

Biophysical effects of croplands on land surface temperature

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Chi Chen^{1,7}✉, Yang Li^{2,7}, Xuhui Wang³, Xiangzhong Luo², Yue Li⁴, Yu Cheng⁵ & Zhe Zhu⁶

Converting natural vegetation to croplands alters the local land surface energy budget. Here, we use two decades of satellite data and a physics-based framework to analyse the biophysical mechanisms by which croplands influence daily mean land surface temperature (LST). Globally, 60% of croplands exhibit an annual warming effect, while 40% have a cooling effect compared to their surrounding natural ecosystems. Aerodynamic resistance is identified as the dominant biophysical factor impacting LST by adjusting latent heat flux. The magnitude of cropland-induced LST change is negatively correlated with the difference in leaf area index between croplands and their surrounding biome types. The strongest warming occurs in temperate dry regions where croplands are surrounded by savannas. However, a lower-than-expected LST disturbance is seen in hot and wet regions where croplands are surrounded by rainforests, attributed to lower cropland fraction and energy limitations. These findings highlight the complex interplay of land use, vegetation, and regional climate, providing valuable insights into sustainable agriculture and land-based climate change mitigation.

Global croplands currently cover 16 million km², representing 14.5% of the world's total vegetated area. The production of primary crops supports a human population of over 8 billion and increased by 54% from 2000 to 2021, reaching 9.5 billion tonnes per year¹. Satellite data confirm that croplands have contributed over a third of the global net increase in leaf area index (LAI) since the 21st century². Cultivating crops requires converting natural ecosystems into croplands, making it one of the largest drivers of tree loss³. Land conversions emit greenhouse gases (GHG) into the atmosphere, leading to global warming^{4,5}. In addition, at local scales, croplands can directly alter land surface energy budget (LSEB) and thus LST by changing biophysical factors, such as surface albedo, roughness, and evaporative power^{6–10}. These effects, shaped by heterogeneous land surfaces and management practices, can outweigh the temperature effects of GHG emissions^{6,9,11–15}. This study focuses on the biophysical effects of

croplands on LSEB and aims to assess LST perturbation contributions from various biophysical pathways.

Due to the lack of sufficient time series and the absence of a spatially explicit history of land conversion^{3,16}, the space-for-time method—comparing croplands to surrounding reference natural biomes—is widely used to quantify the temperature effects of land conversions^{13,14,17–19}. Using this method, we analyse a suite of satellite records spanning two decades to quantify the daily average LST difference (ΔT_s) between croplands and their adjacent natural biomes globally, at a spatial resolution of $0.05^\circ \times 0.05^\circ$. ΔT_s is conceptually identical to the heat/cool island effect, calculated as the LST over croplands minus the mean LST over all available surrounding natural biomes. To locate surrounding natural biomes, we use an adaptive search technique that increases the window size step-by-step until at least one nearby pixel labeled as a natural biome is identified. To

¹Department of Ecology, Evolution, and Natural Resource, Rutgers University, New Brunswick, NJ, USA. ²Department of Geography, National University of Singapore, Singapore, Singapore. ³Sino-French Institute for Earth System Science, College of Urban and Environmental Sciences, Peking University, Beijing, China. ⁴Department of Geography, University of California, Los Angeles, CA, USA. ⁵Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA, USA. ⁶Department of Natural Resources and the Environment, University of Connecticut, Storrs, CT, USA. ⁷These authors contributed equally: Chi Chen, Yang Li. ✉e-mail: chi.chen@rutgers.edu

control for the elevation effect, we ensure that the elevation difference between the target cropland pixel and its surrounding natural biome pixels is within 100 meters^{19–21} (see Methods and Discussion).

Implicit in the space-for-time method is the assumption that temperature differences arising from variations in atmospheric forcings are negligible, attributing observed LST changes solely to differences in land cover (e.g., cropland *vs* natural biomes)^{13,19,20,22,23}. However, this assumption can be problematic in regions where croplands span hundreds of square kilometers, or the terrain is heterogeneous. In such cases, the observed ΔT_s can be confounded by differences in background climate, such as air temperature and humidity²⁴. To address this issue, we use a physics-based attribution framework, termed the Two Resistance Mechanism (TRM) framework, to separate ΔT_s into contributions from changes in biophysical factors ($\Delta T_{s,bio}$) due to cropping land use, and atmospheric conditions ($\Delta T_{s,atm}$) due to variations in background climate^{7,18,25–27} (Eq. 5 in Methods). Our ΔT_s reconstructed by TRM method (i.e., $\Delta T_{s,TRM}$) successfully captures the spatial pattern of satellite-observed ΔT_s (i.e., $\Delta T_{s,obs}$) with a negligible mean bias of -0.0209 ± 0.0002 K (95% confidence interval (CI), Supplementary Fig. 1). The analyses of $\Delta T_{s,bio}$ highlight diverse biophysical impacts of croplands across various surrounding natural biome types, climate zones, and administrative boundaries, emphasizing a dominant role of cropping activities in affecting the local LSEB.

Results

Significant cropland biophysical impacts

We show strong but contrasting cropland biophysical impacts on annual daily mean LST (i.e., $\Delta T_{s,bio}$) across the six inhabited continents (Fig. 1). Globally, 60% of the global croplands are warmer than their surrounding natural biome types (a positive $\Delta T_{s,bio}$), while 40% shows a cooling effect (Supplementary Table 1). The global croplands cause a mean warming of 0.13 ± 0.002 K. This translates to a net instantaneous “land surface” radiative forcing (ILSRF) of 0.93 ± 0.012 Wm⁻² over the global cropland area, which is equivalent to a 0.5% increase of the daily mean incident shortwave radiation forcing over the crop canopy (mean $SW_{in,crop} = 187$ Wm⁻²). Hereafter, we refer to areas with positive and negative $\Delta T_{s,bio}$ as cropland-warmer areas and cropland-cooler areas, respectively. The mean $\Delta T_{s,bio}$ over cropland-warmer regions (0.54 ± 0.002 K) and cropland-cooler regions (-0.54 ± 0.003 K) are comparable in magnitude. However, due to the difference in

background climate between these two groups, the local ILSRF differs. It averages 3.42 ± 0.012 Wm⁻² in cropland-warmer regions (1.8% of $SW_{in,crop}$), while it averages -2.68 ± 0.015 Wm⁻² in cropland-cooler areas (1.4% of $SW_{in,crop}$), a 22% reduction in magnitude compared to cropland-warmer regions. This result indicates that cropland-warmer areas have a higher mean background LST compared to cropland-cooler areas. At pixel scales, the cropland warming hotspots ($\Delta T_{s,bio} > 1$ K) are located in the US Central Lowlands and the Mississippi River Basin, north of the Black Sea in Eastern Europe, southern India, Southeast Asia, and Northern China, while the cooling hotspots are found in the Great Plains of North America, Sub-Sahel Africa, northwestern India and Pakistan, and the lower Yangtze River Basin in China (Fig. 1).

We ranked the mean $\Delta T_{s,bio}$ for the top 30 countries with the largest cropland areas (Fig. 2a). Twenty-five of these countries show that croplands are warmer than their surrounding natural biomes, with Thailand, Romania, Myanmar, Indonesia, Uganda, and Ukraine exhibiting the highest mean warming of over +0.5 K (78% of their cropland area showing positive $\Delta T_{s,bio}$). For these six countries, 71% of their croplands are surrounded by tree-dominated biomes (Fig. 2b). As a result, these countries have significantly lower cropland LAI than their surroundings (Fig. 2a) and are located in tropical to sub-tropical humid regions where trees dominate their surroundings (Fig. 2b). Given the relatively high background temperature in these countries, both crop yield and residents near croplands could be vulnerable to heat stress^{28–30} – yield losses could be over 10% for every 1 °C increase in temperature³¹. In contrast, five of these countries, such as Pakistan, Iran, Turkey, Sudan, and Chad located in arid to semi-arid regions, show a cropland cooling effect (Fig. 2a), likely due to irrigation³². The LAI difference between croplands and their surroundings (ΔLAI) in these countries is near zero or negative, with grasses and shrubs/barren being the dominant surrounding biomes.

There are four countries with over 1 million km² cropland area – India, the United States, China, and Russia – altogether occupying 44% of the global total cropland area, with 43% of their croplands is surrounded by tree-dominated biomes (Fig. 2b). Despite ranking in the middle in terms of mean $\Delta T_{s,bio}$, these countries still exhibit significant cropland warming hotspots, with 55% of their cropland areas being warmer than the surrounding regions. In their cropland-warmer areas, the mean ΔLAI is -0.1 m² m⁻², while in their cropland-cooler areas, the mean ΔLAI is 0.05 m² m⁻². The above results collectively suggest that ΔLAI is an important indicator of whether croplands cause warming or

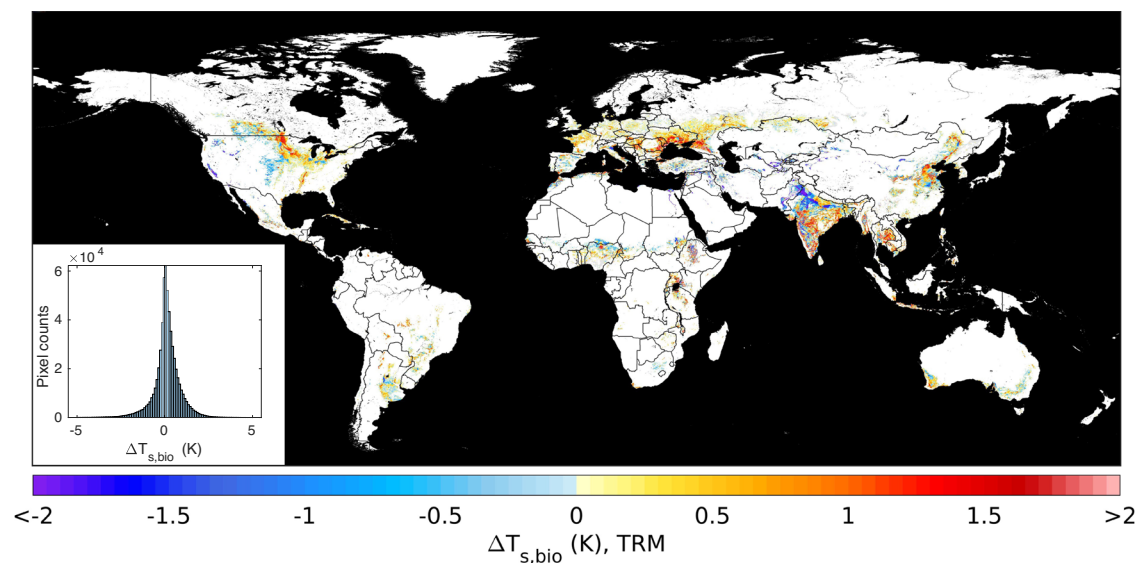


Fig. 1 | Global pattern of cropland-induced biophysical contribution on annual daily mean land surface temperature change ($\Delta T_{s,bio}$) averaged from 2001 to 2023. The inset shows the histogram of $\Delta T_{s,bio}$ by pixel count.

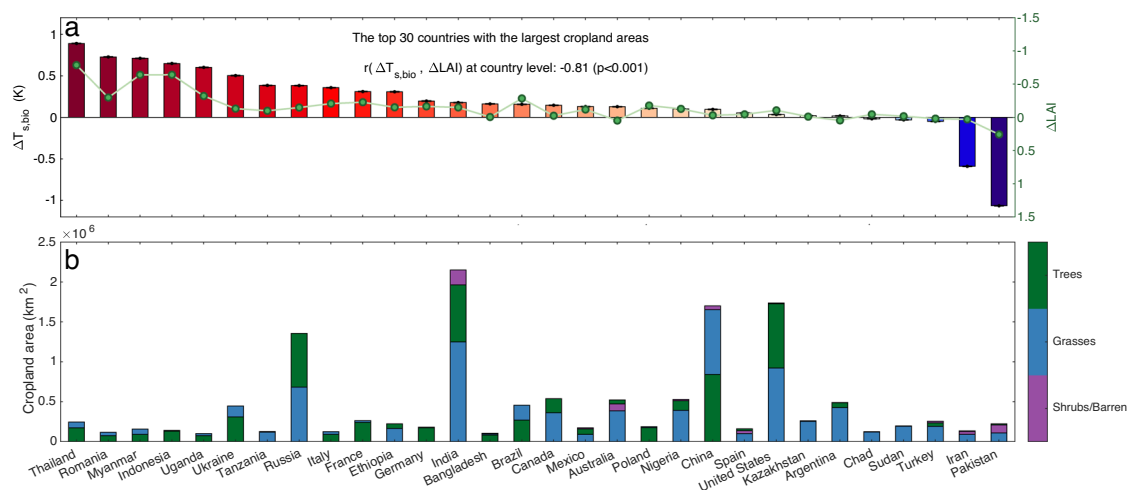


Fig. 2 | Impact of croplands on land surface temperature (LST) in the top 30 countries with the largest cropland areas. **a** Cropland-induced mean biophysical contribution annual daily mean LST change ($\Delta T_{s,bio}$, left axis). The error bar indicates the 95% confidence interval over spatial aggregation. The green dots indicate the mean of difference of leaf area index (ΔLAI , right axis) between croplands and surrounding natural biomes for each country. $r(\Delta T_{s,bio}, \Delta LAI)$ is the Pearson's

correlation. **b** The corresponding cropland areas in these countries. The bars are color-coded to rank the fraction of the dominant surrounding biome for the croplands in these countries. The color at the bottom indicates the highest fraction of a natural biome that surrounds croplands, while the color at the top indicates the lowest fraction.

cooling. In fact, the $\Delta T_{s,bio}$ is inversely correlated to ΔLAI at the country level ($r = -0.81, p < 0.001$). In addition, the ranking of cropland warming and cooling at the country scale suggests a strong sensitivity of cropland biophysical impacts to precipitation levels, which will be discussed later.

Convective efficiency dominates cropland biophysical effects on LST

To explore how croplands change LST biophysically compared to their surrounding natural biomes, our TRM framework provides a detailed breakdown of the LST difference contributions from individual pathways (i.e., albedo, aerodynamic resistance, surface resistance, emissivity, and ground heat flux). Our results show that croplands affect LST primarily through changing aerodynamic resistance (r_a) (Fig. 3). Lower r_a (often associated with higher roughness) indicates a higher ability of the land surface to convect sensible heat and water vapor (i.e., latent heat flux) to the atmosphere, thereby reducing LST, i.e., a positive sensitivity of LST to r_a ^{7,33–35}. In cropland-warmer regions, croplands have higher r_a than their surrounding biomes ($\Delta r_a = 27.3 \pm 0.1 \text{ s m}^{-1}$), leading to reduced sensible and latent heat fluxes^{7,36}. In contrast, in cropland-cooler regions, croplands have lower r_a than their surrounding biomes^{7,36} ($\Delta r_a = -17.6 \pm 0.1 \text{ s m}^{-1}$). Pixel-wise analysis shows that r_a is the most important biophysical factor in shaping the $\Delta T_{s,bio}$ pattern in over 65% of the cropland areas (Fig. 3c).

However, surface resistance (r_s), which describes the ability of the land surface converting liquid water to water vapor to form a hypothetical saturated evaporative surface (with higher r_s indicating a lower ability)³⁷, only dominates 11% of the global cropland areas at pixel scales (Fig. 3c). Despite a less important role of r_s , global attribution analysis indicates that the cropland activities typically lead to identical directional changes in r_s and r_a , and thus the sign of the LST effect (Fig. 3a, b). A change of both resistances in cropland-warmer and -cooler areas correspond to decreased and increased turbulent fluxes, respectively ($r = -0.3, p < 0.001$, Supplementary Fig. 2b). In addition, we note that the combined effect of cropland perturbations in these two resistances causes the latent heat flux to predominate over sensible heat flux due to latent heat flux's higher heat dissipation efficiency^{8,38,39} (Supplementary Fig. 2).

Satellite data reveal a mean albedo difference of less than 2% (absolute albedo) between croplands and their reference natural

biomes across the globe. Consequently, albedo dominates the LST change in only about 8% of the cropland areas (Fig. 3c). Croplands typically have higher albedo compared to surrounding natural biomes, regardless in cropland-warmer or -cooler regions, and hence contributes to a cooling effect (Fig. 3a, b). The relatively lower importance of r_s compared to r_a can also be indirectly inferred from the smaller area of $\Delta T_{s,bio}$ dominated by albedo. According to plant physiology, r_s is mostly determined by the stomatal resistance over vegetated areas, and the amount of absorbed photosynthetically active radiation (about 45% of shortwave radiation that is regulated by albedo) is one of the key energy sources of the opening and closing of stomata^{40,41}.

In this study, we took the ground heat flux (G) as the residual of the LSEB equation and as a forcing term to the LST, similar to the approach used in the Penman–Monteith equation^{25,35}. We find that ΔG is the second most important factor to $\Delta T_{s,bio}$, dominating 17% of the cropland areas (Fig. 3c). This is mostly seen in regions where grasslands are the dominant surrounding biome of croplands⁴², such as in the North America Great Plains, the circum-Mediterranean region, Central Asia, Central China, and India (Fig. 3c). A lower G ($\Delta G = -2.8 \pm 0.03 \text{ W m}^{-2}$) over croplands is associated with a higher LST, which is observed in cropland-warmer regions, while a higher G ($\Delta G = 1.4 \pm 0.03 \text{ W m}^{-2}$) over croplands corresponds to a lower LST observed in cropland-cooler regions.

Biome-climatic interactions

Previous studies suggest that background climate plays an important role in determining the impact of land-cover change on regional climate²⁴. Here, we define nine categorical background climates, a combination of Cool, Warm, and Hot climates based on mean annual air temperature (MAT), and Dry, Humid, and Wet climates based on annual total precipitation (ATP) (Supplementary Fig. 2). MAT thresholds for Cool, Warm and Hot climates are 10 °C and 20 °C, and ATP thresholds for Dry, Humid, and Wet climates are 500 mm and 1500 mm. Focusing on the change of $\Delta T_{s,bio}$ along with ATP variation under the same MAT category, we find two key points from Fig. 4a: First, an increase in annual ATP correlates positively with an increase in $\Delta T_{s,bio}$; Second, the negative correlation between $\Delta T_{s,bio}$ and ΔLAI still holds. This negative correlation between $\Delta T_{s,bio}$ and ΔLAI is also observed along the biome gradient from trees to grass and to sparsely vegetated cropland surroundings (Fig. 4b–d, the first bar of each panel).

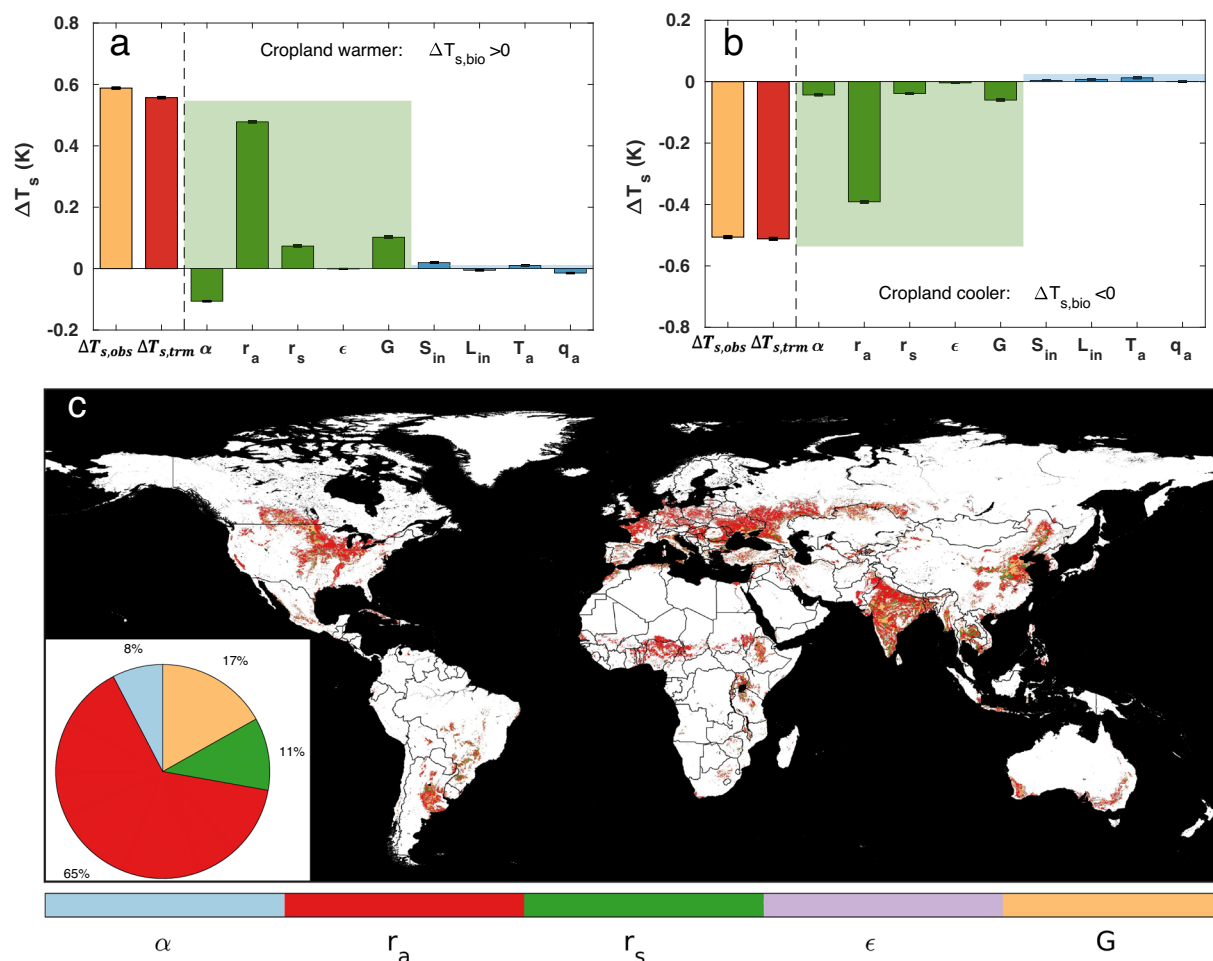


Fig. 3 | Attribution analysis for temperature contrast between cropland and reference natural biomes. The contribution from each biophysical factor to total land surface temperature (LST) difference (ΔT_s) over **a** cropland-induced warming and **b** cropland-induced cooling regions. The error bars indicate the 95% confidence interval over spatial aggregation. $\Delta T_{s,obs}$ is the MODIS-derived LST difference, which is the apparent total LST difference and used as a reference to evaluate the TRM accuracy. $\Delta T_{s,TRM}$ is the TRM reconstructed total LST difference. The green shading is the sum of temperature difference contribution from biophysical

factors, denoted as $\Delta T_{s,bio}$, and the blue shading is the sum of temperature difference contribution from atmospheric conditions, denoted as $\Delta T_{s,atm}$. **c** Dominant biophysical factors in regulating cropland-induced $\Delta T_{s,bio}$. The inset summarizes the fractional area of each dominant factor. albedo: α ; aerodynamic resistance: r_a ; surface resistance: r_s ; emissivity: ϵ ; ground heat flux: G ; S_{in} and L_{in} : incoming shortwave and longwave radiation, respectively; T_a : potential temperature of air; q_a : specific humidity of air.

In Fig. 4a, focusing on the change of $\Delta T_{s,bio}$ along with MAT variation under the same ATP category, the $\Delta T_{s,bio}$ decreases as MAT increases in Dry climates. Specifically, croplands show minor warming in the Cool-Dry zone, minor cooling in the Warm-Dry zone, and strong cooling in the Hot-Dry zone. However, $\Delta T_{s,bio}$ responds minimally to MAT in Humid and Wet zones. These results suggest that while $\Delta T_{s,bio}$ responds to ATP under all background MAT, it becomes saturated with respect to MAT under moist climates due to energy limitation on evapotranspiration (ET)⁴³.

We next investigate the interactions of $\Delta T_{s,bio}$ with the surrounding natural biome types and the background climate. More than half (53%) of global croplands is surrounded by grass-dominated biomes (Supplementary Fig. 3). These croplands exhibit a minor and uncertain mean warming effect of 0.05 ± 0.003 K, with 47% of them actually showing a cooling effect (Supplementary Table 1) and a mean ΔLAI near zero. These grass-surrounded croplands are widespread across all inhabited continents (Supplementary Fig. 3). The response of $\Delta T_{s,bio}$ to climate zones for croplands surrounded by grass-dominated biomes is similar to those all types of surrounding biomes are considered (Fig. 4a, c). Croplands surrounded by shrub/barren-dominated biomes exhibit a cooling effect of -0.77 ± 0.004 K (Fig. 4d). These two types

constitute 5% of the global cropland area, mostly seen in the India-Pakistan border, the circum-Mediterranean regions and Australia (Supplementary Fig. 3), where climate zones are classified as Warm-Dry and Hot-Dry.

Croplands surrounded by tree-dominated biomes show the strongest mean warming effect of 0.31 ± 0.002 K and LAI deficit (i.e., ΔLAI) of -0.33 ± 0.003 m²m⁻². This result is consistent with the fact that 72.8% of such cropland areas are warmer than their surrounding natural biome at pixel scales (Supplementary Table 1). The tree-dominated natural biomes set a high roughness to the land surface, thereby lowering r_a , facilitating land-atmosphere turbulent mixing, and thus forming a strong LST gradient to croplands⁴⁴. These croplands with tree-dominated surroundings are primarily found in the northern hemisphere, constituting 42% of the global cropland area (Supplementary Fig. 3). Croplands in tropical forests-surrounded regions (Hot-Humid and Hot-Wet) causes a stronger warming effect than croplands in boreal forests-surrounded regions (Cool-Humid) (Fig. 4b).

However, the biome-climatic interactions in shaping $\Delta T_{s,bio}$ are more complex in these croplands surrounded by trees than those croplands surrounded by grasses or shrubs. The strongest warming

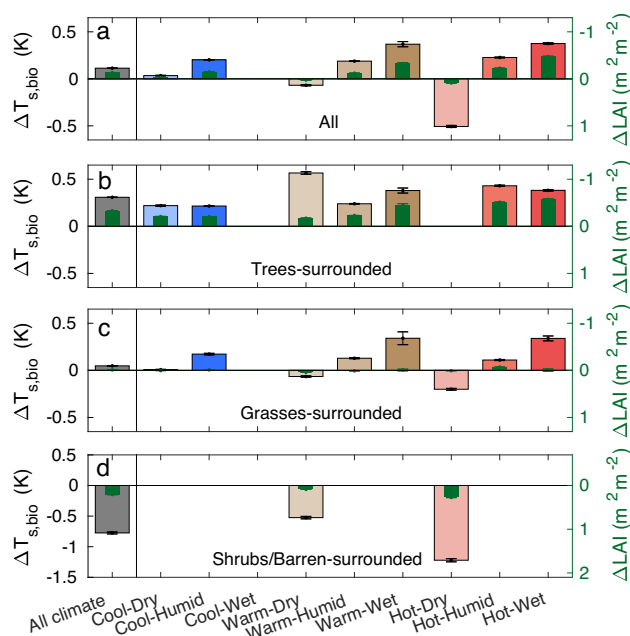


Fig. 4 | Biome-climatic interaction on cropland-induced biophysical contribution on annual daily mean land surface temperature change ($\Delta T_{s,bio}$). Mean $\Delta T_{s,bio}$ (left axis) under different climate zones for **a** croplands surrounded by all biomes, **b** croplands surrounded by tree-dominated biomes, **c** croplands surrounded by grass-dominated biomes, **d** croplands surrounded by shrubs/barren-dominated biomes. Climate zones are defined based on annual mean air temperature (MAT) and annual total precipitation (ATP). The MAT thresholds for cool, warm, and hot zones are 10 °C and 20 °C, and the ATP thresholds for dry, humid, and wet zones are 500 mm and 1500 mm. The first bar of each panel indicates the mean $\Delta T_{s,bio}$ under all climates. The mean difference of leaf area index between croplands and reference natural biomes (ΔLAI) is shown in the green bars with reversed y-axis (right axis). The error bars indicate the 95% confidence interval over spatial aggregation.

effect of croplands surrounded by tree-dominated biomes is seen in the Warm-Dry zone (Fig. 4b). These croplands account for about 10% of croplands in this climate zone and are primarily surrounded by savannas (10–30% tree cover). This strong warming effect is due to a synergistic effect of multiple factors (Supplementary Fig. 4). First, both the sensitivity of LST to r_a (i.e., $\partial T_s / \partial r_a$) and the difference in r_a (i.e., Δr_a) between croplands and their nearby biomes in the Warm-Dry zone are high (Supplementary Fig. 5b). The change of LST is the product of the two. Therefore, the warming contributed by the r_a pathway is the highest among all climate zones (Supplementary Fig. 4). Second, the difference in G between croplands and their nearby biomes contributes to warming and is reflected in the final $\Delta T_{s,bio}$ in the Warm-Dry zone, whereas in humid and wet climate zones, the difference in G usually contributes to cooling (Supplementary Fig. 4). Third, the contribution of r_s to the warming of $\Delta T_{s,bio}$ in the Warm-Dry zone is also significant (Supplementary Fig. 4). This highlights the priority of protecting tropical savannas and preventing their conversion to croplands, which are likely to generate low yields and incur high water demand costs due to the Warm-Dry nature of these regions.

In addition, for trees-surrounded croplands, we observe a saturated or even lower $\Delta T_{s,bio}$ in the Hot-Wet zone compared to the Hot-Humid zone (Fig. 4c), which contrasts with the global trend where wetter regions typically show a stronger cropland warming effect (Fig. 4a). This finding is also inconsistent with their corresponding ΔLAI gradient, where the Hot-Wet zone in fact shows a more negative ΔLAI than the Hot-Humid zone (Fig. 4c). Further investigation reveals that this discrepancy is due to the reduced role of r_s (Supplementary Figs. 4f, g). Specifically, there is a reduced Δr_s between croplands and

their surrounding natural biomes in the Hot-Wet zone compared to the Hot-Humid zone (Supplementary Fig. 5c). Although the sensitivity of LST to r_s in the Hot-Wet zone is higher than in the Hot-Humid zone (Supplementary Fig. 5c), the contribution from the reduced Δr_s outweighs the sensitivity difference (Supplementary Figs. 4f, g). This is because land cover within remote sensing pixels is heterogeneous, and cropland pixels are mixed with natural vegetation. For croplands surrounded by tree-dominated natural biomes, the mean crop fraction in the Hot-Wet zone (41.4%) is lower than in the Hot-Humid zone (52.4%) (Supplementary Table 2). In these regions, ET is energy limited and governed by net shortwave radiation⁴³, and the existing natural biomes mixed within the cropland pixels already consume nearly all available energy for ET. Combined with the plant physiology discussed earlier, this limited energy prevents the formation of a large r_s gradient between the cropland pixels and their surrounding natural biomes in the Hot-Wet zone. These results also suggest that to prevent a significant warming effect, it is crucial to protect the rainforests or at least maintain the croplands with heterogeneous land covers at remote sensing scales in these wet rainforests regions^{21,45,46}.

Discussion

The $\Delta T_{s,bio}$ calculated in our study partially depends on the reference surrounding biome types. Therefore, it is important to demonstrate the robustness of the adaptive search window technique. We provide at least three lines of evidence to support this. First, we show that contributions from the difference in atmospheric conditions ($\Delta T_{s,atm}$) to the total LST difference (ΔT_s) are minor (Fig. 3a, b). We note that this $\Delta T_{s,atm}$ is always removed from our analyses of $\Delta T_{s,bio}$. This also suggests that the selected reference areas are reasonable to represent the pre-land conversion status of the current croplands. Second, 10% of the cropland pixels used larger search windows than $1^\circ \times 1^\circ$ to locate their reference natural biomes (Supplementary Fig. 6). We demonstrate that increasing the search window size does not introduce large difference in background atmospheric conditions, and the contributions from $\Delta T_{s,atm}$ remain small (Supplementary Fig. 7). Third, even if the contributions of background climate are nonnegligible, the TRM method provides high confidence in extracting the biophysical effect of cropland by removing the $\Delta T_{s,atm}$. To prove this, we conducted another experiment by relaxing the elevation control, thus changing the population for the reference surrounding biomes of the croplands. In this case, the $\Delta T_{s,atm}$ increases and is negatively correlated with $\Delta \text{Elevation}$ (cropland elevation minus surrounding biomes' elevation, $r = -0.75$, $p < 0.001$). This is primarily due to elevation-induced changes in air temperature, which strongly force the LST to change⁷ (Supplementary Fig. 8). However, the $\Delta T_{s,bio}$ remains almost the same (with elevation control: $\Delta T_{s,bio}$ is 0.54 ± 0.002 K and -0.54 ± 0.003 K for cropland-warmer/cooler regions, respectively, see in Fig. 3b; without elevation control: $\Delta T_{s,bio}$ is 0.57 ± 0.002 K and -0.56 ± 0.003 K for cropland-warmer/cooler regions, respectively, see in Supplementary Fig. 8), demonstrating the robustness of the TRM method. This analysis also suggests the importance of considering the elevation effect in such space-for-time method analysis. The actual cropland biophysical impact of LST, i.e., $\Delta T_{s,bio}$, is smaller than the satellite observed ΔT_s in cropland-warmer regions, but it is larger than ΔT_s in cropland-cooler regions, if elevation is not controlled (Supplementary Fig. 8). Lastly, we acknowledge that irrigation can also influence LST through biophysical factors^{32,47}, which are implicitly captured by our TRM framework. We observe a modest negative correlation ($r = -0.07$, $p < 0.001$) between irrigation fraction and $\Delta T_{s,bio}$ globally. However, this study does not aim to separate the specific effects of irrigation, but rather focuses on the overall changes in biophysical factors due to cropping activities.

Our study provides a comprehensive understanding of the biophysical effects of cropland on LST and explores their interactions with land management, background vegetation types, and land-air interactions. While we report that a substantial proportion of cropland shows a

cooling effect, the predominant signal remains warming. We find that cropland activities cause changes in LST primarily through aerodynamic resistance, which determines the efficiency of heat dissipation through land-atmosphere interactions. The strongest cropland warming effect is observed in Warm-Dry regions where savannas, considered tree-dominant in this study, are the dominant surrounding biome types. Our biome-climatic analysis further demonstrates that the surrounding biome types and LAI differences are major factors shaping the LST difference between cropland and their natural surroundings. To mitigate the cropland warming effect, it is recommended to reduce the LAI difference between cropland and its surroundings, maintain small, patchy croplands (i.e., heterogeneous land covers), and limit cropland expansion near natural biomes with high surface roughness (e.g., trees). Altogether, these findings offer valuable insights for sustainable land-use management in the future^{48,49}.

Methods

Satellite data

Land surface temperature and emissivity. In this study, we use the Level-3 monthly Terra MODIS Land Surface Temperature/Emissivity product (MOD11C3, version 061) at a climate modeling grid (CMG) resolution of 0.05°⁵⁰. All available data from 2001 to 2023 are used. Terra MODIS is a sun-synchronous satellite with overpass times of 10:30 a.m. and 10:30 p.m. The mean of these two instantaneous LST acquisitions is calculated as the daily mean temperature for further analysis^{8,51}. We apply a quality flag ensuring an average LST error ≤ 3 K and an average emissivity error ≤ 0.04 . The MODIS LST product has achieved NASA's Stage 2 validation, with product accuracy estimated over a significant set of locations and time periods by comparison with reference in situ measurements and globally with similar products⁵².

Land cover. We use two land cover products to define the cropland area and its surrounding natural ecosystems. First, we use the Level 3 yearly Terra-and-Aqua-combined MODIS Land Cover Type product (MCD12C1, version 061) at a CMG resolution of 0.05°⁵³. We then stack the International Geosphere-Biosphere Programme (IGBP) classification layer of MCD12C1 from 2001 to 2021, count the number of times a pixel is assigned to a certain class, and use the mode number as the final class. The MODIS land cover product has achieved NASA's Stage 2 validation. Second, we use additional information of cropland extent at 30-m spatial resolution derived from Landsat⁵⁴. The crop extent mapping was performed every four years (2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019). We aggregate the 30-m resolution binary data (crop, non-crop) to a 0.05° resolution as crop fraction in percent and compute the mean crop fraction through the time series. Finally, we define our croplands as MODIS IGBP Class 12 (Croplands, >60% cultivation) and Class 14 (Cropland/Natural Vegetation Mosaics, 40–60% cultivation), or those with Landsat cropland fraction greater than 40%. This ensures minimal omission error for croplands.

We define the natural biome types as follows according to MODIS IGBP but exclude any croplands defined before. (1) Trees: The category includes forests and savannas, including IGBP classes 1 to 5 (Evergreen Needleleaf, Evergreen Broadleaf, Deciduous Needleleaf, Deciduous Broadleaf, and Mix forests), and IGBP classes 8 and 9 (Woody Savannas, Savannas). (2) Grasses: IGBP classes 10 and 11 (Grasslands, Permanent Wetlands). (3) Shrubs/Barren: IGBP Classes 6 and 7 (Closed Shrublands, Open Shrublands) and IGBP Classes 15 and 16 (Permanent Snow and Ice, Barren). We exclude urban and built-up lands (IGBP class 13) in all our analyses. Supplementary Fig. 3 shows the final map of the dominant surrounding biome types, displayed at the locations corresponding to the cropland pixels.

Surface albedo. The Level-3 daily Terra-and-Aqua-combined MODIS Albedo product (MCD43C3) at 0.05° resolution from 2001 to 2023 is used in our analysis⁵⁵. Specifically, we use the white sky albedo for

shortwave broadband to represent the surface albedo. We calculate the monthly mean for further analysis in our study. The MCD43C3 product has achieved the highest Stage 4 validation with the most extensive temporal and spatial examinations⁵⁵.

Latent heat flux. The Level-4 8-day gap-filled Terra MODIS Evapotranspiration (ET) product at 500 m resolution (MOD16A2GF, version 6.1) from 2001 to 2023 is used⁵⁶. This product initially provides daily ET values, which are converted into latent heat fluxes using the latent heat of vaporization. The product is aggregated temporally to a monthly scale through a weighted average, considering the number of days within each 8-day period that overlap with each respective month. Subsequently, it is resampled to a CMG 0.05° resolution. The MOD16A2GF product is Stage-3 validated⁵⁶.

Downward (incoming) shortwave radiation. We use the Level-3 Terra MODIS daily downward shortwave radiation (MCD18C1, Version 6.1) from 2001 to 2023 at a spatial resolution of CMG 0.05°⁵⁷. In this study, the product is temporally averaged to a monthly scale. The MODIS downward shortwave radiation product has achieved NASA's Stage 1 validation.

Leaf area index (LAI). We use the Level 3 8-day MODIS Terra and Aqua combined LAI product (MCD15A2H, version 061) from 2001 to 2023 at a sinusoidal resolution of 500 m⁵⁸. The MODIS LAI data is also achieved Stage 2 validation⁵⁹ and we refine and aggregate the data to a monthly frequency at 0.05° CMG grid, following our earlier study².

Digital elevation model (DEM). We use the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010), which offers a spatial resolution of 30-arc-second⁶⁰. This digital elevation model (DEM) is produced by the U.S. Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA), integrating data from sources including the Shuttle Radar Topography Mission (SRTM), Canadian elevation data, Spot 5 Reference3D data, and measurements from the Ice, Cloud, and land Elevation Satellite (ICESat). We resample the DEM data to CMG 0.05° resolution.

Irrigation fraction. The global irrigation data is obtained from the Landsat-Derived Global Rainfed and Irrigated-Cropland Product (LGRIP) at 30 m resolution. LGRIP data are produced using Landsat-8 time-series data for the period of 2014–2017 and created a nominal 2015 product. We aggregated the LGRIP data into irrigation fraction at a CMG 0.05° resolution.

Reanalysis Data

ERA5-Land meteorological data. We use the meteorology variables from ERA5-land monthly (2001–2023, 0.1°) to conduct our attribution analysis⁶¹. The following variables are used: '2 m temperature', 'surface pressure', '2 m dew point temperature' (converted to specific humidity), 'surface pressure', 'Surface sensible heat flux', and 'Total precipitation'. We use the bilinear method to resample the data from 0.1° to 0.05°. In our following analysis, we convert the '2 m temperature' to the reference air temperature at 100 m above the land surface using a dry adiabatic lapse rate of -9.8 K per 1000 meters. This adjustment helps minimize the occurrence of negative values in aerodynamic and surface resistance, which are physically meaningless. Additionally, we ensure that the reference air temperature does not fall below the '2 m dew point temperature' by assuming a constant specific humidity for the near-surface atmosphere. If the calculated reference air temperature is lower than the dew point temperature, we replace it with the dew point temperature. The uncertainty within the ERA5-land reanalysis has been comprehensively evaluated against various reference data sets and modeling tools, showing improved quality in its energy partitioning terms and near-surface meteorological variables

compared to ERA-Interim^{61,62}. However, despite such improvements, the sensible heat flux used in this study could still be underestimated due to an overestimation of latent heat flux.

Climate zones. We use the mean annual 2 m air temperature and mean annual total precipitation from ERA5-land to define nine climate zones. The thresholds for cool, warm, and hot zones are 10 °C and 20 °C, and the thresholds for dry, humid, and wet zones are 500 mm and 1500 mm. These thresholds effectively separate and identify nine distinct croplands warming and cooling zones in the two-dimensional precipitation-air temperature space (Supplementary Fig. 9a). Their spatial distribution and the area of croplands for each climate zone are shown in Supplementary Fig. 9b–k.

The adaptive search technique

We use an adaptive search technique to locate the reference natural biome types surrounding the cropland. The search window starts with a $0.15^\circ \times 0.15^\circ$ box and increases by 0.1° in both meridional and latitudinal directions if the smaller window fails to identify a nearby pixel labeled as natural biome types. The elevation difference between the target cropland pixel and its surrounding natural biome pixels must be within 100 m^{19,20}. The algorithm will expand its search window until at least one pixel of any natural biome type is located (Supplementary Fig. 6a). Our statistics show that 35% of the cropland pixels can locate their natural reference biome pixels within a $0.15^\circ \times 0.15^\circ$ box, 53% cumulatively within a $0.25^\circ \times 0.25^\circ$ box, and 90% cumulatively within a $1^\circ \times 1^\circ$ box (Supplementary Fig. 6b).

Two Resistance Mechanism (TRM) framework

A common but often implicit assumption in physics-based attribution studies is that the attributing variables are independent of each other in the land surface energy balance equation. For example, changes in the Bowen ratio or changes in ET are not independent of changes in aerodynamic resistance^{14,38}. Our previous studies have highlighted that such “independence” assumptions are important and can lead to different attribution results^{7,18,26}. The TRM method ensures its attributing variables to be independent in the LSEB scheme, including – biophysical factors (Category I): albedo, aerodynamic resistance, surface resistance, emissivity, and ground heat flux; and atmospheric conditions (Category II): incoming shortwave radiation, incoming longwave radiation, air temperature, and air specific humidity. In other words, TRM framework require these biophysical factors and atmospheric conditions as inputs. Variables like LAI, irrigation, and elevation are not directly considered as attributable within the TRM framework. However, their influence on the LSEB is implicitly captured through the meteorological inputs. The theoretical accuracy of the TRM framework has been thoroughly evaluated, demonstrating minimal errors in LST when input data are accurate²⁵. However, in practice, uncertainties in the input data can propagate into the TRM results. We refer these input data uncertainties by citing relevant studies in their corresponding data sections.

The TRM framework is derived from the LSEB equation (Eq. 1):

$$R_n = S_{in}(1 - \alpha) + \epsilon L_{in} - \epsilon \sigma T_s^4 = H + LE + G \quad (1)$$

where R_n is the net radiation; S_{in} and L_{in} are the incoming shortwave and longwave radiation, respectively; α and ϵ are the albedo and emissivity, respectively; G is ground heat flux; $\epsilon \sigma T_s^4$ is the outgoing longwave radiation ($= L_{out}$) where σ is the Stefan-Boltzmann constant ($5.670367 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$) and T_s is the LST. Further connecting H and LE with LST through the aerodynamic resistance (r_a) and surface resistance (r_s) concepts gives,

$$H = \frac{\rho c_p}{r_a} (T_s - T_a) \quad (2)$$

$$LE = \frac{\rho L_v}{r_a + r_s} [q_s^*(T_s) - q_a] \quad (3)$$

where ρ is the air density, c_p is the specific heat of air at constant pressure ($1004.64 \text{ J kg}^{-1} \text{ K}^{-1}$), L_v is the latent heat of vaporization ($2.4665 \times 10^6 \text{ J kg}^{-1}$), T_a is the potential temperature of air, q_a is the specific humidity of air, r_a is the aerodynamic resistance, and r_s is the surface resistance. We note that r_a and r_s are computed through inverting Eq. 2 and 3 given all other terms are obtained from the ERA5-land and MODIS. All negative values of r_a and r_s , which are physically meaningless, are excluded from analysis. Air density ρ is computed as $\rho = \frac{P - e_a}{RT_a} + \frac{e_a}{R_v T_a}$, where P is the surface pressure, e_a is the vapor pressure, R is the dry air gas constant ($287.058 \text{ J kg}^{-1} \text{ K}^{-1}$), R_v is the water vapor gas constant ($461.5 \text{ J kg}^{-1} \text{ K}^{-1}$). We also note that the impact of variability in ρ between croplands and adjacent biome types is negligible and therefore not accounted for in our attribution.

Substituting Eq. 2 and 3 into Eq. 1 yields a non-linear equation for T_s provided that all other variables are given as inputs. By using the first-order Taylor series expansion of non-linear LST-related terms in the LSEB (i.e., $\epsilon \sigma T_s^4$ and LE), one can yield an analytical solution for T_s (Eq. 4)^{7,18,25,26}.

$$T_s = \frac{\lambda_o \left[R_n^* - G - \left(\frac{\rho L_v}{(r_a + r_s)} (q_a^*(T_a) - q_a) \right) \right]}{1 + f} + T_a \quad (4)$$

where shortcuts $R_n^* = S_{in}(1 - \alpha) + \epsilon L_{in} - \epsilon \sigma T_a^4$, $f = \frac{r_a}{r_a} \left[1 + \frac{\delta}{\gamma} \left(\frac{r_a}{r_a + r_s} \right) \right]$, $\delta = \frac{\partial \epsilon^*}{\partial T} \Big|_{T_a}$, $r_o = \rho c_p \lambda_o$, $\gamma = \frac{c_p P}{0.622 L_v}$, and $\lambda_o = \frac{1}{4 \epsilon \sigma T_a^3}$; ϵ^* is saturation vapor pressure³⁷ calculated as $\epsilon^* = 611 \times \exp \left[\frac{17.27(T_a - 273.15)}{T_a - 35.85} \right]$, P is surface pressure. When vegetation and bare soil coexists, T_s is a single, representative surface temperature while r_s is the bulk surface resistance.

Based on the analytical expression of T_s , one can attribute the LST changes as follows (Eq. 5):

$$\begin{aligned} \Delta T_s &= \Delta T_{s,bio} + \Delta T_{s,atm} \\ &= \left(\frac{\partial T_s}{\partial \alpha} \right) \Delta \alpha + \left(\frac{\partial T_s}{\partial r_a} \right) \Delta r_a + \left(\frac{\partial T_s}{\partial r_s} \right) \Delta r_s + \left(\frac{\partial T_s}{\partial \epsilon} \right) \Delta \epsilon + \left(\frac{\partial T_s}{\partial G} \right) \Delta G \\ &\quad + \left(\frac{\partial T_s}{\partial S_{in}} \right) \Delta S_{in} + \left(\frac{\partial T_s}{\partial L_{in}} \right) \Delta L_{in} + \left(\frac{\partial T_s}{\partial T_a} \right) \Delta T_a + \left(\frac{\partial T_s}{\partial q_a} \right) \Delta q_a \end{aligned} \quad (5)$$

where Δ represents a change and it represents the difference in any variables between cropland and adjacent natural ecosystems. Together, $\Delta T_{s,bio}$ and $\Delta T_{s,atm}$ account for the impact on ΔT_s from changes in biophysical factors and atmospheric conditions, respectively. The LST sensitivities to biophysical factors and atmospheric conditions (i.e., the partial derivatives), as well as the differences in these variables between cropland and natural vegetation (i.e., the Δ terms), need to be estimated. The LST sensitivities to individual biophysical factors and atmospheric conditions are detailed in Eqs. 6–14.

$$\frac{\partial T_s}{\partial \alpha} = -\frac{\lambda_o S_{in}}{1 + f} \quad (6)$$

$$\begin{aligned} \frac{\partial T_s}{\partial r_a} &= \frac{\lambda_o \rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)^2} \frac{1}{(1 + f)} \\ &\quad + \lambda_o \left\{ \frac{r_o}{r_a^2} \left[1 + \frac{\delta}{\gamma} \left(\frac{r_a}{r_a + r_s} \right)^2 \right] \right\} \left[R_n^* - G - \frac{\rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)} \right] \frac{1}{(1 + f)^2} \end{aligned} \quad (7)$$

$$\frac{\partial T_s}{\partial r_s} = \frac{\lambda_o \rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)^2} \frac{1}{(1+f)} + \lambda_o \left[\frac{\delta}{\gamma} \frac{r_o}{(r_a + r_s)^2} \right] \left[R_n^* - G - \frac{\rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)} \right] \frac{1}{(1+f)^2} \quad (8)$$

$$\frac{\partial T_s}{\partial \epsilon} = \frac{\lambda_o}{1+f} \left[\left(L_{in} - \sigma T_a^4 \right) - \frac{R_n^* - G - \frac{\rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)}}{\epsilon(1+f)} \right] \quad (9)$$

$$\frac{\partial T_s}{\partial G} = -\frac{\lambda_o}{1+f} \quad (10)$$

$$\frac{\partial T_s}{\partial S_{in}} = \frac{\lambda_o(1-\alpha)}{1+f} \quad (11)$$

$$\frac{\partial T_s}{\partial LW_{in}} = \frac{\lambda_o \epsilon}{1+f} \quad (12)$$

$$\frac{\partial T_s}{\partial T_a} = \frac{\lambda_o}{1+f} \left[\frac{\partial R_n^*}{\partial T_a} - \frac{\rho L_v}{(r_a + r_s)} \frac{\partial q_a^*}{\partial T_a} \right] + \frac{\left[R_n^* - G - \frac{\rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)} \right]}{1+f} \frac{\partial \lambda_o}{\partial T_a} - \frac{\lambda_o \left[R_n^* - G - \frac{\rho L_v (q_a^*(T_a) - q_a)}{(r_a + r_s)} \right]}{(1+f)^2} \frac{\partial f}{\partial T_a} + 1 \quad (13)$$

$$\frac{\partial T_s}{\partial q_a} = \frac{\lambda_o \rho L_v}{(1+f)(r_a + r_s)} \quad (14)$$

where shortcuts $\frac{\partial R_n^*}{\partial T_a} = -4\epsilon\sigma T_a^3$, $\frac{\partial \lambda_o}{\partial T_a} = -\frac{3}{4\epsilon\sigma T_a^4}$, $\frac{\partial q_a^*}{\partial T_a} = \frac{0.622}{P} \delta$, $\frac{\partial f}{\partial T_a} = \frac{\rho c_p}{r_a} \left[1 + \frac{\delta}{\gamma} \left(\frac{r_a}{r_a + r_s} \right) \right] \frac{\partial \lambda_o}{\partial T_a} + \frac{r_o}{\gamma(r_a + r_s)} \frac{\partial \delta}{\partial T_a}$, and $\frac{\partial \delta}{\partial T_a} = \frac{\partial^2 \epsilon}{\partial T^2} \Big|_{T_a}$.

The Taylor series linearization can introduce errors to the TRM reconstructed ΔT_s , especially over large contrasts between the land covers (e.g., cropland vs forest)²⁵. Additionally, the differing sensitivity of LST to biophysical factors between croplands and surrounding biomes raises the question of which sensitivity to apply in the attribution model⁶³. One solution is to include higher-order terms from the Taylor series expansion to the attribution problem, while this will significantly increase the complexity of the attribution framework²⁵. Therefore, we decide to use the linearized framework but introduce a weighted average approach to minimize the errors by considering both the LST sensitivities over croplands and their surrounding natural biomes¹⁸, and the final LST sensitivities are adjusted by Eq. 15.

$$\frac{\partial T_s}{\partial X} = \frac{\frac{\partial T_s}{\partial X} \Big|_{\text{natural}} + m \frac{\partial T_s}{\partial X} \Big|_{\text{crop}}}{1+m} \quad (15)$$

where X represents any attributing variables of biophysical factors and atmospheric conditions, and m is a parameter to be calibrated (varying from 0 to 10). When m is between 0 to 1, the final sensitivity $\partial T_s / \partial X$ is contributed more by the surrounding natural biomes, and when m is between 1 and 10, the final sensitivity $\partial T_s / \partial X$ is contributed more by the cropland. For a single pixel, we note that m has the same value throughout the sensitivities of LST to the nine attributing variables – that said, m does not alter the relative importance among the attributing variables. After introducing this weighted average approach, our TRM reconstructed ΔT_s can successfully reproduce the spatial pattern of satellite observed ΔT_s from Terra MODIS averaged from 2001 to 2023. A

further examination shows that the bias of the TRM-reconstructed ΔT_s is negligible compared to its satellite counterpart (mean bias and 95% CI = -0.0209 ± 0.0002 K) (Supplementary Fig. 1).

Temporal and spatial average

We use the surrounding biome mask generated from the adaptive search technique to first compute the spatial mean of any variables over the surrounding natural biomes (one cropland pixel corresponds to at least one surrounding natural biome pixel). Next, we compute the difference in MODIS LST between croplands and the mean of surrounding natural biomes, i.e., using the variable over cropland minus the mean of that variable over surrounding natural biomes, as well as the differences in biophysical factors and meteorological forcings used in the TRM attribution framework. At this step, all data represent a monthly 24-h mean. We then calculate the 12-month average to represent the annual mean. The TRM framework is applied after we obtain the annual mean data. Finally, we calculate the temporal average of all our results by averaging values from individual years throughout 2001 to 2023. We also examined the temporal variability of our estimated $\Delta T_{s,bio}$ due to year-to-year fluctuations in cropland activity and found the range of 95% CI is below 0.01 K at the global level.

Instantaneous land surface radiative forcing

The instantaneous land surface radiative forcing (ILSRF) is first evaluated for each cropland pixel, and then spatially averaged for all cropland pixels (Eq. 16)

$$ILSRF = \langle \epsilon_c \sigma (T_{s,c} - \Delta T_{s,atm})^4 - \langle \epsilon_n \sigma T_{s,n}^4 \rangle \rangle \quad (16)$$

where $T_{s,c}$ and $T_{s,n}$ are Terra MODIS LST over cropland and the surrounding natural biome types, respectively, $\Delta T_{s,atm}$ is the TRM reconstructed LST difference not due to cropland biophysical impacts, $\langle x \rangle$ represents the spatial average weighted by the area of each grid cell. The ILSRF does not aim to explicitly adjust for atmospheric feedback, such as changes in cloud cover over large cropland areas compared to their surrounding areas, because this will introduce further uncertainties, and the focus of this study is land. Instead, the effects of atmospheric feedback are implicitly included in the TRM reconstructed ΔT_s through the reanalysis meteorological inputs, i.e., the ERA5-land atmospheric forcings. We also emphasize that the ILSRF is not directly comparable to the effective radiative forcing used in Intergovernmental Panel on Climate Change (IPCC) reports^{64–66}. Therefore, we limit our comparison of ILSRF to the daily mean incident shortwave radiation at the top of the canopy.

Data availability

All data and materials used in this study are publicly available as referenced within the article. MODIS LST is available from <https://lpdaac.usgs.gov/products/mod11c3v061/>. MODIS land cover is available from <https://lpdaac.usgs.gov/products/mcd12c1v061/>. Landsat global cropland fraction is available from <https://glad.umd.edu/dataset/croplands>. MODIS albedo is available from <https://lpdaac.usgs.gov/products/mcd43c3v061/>. MODIS ET is available from <https://lpdaac.usgs.gov/products/mod16a2gfv061/>. MODIS downward shortwave radiation is available from <https://lpdaac.usgs.gov/products/mcd18a1v061/>. MODIS LAI is available from <https://lpdaac.usgs.gov/products/mcd15a3hfv061/>. Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) is available from <https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation>. Irrigation data (LGRIP): <https://lpdaac.usgs.gov/products/lgrip30v001/>. ERA5-Land is available from <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means>.

Code availability

The code used to generate the results of this study is available at https://github.com/yaoganchenchi/Crop_LST/.

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Author contributions

C.C. and Y.L. designed the project, performed analysis and interpreted the results. C.C. wrote the manuscript. X.W., X.L., Y.L., Y.C., and Z.Z. provided feedback on the result interpretation and manuscript writing.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Chi Chen.

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