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Regional to Global Biogenic Isoprene Emission Responses to Changes in Vegetation From 2000 to 2015

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Key Points:
- Variations of global tree coverage during 2000 and 2015 results in a global total isoprene emission decrease of only 1.5%
- Significant decrease of tree coverage in some tropical areas results in a ~10% reduction of regional isoprene emission
- Deforestation and afforestation associated with economic plantations does not only affect the total forest coverage, but also impacts the average isoprene emission capacity, which can result in accelerated isoprene emission variations

Supporting Information:
- Supporting Information S1

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Abstract Isoprene, a dominant biogenic volatile organic compound that is mainly emitted by trees, has a significant impact on the atmospheric chemistry. Regional to global changes in biogenic isoprene emission associated with vegetation variations between 2000 and 2015 were estimated using the MEGAN model with satellite land cover data for inputs in this study. The satellite data estimates of land cover changes were compared to results from previous investigators that have either conducted regional studies or have used lower resolution land cover data. The analysis indicates that tree coverage increases of >5% occurred in 13% of locations including in central China and Europe. In contrast, a decrease of >5% was observed in about 5% of locations, especially in tropical regions. The trends in global tree coverage from 2000 to 2015 resulted in a global isoprene emission decrease of only 1.5%, but there were significant regional variations. Obvious decreases in tree coverage in some tropical areas (e.g., Amazon Basin, Western Africa, Southeast Asia) resulted in a ~10% reduction of regional isoprene emission due to agricultural expansion. Distinct increments of isoprene emission (5–10%) were mainly found in Northeast China and India and were associated with afforestation efforts. Deforestation and afforestation associated with managed plantations does not only affect the total forest coverage but also impacts average isoprene emission capacity, which can result in accelerated isoprene emission variations. Consequently, isoprene variation assessments are needed that not only account for changes in vegetation fractions but also consider the changes in plant species compositions of forests and other landscapes.

1. Introduction

Global annual biogenic volatile organic compound (BVOC) emissions have been estimated to be around 1,000 Tg C/year (Guenther et al., 1995, 2012) with about 70% of BVOCs attributed to terrestrial vegetation (Guenther et al., 1995, 2006). Due to the large emission and their high reactivity, BVOCs, especially isoprene, are of great importance to atmospheric chemistry, as they interact with anthropogenic NO*x* emissions through photochemical reactions affecting ozone and secondary organic aerosol (SOA) formation, and ultimately air quality and climate (Arneth et al., 2011; Situ et al., 2013; Tang et al., 2016; Wang et al., 2014).

Driving variables associated with land use and land cover (LULC) change and non-LULC drivers (e.g., climate change) play key roles in controlling BVOC emissions variations. The response of isoprene emission to changing short-term environmental conditions, such as temperature and light, has been firmly established experimentally (Guenther et al., 2006, 2012). Most of the regional to global studies that have considered BVOC emissions changes have concluded that non-LULC factors, due to climate change, are the largest factor affecting BVOC emissions in the long-term (100 years) periods (Arneth et al., 2016; Sanderson et al., 2003; Wiedinmyer et al., 2006; Xie et al., 2016). The changes are primarily associated with elevated temperature that increases isoprene emission, while elevated CO_2 can inhibit isoprene emission (Arneth, Miller, et al., 2007; Arneth, Schurgers, et al., 2007; Heald et al., 2009; Tai et al., 2013; Tang et al., 2016). However, climate change during recent decades is associated with relatively small changes in BVOC emissions compared to LULC drivers (Purves et al., 2004). Therefore, human-induced LULC, associated with urbanization, deforestation, and reforestation or afforestation, may be a dominant factor impacting BVOC emissions at regional scales during relatively short-term periods (Unger, 2014). It has been estimated that the human-induced LULC change has impacted about half of the Earth's land surface (Hurtt, 2011). Several studies have been conducted to investigate the potential effect of LULC on BVOC emissions. These studies differ in the way they treat LULC change. Some studies used a simple approach to process LULC change, which meant a specific land use type was replaced by another land use type within a certain region or with a certain replacement proportion (Ganzeveld & Lelieveld, 2004; Lathière et al., 2006; Steiner et al., 2002; Wiedinmyer et al., 2006). For example, these studies show that the replacement of tropical broad-leaved trees with tropical crops, grass, and pasture in South America, Africa, Indonesia, and East Asia could result in the decrease of BVOC emissions estimates ranging from 9 to 30%. Other studies examined changes in specific plant species within certain regions and found, for example, that the expansion of red maple and oil palm was estimated to result in a 70% reduction and a 10% increment in isoprene emission in the northeastern United States and Indonesia, respectively (Drewniak et al., 2014; Stavrakou et al., 2014). Dynamic Global Vegetation Models (DGVM), which simulate the interaction of LULC and climate change, have also been applied to probe the factors affecting BVOC emissions (Arneth, Miller, et al., 2007; Arneth et al., 2011). DGVMs attempt to comprehensively simulate the response of vegetation to meteorological conditions, including future climate change and so can be used to investigate the impact of both vegetation changes and climate changes on BVOC emissions. For example, Tang et al. (2016) applied the dynamic ecosystem model LPJ-GUESS to investigate the response of BVOC emissions to Arctic climate warming and concluded that the isoprene and monoterpene emission has elevated by 55 and 57% due to a 2 °C summertime warming. Arneth, Miller, et al. (2007) and Arneth et al. (2011) applied LPJ-GUESS on a global scale and found that the variations of vegetation and climate inputs yielded an increase or decrease in annual BVOC emissions by more than 30%. The quality of the LULC data is of vital importance for the assessment of LULC on BVOC emissions. Satellite observations of LULC, which is a relatively direct estimate of historical LULC trends, is considered the most accurate and is widely used at larger scales (Hansen et al., 2010; Zhan et al., 2002).

It is not well known how and to what extent LULC, especially vegetation coverage, controls BVOC emissions trends in different regions. In this study, we evaluate the quality of satellite vegetation data by comparison with survey data and then examine the variation of vegetation cover during a 15-year period. Although the response of biogenic isoprene emission is highly uncertain, we investigate the impact of vegetation variations at regional to global scales with modeled isoprene emission using meteorological data for a single year (2003), to hold climate constant, and satellite vegetation data for a 15-year period between 2000 and 2015.

2. Materials and Methods

Annual isoprene emission was estimated with MEGAN2.1 (Model of Emissions of Gases and Aerosols from Nature, Guenther et al., 2012) coupled with Community Land Model (CLM4.5), which is part of the Community Earth System Model (Gent et al., 2011). MEGAN accounts for the major land cover factors, leaf area index (LAI) and plant functional types (PFT), and meteorological factors (solar radiation, temperature, and soil moisture) and CO_2 inhibition (Guenther et al., 2006, 2012). Hourly isoprene emission for each location was calculated as

$$\text{Emission} = \text{EF} \times \text{LAI} \times \text{EA} \tag{1}$$

where EF is emission factor, LAI is leaf area index, and EA is the product of individual emission activity factors that account for solar radiation, temperature, leaf age, soil moisture, and CO_2 concentration. The emission factor (EF) is determined as the weighted average of the emission factor for each vegetation category. In this study, we investigated the contributions from changes in broad-leaved trees (BT), needle-leaved trees (NT), and non-trees vegetation to the total change in EF as follows:

$$\text{EF} = \text{EF}_{\text{BT}} \times F_{\text{BT}} + \text{EF}_{\text{NT}} \times F_{\text{NT}} + \text{EF}_{\text{Non-Trees}} \times F_{\text{Non-Trees}} \tag{2}$$

where F_{BT}, F_{NT}, and $F_{\text{Non-Trees}}$ were associated with the fraction of BT, NT, and Non-Trees, respectively. Hourly EA for each location was calculated using meteorological data for a single year (2003). We used the same EA for simulations of the years 2000 and 2015 in order to examine the changes due only to land cover (EF and LAI in equation (1)). Therefore, isoprene emission variations were estimated by the MEGAN model driven by

Table 1
Description of Data Sets Used for This Study

Data type	Item	Abbr.	Year	Resolution	Source	Reference
Satellite data	Maximum green vegetation fraction	MGVF	2001–2012	1 km	MODIS	Hueter et al. (2002) and Friedl et al. (2010)
	Vegetation continuous fields	VCF	2000–2010	250 m	MODIS	DiMiceli et al. (2011)
	Landsat tree cover continuous fields	LTCC	2000, 2005, 2010, 2015	30 m	MODIS + Landsat	Sexton et al. (2013)
	Plant functional type data	CLM PFT	2000	0.05 arc-degree	Modis + AVHRR	Bonan et al. (2002) and Oleson et al. (2010)
Simulation data	Isoprene emission		2000	0.5 arc-degree	MEGANv2.1	Guenther et al. (2012)
Survey data	Global Forest assessment data	FRA	2000, 2005, 2010, 2015	Country level	Survey	FAO (2001, 2005, 2010, 2015)

satellite vegetation data from 2000 to 2015 but meteorological data for just a single year (2003). The data sets used in this study, including the satellite data inputs, model simulation outputs, and survey data are listed in Table 1.

2.1. Satellite Data

2.1.1. Satellite Total Vegetation Cover Data

Global annual MODIS-based maximum green vegetation fraction (MGVF) data at a 1 × 1-km resolution, which were developed based on the 12 years (2001–2012) of MODIS Collection-5 NDVI data (MOD13A2 normalized difference vegetation index (NDVI) data; Hueter et al., 2002) and MODIS Collection-5.1 land cover data (MC12Q1; Friedl et al., 2010), were used to quantify the total vegetation abundance for this study. The time period for the MGVF was limited to 2001 to 2012. Therefore, MGVF in 2001 and 2012 was used to represent the total vegetation in the years 2000 and 2015, respectively. The data were accessed at http://landcover.usgs.gov/green_veg.php.

2.1.2. Satellite Tree Coverage Data

MODIS Vegetation Continuous Fields (hereafter called VCF) tree coverage data set, version 5, was used with a 250 × 250-m resolution globally from 2000 to 2010 (DiMiceli et al., 2011). The data were accessed at http://glcf.umd.edu/data/vcf/index.shtml.

Another data set, the 30 × 30-m resolution continuous fields of tree coverage from the year 2000 to 2015, was developed by rescaling the MODIS VCF using Landsat images (Landsat Tree Cover Continuous Fields, LTCC, Sexton et al., 2013). The data set was accessed at the Global Land Cover Facility website: http://landcover.org/data/landsatTree cover/.

2.1.3. Satellite Plant Functional Type Data

Distributions of 16 PFT developed for the CLM4.0 were inferred from 1-km multiple satellite data sets collected around the year 2000, including MODIS continuous vegetation fields, AVHRR continuous fields tree cover, MODIS land cover, and aggregated to the 0.05 × 0.05 arc-degree grid resolution by Bonan et al. (2002). Individual area fraction of PFT was estimated by the percentage of land area of individual PFT data to the total land area in each grid cell, respectively. BVOC emissions characteristics of each PFT were based on Table 3 of Guenther et al. (2012). For this study, the 16 PFT data sets were grouped into Trees and Non-Trees. Trees included BT (Types 1 to 3 in Table 3 of Guenther et al. (2012)) and NT (Types 4 to 8 in Table 3 of Guenther et al. (2012)), while the Non-Trees were assumed to be all shrubs, grasses, and crops (Types 9 to 15 in Table 3 of Guenther et al. (2012)).

2.2. Global Forest Assessments Data

The Forest Resources Assessments (FRA) data, which have been published every 5 to 10 years since 1948 by the Food and Agriculture Organization (FAO) of the United Nations, is a global database of official national statistics on forests properties. Country reports were provided by National Correspondents and remote sensing data. The online version of the global forest resources assessment report was accessed at http://www.fao.org/forest-resources-assessment/past-assessments/en/. Data retrieved from FRA for 2000, 2005, 2010, and 2015 were used in this study to evaluate the quality of the satellite tree cover data (Food and Agriculture Organization, FAO, 2001, 2005, 2010, 2015).

2.3. Methodology

We investigated the contributions from changes in BT, NT, and Non-Trees vegetation to the total change in EF in equation (1). To match the spatial resolution of the model simulation, all satellite data sets were aggregated to 0.5 arc-degree using ArcGIS.

First, the Non-Trees Coverage was estimated as the difference between the total vegetation coverage (MGVF) and the tree coverage (LTCC), and the corresponding variation of Tree coverage and Non-Trees coverage between 2000 and 2015 (ΔTree Coverage and ΔNon-Trees Coverage) was retrieved by separately calculating the difference of Tree Coverage and Non-Trees Coverage in the year 2000 and 2015 (i.e., value for 2015 minus the value for 2000).

Second, we assumed that the pattern of BT, NT, and Non-Trees proportion (BT%, NT%, and Non-Trees%) remained unchanged, but the absolute proportion could change between 2000 and 2015. Therefore, differences in the proportion of BT and NT between 2000 and 2015 *(*ΔBT% and ΔNT%) were associated with ΔTree Coverage, and BT% and NT%, respectively. In a similar way, the trend in ΔNon-Tree Coverage was determined from the ΔNon-Tree Coverage and the Non-Trees%.

Equation (1) assumes that the response of isoprene emission to changes in vegetation distributions is linear, and the pattern and proportion of isoprene emitters within BT, NT, and Non-Trees categories (Isop_BT, Isop_NT, and Isop_Non-Trees) remained the same, but the absolute value could change between 2000 and 2015. Note that this study did not contain any representation of environmental dynamical processes such as variations of species composition, growth status of plants, or the effect of meteorological conditions on leaf level BVOC emissions.

We expect that there could be significant changes in isoprene emitters within these PFT categories. However, there are currently no global data sets available for investigating this issue. Accordingly, the variation of isoprene emitted from BT, NT, and Non-Trees between 2000 and 2015 (ΔIsop_BT, ΔIsop_NT and ΔIsop_Non-Trees) was calculated separately as the product of ΔBT%, ΔNT%, and ΔNon-Trees%, and the simulated Isop_BT, Isop_NT, and Isop_Non-Trees.

3. Results and Discussion

3.1. Evaluation of Satellite Data With FRA Data

Our comparison of the tree coverage derived from VCF and LTTC shows that these two data sets generally had a similar pattern and magnitude of variations between 2000 and 2010, but for some regions the VCF (Figure S1 in the supporting information) and LTTC data (Figure S2) showed an opposite trend, especially near the border between northeast United States and Southeast Canada, within Europe, and in the northern regions of Russia and Indonesia (green dot circle in Figures S1 and S2). We also compared these two data sets with FRA data, and found that the variations of VCF between 2000 and 2010 did not agree with the FRA data. Previous research has pointed out that many land cover changes occur in patches less than 250 × 250-m resolution (Townshend & Justice, 1988), so we expect the higher-resolution data set, LTTC (30 × 30 m), to be more accurate and use the LTTC data for subsequent analyses.

LTCC was compared and evaluated with FRA data at a country level (Figure 1a). Overall, satellite tree coverage was underestimated irrespective of spatial and temporal scales. The satellite-derived tree coverage was about half to two thirds of that reported in the FRA. At the country level, the satellite data matched FRA data better in some cases, such as Australia, China, United States, and Indonesia. However, the satellite data still underestimated tree coverage, especially for countries with high tree coverage (above 50%) including Brazil, Japan, South Korea, and Sweden. The normalized FRA and LTTC tree coverage in 2005, 2010, and 2015, compared to the year of 2000, is shown in Figures 1b and 1c. For FRA, the increase was highest in China, followed by France and India. In the tropical zone, Indonesia had the highest decrease followed by Brazil. The LTTC data indicated that France, China, and India also showed an increase trend, but the highest increment was found in France.

The considerable difference between satellite and FRA data could be due to the definition of tree coverage, the difference in evaluation periods, and errors in satellite data, particularly the method for satellite data retrieval related to tree detection, recognition, resolution, and other factors (Keenan et al., 2015). A

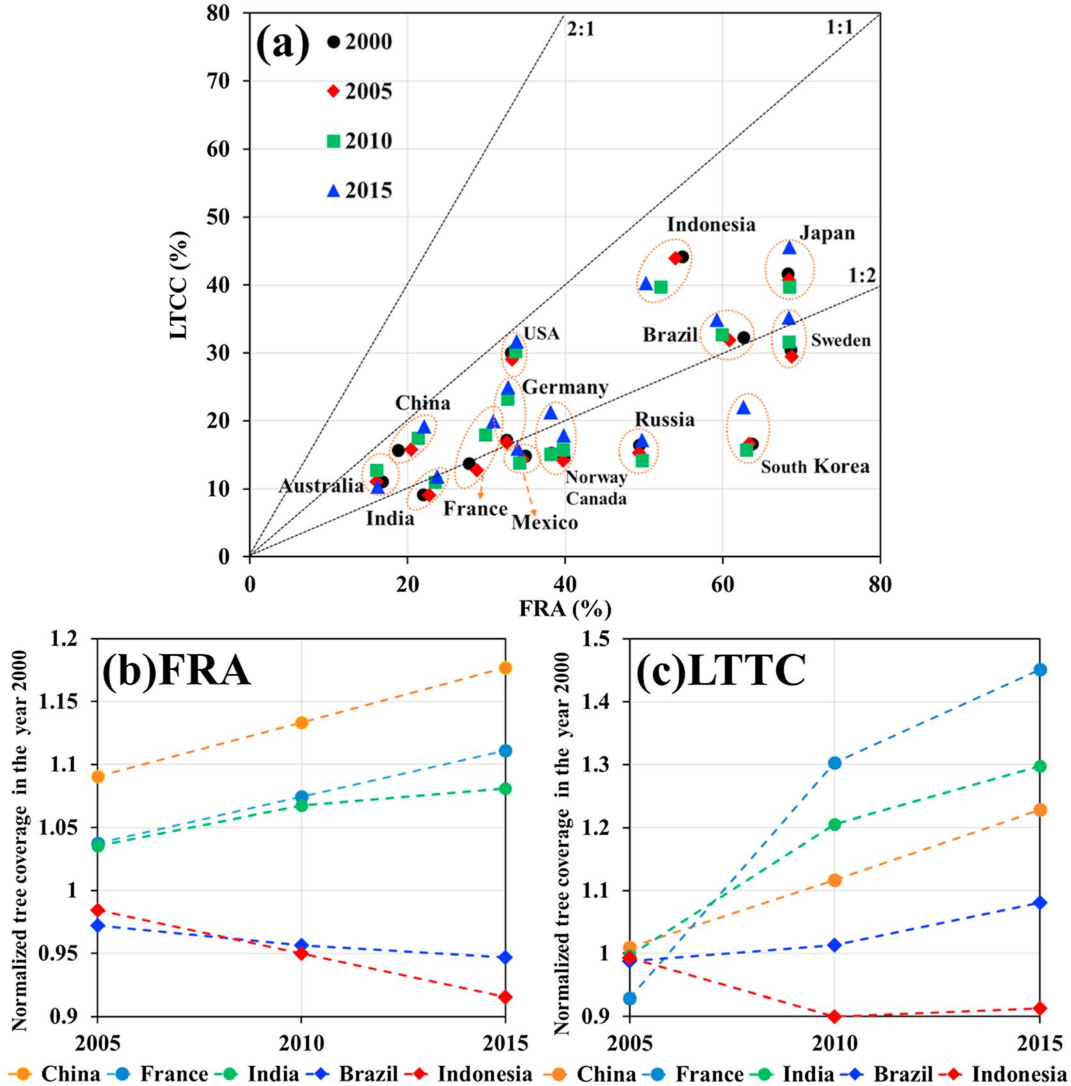

Figure 1. (a) The scatter plots of FRA and LTCC in 14 major countries and the tree coverage in 2005, 2010, and 2015 normalized to the tree coverage in the year 2000 for (b) FRA and (c) LTTC in the five countries.

global definition of forests has been proposed by the FAO, including a minimum threshold for the height of trees (5 m), at least 10% crown cover (canopy density determined by estimating the area of ground shaded by the crown of the trees), and a minimum forest area size (0.5 ha), with urban parks, orchards, and other agricultural tree crops excluded from this definition (FAO, 2000). The proposed FAO definition, however, is currently not used in all assessments, and instead, the definition of forest currently differs from region to region and country to country. There are over 800 definitions across the world and each country uses its own approach to estimate tree coverage (Lund, 2015). China, for example, defines tree coverage as a tree crown cover of above 20% with the minimum forested area of 0.67 ha and minimum tree height of 2 m, and includes bamboo, shrub, orchards, and other economic forest and roadside trees (China State Council, 2000). The corresponding definition for Brazil is 30%, 1.0 ha, and 5 m (Lund, 2015). LTTC tree cover is defined as vegetation higher than 5 m with at least 25% crown canopy, which is more than the value defined by FAO, contributing to the relatively lower tree coverage for satellite data than for FAO data (Hansen et al., 2010). Although an underestimation was found for LTCC, it still had a similar trend as the FRA, such as a decreasing trend in Africa and South America, and an increasing trend in Asia. As a result, we expect that the LTCC can still provide valuable information about worldwide tree cover trends.

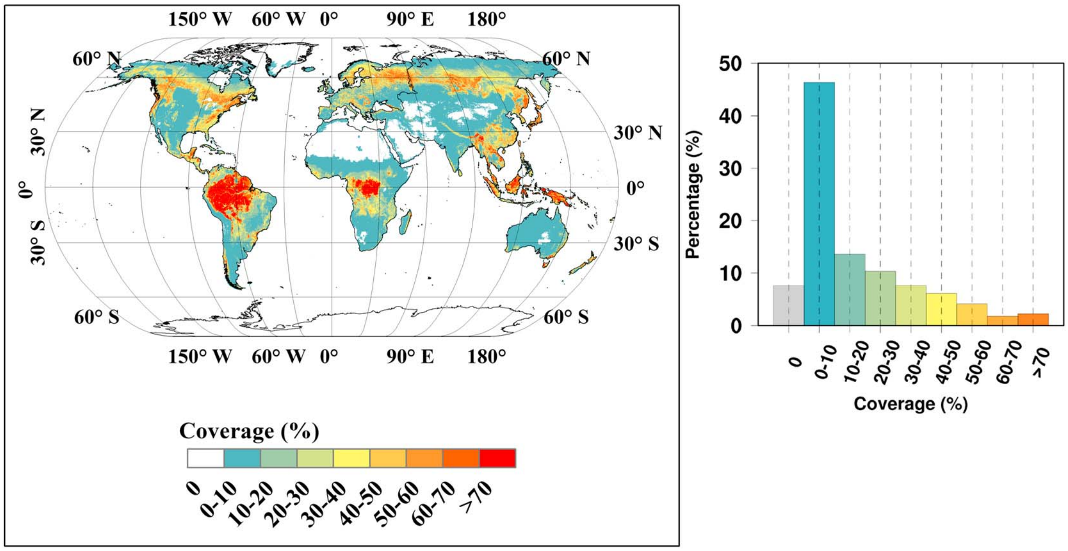

Figure 2. The global distribution of the mean (left) and histogram (right) of average tree coverage for the year 2000 to 2015.

3.2. Changes in Tree Coverage Between 2000 and 2015

As shown in Figure 2, high tree coverage was found in tropical areas, including the Amazon rain forest, Central Africa (mainly in the Republic of Congo), and Indonesia, with an average tree coverage of >60%. We also calculated the histogram of tree coverage, as shown in the right panel of Figure 2, and determined that 8% of locations were without trees while ~46% had tree coverage within the range of 0–10%. About 10% of locations had tree cover between 10 and 20%, and only around 20% have coverage larger than 30%.

The tree coverage variations with respect to distribution and magnitude between 2000 and 2015 are shown in Figure 3. The variations are divided into seven categories and the percentage of area within each category

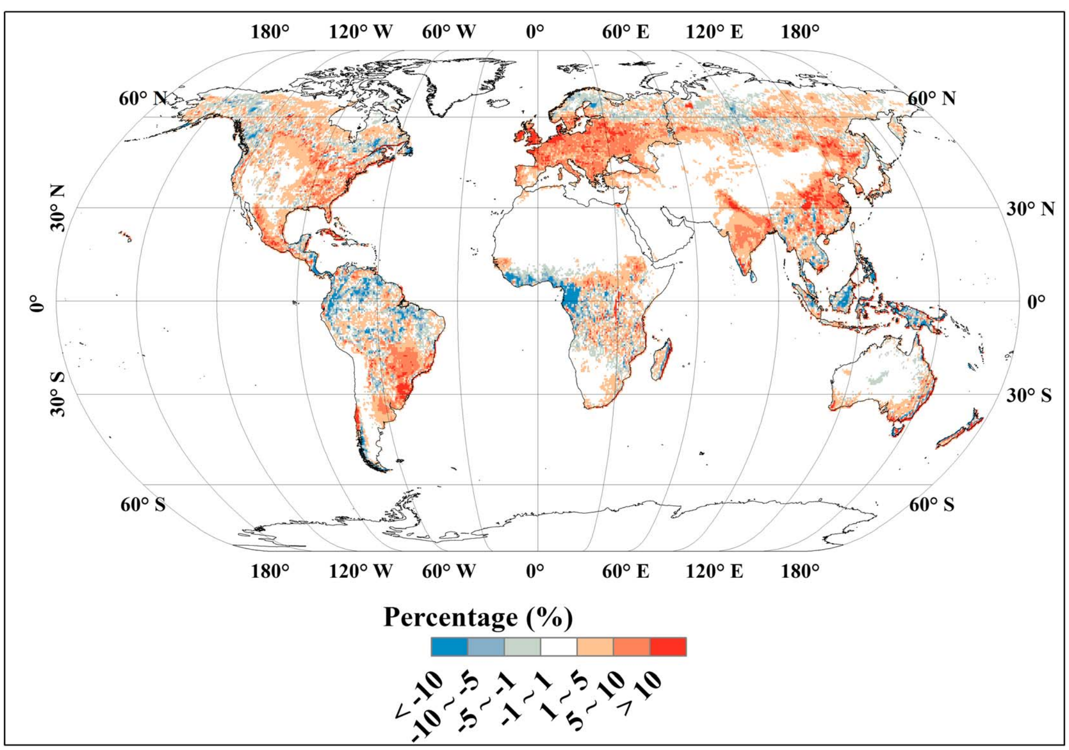

Figure 3. The global distribution of the change in tree coverage from year 2000 to 2015.

Table 2
The Percentage of Area Within Each Category of Tree Coverage Change

Difference (%)	Percentage (%)
≤ −10	1.9
(−10, −5]	3.0
(−5, −1]	10.2
(−1, 1]	47.5
(1, 5]	24.4
(5, 10]	10.2
> 10	2.7

is shown (Table 2). About half of the total area had experienced a small change with differences of less than ±1%. About 10% (25%) of these landscapes experienced a moderate decrease (increase) of 1 to 5% tree coverage. A larger increase in tree coverage was calculated for about 13% of the area, mainly in Central Europe and the central part of China (Figure 3), where the country has focused its main reforestation efforts. About 5% of locations had a higher decrease in tree coverage, mainly distributed in northwestern South America (e.g., Colombia, Venezuela, and Ecuador), western parts of Africa (e.g., Cameroon, Equatorial Guinea, and Congo), Southeast Asia (e.g., Indonesia, Malaysia, and Cambodia), and eastern Australia. A more detailed explanation can be found in section 3.4.

3.3. Spatial Distribution of Simulated Isoprene Emission in 2000

The estimated annual global isoprene emission from all vegetation was 421 Tg C/year in 2000 with the emission from BT, NT, and Non-Trees comprising 347.5, 11.2, and 62.6 Tg C/year, respectively, and accounting for 82.3%, 2.7%, and 14.9% of the total emission. In general, broad-leaved trees were the dominant isoprene emitter worldwide excluding a few regions such as western Australia.

As shown in Figures 4 and 5, emission from broad-leaved trees was mostly found in tropical regions. In comparison, relatively higher emission from needle-leaved trees was found in Canada and southern China, where the needle-leaved trees contributed 30–60% of the total emissions. But it is worth noting that Wang et al. (2011, 2016) found that the MODIS-based PFT data greatly overestimated needle-leaved trees and underestimated broad-leaved trees in southern China, in comparison with the local survey data, so these data are expected to overestimate needle-leaved isoprene emission in southern China. Isoprene emission from Non-Trees was sparsely distributed in southwestern United States, Northeast Brazil, south and sub-Sahara

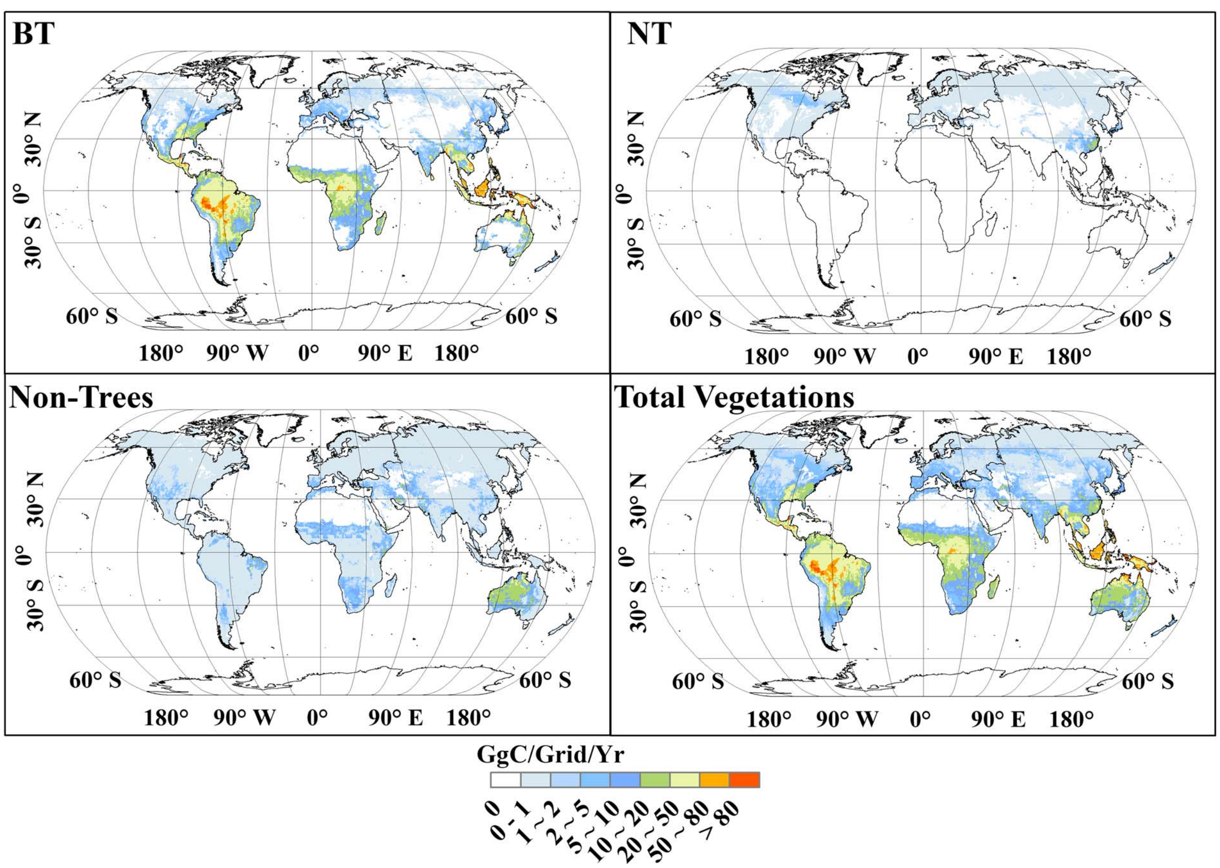

Figure 4. The global distribution of annual isoprene emission from BT, NT, Non-Trees, and total vegetation in 2000.

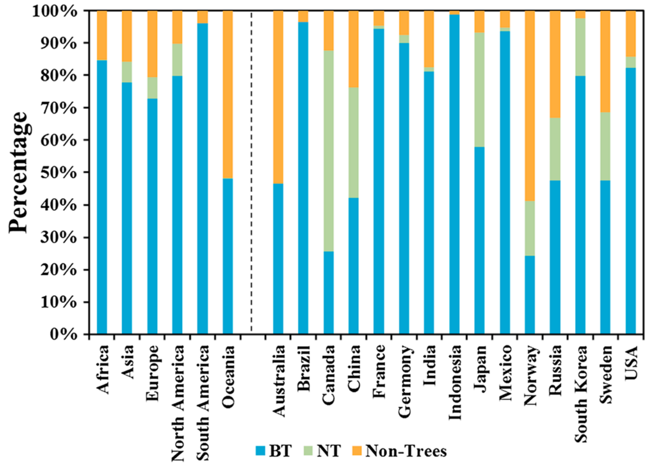

Figure 5. The proportion of isoprene emission from BT, NT, and Non-trees in the six continents and 15 major countries in 2000.

Africa, and western regions of Asia and Australia. Non-Trees contributed about half of isoprene emission in Australia and Norway.

3.4. The Response of Isoprene Emission to Vegetation Variations

Globally, annual isoprene emission was estimated to be 415 Tg C/year in 2015 with emission from BT, NT, and Non-Trees contributing 341.3, 11.3, and 62.3 Tg C/year, respectively. Compared with that of 2000, isoprene emission from BT and Non-Trees decreased by 1.8% and 0.5%, while isoprene from NT increased by 0.9%. In general, isoprene emission from global total vegetation declined by 1.5% from 2000 to 2015.

The relative changes of annual isoprene emission due to total vegetation cover variation are characterized in Figure 6. As expected, the geographic variation pattern of isoprene emission was similar to that of tree coverage variations in most areas. Although a small relative change was found for the global isoprene emission from all vegetation during 2000 and 2015, a relatively large change was found in some specific regions. A distinct reduction of more than 10% of isoprene emission was estimated for some tropical areas (e.g., Amazon Basin, West Africa, and Southeast Asia), Midwest United States, and Central Australia. A significant increment of more than 10% was mainly distributed in Southeast Brazil and East Australia, Western Europe, and central China.

3.4.1. Effect of Deforestation on Isoprene Emission in Tropical Areas

Land management activities, including the conversion of forested land to agricultural land and the conversion of primary forest to economic tree plantations, was one of the primary threats causing tropical forest losses. The 10–20% reduction of isoprene emission in West Africa (e.g., Gabon and Cameroon) was mainly from broad-leaved tree removal (Figure S3) related to commercial deforestation and self-sustaining agriculture expansion. Decreases in isoprene emission were estimated for the Amazon Basin (5 to 10%) and Southeast Asia (up to 4%), and was also related to losses of broad-leaved trees. Amazon Basin and

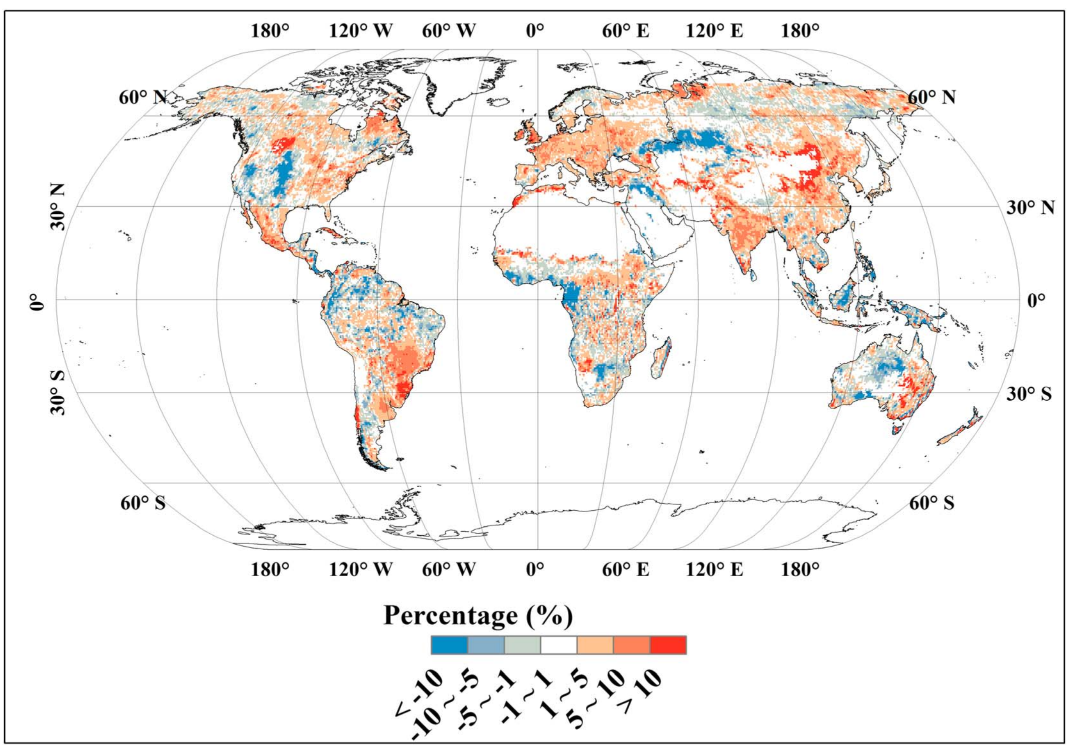

Figure 6. The change of annual isoprene emission associated with the change in vegetation coverage from the year of 2000 to 2015.

Southeast Asia has experienced considerable conversion of natural forests to rubber (*Hevea brasiliensis*) and oil palm (*Elaeis guineensis*) plantations, respectively (FAO, 2005; Stavrakou et al., 2014; Vijay et al., 2016).

Colombia, where the tree coverage losses since 2001 have accelerated faster than any other country in the world, has experienced substantial conversion of forests to rubber plantations (Petersen et al., 2015). Rubber is regarded as a strong emitter of light-dependent monoterpenes (Wang et al., 2007), but compared with tropical forest (isoprene emission flux reported to be 2,000–8,000 $ug \cdot m^2 \cdot h$, Greenberg et al., 2004; Karl et al., 2007; Kuhn et al., 2007), rubber trees emit less isoprene (isoprene emission flux was 192–1,661 $ug \cdot m^2 \cdot h$, Baker et al., 2005). Furthermore, the current administration is expanding oil palm and sugar cane production by encouraging large-scale plantations, and demand for agrofuels has also had a significant impact on Colombia's forest. Vijay et al. (2016) found that although the conversion of previously deforested land to oil palm resulted in lower levels of net forest change during 1984 and 2010, the expanding production of coca, cocoa, coffee bean, and sugar cane also contributed to tropical forest destruction in Colombia. Therefore, decreased isoprene emission was expected due to the loss of broad-leaved trees and the expansion of rubber plantations at the expense of tropical forest in Colombia and adjacent regions (Figure S3). Owing to the lower tree coverage and lower isoprene emission capacity of rubber plantations, it is expected that isoprene emission is lower than the value we currently estimated for the Amazon Basin.

Indonesia and Malaysia are two of the countries with the highest deforestation rates in the world (Henders et al., 2015; Pan et al., 2011). Oil palm production in Southeast Asia has grown by a factor of 5 over the past 20 years and keeps increasing at a rate of +7% per year in Indonesia and Malaysia (FAO, 2015), and 13% of the land area is occupied by oil palm plantation in Malaysia at present. The rapid expansion of oil palm not only drove the conversion of rainforest to economic plantations but also increased isoprene emission due to the relatively high isoprene emission capacity of oil palm, which is 5 times greater than that from primary tropical forest landscapes (Hewitt et al., 2009). Our results, which only considered the losses of broad-leaved trees while ignoring the changes in isoprene emission capacity, showed that the estimated isoprene emission had declined by about 4% in these regions. Meanwhile, Stavrakou et al. (2014) estimated that the rapid expansion of oil palm brought about 3–11% decreases of isoprene emission in Indonesia and Malaysia between 1979 and 2007 when considering the variation of tree coverage and isoprene emission capacity. Still, it is worth noting that the reduction of isoprene emission related to losses of broad-leaved trees might be offset by the increase of isoprene emission associated with higher isoprene emission capacity. Consequently, additional studies, accounting for both the variations of tree coverage and emission capacity, are needed.

3.4.2. Effect of Wildfires on Isoprene Emission in Midwest United States and Australia

The extent of wildfires is another factor affecting vegetation coverage, especially in Midwest United States and Australia. Studies have shown that climate change is a dominant factor affecting wildfires in the western United States (Mayer & Swetnam, 2000; McKenzie et al., 2004). Estimated net decreases in isoprene emission from western United States were relatively extensive in terms of both spatial distribution and magnitude. The value reached 20% in the states of Colorado, New Mexico, and Nevada. These states and adjacent states (Utah, Wyoming, Arizona, South Dakota, and California) experienced one of the worst forest fire seasons on record in 2012 due to extremely dry conditions. Therefore, predicted isoprene emission declined dramatically in 2012, which was mainly associated with the decrease in emission from Non-Trees (Figure S5).

A 5 to 10% decrease in isoprene emission was estimated for northern Australia. Due to the fire-sensitive vegetation elements embedded within the savanna, northern Australia also suffered from wildfires (Russell-Smith et al., 2012) over an extensive spatial distribution with a decrease of 5 to 15%, but Liu et al. (2015) report that owing to the increasing rainfall, the savanna area is presently spreading into arid regions, which is expected to increase isoprene emission.

3.4.3. Effect of Afforestation on Isoprene Emission in China, India, and Europe

Despite the reduction of tree coverage that is continuing in some regions across the world, the rate of net reduction has slowed down because of the offsetting large-scale afforestation activities being taken in other regions. As a consequence of extensive afforestation efforts and the implementation of strict legal protection, forest coverage has increased in Europe, United States, India, and China, leading to the increase of isoprene emission. For example, China's "Green Great Wall," also called "the Three-North Shelterbelt Development Program," is one of the world's largest ecological engineering projects. It was launched in 1978 with the aim of curbing drought, sand hazard, water and soil erosion, through afforestation in northwest, north, and northeast China, and has promoted the forest coverage from 5.05% in 1977 to 12.4% at present (State Forestry Administration of China, 2010). In terms of planted species, *Robinia pseudoacacia, Populus L., Salix,* and *Ulmus pumila L.* are the four common broad-leaved trees selected for the program, of which, the first three are high isoprene emission potential species (Klinger et al., 2002). In response to this ecological project, the isoprene derived from broad-leaved and Non-Trees increased by as much as 10% in northern China (Figures S3 and S5), and the net increase was 3.6% and 5.4% over all of China, respectively. Zhang et al. (2016) used a MEGAN simulation to estimate that isoprene emission had increased 58% from 1982 to 2010 in the central northern China region.

Forest in India is mainly distributed in the southwestern and eastern regions. Agricultural land is widely spread over India, and the area of irrigated cropland has increased by a factor of 20 since the 1960s under the Agricultural Green Revolution (Roy et al., 2007). The implementation of strict forest law enforcement, such as the Joint Forest Management policy (Bhushan, 2016), has slowed down the deforestation rate and even resulted in an increase of forest coverage. About half of the tree species typically selected for planting in India are moderate to high emitters of isoprene (Singh et al., 2008). As a result, isoprene emission from trees increased 2% from 2000 to 2015. Isoprene emission increase from Non-Trees was highest (3% to 5%) in central and northwestern India due to the expansion of agricultural land (Roy et al., 2007; Singh & Narayanan, 2013).

Sustainable management of forests growing on abandoned agricultural land, which is common in some European countries, has been implemented since the early 1990s. The combined effect of reduction of agricultural land, afforestation, and the implementation of forest protection laws enhanced forest coverage in Europe during this period. Therefore, increased isoprene emission was widely distributed in the southern regions of Europe with a net increase of ~2% in total, and the elevated isoprene was related to the increment of both broad-leaved and needle-leaved trees. Lathière et al. (2006) concluded that European isoprene emission was significantly affected by European afforestation with an isoprene emission increase of 126% from 1983 to 1995, since crops were substituted with temperate broadleaf evergreen trees resulting in the enhancement of isoprene emission capacity by a factor of 9. However, it should be noted that the broad-leaved tree silver birch (*Betula pendula Roth*) and the needle-leaved tree Scot pine (*Pinus sylvestris L.*), which are regarded as low isoprene emitters, were the dominant species for European afforestation (Deptula et al., 2017); hence, the actual increment of isoprene emission should be much lower than the value derived from the work of Lathière et al. (2006). A net increase of about 4% in Germany and France was contributed by both broad-leaved and needle-leaved trees. In contrast, there was a small net decrease in Norway, located in Northern Europe, due to the loss of agricultural grassland, while the forest cover was stable. Agriculture Census reported the total area of grassland decreased by 2% from 1990 to 2012 (Antman et al., 2015), leading to about 2% loss of isoprene emission from Non-Trees.

Afforestation has positive benefits, but also increases isoprene emission which could impact regional air pollution. This can be minimized by selecting low isoprene-emitting plant species for planting programs in order to increase forest coverage and maintain isoprene emissions simultaneously.

3.5. Comparison of Isoprene Emission Variations With Other Studies

Published estimates of annual change (%) in isoprene emission associated with LULC are listed in Table 3. The results represent a wide range of different models and driving variables, but there is a large uncertainty associated with estimates of LULC and the associated impacts on isoprene emission. Decrease in isoprene emissions were reported for regional to global scale studies, indicating the ubiquity of deforestation across the world. The largest decrease was estimated for northeastern forests of the United States where a 7.8%/year reduction in isoprene emission was calculated for the replacement of oak trees by red maple (Drewniak et al., 2014). A relatively large decrease of up to 3.1%/year was also calculated for tropical regions, which was mainly due to the severe deforestation during the 1980s to 2000s (Lathière et al., 2006; Stavrakou et al., 2014; Steiner et al., 2002). In addition, Lathière et al. (2006), Leung et al. (2010) and Fu and Tai (2015) found that the isoprene emission had increased by 10.5, 0.64, and 0.07%/year during the 1980s to 2000s due to the afforestation in Europe, Hong Kong, and East Asia. All of the previous studies applied BVOC estimation models (e.g., MEGAN, BEIS, and G95) that in some cases were driven by a DGVM model (e.g., ORCHIDEE, SDGVM) to investigate the response of BVOC variations to LULC with the average annual

Table 3
Published Estimates of Annual Change (%) in Isoprene Emission Associated With LULC

No.	Study period	Base year	Study region	Method	Annual change	Reference
1	2015	2000	Global	Linear	−0.10	This study
2	2000	1865	Global	HadGEM2-ES	0.14	Hollaway et al. (2016)
3	2000	1880	Global		−0.18	Unger (2013)
4	2002	1901	Global	SDGVM	−0.15	Lathière, Hewitt, and Beerling (2010)
5	2007	1979	China	MEGAN-MOHYCAN	0.23	Stavrakou et al. (2014)
5	2007	1979	India	MEGAN-MOHYCAN	−0.96	Stavrakou et al. (2014)
5	2007	1979	Indonesia	MEGAN-MOHYCAN	−1.40	Stavrakou et al. (2014)
5	2007	1979	Malaysia	MEGAN-MOHYCAN	−0.62	Stavrakou et al. (2014)
5	2007	1979	Thailand-Laos-Vietnam	MEGAN-MOHYCAN	−0.25	Stavrakou et al. (2014)
5	2007	1979	Myanmar	MEGAN-MOHYCAN	−0.23	Stavrakou et al. (2014)
5	2007	1979	Japan	MEGAN-MOHYCAN	−0.41	Stavrakou et al. (2014)
5	2007	1979	Indonesia	MEGAN-MOHYCAN	0.38	Stavrakou et al. (2014)
5	2007	1979	Malaysia	MEGAN-MOHYCAN	−0.12	Stavrakou et al. (2014)
6	1999s	1980s	East Asia	BEIS2	−3.12	Steiner et al. (2002)
7	2010	1980	East Asia	GEOS-Chem	−0.09	Fu and Tai (2015)
7	2010	1980	China	GEOS-Chem	0.07	Fu and Tai (2015)
8	2010	1982	Northern China	MEGAN	2.07	Zhang et al. (2016)
9	1995	1983	Global	ORCHIDEE	−2.42	Lathière et al. (2006)
9	1995	1983	Tropics	ORCHIDEE	−2.92	Lathière et al. (2006)
9	1995	1983	Global	ORCHIDEE	0.33	Lathière et al. (2006)
9	1995	1983	Europe	ORCHIDEE	10.50	Lathière et al. (2006)
10	1999	1990	Northeastern United States	GloBEIS	−7.78	Drewniak et al. (2014)
10	1999	1990	Northeastern United States	GloBEIS	2.20	Drewniak et al. (2014)
10	1999	1990	Northeastern United States	GloBEIS	−3.91	Drewniak et al. (2014)
11	2000	1990	China	GEOS-Chem-MEGAN	−0.35	Fu and Liao (2014)
12	2000	1990	Global	G95	−0.90	Wiedinmyer et al. (2006)
12	2000	1990	Global	G95	3.74	Wiedinmyer et al. (2006)
13	2006	1995	HongKong	MEGAN	0.64	Leung et al. (2010)
14	2050	2000	Global	EMAC	−0.24	Ganzeveld et al. (2010)
15	2095	2000	Global	UKCA	−0.43	Squire et al. (2015)
15	2095	2000	Global	Megan+SDGVM	−0.42	Squire et al. (2014)
16	2020	2005	Global	HadGEM2	0.07	Ashworth et al. (2012)
17	2079–2090	1990–2000	Global	G95	0.01	Wiedinmyer et al. (2006)
18	2100–2109	2000–2009	Global	HadGEM2	−0.08	Pacifico et al. (2012)

change of isoprene emission of −0.20 ± 2.64%/year (range of −7.8 to +10.5%/year). In comparison, our study estimated that the rate of change was −0.1%/year on the global scale, which is at the middle of the range of these previous studies. Although large uncertainties still exist, there are clear indications that historical vegetation changes in recent years can impact regional isoprene emission.

4. Summary and Conclusions

The spatiotemporal variations of global satellite tree coverage were evaluated for the period between 2000 and 2015. The results showed that satellite tree coverage estimates were about one-third lower than the forest survey data, but captured the trend well at regional to global scales. The highest increases (5 to 10%) of tree coverage between 2000 and 2015 were found in North China, India, and Central Europe, while the greatest decreases (~10%) were observed in tropical regions, such as Brazil, West Africa, and South Asia. The MEGAN model was used to estimate the isoprene emission change due to land cover by keeping the meteorological drivers constant while varying the land cover driving variables. Globally, isoprene emission was estimated to have declined by 1.5% on average due to the combined impact of a 0.9% increase in isoprene emission from needle-leaved trees and a decrease of 1.8% and 0.5% in isoprene emission from broad-leaved trees and Non-Trees. Although changes in isoprene emission were small on the global scale, the difference was much greater in certain regions. Corresponding to the variation of tree coverage, a relatively large reduction (~10%) of isoprene emission was found for Southeast Asia, Amazon basin, West Africa, Midwest United States, and Central Australia, which was related to deforestation and wildfire. The largest increases (5–10%) were mainly found in Western Europe and mid-Asia, which was due to large-scale afforestation activities. The expansion of economic tree plantations (e.g., rubber and oil palm) is a common phenomenon in some areas. The economic plantations expansion can not only affect the total forest coverage but also alter the regional average isoprene emission capacity. The change in total forest coverage versus the change in isoprene emission capacity can have a similar or opposite effect on isoprene emission variations, depending on the plant species of the economic plantations. Hence, future isoprene variations assessments should not only account for changes in vegetation fractions but also consider the changes in plant species compositions of forests.

There are large uncertainties and limitations associated with the methodology used for this study including the satellite land cover data and the isoprene emission model. With respect to satellite data, the uncertainty was systematic due to the overestimation of trees in sparse regions (e.g., agricultural land) and underestimation in dense forests (Sexton et al., 2013). In terms of modeling isoprene emission, the uncertainties were related to the input data [e.g., meteorological parameters, PFT, LAI, and EF in equations (1) and (2)], and the mechanisms and parameters used in the model (Situ et al., 2014; Zhao et al., 2016). It has been estimated that the uncertainty in BVOC emissions at specific locations could be 300–500% in the United States and Europe (Guenther et al., 1995; Simpson et al., 1999). We assumed that the fraction of isoprene emitters in a PFT was stable between 2000 and 2015, which also introduces error. Since we only considered the difference in PFT fraction, known changes in plant species composition, such as the expansion of rubber and oil palm, were not accounted for in the simulated variations of isoprene emission. Despite the uncertainties and limitations mentioned above, the general direction, spatial distribution, and relative magnitude of the changes in tree coverage and isoprene emission are useful for examining the potential response of isoprene emission to land cover change on decadal scales.

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