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Quantifying the contribution of environmental factors to isoprene flux interannual variability

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ABSTRACT

Terrestrial isoprene emissions directly respond to leaf temperature, photosynthetically active radiation (PAR), soil moisture, and plant characteristics such as leaf area index (LAI). Prior work has estimated isoprene interannual variability at 5–25%, however the relative contributions of individual environmental factors have not been delineated. A biogenic isoprene emissions model (MEGAN) is coupled to a regional climate model (RegCM4-CLM) to evaluate variations in monthly isoprene emissions. We use a novel approach to estimate the contribution of environmental factors to monthly averaged isoprene flux variability and analyze regional differences over the contiguous U.S. for summers spanning 1994–2008. Consistent with earlier studies, isoprene flux varies 8–18% interannually with the greatest variability occurring in July. Yearly changes in isoprene flux are poorly described by any single environmental factor, yet temperature and soil moisture together account for at least 80% of the total isoprene flux variations for all regions during the summer. Soil moisture plays the most significant role in controlling variability over the Northeast and Southeast, but only exceeds temperature in importance during August in the Northeast and July in the Southeast. PAR and LAI are nearly negligible contributors to summer interannual variability. Uncertainty in climate model soil moisture parameterizations can drive large variability in isoprene fluxes when including the isoprene soil moisture dependency factor, suggesting a need for further validation.

1. Introduction

Isoprene (C_5H_8) is an important ozone precursor in the presence of nitrogen oxides (NO_x) (Chameides et al., 1988) and its oxidation products can condense to produce secondary organic aerosols (Dentener et al., 2009). Both tropospheric ozone and atmospheric aerosols can lead to poor air quality and also influence the Earth's radiative budget either directly or indirectly (Andreae and Rosenfeld, 2008; Zhao et al., 2011). The primary source of isoprene to the atmosphere is emissions from terrestrial vegetation, with global estimates between 400–700 Tg yr^{-1} (Guenther et al., 2006; Arneth et al., 2008; Muller et al., 2008; Ashworth et al., 2010). Isoprene emissions are known to be controlled by several environmental factors, including temperature (Petron et al., 2001), light (Sharkey et al., 1996), soil moisture (Llusia et al., 2008), ambient carbon dioxide (CO_2) concentrations (Wilkinson et al., 2009), and phenology (Kuhn et al., 2004). As coupled climate-chemistry models move toward long-term simulations of tropospheric chemical environments (Fu et al., 2011), it is necessary to understand how individual environmental factors contribute to interannual isoprene flux variability.

Past studies have used observed isoprene concentrations and fluxes to estimate isoprene flux variability. In a hardwood forest site in Michigan, four years of canopy-level isoprene flux measurements showed low (~10%) inter-annual variability during the summer (Pressley et al., 2005). Although year-to-year variability at this site was strongly correlated to light and temperature, other unnamed environmental variables were implicated in controlling emissions variations. In Texas, two studies have investigated isoprene flux interannual variability (Gulden et al., 2007; Warneke et al., 2010). Gulden et al. (2007) concluded that modeled summer emissions yielded greater interannual variability when leaf area index (LAI) was allowed to respond to atmospheric forcing data

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(25%) as opposed to the typical LAI annual climatology (12%). In the second study, aircraft measurements of isoprene concentrations were used to infer isoprene emissions over northeastern Texas in 2000 and 2006 (Warneke et al., 2010) and found a factor of two difference in isoprene flux estimates between the two years. This difference was attributed to the unusually warm and dry conditions recorded in the summer of 2000, however the factor of two uncertainty in the inferred isoprene emissions is comparable to inter-annual variability. Comparing these inferred isoprene fluxes to several emissions inventories, Warneke et al. (2010) further demonstrated that models had difficulty capturing the observed interannual variation and was likely due to the lack of a direct soil moisture suppression of emissions during drought stress and/or lack of yearly varying LAI. However, neither of the two Texas studies account for direct emission suppression under decreasing soil moisture, which has been found to reduce global emissions by 20% (Muller et al., 2008).

At the regional scale, satellite-derived observations of formaldehyde column concentrations have been used to infer top-down isoprene emission fluxes and quantify isoprene flux interannual variability (Abbot et al., 2003; Palmer et al., 2006; Duncan et al., 2009). Abbot et al. (2003) used this technique with the Global Ozone Monitoring Experiment (GOME) satellite to estimate August interannual variability of 30% over the southeastern United States. They found that flux variations followed surface air temperature but interannual changes in temperature alone could not explain the variations in isoprene emissions. Palmer et al. (2006) also used GOME formaldehyde measurements to quantify interannual variability and estimated a range between 22–35% during the summer and suggested that 75% of variations are controlled by surface temperatures. In Palmer et al. (2006), the temperature-driven variation was estimated from the temperature dependency algorithm of an empirically-based isoprene emissions model (Guenther et al., 1995). A subsequent study focusing on the southeastern U.S. and utilizing higher resolution formaldehyde measurements (Ozone Monitoring Instrument; OMI) were in agreement with earlier estimates of variability (22% for the summer) and also implicated temperature as the primary driver (Duncan et al., 2009).

A global study using an interactive vegetation model supports the importance of land use in emissions calculations and estimates lower interannual variability (10%) for North America (Lathiere et al., 2006), yet we note that this study also does not account for emissions reductions due to soil water limitations (Guenther et al., 1995). Arneth et al. (2011) found that different isoprene emissions algorithms using the same climate forcing data estimated similar isoprene flux interannual variability. This suggests that climate variables (e.g. temperature, radiation, LAI, and soil moisture) play a strong role in controlling year-to-year emissions changes. Further, Arneth et al. (2011) found that interannual variability over the mid-latitudes was relatively small (5–10%) and attributed this to conflicting climate variable interactions. For example, warmer temperatures that increase emissions are well correlated with drier soils, which decrease emissions. This further emphasizes the need to quantify the role each control variable has on emissions variations.

Several of these studies (Pressley et al., 2005; Duncan et al., 2009; Warneke et al., 2010) cited are for specific locations where differences in observed isoprene flux variability may reflect regional differences. This highlights the need for a multi-region analysis of isoprene variability. As noted by Duncan et al. (2009), evaluating the influence of an individual climate variable on observed isoprene flux variability is difficult due to the strong correlations between climate variables. Although prior studies have provided estimates of the isoprene flux variability, there is little attribution of each environmental factor to flux variability that accounts for the direct effect of soil water limitations on emissions. Studies that include the soil moisture dependency can reduce global emissions up to 7–20% (Guenther et al., 2006; Muller et al., 2008) and can improve regional agreement with observations (Muller et al., 2008). Additionally, most studies operate on global domains and use land models forced with half-hourly or longer atmospheric data, resulting in coarse temporal and/or spatial resolution. Due to the heterogeneous nature of isoprene source strength and the sensitivity to temporal resolution of climate data (Ashworth et al., 2010), using a coupled, high-resolution regional model is likely to improve understanding of the influence of environmental factors on isoprene flux variability. The primary objectives of this study are to quantify the relative contributions of temperature, light, LAI, and soil moisture on isoprene emissions variability and to assess regional differences in the environmental variables controlling emissions over the contiguous U.S. A secondary goal is to introduce a simple methodology for calculating percent contributions of the environmental dependency factors that could be applied to other environmental control variables not considered in this study.

2. Methods

A biogenic emissions model (the Model of Emissions of Gases and Aerosols from Nature; MEGAN) (Guenther et al., 2006), described in Section 2.1, is coupled to the International Centre for Theoretical Physics (ICTP) Regional Climate Model version 4 (RegCM4; (Giorgi et al., in press)) to examine the relative contributions of leaf temperature, soil moisture, photosynthetically active radiation (PAR), and LAI to biogenic isoprene emissions. RegCM4 is a compressible, hydrostatic, primitive-equation model with a land surface described by the Community Land Model version 3.5 (Oleson et al., 2008), which determines the canopy-scale environment variables for input into MEGAN (Section 2.2). Based on RegCM4-CLM-MEGAN model output, the contribution of individual environmental factors is calculated as described in Section 2.3.

2.1. Biogenic isoprene emissions model: MEGAN

MEGAN is a biogenic emissions model (Guenther et al., 2006) that parameterizes observed relationships to estimate emissions. The canopy environment version of MEGAN determines isoprene emissions for each model grid cell as:

$$E = \varepsilon \rho C_{CE} \gamma_{PT} \gamma_{SM} \gamma_{age} \mathrm{LAI} \quad (1)$$

$$\gamma_{PT} = \gamma_T(\gamma_{Psun} + \gamma_{Pshade}) \quad (2)$$

where E is the isoprene emission flux ($\mu g\, h^{-1}\, m^{-2}$), ε is a standard emission factor taken at standard conditions described in Guenther et al. (2006) ($\mu g\, h^{-1}\, m^{-2}$), ρ is the in-canopy loss or production factor (=0.96), C_{ce} is an empirical adjustment factor for the canopy environment (=0.4), and γ_T, γ_P, γ_{SM}, and γ_{age} describe the influence of leaf temperature, PAR, soil moisture, and leaf age on isoprene emissions, respectively. The canopy description is based on that of the RegCM4 land model, the CLM version 3.5. CLM contains a single layer canopy model that is divided into sunlit and shaded fractions, which allows the calculation of γ_P and emissions based on the fraction of sunlit and shaded leaves (Eq. (2)). A high-resolution 30″ emission factor map, ε, is used (http://cdp.ucar.edu) and bi-linearly interpolated to the model gridcell-level and is not linked to the CLM land cover type. The effects of past temperature and light conditions on time scales of 24 hours and 10 days are included in the current implementation.

The response of isoprene emissions to soil moisture is defined as (Guenther et al., 2006)

$$\gamma_{SM} = \sum_j f_{root}^j \max\left(0, \min\left(1, \left(\theta^j - \theta_{wilt}\right)/0.06\right)\right) \quad (3)$$

where f_{root}^j is the fraction of root in a given model soil layer(j), θ_{wilt} is the wilting point, and θ^j is the volumetric soil moisture ($m^3\ m^{-3}$) at a given layer. The current parameterization only captures the effects of long-term drought conditions and can only reduce emissions (Pegoraro et al., 2004); short-term drought responses are not included. Inclusion of γ_{SM} in isoprene emissions models indicates improved measured-modeled agreement for isoprene fluxes (Muller et al., 2008). The CLM method for calculating γ_{SM} includes ten unevenly spaced soil layers and determines f_{root}^j for each soil layer using plant functional types (PFT). Up to four different PFTs can exist in a single grid cell providing a more detailed land surface description in regions with heterogeneous vegetation types. All gamma dependency factors are calculated at the PFT-level and then aggregated to the gridcell-level.

2.2. RegCM4-CLM experiment design and input data

RegCM4-CLM has been shown to reproduce mean climatological conditions over the contiguous United States (Tawfik and Steiner, 2011). The horizontal grid spacing is 60 km centered at 96W and 38N over the continental US (Fig. 1) and the atmosphere contains 18 vertical layers in hybrid-sigma coordinates. The time resolution is 200 seconds for the dynamical core, and the land surface (CLM) and biogenic emissions model (MEGAN) are called every 600 seconds within the coupled model framework. Because RegCM4 is a limited area model, we use 6-hourly European Centre for Medium-Range Weather Forecasts Interim Reanalysis (ERA-Interim) boundary conditions for the atmosphere and weekly-prescribed ERA sea surface temperatures to drive the RegCM4-CLM (Dee et al., 2011). Simulations are performed from 1992–2008, and the model is initialized in June 1992 using average soil moisture from the Global Land Data Assimilation System (GLDAS) CLM model realization (Rodell et al., 2004) and run for 1.5 years to achieve model equilibrium. Model output is analyzed for the last 15 simulation years (1994–2008).

As prior studies have demonstrated, accurate biomass density information can play a key role estimating regional isoprene emission rates (Lathiere et al., 2006; Gulden et al., 2007). Therefore, a half-degree daily satellite-derived LAI product (Stockli et al., 2011) is used to represent seasonal and interannual variations in LAI. The LAI data are spatially bi-linearly interpolated to the model grid and 1994 LAI is used for the model spin-up years. The summer (June–July–August; JJA) is the focus of analysis due to the high isoprene emission rates and its corresponding relevance to air quality.

2.3. Variability attribution calculation

To assess each variable's relative contribution to emissions, a first order Taylor series approximation is performed on isoprene emissions (E). E can be written in two ways, as a Taylor series (Eq. (4)) and as a variation about a mean (Eq. (5)):

$$E = \overline{E} + \frac{\partial E}{\partial \gamma_T}\Delta\gamma_T + \frac{\partial E}{\partial \gamma_{SM}}\Delta\gamma_{SM} + \frac{\partial E}{\partial \gamma_P}\Delta\gamma_P + \frac{\partial E}{\partial LAI}\Delta LAI + O^2 \quad (4)$$

$$E = \overline{E} + dE \quad (5)$$

Setting these equations equal to one another and dropping higher order terms (O^2), the equation becomes

$$dE = \frac{\partial E}{\partial \gamma_T}\Delta\gamma_T + \frac{\partial E}{\partial \gamma_{SM}}\Delta\gamma_{SM} + \frac{\partial E}{\partial \gamma_P}\Delta\gamma_P + \frac{\partial E}{\partial LAI}\Delta LAI \quad (6)$$

where dE is the total variability about the mean and each term on the right hand side is a single dependency factor's contribution to the total variability. The Δ term on the right-hand side of the equation is the deviation from the mean for a particular year and month of a given dependency factor. Hereinafter, we refer to each γ term as a dependency factor (e.g., γ_T is the "temperature dependency factor"). To retrieve a percent contribution to the total variation, dE, each term on the right hand side is correlated with dE. The R^2 correlation coefficient measures the percent to which a dependency factor can explain variations in dE using a linear relationship. The influence of higher order, non-linear terms on reconstructing dE was found to contribute less than 10% to the total calculated flux, suggesting that 1st order linear terms represent a majority of dE and gamma dependency factors are largely independent of one another. This simple Taylor series approach could be applied to other environmental factors not considered in this study such as CO_2 (Heald et al., 2009).

3. Results

3.1. Comparison with observed flux measurements

The highest absolute modeled isoprene emissions occur over the southern Plains and southeastern U.S. during JJA (>5 mg $m^{-2}\ h^{-1}$;

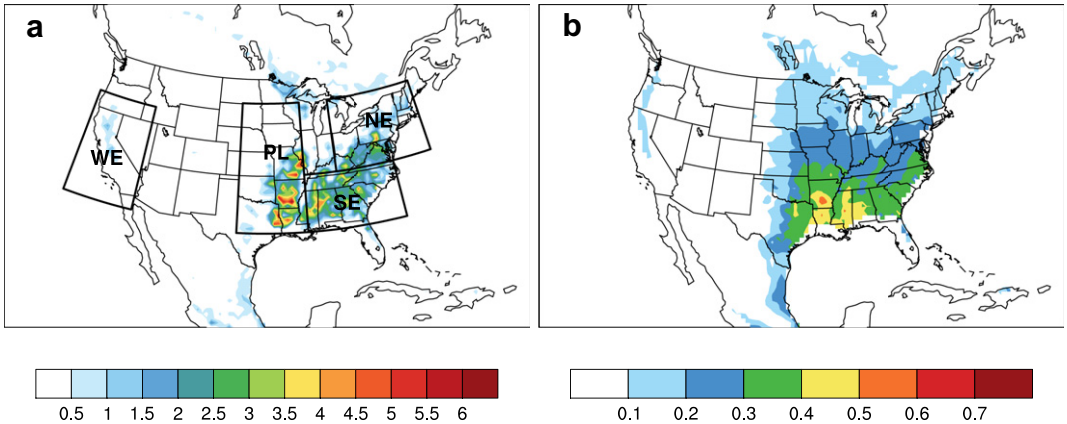

Fig. 1. Summer (June–July–August) average of (a) absolute isoprene emissions (mg $m^{-2}\ h^{-1}$) and (b) normalized isoprene flux, E_N, for 1994–2008 with averaging regions for the Southeast (SE), Northeast (NE), Plains (PL), and West (WE).

Fig. 1a) due to the underlying vegetation cover and high isoprene-emitting vegetation located in this region. Fig. 2 compares the average diurnal isoprene emissions from RegCM4-CLM against two mid-latitude measurement sites, Harvard Forest for July 1995 (Goldstein et al., 1998) and the University of Michigan Biological Station (UMBS) for July 2000 (Pressley et al., 2005). RegCM4-CLM generally underestimates emissions at both locations with the largest underestimate occurring at UMBS by a factor of 4 during the daily maximum. Model evaluation improves when compared to Harvard Forest emissions, where the model underestimates the midday peak by only 2 mg m^{-2} h^{-1}. These emissions are consistent with other modeling studies comparing MEGAN versus Harvard forest measurements, with the model underestimating emissions by a factor of 1.35 (Muller et al., 2008). For the north- and southeastern U.S., other modeling studies find MEGAN overestimates emissions by a factor of 2 (Stavrakou et al., 2009; Warneke et al., 2010). Because absolute isoprene flux emissions depend heavily on the ε map (Arneth et al., 2008), the large biases found at UMBS may be due to underestimated ε at that particular model gridcell.

3.2. Normalized isoprene emissions and interannual variability

To remove the isoprene emissions bias related to vegetation information contained within ε found in Section 3.1, we calculate a normalized isoprene flux ($E_N = E/\varepsilon$). Using E_N isolates the effects of the dependency factors on emissions (Eq. (1)) because the canopy chemical production/loss factor, ρ, and empirical coefficient, C_{ce}, do not vary spatially. Normalized isoprene emissions are greatest East of the Rockies with the highest fluxes over the eastern half of Texas into Arkansas and Louisiana (Fig. 1b). Additionally, the locations with the greatest E_N generally correspond to regions with the greatest absolute emissions (E) (Fig. 1a). This implies that areas containing the highest base ε also have the strongest contributions from environmental controls. Because the temperature and light dependency factors vary non-linearly, a 1 K temperature decrease (10%) and 15 W m^{-2} decrease in radiation (11%) corresponds to a 0.45 mg m^{-2} h^{-1} (or 22%) reduction in E. Both LAI and soil moisture modify emissions linearly in the current parameterization and are unlikely to be important intra-seasonally when changes in temperature and light vary most.

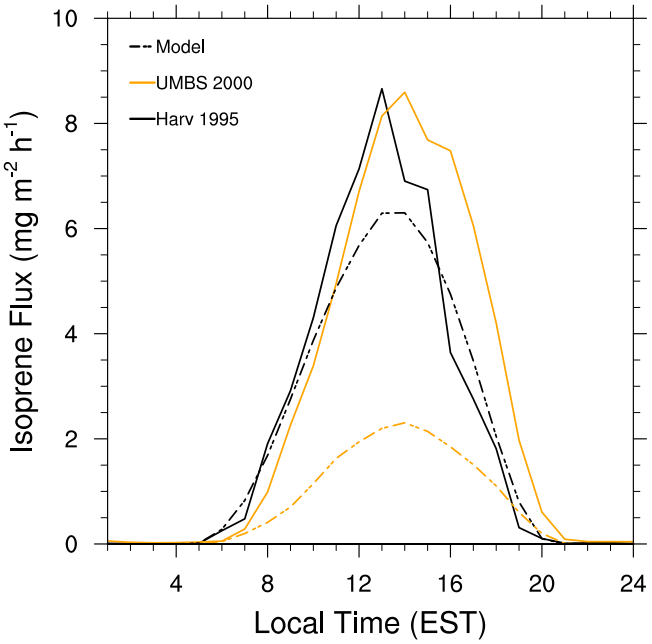

Fig. 2. Average diurnal cycle of absolute isoprene emissions (mg m^{-2} h^{-1}) at two mid-latitude stations: July 1995 at Harvard Forest (black) and July 2000 at the University of Michigan Biological Station (orange). Dashed lines are from modeled RegCM4-CLM-MEGAN output (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

Interannual variability (IAV) of isoprene emissions for each month and region is calculated using E_N (Table 1). Here we define IAV as the average absolute percent departure from the mean for a particular month:

$$\mathrm{IAV} = \frac{1}{n}\sum_{y=1}^{n}\left|\frac{x_{y,m} - \overline{x_m}}{\overline{x_m}}\right| \times 100 \qquad (7)$$

where $x_{y,m}$ is isoprene flux for a particular year (y) and month (m), $\overline{x_m}$ is the average isoprene flux for month m over all years of the simulation (1994–2008) and n is the total number of simulation years.

In the Southeast, IAV ranges from 13% in July to 7.8% in August. The northeast demonstrates similar behavior with greatest variability in July (13.7%) but comparably weaker variability in June and August. Year-to-year variations in isoprene emissions over the Plains peak in early summer (10.4%) and gradually decrease as the summer progresses. IAV for the West is greatest relative to the other regions with up to 18.4% variability on average for July. The consistently high IAV in summer emissions in the West can be attributed to high single-year departures from the mean, such as in August and July of 1998. This was a known strong El Niño year where percent departure from mean reached 60% (Fig. 3) and is consistent with prior studies demonstrating global isoprene emissions are higher during strong El Niño events (Naik et al., 2004; Lathiere et al., 2006). When excluding these single year extremes, yearly departures from the mean more closely resemble variability seen in other regions. It should also be noted that the West has weaker emissions (Fig. 1), therefore a 40% departure from the mean in the aggregate dependency factors results in only a 0.016 mg m^{-2} h^{-1} change in absolute emissions. Other regions occasionally show large departures, such as the Southeast in June 1998 and the Northeast in July for 2005 and 2007 (Fig. 3). The large deviations from the mean found in the Southeast for July occur in 2000 and 2007, corresponding with strong drought years (Lawrimore et al., 2001; Luo and Wood, 2007).

3.3. Variability of dependency factors and relationship with isoprene emissions

Two metrics are used to assess the sensitivity of emissions to each dependency factor. The first is linear correlation, where strong correlations indicate the specific dependency factor has a large effect on emissions. Fig. 4 shows the relationships between a dependency factor (γ_T, γ_P, γ_{SM}, and LAI) and E_N for each region. The second metric is the IAV of the individual dependency factors (Fig. 5). The behavior of these metrics and implications on controlling variability are discussed for each region below.

For the Southeast, γ_T is well correlated with E_N for June ($R = 0.64$) and August ($R = 0.65$), but decreases for July ($R = 0.3$). IAV of γ_T peaks in August (16%) and has minimum variations in July

Table 1
Interannual variability (IAV) of isoprene flux by region and month, 1994–2008.

Region	June	July	August
Southeast	11.8%	13.0%	7.8%
Northeast	10.5%	13.7%	10.2%
Plains	10.4%	8.4%	8.1%
West	17.7%	18.3%	14.9%

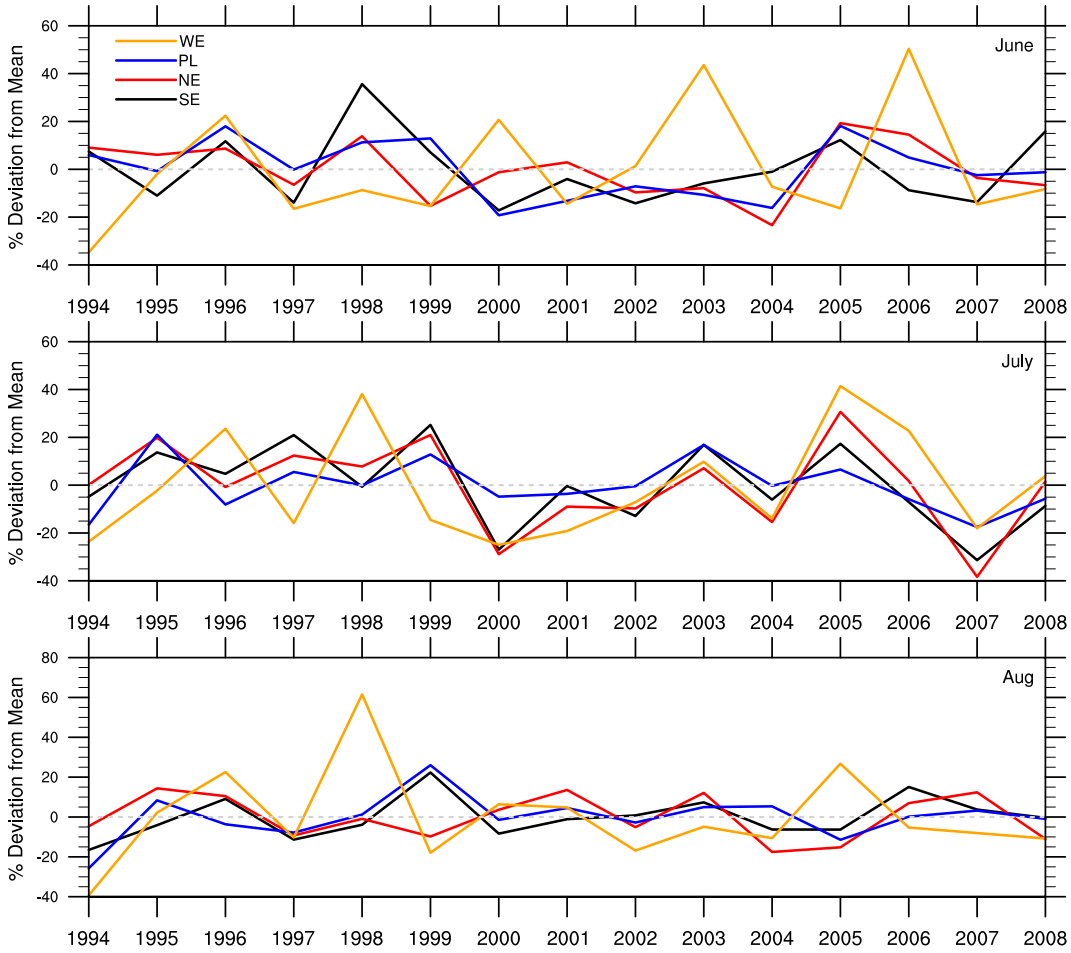

Fig. 3. Percent departure from mean of normalized isoprene flux (E_N) for June, July, and August over the (black) Southeast, (red) Northeast, (blue) Plains, and (orange) West regions (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

(11.5%; Fig. 5). Variations in γ_P are weak for the Southeast (<4.5%), but exhibit good correlation with E_N for July ($R = 0.59$) and August ($R = 0.58$). In July, the soil moisture dependency factor, γ_{SM}, and LAI are also well correlated to E_N ($R = 0.56$ and $R = 0.66$, respectively); however, LAI varies by less than 2% from year to year (Fig. 5) and is further highlighted by the tight clustering pattern around a single LAI value in Fig. 4. γ_{SM} and γ_T are the only dependency factors to exhibit strong correlation with E_N as well as IAV greater than a few percent (11.5% for γ_{SM}; Fig. 5). We note that γ_{SM} and γ_T are strongly negatively correlated ($R = -0.69$, -0.59, and -0.85 for JJA) and correlations between γ_{SM} and E_N are weak outside of July ($R = 0.08$ for June and $R = -0.27$ for August). The implications of the strong correlation between γ_{SM} and γ_T are discussed in Section 3.4.

The Northeast consistently demonstrates the strongest relationship between temperature and E_N with correlations of 0.81, 0.83, and 0.53 for June, July, August, respectively. Throughout the summer, IAV in γ_T is also large relative to other dependency factors (11–18% for JJA). For light dependence, July is the only month that γ_P shows good correlation with E_N ($R = 0.55$). The soil moisture dependency factor, γ_{SM}, exhibits weak correlation with E_N throughout the summer. IAV of γ_{SM} for a given month increases as summer drying deepens from June (3.8%) to August (10.5%). Similar to the Southeast, γ_T and γ_{SM} are negatively correlated for JJA (see Section 3.4). Finally, LAI is not well correlated with normalized emissions and year-to-year variability is low (<1.5%) throughout the summer, making it an unlikely driver of emissions in the Northeast.

The Plains exhibit the highest average temperatures of all the regions especially in August of 2000 ($\gamma_T = 2.05$ and a corresponding average temperature of 303 K), a drought year (Warneke et al., 2010). Despite the relatively warm temperatures and large IAV of γ_T (19, 13, and 21% for JJA), γ_T correlates well with E_N only in early summer ($R = 0.69$ in June; Fig. 4). The influence of γ_T on E_N is dampened later in the summer for July ($R = 0.1$) and August ($R = 0.38$) due to the negatively correlated relationship between γ_T and γ_{SM}. The light dependency factor, γ_P, is the only dependency factor to remain well correlated for all months in this region ($R = 0.5$–0.58), although IAV of γ_P is small (e.g. less than 4.5% variability). LAI and γ_{SM} do not show any strong correlation with E_N over the Plains throughout the summer. The soil dependency factor, γ_{SM}, varies between 11–17% interannually which is much greater than γ_P variability (Fig. 5). The possible consequence is that although γ_{SM} has a weaker correlation with E_N, higher variability may still influence E_N IAV to a greater degree than γ_P. LAI has the lowest interannual variations of all the dependency factors at less than 3%.

E_N for the West are the lowest and do not vary by more than 0.38, or 0.1 mg m^{-2} h^{-1} in absolute emissions. Low emissions notwithstanding, γ_T is identified as the dependency factor with the strongest influence on E_N for the West in June ($R = 0.51$) and comparable to γ_{SM} in August ($R = 0.56$). Light dependency is poorly correlated ($R = 0.03$–0.31) with E_N throughout the summer, as is LAI. The response of E_N to changes in soil moisture is important for

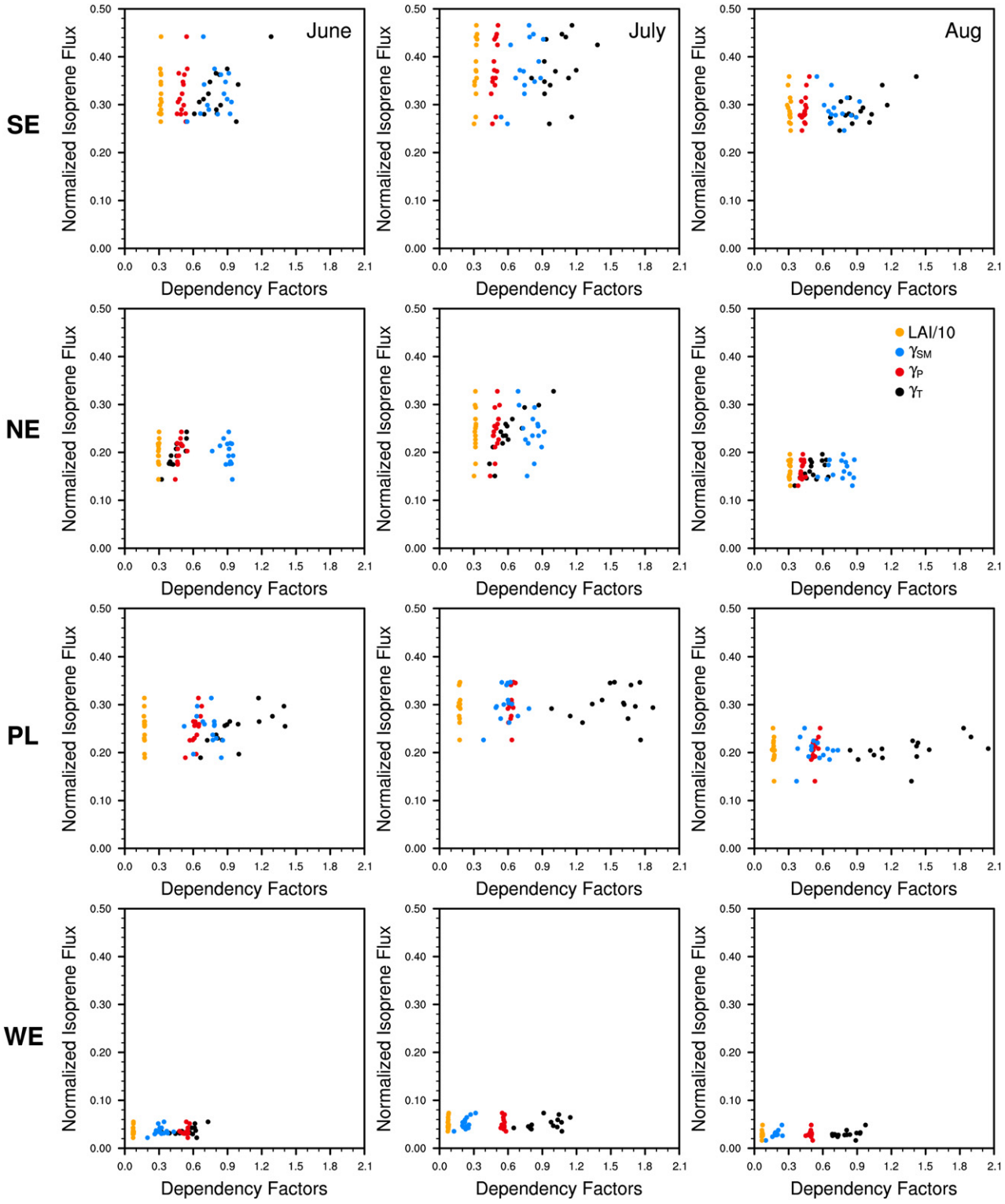

Fig. 4. Dependency factors, (orange) LAI, (black) γ_T, (blue) γ_{SM}, and (red) γ_P, versus E_N for the Southeast, Northeast, Plains, and West regions (Fig. 1). Note that LAI is divided by 10 for illustrative purposes. Each marker represents the monthly average for one simulation year averaged over the specified region (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

July and August with correlations of 0.57 and 0.58, respectively. Unlike other regions, the temperature–soil moisture relationship found in the West is not as pronounced for July and August with correlation coefficients of −0.36 and −0.14, respectively. June is the only month that is well correlated for the West ($R = -0.65$). This indicates that soil moisture and temperature are largely decoupled for this region and can be considered independent of one another outside of June.

In summary, the response of E_N to environmental factors can vary from region to region due to differences in regional climate.

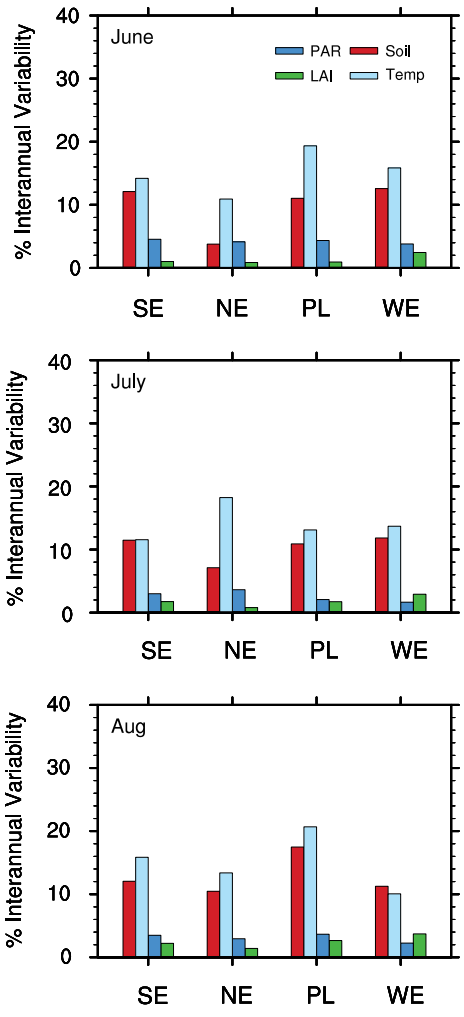

Fig. 5. Percent interannual variability of temperature, PAR, soil moisture, and LAI dependency factors (Eq. (1)).

One similarity is that LAI and γ_P exhibit weak IAV across all regions (Fig. 5) and, in the case of LAI, rarely correlates well with normalized and absolute emissions. This lack of variability limits the importance of LAI and γ_T as drivers of year-to-year emissions changes. γ_T and γ_{SM} generally have the largest IAV coinciding with strong correlations with E_N, although correlations with E_N are often dampened by the negative correlation between γ_T and γ_{SM}. Additionally, γ_{SM} has the best correlation with E_N where deeper root structures are collocated with summer root soil drying.

It should be noted that γ_{SM} values from this study are generally 0.2 lower than values quoted by other studies (Guenther et al., 2006; Muller et al., 2008). This reduced γ_{SM} is attributed to the higher wilting point in RegCM4-CLM. More specifically, wilting point ranges from 0.204–0.222 $m^3\,m^{-3}$ for this study over all U.S. regions, which is considerably higher than values used by Muller et al. (2008) (0.171 $m^3\,m^{-3}$ constant for all locations) and Guenther et al. (2006) (0.01 $m^3\,m^{-3}$ for sand and 0.138 $m^3\,m^{-3}$ for clay). This highlights the wilting point as an important model parameter affecting the magnitude of γ_{SM}. Furthermore, lower γ_{SM} in this study reduces the total U.S. summer monthly emissions by 5–8 Tg C $month^{-1}$ as compared to Palmer et al. (2006), a study that did not account for soil moisture effects on isoprene emissions (e.g. $\gamma_{SM} = 1$).

3.4. Attribution of dependency factors to interannual variability

Using the first-order Taylor series approximation (Eq. (6); Section 2.3), each dependency factor component is correlated with dE. This correlation, R^2, quantifies the degree to which variations in dE can be explained by the linear relationship between dE and a specific dependency factor (Fig. 6). The light dependency factor, γ_P, shows poor correlation with dE ($R^2 < 0.3$) for all regions throughout JJA, with the exception of June and July over the Northeast and all of JJA for the Plains (Fig. 6). Although absolute emissions are sensitive to changes in γ_P on daily to hourly timescales, low year-to-year variability (Fig. 5) and poor correlation for most regions indicate that γ_P is likely not the primary driver of interannual changes in isoprene emissions. Variations in LAI exhibit an even weaker control on isoprene flux variability with R^2 less than 0.2 (Fig. 6). This is contrary to prior studies suggesting that variations in LAI play a comparable role to temperature and light over the eastern half of Texas (Gulden et al., 2007). However, we note that Gulden et al. (2007) used an observationally constrained phenology model to estimate LAI and did not include the influence of soil water limitations on emissions. The indirect influence of soil moisture on LAI variability may be the reason for this difference in attribution and is discussed further in Section 4.

The soil moisture dependency factor, γ_{SM}, consistently shows good correlation with dE for the West ($R^2 > 0.5$) and can account for at least 50% of dE variations for the West. It should be noted that this was the only region where γ_T and γ_{SM} were not well correlated (e.g. the dependency factors were decoupled). Similarly, the Northeast in June and July has an R^2 between dE and γ_T greater than 0.4. Aside from the West and early summer in the Northeast, no

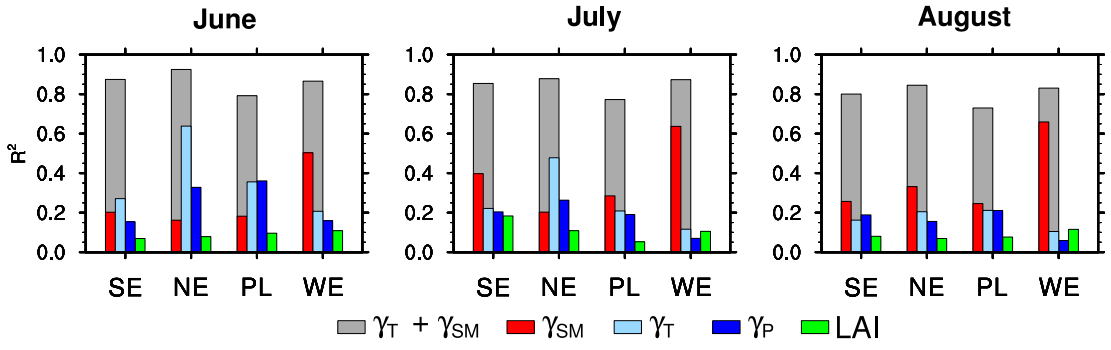

Fig. 6. Correlation between (cyan) temperature, (blue) PAR, (red) soil moisture, (green) LAI dependency terms, and (gray) the sum of the temperature and soil moisture dependency factors against total isoprene flux interannual variability, dE. See Eq. (6) for dependency terms (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

dependency factor is well correlated with dE suggesting that no single dependency factor is a good predictor of emissions variability despite the clear linear dependence of the parameterization (Eq. (1)). This lack of correlation between any particular dependency factor and dE (Fig. 6) likely arises from the opposite effects between the dependency factors, such as with γ_T and γ_{SM}. When the negative correlation is strong between γ_{SM} and γ_T, the terms on the right hand side of Eq. (6) are opposite in sign and can weaken the influence each variable has on emissions variability (dE) (e.g., weak correlations in Fig. 6). Summing the γ_{SM} and γ_T terms in Eq. (6) and calculating an R^2 correlation with dE, we find that over 80% of the variations in isoprene emissions can be explained by the net contribution of soil moisture and temperature (Fig. 6).

4. Discussion and conclusions

Temperature (Palmer et al., 2006; Duncan et al., 2009), land use (Lathiere et al., 2005), and LAI (Gulden et al., 2007) have all been implicated as important drivers of isoprene interannual variability over the U.S. Here we evaluate isoprene flux IAV and compare the relative importance of each dependency factor using a regional climate model coupled with MEGAN, a widely used biogenic emissions model. Average interannual variations of isoprene emission fluxes are between 8–18%, similar to earlier work.

Past studies have suggested that emissions variability is largely driven by the choice of climate forcing data (Arneth et al., 2011), and in this study, MEGAN was contained within the RegCM4-CLM model framework and isoprene fluxes were calculated every 10 min. Model biases in the underlying climate variables relevant to MEGAN may serve to either amplify or dampen the percent contribution of environmental factor presented in this study. As Tawfik and Steiner (2011) have shown, RegCM4-CLM overestimates summer temperatures over the Plains by an average of 2–4 K. This warm model bias in the Plains region may result in overestimates of absolute emissions, but likely does not influence the contribution analysis because deviations about mean conditions are used. RegCM4 overestimates temperature IAV in the Southeast and underestimates the variability in the Plains, which overestimate (underestimate) the total isoprene IAV (Table 1) for the Southeast (Plains). Additionally, recent land surface model development has shown that CLM3.5 tends to be too wet (Oleson et al., 2008; Decker and Zeng, 2009), which would underestimate the soil moisture contribution to variability especially in regions with highly variable summer soil drying.

One of the primary differences between this study and prior modeling work (Lathiere et al., 2006; Gulden et al., 2007) is the implementation of the soil moisture dependency factor. The exclusion of the soil moisture dependency factor neglects the direct suppression of isoprene emissions and could lead to an overestimate of isoprene emissions in these models. Gulden et al. (2007) and Lathiere et al. (2006) utilize dynamic vegetation models that constrain LAI using remotely sensed vegetation products, which indirectly account for soil moisture effects on emissions through modification of LAI. Therefore, a portion of the attribution to LAI as a significant driver in Gulden et al. (2007) may include the indirect response of soil moisture. In this work, LAI is a diagnostic model state prescribed from a daily satellite-based reanalysis dataset, which is not responsive to modeled soil moisture; the indirect influence of realistic soil moisture is captured, however, and LAI can modify atmospheric conditions. As a result, any feedback related to model biases in temperature, incident radiation, or soil moisture are not amplified by modifications to LAI, which likely decreases the control LAI may have on isoprene emissions. A simulation was performed using the 1994 daily LAI map for each year (e.g. removing LAI interannual variations; not shown), and percent contributions and interannual variations presented in Section 3 were not significantly affected. This is consistent with Muller et al. (2008) who also found that interannual variations in LAI play a small role in determining yearly changes in isoprene flux globally.

Although estimates of isoprene interannual variability appear to be consistent across studies and different versions of the Guenther algorithms (Guenther et al., 1995, 1999, 2006), attribution to a single environmental variable is difficult. The results presented in this study highlight the importance of using the soil moisture dependency factor and quantify the relative contributions of temperature, soil moisture, PAR, and LAI to yearly changes in isoprene flux. We demonstrate that no single environmental factor serves as a good predictor or driver of isoprene flux and that the combined first-order contributions of the soil moisture and temperature dependency factors account for at least 80% of modeled isoprene flux variations. Because the soil moisture-temperature relationship controls yearly variations in isoprene emissions, greater attention should be given to improving soil moisture isoprene flux parameterizations and soil moisture representations in models.

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