The Nonradiative Effect Dominates Local Surface Temperature Change Caused by Afforestation in China

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(Manuscript received 11 November 2018, in final form 18 April 2019)

ABSTRACT

China is several decades into large-scale afforestation programs to help address significant ecological and environmental degradation, with further afforestation planned for the future. However, the biophysical impact of afforestation on local surface temperature remains poorly understood, particularly in midlatitude regions where the importance of the radiative effect driven by albedo and the nonradiative effect driven by energy partitioning is uncertain. To examine this issue, we investigated the local impact of afforestation by comparing adjacent forest and open land pixels using satellite observations between 2001 and 2012. We attributed local surface temperature change between adjacent forest and open land to radiative and nonradiative effects over China based on the Intrinsic Biophysical Mechanism (IBM) method. Our results reveal that forest causes warming of 0.23°C ($\pm 0.21^\circ\text{C}$) through the radiative effect and cooling of -0.74°C ($\pm 0.50^\circ\text{C}$) through the nonradiative effect on local surface temperature compared with open land. The nonradiative effect explains about 79% ($\pm 16\%$) of local surface temperature change between adjacent forest and open land. The contribution of the nonradiative effect varies with forest and open land types. The largest cooling is achieved by replacing grasslands or rain-fed croplands with evergreen tree types. Conversely, converting irrigated croplands to deciduous broadleaf forest leads to warming. This provides new guidance on afforestation strategies, including how these should be informed by local conditions to avoid amplifying climate-related warming.

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1. Introduction

Afforestation is one mitigation strategy that has been proposed to help efforts to limit global warming to 2°C above preindustrial levels, as trees are long-lived stores of carbon (Canadell and Raupach 2008; Jackson et al. 2008; Pacala and Socolow 2004). However, afforestation also affects local and regional climate through biophysical processes (Anderson et al. 2011; Bonan 2008; Bright et al. 2015). For example, forests tend to have lower albedo than grasslands and croplands, which can cause warming of local temperature following afforestation (the radiative effect). Forests also tend to have larger leaf area index, deeper roots, and higher aerodynamic roughness length, which promote evapotranspiration and cooling of local temperature (the nonradiative effect). The balance of the radiative and nonradiative effects explains whether afforestation would reduce or amplify cooling benefits associated with the removal of atmospheric CO₂ following afforestation.

Evidence from both observations (Alkama and Cescatti 2016; Duveiller et al. 2018; Lee et al. 2011; Li et al. 2015) and models (Arora and Montenegro 2011; Bala et al. 2007; Davin and de Noblet-Ducoudré 2010; Devaraju et al. 2018) suggests that the radiative effect of afforestation dominates at high latitudes and the nonradiative effect is more important in the tropics. In temperate regions, the radiative and nonradiative effects tend to counterbalance (Perugini et al. 2017). Climate models (Arora and Montenegro 2011; Bala et al. 2007; Davin and de Noblet-Ducoudré 2010) simulate a warming effect while observations (Alkama and Cescatti 2016; Burakowski et al. 2018; Duveiller et al. 2018; Li et al. 2015; Schultz et al. 2017; Wang et al. 2018) point to cooling. Recent studies also suggest afforestation can impact temperature extremes (Findell et al. 2017; Skinner et al. 2018; Teuling et al. 2010) although modeling of these processes is very uncertain (Avila et al. 2012; Li et al. 2018; Pitman et al. 2012). Despite these uncertainties, the biophysical effects of afforestation on climate need to be considered, especially at local and regional scales where afforestation strategies are being implemented, to avoid risk of maladaptation (Anderson et al. 2011; Bonan 2008).

To separate the radiative and nonradiative effects of land use and land cover change (LULCC), extensive studies (e.g., Davin and de Noblet-Ducoudré 2010; Juang et al. 2007; Lee et al. 2011; Luyssaert et al. 2014) have been carried out in the past decade. These studies can be basically divided into two categories based on the method utilized. One group uses sensitivity experiments based on climate models (Davin and de Noblet-Ducoudré 2010). For example, using a fully coupled global climate model, Davin and de Noblet-Ducoudré

(2010) quantified the radiative and nonradiative effects of global deforestation via sensitivity experiments examining parameters associated with albedo, roughness, and evapotranspiration efficiency. A second group uses a decomposition of the surface energy balance equation based on observations from adjacent in situ sites with different land covers (e.g., Juang et al. 2007; Lee et al. 2011; Luyssaert et al. 2014). For example, the Intrinsic Biophysical Mechanism (IBM) method (Lee et al. 2011) attributes local surface temperature change to a radiative forcing term associated with changes in albedo, and an energy redistribution term associated with changes in both the surface aerodynamic resistance and the partitioning of sensible and latent heat fluxes. An advantage of the IBM method lies in a distinction between external forcing and internal feedback (Lee et al. 2011). Thus, the IBM method is efficiently applicable to the separation of the radiative and nonradiative processes caused by afforestation or deforestation. However, both methods have apparent limitations. The in situ observations are geographically restricted, while climate models are subjected to uncertainties in the implementation of land cover change, the representation of crop phenology, and the parameterization of albedo and evapotranspiration (Pitman et al. 2009). Recently, satellite observations have been widely used to investigate the impact of LULCC on local surface temperature (Duveiller et al. 2018; Li et al. 2015; Peng et al. 2014). Bright et al. (2017) further utilized satellite observations to quantify the radiative and nonradiative effects of historical LULCC globally filling the gap between in situ observations and model simulations.

To address growing environmental and ecological concerns associated with rapid economic growth, the Chinese government has initiated a series of national afforestation programs including the Three-North Shelterbelt Development Program, the Natural Forest Conservation Program, and the Grain for Green Program (Bryan et al. 2018; Fu et al. 2017; Liu et al. 2008). Benefiting from these afforestation programs, China has exhibited a world-leading greening trend in the past few decades (Hua et al. 2017; Liu et al. 2015; Piao et al. 2015; Chen et al. 2019). However, the radiative and nonradiative effects of afforestation over China remains uncertain, although the local cooling effect of afforestation has been widely demonstrated by modeling (Ma et al. 2013), in situ observations (Wang et al. 2018), and satellite observations (Ma et al. 2017; Peng et al. 2014). Very few studies attributed the afforestation-induced local surface temperature change to the radiative and nonradiative effects over China, although we note that Wang et al. (2018) did examine this issue using a pair of sites over northern China. Bright et al. (2017)

TABLE 1. Information for IGBP classes.

Class	Class name	Description
1	Evergreen needleleaf forests (ENF)	Lands dominated by needleleaf woody vegetation with a percent cover > 60% and height exceeding 2 m. Almost all trees remain green all year. Canopy is never without green foliage.
2	Evergreen broadleaf forests (EBF)	Lands dominated by broadleaf woody vegetation with a percent cover > 60% and height exceeding 2 m. Almost all trees and shrubs remain green year round. Canopy is never without green foliage.
3	Deciduous needleleaf forests (DNF)	Lands dominated by woody vegetation with a percent cover > 60% and height exceeding 2 m. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
4	Deciduous broadleaf forests (DBF)	Lands dominated by woody vegetation with a percent cover > 60% and height exceeding 2 m. Consists of broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods.
5	Mixed forests (MF)	Lands dominated by trees with a percent cover > 60% and height exceeding 2 m. Consists of tree communities with interspersed mixtures or mosaics of the other four forest types. None of the forest types exceeds 60% of landscape.
10	Grasslands (GRA)	Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.
12	Croplands (CRO)	Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems). Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type.

investigated the radiative and nonradiative effects as a result of LULCC globally, while they performed less analysis on the local impact of afforestation in China. Here we choose to focus on China and tackle the radiative and nonradiative effects of afforestation at more local scale.

Our study aims to attribute afforestation-induced local surface temperature change to the radiative and nonradiative effects over mainland China. This is crucial in understanding the local biophysical effects of historical and future afforestation in this midlatitude country, where large uncertainties remain. To this end, we first examine the local impact of afforestation using satellite observations by “trading space for time,” that is, pairing adjacent forest and open land pixels. We then applied the IBM method to each paired set of pixels to quantify the radiative and nonradiative effects of afforestation. The space-for-time strategy makes our study performed at more local scale than [Bright et al. \(2017\)](#). Moreover, our use of the space-for-time strategy can help to compare the local surface temperature change between forest and open land calculated by the IBM method against the observed value at the continental scale. We also examined the relative benefit of one forest functional type over another in contributing to local surface temperature change. Investigation of the overall impact of afforestation over China is urgent since the Chinese government plans to expand afforestation in the near future ([Bryan et al. 2018](#); [Fu et al. 2017](#); [Liu et al. 2008](#)). We therefore seek to explore whether these plans are likely to warm or cool mainland China, and to help resolve the large uncertainty in the balance of radiative

and nonradiative processes influencing local surface temperature over the midlatitudes.

2. Methods and datasets

a. Space-for-time method

A space-for-time strategy ([Zhao and Jackson 2014](#)) based on the land cover product was used to investigate the local impacts of afforestation. This method is based on the assumption that adjacent forest and open land pixels share the same background climate so that local differences between forest and open land pixels can be attributed to land cover change ([Li et al. 2015](#); [Peng et al. 2014](#); [Zhao and Jackson 2014](#)). Land cover type was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) yearly land cover product (MCD12C1, version 051; [Friedl et al. 2010](#)), which provides dominant land cover type based on the International Geosphere Biosphere Programme (IGBP) scheme ([Table 1](#)) at a spatial resolution of 0.05° from 2001 to 2012. Year-to-year variation in land cover is common in the MODIS product, caused by either actual land cover changes or misclassification ([Friedl et al. 2010](#)). To minimize this problem, we only used pixels with the same class for at least 9 of the 12 years (from 2001 to 2012; [Ma et al. 2017](#)). A 12-yr synthesized land cover map is shown in [Fig. 1a](#). In our study “forest” contains five IGBP classes including evergreen needleleaf (ENF), evergreen broadleaf (EBF), deciduous needleleaf (DNF), deciduous broadleaf (DBF), and mixed (MF) forest. “Open land” contains grasslands

FIG. 1. (a) A 12-yr (2001–12) synthesized land cover map (see section 2) over mainland China and embedded schematic of the space-for-time method. To calculate the local differences between forest and open land in each paired site, in this example an average was first calculated over mixed forests and compared with the central croplands pixel (including both irrigated and rain-fed crops). This calculation was repeated for every croplands pixel. We then aggregated this to a $1^\circ \times 1^\circ$ grid cell. (b) Spatial and (c) latitudinal distribution of grid cells containing valid samples. Colors denote terrain height (m). Large, medium, and small dots represent more than 40, between 10 and 40, and less than 10 samples at each $1^\circ \times 1^\circ$ grid cell, respectively (note that calculations were performed at native resolution, but displayed at $1^\circ \times 1^\circ$).

(GRA) and croplands (CRO). Following the MODIS classification, CRO includes both rain-fed croplands (RFC) and irrigated croplands (IRC) (Table 1).

To pair adjacent forest and open land pixels, we defined a circle area with a radius of 20 km centered on

an open land pixel (Fig. 1a). Any forest pixels within the circle area and the reference open land pixel were paired as a valid sample. To reduce the influence of altitudinal differences between the paired forest and open land pixels, especially on surface temperature, the forest

TABLE 2. Details of the specific datasets used in this study.

Variables	Resources	Time span	Temporal resolution	Spatial resolution
Land cover	MCD12C1	2001–12	Yearly	0.05°
Land cover	MCD12Q1	2001–12	Yearly	500 m
Irrigation area	HID	2005	Yearly	5'
Land surface temperature	MOD11C3	2001–12	Monthly	0.05°
	MYD11C3	2002–12	Monthly	0.05°
Albedo	GLASS	2001–12	8 days	0.05°
Albedo look-up maps	LUMs	—	Monthly	0.05°
Latent heat flux	MOD16A2	2001–12	Monthly	0.05°
Elevation	SRTM30	—	—	30''
Air temperature	ITPCAS	2001–12	Monthly	0.1°
Precipitation	ITPCAS	2001–12	Monthly	0.1°
Downward shortwave	ITPCAS	2001–12	Monthly	0.1°
Downward longwave	ITPCAS	2001–12	Monthly	0.1°
Leaf area index	GLASS	2001–12	8 days	0.05°
Snow cover	MOD10CM	2001–12	Monthly	0.05°
	MYD10CM	2002–12	Monthly	0.05°

pixels within the circle but with elevation bias exceeding 100 m compared with the reference open land pixel were discarded. Elevation was from the Shuttle Radar Topography Mission (SRTM30 version 2.0) digital elevation model with a spatial resolution of 30'', and then aggregated to 0.05° for consistent spatial resolution with land cover. The space-for-time strategy was applied to every open land pixel covering mainland China, producing 10 971 samples in total. We then aggregated these samples to 1° × 1° grid cells to aid visualization (Fig. 1b). Aggregating these samples to a finer resolution (e.g., 0.5° × 0.5°) causes negligible impact on our result (not shown). The 20-km limit is within the range of distance limits specified in previous studies (Lee et al. 2011; Peng et al. 2014; Zhang et al. 2014; Zhao and Jackson 2014). A sensitivity test shows a very small impact from varying distance limits within reasonable range between adjacent forest and open land pixels (Li et al. 2015).

b. Quantification of the observed local impacts of afforestation

Local impact of afforestation in each sample for a given year and month is quantified by

$$\Delta\zeta = \overline{\zeta_{\text{forest}}} - \zeta_{\text{openland}}, \quad (1)$$

where ζ could denote a monthly climate variable [e.g., albedo (α), leaf area index (LAI), latent heat flux (Q_E), sensible heat flux (Q_H), and surface temperature (T_s); Table 2]; the overbar represents the averaged value of the forest pixels in each sample. The monthly $\Delta\zeta$ was then averaged to achieve multiyear monthly mean or annual mean values of the ζ change.

Albedo α was obtained from the GLASS 8-day albedo product with a spatial resolution of 0.05° (Liang and Liu

2012; Table 2). As the MODIS land cover product is only available from 2001 to 2012, we used the same time range for other data to ensure temporal consistency. The MODIS product provides directional hemispherical albedo (black-sky albedo), bihemispherical albedo (white-sky albedo), and actual albedo (blue-sky albedo), and we used the blue-sky albedo. We only used the “good” data (with the criterion of an uncertainty of less than 0.01 absolutely or 5% relatively) and “acceptable” data (with the criterion of an uncertainty of less than 0.05 absolutely or 10% relatively).

We used the GLASS 8-day LAI product from 2001 to 2012 derived from the MODIS surface reflectance products (Liang and Xiao 2012; Table 2) due to its relatively high spatial resolution (0.05°). Extensive validations demonstrate that the retrieval method used in the LAI product can estimate temporally continuous LAI profiles with better accuracy compared with current MODIS and CYCLOPES LAI products (Xiao et al. 2014). To match other data in the temporal resolution, both the GLASS 8-day α and LAI data were composed to monthly data (Gao et al. 2014).

We obtained Q_E from the MODIS monthly terrestrial evapotranspiration product (MOD16A; Mu et al. 2011; Table 2) ranging from 2001 to 2012. The algorithm of MOD16A is based on the Penman–Monteith equation, which is implemented to calculate the soil evaporation, the canopy evaporation, and the plant transpiration. Following the separate calculations, all components are summed to achieve surface Q_E (Mu et al. 2011). The MOD16A terrestrial evapotranspiration product has been proven to perform well through validating estimated Q_E against the observed values across 46 field-based eddy covariance flux towers (Running et al. 2017).

Values of T_s were obtained from MODIS *Terra* (MOD11C3, version 006) and *Aqua* (MYD11C3, version 006) monthly land surface temperature/emissivity products (Wan 2014) from 2001 to 2012 (MYD11C3 started from July 2002). Both provide daytime (1030 LT for *Terra* and 1330 LT for *Aqua*) and nighttime (2230 LT for *Terra* and 0130 LT for *Aqua*) T_s under clear-sky condition at a spatial resolution of 0.05° . Only “good quality data” and “other quality data” but with estimated emissivity error ≤ 0.02 and T_s error ≤ 1 K were used (Li et al. 2015). Daily mean T_s can be estimated by averaging daytime and nighttime T_s obtained either from MOD11C3 or MYD11C3. If the daily mean T_s was available from both MOD11C3 and MYD11C3, we used the mean value of both; otherwise, we used the available one (Chen et al. 2017).

Because Q_H cannot be directly acquired from satellite observations, the Q_H change was calculated from the surface energy balance equation:

$$SW\downarrow(1 - \alpha) + LW\downarrow - \sigma T_s^4 = Q_H + Q_E + G, \quad (2)$$

where $SW\downarrow$ and $LW\downarrow$ are downward shortwave and longwave radiation, respectively, σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$), and G is the heat storage in the soil and biomass. As the space-for-time method assumes that the adjacent forest and open land pixels share the same background climate, the difference in $LW\downarrow$ can be ignored. It is also reasonable to omit the difference in G between adjacent forest and open land pixels as this value is negligible at time scales longer than one day (Lee et al. 2011). Ignoring the change in $LW\downarrow$ and G , the difference in Q_H between forest and open land is

$$\Delta Q_H = -SW\downarrow \Delta\alpha - \sigma(T_{s,\text{forest}}^4 - T_{s,\text{openland}}^4) - \Delta Q_E, \quad (3)$$

where $\Delta\alpha$ and ΔQ_E are the differences in albedo and latent heat flux, respectively, between forest and open land calculated from Eq. (1), and $T_{s,\text{forest}}$ and $T_{s,\text{openland}}$ are land surface temperature at forest and open land pixels, respectively; $SW\downarrow$ was from the China Meteorological Forcing Dataset (Yang et al. 2010) from 2001 to 2012 at a spatial resolution of 0.1° (Table 2). The dataset is produced by merging multiple data sources and has the highest spatiotemporal resolution among all reanalysis data covering China. The $SW\downarrow$ data were bilinearly interpolated to a spatial resolution of 0.05° . Note that as ΔQ_H is calculated based on other variables, ΔQ_H inevitably inherits uncertainties contained in other dataset including $SW\downarrow$, α , and Q_E and therefore a larger uncertainty in ΔQ_H should be expected.

c. Attribution of local surface temperature change

The IBM method (Lee et al. 2011) was used to attribute afforestation induced local T_s change to radiative and nonradiative effects. The IBM method is derived based on some basic assumptions. In addition to the same amount of downward shortwave and longwave radiation received by adjacent forest and open land, the IBM method assumes air is sufficiently blended within the boundary so that air temperature at blending height is identical between forest and open land (Lee et al. 2011). This assumption is also supported by Winckler et al. (2018), who concluded that there is basically no difference in the temperatures of the lowest atmospheric layer between neighboring model grid boxes with forest and open land. Ignoring minor change in surface emissivity (Lee et al. 2011; Juang et al. 2007), changes in monthly mean T_s due to land cover change can be decomposed into three terms:

$$\Delta T_s = \frac{\lambda_0}{(1+f)} \Delta R_n^* + \frac{-\lambda_0}{(1+f)^2} (R_n^* - G) \Delta f + \frac{-\lambda_0}{(1+f)} \Delta G, \quad (4)$$

where λ_0 is monthly mean land surface temperature sensitivity resulting from the longwave radiation feedback ($\lambda_0 = 1/4\sigma T_s^3$) and f is the monthly mean energy redistribution factor:

$$f = \frac{\rho C_p}{4r_a \sigma T_s^3} \left(1 + \frac{1}{\beta}\right), \quad (5)$$

where ρ is monthly mean air density, C_p is monthly mean specific heat of air at constant pressure, r_a is monthly mean aerodynamic resistance, β is monthly mean Bowen ratio (defined as the ratio of monthly mean Q_H and Q_E), and R_n^* is monthly mean apparent net radiation:

$$R_n^* = SW\downarrow(1 - \alpha) + LW\downarrow - \sigma T_a^4, \quad (6)$$

where T_a is monthly mean air temperature at a blending height within the atmospheric boundary layer, which approximates monthly surface air temperature. The IBM method further assumes $\Delta R_n^* = -SW\downarrow \Delta\alpha$ and $R_n^* \approx SW\downarrow(1 - \alpha) + LW\downarrow - \sigma T_s^4$. The first, second, and third right-hand terms of Eq. (4) represent the afforestation-induced local T_s change driven by α , f , and G change, respectively. Equation (4) slightly differs from the original IBM equation (Lee et al. 2011) as we retained the local T_s change driven by G to keep the consistency with the equation used by Bright et al. (2017). To differentiate, the local T_s changes obtained from Eqs. (1) and (4) are called the observed and calculated T_s change, respectively, hereafter.

TABLE 3. Values and standard errors shown in parentheses of parameters required in the semi-mechanistic empirical model used to estimate the energy redistribution factor for each IGBP class (ENF: evergreen needleleaf forest, EBF: evergreen broadleaf forest, DBF: deciduous broadleaf forest, GRA: grasslands, IRC: irrigated croplands, RFC: rain-fed croplands; Bright et al. 2017).

	k_1	k_2	k_3	a	b	c	m	n
ENF	-0.49 (0.07)	3.89 (0.07)	-3.2×10^{-3} (5.7×10^{-4})	315 (0.34)	5.2 (0.01)	-0.53 (0.11)	-3.98 (0.09)	0.030 (5.9×10^{-4})
EBF	-0.72 (0.92)	3.29 (0.08)	-9.4×10^{-5} (5.9×10^{-4})	327 (0.88)	5.4 (0.03)	-3.4 (0.12)	-5.29 (0.18)	0.044 (1.3×10^{-3})
DBF	1.04 (0.43)	4.22 (0.31)	-8.7×10^{-3} (7.2×10^{-4})	324 (0.57)	5.3 (9.4×10^{-3})	-2.1 (0.08)	-5.90 (0.21)	0.032 (1.1×10^{-3})
GRA	-0.52 (0.06)	5.80 (0.13)	-8.5×10^{-3} (6.3×10^{-4})	323 (0.08)	5.3 (3.1×10^{-3})	-0.02 (0.06)	-7.19 (0.23)	0.054 (1.4×10^{-3})
IRC	-0.08 (0.18)	4.36 (0.27)	-6.6×10^{-3} (1.7×10^{-3})	312 (0.19)	5.8 (6.1×10^{-3})	0.26 (0.07)	-6.85 (0.35)	0.058 (2.6×10^{-3})
RFC	-0.52 (0.09)	5.12 (0.19)	-6.8×10^{-3} (1.6×10^{-3})	312 (0.19)	5.8 (6.1×10^{-3})	0.26 (0.07)	-6.85 (0.35)	0.058 (2.6×10^{-3})

The aerodynamic resistance r_a , which is required in calculating f [Eq. (5)], is absent at continental scale. Thus we estimated monthly mean vegetation dependent f_v using a semi-mechanistic empirical f model developed by Bright et al. (2017) as

$$f_v = k_1 + \frac{1/4\sigma T_a}{k_2 \exp(\alpha_v) + k_3 P} [\text{SW} \downarrow (1 - \alpha_v) + \text{LW} \downarrow - \text{LW} \uparrow_v - G_v], \quad (7)$$

where k_1 , k_2 , and k_3 are empirical parameters (Table 3) and P is monthly total precipitation (mm month^{-1}). The subscript v used here denotes the vegetation dependent variable. Also, α_v , $\text{LW} \uparrow_v$, and G_v were calculated following Bright et al. (2017) as

$$\alpha_v = \alpha_{\text{sc},v}(F_{\text{sc}}) + \alpha_{\text{sf},v}(1 - F_{\text{sc}}), \quad (8)$$

$$\text{LW} \uparrow_v = a + b(T_a) + c(\text{LAI}), \quad \text{and} \quad (9)$$

$$G_v = m + n\text{SW} \downarrow_v(1 - \alpha_v), \quad (10)$$

where $\alpha_{\text{sc},v}$ and $\alpha_{\text{sf},v}$ are monthly mean albedo under snow cover and snow-free conditions respectively, F_{sc} is monthly mean snow cover percentage, LAI is multiyear (2001–12) annual mean leaf area index from GLASS, and a , b , c , m , and n are empirical parameters derived from global FLUXNET data (Bright et al. 2017; Table 3).

The terms $\alpha_{\text{sc},v}$ and $\alpha_{\text{sf},v}$ were from multiscale climatological albedo look-up maps (LUMs; Gao et al. 2014), which provide monthly statistics of white-sky and black-sky albedo for each IGBP class for shortwave broadband under both snow-free and snow-covered conditions with a spatial resolution of 0.05° (Table 2). It is generated using a multiscale hierarchical approach based on the MODIS bidirectional reflectance distribution function (BRDF)/albedo products from 2001 to 2011 and Landsat imagery. Unlike traditional look-up tables, the LUM data are geographically specific, which means that albedo for a given land cover type varies spatially to reflect the diversity in vegetation type, soil background or land management (Gao et al. 2014; Ghimire et al. 2014). To obtain the blue-sky albedo, we simply averaged the black-sky and white-sky albedo owing to a small difference and a high correlation coefficient between the average value and blue-sky albedo (Li et al. 2015).

The term F_{sc} was obtained by averaging snow cover percentages provided from MODIS *Terra* (MOD10CM, version 006) and *Aqua* (MYD10CM, version 006) monthly snow cover products (Hall and Riggs 2015) with a spatial resolution of 0.05° from 2001 to 2012 (Table 2).

The terms T_a , P , and $LW\downarrow$ were from the China Meteorological Forcing Dataset (Yang et al. 2010) from 2001 to 2012 and bilinearly interpolated to a spatial resolution of 0.05° (Table 2). All input variables in Eqs. (7)–(10) except LAI are multiyear averaged monthly mean values following Bright et al. (2017). Applying the IBM method and the f model to each sample, we obtained the potential T_s change as well as each component driven by α , f , and G change respectively caused by converting one forest class to one open land class.

d. Calculation of actual T_s change

To facilitate comparing the calculated T_s change against the observed value, we then calculated the actual T_s change. The area percentage should be taken into consideration as one forest or open land pixel is often covered by multiple vegetation classes. We assume the calculated T_s change caused by one conversion type is proportional to the area percentage of both classes before and after this conversion. Thus the actual T_s change between forest and open land pixels in each sample is expressed as

$$\Delta T_s = \sum_{i=\text{GRA,IRC,RFC}} \sum_{j=\text{ENF,EBF,DBF}} F_i F_j \Delta T_{s,i \rightarrow j}, \quad (11)$$

where $\Delta T_{s,i \rightarrow j}$ is potential T_s change caused by land cover changing from class i to j calculated from Eqs. (4)–(10), F_i is the area percentage of GRA, IRC, or RFC at the open land pixel, and F_j is the averaged area percentage of ENF, EBF, or DBF at paired forest pixels for each sample.

The area percentage of each IGBP class at every pixel is provided in MCD12C1 but there are two challenges to overcome. First, a large portion of forest is dominated by mixed forest (MF) class in China (Fig. 1a), which cannot be calculated from Eqs. (7)–(10) due to missing parameters (e.g., k_1 , m) required for this class. Second, the croplands are not separated into IRC and RFC in the MODIS land cover product. To compromise, we assume MF as a proportional combination of ENF, EBF, and DBF based on the area percentage of plant function type (PFT), which are multiyear averaged values in the same period from MCD12Q1 PFT scheme (Table 2, Fig. 2). The area percentage of IRC was from the Historical Irrigation Dataset (Siebert et al. 2015; see Table 2 and Fig. 2 herein). The residual of CRO by subtracting IRC is assumed as RFC (Fig. 2). DNF is not considered due to absent values of parameters (e.g., k_1 , a , m) and its relative rarity in mainland China (Fig. 2). Similarly, the calculated T_s change as well as local T_s change driven by α , f , and G change from Eqs.

(4) to (11) were obtained at a spatial resolution of 0.05° and then aggregated to $1^\circ \times 1^\circ$ grid cells to aid visualization and facilitate comparison between observed and calculated T_s change.

e. Quantification of the contribution from nonradiative effects

The T_s change driven by α [$\Delta T_{s,\alpha}$; first right-hand term of Eq. (4)] is defined as the radiative effect and both the T_s change driven by f [$\Delta T_{s,f}$; second right-hand terms of Eq. (4)] and G [$\Delta T_{s,G}$; third right-hand terms of Eq. (4)] are defined as the nonradiative effect. Thus, a non-radiative forcing index (NRFI; Bright et al. 2017) was used to compare the importance of the radiative and nonradiative effects of afforestation in driving local T_s change:

$$\text{NRFI} = \frac{|\Delta T_{s,f}| + |\Delta T_{s,G}|}{|\Delta T_{s,\alpha}| + |\Delta T_{s,f}| + |\Delta T_{s,G}|} \times 100\%. \quad (12)$$

The NRFI ranges between 0% and 100%, with a larger value corresponding to a stronger contribution from nonradiative effects of afforestation. The NRFI was also obtained at 0.05° resolution and then aggregated to $1^\circ \times 1^\circ$ for better visualization.

f. Significance test

The statistical significance test used in our study is based on the two-tailed Student's t test. We applied the t test to each $1^\circ \times 1^\circ$ grid cell to examine whether the local biophysical difference between forest and open land pixels within each grid cell is statistically significant at a 95% confidence level.

g. Uncertainty test

The calculated T_s change could be potentially affected by the reasonable ranges of the parameters (Table 3) employed in the f model [Eq. (7)]. To quantify this impact, we performed an uncertainty test by adding a perturbation to the parameters in the f model:

$$f_{v,\pm\sigma} = (k_1 \pm \sigma_{k_1}) + \frac{1/4\sigma T_a}{(k_2 \pm \sigma_{k_2})\exp(\alpha_v) + (k_3 \pm \sigma_{k_3})P} \times [\text{SW}\downarrow(1 - \alpha_v) + \text{LW}\downarrow - \text{LW}\uparrow_v - G_v], \quad (13)$$

where the terms σ_{k_1} , σ_{k_2} , and σ_{k_3} are the standard errors of k_1 , k_2 , and k_3 respectively (Table 3). Equation (13)

FIG. 2. Area percentage (%) of (a) evergreen needleleaf forest, (b) deciduous broadleaf forest, (c) evergreen broadleaf forest, (d) grasslands, (e) irrigated croplands, (f) rain-fed croplands, and (g) deciduous needleleaf forest at a spatial resolution of 0.05° over mainland China.

shows that f_v is calculated with plus and minus one standard error in the parameters k_1 , k_2 , and k_3 , respectively. Other parameters (a , b , c , m , and n) are not considered here owing to more negligible influences caused by the reasonable variations in these parameters (Bright et al. 2017). We note that we are not trying to quantify the range of the calculated T_s change induced by the uncertainty in the parameters owing to a highly nonlinear relationship between the calculated T_s change and those parameters. Instead we simply test how much the calculated T_s change can be impacted by plus or minus a standard error in the parameters utilized in the f model.

3. Results

a. Impacts on land surface biophysical parameters

Converting open land to forest directly affects the land surface biophysical parameters (e.g., α , LAI, and Z_0) and we therefore first examined differences between

forest and open land. Averaged over the colored grid cells, forest has a lower α ($-2.63\% \pm 2.72\%$, spatial mean $\pm$ spatial standard deviation hereafter) than open land (Fig. 3a). The α difference between forest and open land varies spatially, with a larger decrease ($>15\%$) in the high latitudes and altitudes, and a smaller decrease ($<3\%$) in most mid- and low latitudes and altitudes (Figs. 1b, 3a). This spatial heterogeneity of α change is associated with snow cover that is common or long-lived at high latitudes and high altitudes. Snow cover is infrequent or short lived in middle and low latitudes and altitudes [see Li et al. (2008) for details of the temporal and spatial variability in snow cover over China]. Under snow cover conditions α can be further decreased by the “masking effect” of snow under taller canopy of forest. This is more evident from an enhanced α decrease shown at high latitudes in cold seasons (Fig. 3b). Forest has a greater LAI ($0.70 \pm 0.37 \text{ m}^2 \text{ m}^{-2}$) than open land averaged over the colored grid cells (Fig. 3c). A larger increase in LAI occurs in the southeast coastal region (Fig. 3c) mainly due to a large proportion of EBF

FIG. 3. Annual mean differences in (a) albedo α (%) and (c) LAI ($\text{m}^3 \text{m}^{-3}$) between forest and open land (forest minus open land), and seasonal and latitudinal differences in (b) α and (d) LAI between forest and open land (forest minus open land). Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

(Fig. 2c), which can maintain a larger LAI than open land throughout the year (Fig. 3d). For other regions dominated by DBF, LAI increases more in warm seasons ($>0.6 \text{ m}^2 \text{m}^{-2}$) and changes little in cold seasons ($<0.3 \text{ m}^2 \text{m}^{-2}$) (Fig. 3d). As would be expected, replacing open land with forest darkens and “greens” the surface. Overall, the magnitude of changes in α and LAI mainly depends on seasonal snow cover and the type of forest grown respectively.

Forests usually have a greater Z_0 than open land owing to their height and canopy structure (Monteith 1975). While an increase in LAI would tend to increase Q_E if moisture is available, a greater Z_0 increases both Q_H and Q_E at the same time through enhanced turbulence. How the surface available energy is partitioned between Q_H and Q_E changes due to afforestation thus depends on how both LAI and Z_0 change. The energy redistribution factor f derived from the IBM method is inversely related to both aerodynamic resistance and the Bowen ratio [Eq. (5)], suggesting f can be intensified by high surface roughness and larger evapotranspiration.

The f is therefore a measure of the combined biophysical and physiological control of vegetation on energy partitioning. Converting open land to forest causes an increase in f in most cases, but the magnitude of the change varies with forest and open land types (Fig. 4). A larger increase in f can be achieved by converting open land to EBF, while a smaller increase in f occurs when open land is replaced by DBF. The choice of open land types can further modulate this process and converting GRA and RFC to forest tends to cause a larger f increase, but converting IRC to forest leads to a smaller increase in f . These discrepancies in f responses to various conversion types are mainly explained by a large difference in f change in warm seasons, when converting GRA or RFC to EBF increases f by up to 4.0 but converting IRC to DBF increases f by no more than 1.0 and decreases f occasionally (Fig. 5).

b. Impacts on land surface fluxes

We next examined how the land surface fluxes respond to biophysical change. Averaging over the colored grid

FIG. 4. Annual mean differences in energy redistribution factor f between forest (ENF: evergreen needleleaf forest, DBF: deciduous broadleaf forest, EBF: evergreen broadleaf forest) and open land (GRA: grasslands, IRC: irrigated croplands, RFC: rain-fed croplands, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows the difference in f between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

cells, forest has a larger Q_E ($4.91 \pm 5.20 \text{ W m}^{-2}$) than open land at annual scales (Fig. 6a). Locally, the increase in Q_E can exceed 25 W m^{-2} , such as in the southeast coast region; however, the Q_E change is negligibly small in a few western regions. The Q_H difference between forest and open land is overall small ($0.49 \pm 7.00 \text{ W m}^{-2}$) over colored grid cells because of a large spatial variability, varying from an increase of exceeding 25 W m^{-2} in the west to a decrease of up to 20 W m^{-2} in the southeast (Fig. 6c). The Q_H change presents clear seasonal variations, with an increase in cold seasons and a decrease in warm seasons (Fig. 6d). The term Q_E shows an opposite overall pattern to Q_H although the change in cold seasons is very weak (Fig. 6b). These latitudinal and seasonal variations of Q_H and Q_E are closely associated with the biophysical changes. Specifically, afforestation increases LAI (Figs. 3c,d) and Z_0 , which increase the evapotranspiration efficiency (represented by f , Figs. 4 and 5). Also, Q_E is further enhanced by the decrease in α (Figs. 3a,b). In addition, we also note an important role of background

climate in determining Q_H and Q_E changes driven by afforestation. This is evident in some western and northern regions that are characterized by arid or semiarid background climate (Fig. 6a). Here, the impact of afforestation on Q_E is likely to be water limited. In this case the increased absorbed radiation caused by the α decrease is more efficiently dissipated via Q_H over forest (Fig. 6c) enabled by the larger Z_0 and lower aerodynamic resistance. This phenomenon was also previously reported in other semiarid regions where forest is compared to open land (Rotenberg and Yakir 2010).

c. Impacts on land surface temperature

The observed T_s change between forest and open land over the colored grid cells mainly shows a cooling effect ($-0.32^\circ \pm 0.37^\circ\text{C}$) at the annual scale (Figs. 7a and 8). Coincident with the biophysical and surface fluxes changes, the observed T_s change depicts seasonal and latitudinal variability, with a cooling in warm seasons and warming in cold seasons at high latitudes (Fig. 7b).

FIG. 5. Seasonal and latitudinal differences in energy redistribution factor f between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows the difference in f between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

FIG. 6. Annual mean differences in (a) latent heat flux Q_E (W m^{-2}) and (c) sensible heat flux Q_H (W m^{-2}) between forest and open land (forest minus open land), and seasonal and latitudinal differences in (b) Q_E and (d) Q_H between forest and open land (forest minus open land). Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

Before the attribution of afforestation induced local T_s change to radiative and nonradiative effects, we first validated the calculated T_s change against the observed value. Annually the calculated T_s change can produce a similar cooling effect ($-0.53^\circ \pm 0.48^\circ\text{C}$) compared to the observed T_s change over the colored grid cells (Figs. 7c and 8). A larger difference between the observed and calculated T_s changes mainly occurs in the southwestern and northeastern regions (Figs. 7a,c). In terms of latitudinal and seasonal pattern, the calculated and observed T_s changes are overall consistent, with the calculated T_s change showing a warm bias at high latitudes in cold seasons and a cooling bias at low latitudes in warm seasons (Figs. 7b,d). In general, the calculated T_s change is spatially and temporally consistent with the observed T_s change (Figs. 7a–d) although with some discrepancies between them, which are detailed in the discussion section (section 4). The calculated T_s change caused by afforestation is a function of forest and open land classes (Figs. 9–11). In each conversion type, the area percentages of forest and open land

classes are not considered, indicating a theoretical maximum potential local T_s change associated with afforestation. A larger decrease in local T_s can be achieved by converting open land to EBF, followed by ENF and DBF (Figs. 9 and 10). Among all conversion types, replacing GRA with EBF has the largest cooling effect on local T_s ($-4.35^\circ \pm 1.15^\circ\text{C}$), although replacing GRA with ENF and DBF also results in about half the amount of cooling. Converting RFC to forests has a similar cooling effect to the GRA cases. However, the choice of IRC can weaken the cooling effect of afforestation, and occasionally generates an unexpected warming effect. This large variability in the cooling effect associated with different conversion types is mainly attributed to the local T_s change in warm seasons or at low latitudes (Fig. 11). In these cases local T_s can be decreased by over 5°C when GRA is converted to EBF but the replacement of IRC by DBF causes negligible change in local T_s . In cold seasons and at high latitudes afforestation always causes a warming effect.

FIG. 7. Annual mean values of (a) the observed surface temperature change $\Delta T_{s,obs}$ (°C), (c) the calculated T_s change $\Delta T_{s,cal}$ (°C), (e) the T_s change driven by albedo change $\Delta T_{s,\alpha}$ (°C), and (g) the T_s change driven by energy redistribution factor change $\Delta T_{s,f}$ (°C) between forest and open land (forest minus open land), and seasonal and latitudinal (b) $\Delta T_{s,obs}$, (d) $\Delta T_{s,cal}$, (f) $\Delta T_{s,\alpha}$, and (h) $\Delta T_{s,f}$ between forest and open land (forest minus open land). Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

FIG. 8. Annual mean values of the observed surface temperature change $\Delta T_{s,obs}$ (°C), the calculated surface temperature change $\Delta T_{s,cal}$ (°C), the surface temperature change driven by albedo change $\Delta T_{s,\alpha}$ (°C), the surface temperature change driven by energy redistribution factor change $\Delta T_{s,f}$ (°C), and the surface temperature change driven by the heat storage change $\Delta T_{s,G}$ (°C) between forest and open land (forest minus open land) averaged over colored grid cells (Fig. 7). The vertical error bar denotes the standard deviation. The circle and cross represent the values achieved by plus ($f + \sigma$) or minus ($f - \sigma$) a standard error in the parameters utilized in the f mode (see section 2), respectively. The values (spatial mean $\pm$ spatial standard deviation) of surface temperature change are provided at the bottom, and the nonradiative forcing index (NRFI) is provided at the top-right corner.

The radiative process driven by the α change causes a warming effect of 0.23°C ($\pm 0.21^\circ\text{C}$) on annual mean local T_s over the colored grid cells (Figs. 7e and 8). Larger values ($>0.5^\circ\text{C}$) mainly occur in the boreal and some mountain regions (Fig. 7f) due to an amplified α increase in cold seasons associated with snow (Fig. 3a). Forest and open land classes have a negligible impact on the radiative effect at annual scales, with a slightly larger warming effect achieved when open land is converted to ENF (Figs. 10 and 12). This can be mostly explained by a larger increase in local T_s driven by the change in α in warm seasons when open land is converted to ENF (up to 1.0°C ; Fig. 13).

The nonradiative process associated with f change generates a cooling effect of -0.74°C ($\pm 0.50^\circ\text{C}$) on the annual mean local T_s over all colored grid cells (Figs. 7g and 8). A much stronger cooling effect occurs in southwestern region, explaining much of the cooling bias in the calculated T_s change compared with the observed value. In contrast with the radiative effect, the cooling effect driven by f change is relatively small in cold seasons but prominent in warm seasons (Fig. 7h). The f change-induced local T_s change is also strongly dependent on forest and open land class (Figs. 10, 14, and 15). On

annual time scales, a much stronger cooling effect can be achieved by planting EBF, followed by ENF and DBF (Figs. 10 and 14). In terms of open land types, a similar amount of cooling generated by f change can be maintained in GRA- and RFC-related conversions, while it is diminished in IRC-related conversion. On seasonal scale, the cooling effect varies from over -5°C for GRA or RFC cases to negligibly small when IRC is converted to DBF in warm seasons. We also note that a large discrepancy in the local T_s change driven by f change occurs at high latitudes in cold seasons. Here, converting IRC to DBF mostly causes warming (up to 2°C) while converting RFC to EBF mostly cools (by 5°C). The contribution of soil and biomass heat storage to local T_s change perturbed by afforestation is negligible across all latitudes, seasons, and conversion types (not shown).

To compare the radiative and nonradiative effects, a nonradiative forcing index (NRFI) (see section 2) was utilized. Overall annual mean NRFI averaged over the colored grids is 79% ($\pm 16\%$), indicating that the nonradiative effect is much more important than the radiative effect (Fig. 8). Consistent with radiative and nonradiative effects, annual mean NRFI increases as latitude decreases, and its magnitude varies with forest and open land types (Fig. 16). In most cases NRFI remains above 50% except for some regions north of 45°N when IRC is converted to ENF and DBF or RFC is converted to DBF. Averaging over all colored grid cells, the larger NRFI (ranging from 85% to 90%) occurs in the EBF-related conversions due to a larger cooling effect driven by f change (Fig. 10). The smallest NRFI of 53% occurs when IRC is converted to ENF.

d. Sensitivity of the calculated T_s change to the parameters

The calculated T_s change caused by afforestation based on the IBM method can be impacted by the reasonable variations in the parameters employed in the f model (Fig. 8). The calculated T_s change varies from -0.82° to -0.25°C with plus and minus a standard error in the parameters, respectively. Not surprisingly, such a variation of the calculated T_s change mostly results from a strong sensitivity of f change-induced local T_s change to the parameters. However, α and G change-induced local T_s changes show very weak sensitivity to the uncertainty in the parameters. Accordingly NRFI varies from 85% to 72% with plus and minus a standard error in the parameters respectively (Fig. 8).

The sensitivity of the calculated T_s change to the uncertainty in the parameters also depends on the conversion types. This impact is evident in the DBF-related conversion types but is very small in other conversion types (Fig. 10). For example, the calculated T_s changes

FIG. 9. Annual mean values of the calculated surface temperature change $\Delta T_{s,cal}$ ($^{\circ}\text{C}$) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,cal}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

are -2.05° and 0.75°C , and NRFI values are 88% and 64%, as a result of plus and minus a standard error in the parameters, respectively, when RFC is converted to DBF (Fig. 10h).

This highlights a large uncertainty in the calculated T_s change and NRFI caused by the parameters used in the f model, especially in the case of replacing open land with DBF. We also note that NRFI always stays above 50% in most cases despite the uncertainty in parameters. It suggests that the dominant role of nonradiative effect of afforestation in driving local T_s is robust although uncertainty remains in the calculated T_s change.

4. Discussion

Using satellite observations, we investigated the local biophysical difference between forest and open land over mainland China. We also attributed local surface temperature change between forest and open land to radiative and nonradiative effects. Based on the satellite

observations and the space-for-time method, the annual mean local T_s change between adjacent forest and open land is observed to be -0.32°C ($\pm 0.37^{\circ}\text{C}$), which is broadly consistent with previous studies (Ma et al. 2017; Peng et al. 2014). Although these studies also used the space-for-time method based on satellite observation, they did not attribute the local T_s changes between adjacent forest and open land to radiative and nonradiative processes. We therefore quantified the radiative and nonradiative effects in driving the local T_s change between forest and open land at a continental scale over China based on the IBM method (Lee et al. 2011) combined with the f model (Bright et al. 2017). In our analysis, the radiative process associated with the α change leads to a local warming of 0.23°C ($\pm 0.21^{\circ}\text{C}$) and the nonradiative process associated with energy partitioning leads to a local cooling of -0.74°C ($\pm 0.50^{\circ}\text{C}$) and resulting a local cooling of -0.53°C ($\pm 0.48^{\circ}\text{C}$) in total when converting open land to adjacent forest. Importantly, the nonradiative effect explains about 79% of

FIG. 10. Annual mean values of the calculated surface temperature change $\Delta T_{s,cal}$ (°C), the surface temperature change driven by albedo change $\Delta T_{s,\alpha}$ (°C), the surface temperature change driven by energy redistribution factor change $\Delta T_{s,f}$ (°C), and the surface temperature change driven by the heat storage $\Delta T_{s,G}$ (°C) change between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows the surface temperature change between ENF and GRA. The vertical error bar denotes the standard deviation. The circle and cross represent the values achieved by plus ($f + \sigma$) or minus ($f - \sigma$) a standard error in the parameters utilized in the f mode (see section 2), respectively. The NRFI (spatial mean $\pm$ spatial standard deviation) is provided at the bottom-right corner of each panel.

local T_s change, indicating a dominant role in the local biophysical impact of afforestation. Our results are generally consistent with previous conclusions from in situ observations (Burakowski et al. 2018; Lee et al. 2011). For example, Lee et al. (2011) found that the T_s bias between a grasslands site and pine and oak/hickory forest site in a temperate region of North America is attributed

by 0.5°C from the radiative process and -0.8°C from the nonradiative process. A series of previous studies (Guo et al. 2016; Wang et al. 2017) focusing on the lower reaches of Yangtze River valley over southeast China used in situ observations and also demonstrated the non-radiative effect to be larger than the radiative effect caused by LULCC. Guo et al. (2016) and Wang et al.

FIG. 11. Seasonal and latitudinal values of the calculated surface temperature change $\Delta T_{s,cal}$ ($^{\circ}\text{C}$) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,cal}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

FIG. 12. Annual mean values of the surface temperature change driven by albedo change $\Delta T_{s,\alpha}$ (°C) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,\alpha}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's *t* test.

(2017) did not consider conversion from open land to forest due to few paired sites being available. Their findings that conversion of open land to shrubs had a larger nonradiative effect than radiative effect is consistent with our results, but likely to underestimate the nonradiative effects given that forests have larger evapotranspiration efficiencies than other land cover types. Our results are also consistent with Bright et al. (2017), who highlighted the role of the nonradiative effect of historical LULCC on local climates at the global scale. However, our estimated radiative and nonradiative effects of each conversion type are larger than those shown by Bright et al. (2017). For example, the *f* change-induced local T_s change as a result of converting GRA to ENF in China is estimated to be about -1.2°C in Bright et al. (2017) but about -3.0°C in this study. It is not surprising as we used different methods and datasets and performed the calculation at a finer resolution. We also note that the IBM method may overestimate the contribution of the aerodynamic resistance by improperly assuming independence between the aerodynamic resistance

and the Bowen ratio (Rigden and Li 2017). This would tend to overestimate the contribution of the nonradiative effects relative (which we found to dominate) compared to the radiative effects.

We compared the observed and calculated T_s change using the IBM method combined with the *f* model between adjacent forest and open land at continental scale. We find a discrepancy between the observed T_s change and the calculated T_s change, with an overestimation of the cooling effect produced by the calculated T_s change as a whole. This bias is not surprising, and it can be explained by several factors. First of all, the accuracy of the calculated T_s change is subjected to the limitations in the assumptions of the IBM method. For example, air temperature at a blending height within the atmospheric boundary layer is assumed to be identical between forest and open land (Lee et al. 2011). This assumption is not always met as air temperature is usually measured at a fixed height instead of the time dependent blending height, so that a term accounting for air temperature differences between forest and open land should ideally

FIG. 13. Seasonal and latitudinal values of the surface temperature change driven by albedo $\Delta T_{s,\alpha}$ ($^{\circ}\text{C}$) change between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,\alpha}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

FIG. 14. Annual mean values of the surface temperature change driven by energy redistribution factor change $\Delta T_{s,f}$ ($^{\circ}\text{C}$) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,f}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

be included (Burakowski et al. 2018; Wang et al. 2018). Moreover, a linearization of surface upward longwave radiation in the formulation of f can also cause a bias in the calculated T_s , and this bias tends to be larger when the f difference between forest and open land increases (Bright et al. 2017). Second, the calculated T_s change can be impacted by the uncertainty in the estimated parameters employed in the f model. Larger uncertainty mainly occurs when open land is converted to DBF, in which case the T_s change driven by f change is strongly sensitive to the parameters used in the f model. Third, the observed T_s change represents the impact of afforestation under clear-sky condition as T_s is best retrieved by satellite in cloud-free conditions. In contrast the calculated T_s change includes the both impact of afforestation under clear-sky and cloudy conditions. Fourthly, we note a large bias between the observed and the calculated T_s change in southwest China. This bias may be associated with the complex terrain although these areas are unlikely to be prioritized for afforestation. Finally,

the observed T_s change as a result of afforestation is more spatially heterogeneous than the calculated T_s change. This is hint that the calculated T_s change is likely not to sufficiently account for variability in biophysical parameters (e.g., soil hydraulic conductivity) that affect energy exchange.

We used satellite observations with a goal of filling the gap between in situ observations and model simulations. However, there are caveats that need to be considered when comparing our results with the result from climate model. The most critical question we should consider is the fairness of comparing the space-for-time method based result with the climate model based result. First, the space-for-time method assumes the adjacent sites or pixels share an equivalent background climate (e.g., downward shortwave and longwave radiation), suggesting the atmospheric feedbacks to LULCC are ignored. However, LULCC can affect local temperature indirectly through a feedback from atmosphere (Chen and Dirmeyer 2016; Devaraju et al. 2018; van der Molen

FIG. 15. Seasonal and latitudinal values of the surface temperature change driven by energy redistribution factor change $\Delta T_{s,f}$ ($^{\circ}\text{C}$) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows $\Delta T_{s,f}$ between ENF and GRA. Black dots denote significance at the 95% level tested by a two-tailed Student's t test.

FIG. 16. Annual mean values of the NRFI (%) between forest (ENF, DBF, EBF) and open land (GRA, IRC, RFC, forest minus open land). Changes with respect to (left) ENF, (center) DBF, and (right) EBF. Changes with respect to (a)–(c) GRA, (d)–(f) IRC, and (g)–(i) RFC. For example, (a) shows the NRFI between ENF and GRA.

et al. 2011; Xu et al. 2015). For example, afforestation causes an increase in surface evapotranspiration, which in turn tends to increase atmospheric water vapor and cloudiness formation. The higher water vapor and cloud cover increase downward longwave radiation, which warms T_s , and simultaneously decrease downward shortwave radiation and cool T_s . Second, Winckler et al. (2017) further demonstrated that in the climate model LULCC could robustly affect the surface temperature of neighboring grids through nonlocal effects with the radiative process having a larger nonlocal effect than the local effect in temperate regions; these nonlocal effects are also ignored in the space-for-time method based results. Third, as the T_s can only be measured by satellite when cloud is absent, the observed T_s change based on satellite observation to be more precisely reflects the impact of afforestation under clear-sky conditions. As a result, comparing the space-for-time method based results with coupled model simulations is therefore a challenge as these boundary layer feedbacks are explicitly considered in climate models (Boisier et al. 2012;

Davin and de Noblet-Ducoudré 2010; Devaraju et al. 2018). Also, care needs to be taken in assuming that results for T_s can be extrapolated to T_a . While T_a depends on T_s , it is affected by other factors such as atmospheric conditions including air advection, implying that T_s is more sensitive to LULCC than T_a (Alkama and Cescatti 2016; Li et al. 2015; Luyssaert et al. 2014; Meier et al. 2018). It is also demonstrated in Winckler et al. (2018) that near-surface air temperature is affected by the local effects of LULCC only about half as much compared to surface temperature in climate models. Thus, which temperature is chosen should be carefully taken into consideration when comparing observation and modeling based results.

There are some ways to take our analysis further. For example, our analysis is mainly performed on monthly and annual time scales, suggesting that the characteristics of the local T_s change in response to afforestation at finer time scales cannot be identified here. Increasing in situ studies (Burakowski et al. 2018; Lee et al. 2011; Wang et al. 2018) and satellite observations (Li et al.

2015; Peng et al. 2014; Schultz et al. 2017) have further demonstrated the diurnal asymmetry of the surface temperature in response to afforestation. In contrast to the strong cooling effect of forest in daytime, forest tends to warm the surface temperature compared to open land in nighttime because of strong turbulence of forest, which brings heat from aloft to surface during stable atmospheric conditions combined with the release of heat stored in daytime (Lee et al. 2011; Schultz et al. 2017; Peng et al. 2014). Thus the radiative and nonradiative effects of afforestation on local T_s function differently in daytime and nighttime (Lee et al. 2011; Wang et al. 2018). At this finer time scale, the soil heat storage change induced nonradiative effect even plays a considerable role in driving local T_s in both daytime and nighttime (Lee et al. 2011; Wang et al. 2018). Thus, the attribution of afforestation-induced T_s changes to radiative and nonradiative effects in daytime and nighttime separately at continental scale needs further investigation. Our analysis is built upon single snapshots in time of T_s (1030 and 2230 LT for *Terra* and 0130 and 1330 LT for *Aqua*), averaged over a month, as opposed to a full diurnal analysis. Our analysis would not therefore accurately estimate the precise magnitude of the cooling induced by afforestation. The magnitude of the calculated T_s change when switching between GRA and EBF ($-4.35^\circ \pm 1.15^\circ\text{C}$) is such large that further analysis is now warranted in this space to capture the full temporal impact of cooling. This gap in our knowledge might be addressed through a combination of diurnal T_s measurements and mobile eddy-covariance measurements of Q_E .

Our results reveal that the relative importance of the radiative and nonradiative effects varies with forest type, a result of value to policy makers focused on mitigation strategies. In terms of local T_s , afforestation of GRA and RFC by planting EBF is most beneficial, but afforestation with both DBF and ENF may also lead to cooling. Little benefit can be achieved from converting IRC to DBF or ENF. Given challenges associated with food production, afforestation of RFC is unlikely to be feasible on a large scale. This suggests that targeting GRA with afforestation with EBF is a reasonable strategy to locally mitigate climate warming where possible, with afforestation using DBF and ENF also being beneficial. Afforestation of IRC has little positive benefit on cooling temperatures and is infeasible on a large scale due to the need to feed China's growing population. In addition, as the forest cools surface temperature by transpiring more water, reforestation adds additional risk to the resilience of local and regional water resources. The adaptation of planted forests to the local climate including water availability and

energy demands necessary for tree growth and the local environment including soil conditions is also not fully accounted for here, although we do map the local surface temperature change driven by all conversion types over mainland China. For example, the energy and water demands of EBF make it unsuitable in more northern latitudes or higher-altitude regions. Thus, the large cooling effect achieved by converting open land to EBF in those growth unsuitable regions should be interpreted as a sensitivity study, not as a feasible mitigation option. In the northern arid and semiarid regions where the extreme high temperature risk is small but the water supply is limited, afforestation probably exacerbates any water deficit (Cao et al. 2011; Chen et al. 2015; Feng et al. 2016). As a result, large-scale afforestation programs must be aligned with local conditions, and total water usage may be an important consideration when weighing the benefits of one tree functional type over another in any afforestation strategy. Prioritizing afforestation in regions that were formerly forest rather than naturally grasslands could be most beneficial to avoid negative effects of climate and water availability (Cao et al. 2011; Fu et al. 2017; Jian et al. 2015).

5. Conclusions

Using satellite observations between 2001 and 2012, we have investigated the local biophysical effects of afforestation in China. A novel aspect of our study is that we quantify the radiative and nonradiative effects of afforestation on local surface temperature at continental scales based on space-for-time method combined with the Intrinsic Biophysical Mechanism (IBM) method. We find that the forest has a smaller albedo ($2.63\% \pm 2.72\%$) and a larger leaf area index ($0.70 \pm 0.37 \text{ m}^2 \text{ m}^{-2}$), and subsequently a larger energy redistribution factor than open land averaged over colored grid cells. The increased absorbed radiative energy tends to be more easily dissipated via latent heat ($4.91 \pm 5.20 \text{ W m}^{-2}$) rather than sensible heat ($0.49 \pm 7.00 \text{ W m}^{-2}$) over the forest compared with open land. As a result, the impact of afforestation on the annual mean local T_s change is observed to be -0.32°C ($\pm 0.37^\circ\text{C}$), while the local T_s change in response to afforestation is calculated to be -0.53°C ($\pm 0.48^\circ\text{C}$). Radiative processes cause local warming of 0.23°C ($\pm 0.21^\circ\text{C}$) over paired-site regions. However, the majority ($79\% \pm 0.16\%$) of the changes in temperature over afforested regions are associated with nonradiative processes which explain local cooling of $-0.74^\circ \pm 0.50^\circ\text{C}$. We have also demonstrated that the nonradiative effect varies with the forest and open land types with the largest cooling achieved by replacing GRA or RFC with evergreen tree types such EBF or ENF. In

contrast, converting IRC with ENF and DBF could even warm local surface temperature, suggesting that the improper choice of conversion types may risk of aggravating local temperature increases. Thus our study further highlights the necessary of considering local biophysical impact in the case of afforestation. It also provides valuable information in the perspective of local temperature for the policy makers who plan to expand the afforestation program over China in the future. We caution that food security, water resources, and the adaptation of the planted trees also need to be taken into account as implementation of large-scale afforestation is considered.

Acknowledgments. This research is supported by the National Key Research and Development Program of China (2017YFA0603803), the Natural Science Foundation of China (41775075, 41475063), and the Jiangsu Collaborative Innovation Center for Climate Change. This work is also supported by the Australian Research Council (ARC) via the ARC Centre of Excellence for Climate Extremes (CE170100023). J.G. gratefully acknowledges financial support from China Scholarship Council. M.D.K. acknowledges support from the Australian Research Council Centre of Excellence for Climate Extremes (CE170100023) and the New South Wales Research Attraction and Acceleration Program. We thank Dr. Feng Gao of ARS, USDA, Beltsville, Maryland, USA, who provided the climatological albedo look-up maps. We also appreciate three anonymous reviewers for their constructive and valuable suggestions for the great improvements to the manuscript. The MODIS land cover type (MCD12C1 and MCD12Q1), land surface temperature (MOD11C3 and MYD11C3), and albedo (MCD43C3) products are retrieved from <https://lpdaac.usgs.gov>, maintained by the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC) at the USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota. The evapotranspiration (MOD16A) product is downloaded from http://files.ntsug.umd.edu/data/NTSG_Products/MOD16/. The area equipped for irrigation is from Historical Irrigation Data, <https://mygeohub.org/publications/8/2>. SRTM30 DEM data are available from the U.S. Geological Survey, https://dds.cr.usgs.gov/srtm/version2_1/SRTM30/. The ITPCAS meteorological forcing dataset is developed by the Data Assimilation and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences, <http://westdcwestgis.ac.cn/>. The GLASS albedo and LAI product is from Global Land Cover Facility, <http://glcf.umd.edu/>.

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