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Key Points:

- Potential impact of forest change on temperature is defined by the LST difference between forest and nearby nonforest land
- Actual impact of forest change on temperature is defined by the LST trend difference between deforested/afforested and nearby stable lands
- Agreement between potential and actual impacts allows quantifying and predicting temperature change caused by forest cover change

Supporting Information:

- Supporting Information S1

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Potential and Actual impacts of deforestation and afforestation on land surface temperature

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Abstract Forests are undergoing significant changes throughout the globe. These changes can modify water, energy, and carbon balance of the land surface, which can ultimately affect climate. We utilize satellite data to quantify the *potential* and *actual* impacts of forest change on land surface temperature (LST) from 2003 to 2013. The potential effect of forest change on temperature is calculated by the LST difference between forest and nearby nonforest land, whereas the actual impact on temperature is quantified by the LST trend difference between deforested (afforested) and nearby unchanged forest (nonforest land) over several years. The good agreement found between potential and actual impacts both at annual and seasonal levels indicates that forest change can have detectable impacts on surface temperature trends. That impact, however, is different for maximum and minimum temperatures. Overall, deforestation caused a significant warming up to 0.28 K/decade on average temperature trends in tropical regions, a cooling up to −0.55 K/decade in boreal regions, a weak impact in the northern temperate regions, and strong warming (up to 0.32 K/decade) in the southern temperate regions. Afforestation induced an opposite impact on temperature trends. The magnitude of the estimated temperature impacts depends on both the threshold and the data set (Moderate Resolution Imaging Spectroradiometer and Landsat) by which forest cover change is defined. Such a latitudinal pattern in temperature impact is mainly caused by the competing effects of albedo and evapotranspiration on temperature. The methodology developed here can be used to evaluate the temperature change induced by forest cover change around the globe.

1. Introduction

Forest change, defined here as either an increase or decrease in forest land cover, has proven to be a key driver of anthropogenic climate change in the past century [*Betts*, 2001; *Bounoua et al.*, 2002; *Bonan*, 2008; *Allen et al.*, 2015]. Forest change has, and will continue to, affect climate through associated biophysical changes that modify the water cycle and surface energy balance [*Eltahir and Bras*, 1996; *Bonan*, 2008] and also through alterations to the carbon balance [*Jackson et al.*, 2008; *Montenegro et al.*, 2009; *Bathiany et al.*, 2010; *Zhao and Jackson*, 2014]. In recent decades, forests have experienced significant changes globally [*Food and Agriculture Organization*, 2010; *Hansen et al.*, 2013; *W. Li et al.*, 2016] due to the combined effects of natural factors (e.g., fire and drought [*Allen et al.*, 2015]) and human activities like agriculture [*Kim et al.*, 2015] and forestry [*Rudel*, 2012]. Human activities play an increasingly larger role in global forest dynamics with marked regional characteristics [*Hansen et al.*, 2013; *W. Li et al.*, 2016]. For example, the total forest area in China has rapidly increased since the 1990s [*Zhang and Song*, 2006] due to a national afforestation policy [*Viña et al.*, 2016]. In contrast, drastic forest loss continues in tropical countries like Indonesia [*Margono et al.*, 2014; *Richards and Friess*, 2015]. It is apparent that these forest changes can directly affect local temperatures

[*Peng et al*., 2014; *Li et al*., 2015]. However, it is less clear as to what extent such changes can affect the long-term temperature change (i.e., the trend).

Climate models and in situ measurements are often used to estimate the climatic impact of forest change [*Bonan*, 2008]. These two approaches present major limitations in addressing this particular problem. First, in most cases deforestation occurs in small patches that are difficult to capture by coarse-resolution climate models or in areas where long-term, reliable meteorological data are lacking [*Lee et al*., 2011; *Lawrence and Vandecar*, 2014]. Second, climate models are subject to large uncertainties in physical processes, parameterization, and input data [*Oleson et al*., 2004; *Pitman et al*., 2009], while in situ measurements are relatively sparse at large scales and thus suffer from insufficient spatial sampling. For instance, areas where forest cover change is prevalent, like South America and Africa [*Hansen et al*., 2013; *W. Li et al*., 2016], are underrepresented in the Global Historical Climate Network [*Montandon et al*., 2011].

Remote sensing can overcome these limitations in local scale and spatial sampling by providing data with high spatiotemporal resolution at the global scale. Previous studies have shown that land surface temperature (LST) is able to characterize the effect of forest on temperature and can be used to indicate the local climate impact [*Nemani et al*., 1996; *Loarie et al*., 2011; *Mildrexler et al*., 2011; *Wickham et al*., 2012; *Li et al*., 2015].

In a global analysis of the biophysical effects of forest on local climate, *Li et al.* [2015] showed the latitudinal variation and distinct seasonal warming and cooling effects of the Earth's major forest types on daytime, nighttime, and daily average LST. The temperature effects shown in *Li et al.* [2015] are the potential impacts of forest change (a priori impact) estimated in places where forest changes have not occurred yet. Given the fact that forest cover changes have taken place around the globe in the last decade, it is beneficial to ask (1) whether recent forest cover changes have an observable impact (a posteriori impact) on local climate that can help to mitigate or, contrarily, accelerate the climate warming due to increasing greenhouse gases on a regional basis and (2) if this actual impact of forest changes on temperature can be predicted in advance by using knowledge from the potential effect? Answering these questions can advance our knowledge of the local effects of actual deforestation that have important ecological impacts. The large change in temperature caused by deforestation can result in the loss of microclimate conditions associated with forests and could have severe consequences for biological organisms [*D'Odorico et al*., 2013]. Although there is significant evidence for the temperature difference between forests and nearby cleared areas in the literature [see, e.g., *Runyan and D'Odorico*, 2016, and references therein], a global-scale assessment of actual impacts of forest cover change is still lacking. A recent work by *Alkama and Cescatti* [2016] made a valuable contribution to the first question by using high-resolution Landsat forest change data to assess the impact of recent forest cover change on both LST and air temperature at global scale. However, the temperature impacts are derived using pairs of years, which are subject to the influence of interannual climate variability. One remaining question is whether forest cover change can significantly influence longer-term temperature trends in the last decade.

To address the aforementioned questions, the objectives of this paper are to (1) quantify the impact of forest change on temperature trends from 2003 to 2013 globally and (2) compare these actual observed impacts of forest change to their corresponding potential impacts, developed by *Li et al.* [2015], to determine whether the latter could be used as an evaluation tool. This is the first study—independent and different from the work of *Alkama and Cescatti* [2016]—to provide a comprehensive, observation-driven, global assessment of the forest change impact on temperature trends using remote sensing data from satellite.

2. Methods and Data

We utilize three satellite data sets to quantify the impact of forest change on temperature trends globally—two for detecting forest cover change and one for estimating temperature trends. These data sets provide systematic and continuous spatial information needed to develop repeatable, quantitative, long-term measures of the impacts of forest cover change on temperature.

2.1. Data Sets for Forest Cover Change

Accurately detecting deforestation, afforestation, and undisturbed forests is an important prerequisite to the assessment of forest change impacts on temperature. Here we use forest cover change detected from two independent data sets: Moderate Resolution Imaging Spectroradiometer (MODIS) land cover (LC) data

[*Friedl et al*., 2010] and Global Forest Change (GFC) data [*Hansen et al*., 2013]. Using two data sets generated from different sources can reduce the uncertainty in detecting forest cover change. The results based on each of these two data sets are reported separately for the purpose of cross-validation.

MODIS LC data set (MCD12C1 version 5.1) provides land cover information annually from 2002 to 2012 at a spatial resolution of 0.05°. The data set consists of 17 land cover classes defined by the International Geosphere-Biosphere Programme classification scheme. Among them, five forest classes—including evergreen needleleaf, evergreen broadleaf, deciduous needleleaf, deciduous broadleaf, and mixed forests—are considered as "forest" in the following analysis, whereas the other land classes are considered as "nonforest."

Since the GFC data set is produced from Landsat imagery, it provides information on forest cover change that is independent from MODIS LC and at a much higher spatial resolution. The data set contains a baseline tree cover percentage in 2000 and a nominal class for forest gain or loss throughout the period of 2000 to 2012. Because original GFC data are at 30 m spatial resolution, we aggregate the data to 0.05° to match the MODIS resolution. In the reprocessed GFC data, tree cover, forest gain, and forest loss are all expressed as a percentage at 0.05° resolution. A forest threshold is needed to define forest and nonforest in GFC. We choose 50% tree cover percentage as the threshold, which means a pixel with tree percentage larger (smaller) than 50% is defined as forest (nonforest).

2.2. Extracting Forest Cover Change

Forest cover change in this study refers to either an increase or decrease in forest cover seen by satellite data, which can be interpreted as deforestation (forest loss), afforestation (forest gain), or reforestation without specifying the cause of the change. When describing forest cover change, we use deforestation/afforestation for MODIS LC. We use forest loss/gain specifically for GFC due to the inherent difference of these two data sets. To describe forest change common to both data sets and in a general context, we use deforestation/afforestation, consistent with their usage in the literature. The climate impacts of deforestation/afforestation and forest loss/gain are essentially the same in the context of this paper. In principle, forest cover change can be identified from either a conversion between well-defined forest and nonforest class in MODIS LC or tree cover changes in GFC. However, in practice, this is complicated by noise and uncertainty in the data that often bring in false change signals, and thus additional filtering procedures are required. The specific filtering procedures are not identical for the MODIS LC and GFC data due to their different data structures. These procedures are explained below.

2.2.1. Forest Cover Change in MODIS LC

It is known that MODIS LC data contain interannual variations that are unrelated to actual land cover changes [*Friedl et al*., 2010] and could reduce the credibility of derived forest cover change for adjacent years. This issue is alleviated through the following two procedures. First, forest change is not directly extracted from two individual years. Instead, we deduce forest cover change by comparing two stable land cover maps created for the period of 2002–2006 and 2008–2012 by the most frequent land cover type recorded at each pixel during each 5 year period. The resulting stable land maps largely eliminate those unrealistic changes in land cover types between years and thus improve the reliability of the identified forest changes. Next, forest changes identified in the first step are further filtered by tree cover change of GFC data. The rationale behind this filtering process is that the unrealistic forest change in MODIS LC, if any, would be inconsistent with the tree cover change in GFC, because the latter are produced at a much higher resolution and are presumably more accurate. For example, if MODIS LC data show deforestation but GFC data show increased tree cover, this "deforested" pixel is probably an unrealistic change and is hence discarded. The effective deforested (afforested) pixels in MODIS LC must be accompanied with a minimal net tree cover decrease (increase) of 5% in GFC (this 5% minimal threshold will be explained in the next paragraph). In addition, the effective unchanged forest and nonforest pixels in MODIS LC must come with tree cover change <5% to remove any forest cover changes undetected with MODIS LC. The resulting forest cover changes with their land conversion types are shown in Figure S1 in the supporting information.

2.2.2. Forest Cover Change in GFC

Ideally, forest cover change in GFC from 2000 to 2012 can be directly extracted from tree cover change. However, we found that 63.57% of nonice land pixels in GFC experienced some degree of nonzero tree cover change, which is 2 times greater than the total forest pixels (20.73%) defined by MODIS LC. Apparently, most of these instances are noise rather than real forest change, as can be seen from their very small values (Figure S2a). Including all these pixels would push the total forest change unrealistically high. To mitigate this effect, we choose a minimal 5% threshold to separate real forest cover change signal and noise. This threshold can greatly reduce the total forest cover change pixels to less than 8% (Figure S2a), a rate comparable to the 10.6% raw forest cover change pixels derived from the MODIS LC stable land maps over the two periods 2002–2006 and 2008–2012. A more stringent threshold (>5%) would have limited effects in further reducing forest change pixels (Figure S2a). This threshold (5%) is also used to define unchanged forest and nonforest in both GFC and MODIS LC.

Previous studies [*Wickham et al.*, 2013; *Li et al.*, 2015; *Alkama and Cescatti*, 2016] found that the choice of threshold values used in detecting forest cover change will affect the magnitude of the forest change impacts on temperature. To minimize the threshold influence in the determined forest change when comparing the results between MODIS LC and GFC, we extract forest change pixels in GFC data that have similar average tree cover change to those in MODIS LC. We choose the tree cover change thresholds of −0.15 and 0.10 because they can produce forest loss and gain pixels in GFC data with average tree cover change (−0.34 and 0.19 for forest loss and gain, respectively; Figure S2b) very close to those deforestation and afforestation pixels in MODIS LC (−0.31 and 0.17 for deforestation and afforestation, respectively). Moreover, additional sensitivity analysis is performed on GFC data to examine how forest cover change impacts on temperature vary with different thresholds to determine forest loss and forest gain pixels.

2.3. Temperature Data and Processing

The LST data are from MODIS 8 day Aqua LST (MYD11C2) from July 2002 to December 2013 at 0.05° spatial resolution. The overpass time of Aqua (around 13:30 and 01:30 local solar time at the equator) approximates to the time of daily maximum (T_{max}) and minimum (T_{min}) temperature. The 8 day maximum and minimum temperature data are further aggregated to seasonal and annual values for each year. The arithmetic mean of those values is used to represent daily average temperature (T_{ave}). It should be noted that MODIS 8 day LST data are the average only for the clear-sky condition, because clouds inhibit satellite observations in the thermal infrared spectral ranges [*Wan*, 2008]. The LST data have been processed in the same way as described in *Li et al.* [2015]; only high-quality data are selected based on the quality control flag system that comes with the product.

Climate Research Unit (CRU) monthly air temperature data are used to compare temperature trends with those that are derived from LST. CRU data are at 0.5° and from 2003 to 2013, including both maximum and minimum air temperatures.

Temperature trends are estimated by linear regression at annual and seasonal scales over the period of 2003 to 2013. Time (year) is the independent variable, temperature is the dependent variable, and the trend is given by the slope. The linear regression method is more robust than using two pairs of years because it extracts information from a full time series of temperature data (between 6 and 11 data points in this study). MODIS LST data in 2002 are not used since the data collection starts in July and there is not a full year's worth of data. In a similar practice, pixels with less than 6 years of valid data are discarded in the trend estimation. Trends for CRU air temperature are estimated over the same period. We find that temperature trends for MODIS LST (aggregated to 0.5°) and CRU air temperature exhibit similar spatial patterns ($r = 0.47$ and 0.52 for T_{max} and T_{min}, respectively), but trends in LST are larger than that in air temperature as indicated by their regression slope in Figure S3. In addition, LST contains more spatial details that are not captured by the air temperature, because of the much higher spatial resolution of LST compared to the air temperature gridded from a relatively sparse distribution of weather stations.

2.4. The Potential and Actual Impacts of Forest Cover Change

The impact of forest cover change on temperature trends is assessed through its *potential* and *actual* impacts. The terms "Potential impact" and "Actual impact" throughout the paper are used to differentiate the impacts estimated from hypothetical forest change and from actual forest change that has already occurred in reality.

2.4.1. The Potential Impact

The potential impact of forest cover change on LST is quantified by multiyear averaged LST difference (ΔLST) between unchanged forest and nearby nonforest (excluding water, ice, and urban), as quantified in equation (1):

$$\Delta \mathrm{LST} = \mathrm{LST}_{\mathrm{forest}} - \mathrm{LST}_{\mathrm{nonforest}} \tag{1}$$

where $\mathrm{LST}_{\mathrm{forest}}$ and $\mathrm{LST}_{\mathrm{nonforest}}$ are the multiyear averaged LST, calculated from 2003 to 2013, for unchanged forest and nearby unchanged nonforest, respectively. The potential impacts are estimated at locations in the vicinity of observed forest changes. The ΔLST indicates the different effects of forest and nonforest in regulating local temperature as a consequence of their different biophysical properties. In this way, ΔLST provides an a priori estimation for the potential impact of forest cover change on temperature, using the existing vegetation before any forest cover changes have actually occurred, representing a hypothetical change situation.

2.4.2. The Actual Impact

When forest cover actually changes, it affects temperature regulation, which contributes to temperature trends. The impact on the observed temperature trend caused by this change is defined in this study as "actual" effect. It can be quantified by the difference in LST trends (ΔTrend) of *deforested* pixels minus nearby unchanged *forest* for deforestation impact (equation (2)) and *afforested* pixels minus nearby unchanged *nonforest* for afforestation impact (equation (3)):

$$\text{Deforestation: } \Delta\mathrm{Trend}_{\mathrm{deforested}} = \mathrm{Trend}_{\mathrm{deforested}} - \mathrm{Trend}_{\mathrm{unchanged\ forest}} \tag{2}$$

$$\text{Afforestation: } \Delta\mathrm{Trend}_{\mathrm{afforested}} = \mathrm{Trend}_{\mathrm{afforested}} - \mathrm{Trend}_{\mathrm{unchanged\ non\text{-}forest}} \tag{3}$$

where Trend is the linear LST trend from 2003 to 2013 as explained in section 2.3. ΔTrend gives an a posteriori estimation for the actual impact at pixels that forest change has occurred. It is assumed in equations (2) and (3) that two pixels in close distance share similar large-scale climate forcings; hence, nonlocal signals related to background climate (e.g., natural variability) will be removed, and the resulting LST trend difference (ΔTrend) is largely attributable to forest cover change. The validity of this assumption depends on the strength of the target signal relative to background environment variability. The nonlocal factors (e.g., advection [*West et al*., 2011]) could still have some residual effects on ΔTrend when the background environment is heterogeneous. These residual effects could be greatly reduced through averaging ΔLST from a number of pixels and comparison samples (as explained below) and are therefore expected to have limited impact on the global-scale results. This strategy shares the same root as other well-established techniques in detecting the urbanization and land cover change impacts, such as the "urban minus rural" and "observation minus reanalysis" methods [*Kalnay and Cai*, 2003], and has been successfully applied to isolating the forest change impact in other studies [*Peng et al*., 2014; *Alkama and Cescatti*, 2016].

The comparison samples of forest, nonforest, deforested, and afforested pixels involved in the estimation of potential and actual impacts are acquired by a window searching strategy [*Li et al*., 2015] (more details can be found in this reference), with a moving window of 9×9 pixels ($0.45 \times 0.45°$). The window searching strategy is performed on MODIS LC and GFC data separately to collect independent comparison samples across the globe (the number of comparison samples can be found in Figures S4 and S5). The results are also reported separately.

It is worth noting some key differences in the comparison samples obtained by MODIS LC and GFC. MODIS LC comparison sample requires specific land cover type involved in a forest conversion; therefore, forest conversion types are used to find deforestation and afforestation comparison samples (Figure S1). For example, when forest is converted to cropland, the potential effect is calculated by comparing LST between unchanged forest and nearby unchanged cropland. When multiple conversions exist (e.g., converted from/to cropland, grass, or shrub) in a search window, the dominant (i.e., majority) conversion type is chosen as a representative. In contrast, forest cover change in GFC data has no land cover type information except quantitative tree cover change. The potential impact in this data set is computed without considering land cover types, but instead by the LST difference between unchanged forest and all nearby nonforest in the search window. In short, the major difference between the potential or actual impact derived from MODIS LC and GFC data is that the former is pertaining to one specific land cover type while the latter is not. This distinction allows us to examine if forest change impact is sensitive to the type of land converted from/to forest. Previous studies have shown that LST is a function of land cover [*Jin and Dickinson*, 2010] and vegetation

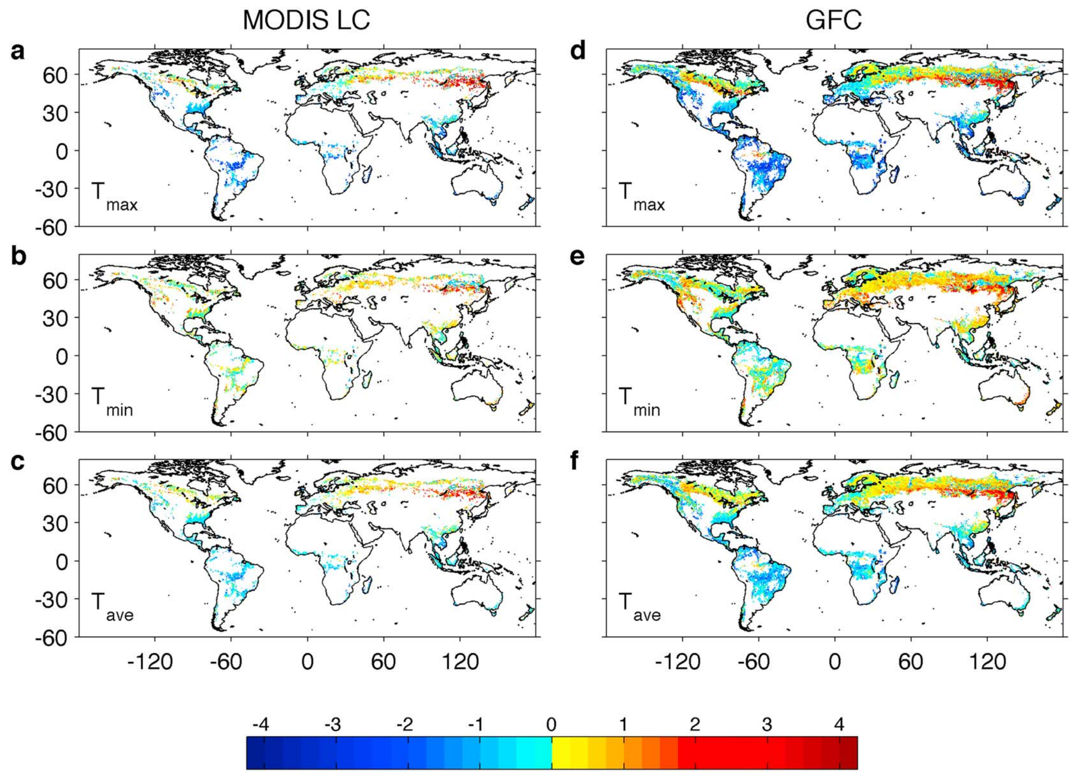

Figure 1. Potential impact of forest change on land surface temperature (LST) based on (a–c) MODIS LC and (d–f) GFC data for maximum (T_{max}), minimum (T_{min}), and daily average (T_{ave}) LST, in Kelvin (K). The potential impact is estimated by the annual LST difference of forest minus nearby nonforest (ΔLST). T_{max} and T_{min} refer to LST retrieved at 13:30 and 01:30 local time by Aqua, respectively, and their arithmetic mean gives T_{ave}. Results are averaged at 0.5° for display.

index [*Lambin and Ehrlich*, 1996; *Lim et al*., 2008], indicating that the conversion of forest to crop versus bare land could have a very different impact on temperature, even if both cases are deforestation in a broader sense.

3. Results

3.1. Potential Impact of Forest Change on LST

The multiyear averaged LST difference of forest minus nearby nonforest (ΔLST) indicates the potential impact of forest change on temperature. Figure 1 shows the ΔLST estimated from MODIS LC and GFC data. The spatial pattern of ΔLST, which shows the local cooling and warming effects of forest, is consistent between MODIS LC and GFC. These results are also consistent with the results reported in *Li et al.* [2015], which compares forest with open land, although GFC has more comparison samples and better coverage. The broad agreement is also confirmed by the high correlation found in ΔLST derived from MODIS LC and GFC (Figure S6). Overall, most forests have a cooling effect on T_{max} (negative ΔLST) in tropical and temperate regions—with the strongest cooling effect in tropical forests (20°S–20°N) and moderate cooling in temperate forests (20°N–50°N and 20°S–50°S)—and warming effect (positive ΔLST) in boreal regions (50°N–90°N). In contrast, most forests have a warming effect on T_{min}, especially in midlatitude, while tropical forests show a slight cooling effect. Considering this, the potential effect is that deforestation increases T_{max} in low- and mid-latitude regions, decreases T_{max} at high-latitude regions, decreases T_{min} in extratropical regions, and marginally increases T_{min} in tropical regions. The impact on T_{ave} largely follows the impact on T_{max} due to its greater magnitude and dominant contribution. Afforestation would have the opposite warming/cooling effect on the three temperature variables.

Potential impacts also exhibit considerable spatial variability. For example, large longitudinal variability that can modify the global latitudinal pattern described above is observed. This is especially evident in the west coastal areas of North America and Europe, where the oceanic influence is strong (maritime climate). Forests

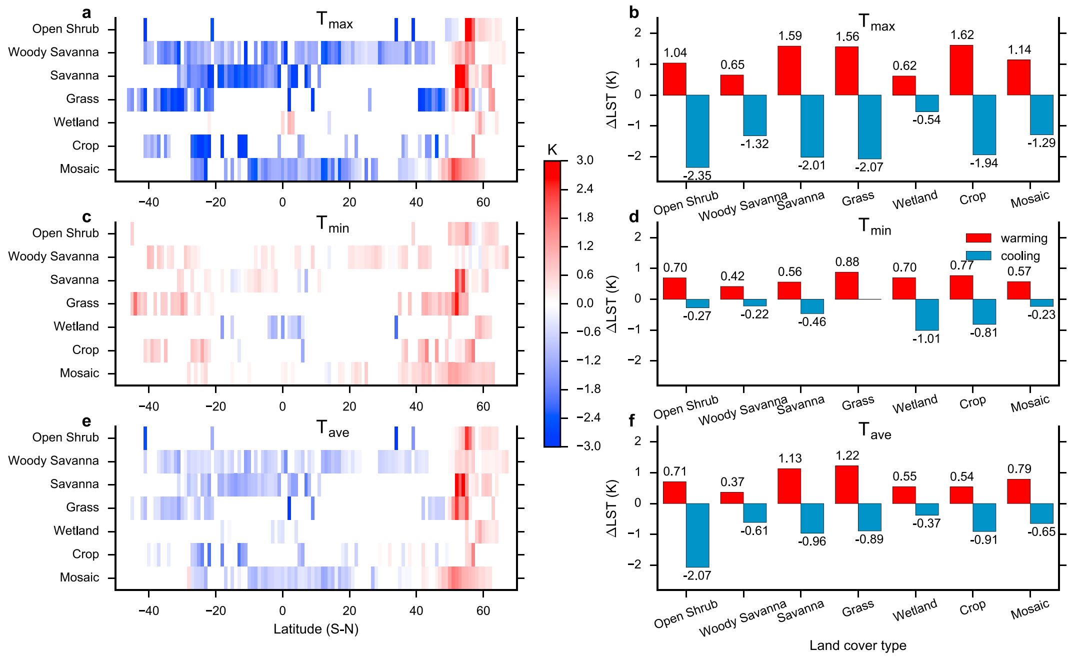

Figure 2. Potential impacts (ΔLST) of forest cover change on LST as a function of land cover types. ΔLST is calculated as the LST difference of forests minus nearby nonforest land cover types, representing the potential impacts of afforestation. The impact of deforestation is opposite in sign. (a, c, and e) The latitudinal pattern of ΔLST for each land cover type at 1° bands with insignificant difference masked out by *t* test at 95%. (b, d, and f) The magnitude of cooling and warming for each land cover type averaged from their latitudinal patterns in Figures 2a, 2c, and 2e.

in these areas have a cooling effect as can be seen from GFC data, which is contrary to the warming effect expected from regions of similar latitude (>50°N). The cooling of European forests is a robust phenomenon that has also been confirmed by *West et al.* [2011] and *Li et al.* [2015]. This clearly demonstrates the oceanic influence along the west coasts that leads to a warmer climate condition and less frequent snow presence than inland areas (Figure S7). Warmer environment can suppress the snow-amplified albedo warming effect of forest [*Li et al.*, 2015].

Figure 2 shows the potential impact of forest cover change as a function of different land cover types in MODIS LC, representing the potential impact of forests converted from nonforests (i.e., afforestation and forest gain). Forest cover change generally results in large changes to T_{max} compared with T_{min} across latitude and land cover types (except for wetlands; Figure 2), reflecting that daytime and nighttime temperatures are regulated by different biophysical processes [*Li et al.*, 2015] and different biophysical properties associated with each land cover type (e.g., albedo [*Gao et al.*, 2005]). The effect of forest change on T_{max} is greatest for land cover types with less biophysical regulation of maximum temperatures (i.e., open shrublands, savannas, grasslands, and croplands), and it is weaker for land cover types that cools T_{max} due to increased tree cover (woody savannas) or evaporation (wetlands). T_{min} shows a steady warming response to afforestation across land cover types, demonstrating the uniform effect of reduced albedo on T_{min} at night [*Li et al.*, 2015] when converting to forest.

3.2. Actual Impact of Deforestation on LST

In this section, we investigate whether the estimated potential impacts can be realized in actual temperature change where forest change took place. The actual impact of deforestation on LST (ΔTrend) during 2003–2013 derived from MODIS LC and GFC can be seen in Figure 3, with potential impact in red and actual impact in blue. The potential impact here, given by ΔLST, has the opposite sign to Figure 1, so that nonforest minus forest indicates deforestation. The actual impact of deforestation significantly departs from the zero line, illustrating a detectable impact of deforestation on temperature trends. For each temperature variable, the actual impact of deforestation in most regions is very similar to the potential impact in terms of sign (i.e., positive or negative) and latitudinal pattern. However, less agreement for T_{max} is observed in

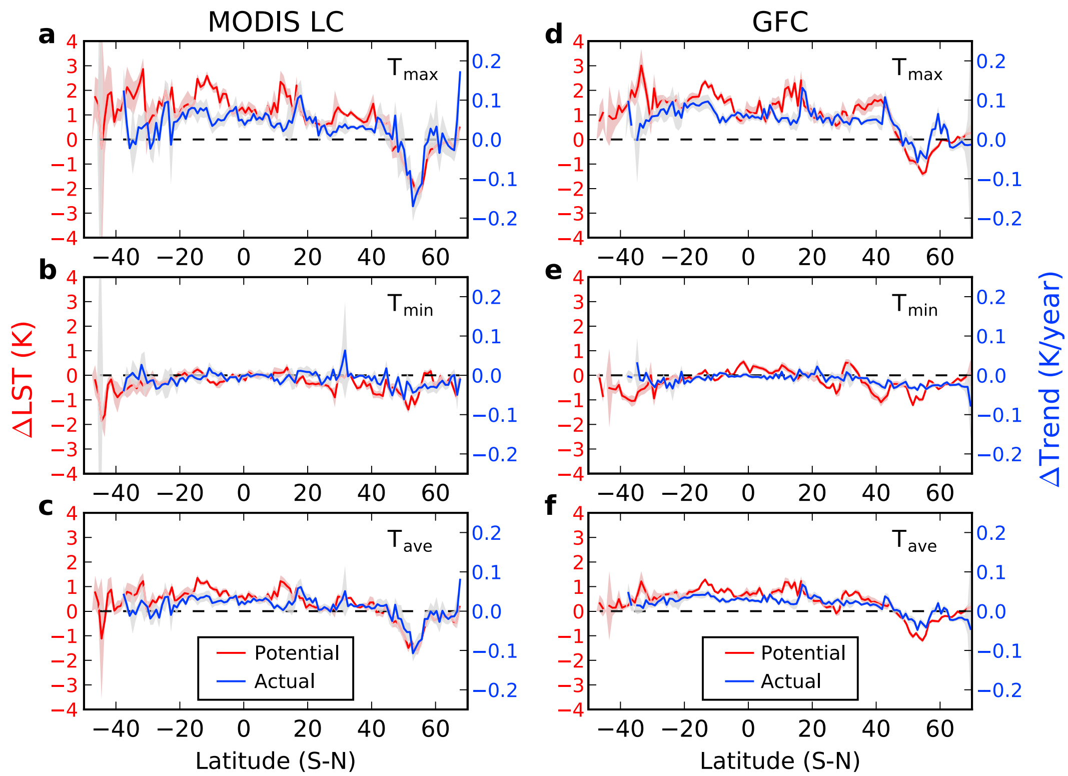

Figure 3. Actual impact of deforestation on LST during 2003–2013 based on (a–c) MODIS LC and (d–f) GFC data (K/yr), calculated as the LST trend difference of deforested minus unchanged forests (ΔTrend in equation (2)). Potential impact (ΔLST; K) is shown in red for comparison. When forest cover actually changes, its potential impact on temperature is realized, and the contribution on the observed temperature trend is the actual effect of forest cover change. The shaded area represents the 95% confidence interval estimated by *t* test for each 1° latitude band. Only comparison samples at locations where both potential and actual impacts are available are used to produce this figure as well as Figures 3–5.

northern high-latitude regions for GFC data. This could reflect the influences of longitudinal variations at high latitude as well as the local variability associated with each comparison sample because they may not necessarily be collected from the same locations as MODIS LC (Figure S4). Nevertheless, it clearly demonstrates that the actual impact of deforestation on LST trends is consistent with the potential impact derived from ΔLST, regardless of the forest change data set used. In terms of magnitude, the actual impact and potential impact are not directly comparable. The latter assumes a complete and immediate conversion between forest and nonforest, but in reality deforestation process is often nonuniform in space and time (e.g., partial and scattered deforestation and forest removed at a variable pace over many years). Assuming that deforestation occurred uniformly in space and time, one might be able to make the actual and potential impacts roughly comparable in magnitude by dividing the potential impact by the length of time during which deforestation has taken place (e.g., 11 years in our study). However, discrepancy is expected in such comparison because the complex situation in the real world often violates the uniform assumption and causes the actual impact to deviate from the potential effect.

Deforestation can either warm or cool LST trends, mainly depending on latitudes. Consistent with ΔLST, the largest impact appears on T_{max} trend that leads to greater warming in tropical and midlatitude regions (Figures 3a and 3d). In northern high-latitude regions, a strong cooling is observed by MODIS LC, although less evident in GFC data. Differently, deforestation impact on T_{min} trend is smaller in magnitude, with significant cooling only present in parts of mid- and high-latitude regions (Figures 3b and 3e). As a result, the net impact is warming on T_{ave} trend in tropical and most temperate regions (weak) due to greater magnitude in T_{max} and cooling on T_{ave} trend in boreal regions with an increased contribution from T_{min} (Figures 3c and 3f).

The deforestation impact on seasonal LST trends is also evident with a strong latitudinal influence. In low latitudes, the warming on T_{max} trend is present throughout the year, while no significant effect on T_{min} trend

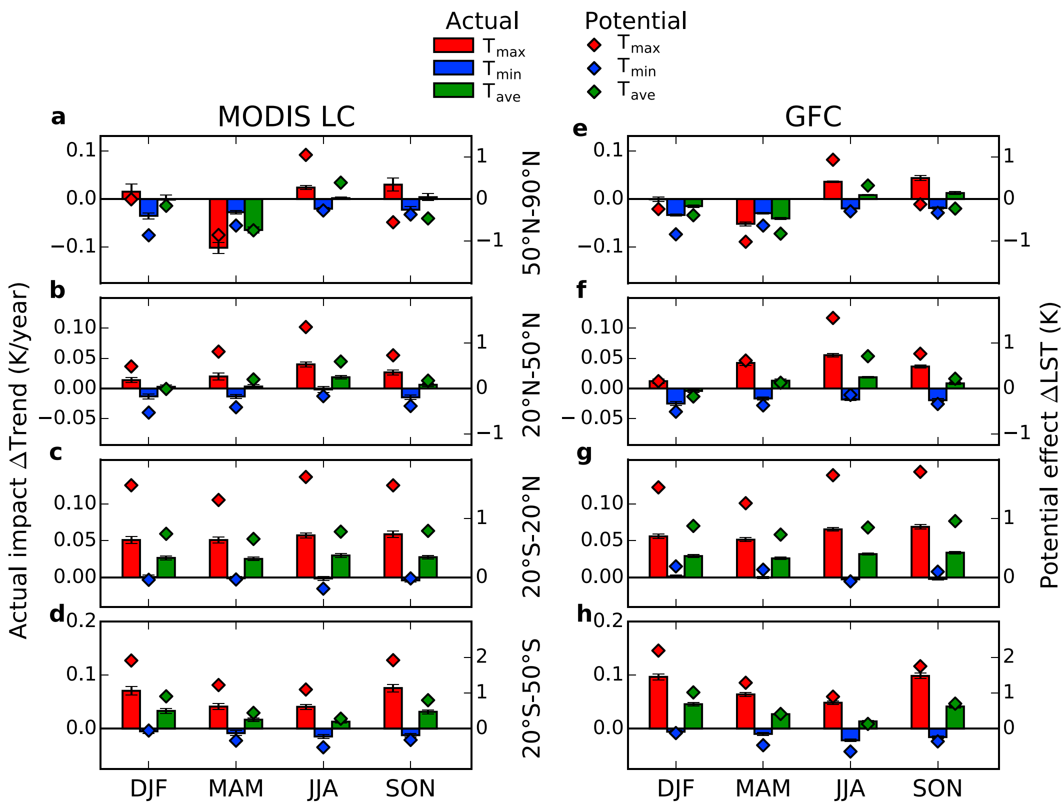

Figure 4. Seasonal impact of deforestation on LST based on (a–d) MODIS LC and (e–h) GFC data in different climate zones. The bar chart shows the actual impact of deforestation given by the trend difference of deforested minus nearby unchanged forest (ΔTrend; K/yr) on the left *y* axis. The vertical lines on each bar represent the confidence interval at 95% estimated by *t* test. The scattered diamond chart on the right *y* axis shows the potential impact of deforestation estimated from the LST difference (ΔLST; K) of nonforest minus forest. DJF is December-January-February, MAM is March-April-May, JJA is June-July-August, and SON is September-October-November.

is observed (Figure 4c). In the extratropics, seasonality on the T_{max} trend manifests as stronger warming in summer and weaker warming in winter (Figures 4a and 4b). Conversely, seasonality on T_{min} trend results in weaker cooling in summer and stronger cooling in winter. This implies that the presence of forests can diminish the diurnal and seasonal temperature variations of their environment, analogous to the role of trees known as ecosystem engineers since they can regulate their own microclimate (e.g., nocturnal warming) to favor their own survival [*D'Odorico et al.*, 2013]. This function is particularly important to trees close to the boreal or alpine treelines, as they are very sensitive to low temperatures (i.e., freezing-induced mortality [*He et al.*, 2015a]). But deforestation breaks off this buffering effect, which can mitigate cold stress, and triggers a positive feedback to increase diurnal temperature range [*Alkama and Cescatti*, 2016].

The counteracting effects on T_{max} and T_{min} trends that are out of phase make the seasonal impact on T_{ave} trend less significant and sometimes conflicting between different data. For example, in midlatitudes, deforestation shows an apparent warming impact on T_{ave} trend in summer, but no consistent impact is observed in winter—since MODIS LC shows no detectable impact and GFC even shows a slight cooling impact (Figures 4b and 4f). In a similar example, in boreal regions, deforestation induces a strong cooling on T_{ave} trend in spring, but for other seasons only an insignificant or very weak impact is found from MODIS LC (Figure 4a) and GFC data (Figure 4e). In contrast, impact on T_{ave} trend is more detectable and consistent in the southern hemisphere due to dominant effect from T_{max}, and a persistent warming on T_{ave} trend is observed in midlatitudes across all seasons (Figures 4d and 4h).

3.3. Actual Impact of Afforestation on LST

Afforestation is a reverse process to deforestation and thus should have the opposite impact on LST. In most cases, we do see impacts from afforestation on T_{max} and T_{min} trends that are opposite in sign compared to

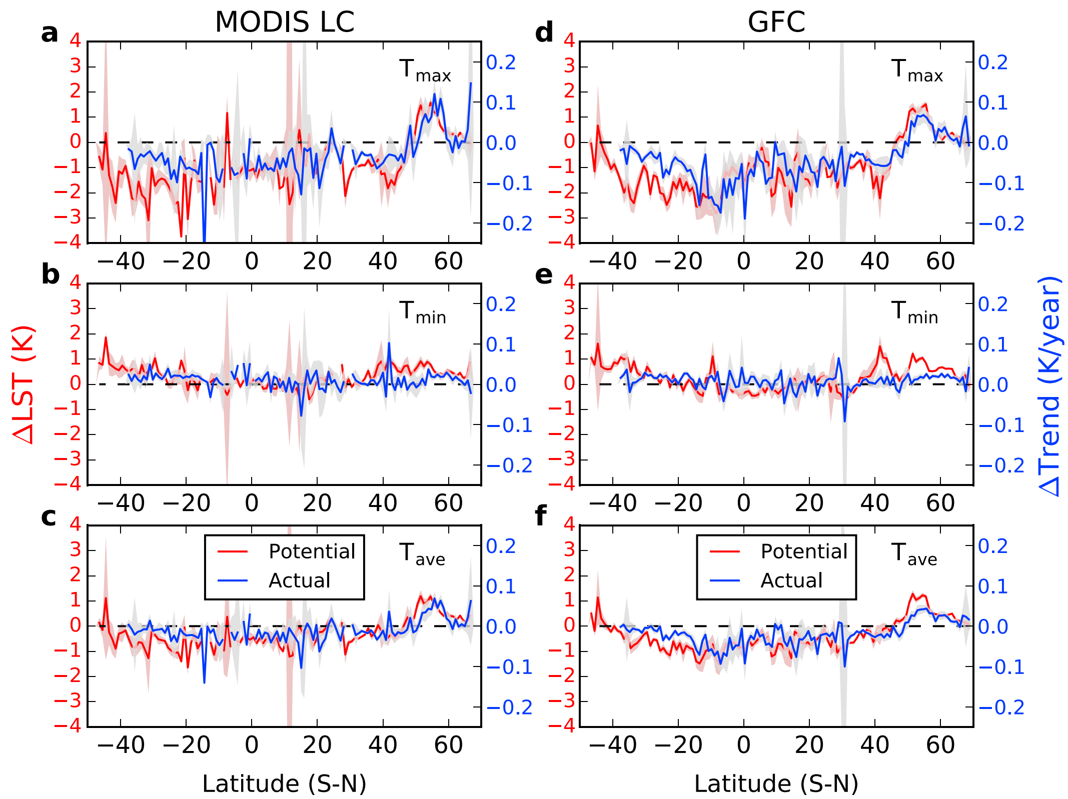

Figure 5. Actual impact of afforestation on LST during 2003–2013 based on (a–c) MODIS LC and (d–f) GFC data in different climate zones (K/yr), calculated as the LST trend difference of afforested minus unchanged nonforests (ΔTrend in equation (3)). Potential impact (ΔLST; K) is shown in red for comparison.

deforestation impacts, supported by both MODIS LC and GFC data (Figure 5). That is, afforestation in tropical region cools down T_{ave} trends due to T_{max} but warms up all three LST trends significantly in high latitudes. Seasonal impact of afforestation is generally contrary to that of deforestation, which further adds to the credibility of the forest change impact on temperature trends (Figure 6).

3.4. Robustness of Forest Change Impacts on LST

Collectively, evidence for deforestation and afforestation impacts is summarized in Tables 1 and 2 for MODIS LC and GFC data, respectively, with different consistency labels. These consistency labels are chosen to assess the robustness of the results from different perspectives, including (1) statistical significance of the actual impact (*S*), (2) whether the impact is consistent in sign with the potential impact (ΔLST; *L*), (3) whether the impact is opposite in sign between deforestation and afforestation (*F*), (4) whether impact is consistent in sign between MODIS LC and GFC data (*D*), and (5) whether the difference in the magnitude of the estimated impacts between MODIS LC and GFC is greater than their averages by 100% (asterisk indicates within the range). Hence, more labels for each entry in Tables 1 and 2 suggest higher confidence for the corresponding temperature impact. Most forest change impacts show high confidence in terms of significance and sign except for southern high-latitude regions, where the number of comparison sample is very limited. In terms of magnitude, the deforestation impact on T_{max} in the boreal regions shows weaker agreement due to larger differences in magnitude and inconsistent sign between MODIS LC and GFC data, whereas the afforestation impact shows better consistency.

It should be noted that the estimated impacts also depend on the thresholds used to define forest cover change, as discussed in section 2.2. The sensitivity analysis shows that a higher threshold to define forest change leads to stronger impacts on temperature (Figure S8). Because the results of latitudinal patterns are the average from a number of comparison samples, it does not necessarily mean that every deforested/afforested location follows a similar pattern. For each individual case, the influence from local background environment variability could be strong and play a nonnegligible role in temperature effects

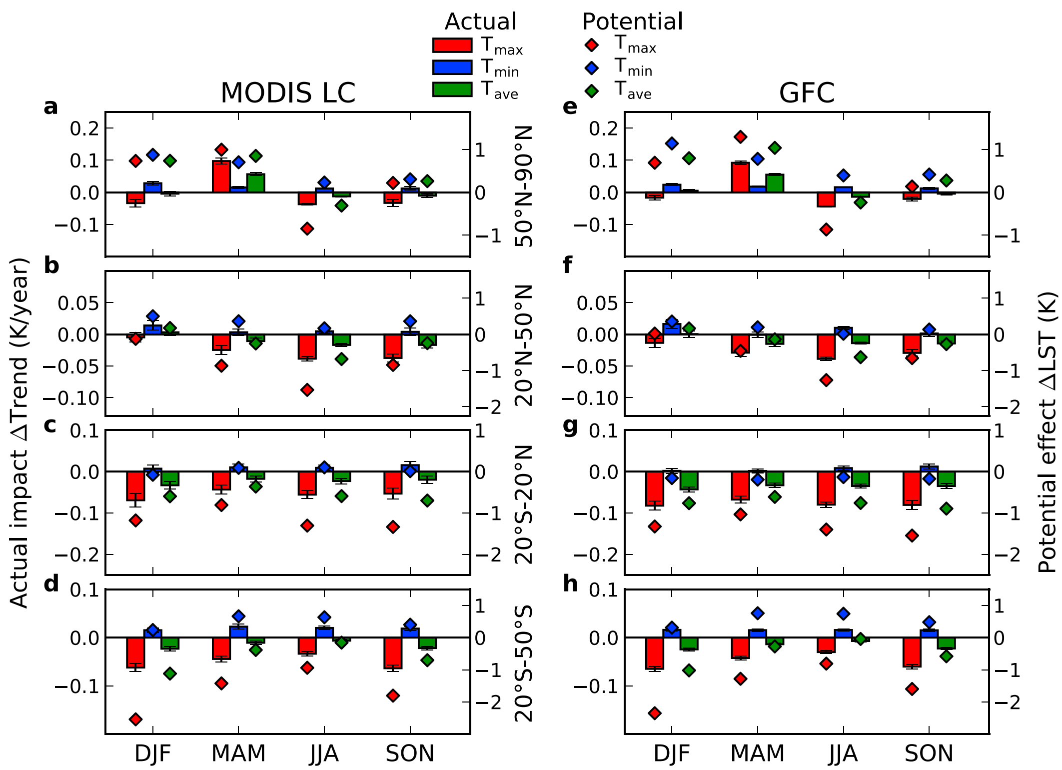

Figure 6. Seasonal impact of afforestation on LST based on (a–d) MODIS LC and (e–h) GFC data in different climate zones. The bar chart shows the actual impact of afforestation given by the trend difference of afforested minus nearby unchanged nonforest (ΔTrend; K/yr) on the left *y* axis. The vertical lines on each bar represent the confidence interval at 95% estimated by *t* test. The scattered diamond chart on the right *y* axis shows the potential effect of afforestation estimated from the LST difference (ΔLST; K) of forest minus nonforest.

attributable to forest change, especially over complex terrain [*Bellasio et al.*, 2005; *Chen et al.*, 2013]. The associated uncertainty can cause the actual impact to be different in both magnitude and sign compared to the latitudinal pattern in which spatial variations are smoothed out. Thus, it is necessary to take a region-specific perspective when investigating this impact for individual local cases.

4. Discussion

Our analysis presents strong and clear evidence of the impact of forest cover change on surface temperature by using LST data from satellites. We find that LST trends closely resemble air temperature trends (see Figure S3). Thus, it is reasonable to infer from LST changes that forest change could influence the observed air temperature

Table 1. Impact of Forest Change on Annual LST Based on MODIS LC at Different Latitudinal Zones With Consistency Labels (K/Decade)[a]

	Deforestation			Afforestation		
	T_{max}	T_{min}	T_{ave}	T_{max}	T_{min}	T_{ave}
50°N–90°N	−0.76$^{\text{SLF}}$	−0.35$^{\text{SLFD*}}$	−0.55$^{\text{SLFD}}$	0.39$^{\text{SLFD*}}$	0.17$^{\text{SLFD*}}$	0.28$^{\text{SLFD*}}$
20°N–50°N	0.13$^{\text{SLFD*}}$	−0.11$^{\text{SLFD*}}$	0.01$^{\text{LFD*}}$	−0.24$^{\text{SLFD*}}$	0.04$^{\text{SLFD*}}$	−0.10$^{\text{SLFD*}}$
20°N–20°S	0.58$^{\text{SLFD*}}$	−0.02$^{\text{SLFD*}}$	0.28$^{\text{SLFD*}}$	−0.65$^{\text{SLFD*}}$	0.09$^{\text{SLFD*}}$	−0.28$^{\text{SLFD*}}$
20°S–50°S	0.68$^{\text{SLFD*}}$	−0.13$^{\text{SLFD*}}$	0.28$^{\text{SLFD*}}$	−0.68$^{\text{SLFD*}}$	0.23$^{\text{SLFD*}}$	−0.23$^{\text{SLFD*}}$
50°S–90°S	0.25$^{\text{L}}$	−0.28$^{\text{L}}$	−0.02$^{\text{L}}$	Not applicable (NA)	NA	NA

[a] More consistency labels indicate higher confidence of the result. Warming is in red and cooling is in blue. *S* indicates that the actual impact (ΔTrend) is significant at 95% level estimated by *t* test. *L* indicates that the sign of actual impact is consistent with potential effect (ΔLST). *F* indicates that actual impacts of deforestation and afforestation are opposite in sign. *D* indicates that the sign of actual impact is consistent between MODIS and GFC data. The asterisk indicates that the difference in the magnitude of the estimated impacts between MODIS LC and GFC is not greater than their averages by 100%.

Table 2. Impact of Forest Change on Annual LST Based on GFC at Different Latitudinal Zones With Consistency Labels (K/Decade)[a]

	Deforestation			Afforestation		
	T_{max}	T_{min}	T_{ave}	T_{max}	T_{min}	T_{ave}
50°N–90°N	0.04^{S}	-0.26^{SLFD*}	-0.11^{SLFD}	0.31^{SLD*}	0.19^{SLFD*}	0.25^{SLFD*}
20°N–50°N	0.26^{SLFD*}	-0.19^{SLFD*}	0.03^{SLFD*}	-0.18^{SLFD*}	0.05^{SLFD*}	-0.07^{SLFD*}
20°N–20°S	0.58^{SLFD*}	-0.02^{SFD*}	0.28^{SLFD*}	-0.89^{SLFD*}	0.07^{SFD*}	-0.41^{SLFD*}
20°S–50°S	0.77^{SLFD*}	-0.13^{SLFD*}	0.32^{SLFD*}	-0.58^{SLFD*}	0.17^{SLFD*}	-0.21^{SLFD*}
50°S–90°S	Not applicable (NA)	NA	NA	-0.53^{S}	-0.30^{S}	-0.41^{S}

[a]Same as Table 1 but for GFC data.

records [*Lim et al.*, 2008; *Fall et al.*, 2010]. Since air temperature measurements usually do not coincide with the locations of forest change, it is still difficult to assess the actual impact of forest change on air temperature. Recently, *Alkama and Cescatti* [2016] used a semiempirical model to infer air temperature from MODIS LST, and they found consistent impacts of forest cover change on these two temperature variables. These studies suggest a smaller impact on air temperature than on LST [*Juang et al.*, 2007; *Li et al.*, 2015; *Alkama and Cescatti*, 2016]. More work is needed to clarify the relationship between LST and air temperature changes. Model simulations could be particularly useful in revealing the underlying mechanisms.

The overall picture of the observed impact in this study supports findings of earlier modeling [*Snyder et al.*, 2004; *Gibbard et al.*, 2005] and empirical studies [*Lee et al.*, 2011; *Li et al.*, 2015] about the latitudinal impact of forest change—a transition from warming in the low latitudes to cooling in high latitudes when forest is lost. We notice an apparent disagreement between our results and those of *Alkama and Cescatti* [2016] over boreal regions. Our results suggest that deforestation induces significant cooling in boreal regions, while the results of *Alkama and Cescatti* [2016] show a marginal annual warming on T_{ave}. The reason for this contradictory finding is still unclear, even though similar LST data and methodology are used. Possible reasons could be due to the opposite diurnal (T_{max} and T_{min}) and seasonal (summer and winter) impacts that have similar magnitudes and hence cancel each other on daily and annual scales, or due to sample distribution affected by the substantial spatial variations in boreal regions, where both warming and cooling are prevalent (e.g., Figure 1). Further studies are needed to investigate this difference. But our results are in line with the existing understanding for the biophysical warming effect of boreal forests [*Bonan*, 2008]. Our study differs from previous climate model sensitivity experiments in detecting forest change signal in temporal temperature changes rather than based on a hypothetical change scenario or a single slice of time. While the temperature impacts by *Alkama and Cescatti* [2016] are derived using pairs of years, we provide direct observational evidence for such impact on temperature *trends*, estimated using the full 11 year data (January 2003 to December 2013) at the global scale.

The detectable impact on surface temperatures is caused by altered biophysical properties of the land surface as a consequence of forest change. The underlying mechanism is given by the associated changes in surface albedo, evapotranspiration, and roughness [*Gibbard et al.*, 2005; *Davin and de Noblet-Ducoudré*, 2010; *Bright et al.*, 2015; *Y. Li et al.*, 2016], which, in turn, are responsible for the impact and also determine the latitudinal pattern [*Li et al.*, 2015, 2016]: deforestation leads to a local increase in albedo but decreases in evapotranspiration and roughness. The warming effect of reduced evapotranspiration exceeds the cooling effect of albedo increase in low latitudes; the opposite is true in high latitudes, especially in winter when snow is present. Reduction in surface roughness can suppress turbulent energy exchange between the land and atmosphere and increase the outgoing longwave radiation, a mechanism very important in tropical [*Davin and de Noblet-Ducoudré*, 2010] and arid areas [*Rotenberg and Yakir*, 2011]. A similar mechanism applies for afforestation in an opposite way. The land cover specific results reported in Figure 2 also highlight how the different biophysical properties of land cover types, such as albedo and evapotranspiration, result in different effects of forest cover change on temperature. These effects are critical for making informed a priori estimations of the local temperature effect of forest cover change.

These findings are also helpful for understanding the vegetation-climate feedback in a broader sense. It has been reported that a poleward treeline shift [*Harsch et al.*, 2009] and shrub expansion associated with warming have occurred in high latitudes [*Tape et al.*, 2006] and desert areas [*D'Odorico et al.*, 2010; *He et al.*, 2015a, 2015b] over the last several decades, and it is predicted to continue in the future [*Pearson et al.*, 2013].

The advancing vegetation mimics afforestation shown here and is thus likely to accelerate climate warming through albedo-vegetation feedback [*Chapin et al*., 2005; *Swann et al*., 2010] as the warming effect further enhances woody plant establishment [*D'Odorico et al*., 2010, 2013; *He et al*., 2015b]. Nevertheless, the degree of influence is largely undetermined. Analogously, drought-induced tree mortality [*Allen et al*., 2015], logging, and fires that cause tree cover loss could have a similar impact as deforestation in our results. Furthermore, warming effect from deforestation could exacerbate tree mortality under high temperatures and induced water stress [*Park Williams et al*., 2012; *Allen et al*., 2015], further reducing forest cover.

5. Conclusions

In this study we propose a method to quantify forest change impact on surface temperature change. Since forest change is occurring widely but nonuniformly across space and time, such potential impact could be very useful to predict the possible temperature impact of forest changes that have not yet occurred, while actual impact could be used to understand how much the forest changes that have taken place have contributed to the observed temperature change. This approach can help build a necessary evaluation tool, which is currently not available, to assess local climate impacts of forest change and other types of land cover change at the global scale. It would benefit climate models in developing new metrics to evaluate model performance [*Lawrence et al*., 2016] and also provides independent observational evidence to verify model results [*Winckler et al*., 2016] on the land cover change impact. Meanwhile, it highlights the need for climate modeling to incorporate more realistic scenarios that can provide useful information relevant to forest and agriculture planning. For the first time, we provide direct observational evidence for the impact of forest change on temperature trends at the global scale. Our results have important implications for guiding forestry policy. It clearly supports the cooling benefits of afforestation and preventing deforestation on local climate in low and middle latitudes. The opposite is observed in high latitudes, where deforestation leads to cooling while afforestation leads to warming. These results can raise public understanding of how changes in nearby forest cover can change local climate and can also inform forest policy making at local and regional scales.

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