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Analysis of Land Surface Temperature Sensitivity to Vegetation in China

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Abstract: China has emerged as one of the global leaders in greening, achieved through human land use management practices, particularly afforestation projects. However, accurately calculating the energy balance processes of vegetated areas remains challenging because of the complexity of physical mechanisms, parameterization schemes, and driving dataset used in current research. In this study, we address these challenges by employing moving window methods in space inspired by “space-for-time”. This approach allows us to eliminate the influence of climate signals on vegetation development over long periods and determine the sensitivity of seasonal contributions of Land Surface Temperature (LST) to Leaf Area Index (LAI) in China from 2001 to 2018. Our findings reveal that the sensitivity of LST to LAI in the climatology period is approximately $-0.085 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$, indicating a cooling effect. Moreover, the climatological trend remains negative, suggesting that Chinese vegetation greening is playing an increasingly important role in cooling the land surface. Considering the energy balance equation, we further investigate the underlying mechanisms. It is observed that the radiative feedback consistently contributes positively, while the non-radiative feedback always exerts a negative influence on the sensitivity. These results provide valuable insights into the complex interactions between vegetation greening and land surface temperature in China, providing informed land management and climate adaptation strategies. Understanding these trends and mechanisms is essential for sustainable and effective environmental planning and decision making.

Keywords: land surface temperature; space-for-time; sensitivity analysis; energy balance



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1. Introduction

Using observational satellite data, the Earth has undergone widespread greening since the 1980s. This phenomenon can be primarily attributed to global climate change and the fertilization effects of CO₂ [1,2]. This greening phenomenon has the potential to mitigate global warming through a negative biochemical feedback mechanism, as it enhances the removal of CO₂ from the atmosphere through photosynthesis by vegetation [3–5]. While the impact of climate change on the hydrological cycle has been extensively studied, the role of vegetation in influencing the Earth’s water resources and energy balance has not been fully assessed [6,7].

Until now, research has revealed that Earth greening not only affects vegetation growth but also alters surface biophysical properties [8,9]. This includes two key processes: the radiative process, which involves a decrease in albedo and enhances the absorption of short-wave radiation, and the non-radiative process, which entails a decrease in aerodynamic or surface resistance and improves the water evaporation effects or energy convection between the land surface and atmosphere. Additionally, the increase in LAI during the summer, facilitated by CO₂ fertilization, can lead to enhanced transpiration in regions

with higher soil moisture [10]. Consequently, these regions experience surface cooling during periods of high transpiration demand, such as dry and hot days. This has been observed in irrigated croplands, where greater soil moisture has resulted in fewer summer hot extremes [11]. However, it is important to note that reduced stomatal conductance during the summer can offset the positive effects of increased LAI and soil moisture, leading to elevated summer temperatures and an increased frequency, intensity, and duration of heat waves [12]. These biophysical feedbacks have a significant impact on the energy budget of the Earth system and subsequently influence LST [13]. Their effects can either reinforce, compensate for, or even counteract the biochemical mechanisms that mitigate global warming, thus generating substantial interest in these feedback mechanisms during recent years [14].

To mitigate land degradation and promote sustainable development, China has implemented several large-scale conservation programs, including the Key Shelterbelt Construction Program, Natural Forest Conservation Program, and the Grain to Green Program, since the late 1970s [15]. Remarkable greening in China has been observed through satellite observations from 2000 to 2017, demonstrating the success of these initiatives [5]. However, understanding the climate implications of this greening and assessing its environmental impact is crucial. The period from 1982 to 2011 in China demonstrated notable responses to vegetation greening, with significant spring cooling observed in North and Southeast China, while the increase in precipitation remained negligible [16,17]. It has been suggested that the limited changes in LAI during summer from 1982 to 2011 contribute to the weak climatic responses during that season [18]. These studies have also raised important concerns. For instance, the greening of vegetation is expected to increase evapotranspiration, which may lead to a decrease in soil moisture, posing a potential water resource issue. However, an Earth System Model (ESM)-based study indicated that although the increase in precipitation resulting from vegetation greening in North and Southeast China is statistically insignificant, it may offset enhanced evapotranspiration, resulting in a limited impact on soil moisture [19,20]. Further investigation is needed to understand the regional responses of the water cycle and changes in energy balance due to vegetation greening. As a result, the greening efforts in China have shown promising results, but their implications for the climate and the environment require comprehensive evaluation. The complex interactions between vegetation greening, temperature, precipitation, evapotranspiration, and soil moisture necessitate further research to enhance our understanding of the regional water cycle and energy balance responses to vegetation greening in China.

With the advancements in observational remote sensing facts and Earth System Models (ESMs), it has become more convenient to disentangle the issue of the climate effects of greening [21,22]. Nevertheless, the complexity of physical mechanisms, parameterization schemes, and driving data presents challenges for models, resulting in difficulties in precisely replicating the energy partitioning processes of vegetation surfaces. As a consequence, variations in their outcomes can arise [23,24]. Moreover, differentiating the impact of greening on the regional climate from the co-evolving observational vegetation and temperature variations poses a significant challenge. As a result, uncertainties remain in research regarding the direction and magnitude of temperature response to vegetation greening [25].

The objective of this study is to establish reliable observational limitations regarding the biophysical consequences of green trends on regional LST. In order to achieve this goal, we evaluate the possible temperature changes in response to variations in greenness between 2001 and 2018 of China, utilizing satellite-derived LST and LAI as diagnostic parameters. Since vegetation growth and temperature fluctuations have a complex bidirectional relationship, to mitigate the influence of climate impacts on vegetation development over long periods and establish the sensitivity of LST to LAI, we adopt a moving window in space derived from the “space-for-time” method [26,27]. Subsequently, we discuss the obtained LST sensitivity, considering both climatological and seasonal scales. Furthermore,

we break down the results into non-radiative, radiative, and indirect climatic feedbacks to further disentangle the possible driving elements.

The structure of this paper is outlined as follows. Section 2 provides an introduction to the materials and methods employed in this study. Section 3 presents all the obtained results. In Section 4, a thorough discussion of our findings is conducted, and Section 5 concludes the paper by summarizing the key conclusions drawn from the study.

2. Materials and Methods

2.1. Data and Pre-Processing

In our research, we utilized climate data over the periods of 2001 to 2018. Specifically, we apply the 2 m temperature of the land surface sourced from ERA5 as the LST. In our model, 2 m air temperature is commonly used to represent land surface temperature. LST exhibits a strong correlation with 2 m air temperature, and in certain scenarios, 2 m air temperature can serve as a rough estimate or substitute for LST, depending on the research objectives and available data [28]. Additionally, our model does not involve detailed processes such as soil temperature variations. Based on the above reasons, for our climate change and trend analyses, 2 m air temperature can be employed as a proxy for LST. In addition, radiation data and turbulence fluxes are also obtained from the ERA5-Land monthly averaged reanalysis. The radiation datasets employed encompass surface downward shortwave radiation (SW) and downward longwave radiation (LW).

Furthermore, we incorporated turbulence fluxes, one of which is latent heat (LE). Latent heat refers to the heat energy that is absorbed or released during the phase change of a substance, such as during evaporation or condensation. The other sensible heat (H). Sensible heat refers to the heat energy that is transferred through conduction or convection and results in a variation in the temperature without any phase change. LE and H are both sourced from ERA5-Land monthly averaged reanalysis. To facilitate further analysis, all the datasets were resampled to a spatial resolution of $0.1^\circ \times 0.1^\circ$, serving as the contributing factors in our subsequent analysis.

This study utilizes LAI (m^2/m^2) data as a measure of vegetation greenness and structural properties. LAI data selected for analysis span the period from 2001 to 2018 and are sourced from the Global Land Surface Satellite (GLASS). This processing underwent steps such as atmospheric correction, geometric correction, removal of cloud and snow cover, and filling and filtering of missing pixels to obtain temporally and spatially continuous reflectance data. Then, high-precision LAI data were selected as training data for the Generalized Regression Neural Networks. Validation results indicate the reliability of GLASS LAI [29,30]. Surface reflectance data obtained after atmospheric correction often contain cloud contamination. Therefore, preprocessing these data is a crucial step in mitigating the impact of this interference. Various algorithms have been developed to generate continuous and smoothed time series of surface reflectance [31]. The quality of GLASS LAI products is intricately tied to the quality of the preprocessed reflectance data. Even though MODIS surface reflectance data (MOD09A1) are still affected by lingering clouds, as well as sensor malfunctions causing some regions or specific time periods to lack surface reflectance data, the project's preprocessing team has taken steps to rectify these issues. They have effectively removed clouds, cloud shadows, snow, and erroneous data from the MOD09A1 dataset, and have performed interpolation and data filling procedures. The outcome is a dataset that is both spatially complete and temporally sensible in terms of reflectance values [32]. The original LAI product has a resolution of 0.5° in space and resolution of 8-day intervals in time. However, for the purposes of this research, the spatial resolution is remapped to a finer resolution of 0.1° , and the resolution in time is aggregated to the monthly scale by computing the mean values.

The albedo data (α) for the period from 2001 to 2018 were obtained from 6 datasets of the MODIS collection, called MCD43C3. To determine the albedo value for each pixel, we take the average value of the black sky and white sky measurements [33]. This approach is adopted due to the high correlation and minimal difference between the two

measurements. The data are derived by aggregating the original data through average value calculations. In order to align with the spatial resolution of other datasets, the albedo data are remapped accordingly.

The digital elevation model (DEM) is utilized to account for the influence of altitude on local temperature. The DEM data used in this study are derived from the fourth version of the Shuttle Radar Topography Mission, having a resolution of 90 m. Maps depicting land cover over the period of 2001–2018 are acquired from the MODIS product MCD12C1. To ensure consistency in resolution spatially, both the digital elevation model (DEM) and land cover datasets are remapped to 0.1°.

2.2. Sensitivity Analysis of LST to LAI

To obtain the sensitivity of Land Surface Temperature (LST) to Leaf Area Index (LAI), we employ a moving window method in space based on “space-for-time”. The “space-for-time” approach has been utilized in studying the temperature effects of Land Use and Land Cover Change (LULCC) widely. This approach presupposes that the target pixel possesses a comparable climate to neighboring pixels within the moving window. As a result, any difference in LST between the pixels in the target and comparison is primarily influenced by biophysical feedback resulting from land cover change [26,27]. Likewise, we have the assumption that greenness is the dominant driving factor behind spatial variations in LST under certain restrictions. By examining spatially adjacent LAI and LST observations, we can derive the biophysical sensitivity of LST to LAI through regression analysis. This method presents an advantage over the previously mentioned temporal regression strategy by excluding the impact of climate variations in nature or warming trends over a long period of time on vegetation. This is achieved by ensuring that pixels with varying LAI within the moving window share consistent climate conditions.

The moving window method aims to obtain the study time range monthly. For the purpose of comparison, we exclusively consider nearby spatial pixels within the moving window for each target pixel. The dimensions of this moving window, as established in previous studies, are set at 50 km × 50 km. Additionally, to mitigate the effects of differences between land cover and elevation, two screening criteria are implemented. Firstly, the chosen pixel should have a matching primary land cover type to the target pixel, with a coverage disparity of less than 10% based on MODIS land cover data. Secondly, the elevation discrepancy between the chosen and target pixels must not exceed 100 m. By calculating the differences in LAI and LST between the target pixel and all the selected comparison pixels, we can derive the sensitivity specific to the target pixel.

To address the potential issue of skewed distribution in the samples, we employ the non-parametric Theil–Sen’s slope as a regression method [34]. By calculating the differences in LAI and LST between the target pixel and all the selected comparison pixels, we can derive the sensitivity specific to the target pixel. To address the potential issue of skewed distribution in the samples, we employ the non-parametric Theil–Sen slope as a regression method after sorting the pixels into spatial windows by LAI values [34]:

$$\text{slope} = \text{median}\left(\frac{y_i - y_j}{x_i - x_j}\right) \quad (1)$$

In Equation (1), x and y represent the differences in leaf area index and land surface temperature, respectively, while i and j represent the locations of the window. The Theil–Sen slope calculation is designed to be robust against statistical outliers, as it takes into account the median value of a range of potential slopes. Furthermore, to ensure the reliability of our findings, we calculate the sensitivity only when there are a minimum of four valid samples available. Additionally, to enhance the robustness of our results, we set the criterion that a minimum LAI should be larger than 0.1 m²/m². It is important to note that a positive sensitivity indicates that vegetation contributes to an increase in local temperatures and vice versa.

2.3. Decomposition of the Sensitivity

In order to disentangle the contribution of different elements to the LST sensitivity to LAI, we apply the decomposition on the energy budget equation [35]:

$$SW(1 - \alpha) + \varepsilon LW - \varepsilon \sigma LST^4 = H + LE + G \quad (2)$$

In the left-hand terms of Equation (2), SW and LW represent the downward shortwave and longwave radiation, respectively. α denotes the albedo, and σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ W} \cdot \text{m}^{-2} \cdot \text{K}^{-4}$). ε ($0.99 - 0.16\alpha$) represents the surface emissivity, which characterizes the efficiency of surface radiation emission, and can be estimated empirically by establishing a relationship about albedo specifically tailored for vegetated areas [36,37]. On the right-hand side of the equation, H , LE , and G correspond to sensible heat, latent heat, and ground heat flux, respectively. To ensure a closed energy balance, we employ the Bowen ratio method [38]. The corrected equation is presented below, assuming that the ratio of H to LE remains constant:

$$LE_c = R_n \frac{LE}{LE + H} \quad (3)$$

$$H_c = R_n \frac{H}{LE + H} \quad (4)$$

$$R_n = SW(1 - \alpha) + \varepsilon LW - \varepsilon \sigma LST^4 \quad (5)$$

Note that the ground flux term is ignored due to the fact that its effects are relatively small. Then, we divided the obtained monthly LST sensitivity into the contribution of each term by Taylor expansion in the first order, and the equation can be written as follows:

$$\frac{dLST}{dLAI} = \frac{dLST^\alpha}{dLAI} + \frac{dLST^{LE}}{dLAI} + \frac{dLST^H}{dLAI} + \frac{dLST^{SW}}{dLAI} + \frac{dLST^{LW}}{dLAI} \quad (6)$$

The method used in this study to decompose the surface temperature signal into its major components was adapted from Juang et al. [36]. We adjust this method in China to disentangle the regional LST sensitivity and the seasonal contributions. When using an energy budget approach (Equation (6)), land surface temperature is the straightforward choice as a metric for temperature. The choice for radiative surface temperature implies that the analysis takes an ecosystem rather than a climate perspective and that the analysis can be complemented by the land surface temperature product from remote sensing [39]. The right-hand-side terms of Equation (6) can be derived from

$$\frac{dLST^\alpha}{dLAI} = -\beta \frac{d\alpha}{dLAI} SW \quad (7)$$

$$\frac{dLST^{LE}}{dLAI} = -\beta \frac{dLE}{dLAI} \quad (8)$$

$$\frac{dLST^H}{dLAI} = -\beta \frac{dH}{dLAI} \quad (9)$$

$$\frac{dLST^{SW}}{dLAI} = \beta \frac{dSW}{dLAI} (1 - \alpha) \quad (10)$$

$$\frac{dLST^{LW}}{dLAI} = \beta \frac{dLW}{dLAI} \varepsilon \quad (11)$$

In the equations above, β can be calculated by the first-order Taylor expansion, which is formulated as follows:

$$\beta = \frac{1}{4\epsilon\sigma LST^3} \quad (12)$$

All the decomposed terms are calculated at the monthly scale by the spatial resolution of 0.1° . Figure 1 shows the flowchart of this study.

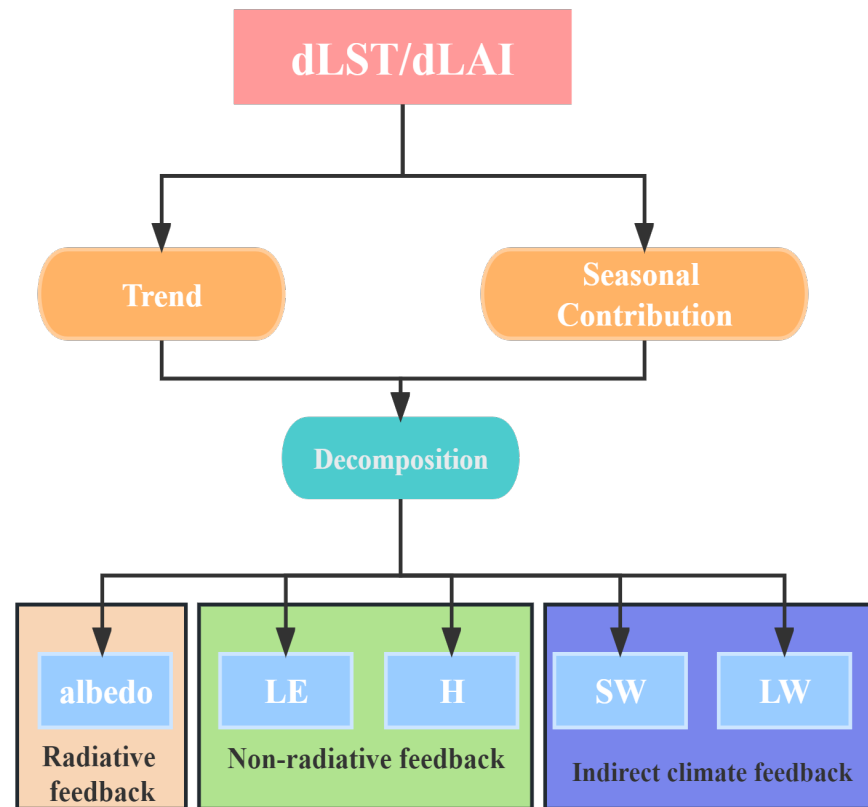


Figure 1. Flowchart of this work.

2.4. Climatological and Seasonal Sensitivities

Using the regression method described above in space, we derive the monthly biophysical sensitivity of LST to LAI for the period spanning from 2001 to 2018. Furthermore, we break down the sensitivity of energy budget equations concerning LAI. To capture the overall conditions during the timeframe studied, we calculate the average for every month across the timeframe. To ensure robustness and remove the influence of outliers, we exclude the maximum and minimum 5% values based on the cumulative distribution frequency (CDF) from the average results prior to temporal aggregation. Subsequently, if all sensitivities are valid at one given area, the sensitivities are obtained by averaging the corresponding monthly values. These calculated climatology sensitivities reflect patterns in space and season, as well as the decomposition calculations.

3. Results

3.1. Annual and Seasonal Sensitivities of LST to LAI

Figure 2 presents the annual and seasonal sensitivities ($\frac{dLST}{dLAI}$) of Land Surface Temperature (LST) to Leaf Area Index (LAI) for the period ranging from 2001 to 2008. It illustrates the potential average change in annual LST per unit increase in LAI. The annual mean sensitivity value for China is $-0.085 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$ (Figure 2a). Analyzing the annual sensitivities of LST to greening, a clear distinction is observed between arid and humid regions. In most vegetated humid areas (most in the northeast, center, and south of China), negative sensitivities are evident, indicating that vegetation in these regions has a cooling effect on

the land surface. Conversely, arid areas (most in the northwest and southwest of China) exhibit positive sensitivities. This suggests that in water-limited dry regions, vegetation's physiological influence restricts transpiration and enhances the ratio of sensible heat to latent heat fluxes at the vegetated surface, leading to increased temperatures of the boundary layer. Furthermore, the CO₂ fertilization effect contributes to increased LAI during the early stage of vegetation growth and in non-water-limited areas. Under sufficient moisture supply, an increased LAI can boost transpiration and evaporative cooling at the surface.

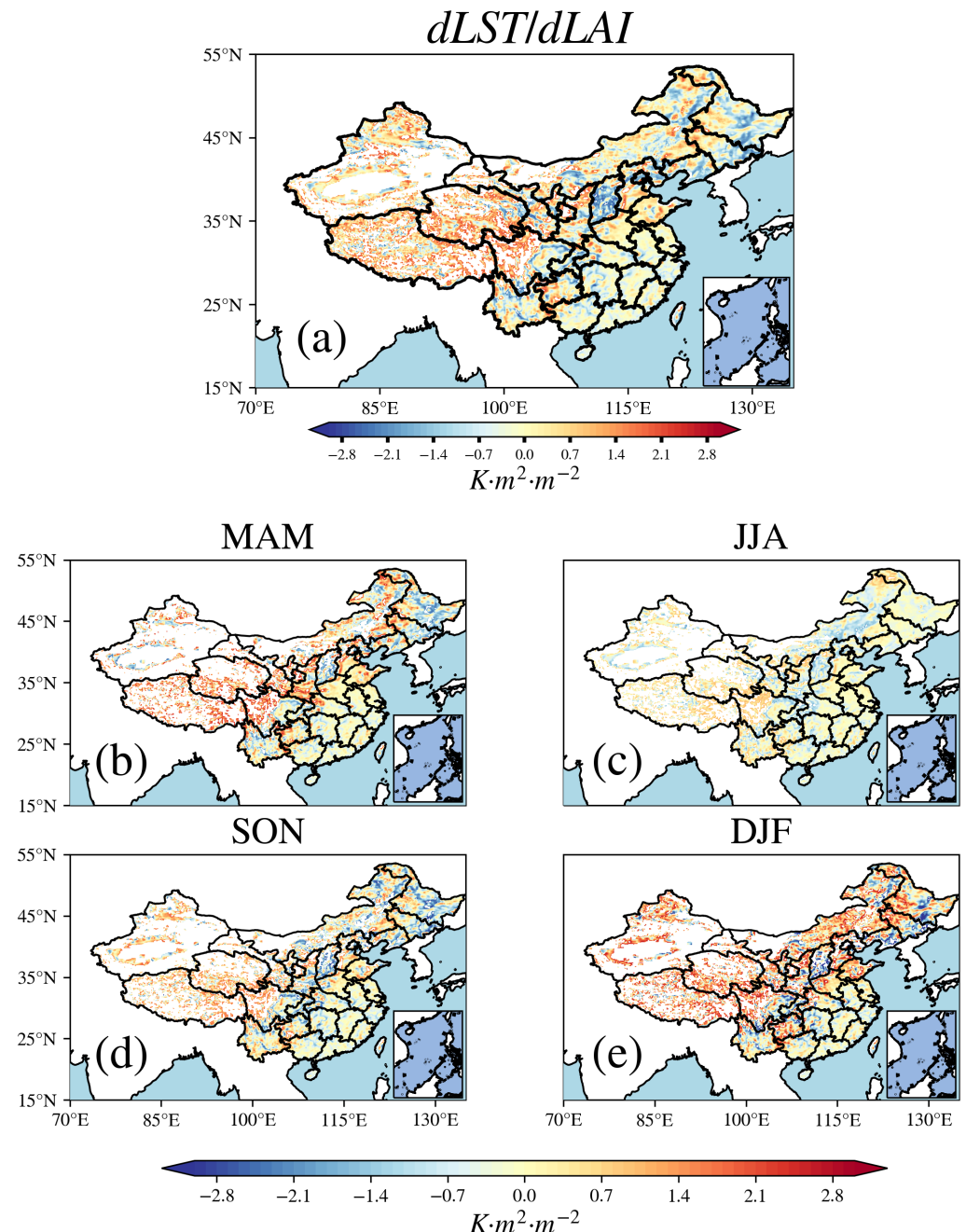


Figure 2. The annual and seasonal contributions to the sensitivity of LST to LAI over the period of 2001–2018. (a) depicts the spatial map illustrating the sensitivity distribution in China. (b–e) present the seasonal contributions, with MAM representing spring, JJA representing summer, SON representing autumn, and DJF representing winter.

Additionally, we analyze the seasonal contributions of sensitivity. In Figure 2b–e, the four seasons of China are taken into consideration. All the seasons have the same dis-

inction between humid and arid area. Spring (MAM) and winter (DJF) have a strong positive and negative value. The averages of China are $0.076 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$ and $0.11 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$. Spring and winter contribute the positive LST sensitivity. However, summer (JJA) and autumn (SON) have a negative contribution to the sensitivity. They are $-0.15 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$ and $-0.12 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$, respectively. It may be because that in summer, vegetation is in the growth season, the cooling effect of vegetation transpiration is dominant.

3.2. Decomposition of LST Sensitivity to LAI

The sensitivity of LST is influenced by different climatic conditions, although the exact energy mechanism behind it remains uncertain. To address this issue, we utilize the energy balance equation (as described in the methods section) to break down the LST sensitivity to LAI into five components. These components are albedo (α), latent heat (LE), sensible heat (H), downward longwave radiation (LW), and downward shortwave radiation (SW), respectively. For the sake of convenient comparison, we express the intensity of each process using the same unit ($\text{K} \cdot \text{m}^2 \cdot \text{m}^{-2}$).

The albedo term exhibits a predominantly positive sensitivity to LAI, as depicted in Figure 3a. This indicates that an enhancement in vegetation leads to loss in albedo, causing the land surface to reflect less radiation back into the atmosphere. Consequently, the land surface absorbs more energy, resulting in an eventual rise in LST. In the case of China, the albedo term is approximately $1.15 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$. Supplementary Figure S1 illustrates the seasonal contributions of albedo. Across spring to winter, the mean values for China are 0.46, 0.21, 0.16, and $0.32 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$, respectively. The contributions from spring and winter are more pronounced compared to summer and autumn. This discrepancy may be attributed to vegetation playing a more significant role during the colder seasons, while its effects are relatively limited during the growing seasons.

The latent heat term and sensible heat term (Figure 3b,c) exhibit a similar pattern. In contrast to the albedo term, the sensitivity of latent heat and sensible heat to LAI is predominantly negative. The mean values for the latent heat term and sensible heat term are approximately -0.69 and $-0.63 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$. This indicates that both latent heat and sensible heat have a negative impact on LST sensitivity, resulting in a cooling effect. The seasonal contributions are shown in Supplementary Figures S2 and S3. For the latent heat term, the mean values from spring to winter are -0.25 , -0.13 , -0.19 , and $-0.12 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$, respectively. Similarly, for the sensible heat term, the mean values from spring to winter are -0.14 , -0.11 , -0.15 , and $-0.22 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$, respectively. It is worth noting that the contributions during summer are the least significant among the seasons for both terms.

The downward longwave term and shortwave term have contrasting effects on the sensitivity of Land Surface Temperature (LST) to Leaf Area Index (LAI), as depicted in Figure 3d,e. The mean values for China are 0.58 and $-0.49 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$. Downward longwave radiation, also known as terrestrial or infrared radiation, refers to the thermal energy emitted by the Earth's surface and the atmosphere towards the surface. It significantly influences land surface temperature by contributing to the energy balance at the surface. If there is a higher concentration of greenhouse gases in the atmosphere, more longwave radiation is trapped and re-emitted back to the surface [40]. This leads to an increase in land surface temperature, resulting in positive contributions to the sensitivity of LST to LAI. Supplementary Figure S4 illustrates the seasonal contributions of downward longwave and shortwave radiation. In terms of longwave radiation, winter ($0.21 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$) demonstrates opposite effects to summer ($-0.08 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}$). In contrast, the absorption of shortwave radiation by the land surface results in an increase in surface temperature. This energy is converted into heat, contributing to the warming of the surface and subsequent rise in LST. However, the reflection of shortwave radiation can have a cooling effect on the land surface. Surfaces with higher albedo, such as areas experiencing vegetation greening in water-limited regions, reflect a significant portion of the incoming shortwave radiation back into the atmosphere. This reflection reduces the energy absorbed by the surface, resulting in lower LST. Supplementary Figure S5 further illustrates the seasonal

contributions of shortwave radiation. While the overall average term is negative, winter exhibits positive effects on sensitivity.

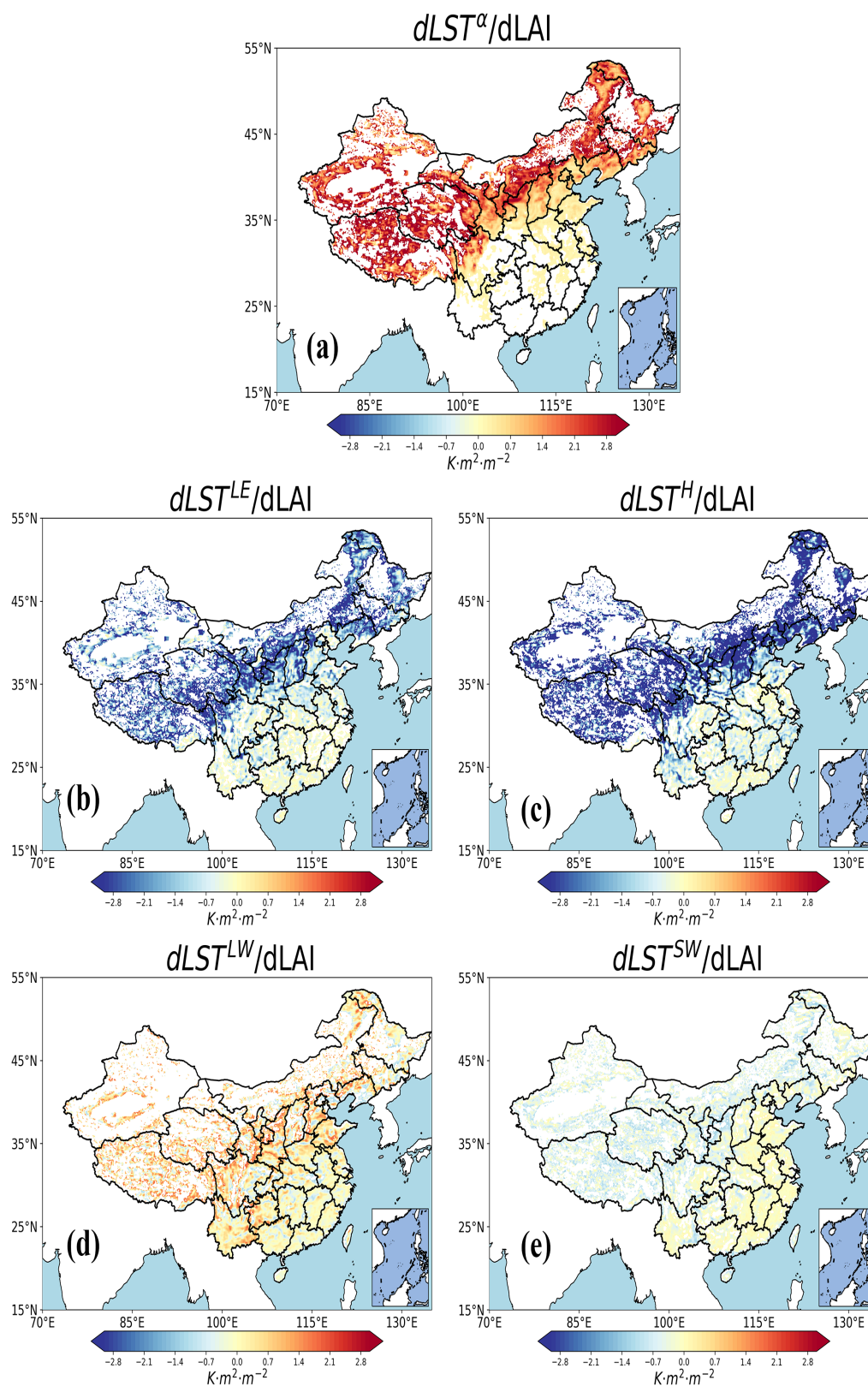


Figure 3. Decomposition of annual sensitivity of LST to LAI over the period of 2001–2018. (a) Albedo term. (b,c) Latent heat term and sensible heat term. (d,e) Downward longwave and shortwave term.

Figure 4 presents a detailed breakdown of the LST sensitivity to LAI, categorizing it into calculations from non-radiative feedback ($\frac{dLST^{LE}}{dLAI} + \frac{dLST^H}{dLAI}$), radiative feedback ($\frac{dLST^R}{dLAI}$), and indirect climatic feedback ($\frac{dLST^{LW}}{dLAI} + \frac{dLST^{SW}}{dLAI}$) based on the energy balance. Notably, the radiative feedback consistently exhibits the most pronounced positive effects on sensitivity throughout the analyzed periods. Moreover, it demonstrates the strongest positive effects during the winter season. In contrast, the non-radiative feedback consistently exerts negative influences on sensitivity, with the highest negative effects observed during the spring season. As for the indirect climatic feedback, it displays positive feedback during autumn and winter, while demonstrating negative effects during spring and summer seasons.

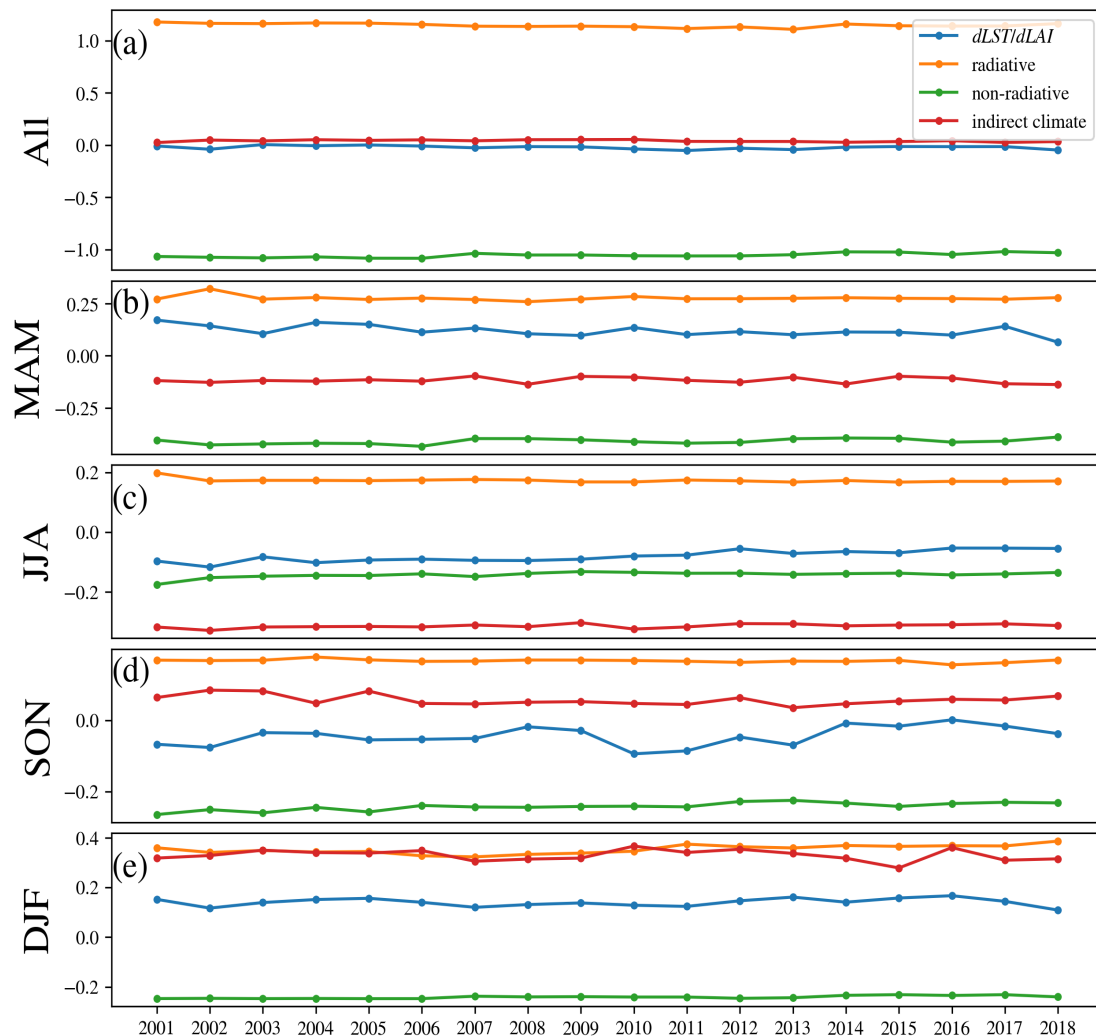


Figure 4. The attribution of Land Surface Temperature (LST) sensitivity to Leaf Area Index (LAI) is analyzed for the period spanning from 2001 to 2018. (a) represents the annual average, while (b–e) display the seasonal scale averages from spring (MAM) to winter (DJF). The blue line represents the $\frac{dLST}{dLAI}$ (LST sensitivity to LAI), the orange line represents the radiative feedback ($\frac{dLST^R}{dLAI}$), the green line represents the non-radiative feedback ($\frac{dLST^{LE}}{dLAI} + \frac{dLST^H}{dLAI}$), and the red line represents the indirect climate feedback ($\frac{dLST^{LW}}{dLAI} + \frac{dLST^{SW}}{dLAI}$).

3.3. Trend of LST Sensitivity to LAI

In Figure 5, we delve into the analysis of the trend in Chinese LST sensitivity to LAI for the period from 2001 to 2018. The results reveal an overall negative trend with an average sensitivity of $-0.012 \text{ K} \cdot \text{m}^2 \cdot \text{decade}^{-1}$. Notably, a predominant portion of the northern regions exhibits a negative trend, indicating a cooling effect resulting from

vegetation in these areas. In contrast, the southern regions of China display a positive trend in LST sensitivity to LAI, with some areas even showing a significant trend. This regional difference suggests that the cooling effects due to vegetation have become more pronounced in the northern regions over the recent years.

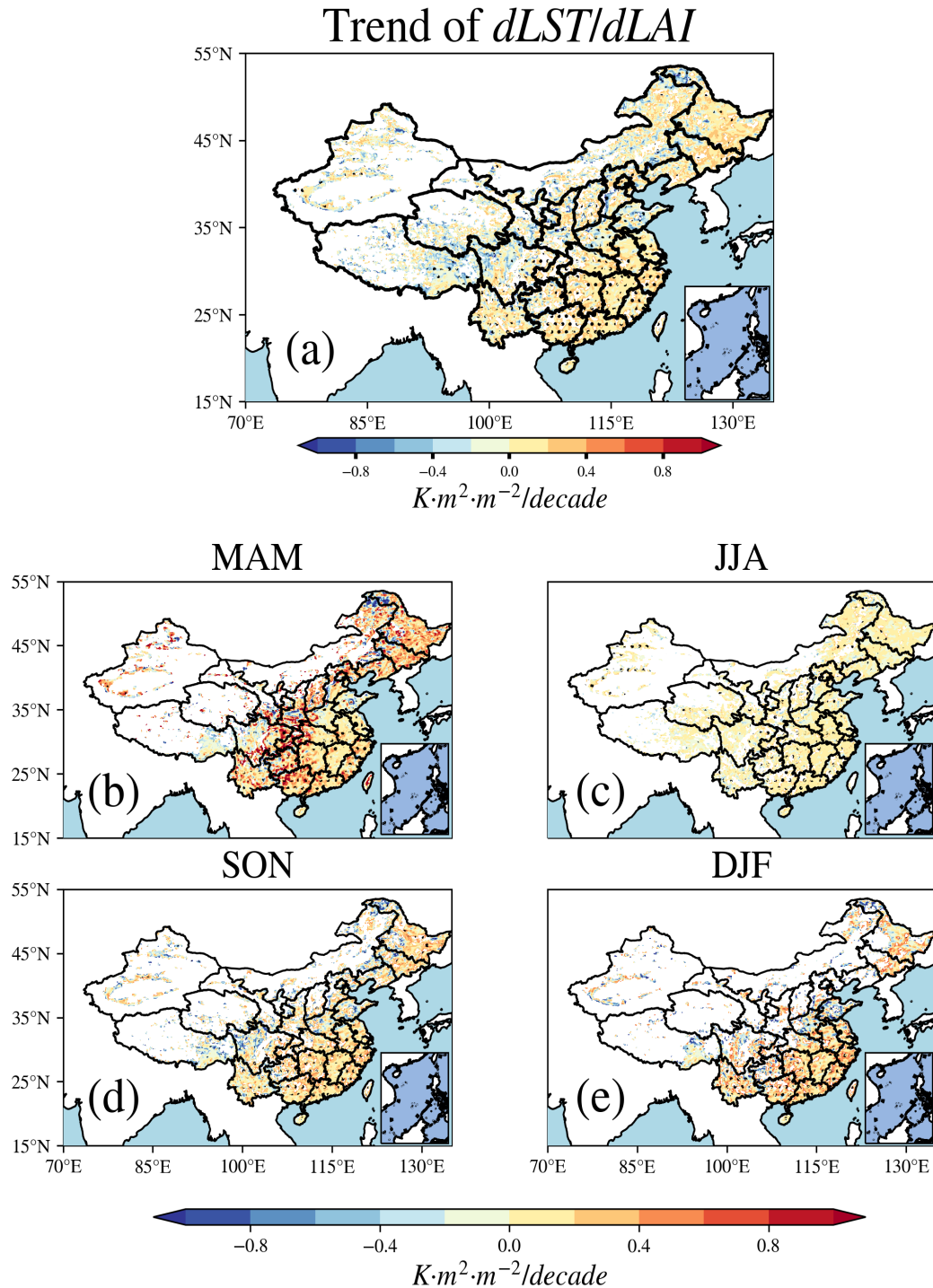


Figure 5. The annual and seasonal contributions to the sensitivity of LST to LAI trend over the period from 2001 to 2018. (a) depicts the spatial map illustrating the sensitivity distribution in China. (b–e) present the seasonal contributions, with MAM representing spring, JJA representing summer, SON representing autumn, and DJF representing winter. Stippling denotes regions that have passed a significance test at the 5% level.

The analysis of seasonal contributions further highlights interesting patterns. During spring, autumn, and winter, all three seasons contribute positively to LST sensitivity, indicating that vegetation during these periods has the trend of a warming effect on the land surface. However, in the case of summer, a negative contribution of $-0.051 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}/\text{decade}$ is observed, implying that vegetation during this season might lead to a cooling trend on the land surface temperature. Overall, this comprehensive analysis provides valuable insights into the changing dynamics of Chinese LST sensitivity to LAI and highlights the significance of seasonal variations in understanding the complex interactions between vegetation and land surface temperature.

3.4. Decomposition of Trend of LST Sensitivity to LAI

We further analyze the trend of LST sensitivity to LAI by decomposing it into five terms (Figure 6) based on the energy balance equation and seasonal contributions (Supplementary Figures S6–S10). The albedo term stands out as a major contributor to the negative trend of sensitivity, with a substantial decrease of $-0.21 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}/\text{decade}$. Particularly, in the northern regions of China, the albedo term exhibits the strongest negative trend, indicating a weakening of the warming effects caused by albedo changes. This observation suggests that the reflective properties of the land surface are becoming less influential in driving temperature trends. Regarding the seasonal trend contributions, summer, autumn, and winter, but not spring, show a negative trend in the Chinese average. In these seasons, vegetation leads to cooling effects on the trend around the land surface. However, during spring, a different pattern emerges, with most areas of China and the southern regions in winter exhibiting a positive trend. This suggests that in spring, vegetation may contribute to slight warming in these regions.

Vegetation significantly impacts the exchange of latent and sensible heat between the land surface and the atmosphere. With increased vegetation density and leaf area, evapotranspiration leads to higher latent heat fluxes, resulting in a cooling effect on the land surface. Moreover, dense vegetation can reduce sensible heat fluxes by limiting heat absorption, contributing to cooler land surface temperatures. These processes demonstrate the intricate interactions between vegetation, heat fluxes, and land surface temperature, playing a pivotal role in shaping climate patterns. In the context of China, both latent heat and sensible heat exhibit similar trends (Figure 6b,c). They both show a positive trend (0.079 and $0.10 \text{ K} \cdot \text{m}^2 \cdot \text{m}^{-2}/\text{decade}$), indicating that the cooling effects of these heat fluxes are diminishing. When considering the seasonal contributions (Supplementary Figures S7 and S8), all seasons for both sensible heat and latent heat demonstrate a positive trend. This suggests that the warming effects of these heat fluxes are becoming more prominent throughout the different seasons. These trends provide valuable insights into the changing dynamics of heat exchange due to vegetation and its implications on land surface temperature in China. The trends of downward longwave and shortwave radiation are not obvious (Figure 6d,e).

This comprehensive decomposition analysis provides valuable insights into the various factors influencing LST sensitivity to LAI trends across different seasons and regions of China. The results shed light on the dynamic interplay between vegetation-induced changes and the land surface temperature, helping us better understand the complex relationship between vegetation and climate.

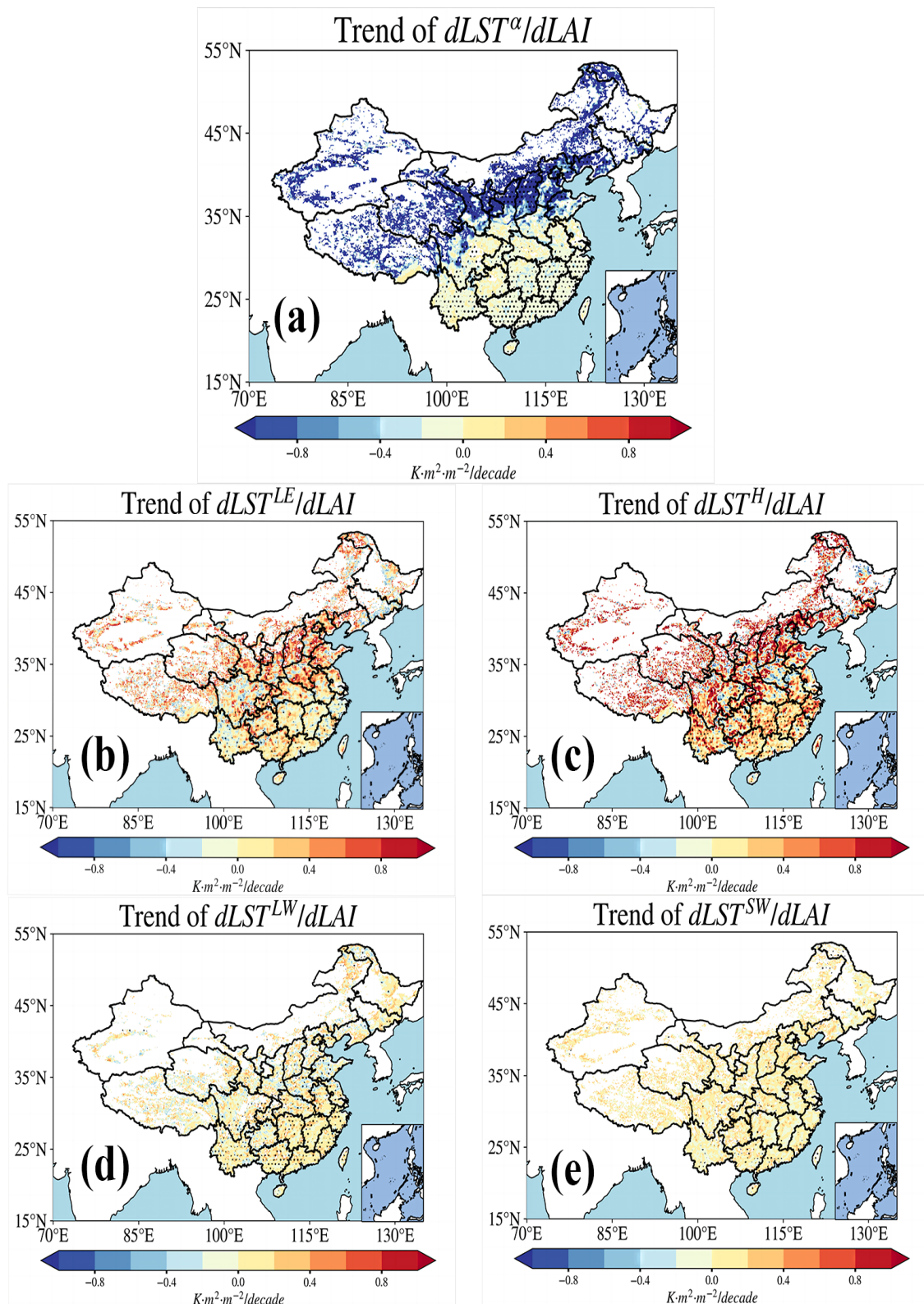


Figure 6. Decomposition of sensitivity of LST to LAI trend over the period of 2001–2018. (a) Trend of albedo term. (b,c) Trend of latent heat term and sensible heat term. (d,e) Trend of downward longwave and shortwave term. Stippling denotes regions that have passed a significance test at the 5% level.

4. Discussion

Using satellite observations, our study examines the effects of Chinese vegetation greening on Land Surface Temperature from 2001 to 2018. To accurately assess the influence of vegetation greening on LST while accounting for the simultaneous effects of climate change, we develop a spatial regression model. This model helps reveal the LAI-LST influence through the combined signals of climate variations and vegetation development. Previous research has identified China as one of the global leaders in greening during recent decades, achieved through land use practices, such as China's afforestation projects [41,42]. This highlights the significant potential of human land use approaches and ecological projections in mitigating climate pressure, not solely by absorbing carbon in the atmosphere but also through biophysical measurement.

Our study employs experiments using the 'space-for-time' method to derive the LST sensitivity to vegetation variations in China. By doing so, we disentangle the climate influence of greening, which exhibits considerable spatial and seasonal variations. However, we must acknowledge certain caveats in our study due to data and method limitations. (1) Our mapped results may exhibit larger uncertainty in regions with water-limited areas. In these areas, the slope may be sensitive to the noise present in the input data, especially when the variation among the LAI values is low. Nevertheless, we have implemented a filter to make our results more robust by restricting the minimal LAI difference. It is essential to note that this sensitivity of uncertainty also influences the temperature uncertainty effects when combined with observed LAI changes. Therefore, we acknowledge the potential for uncertainty in our findings and recognize the importance of further research and validation to enhance the accuracy and reliability of our conclusions. (2) Our analysis focuses solely on quantifying the temperature signal considering greening, neglecting the broader impact of large-scale feedback on climate, which can be challenging to capture in data-driven studies. Specifically, this indirect climate impact is non-local or teleconnected and is determined by the scale and geographical location of surface changes. Despite this limitation, our findings hold significance for local climate adaptation strategies and provide a valuable benchmark for comparing or evaluating the sensitivity simulations derived from the land surface. Notably, land surface models concentrate solely on land surface processes and do not incorporate atmospheric circulation processes, making our results relevant and complementary in understanding the localized effects of greening on temperature dynamics.

While our research provides valuable insights, there are still areas that require further exploration and improvement to fully understand the complexities of the relationships between vegetation, climate, and land surface temperature.

5. Conclusions

China has been identified as one of the global leaders in environment management during recent decades, achieved through effective land use management, including afforestation projects [43]. The increasing availability of observational remote sensing facts and advanced Earth System Models (ESMs) has facilitated exploring the climate effects of greening. However, the complexity of physical mechanisms, parameterization schemes, and driving data often poses challenges for models in accurately replicating the energy partitioning processes of vegetated areas, leading to variations in their outcomes. Furthermore, distinguishing the signal of greening impacts on the local climate from co-evolving observations of satellite vegetation indices and temperature remains a formidable task. Consequently, uncertainties persist in research regarding the direction and magnitude of the temperature response to vegetation. Despite these challenges, the ongoing advancements in remote sensing technologies and modeling capabilities offer promising opportunities to enhance our understanding of the intricate interactions between vegetation and climate.

Our study employs experiments utilizing the space-for-time methods to determine LST sensitivities to vegetation variations in China. This approach allows us to uncover how

greenness adjusts the climate, revealing significant heterogeneous effects and variability in space and season. In summary, the key conclusions of this study are as follows.

Firstly, it is noteworthy that most areas, except in the northern part of China, exhibit negative sensitivity. This indicates that effective human land use management practices in China have contributed to cooling effects on the land surface in recent years, primarily due to vegetation greening. In water-limited areas, the increase in vegetation may lead to a reduction in albedo, causing the land surface to absorb more energy from radiation, contributing to warming effects. When considering seasonal contributions, spring and winter show a positive LST sensitivity, while summer and autumn have a negative impact on sensitivity. This could be attributed to the dominance of cooling effects from vegetation transpiration during the growth season in summer. Secondly, we further decompose the sensitivity into five terms based on the energy balance equation. The radiative feedback consistently plays a positive role in contributions, while the non-radiative feedback consistently exerts negative influences, with the most significant negative effects observed during the spring season. The indirect climatic feedback displays positive feedback during autumn and winter, while showing negative effects during the spring and summer seasons. Thirdly, we analyze the trend of LST sensitivity to vegetation. The Chinese average trend value is negative, with the negative areas concentrated mainly in the northern regions. Spring, autumn, and winter contribute positively to the trend, while summer contributes negatively. Moreover, after decomposing the trend based on the energy balance equation, the albedo term emerges as the strongest negative contributor. In the context of China, both latent heat and sensible heat exhibit similar trends, showing a positive trend, which indicates that the cooling effects of these heat fluxes are diminishing. Additionally, the trends of downward longwave and shortwave radiation are not as apparent.

These findings provide valuable insights into the complex interactions between vegetation and land surface temperature in different regions and seasons in China. Understanding the underlying mechanisms and trends is essential for informed land management and climate adaptation strategies.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs15184544/s1>, Figure S1. Seasonal contributions of albedo term. Figure S2. Seasonal contributions of latent heat term. Figure S3. Seasonal contributions of sensible heat term. Figure S4. Seasonal contributions of downward longwave term. Figure S5. Seasonal contributions of downward shortwave term. Figure S6. Seasonal contributions of albedo term trend. Figure S7. Seasonal contributions of latent heat term trend. Figure S8. Seasonal contributions of sensible heat term trend. Figure S9. Seasonal contributions of downward longwave term trend. Figure S10. Seasonal contributions of downward shortwave term trend.

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Data Availability Statement: The data that support the research can be accessed openly. The MODIS albedo and land cover data can be download from <https://ladsweb.modaps.eosdis.nasa.gov/search/> (accessed on 19 July 2023). The LAI data are available at <http://www.glass.umd.edu/LAI/MODIS/0.05D/> (GLASS, accessed on 19 July 2023). The ERA5-land reanalysis products can be accessed at <https://cds.climate.copernicus.eu> (accessed on 19 July 2023). The DEM data are available on the Google Earth Engine at https://developers.google.com/earth-engine/datasets/catalog/CGIAR_SRTM90_V4 (accessed on 19 July 2023).

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