REMOTE SENSING OF PHOTOSYNTHETIC LIGHT USE EFFICIENCY OF TROPICAL ECOSYSTEMS

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Abstract. Tropical ecosystems play major roles in the global carbon, water and energy cycles and, as a result, in global climate. The broad goal of this research is to monitor changes in plant physiological parameters, including status of pigments, and water use in connection with drought events in such ecosystems. Specifically, we focus on stress related changes in photosynthetic activity and monitoring of vegetation decline following major stress events by inferring light use efficiency (ε) from measurements of reflectance from the MODIS data. To address our objective, we inferred light use efficiency (ε) from measurements of reflectance from the MODIS data from 2000 to 2012. Our results showed clear seasonality of light use efficiency over tropical forests. Lower values of PRI were found during the driest months of the year (July, August and September). We also conducted an exploratory analysis to assess the potential climate variables that might drive the changes in photosynthetic activity in the Amazon. We were also able to demonstrate close links between changes in the Photochemical Reflectance Index temperature and precipitation.

Keywords: remote sensing, photosynthesis, photochemical reflectance index, MODIS, MAIAC, Amazon

1. Introduction

Tropical ecosystems play major roles in the global carbon, water and energy cycles and, as a result, in global climate. However, these ecosystems have been one of the most active areas of human/environment interaction during the past decades. The resulting changes in vegetation may have a significant influence on tropical ecosystems, affecting water supply, biodiversity, and carbon sequestration. The Amazon basin alone contains a quarter of the world's species and accounts for about 15% of terrestrial gross primary productivity (GPP) (Atkinson et al., 2011; Phillips et al., 2009). Global warming and climate change have altered, for instance, the precipitation patterns. Climate related changes of tropical GPP would, therefore, affect atmospheric CO_2 levels leading to serious damages in the numerous ecosystems services and global climate. Tower measurements are currently one of the only direct ways to measure carbon flux and GPP of an ecosystem. However, these measurements can only effectively measure a single "point" over a certain area. Remote sensing has the ability to extend the knowledge of carbon flux from space and may therefore provide a pathway to assess the carbon flux of whole ecosystem such as the Amazon.

Plant carbon uptake (GPP) is a function of the photosynthetically active radiation (PAR), the fraction of this radiation absorbed by vegetation (*f*PAR) and the efficiency with which this radiation can be utilized to produce sugars and fixate carbon (light use efficiency, ε). PAR and *f*PAR have been determined from remote sensing measurements using vegetation indices such as NDVI, but ε is dependent on complex limitations. Therefore, direct measurements of ε from remotely sensed data is difficult.A Photochemical Reflectance Index (PRI) developed as a method to remotely assess the light use efficiency using spectral bands reflectance (Gamon et al 1992) holds promise to facilitate direct measurements of photosynthetic efficiency. PRI has been used to derive ε at canopy and larger scales as a function of the status of the xanthophyll cycle, a biophysical mechanism that controls the down-regulation of photosynthesis but PRI alone depends on extraneous effects and the sun observer geometry. Recent findings have shown that ε may be inferred from multi-angle observations by relating ε to the slope of PRI with respect to shadow fractions. This technique minimizes background effects and provides an approach that is based on radiative transfer theory. A few studies have focused on an investigation of the PRI and ε relationship using remote sensing data. The majority of the studies, however, have focused on temperate, boreal and Mediterranean ecosystems (Drolet et al., 2005; Garbulsky et al., 2008; Rahman, 2004). The lack of multi-angle data has been the main limitation of this multi-angle technique to be applied over fairly homogeneous tropical regions such as the Amazon basin. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor seems to be the most appropriate currently available to assess PRI as it provides means to monitor changes in tropical forests, for instance, in a comprehensive spatial and temporal fashion. Multi-angle observations may be obtained from a few days of MODIS overpasses over the Amazon basin. However, assessment of tropical vegetation is difficult due to high cloud cover (ranging between 70-99% at any given time of the year) and high aerosol loadings from burning of biomass (Samanta et al., 2012). Improved, time series based cloud screening and atmospheric correction algorithms, such as the multi-angle implementation of atmospheric correction (MAIAC) may allow accurate monitoring of changes in vegetation over time. To obtain multi-angle PRI for the Amazon basin, we took advantage of MAIAC's ability to provides surface reflectance without assuming a Lambertian reflectance model, thereby preserving the multi-angle character of MODIS observations. Our main objective is to monitor changes in plant physiological parameters, including status of pigments, and water use in connection with drought events. Specifically, this research will:

- Focus on stress related changes in photosynthetic activity and monitoring of vegetation decline following major stress events by inferring light use efficiency (ε) from measurements of reflectance from the MODIS data.
- We hypothesize that changes in vegetation cover, as a result of prolonged drought stress, will be preceded by a prolonged depression of photosynthesis and subsequent decline on leaf pigments. Therefore, an exploratory analysis will be carried out to assess the potential climate variables that might drive the changes in photosynthetic activity in the Amazon basin.

2. Methods

2.1 Research site and MODIS data

The Amazon basin is characterized by many different ecosystems, holding alone almost a quarter of the world's terrestrial species (Dirzo and Raven 2003). The Amazon forest spans a large climatic range, with the dry season spanning from July to November and the wet season spanning from December to June with the forest being responsible for almost half of its own rainfall.

There are many standard MODIS data products available and they are related to calibration, atmosphere, land, cryosphere and ocean. In this research, the focus is the land and atmosphere products from a new and improved multi-angle implementation of atmospheric correction algorithm (MAIAC).. This product is gridded to a 1 km resolution for use in land process models and applications. This research will focus on MAIAC monthly composite of MODIS Terra and Aqua observationsat different viewing geometries from 2000 to 2012, totaling 156 mosaics for the band 12 (546-556 nm) and band 11 (526-536 nm) at each geometry view (backscattered and forward scattered). A detailed overview of the data used in this study can be seen in Figure 1.

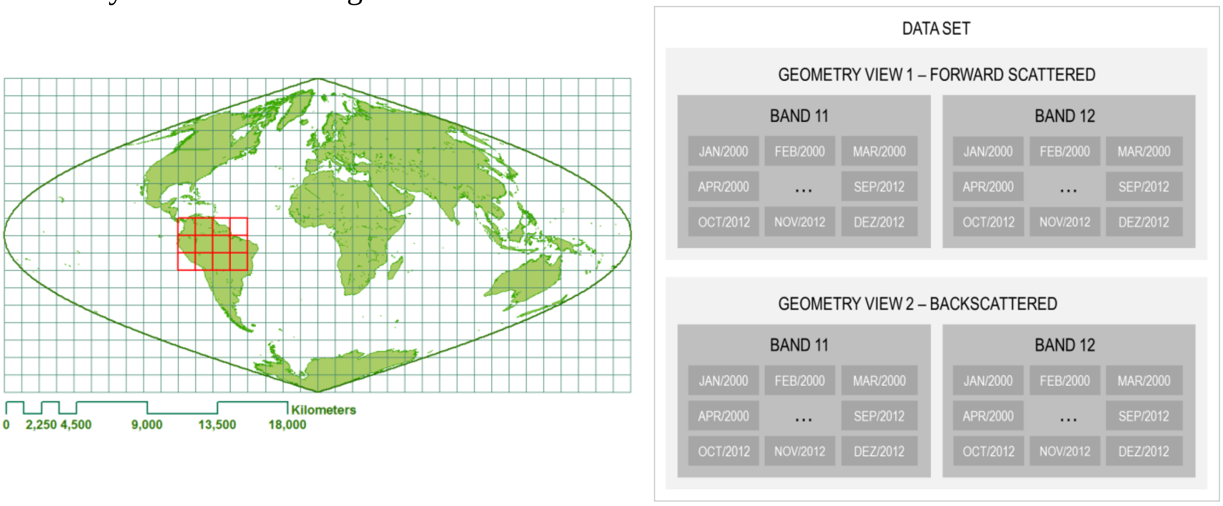

Figure 1. (Left) MODIS imagery grid and tiles over the area of study (highlighted in red). A mosaicking procedure was used in order merge all the tiles for the study area. (Right) Overview of the data set used in this study. MAIAC monthly composite of Terra and Aqua MODIS at different viewing geometries from 2000 to 2012, totaling 156 mosaics for the band 12 (546-556 nm) and band 11 (526-536 nm) at each geometry view.

2.2 Estimating PRI from MODIS data

One of our proposed approaches to address our objective was inferring light use efficiency (ε) from measurements of reflectance from the MODIS data. The GEP (gross ecosystem productivity or photosynthesis) can be written as: $GEP = PAR \times f_{PAR} \times \varepsilon$, where PAR is the photosynthetically active radiation, and; f_{PAR} is the fraction of this radiation absorbed by photosynthetically active vegetation elements, and; ε is the light use efficiency. ε has thus far been difficult to be determined using remotely sensed data. Gamon et al 1992 has shown that ε to the Photochemical Reflectance Index (PRI) . Here, we adjust the definition of PRI to fit the nearest available MODIS bands (Drolet et al 2005):

$$PRI = \frac{\rho_{\mathrm{band11}} - \rho_{\mathrm{band12}}}{\rho_{\mathrm{band11}} + \rho_{\mathrm{band12}}} \tag{1}$$

where ρ are reflectance values in the band 11 and band 12 from the MODIS data. The geometry views will provide different estimations of the surface reflectance due to the portions of the canopy that will be under direct incident radiation (sunlit) and shaded. We accounted the shadow effects in our analysis by computing the PRI for both geometry views: $\mathrm{PRI}_{\mathrm{forward}}$ and $\mathrm{PRI}_{\mathrm{backward}}$, where the former is related to the shaded portion of the canopy and the latter to the sunlit portion of the canopy. The difference between $\mathrm{PRI}_{\mathrm{backward}}$ and $\mathrm{PRI}_{\mathrm{forward}}$ was calculated.

2.3 Climate data

In order to assess the potential climate variables that might drive the changes in photosynthetic activity in the Amazon basin, we carried out an analysis based on weather records available for the study area. However, the available conventional weather stations in the Amazon are not evenly distributed across the entire study area, leading to underrepresentation in data-scarce regions. As a result, the available records may not meaningfully represent the weather occurring across the entire area. To overcome this issue, we took advantage of the National Centers for Environmental Prediction's Climate Forecast System Reanalysis (CFSR) data available at (http://globalweather.tamu.edu/). For further information about the CFSR data, readers are encouraged to refer to the aforementioned link. The CFSR data are available globally for each hour since 1979 and it is gridded at a 38-km resolution. It provides estimates of estimates of temperature (minimum and maximum), precipitation, wind, relative humidity and solar radiation. Based on values of temperature and relative humidity, we calculated the vapor pressure deficit (VPD) as an additional climate variable. We calculated the VPD as follows:

$$SVP = 610.7 \times 10^{\frac{7.5 \times T}{237.3 + T}} \tag{2}$$

$$VPD = 1 - \frac{RH}{100} \times SVP \tag{3}$$

where *SVP* is the saturated vapor pressure (Pa) at a given temperature *T* (ºC), VPD is the vapor pressure deficit (Pa) and *RH* is the relative humidity. In our study we used a comprehensive time series of monthly CFSR data from 2000 to 2010 at four locations across the Amazon Basin. Each plot has a 5º x 5º resolution and contains 272 observations (Figure 2).

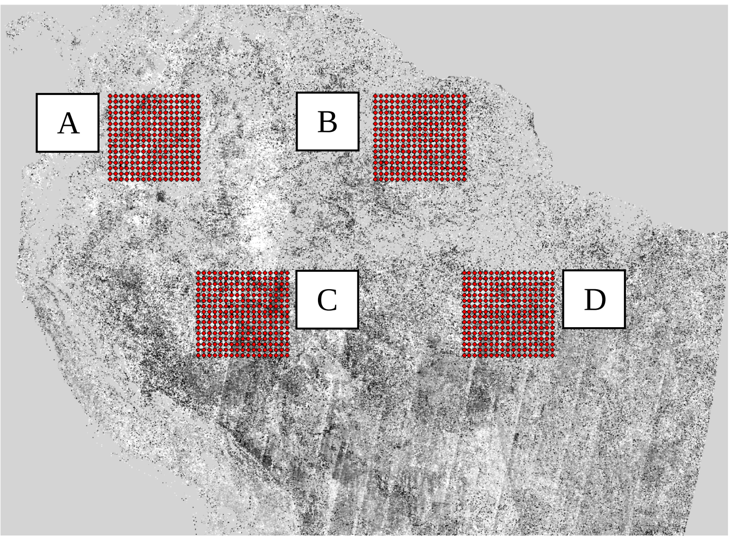

Figure 2. Schematic representation of the locations of the CFSR data used in this study

2.4 Random forest based models for PRI prediction

Random Forest is a general term for ensemble methods using tree-type classifier {DT(x, θk), m = 1,…,}, where the θk are independent identically distributed random vectors and x is an input pattern. The RF classification and regression algorithm is described in detail in Brieman (2001). Briefly, the RF is an ensemble of classification trees, where each tree contributes with a single vote for the assignment of the most frequent class to the input data. Different from decision trees, which use the best predictive variables at the splits, RF uses a random subset of predictive variables in order to reduce the generalization error. The RF presents many desirable properties, such as high accuracy, robustness against over-fitting the training data, and integrated measures of variable importance. For the RFs based models, two user-defined parameters exist: the number of trees used in the model (ntrees), which represents the number of trees to grow in the 'forest', and the number of variables tested in each split of the trees (mtry). Since the number of predictors in our CFSR data set is relatively small, we used all the available predictors in our model and calculated values of PRI. To avoid the subjectivity of randomly choosing the number of trees, we examined a pool of potentials parameters by using a built-in function of the algorithm that chooses the optimal number of the trees based on the raw data. In our study, the optimal number of trees for our data set was 500.

The construction and tuning of the Random Forest model were performed using R version 2.15, a multiplatform, open-source language and software for statistical computing (R Development Core Team, 2010). For the construction of the Random Forest models (RFs) we used the 'randomForest' package available for R. For further information about RF algorithms and its codes, we encourage readers to refer to Breiman (2001).

3. Results and discussion

3.1 PRI - ε relationship

The PRI - ε relationship was assessed by calculating PRI using bands 11 and band 12 from MAIAC. Figure 3 shows the monthly average for the difference between $PRI_{backward}$ and $PRI_{forward}$ from 2000 to 2012. Lower values of PRI were found in the southern part of the study area during the dry season. This season is defined as when less than 100 mm of rainfall are received per month (Asner and Alencar, 2010). This dry season lasts 4 to 5 months in which the rainfall is close to zero for the months of July, August and September. Moreover, the area where values of PRI are the lowest corresponds to the area where Lewis et al. (2011) observed the highest drought intensity during the 2010 drought in the Amazon region.

3.2 PRI prediction and climatic variables

Based on the fact that water stress substantially alters plant metabolism, thereby decreasing effects on growth and photosynthesis, we conducted an exploratory analysis on potential climatic variables that might have driven the changes in PRI across the Amazon region. We selected 4 locations (Figure 2) based on whether the area was going under stress, reflecting in significant changes on PRI values (Figure 2, C and D) or not (Figure 2, A and B). Our Random Forest model showed good capability of predicting PRI values based on the climatic predictors. Figure 5 shows the relationship between the predicted values for PRI and the PRI calculated from MODIS data. All the locations showed a R^2 greater than 0.95. This result led us to conclude that a variable importance assessment would provide meaningful insights about which potential climatic variable might have bigger impact on PRI. We measured the importance of a given predictor by its contribution to the increase of the mean squared error (MSE). In our particular case, if the model randomly permutes a predictor that does not present a significant change in prediction accuracy, then we would expect to see small changes in the MSE. On the other hand, if a given predictor causes significant changes in prediction, this predictor will cause greater changes in the MSE. Therefore, predictors that caused greater changes in the MSE were considered important predictors that might be driving PRI across the Amazon region. Our results showed that predictors such as temperature, wind and solar radiation caused major gains in the MSE for the areas A and B. Although PRI values On the other hand, areas C and D showed predictors such as temperature, precipitation and relative humidity as the main contributors to increment of MSE error. Although these predictors might not present a direct relationship with PRI, our findings showed that processes where a combination of these factors might occur possibly represent the main driver of the light use efficiency across the Amazon region.

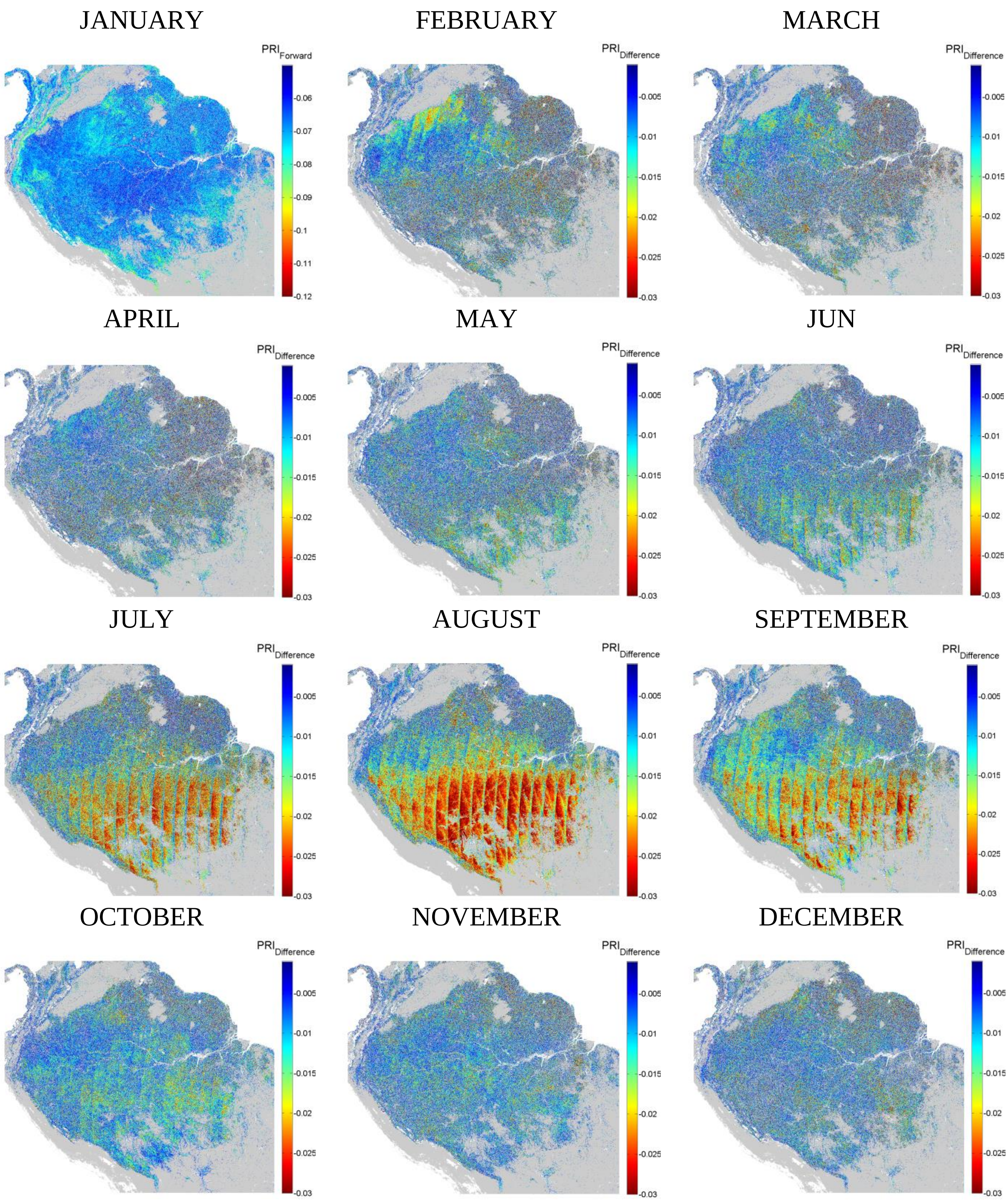

Figure 3. Monthly average for the difference between $PRI_{backward}$ and $PRI_{forward}$ from 2000 to 2012.

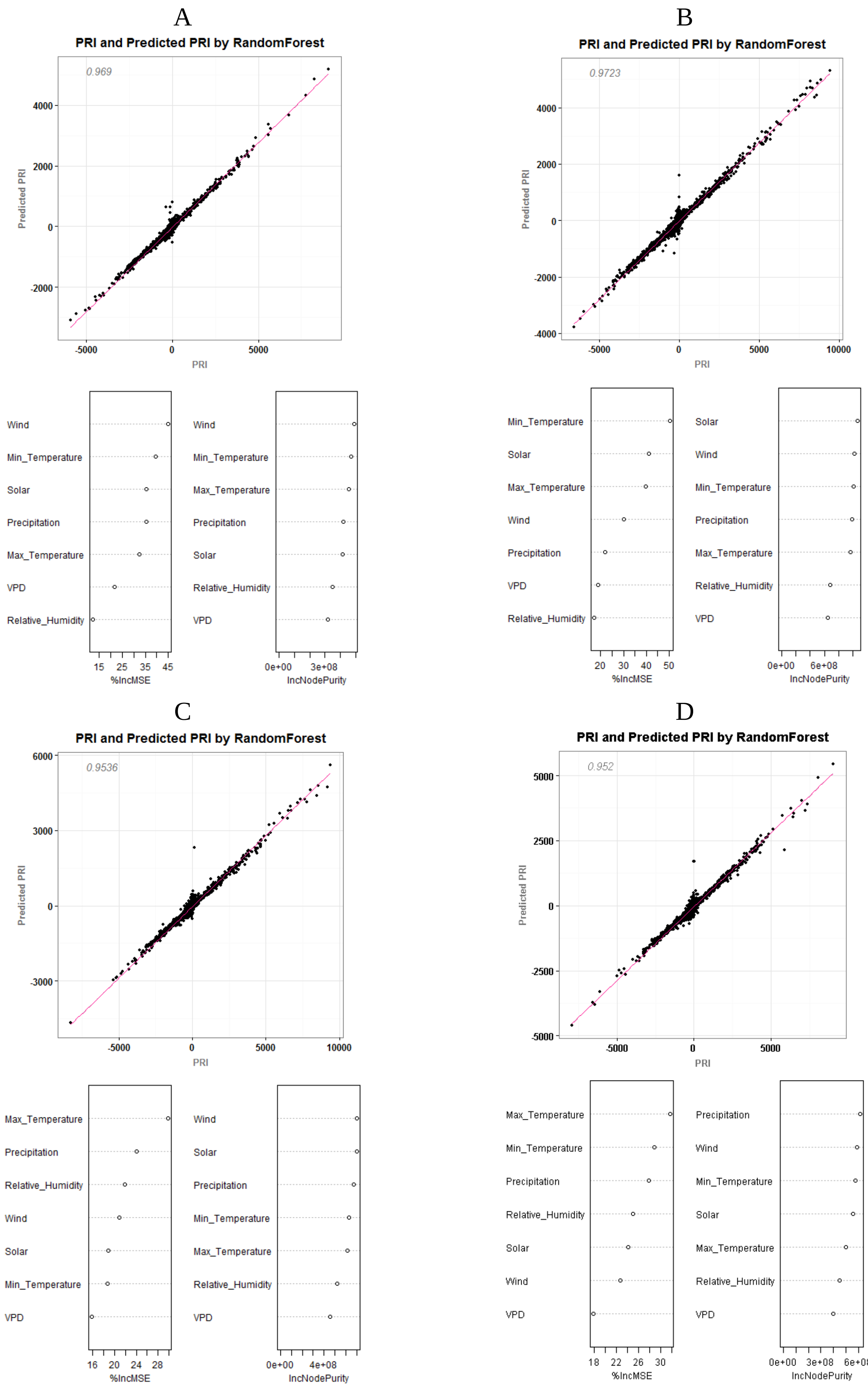

Figure 5. Relationship between observed and predicted values of PRI from 2000 to 2010 (top row). Measures of importance for the predictors at each plot (bottom row). %IncMSE represents the contribution of each predictor to the increment of the mean squared error when this predictor is randomly permuted within the model.

4. Conclusions

This research focused on related changes in photosynthetic activity and monitoring of vegetation decline following major stress events by inferring light use efficiency (ε) from measurements of reflectance from the MODIS data. Our finding show clear seasonality of light use efficiency over tropical forests that are related to dry and wet season cycles and correspond well to flux tower related measurements of photosynthesis. Finally, Multi-angle MODIS observations, while not optimal for measuring short term changes in ε, may provide realistic estimates of photosynthesis over tropical regions.

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