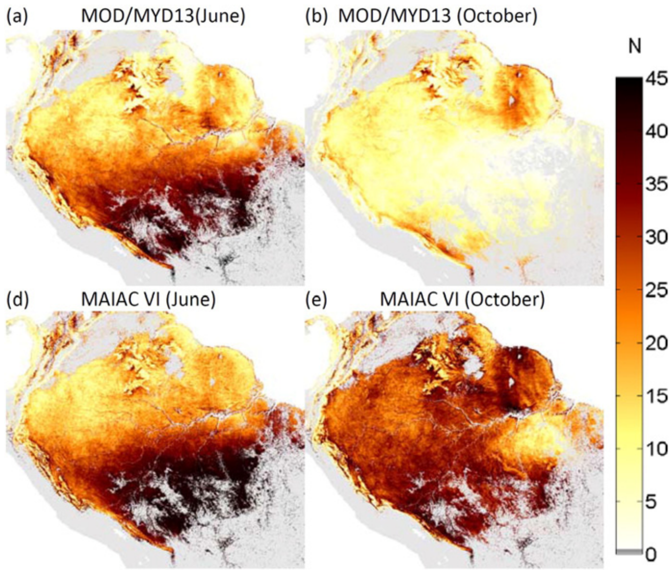

Fig. 4. Number of cloud free observations available from NDVI/EVI composites using one month of observation during a dry season month (August) and a rain season month (March) based on all years, except the extreme drought years of 2005 and 2010. The top row shows the number of observations available from MOD/MYD13, the bottom row shows N from MAIAC, Terra and Aqua combined.

annual variability in vegetation, Myneni et al., 2007). Results are shown in Fig. 10; we are only presenting the results of the daily averaged observations for reasons of brevity. For each pixel, we obtained n and σ from averaged daily observations during June and October, respectively, and defined the mean NDVI (EVI) value for October as the mean NDVI (EVI) acquired in June plus 10%. We then performed a Welch test to determine the statistical significance level with which each time series was able to detect this change given the inherent noise levels which includes directional effects (Fig. 10). The *t*-test performed on the conventional product resulted in high significance levels only in the southern part of the Amazon region. For most of the northern part of the basin, p-values were well below the 95% significance level threshold, suggesting that the ability of the conventional product to detect moderate changes in vegetation greenness was limited. It can be shown that the main driver for low p-values was σ, not n, as artificially doubling n yielded only marginal improvements in the observed significance levels (results not shown). MAIAC was able to detect the 10% change in greenness with high statistical significance ($p > 0.95$) throughout the basin. Compared to NDVI, EVI yielded high significance levels only for the MAIAC BRF_n product (Fig. 9). This is consistent with results presented in Fig. 7.

Figs. 11 and 12 show the results for the reversed problem — namely, given the inherent noise level, what change in NDVI (EVI) can be detected at 95% significance level? The graph illustrates that for MOD09/MYD09, changes in EVI and NDVI would have to exceed 20–25% across most of the northern part of the Amazon basin. Smaller changes in

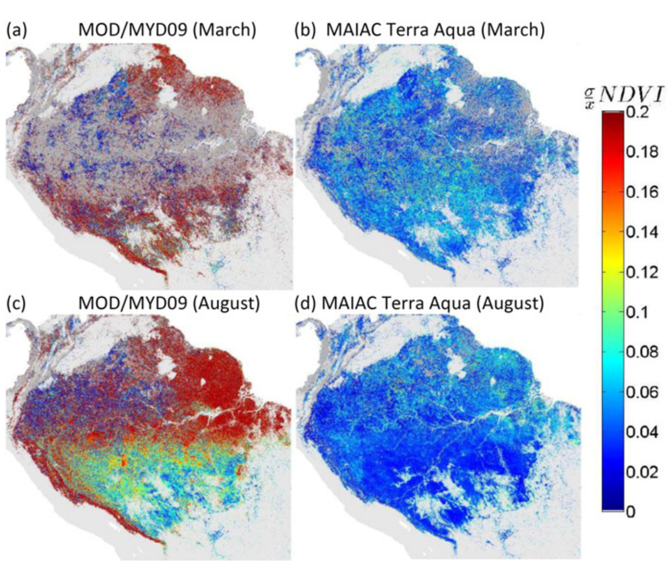

Fig. 5. Coefficient of variation of daily NDVI observations combined from Terra and Aqua datasets averaged during March (top row) and August (bottom row). Estimates from the combined conventional product are shown in Figures (a) and (c), right column shows MAIAC data (datasets not normalized to sun/sensor geometry).

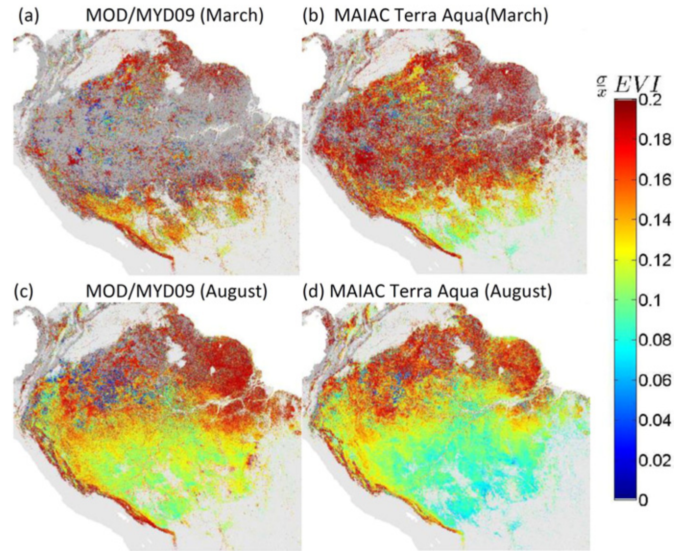

Fig. 6. Coefficient of variation of daily EVI observations combined from Terra and Aqua datasets averaged during March (top row) and August (bottom row). Estimates from the combined conventional product are shown in Figures (a) and (c), right column shows MAIAC data (datasets not normalized to sun/sensor geometry).

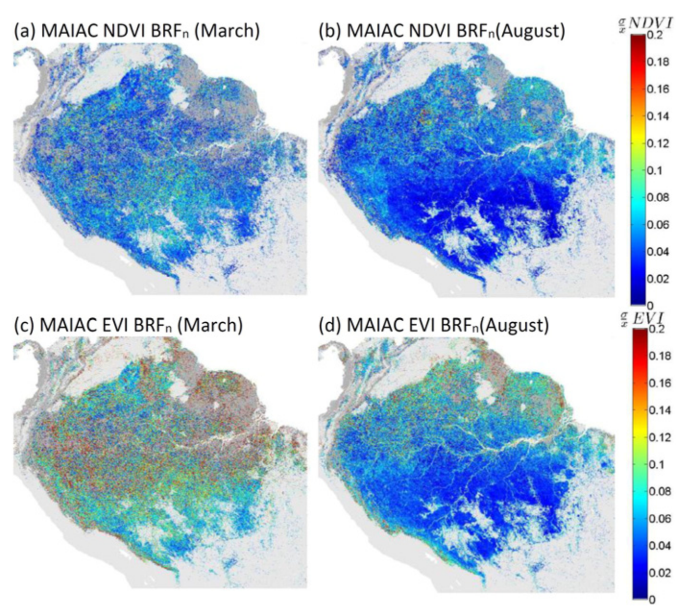

Fig. 7. Coefficient of variation of daily NDVI (top row) and daily EVI (bottom row) observations from directionally normalized (BRFn) Terra and Aqua MAIAC data, averaged during March and August. For the daily conventional product, no BRDF correction was available.

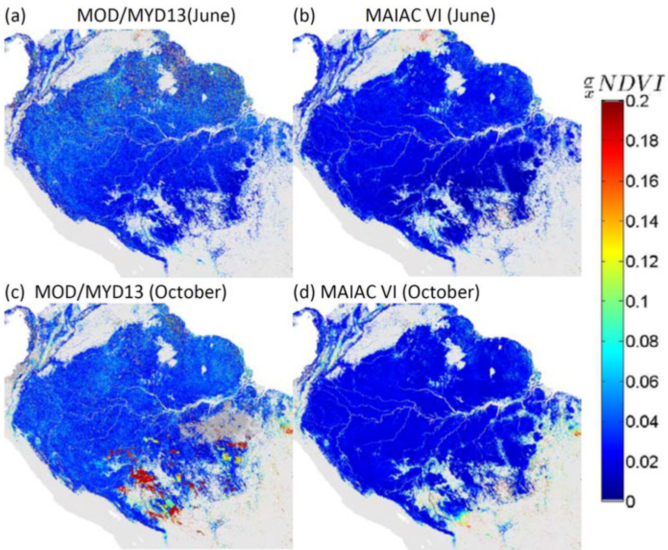

Fig. 8. Coefficient of variation of monthly composite NDVI observations from Terra and Aqua combined during June (top row) and October (bottom row). Estimates from the conventional product (MOD/MYD13) are shown in Figures (a) and (c), the right column shows $\frac{\sigma}{\bar{x}}$ for MAIAC VI.

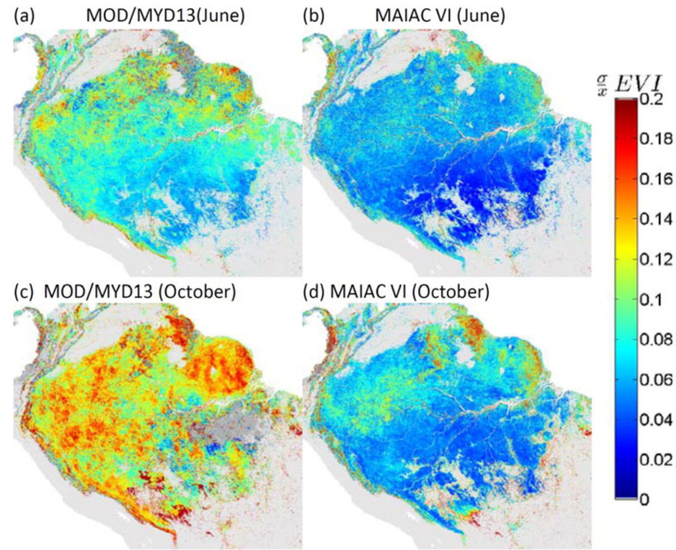

Fig. 9. Coefficient of variation of monthly composite EVI observations from Terra and Aqua combined during June (top row) and October (bottom row). Estimates from the conventional product (MOD/MYD13) are shown in Figures (a) and (c), the right column shows $\frac{\sigma}{\bar{x}}$ for MAIAC VI.

vegetation cover were measurable only in the southern part of Amazonia where observations were less limited by cloud cover. In contrast to MOD09/MYD09, MAIAC was able to detect a 2–6% change in NDVI throughout study area. For monthly composited estimates (Fig. 12), values improved for both NDVI and EVI (note the different scale), however, EVI values still showed greater variability compared to NDVI, particularly for the conventional MOD/MYD13 product. For both daily and monthly composites, EVI derived estimates were useful to detect changes only when using BRDF normalized observations, as otherwise directional reflectance effects prevented most changes to be measurable with both the conventional as well as the MAIAC product, at least in the northern part of the basin.

Both EVI and NDVI are non-linearly related to LAI, and, as a result, a product's ability to predict changes in leaf area is dependent on the saturation effect observed in the VI–LAI relationship. For instance, in dense vegetation canopies, a moderate change in leaf area cannot be as easily detected as in sparse canopies, because vegetation indices saturate with vegetation density. As a result, the actual physiological change on the ground will need to be larger in densely vegetated areas to result in a statistically significant change in vegetation indices than in sparser canopies. In order to estimate how small a change in leaf area can be detected (at a 95% significance level) from both conventional products and MAIAC, we approximated the LAI NDVI relationship for both algorithms using the empirical function described in the Algorithm Theoretical Basis Document (ATDB) of MODIS LAI product for the tropical biome (Tables 2–3, Knyazikhin et al., 1999). For EVI, we used the functional relationship described in Huete et al. (2002) as no official standard is currently available. Our results show that in most areas changes in leaf area have to exceed 2 units leaf area per unit ground surface (expressed in $m^2\ m^{-2}$) to be detectable from the conventional MOD09/MYD09 algorithm (Fig. 13). When using daily observations, EVI did not result in improved estimates compared to NDVI, except in some areas in the north and north-east. Most likely, the more linear character of the relationship between this index and vegetation leaf area was countered by a higher variability of the index and greater sensitivity to directional effects. NDVI estimates from MAIAC were able to detect changes in leaf area in the range of about 0.6–0.8 units with NDVI estimates still being superior to EVI at least across the southern part of the basin. For the composited data, NDVI estimates from MOD/MYD13 were able to detect changes of on average about 0.5 units of leaf area, whereas the statistical significance level for EVI was notably lower and changes had to be between 0.8 and 1.2 units of leaf area before they could be detected at a 95% significance level. Compared to the conventional product, MAIAC composites allowed changes between 0.3 and 0.4 units of leaf area to be detected at 95% significance level (Fig. 14). Note that in case of the MAIAC composite, the more linear character of the relationship between EVI and vegetation leaf area benefited the ability to detect vegetation change at least in the southern and central part of the Amazon basin. Regionally, however, performance of NDVI-based retrieval was more homogeneous than that based on EVI.

4. Discussion

Remote sensing is an essential tool for scaling field measurements across tropical regions and integrating observations in carbon and energy cycle models to better understand the role of tropical vegetation in global climate. Resolving the current controversy from studies that use MODIS land cover products to investigate the response of tropical vegetation to weather and climate is therefore critical for reducing uncertainties in carbon balance models (Davidson et al., 2012; DeFries et al., 2002; Pan et al., 2011) and establishing possible thresholds for forest dieback (Brando et al., 2010). The sensitivity analysis provided in this paper offers new insights into potentials and limitations of daily and composite satellite products and demonstrates new opportunities provided by improved algorithms, such as MAIAC.

The ability to quantify the statistical significance in vegetation indices depends on knowledge of the random error and bias of satellite observations, as well as the effects of environmental influences not related to the surface properties, primarily cloud cover, atmospheric effects, and differences in illumination and viewing geometry. We have estimated random noise using the assumption of no rapid changes in plant canopies from one day to the next. While different methods exist for error and uncertainty analysis (for instance Morton et al., 2014 modeled noise based on best case theoretical assessments rather than evaluated it from the MODIS product), this simple approach provided an effective measure of day to day variability in observed surface reflectance. Even though a certain level of change may be expected during one month, high frequency changes in surface reflectance are most likely an artifact of either residual cloud contamination, aerosol effects or the sun-sensor geometry. Additional uncertainties may be attributable to recently described issues with the MODIS quality flags (Grogan & Fensholt, 2013).

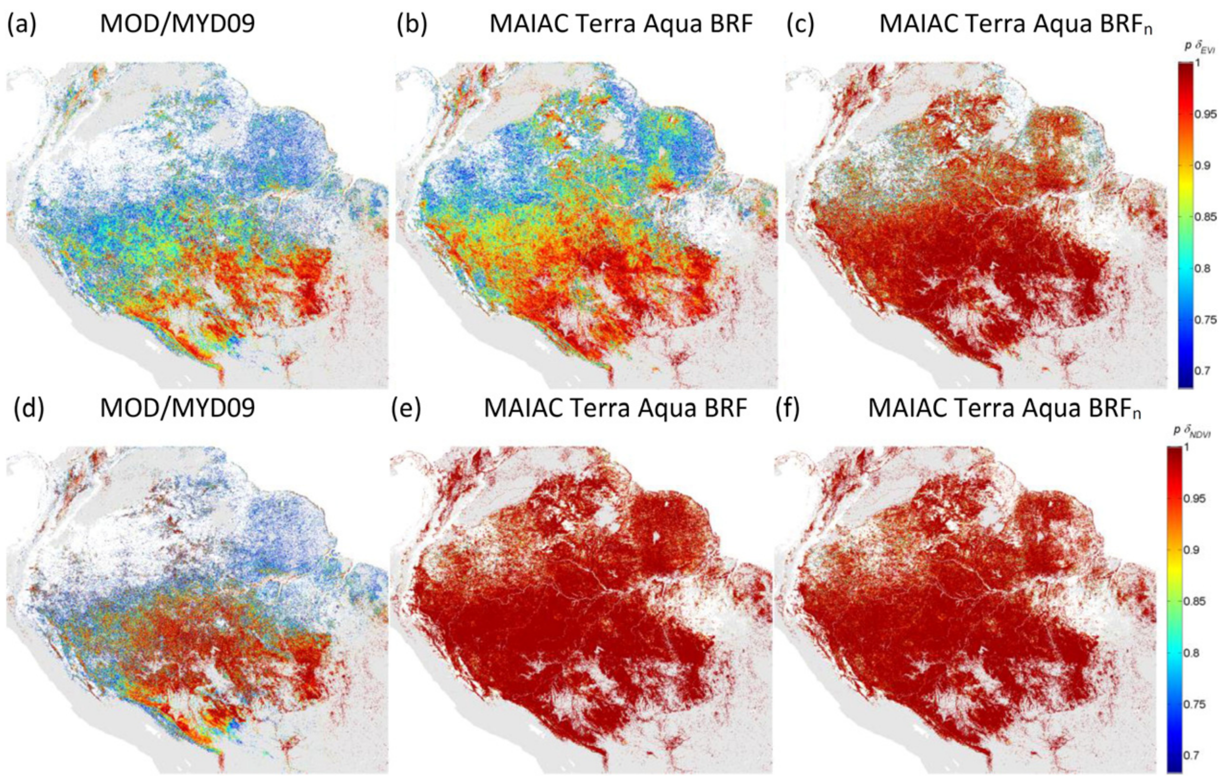

Fig. 10. Percent change detectable at a 95% significance level from EVI (top row) and NDVI (bottom row) between June and October using the combined conventional product (left column) and the non-normalized (center column) and BRF normalized (right column) MAIAC product.

Our analysis assumes the use of all available data for estimation of changes in NDVI (EVI). As most studies examining change in vegetation from remotely sensed indices (Huete et al., 2006; Morton et al., 2014; Myneni et al., 2007; Saleska et al., 2007; Xu et al., 2011), the statistical methods used in our analysis assume a normal distribution of surface reflectance, which does not account for the fact that extraneous effects

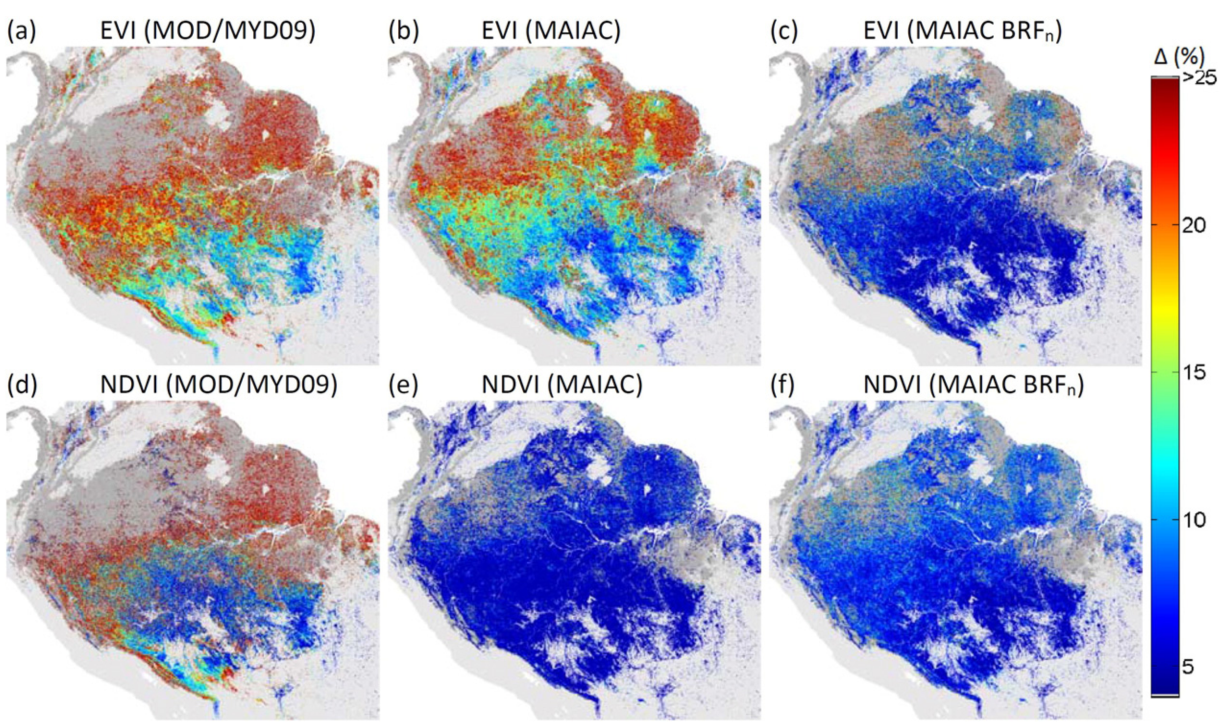

Fig. 11. Ability of MOD/MYD09 (a), non-normalized MAIAC (b) and geometry-normalized MAIAC (c) to predict a 10% increase in EVI, using a 2-sided t-test based on n and σ observed during June (beginning of dry season) and October (end of dry season). The mean EVI value for October was defined as mean EVI acquired in June plus 10%. The figure shows the significance level of the t-statistics. Figures c, d and e show the corresponding results for NDVI.

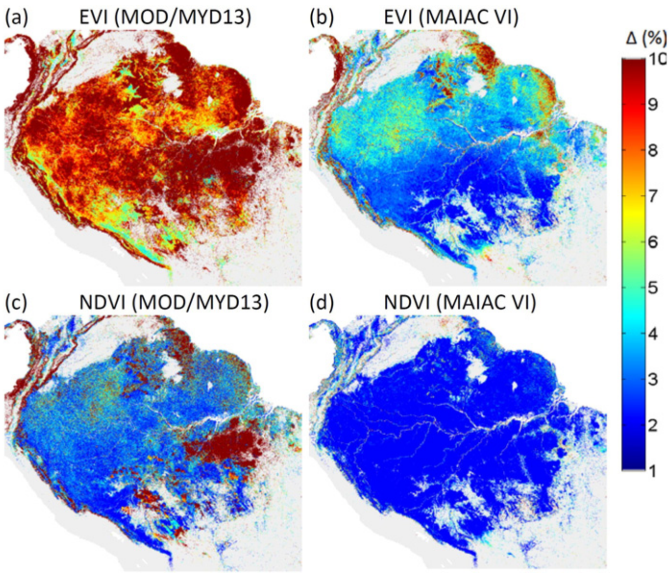

Fig. 12. Percent change detectable at a 95% significance level from EVI and NDVI composites between June and October. MOD/MYD13 is shown in the left column, the right column shows MAIAC VI product.

typically increase reflectance in the visible part of the spectrum, thereby introducing a bias towards the lower end of vegetation indices. This simplification is a limitation to our and other studies examining seasonal and inter-annual changes in vegetation. The true distribution of surface reflectance (and therefore vegetation indices) is currently unknown, and will need to be investigated. Potential means for such a study may be the upcoming GOES-R ABI dataset or already existing SEVERI data collected over tropical forests in Africa.

It should also be stated that we are basing our analysis of both conventional and MAIAC observations solely on quality flags — only accepting best quality observations. Further constraints, for instance with respect to view angle are possible and have been implemented in many studies. These techniques are expected to result in higher measurement accuracy — at the cost of a reduced number of observations. Other improvements could be obtained when attempting to correct for directionality or using directionally normalized conventional observations, such as the MODIS NBAR MCD43 (Schaaf et al., 2002). This study should therefore be understood as an illustration for the need to utilize these constraints, at least when working with conventional non-MAIAC data.

Cloud cover is a major obstacle for remote sensing of tropical regions (Asner, 2001), and as a result, the improved ability of MAIAC to obtain cloud free observations both spatially and temporally (Fig. 1–4) is an important finding of this study (see also Hilker et al., 2012). More frequent observations increase the degrees of freedom and can therefore help to enhance satellite based assessment of vegetation change, forest loss and landscape disturbance over tropical regions (Hansen et al., 2008). This is particularly important during wet season months (Fig. 1) and in regions with large cloud cover fraction (Figs. 2–4), where considerable gaps prevent useful observations from conventional products throughout most of the year. The comparison of contributions from MODIS on Aqua illustrates how the time series approach to cloud screening implemented in MAIAC can help identify more cloud free pixels while maintaining higher levels of accuracy (Hilker et al., 2012). The MAIAC related results presented in Figs. 2–3 show that contributions from PM overpasses can be significant even in wet season months as Aqua observations helped to provide crucial information particularly in the northern and north-eastern part of the study area (Figs. 2e and 3e). These findings make a strong argument that a PM overpass, although not ideal in terms of cloud interference, can be successfully employed in terrestrial applications. Previous results have linked 80% of the improvement found in MAIAC vs. MOD09/MYD09 to an enhanced cloud mask, whereas 20% of the reduced variability can be attributed to a more accurate aerosol retrievals and explicit

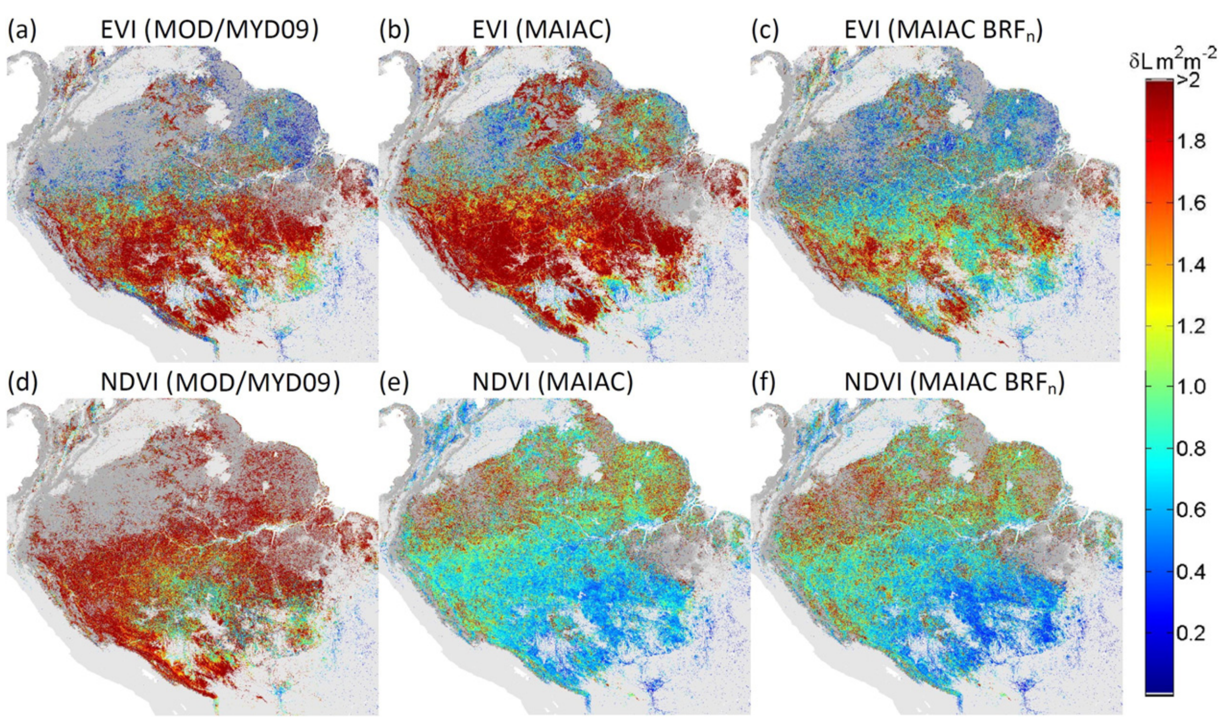

Fig. 13. Detectable change in leaf area at a 95% significance level from EVI (top row) and NDVI (bottom row) showing the combined conventional product (left column) and the non-normalized and BRF normalized MAIAC product (center and right column, respectively). The estimates of EVI were converted to units of leaf area based on Huete et al. (2002), estimates of NDVI were converted to units of leaf area based on the relationship described in the Algorithm Theoretical Basis Document (ATDB) of MODIS LAI product (Knyazikhin et al., 1999).

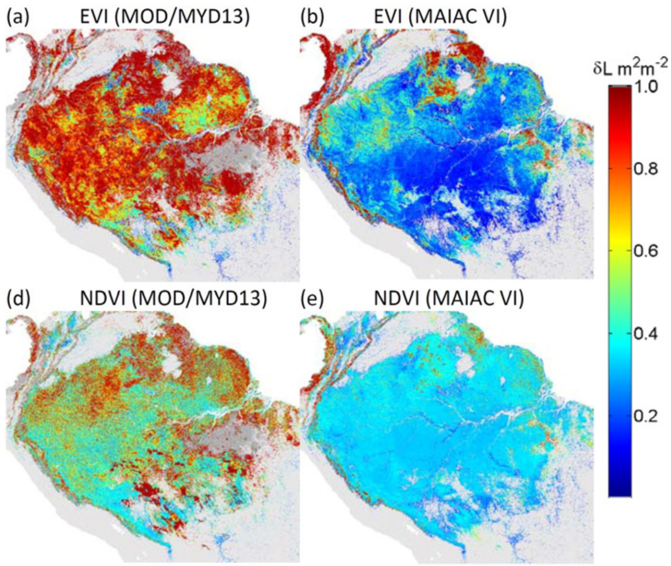

Fig. 14. Detectable change in leaf area at a 95% significance level from EVI composites. Estimates of EVI and NDVI were converted to units of leaf area corresponding to the results presented in Fig. 12.

accounting for the surface anisotropy (BRDF) (Hilker et al., 2012). Results presented in Figs. 5–8 confirm these findings and demonstrate a higher consistency of MAIAC data in space and time.

The results presented in Figs. 10, 11, and 13 demonstrate that moderate changes in vegetation are not easily detectable from conventional approaches across tropical latitudes and in many cases changes would have to exceed 20–25% to be statistically significant at a 95% confidence level. The magnitude of this change is about what has previously been reported (Huete et al., 2006; Myneni et al., 2007), but smaller and important changes arising from dry vs. wet season conditions, or inter-annual variability that is below the 25% threshold can be easily missed when using MOD09/MYD09. Our results show that compositing helps reducing the amount of noise in the data, particularly in case of the conventionally corrected NDVI (Fig. 8), it should, however, be noted that this method effectively reduces the number of observations (and therefore the degrees of freedom). As a result, higher accuracy in remaining observations is then required to detect changes at the same significance level, particularly when trying to detect seasonal responses of vegetation from one month to the next. It can be shown from Eq. (3) that in this extreme case, 16-day composites will require an improvement in accuracy by a factor of up to 5 to detect a 10% change in surface reflectance compared to using daily products. With few exceptions, our results cannot confirm an improved ability of EVI (Huete, Didan, Shimabokuro, Ferreira, & Rodriguez, 2000; Huete et al., 2000, 2002) to detect changes in leaf area compared to the conventional NDVI. EVI was originally designed to account for effects of soil background reflectance using empirical correction factors adjusted for individual soil types (Liu & Huete, 1985). The index has since been implemented with a constant set of parameters across large areas (Huete, Justice, & v. Leeuwen, 1999). The EVI formulation provides different weights for reflective bands, thereby changing the shape of the relationship between leaf area and vegetation index. Nonetheless, sensitivity with respect to changes in vegetation still depends on the ability of individual bands to detect these changes. The increased sensitivity of EVI to bidirectional reflectance effects originates from the constant (empirical) weight factors present in the index (Moura, Galvão, dos Santos, Roberts, & Breunig, 2012): In case of a normalized difference index, such as NDVI, changes in forward and backscattering are less pronounced, particularly in dense vegetation (Hu et al., 2007), because changes in one band are expressed relative to changes in the other (Kaufmann et al., 2000). However, the directional effects in EVI are dominated by the absolute changes in the NIR band (because of the higher weight in the denominator compared to the nominator). The canopy and leaf level scattering in NIR is much larger than scattering in the visible part of the spectrum, because the reflectivity is higher in this part of the spectrum. As a result, the use of EVI for detecting seasonal changes seems questionable, unless normalized to common sun-view geometry (Fig. 10 b and c). No BRDF correction is available from daily MOD/MYD09 surface reflectance, a normalized MOD/MYD09 product was therefore not presented in this study. Improvement in EVI would be expected for both products; the objective of including at least one BRDF corrected EVI in this study was to show that removal of directional effects is needed when using EVI measurements for change detection.

While not explicitly investigated in this study, a two band EVI (Jiang, Huete, Didan, & Miura, 2008) should be subject to the same limitations because of its mathematical formulation that does not normalize the bands with respect to each other. While this study has provided statistical insights, reconciliation of existing discrepancies between remotely sensing observations, ground and tower-based studies of ecosystem fluxes has been addressed separately (Hilker et al., 2014) and will need to be addressed further in future research. The objective here was solely to provide a statistical basis for potentials and limitations to detect vegetation change in the Amazon from MODIS.

5. Conclusion

The presented study provides a straightforward statistical basis for the recent discussion on changes in tropical vegetation observed from remote sensing indices. Our results show that using a the conventional MOD09/MYD09 product, changes in leaf area would have to exceed 2 m^{-2} m^{-2} across most of the Amazon basin, which corresponds to variability of NDVI (EVI) of about 25%, before these changes can be reliably detected. For composited observations, this result improved to about 10% change for NDVI, but when using EVI, directional effects prevented observation of small changes in surface properties. MAIAC atmospheric correction and cloud screening can increase the performance of daily MODIS observations, reducing the amount of observable change to about 0.6–0.8 LAI units and to about 0.4 LAI units for composited analysis of seasonality. This improvement may help overcome some of the limitations currently faced by the scientific community and help reconcile existing discrepancies between remotely sensing observations and ground and tower-based studies of ecosystem fluxes.

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