Impact of Vegetation Variability on Biogenic Emissions

Erin M Chavez-Figueroa*, Daniel S Cohan, Adetutu M Aghedo, and Benjamin Lash
Department of Civil and Environmental Engineering, Rice University, Houston, TX, USA

Jian Bi and Ranga Myneni
Climate and Vegetation Research Group, Boston University, Boston, MA, USA

1. INTRODUCTION

Biogenic emissions are an important input to atmospheric chemistry models. Due to the nonlinear response of ozone formation to nitrogen oxides (NOx) and volatile organic compound (VOC) emissions, accurate simulation of biogenic VOC emissions can be crucial to predicting the relative importance of controlling NOx or VOC emissions (Xiao et al., 2010).

The biogenic emissions model MEGAN (Model of Emissions of Gases and Aerosols from Nature, Guenther et al. 2006) requires numerous inputs. The phenology input to MEGAN include leaf area index (LAI), or the ratio of leaf area to ground area. Recent studies give conflicting conclusions on the impact of interannual variation in LAI on isoprene emissions.

Gulden et al. (2007) indicate that variation in LAI is at least as important as variation in temperature. A more recent paper by Tawfik et al. (2012) disputes this claim, indicating that interannual variation in LAI is actually unimportant, particularly when compared to soil moisture, temperature, or photosynthetically active radiation (PAR). However, it is difficult to compare the results from these two studies directly due to differences in the interannual variability of their LAI data. In light of the disparity in the conclusions drawn by these two studies, we have run MEGAN with two datasets of differing variability with all other considerations held constant.

The root cause for vegetation variability is nutrient availability, namely water, carbon, nitrogen, and phosphorous. Of these, water is the most readily available data at the synoptic scale. Recent studies have tried to quantify the impact of water stress on vegetation at regional and global scales (Bobée et al. 2012). In their analysis of satellite vegetation data, Beck et al. (2012) found that biomes above 45°N displayed varying responses to environmental stressors with some areas increasing primary production and others decreasing primary production. Some have even gone so far as to use vegetation cover as an indication of drought (Aguilar et al. 2012). To better understand what drives variability in LAI, we have made some qualitative comparisons between drought condition and LAI anomaly in the US.

2. METHODS AND RESULTS

2.1 Variability of LAI datasets

Two datasets with different amounts of interannual variation in LAI were chosen for this study. The first dataset consists of ten years–2001 to 2010–of data from the MODIS instrument on the Terra satellite that have been processed using the algorithm detailed by Yuan et al. (2011) (referred to as BU data from here forward). This data shows significant variation (Fig. 1a), with a maximum interannual variation (IAV in Eq. 1, as used by Tawfik et al., 2012) of 94%.

$$\mathrm{IAV} = \frac{1}{\mathrm{n}}\sum_{\mathrm{y}=1}^{\mathrm{n}}\left(\left|\frac{\mathrm{x}_{\mathrm{y,m}}-\bar{\mathrm{x}}_{\mathrm{m}}}{\bar{\mathrm{x}}_{\mathrm{m}}}\right| * 100\%\right) \quad (1)$$

$$n = number\ of\ years$$
$$\mathrm{x}_{\mathrm{y,m}} = value\ for\ month\ and\ year$$
$$\bar{\mathrm{x}}_{\mathrm{m}} = average\ for\ month\ over\ all\ years$$

In the mixed forests (Fig. 2) of the Southeast US, where isoprene emissions are highest, the IAV is actually lowest. Most of this region shows IAV of less than 10% in August. The IAV over open shrublands and grasslands in West Texas is highest at 40 to 50% in August. Well developed vegetation such as forests have less variable LAI since they do not have to devote as much primary production to establishing roots and stems (San Jose and Montes, 2007). Similarly, croplands show more variability since they must grow from seed every year, but not as much variability as native grasslands that do not benefit from irrigation

**Corresponding author:* Erin M Chavez-Figueroa, Department of Civil and Environmental Engineering, Rice University, 6100 Main Street, MS-519, Houston, TX 77005; e-mail: emc4@rice.edu

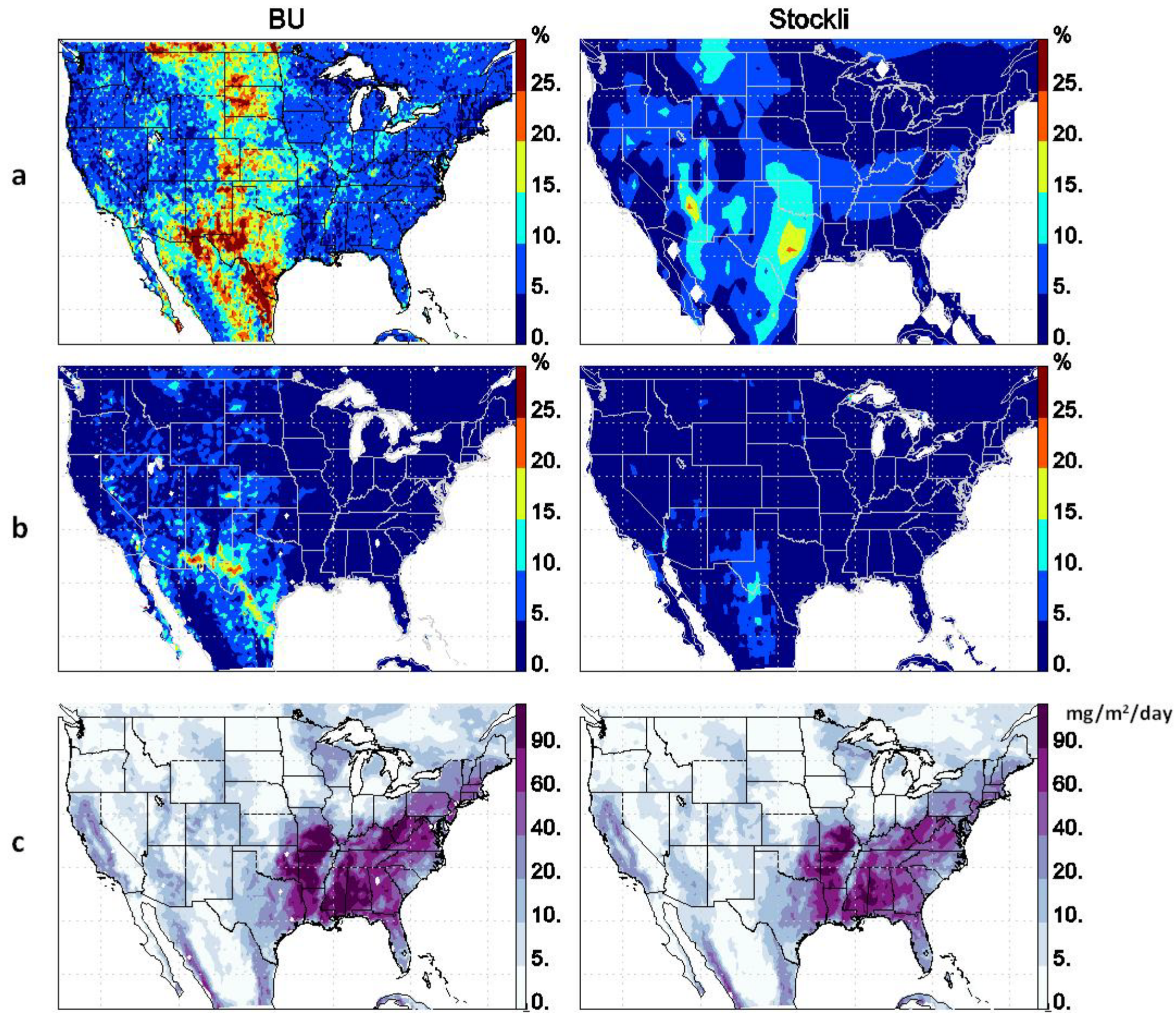

Fig. 1 (a) Interannual variation for the BU (left) and Stockli et al. (right) LAI datasets in August for the years 2001 to 2010. BU data is at quarter-degree resolution while Stockli et al. data is at one-degree resolution. **b)** Interannual variation in MEGAN isoprene emissions for 21 August with the respective LAI inputs. (c) Average MEGAN isoprene emissions for the same day in mg/m^2.

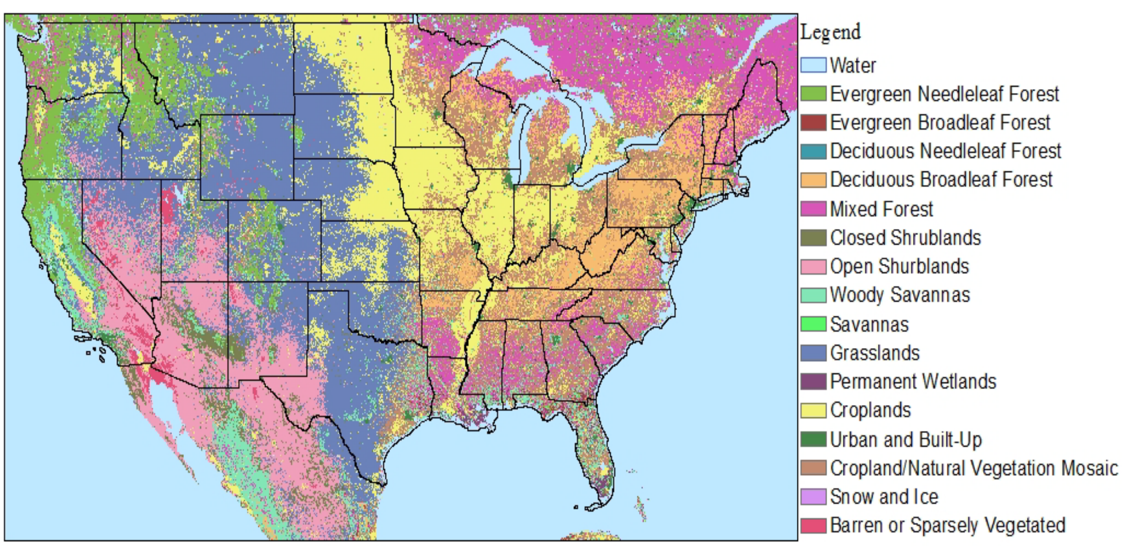

Fig. 2. Biome distributions in the USA from MODIS Land Cover Dataset (MCD12Q1) for 2006 using Land cover Type I.

and fertilization. August showed the highest variability compared to other months, while January showed the lowest.

The second dataset comes from work performed by Stockli et al. (2011) to create a comprehensive phenology dataset. While their dataset also uses MODIS input, it includes the use of extensive reanalysis. The end result is much less variable than the BU data, both spatially and temporally (Fig. 1a). The maximum IAV in the Stockli et al. data for August is 26% while the maximum IAV in the BU data is 94%, a nearly four-fold difference. Also, the IAV in the Stockli et al. data is less than 10% for most of the nation while the IAV in the BU data is greater than 10% for over half of the nation. The broad pattern of variability is similar for both datasets.

The disparity in the variation of these LAI datasets stems from the algorithm used to process MODIS input. The algorithm employed by BU directly utilizes MODIS observations, adjusting the data primarily to correct for error produced by clouds or instrument failure (Yuan et al. 2011). The algorithm employed by Stockli et al. involved extensive constraints on the data, including maximum and minimum LAI values based on biome and use of only data points from MODIS with no quality control flags, including limiting data to days with no cloud cover. Additionally, the Stockli et al. data was put through an empirical phenology model that incorporates moisture and temperature conditions. The main goal of the Stockli et al. data is to correctly identify timing of important phenological events such as budburst, whereas the BU data is focused on presenting the best MODIS data possible. The goal of each is distinct, and therefore produces very different results. Tawfik is the only researcher to have used Stockli et al.'s dataset to run MEGAN to date.

2.2 MEGAN Results from Two Datasets

To assess the impact of interannual variation in LAI on biogenic emissions, we ran MEGAN to compute isoprene emissions using both the Stockli et al. data and the BU data. These runs were performed with static plant functional type (PFT) distributions provided by Alex Guenther on the MEGAN website for the year 2008. Leaf age was computed by MEGAN. We used constant meteorology by replicating the WRF output (also provided on the MEGAN website) for July 20, 2008 to all time steps. PAR was computed from the meteorology input. The results are therefore artificial in that both the variation in meteorological conditions and PAR through the decades is not accounted for. These results therefore show the isolated influence of LAI variability as a driving parameter in MEGAN.

The results from MEGAN indicate less interannual variability in the simulated isoprene emissions than in the LAI input (Fig. 1b). This reflects the response of isoprene emissions to LAI in MEGAN, where isoprene emissions level off at high LAI values (Guenther et al., 2006). The spatial patterns of variability remain, but the magnitude of the IAV is reduced by 5 to 10 percentage points throughout much of the country. The high variability through the center of the country, where isoprene emissions are low (Fig. 1c), is drastically reduced in both cases. Over the Southeast, where isoprene emissions are the highest, the interannual variation in LAI and isoprene emissions is less than 5% in both datasets. Even so, it remains to be seen from photochemical modeling whether the fluctuations from year to year could still be significant to ozone concentrations or sensitivities.

2.3 Correlation of LAI Variability to Meteorological Variability

As a qualitative assessment of the dependence of LAI maxima to the weather patterns in an area, we compared LAI anomaly maps to drought condition maps for the continental United States. Maps of the Palmer Drought Severity Index (PDSI) were taken from the National Climate Data Center (Historical Palmer Drought Indices). LAI anomalies were calculated using the BU data relative to mean conditions for the years 2001 to 2010 and are unitless. Fig. 3 illustrates two years—2005 and 2007— to compare wet and dry conditions in different parts of the country. In 2005, the Southwest and Southeast both experienced wet conditions, while the northwest experienced a drought. The LAI showed positive anomalies in the early spring in the West, but negative anomalies in the Southwest. By August, however, the West shows mostly normal LAI, the Southwest shows positive anomalies, and the region around Illinois shows a depression in LAI that corresponds to the drought in the area that summer.

In 2007, the Southwest and Southeast experienced severe droughts, while most of the Central Plains experienced a wet year. Again, the conditions in the early spring do not necessarily reflect the drought condition, but by late summer there is a general match between wet regions having elevated LAI and drought regions having depressed LAI. In the Southeast, some areas

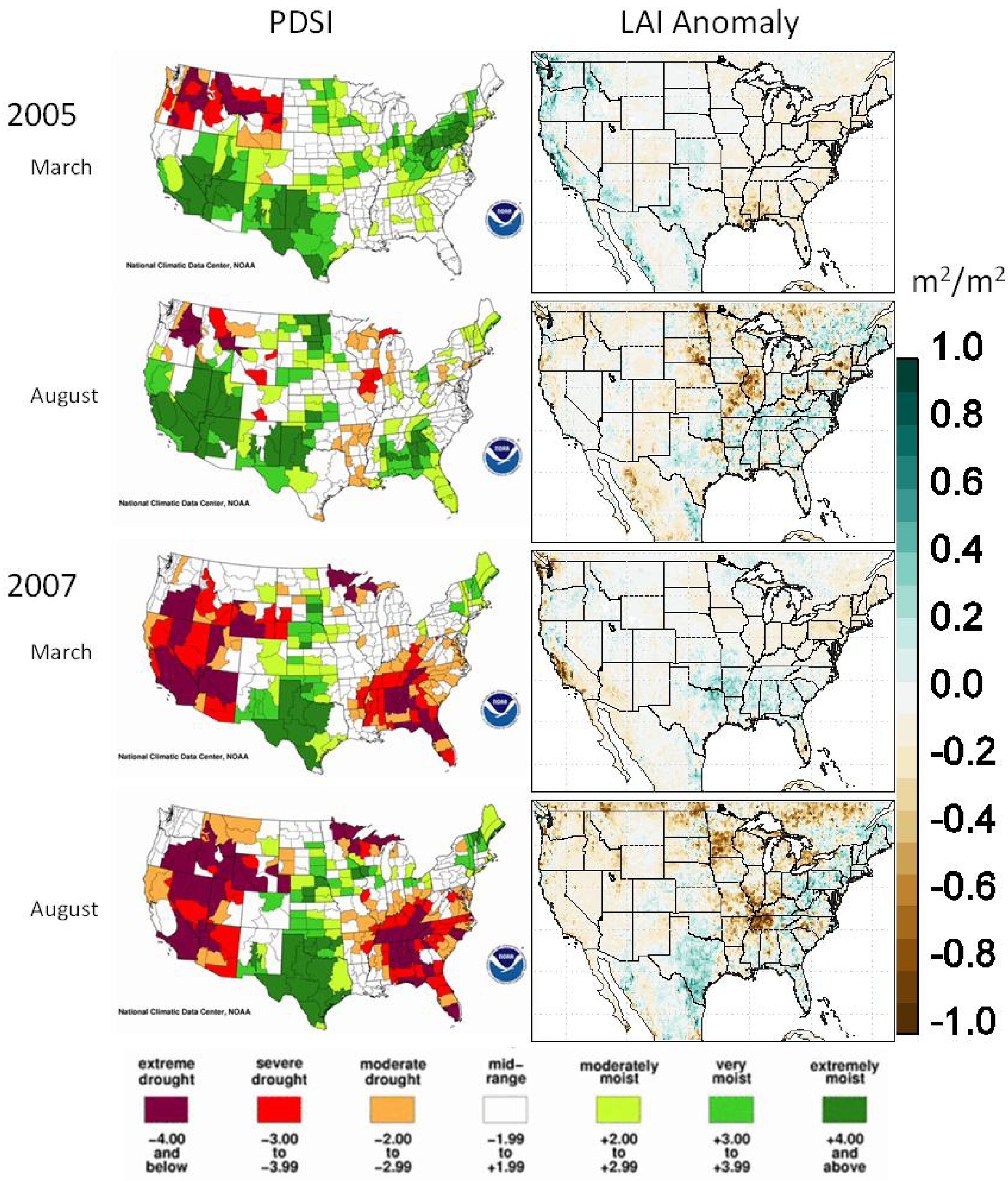

Fig. 3. Drought condition and LAI anomalies for March and August in 2005 and 2007. Drought is county-wide Palmer Drought Severity Index. LAI anomalies come from BU data.

experiencing severe drought show small increases in LAI, even into August. The investigation of these trends, especially to assess any correlation between drought and LAI anomaly for different regions in the United States will be the focus of future research. For our analysis, we will use PDSI data with a Penman-Monteith PE as developed by Dai (2011a). We will also use monthly temperature and precipitation data developed by the PRISM Climate Group at the University of Oregon (Daly 1994, 2002) to compare trends in temperature and precipitation anomalies to LAI anomalies.

3. CONCLUSION

While we have shown that LAI varies significantly from year to year due to meteorological influences, there is disagreement on the magnitude of interannual variation (Gulden et al. 2007, Tawfik et al. 2012). MEGAN runs show a muting of interannual variability of isoprene emissions compared to the amount of variability in the original LAI inputs. If the variability of other factors is amplified in MEGAN output, this could support LAI variability being less important than those factors.

Our future work will include using full dynamic meteorology from WRF so that we can assess the sensitivity of isoprene emissions to temperature, soil moisture, and photosynthetically active radiation as well as LAI. We will also utilize PAR derived from satellite data rather than WRF cloud placement. There is evidence that MEGAN output is particularly sensitive to PAR inputs (Ferreira et al. 2010). Ultimately, we will run a photochemical model such as CMAQ coupled with MEGAN to assess the sensitivity of ozone and secondary aerosol formation to LAI variability.

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