The Biophysical Impacts of Idealized Afforestation on Surface Temperature in China: Local and Nonlocal Effects

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ABSTRACT: Afforestation can impact surface temperature through local and nonlocal biophysical effects. However, the local and nonlocal effects of afforestation in China have rarely been explicitly investigated. In this study, we separate the local and nonlocal effects of idealized afforestation in China based on a checkerboard method and the regional Weather Research and Forecasting (WRF) Model. Two checkerboard pattern-like afforestation simulations (AFF1/4 and AFF3/4) with regularly spaced afforested and unaltered grid cells are performed; afforestation is implemented in one out of every four grid cells in AFF1/4 and in three out of every four grid cells in AFF3/4. The mechanisms for the local and nonlocal effects are examined through the decomposition of the surface energy balance. The results show that the local effects dominate surface temperature responses to afforestation in China, with a cooling effect of approximately −1.00°C for AFF1/4 and AFF3/4. In contrast, the nonlocal effects warm the land surface by 0.14°C for AFF1/4 and 0.41°C for AFF3/4. The local cooling effects mainly result from 1) enhanced sensible and latent heat fluxes and 2) decreases in downward shortwave radiation due to increased low cloud cover fractions. The nonlocal warming effects mainly result from atmospheric feedbacks, including 1) increases in downward shortwave radiation due to decreased low cloud cover fractions and 2) increases in downward longwave radiation due to increased middle and high cloud cover fractions. This study highlights that, despite the unexpected nonlocal warming effect, afforestation in China still has great potential in mitigating climate warming through biophysical processes.

KEYWORDS: Atmosphere-land interaction; Feedback; Surface temperature; Regional models; Land use

1. Introduction

Forests, as huge carbon sinks of terrestrial ecosystems, can absorb atmospheric carbon dioxide through photosynthesis (e.g., Bonan 2008). Thus, afforestation is considered a nature-based solution to mitigate climate warming (Bastin et al. 2019; Jackson et al. 2008; Windisch et al. 2021). Meanwhile, afforestation can impact temperature through biophysical processes as well (Anderson et al. 2011; Bonan 2008, 2016; Bright et al. 2015; Perugini et al. 2017). The biophysical effects can either offset or amplify the cooling effect of carbon sequestration of afforestation (Arora and Montenegro 2011; Bala et al. 2007; Pongratz et al. 2010; Windisch et al. 2021). Specifically, afforestation warms the surface due to the lower albedo and cools the surface through the higher heat dissipation and evapotranspiration efficiency as a result of the larger leaf area, rougher surface, and deeper rooting depth (e.g., Bonan 2008). These effects directly driven by changes in surface properties (e.g., the albedo) and the surface energy balance are referred to as direct effects (Chen and Dirmeyer 2016; Devaraju et al. 2018) or local effects (Winckler et al. 2017). On the other hand, afforestation can influence the atmosphere (e.g., clouds and large-scale circulations) and indirectly impact surface temperature through atmospheric feedbacks (e.g., Xu et al. 2015). Such effects are not limited to afforested areas and can propagate to neighboring (Cohn et al. 2019) and even remote regions (Badger and Dirmeyer 2016; Chen et al. 2012; Hasler et al. 2009). These effects related to atmospheric feedbacks are referred to as indirect effects (Chen and Dirmeyer 2016; Devaraju et al. 2018) or nonlocal effects (Winckler et al. 2017).

The biophysical impacts of afforestation or deforestation on surface temperature have been extensively investigated based on in situ observations (Lee et al. 2011; Zhang et al. 2014, 2020), satellite observations (Alkama and Cescatti 2016; Duveiller et al. 2018a; Li et al. 2015), and models (Davin and de Noblet-Ducoudr´e 2010; Lejeune et al. 2017; Winckler et al. 2017). Observations and models consistently suggest that the biophysical effects depend on latitude, with a warming effect (driven by the lower albedo) in boreal regions and a cooling effect (driven by the higher evapotranspiration efficiency) in tropical regions (e.g., Alkama and Cescatti 2016). In temperate regions, however, observations and models do not agree on the biophysical effects; observations suggest a cooling effect (e.g., Alkama and Cescatti 2016), whereas models suggest a warming effect (e.g., Davin and de Noblet-Ducoudr´e 2010). This disagreement between the observational and modeling results is mainly attributed to the nonlocal effects of afforestation, which are considered in models but not captured by observations (Chen and Dirmeyer 2016, 2020; Winckler et al. 2017). The nonlocal effects are not seen in observations because the observational method mostly follows a “space-for-time” logic (e.g., Lee et al. 2011), that is, comparing forests with neighboring open lands (e.g., grasslands) as a surrogate of afforestation effects. In this case, background atmospheric conditions are assumed to be identical between paired forests and open lands, implying the neglect of atmospheric feedbacks and
nonlocal effects. Therefore, the local and nonlocal effects should be carefully considered when studying the biophysical effects of afforestation. Ignoring either one may lead to an over- or underestimation of the climatic benefit of afforestation, which is relevant to policy decisions.

Winckler et al. (2017) for the first time explicitly separated the local and nonlocal effects of deforestation in a coupled model based on a “checkerboard” method of regularly spaced deforested and unaltered grid cells. Deforested grid cells contained the total (local + nonlocal) effects, whereas unaltered grid cells contained only the nonlocal effects. Subsequently, the local and nonlocal effects can be separated through horizontal interpolation of the results from deforested and unaltered grid cells (see details in section 2c). Using this method, Winckler et al. (2017, 2019a) found that the nonlocal effects exceeded the local effects by a factor of 3 at the global scale, reconciling the disagreement between the observed and modeled surface temperature responses to deforestation. Winckler et al. (2019b) further demonstrated that the roughness change, instead of the albedo change identified in earlier modeling studies, dominates the local effects of deforestation on wintertime surface temperature in boreal regions. Robertson (2019) repeated the experiment of Winckler et al. (2017) and identified a cooling bias of their model (HadGEM2-ES) in representing the local effects of deforestation when evaluated against satellite observations. In summary, the separation of the local and nonlocal effects improves our understanding of the biophysical effects of afforestation or deforestation and their mechanisms.

It should be noted that Winckler et al. (2017, 2019a,b) and Robertson (2019) conducted checkerboard-like pattern deforestation simulations using global models. Global models have coarse resolutions, with the grid space commonly larger than 1°, implying a large size of deforested and unaltered grid cells (or patches) in the checkerboard. The patch size of deforestation, however, can significantly influence the atmospheric response of deforestation (Lawrence and Vandecar 2015; Leite-Filho et al. 2021; Spracklen et al. 2018). Small and large patch sizes of deforestation can cause even contrasting effects on clouds and precipitation (e.g., Lawrence and Vandecar 2015), which may further exert divergent atmospheric feedbacks on surface temperature. In other words, the resolution of the model used to perform the checkerboard-like pattern deforestation simulation may to some degree determine the nonlocal effects. Therefore, we infer that the nonlocal (and/or local) effects of deforestation identified in Winckler et al. (2017, 2019a) may depend on the model resolution.

In this study, we apply the checkerboard method of Winckler et al. (2017) to a regional model. Using the regional model, we can perform high-resolution simulations with a better description of the spatial heterogeneity in the land surface (e.g., topography). More importantly, the high-resolution simulation allows us to configure a checkerboard of altered and unaltered grid cells with a much smaller size than in earlier studies (e.g., Winckler et al. 2017). Since the regional model only covers a finite region, we take China as a case study. China’s forest cover has significantly increased since 2000, benefiting from a series of national policies implemented to conserve and restore forests (Viña et al. 2016). Satellite observations even indicate that China led in global greening from 2000 to 2017, with most contributions (42%) from forests (Chen et al. 2019). While the biophysical effects of afforestation in China have been broadly investigated, earlier studies have focused on either the total effects (Hua et al. 2015; Li et al. 2020; Ma et al. 2013; Xu et al. 2015; Yu et al. 2020) or the local effects (Ge et al. 2019b; Huang et al. 2018; Ma et al. 2017; Peng et al. 2014); the nonlocal effects have rarely been explicitly examined. Winckler et al. (2017) performed global-scale deforestation simulations and showed nonlocal effects in China, but these effects may arise from deforestation in other regions. The nonlocal effects caused by deforestation or afforestation in China remain largely unknown. Thus, further studies are required to disentangle the local and nonlocal effects of afforestation in China. We also perform an attribution analysis to reveal the mechanisms for the local and nonlocal effects of afforestation based on the decomposition of the surface energy balance. These results not only are expected to improve our understanding of the biophysical effects of afforestation but also have implications for policymakers to implement large-scale afforestation programs in China.

2. Methods and datasets

2a. Model introduction and configuration

The Weather Research and Forecasting (WRF) Model with Advanced Research WRF (ARW) dynamic core version 4.0 (Skamarock et al. 2019) is used in this study. WRF is a state-of-the-art regional model in which the land and atmosphere are fully coupled. The equation set for ARW is fully compressible, Eulerian, and nonhydrostatic with a run-time hydrostatic option. WRF uses the Arakawa-C horizontal grid and a hybrid sigma-pressure vertical coordinate with the bottom level following terrain and the top level being a constant pressure surface. WRF has been widely used for regional climate simulations and can reasonably reproduce the climate in China (Li et al. 2016; Tang et al. 2016; Yu et al. 2015). WRF is also a common tool to study the biophysical effects of afforestation or revegetation in China (Ge et al. 2020; Yu et al. 2020; Zhang et al. 2021).

The simulation domain covers mainland China and neighboring regions (Fig. 1). The Lambert conformal projection is used, and the two standard latitudes are 30° and 60° N. The domain is centered at 36° N, 102° E. There are 300 grid cells in the west–east direction and 250 grid cells in the south–north direction, with a grid size of 25 km. There are 40 sigma levels in the vertical direction, and the top level is set to 50 hPa. The main physical parameterization options for WRF used in this study are listed in Table 1. Noah-MP, as the land surface scheme of WRF, provides multiple parameterization options for key land–atmosphere interaction processes (Niu et al. 2011). In this study, Noah-MP is configured with the default options. This suite of parameterization options ensures a better performance of WRF in regional climate simulations in China (e.g., Li et al. 2016).
WRF requires a number of fields as input and the Final (FNL) Operational Global Tropospheric Analysis data (NCEP/NWS/NOAA/U.S. Department of Commerce 2000) are used. The FNL data provide WRF-required atmospheric (including temperature, geopotential height, wind components, and humidity on pressure levels) and surface (including near-surface temperature, pressure, wind components, humidity, and soil temperature and moisture) fields at a horizontal resolution of $1^\circ \times 1^\circ$ and 6-hourly intervals. Within the simulation domain, the prognostic variables are initialized by the FNL data at the beginning of each simulation. The lateral atmospheric boundary conditions of the domain are updated by the FNL data every 6 h during each simulation. Meanwhile, sea surface temperatures are prescribed by the FNL data to evolve seasonally and interannually.

b. Experimental design

We first update the default land cover map of WRF with the map for 2019 from the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product MCD12Q1 (version 6.0; Sulla-Menashe et al. 2019) with a pixel size of 15 arc s ($\sim$500 m at the equator). For MCD12Q1, land cover is categorized into 17 classes based on the International Geosphere Biosphere Programme (IGBP) classification scheme. The default map of WRF also uses the IGBP scheme but with a few modifications; the default map includes three tundra classes in addition to the 17 classes of the IGBP scheme, but tundra is rare in China. We replace the default map with the MODIS map within China. Using the WRF Preprocessing System, we upscale the map to 25 km $\times$ 25 km grid cells and calculate the area percentage of each land cover type in each grid cell.

To separate the local and nonlocal effects of afforestation, we adopt the checkerboard strategy of Winckler et al. (2017) and perform three simulations, including a control simulation (CTL) and two checkerboard-like pattern afforestation simulations (AFF1/4 and AFF3/4). In CTL, the area percentages

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**Table 1. The main parameterization options used in this study for the WRF Model.**

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<thead>
<tr>
<th>Physics</th>
<th>Options</th>
<th>References</th>
</tr>
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<tbody>
<tr>
<td>Microphysics</td>
<td>WRF Single-Moment 6-Class scheme</td>
<td>Hong and Lim (2006)</td>
</tr>
<tr>
<td>Shortwave and longwave radiation</td>
<td>Community Atmosphere Model 3 scheme</td>
<td>Collins et al. (2004)</td>
</tr>
<tr>
<td>Planetary boundary layer</td>
<td>Yonsei University scheme</td>
<td>Hong et al. (2006)</td>
</tr>
<tr>
<td>Surface layer</td>
<td>A revised MM5 scheme</td>
<td>Jiménez et al. (2012)</td>
</tr>
<tr>
<td>Land surface</td>
<td>Community Noah land surface model with</td>
<td>Niu et al. (2011)</td>
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<td>multiparameterization options (Noah-MP)</td>
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of grasslands and croplands are proportionally increased until they fully occupy the vegetated area (excluding water, urban, barren, and permanent snow and ice) in each grid cell in China (Figs. 2a,b). Accordingly, the area percentages of the other vegetation types (e.g., forests and shrublands) are set to zero.

In AFF1/4, we convert all croplands and grasslands to forests in one out of every four grid cells in China based on the map of CTL (Figs. 2c,d). For an afforested grid cell, the total area of grasslands and croplands is allocated to evergreen needleleaf, evergreen broadleaf, deciduous needleleaf, deciduous broadleaf, and mixed forests. The proportion of the five forest types is conserved as in the original map (the MODIS map for 2019), considering the adaptation of planted forests to the local climate. Only grid cells with an original forest cover fraction larger than 0% are likely to be afforested. AFF3/4 is similar to AFF1/4 but for converting croplands and grasslands to forests in three out of every four grid cells (Figs. 2e,f). AFF1/4 and AFF3/4 are designed to examine sensitivities of the local and nonlocal effects to afforestation scales. In any case, the area percentages of nonvegetation types (including water, urban, barren, and permanent snow and ice) in each grid cell are always unchanged to avoid expanding vegetation in areas that are not suitable for vegetation growth. AFF1/4 and AFF3/4 should be regarded as idealized afforestation simulations and of course do not represent afforestation in the real world. This configuration can help to evaluate the local and nonlocal effects of afforestation in as many grid cells as possible in China (Fig. 2). Moreover, using the idealized afforestation simulation also makes it easier to separate the afforestation signal from the noise induced by the internal model variability (e.g., Ge et al. 2019a).

Surface properties, such as leaf area index (LAI), are parameterized by the Noah-MP scheme and depend on land cover types. Thus, land cover type changes lead to modifications in surface properties in afforested grid cells. The dynamic vegetation module is switched off in our simulations, as the responses of vegetation to afforestation-induced climate changes are likely small (e.g., Lawrence et al. 2016). Consequently, changes in surface properties in afforested grid cells...
are prescribed to evolve seasonally but have no interannual variations.

Figure 3 shows the annual mean values of differences in LAI, albedo, and aerodynamic roughness length \( Z_0 \) between CTL and AFF1/4 and between CTL and AFF3/4. Considering seasonal changes in insolation, the annual mean albedo is calculated through the ratio of the annual amount of upward shortwave radiation to that of downward shortwave radiation at the surface. As expected, LAI and \( Z_0 \) increase and albedo decreases in afforested grid cells. Moreover, changes in LAI, albedo, and \( Z_0 \) are spatially varied. Larger increases in LAI (\( > 2.8 \text{ m}^2 \text{ m}^{-2} \)) and \( Z_0 \) (\( > 0.9 \text{ m} \)) occur in southern China (Figs. 3a,b,c,f) because grasslands and croplands are mostly converted to evergreen broadleaf forests in this region (Figs. 2c,e); higher LAI and \( Z_0 \) values are assigned to evergreen broadleaf forests than other forest types in Noah-MP. Afforestation also leads to larger decreases in albedo (\( < -0.18 \)) in boreal regions (e.g., northeastern China) and mountain regions (e.g., the eastern Tibetan Plateau; Figs. 3c,d). These amplified decreases in albedo can be attributed to the masking effect of forests on snow cover (e.g., Anderson et al. 2011).

The three simulations (CTL, AFF1/4, and AFF3/4) each are continuously run from 1 January 2000 to 31 December 2015. For each simulation, the first-year simulation (1 January–31 December 2000) is discarded as a spinup to allow the model to equilibrate. The remaining 15-yr run simulation (1 January 2001–31 December 2015) is used for further analysis.
We note that all forests are completely removed within China in our baseline (CTL) simulation (Fig. 2a). Such a configuration may cause the simulated background climate to deviate from the present-day climate, leading to significant biases in estimates of the local and nonlocal effects of afforestation. We therefore evaluate the climatological mean temperature and precipitation in the CTL simulation against the observational dataset CN05.1 (Wu and Gao 2013). This dataset provides gridded daily 2-m temperature and precipitation in China at a resolution of 0.25° × 0.25° since 1961. This dataset is produced by the interpolation of over 2400 meteorological stations within China. Figure 4 shows the annual and seasonal mean 2-m temperature and precipitation from the CN05.1 dataset and the CTL simulation. Overall, the CTL simulation can reasonably reproduce the observed temperature and precipitation in China in terms of the spatial pattern. The absolute bias between CTL and the observation is mostly within 4°C for temperature and within 2 mm day−1 for precipitation at the annual scale. Biases of such magnitude in background climate are expected not to substantially influence the local and nonlocal effects of afforestation.
afforestation. The agreement between the CTL simulation and the observation also suggests that large-scale circulations play a dominant role in determining the background climate in China.

c. Separation of the local and nonlocal effects of afforestation

Following Winckler et al. (2017), the local effects are confined to afforested grid cells, whereas the nonlocal effects may occur in both afforested and unaltered grid cells. Thus, subtracting CTL from AFF1/4 (or AFF3/4), we obtain the total (local + nonlocal) effects in afforested grid cells and the nonlocal effects in unaltered grid cells, expressed as

\[ \Delta \theta_{\text{aff}} = \Delta_{\text{local}} \theta + \Delta_{\text{nonlocal}} \theta, \]

\[ \Delta \theta_{\text{no-aff}} = \Delta_{\text{nonlocal}} \theta, \]

where \( \Delta \theta_{\text{aff}} \) and \( \Delta \theta_{\text{no-aff}} \) denote differences in a variable \( \theta \) (e.g., surface temperature) between CTL and AFF1/4 (or AFF3/4) in afforested and unaltered grid cells, respectively; \( \Delta_{\text{local}} \theta \) and \( \Delta_{\text{nonlocal}} \theta \) denote the local and nonlocal effects on \( \theta \), respectively. Further assuming that the nonlocal effects in unaltered grid cells are also present in neighboring afforested grid cells, the nonlocal effects are horizontally and bilinearly interpolated to neighboring afforested grid cells to obtain a map of the nonlocal effects. In afforested grid cells, the local effects can be obtained by subtracting the nonlocal effects (interpolated from unaltered grid cells in the previous step) from the total effects, expressed as

\[ \Delta_{\text{local}} \theta = \Delta \theta_{\text{aff}} - \Delta_{\text{nonlocal}} \theta. \]

Similarly, we obtain the map of the local effects through horizontal and bilinear interpolation of the local effects in afforested grid cells to neighboring unaltered grid cells.

Given the spatial heterogeneity in the local effects, we only interpolate the local effects of afforested grid cells to neighboring unaltered grid cells.

To quantitatively explain the local and nonlocal effects of afforestation on surface temperature, an attribution analysis based on the decomposition of the surface energy balance (Luyssaert et al. 2014) is performed. The surface energy balance is expressed as

\[ \text{SW}_\downarrow - \text{SW}_\uparrow + \text{LW}_\downarrow - \text{LW}_\uparrow = \text{SH} + \text{LH} + G, \]

\[ \text{LW}_\uparrow = e \sigma \text{LST}^4, \]

where \( \text{SW}_\downarrow \) denotes downward shortwave radiation (W m\(^{-2}\)), \( \text{SW}_\uparrow \) denotes upward shortwave radiation (W m\(^{-2}\)), \( \text{LW}_\downarrow \) denotes downward longwave radiation (W m\(^{-2}\)), \( \text{LW}_\uparrow \) denotes upward longwave radiation (W m\(^{-2}\)), \( \text{SH} \) denotes sensible heat flux (W m\(^{-2}\)), \( \text{LH} \) denotes latent heat flux (W m\(^{-2}\)), \( G \) denotes ground heat flux (W m\(^{-2}\)), \( e \) denotes surface emissivity, \( \sigma \) denotes the Stefan-Boltzmann constant (5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4} ), and \( \text{LST} \) denotes land surface temperature (K). In Noah-MP, \( e \) is above 0.97 for forests, grasslands, and croplands in China. Here, \( e \) is simply set to 1, and such an approximation does not significantly influence our results (not shown).

Applying the first-order derivative of Eq. (4), afforestation-induced LST changes can be expressed as

\[ \Delta \text{LST} = \frac{1}{4 \sigma \text{LST}^4} (\Delta \text{SW}_\downarrow - \Delta \text{SW}_\uparrow + \Delta \text{LW}_\downarrow - \Delta \text{SH} - \Delta \text{LH} - \Delta G), \]

Further applying Eq. (6) to Eqs. (2) and (3), the local and nonlocal effects of afforestation on LST can be expressed as

\[ \Delta_{\text{local}} \text{LST} = \frac{1}{4 \sigma \text{LST}^4} (\Delta_{\text{local}} \text{SW}_\downarrow - \Delta_{\text{local}} \text{SW}_\uparrow + \Delta_{\text{local}} \text{LW}_\downarrow - \Delta_{\text{local}} \text{SH} - \Delta_{\text{local}} \text{LH} - \Delta_{\text{local}} G), \]

\[ \Delta_{\text{nonlocal}} \text{LST} = \frac{1}{4 \sigma \text{LST}^4} (\Delta_{\text{nonlocal}} \text{SW}_\downarrow - \Delta_{\text{nonlocal}} \text{SW}_\uparrow + \Delta_{\text{nonlocal}} \text{LW}_\downarrow - \Delta_{\text{nonlocal}} \text{SH} - \Delta_{\text{nonlocal}} \text{LH} - \Delta_{\text{nonlocal}} G), \]

where the changes with subscripts local and nonlocal are calculated by Eqs. (3) and (2), respectively. According to Eqs. (7) and (8), the local and nonlocal effects of afforestation on surface temperature can be attributed to changes in downward shortwave radiation (the first right-hand term), upward shortwave radiation (the second right-hand term), downward longwave radiation (the third right-hand term), sensible heat flux (the fourth right-hand term), latent heat flux (the fifth right-hand term), and ground heat flux (the sixth right-hand term), respectively.

As emphasized in Winckler et al. (2017), this decomposition method does not allow the attribution of surface temperature changes to changes in surface properties (e.g., albedo). This is because changes in the individual components of the surface energy balance are the consequence of changes in multiple surface properties and atmospheric feedbacks. For example, the simulated change in LH may result from changes in albedo, LAI, or aerodynamic roughness, or the combination of these three. Instead, this decomposition method only illustrates the relative contributions of the individual components of the surface energy balance to the surface temperature perturbation determined with the surface upward longwave radiation.

We define the calculated \( \Delta_{\text{local}} \text{LST} \) and \( \Delta_{\text{nonlocal}} \text{LST} \) as the changes calculated by the sum of the right-hand terms of Eqs. (7) and (8), respectively. In parallel, we define the simulated \( \Delta_{\text{local}} \text{LST} \) and \( \Delta_{\text{nonlocal}} \text{LST} \) as the changes directly obtained by Eqs. (3) and (2), respectively. To validate the
Table 2. Annual and seasonal mean values of the local effects on surface temperature (ΔLST and ΔLSTc; °C) and the contributions (°C) from changes in downward shortwave radiation (SW↓), upward shortwave radiation (SW↑), downward longwave radiation (LW↓), sensible heat flux (SH), latent heat flux (LH), and ground heat flux (G) in AFF1/4 and AFF3/4. The ΔLST is the identified surface temperature change from the checkerboard method [Eq. (3)]; ΔLSTc is the calculated surface temperature change as the sum of the right-hand terms of Eq. (7). The regional mean value is the average over all colored grid cells shown in Fig. 5a. MAM: March–May; JJA: June–August; SON: September–November; DJF: December–February.

<table>
<thead>
<tr>
<th></th>
<th>Annual mean</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
<th>DJF</th>
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<tbody>
<tr>
<td>ΔLST</td>
<td>−1.00</td>
<td>−0.10</td>
<td>−1.63</td>
<td>−1.64</td>
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<tr>
<td>ΔLSTc</td>
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<td>−0.95</td>
<td>−1.55</td>
<td>−1.56</td>
<td>−0.46</td>
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<tr>
<td>SW↓</td>
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<td>−0.90</td>
<td>−1.07</td>
<td>−1.07</td>
<td>−1.17</td>
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<tr>
<td>SW↑</td>
<td>3.34</td>
<td>3.29</td>
<td>3.56</td>
<td>3.45</td>
<td>2.97</td>
</tr>
<tr>
<td>LW↓</td>
<td>0.07</td>
<td>0.11</td>
<td>0.01</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>SH</td>
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<td>−3.19</td>
<td>−3.60</td>
<td>−3.67</td>
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</tr>
<tr>
<td>LH</td>
<td>−0.44</td>
<td>−0.34</td>
<td>−0.74</td>
<td>−0.59</td>
<td>0.33</td>
</tr>
<tr>
<td>G</td>
<td>0.07</td>
<td>0.08</td>
<td>0.29</td>
<td>0.28</td>
<td>−0.06</td>
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</table>

It should be noted that the local SW↓ and LW↓ effects, which correspond to atmospheric feedbacks to surface temperature, are also included in Eq. (7). According to Winckler et al. (2017), these two terms should ideally equal 0 °C as the local effects are irrelevant to atmospheric feedbacks. Nevertheless, we still preserve these two terms in Eq. (7) to examine whether these two terms are as negligibly small as expected.

e. The observational data on the local effects of afforestation

To validate the simulated local effects of afforestation on surface temperature, a dataset mapping the biophysical effects of vegetation cover change is used (Duveiller et al. 2018b). For this dataset, the biophysical effects are established based on the space-for-time method and multiple satellite observations. Thus, the biophysical effects should be considered the local effects of vegetation cover changes. We use the data mapping the potential changes in daytime (~1330 local time) and nighttime (~0130 local time) surface temperatures as a result of a complete transition from grasslands and croplands to forests. Consistent with our simulations, the definitions of grasslands, croplands, and forests in Duveiller et al. (2018b) are also based on the IGBP scheme. The data are provided at monthly time steps and a horizontal resolution of 1° × 1°. To maintain consistency with the modeling result, the observed daytime and nighttime surface temperature changes are averaged to obtain estimates of changes in daily mean surface temperature (Ge et al. 2019b).

3. Results

a. The local effects of afforestation on surface temperature

We first analyze the local effects of afforestation on surface temperature, which are calculated by Eq. (3). Figures 5a and 5c show the annual mean values of the local effects on surface temperature in AFF1/4 and AFF3/4, respectively. The local effects feature clear latitudinal dependence, with a considerable cooling effect (from −6.6° to −2.6°C) south of 40°N and a weak warming effect (0.2°–1.0°C) north of 40°N. The local effects are statistically significant at the 99% confidence level tested by the Student’s t test (see the embedded figure in the bottom left corner of each panel). The spatial pattern and magnitude of the local effects in AFF1/4 are highly consistent with

Table 3. As in Table 2, but for the nonlocal effects. The ΔLST is the identified surface temperature change from the checkerboard method [Eq. (2)]; ΔLSTc is the calculated surface temperature change as the sum of the right-hand terms of Eq. (8).

<table>
<thead>
<tr>
<th></th>
<th>Annual mean</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
<th>DJF</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔLST</td>
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<td>0.41</td>
<td>0.16</td>
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</tr>
<tr>
<td>ΔLSTc</td>
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<td>0.45</td>
<td>0.16</td>
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<td>0.12</td>
</tr>
<tr>
<td>SW↓</td>
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<td>0.16</td>
<td>−0.04</td>
<td>0.61</td>
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<tr>
<td>SW↑</td>
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</tr>
<tr>
<td>LW↓</td>
<td>0.15</td>
<td>0.57</td>
<td>0.15</td>
<td>0.57</td>
<td>−0.03</td>
</tr>
<tr>
<td>SH</td>
<td>0.07</td>
<td>0.13</td>
<td>0.03</td>
<td>0.16</td>
<td>0.01</td>
</tr>
<tr>
<td>LH</td>
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<td>−0.62</td>
<td>−0.36</td>
<td>−0.76</td>
<td>−0.37</td>
</tr>
<tr>
<td>G</td>
<td>0.00</td>
<td>−0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
</tr>
</tbody>
</table>
those in AFF3/4. The regional mean values of the local effects on surface temperature are $1.00^\circ$C and $1.01^\circ$C for AFF1/4 and AFF3/4, respectively (Table 2; Fig. 7a). This result indicates that the local effects are independent of afforestation scales. The simulated local effects (Figs. 5a,c) are also comparable to those established based on satellite observations in an earlier study (Duveiller et al. 2018a; Fig. 5e), corroborating the robustness of the local effects of afforestation on surface temperature in China.

Figures 6a and 6b show the latitudinal and seasonal changes in the local effects on surface temperature in AFF1/4 and AFF3/4, respectively; the $x$ axis denotes months, and the $y$ axis denotes latitudes. The seasonal pattern of the local effects in AFF1/4 is quite similar to that in AFF3/4, again demonstrating the low sensitivity of the local effect to afforestation scales. To the north of $35^\circ$N, the local effects warm the surface ($0.2^\circ$–$2.6^\circ$C) in cold seasons and cool the surface (from $-2.6^\circ$ to $-0.2^\circ$C) in warm seasons. To the south of $35^\circ$N, the local
effects always cool the surface (from $-2.6^\circ$ to $-0.2^\circ$) during the course of the year. While the seasonal pattern of the local effects is overall consistent between the modeling (Figs. 6a,b) and observational (Fig. 6c) results, a few disagreements can be identified. Particularly in summer, our simulations suggest a weak cooling effect (within $0.6^\circ$), whereas the observations suggest a strong cooling effect (mostly exceeding $1.4^\circ$). Moreover, to the north of $35^\circ$N, the warming effect in cold seasons is larger in our simulations than in the observations.

b. The nonlocal effects of afforestation on surface temperature

We next analyze the nonlocal effects of afforestation on surface temperature, which are calculated by Eq. (2). Figures 5b and 5d show the annual mean values of the nonlocal effects on surface temperature in AFF1/4 and AFF3/4, respectively. In contrast to the local effects, the nonlocal effects show less heterogeneity in space and indicate widespread warming effects in China. Comparing AFF1/4 and AFF3/4, we find that the nonlocal effects are sensitive to afforestation scales. In AFF1/4, the nonlocal effects are small (mostly within $0.6^\circ$) and statistically insignificant in most regions (Fig. 5b). As the afforested grid cells increase, the nonlocal effects in AFF3/4 are strengthened (up to $1.4^\circ$) and become statistically significant in most regions of China, including southern China, northeastern China, and large portions of western China (Fig. 5d). The regional mean values of the nonlocal effects on surface temperature are $0.14^\circ$ and $0.41^\circ$ for AFF1/4 and AFF3/4, respectively (Table 3; Fig. 7f). Furthermore, the nonlocal effects can even propagate to some neighboring regions of China (e.g., the Indo-China Peninsula and India), with magnitudes of $0.2^\circ$–$0.6^\circ$.

Figures 6d and 6e show latitudinal and seasonal changes in the nonlocal effects on surface temperature in AFF1/4 and AFF3/4, respectively. In AFF1/4, the nonlocal effects are negligibly small in most months and at most latitudes (Fig. 6d). In AFF3/4, however, the nonlocal effects are visible and indicate slight and monotonous warming effects ($0.2^\circ$–$1.8^\circ$) throughout the year (Fig. 6e).

c. Attribution of the local effects of afforestation

The local and nonlocal effects can be attributed to the changes in downward shortwave radiation ($SW_\downarrow$), upward shortwave radiation ($SW_\uparrow$), downward longwave radiation ($LW_\downarrow$), sensible heat flux (SH), latent heat flux (LH), and ground heat flux (G). Note that increases (decreases) in $SW_\uparrow$, SH, LH, and G lead to cooling (warming) effects, whereas increases (decreases) in $SW_\downarrow$ and $LW_\downarrow$ lead to warming (cooling) effects [see Eq. (7)].

Figure 8 shows the annual mean values of the local $SW_\downarrow$, $SW_\uparrow$, $LW_\downarrow$, SH, LH, and G effects in AFF1/4 and AFF3/4. In line with the local effects on surface temperature (Figs. 6a,c), the local effects driven by the individual components of the surface energy balance (e.g., the local $SW_\downarrow$ effect) are highly
consistent between AFF1/4 and AFF3/4. Owing to the decrease in albedo (Figs. 3c,d), the local SW↑ effect leads to a widespread warming effect in China (Figs. 8c,d), with regional mean values of 3.34°C and 3.29°C for AFF1/4 and AFF3/4, respectively (Table 2). Consistent with the albedo change, the magnitude of the local SW↑ effect is larger in boreal regions and mountain regions than in other regions. The local SW↑ effect is mostly offset by the local SH effect in most regions of China. The local SH effect leads to a cooling effect (Figs. 8g,h), with regional mean values of 2.30°C and 2.39°C for AFF1/4 and AFF3/4, respectively (Table 3; Fig. 7f); the local SH effect mainly results from the increase in Z0 (Figs. 3e,f). In southern China, however, the local SW↑ effect is mostly offset by the local LH effect, leading to a cooling effect from −4.5°C to −0.5°C (Figs. 8i,j); the local LH effect mainly results from the large increase in LAI (Figs. 3a,b) and Z0 (Figs. 3e,f). The local SW↓ effect, which is related to atmospheric feedbacks, is also considerable. The local SW↓ effect causes an additional cooling effect in China (Figs. 8a,b), with regional mean values of −0.88°C and −0.90°C for AFF1/4 and AFF3/4, respectively (Table 2; Fig. 7a). The local SW↓ effect can be explained by the increase in low and middle cloud cover fractions (Figs. 11a,b,d,e), which causes less solar radiation to reach the surface. The local SW↓ effect is higher in southwestern China and the eastern Tibetan Plateau. This enhanced local SW↓ effect is probably due to the higher terrain, which favors convection and cloud formation. The local LW↓ (Figs. 8e,f) and G (Figs. 8k,l) effects are overall small (within 0.5°C) in China.

Figure 9 shows latitudinal and seasonal changes in the local SW↓, SW↑, LW↓, SH, LH, and G effects in AFF1/4 and AFF3/4. To the north of 25°N, the local SW↓ effect (Figs. 9b,h) is mostly offset by the local SH effect (Figs. 9d,j). Thus, the local SW↑ and SH effects show similar seasonal patterns but with opposite signs; the local SW↑ and SH effects
are overall stronger in cold seasons but weaker in warm seasons. The local LH effect, however, is relatively small throughout the year (Figs. 9e,k). To the south of 25°N, the local SW↑ effect is slightly larger in warm seasons than in cold seasons. Moreover, at low latitudes, the local SW↑ effect is mostly offset by the local SH effect in warm seasons and by the local LH effect in cold seasons. The local SW↓ effect indicates an all-year-round cooling effect, with a larger magnitude in warm seasons and at low latitudes (Fig. 9a). The local LW↓ and G effects (Figs. 9c,i) are always negligibly small during the course of the year.

d. Attribution of the nonlocal effects of afforestation

Figure 10 shows the annual mean values of the nonlocal effects (°C) attributed to the changes in (a),(b) downward shortwave radiation (SW↓), (c),(d) upward shortwave radiation (SW↑), (e),(f) downward longwave radiation (LW↓), (g),(h) sensible heat flux (SH), (i),(j) latent heat flux (LH), and (k),(l) ground heat flux (G) in AFF1/4 in (a), (c), (e), (g), (i), and (k) and AFF3/4 in (b), (d), (f), (h), (j), and (l). Only the grid cells that have valid values [e.g., obtained by Eq. (3) or the spatial interpolation] in both AFF1/4 and AFF3/4 are shown.

Figure 12 shows latitudinal and seasonal changes in the nonlocal SW↓, SW↑, LW↓, SH, LH, and G effects in AFF1/4 and AFF3/4. In general, the seasonal variations in these nonlocal effects are less clear.

4. Discussion

In this study, we comprehensively investigate the local and nonlocal effects of afforestation in China and their mechanisms. Owing to decreases in albedo and increases in LAI and Z0, afforestation influences surface temperature through local and nonlocal effects, as summarized in Fig. 13. In terms of the local effects (denoted by the blue shading in Fig. 13), afforestation warms the surface due to the decreased SW↑. This warming effect coincides with the decrease in low cloud cover fractions (Fig. 11j). LW↓ is increased by the increase in middle and high cloud cover fractions (Figs. 11k,l), leading to a widespread warming effect of 0.5°–1.5°C in central and southern China (Fig. 10f). The nonlocal SW↓ and LW↓ effects are mostly offset by the nonlocal LH effect, causing a moderate cooling effect from −2.5°C to −0.5°C in most regions of China (Figs. 10i,j). The nonlocal SW↑, LW↑, and LH effects are also larger in AFF3/4 than in AFF1/4 (Figs. 7f and 9; Table 3), explaining the dependence of the nonlocal effects on afforestation scales (Figs. 5b,d). The nonlocal SW↑, H, and G are negligibly small in most regions.
cover fractions and subsequently cool the surface due to the decreased \( \text{SW}_d \). The local \( G \) and \( \text{LW}_d \) effects are relatively small. All of these local effects cause a net cooling effect on surface temperature. The simulated local effects vary with latitudes and seasons and are less sensitive to afforestation scales. In terms of the nonlocal effects (denoted by the red shading in Fig. 13), afforestation influences surface temperature mainly via atmospheric feedbacks. Afforestation tends to decrease low cloud cover fractions, causing a warming effect due to the increased \( \text{SW}_u \). Meanwhile, afforestation tends to increase middle and high cloud cover fractions, causing an additional warming effect due to the increased \( \text{LW}_u \). These warming effects are mostly offset by the nonlocal LH effect. The nonlocal \( \text{SW}_u \), SH, and \( G \) effects are trivial overall. All of these nonlocal effects cause a net warming effect on surface temperature. In contrast to the local effects, the nonlocal effects are less dependent on latitudes and seasons but show a higher sensitivity to afforestation scales.

Our results are broadly consistent with earlier studies that used the checkerboard method but coarse-resolution global models (Robertson 2019; Winckler et al. 2017, 2019a,b). However, a few disagreements between this and those studies are noteworthy. First, in terms of the local effects, we emphasize the importance of atmospheric feedbacks, which were largely ignored previously (e.g., Winckler et al. 2017). This disagreement may result from the different model resolutions. Specifically, recalling the isolation of the local effects (see section 2c), if the simulated atmospheric signals are identical between afforested and unaltered grid cells, the local (total minus nonlocal) atmospheric feedback is removed (e.g., Winckler et al. 2017); otherwise, the local atmospheric feedback remains (the case of this study). Observations demonstrate that clouds favor

![Figure 9](image-url)
over open lands through mesoscale circulation as a result of small-scale (commonly <50 km) deforestation (Lawrence and Vandecar 2015; Leite-Filho et al. 2021; Xu et al. 2022). Our regional model has a small grid space (25 km) and allows the mesoscale circulation to be generated in open land (or unaltered) grid cells, causing contrasting atmospheric signals in afforested and unaltered grid cells. Nevertheless, the grid space of a global model is large (>100 km), so mesoscale circulation is rarely generated. As a result, the large-scale atmospheric signal arising from afforestation is horizontal even in afforested and unaltered grid cells. Our results are also corroborated by some recent satellite observations that demonstrate either enhanced or inhibited cloud cover over forests compared to neighboring open lands (Duveiller et al. 2021; Teuling et al. 2017; Xu et al. 2022). In particular, consistent with our results, satellite observations reveal the potential of forests to increase local low cloud cover fractions and cause a cooling effect at the global scale (Duveiller et al. 2021). These modeling and observational results also indicate that forests and neighboring open lands do not always share the same atmospheric conditions, contradicting the traditional view of the space-for-time method. Moreover, we also note that the terms “local effects” and “direct effects” are used interchangeably in earlier studies (Chen and Dirmeyer 2016, 2020; Devaraju et al. 2018; Winckler et al. 2017, 2019a,b). As shown in Fig. 13, however, some indirect effects are also included in the local effects. For small-scale afforestation, so-called local effects and direct effects might be similar, but for moderate- to large-scale afforestation, they are not. Therefore, we call for distinguishing local effects from direct effects and careful use of the terminology.

Second, Winckler et al. (2019a) show that nonlocal effects dominate the biophysical effects of deforestation, with a magnitude exceeding the local effects by a factor of 3 at the global scale. Their simulated nonlocal effects can even propagate to regions that are remote from disturbed regions (e.g., the oceans). In contrast, our results show that the local effects dominate the biophysical effects of afforestation, with a magnitude over 2 times larger than the nonlocal effects. The nonlocal effects are also limited to China and a few neighboring regions. This disagreement mainly arises from different afforestation or deforestation scales; Winckler et al. (2019a) implemented global-scale deforestation, whereas we only implemented afforestation in China. As shown in this study or Winckler et al. (2019a), afforestation scales or numbers of afforested grid cells can significantly influence the magnitude of the nonlocal effects. Moreover, as a regional climate model, the impact outside of the model domain is excluded by design. Thus, the prescribed boundary conditions for the regional model, as well as the prescribed sea surface temperatures, may to some degree suppress the atmospheric response to afforestation, particularly over the oceans.

Unavoidably, our results on the local and nonlocal effects of afforestation are subjected to the performance of the WRF Model. WRF tends to underestimate air temperature over
China, particularly in winter (e.g., Ge et al. 2019a; Tang et al. 2016). This wintertime cold bias may cause an overestimation of snow cover and the warming effect (due to the albedo change) of afforestation on surface temperature (Figs. 6a–c). Moreover, current land surface models struggle to represent the response of the partitioning of sensible and latent heat fluxes to afforestation (Cai et al. 2019; Chen et al. 2018; Meier et al. 2018). The coupled WRF Model also has a similar issue and tends to overestimate the increase in sensible heat flux but underestimate the increase in latent heat flux in response to afforestation in China (Ge et al. 2021). The underestimation of the increase in latent heat flux may partly explain why the simulated local cooling effect is weaker than the observational value in warm seasons (Figs. 6a–c).

Although the afforestation scenario used in our simulations is idealized, the results still have implications for policy
decisions on large-scale afforestation or reforestation programs carried out in China. Based on the results, we infer that ongoing afforestation programs in China mainly cool the surface through local effects. While afforestation warms the surface through nonlocal effects, the nonlocal effects are much smaller than the local effects. Moreover, we and Winckler et al. (2017) show the strong dependence of the nonlocal effects on afforestation scales. This result indicates that the nonlocal effects of afforestation programs may be limited because the afforestation scale in the real world is unlikely to be as large as that in our simulations. Given the large cooling benefit brought by the local biophysical effects as well as the biochemical effects (e.g., carbon sequestration), afforestation has great potential to mitigate climate warming in China.

5. Conclusions

In this study, we separate the local and nonlocal effects of afforestation in China based on two checkerboard pattern-like afforestation simulations (AFF1/4 and AFF3/4) with the WRF model; afforestation is implemented in one out of every four grid cells in AFF1/4 and three out of every four grid cells in AFF3/4. We also reveal the mechanisms based on the decomposition of the surface energy balance. The results show that afforestation cools the surface through local effects (−1.00°C for AFF1/4 and −1.01°C for AFF3/4) and warms the surface through nonlocal effects (0.14°C for AFF1/4 and 0.41°C for AFF3/4) in China. The local effects are mainly attributed to the cooling effect driven by changes in sensible heat flux (−3.10°C for AFF1/4 and −3.19°C for AFF3/4), latent heat flux (−0.44°C for AFF1/4 and −0.34°C for AFF3/4), and downward shortwave radiation (−0.88°C for AFF1/4 and −0.90°C for AFF3/4) and the warming effect driven by changes in upward shortwave radiation (3.34°C for AFF1/4 and 3.29°C for AFF3/4). The nonlocal effects are mainly attributed to the warming effect driven by changes in downward longwave radiation (0.15°C for AFF1/4 and 0.57°C for AFF3/4) and the cooling effect driven by changes in latent heat flux (−0.32°C for AFF1/4 and −0.62°C for AFF3/4). The local effects are less sensitive to afforestation scales but vary with
In contrast, the nonlocal effects are less dependent on latitudes and seasons but are highly sensitive to afforestation scales. Our results again highlight the potential of afforestation to mitigate climate warming in China through biophysical processes, although afforestation may cause an unexpected nonlocal warming effect. Moreover, given the dependence of the local and nonlocal effects identified by the checkerboard method on model resolutions, further efforts are encouraged to investigate these two effects based on higher-resolution simulations (e.g., convection-permitting simulations).

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**Data availability statement.** The Weather Research and Forecasting Model can be downloaded from https://www.mmm.ucar.edu/weather-research-and-forecasting-model. The Final (FNL) Operational Global Tropospheric Analysis data were obtained from https://rda.ucar.edu/datasets/ds083.2/. The Moderate Resolution Imaging Spectroradiometer (MODIS) land cover product MCD12Q1 (version 6.0) was obtained from https://lpdaac.usgs.gov/products/mcd12q1v006/. The dataset mapping the biophysical effects of vegetation cover changes developed by Duveiller et al. (2018b) was obtained from https://jeodpp.jrc.ec.europa.eu/ftp/jrc-opendata/ECOCLIM/Biophysical-effects-vgt-change/v2.0/.

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