ENVIRONMENTAL RESEARCH LETTERS

LETTER • OPEN ACCESS

Global assessment of urban trees' cooling efficiency based on satellite observations

To cite this article: Qiquan Yang et al 2022 Environ. Res. Lett. 17 034029

View the article online for updates and enhancements.

You may also like

- Fault diagnosis and accommodation for multi-actuator faults of a fixed-wing unmanned aerial vehicle Zhenbao Liu, Lina Wang, Yuecheng Song et al.
- <u>Fault detection and fault tolerant control of</u> <u>vehicle semi-active suspension system</u> <u>with magneto-rheological damper</u> Xiumei Du, Gaowei Han, Miao Yu et al.
- Syntheses, characterization, and suppression efficiency of silver & silver iodide nanoparticle for proliferation, migration, and invasion in follicular thyroid carcinoma cells Saeed M Feyadh and Asma H Mohammed

ENVIRONMENTAL RESEARCH LETTERS

LETTER

OPEN ACCESS

CrossMark

RECEIVED

10 November 2021

29 December 2021

ACCEPTED FOR PUBLICATION 17 January 2022

PUBLISHED 25 February 2022

Original content from this work may be used under the terms of the Creative Commons Attribution 4.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



Global assessment of urban trees' cooling efficiency based on satellite observations

Qiquan Yang^{1,2}, Xin Huang^{3,4,*}, Xiaohua Tong^{1,2,*}, Changjiang Xiao^{1,2}, Jie Yang³, Yue Liu³ and Yinxia Cao³

College of Surveying & Geo-Informatics, Tongji University, Shanghai 200092, People's Republic of China

² The Shanghai Key Laboratory of Space Mapping and Remote Sensing for Planetary Exploration, Tongji University, Shanghai 200092, People's Republic of China

- School of Remote Sensing and Information Engineering, Wuhan University, Wuhan 430079, People's Republic of China
- State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing, Wuhan University, Wuhan 430079, People's Republic of China
- Authors to whom any correspondence should be addressed.

E-mail: xhuang@whu.edu.cn and xhtong@tongji.edu.cn

Keywords: urban trees, urban heat islands, land surface temperature, remote sensing, globe Supplementary material for this article is available online

Abstract

Trees are among the most important urban land covers, and their effects on local thermal environments have been extensively evaluated by using the concept of urban trees' cooling efficiency (CE), defined as the magnitude of land surface temperature (LST) reduction by per 1% increase in fractional tree cover (FTC). Existing studies provide quantitative knowledge of the CE at local and regional scales, but global-scale analyses are still lacking. Therefore, this study fills this research gap through investigating the spatiotemporal pattern of CE in 510 global cities. CE is quantified by the opposite value of the regression coefficient of FTC (i.e. $CE = -\partial LST/\partial FTC$) in a multiple linear regression model, where LST is the dependent variable and FTC, surface elevation, and nighttime light intensity are the independent variables. Results show that daytime LST decreases greatly with increasing FTC in most cities, and the globally averaged annual daytime CE reaches 0.063 °C %⁻¹, while at night, the effect of urban trees on LST weakens a lot, with an annual average CE of only 0.007 $^{\circ}$ C $\%^{-1}$ across global cities. CE varies markedly among cities and tends to be higher in hot and dry cities, which can be attributed to the significant nonlinear relation between CE and climatic conditions, in that the increase in temperature and the decrease in humidity can enhance vapor pressure deficit and further promote the heat dissipation by plant transpiration. As expected, CE shows a distinct seasonal variation, generally characterized as being higher in summer and lower in winter. In addition, our results suggest that previous studies based on a bivariate linear regression model have overestimated CE, especially at night when trees' activities are weak. This global-scale study provides new insights into the mitigation of urban thermal stress from the perspective of increasing urban greenery.

1. Introduction

The world has experienced rapid urbanization over the last few decades (Liu *et al* 2020, Xu *et al* 2020). Changes in land cover and intensification of human activities in the process of urban development can alter the urban ecology and climate, causing several environmental problems, the most notable of which is the urban heat island (UHI) effect (Kalnay and Cai 2003, Grimm *et al* 2008, Chen *et al* 2021, She *et al* 2021). The UHI effect refers to urban areas typically having higher temperatures than surrounding rural areas. The UHI effect can influence urban microclimates and exacerbate the intensity and frequency of urban heat waves, affecting the comfort of city dwellers and even endangering their lives (Tan *et al* 2010, Zhou *et al* 2018, Trinder and Liu 2020). Therefore, in the context of today's global warming, how to effectively mitigate the UHI effect has become a worldwide concern.

Numerous studies have shown that vegetated areas tend to have lower temperatures, suggesting

the critical roles of vegetation in affecting urban thermal environments (Susca *et al* 2011, Li *et al* 2012, Maimaitiyiming *et al* 2014, Gunawardena *et al* 2017, Yan *et al* 2020, Liu *et al* 2021). Trees tend to have a stronger transpiration rate than other low vegetation (e.g. grasslands or croplands; Li *et al* 2015); furthermore, their branches and leaves can block solar radiation and the resulting shadows can also have a cooling effect (Jiao *et al* 2017). Therefore, the impact of trees on the UHI effect has received much attention in recent years, and a great deal of work has been done to quantify the impact of trees on urban temperatures (Loughner *et al* 2012, Jiao *et al* 2017, Zhou *et al* 2017, Drake *et al* 2018, Wang *et al* 2018, 2019, 2020, Zhang *et al* 2019, Chinchilla *et al* 2021).

In terms of research methodology, existing studies can be roughly divided into two main categories. The first is model-based analysis, which not only provides a mechanistic understanding of the impact of trees on urban climates, but also effectively quantifies the contribution of different factors (such as transpiration and shading) to the cooling effect of urban trees. For instance, Wang *et al* (2018) investigated the effect of urban trees on climates by using the Integrated WRF (Weather Research and Forecasting)-Urban Modeling System, and found that shadows were the main contributor to urban trees' cooling effect. However, modeling results can be affected by parameters and structure of the model, leading to a great deal of uncertainty (Loughner *et al* 2012).

The second category is observational-based analysis. Traditionally, this kind of research mainly relies on *in-situ* observations, including weather stations and/or field experiments. *In-situ* observations have the advantages of high accuracy and temporal continuity, but are usually sparsely distributed and costly, which limits their applications to large areas. With the development of thermal infrared remote sensing techniques, satellite-derived land surface temperature (LST) has been popularly used for studying the urban thermal environment due to its advantages of spatial continuity and low cost.

To quantify the effect of urban trees on LST, the cooling efficiency (CE), defined as the LST reduction caused by every 1% increase in fractional tree cover (FTC), has been adopted by existing studies based on remotely sensed LST data (Zhou et al 2017, Wang et al 2019, 2020, Zhang et al 2019). Though the CE has been evaluated by numerous local studies across global cities, it is still difficult to obtain a comprehensive understanding by integrating the existing localized results because of their large heterogeneity in data, methods, and scales (Wang et al 2020). Besides, the CE can differ greatly among cities located in different climate zones (Zhou et al 2017), and local studies based on the data in a single or a few cities are not sufficient to reflect the overall patterns of urban trees' effect on LST. Therefore, several studies have attempted to conduct multi-city analyses on a large

scale. For example, using the Moderate Resolution Imaging Spectroradiometer (MODIS) LST product, Wang et al (2019) analyzed the CE in 11 US metropolitan cities, and showed that every 1% increase in FTC resulted in an average decrease in LST of approximately 0.202 °C under extreme heat conditions. Similarly, Wang et al (2020) used Landsat-derived LST data to assess the CE in 118 US cities and showed that, for every 1% increase in FTC, the summer daytime LST was reduced by an average of 0.168 °C. However, it should be noted that the CE of existing large-scale studies was obtained by establishing binary linear regression models of LST and FTC, and did not control the possible effects of other factors (e.g. snow cover, topographic relief, and anthropogenic heat), which may lead to an overestimation of the CE, or even result in a strong 'pseudo-cooling effect' of urban trees in winter or at night (Wang et al 2019). Furthermore, most of the current findings are drawn from cities in China, Europe, and the USA, with a lack of attention to cities located in Africa, South America, and the Middle East.

Given all the above, this study will make a systematic analysis of the CE in global cities by using multisource satellite observations. The aims of this study are to present a more comprehensive insight into the spatial and temporal variability of CE, and to provide mechanistic explanations of the spatiotemporal patterns of CE from the perspective of climatic conditions. In addition, this study has also improved previous large-scale studies in the way of quantifying CE, and is able to provide a more reliable assessment of the impact of urban trees on the ground surface.

2. Data and methods

2.1. Extraction of study area

A total of 713 global cities were included in this study, and the boundaries of these cities were extracted based on the global artificial impervious area developed by Gong *et al* (2020). The region within the boundary consists of the core and its equal-area surroundings of the city; please refer to our previous study for details (Yang *et al* 2021). In this study, we further censored the cities by removing those cities with severe missing LST data or lack of meteorological stations (see the next section). Finally, 510 cities were finally included in the study (figure 1), and these cities were divided into nine biomes according to the global terrestrial ecoregions defined by the Word Wildlife Fund (WWF) (table S1, available online at stacks.iop.org/ERL/17/034029/mmedia).

2.2. Data selection and processing

The global FTC was obtained from the Copernicus Global Land Service (CGLS) dataset (2015). The accuracy assessment based on over 20 000 random samples reported that the CGLS dataset has an overall accuracy of better than 80% for all land-cover types



Figure 1. The spatial distribution of 510 global cities and the biomes to which they belong. Taking the city of Beijing as an example, we show the spatial pattern of fractional tree cover (FTC), surface elevation, nighttime light intensity (NLI), and land surface temperature (LST). The location of Beijing is shown on the global map by a black star.

and a global average absolute error of 9% for the FTC layer (Buchhorn *et al* 2020). The CGLS FTC has a spatial resolution of 100 m, and was resampled to 1×1 km by calculating the mean FTC in each MODIS LST pixel.

The LST was derived from the collection-6 MODIS daily LST products (MOD11A1 and MYD11A1), with a spatial resolution of 1 km. MOD11A1 and MYD11A1 are from the Terra and Aqua satellites, respectively, and together provide four LST observations per day (daytime: ~10:30 and \sim 13:30, nighttime \sim 1:30 and \sim 22:30). This study used all the available MODIS LST data between 2014 and 2016, with a total of 4366 images (half for day and half for night). In each city, we removed the LST pixels from each image that met any of the following conditions: (1) pixels with poor quality or no data (due to cloud coverage or other reasons) according to the quality assessment (QA) layer; (2) pixels covered by water according to the global surface water dataset produced by Pekel et al (2016); and (3) pixels contaminated by snow according to the MODIS daily snow cover products. The above filtering processes can largely reduce the bias caused by LST observations, but may also result in serious data gaps for several LST images in some cities. To reduce uncertainty in the calculated CE caused by missing data, we only retained the MODIS LST images with a percentage of the remaining pixels above 50% in each city (Yang et al 2021). Furthermore, previous studies have indicated that urban trees' activities can vary greatly among seasons (Wang et al 2012, Meili et al 2021). To avoid seasonal imbalance in the calculated CE, we required that the retained daytime/nighttime LST images in each city must cover every season of a year, otherwise the city would be discarded from the study.

Vegetation activity can be largely influenced by climatic conditions. Most typically, transpiration of trees' leaves is likely to increase with the enhancement of temperature or wind speed (WS), and is expected to decrease with the enhancement of humidity. This implies that climatic conditions might have a critical impact on the CE of urban trees. To investigate the dependence of CE on climatic conditions, a global sub-daily station dataset, referred as HadISD (Dunn et al 2012), was used in this study. This dataset contains hourly meteorological records of 6103 stations worldwide, comprising several climatic variables such as air temperature (T_a , °C), dew-point temperature (T_d , °C), and WS (m s⁻¹). Additionally, other climatic variables that are closely linked to vegetation activity, including relative humidity (RH, %) and vapor pressure deficit (VPD, kPa), were also obtained by integrating the existing HadISD climatic variables. The HadISD data used in this study cover the period from 2014 to 2016, which is consistent with the MODIS LST data. In addition, given that the spatial coverage of HadISD data is insufficient and its observation moments are not exactly the same as the MODIS LST data, we imposed space-time constraints on the HadISD data, and removed some cities lacking HadISD stations (see the supplementary material for details). After all the data processing mentioned above, 510 cities were finally included in the analysis.

2.3. Calculation and analysis of urban trees' cooling efficiency

In previous studies, the CE is typically defined as the change rate of LST to FTC (i.e. the LST reduction by per 1% increase in FTC). In terms of calculation methods, existing large-scale studies typically built a binary linear regression model with LST as the dependent variable and FTC as the independent variable, and regarded the regression coefficient (or its opposite) as the CE (Wang et al 2019, 2020). This approach has the advantage of being straightforward and easy to understand, but it does not consider the influence of other factors (e.g. snow cover, topographic relief, and anthropogenic heat), which may cause an overestimation of the CE of urban trees and even lead to a 'pseudo-cooling effect' (Wang et al 2019). Therefore, this study constructed a multiple linear regression model with LST (after removing snow-contaminated pixels) as the dependent variable, while FTC, surface elevation, and nighttime light intensity (NLI) were independent variables, and regarded the opposite of the regression coefficient of FTC as the CE; i.e. $CE = -\partial LST / \partial FTC$. The NLI was obtained from the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) dataset, which provides monthly average NLI observations with a spatial resolution of 500 m. Remotely sensed NLI has been proved to be a good proxy of the anthropogenic heat release in cities (Yang et al 2017). Surface elevation was provided by the Global 30 Arc-Second Elevation (GTOPO30) dataset. All the VIIRS DNB and GTOPO30 images were resampled to 1 km in order to be consistent with the MODIS LST data. In each city, we calculated the CE for every MODIS LST image that was retained after the data processing described in the previous section. Besides, the average values of CE were also calculated for different time periods (day and night) and different seasons (spring, summer, autumn, and winter) in each city. For cities located in the northern (southern) hemisphere, spring, summer, autumn, and winter are defined as from March to May (September to November), June to August (December to February), September to November (March to May), and December to February (June to August), respectively.

Similar to CE, climate variables (T_a , RH, WS, and VPD) at different time periods were also seasonally averaged, and were used to analyze the spatiotemporal dependence of CE on climatic conditions. Climatic conditions may affect CE in a linear or nonlinear manner (Wang *et al* 2020). Therefore, two types of regression models, linear (y = ax + b) and quadratic ($y = ax^2 + bx + c$) regression models, were separately used to investigate the spatial correlation between CE and each climatic variable across the globe. The goodness of fit was evaluated by the Akaike Information Criterion (AIC), and the model with the lower AIC score was considered the better one (Vrieze 2012). All the analyses were performed in R software.



Figure 2. Diurnal contrast of the annually average urban trees' cooling efficiency (CE). The bars and lines represent the mean and 95% confidence interval of CE for 510 global cities, respectively. The observational times are \sim 13:30 and \sim 1:30 for Aqua, and \sim 10:30 and \sim 22:30 for Terra.

3. Results

3.1. Spatial patterns of CE and their diurnal contrasts

During daytime, the globally averaged annual mean CEs are 0.057 [0.051, 0.062] °C %⁻¹ (95% confidence interval in parentheses, hereinafter) and 0.070 [0.063, 0.076] °C %⁻¹ for the local time of ~10:30 (Terra) and ~13:30 (Aqua), respectively (figure 2). Their mean value, 0.063 [0.057, 0.069] °C %⁻¹, is considered as the general effect of urban trees on annual daytime LST across global cities. This means that every 1% increase in urban FTC (i.e. fractional tree cover) can averagely reduce global urban annual daytime LST by about 0.063 °C. In terms of spatial distribution, cities located in northwestern China, southwestern USA, and the Middle East generally have a higher CE (figure 3(a)). The CE differs greatly among biomes, and the average annual daytime CE of cities located in the desert biome (i.e. Biome 8) reaches 0.170 [0.139, 0.201] °C %⁻¹, significantly (p < 0.05, t-test, hereinafter) higher than that of other biomes (figure 3(c)). It is noteworthy that the average annual daytime CE is higher in cities dominated by low vegetation (e.g. grasslands and shrublands) than in cities dominated by tall vegetation such as forests (e.g. Biome 3 > Biome 1; Biome 6 > Biome 4; figure 3(c)). In addition, cities with the same biome but different climatic conditions can show significant differences in CE. Most typically, Biome 4 and Biome 5 are both tropical and subtropical biomes with broadleaf forests, but differ in dry-wet conditions (moist vs. dry; table S1), which is probably the main reason for their significant difference in the average annual daytime CE (0.054 [0.047, 0.061] vs 0.087 [0.064, 0.109] $^{\circ}$ C %⁻¹, p < 0.05; figure 3(c)).

At night, the CE is generally lower than that of the daytime, with globally averaged annual mean values of 0.005 [0.003, 0.008] $^{\circ}$ C %⁻¹ at the local time of



~1:30 (Aqua), and 0.008 [0.006, 0.011] °C %⁻¹ at the local time of \sim 22:30 (Terra; figure 2). The average of them is around 0.007 [0.004, 0.009] $^{\circ}C$ %⁻¹, which is about one-tenth of the daytime value, signifying a relatively weak effect of urban trees on nighttime LST. However, nighttime CE shows higher spatial heterogeneity compared to daytime. As shown in figure 3(b), cities with stronger nighttime CE are mainly located in tropical and subtropical regions at low latitudes or in arid regions such as the Middle East, while in other regions, nighttime CE is generally small. It should be noted that the annual nighttime CE is negative in several cities located in China, Europe, and the USA (figure 3(b)), suggesting that urban trees may exhibit a weak warming effect on nighttime LST in these cities. When comparing across biomes, the average annual nighttime CE is highest in the desert biome (i.e. Biome 8), followed by the tropical and subtropical biomes, and is lowest in the Mediterranean biome (i.e. Biome 7; figure 3(d)).

3.2. Seasonal variations of CE and their spatial heterogeneity

As expected, the CE shows obvious seasonal variations (figures 4 and S1). During daytime, the global average CE is strongest in summer (0.087 [0.079, 0.095] °C $\%^{-1}$), followed by spring (0.070 [0.063, 0.095] °C $\%^{-1}$), autumn (0.062 [0.056, 0.068] °C $\%^{-1}$), and winter (0.034 [0.031, 0.038] °C $\%^{-1}$; figure 4(a)). This seasonal pattern of daytime CE is observed in all biomes, but with a remarkable difference in the magnitude of seasonal difference (figure S1). For instance, the average daytime CE of the desert biome (i.e. Biome 8) reaches

0.231 [0.189, 0.274] °C %⁻¹ in summer, which is considerably higher than that in winter (0.092 [0.072, 0.112] °C %⁻¹). In contrast, in the tropical and subtropical biomes (e.g. Biomes 4, 5, 6), the difference in the daytime CE among seasons is relatively small (figure 4(c)). At night, the seasonal pattern of CE is generally consistent with that of the daytime (i.e. summer > spring > autumn > winter) for the global urban averages, but shows some variability in the results among biomes. The most typical example is that tropical and subtropical biomes (Biomes 5 and 6) experience a lower nighttime average CE in summer than in winter (figure 4(d)).

3.3. Spatiotemporal dependence of CE on climatic conditions

For the overall picture, there is a good agreement between CE and climatic variables (T_a , RH, WS, and VPD) for seasonal patterns (figures 4 and S2). The spatial dependence of CE on climatic variables was examined across global cities by using linear and quadratic regression models, and it is found that CE is nonlinearly related to climatic variables in most cases (figure 5). Daytime CE increases significantly along the incremental direction of T_a , and the change rate gradually accelerates with the enhancement of $T_{\rm a}$ (figure 5(a)). In contrast, daytime CE decreases significantly with the increase in RH, accompanied by a slowing down of the change rate (figure 5(b)). Besides, daytime CE shows an increasing trend with the growth of WS, but with a very weak correlation (figure 5(c)). These results jointly suggest that urban trees in hot, dry, and windy climates tend to have stronger CE. In addition, the relationship between



daytime CE and VPD is as expected; i.e. daytime CE increases significantly with the enhancement of VPD (figure 5(d)). Moreover, the trend of nighttime CE along each climatic variable is basically in line with the daytime results, but the explanatory degree (R^2) of the nighttime regression model is lower than that of the daytime (figures 5(e)–(h)).

4. Discussion

4.1. Spatiotemporal variations of urban trees' cooling efficiency

Our results show that an increase in FTC can reduce daytime LST, leading to a considerable cooling effect, especially for cities located in the desert biome (figure 3). The spatial pattern of daytime CE is closely related to climatic conditions. Specifically, daytime CE has a strong positive correlation with T_a and a significant negative relation with RH, which implies that urban trees tend to have a stronger cooling effect on daytime LST in hotter and drier cities. This is due to the fact that an increase in temperature and/or a decrease in humidity can cause a rise in VPD, which will promote the transpiration of tree leaves and take away more surface heat (Will et al 2013, Grossiord et al 2020). For example, a modelling study showed that each 2.9 °C increase in average daily temperature enhanced the transpiration rate and stomatal conductance of betula utilis leaves by 21.4% and 33.9%, respectively (Zhen-Feng et al 2010). More

importantly, this mechanism is supported by our results that daytime CE is significantly and positively correlated with the VPD (figure 5(d)). In addition, theoretically, an increase in WS would enhance the turbulent exchange rate of leaves and their evaporation, thus promoting the cooling efficiency of urban trees (Yu *et al* 2018). However, as revealed by this study, the effect of WS on daytime CE seems to be much weaker compared to T_a and RH. Overall, the increase in FTC can be regarded as an effective way to mitigate daytime UHI effect, especially for cities with a hot and dry climate.

At night, the effect of urban trees on LST has actually become very weak, with a global average of nighttime CE being nearly close to zero (figure 2). This is mainly due to the fact that the activity (e.g. transpiration) of urban trees weakens or even disappears at night (Peng et al 2014). Accordingly, the influence of climatic conditions on nighttime CE is much weaker than that of daytime. It is also worth noting that, for numerous cities located in temperate regions (e.g. Europe, Eastern Asia, and Eastern USA), an increase in FTC may cause a potential warming effect on nighttime LST (figure 3(b)). This can be explained by the change in surface albedo due to increased FTC. Previous studies have shown that trees may have lower albedo than other land covers (e.g. bare soil, cultivated land, and buildings). Thus, the increase in FTC can cause a decrease in surface albedo, leading to more solar energy absorption during the



Figure 5. Scatterplots of the relationship between annually average urban trees' cooling efficiency (CE) and climatic variables, including air temperature (T_a), relative humidity (RH), wind speed (WS), and vapor pressure deficit (VPD). The left sub-figures (a)–(d) are daytime results, and the right sub-figures (e)–(h) are nighttime results. Their relationship was fitted by either a linear (y = ax + b) or quadratic ($y = ax^2 + bx + c$) regression model, depending on the Akaike Information Criterion (AIC). In each sub-figure, the solid black lines and the formula above represent the fitted results for all the 510 global cities; the dashed black line and the formula below represent the fitted results after dropping off the data of cities located in Biomes 7 and 8; and the grey shaded areas around the regression lines are 95% confidence intervals.

daytime (Lukeš *et al* 2013, Kuusinen *et al* 2016). This extra energy will be released at night, and causes an elevation in nocturnal LST. In addition, the increase in FTC may also reduce ventilation and impede heat dissipation, especially for regions with tall and dense trees, where warm air can be trapped beneath the crowns (Wujeska-Klause and Pfautsch 2020). Therefore, it is reasonable to infer that, for several cities, increasing FTC alone may not be able to achieve the goal of alleviating the nocturnal heat island, and may even cause a counterproductive effect.

CE differs greatly among seasons, and is generally characterized as stronger in summer than in winter (figures 4 and S1). This is understandable because urban trees' activities are typically seasonally dependent. For example, urban trees tend to be leafy in summer and their powerful transpiration can effectively reduce the LST in the vegetated areas and surrounding regions (Peters et al 2010). In winter, urban trees' activities, along with their effects on LST, become weak due to physiological phenomena such as leaf fall. In addition, although some tropical trees (e.g. evergreen forests) do not have great physiological variations among seasons, change in climate conditions (e.g. temperature and humidity) can still affect urban trees' activities, which will pose a seasonal effect on the CE (David et al 2004).

4.2. Comparative analysis of CE calculated by different methods

It should be noted that this paper differs from previous studies in the calculation of CE. Previous studies preferred to build a binary linear regression model with LST as the dependent variable and FTC as the independent variable, and treated the regression coefficient (or its opposite) as the CE (Wang et al 2019, 2020). However, this approach ignores the influence of other factors (e.g. snow, topographic relief, and anthropogenic heat). Firstly, snow cover can mask temperature variations caused by land-cover differences, and the removal of snow is essential for obtaining true CE. Secondly, temperature changes with elevation, and ignoring the influence of topographic relief will cause bias in the calculated CE. More importantly, anthropogenic heat released by the production and life of urban dwellers results in an increase of local temperature, creating temperature gradients from the urban center (with lower FTC) to its neighboring regions (with higher FTC). This means that ignoring the influence of anthropogenic heat may cause an overestimation of CE and may even lead to a 'pseudocooling effect' (Wang et al 2019). Therefore, in this study, we removed pixels contained by snow cover, and further established a multiple linear regression model with FTC, elevation, and NLI incorporated, so as to suppress the bias of CE caused by topographic relief and anthropogenic heat.

By comparison, it can be found that the CE obtained by the multiple linear regression model in



Figure 6. Urban trees' cooling efficiency (CE) calculated by different regression models. In the binary linear regression model, land surface temperature (LST) is the dependent variable and fractional tree cover (FTC) is the independent variable; in the multiple linear regression model, LST is the dependent variable, and FTC, surface elevation, and nighttime light intensity (NLI) are the independent variables. The bars/points and vertical lines represent the mean and 95% confidence interval, respectively.

this study is significantly lower than that calculated by the binary linear regression model in previous studies, especially for the nighttime results (figure 6). This is because trees' activities (e.g. transpiration) greatly weaken at night, and the spatial variation of LST is actually dominated by other factors, especially anthropogenic heat (Sailor 2011). Thus, the CE obtained by the binary linear regression model cannot truly reflect the influence of trees themselves on the urban surface thermal environment. Overall, the comparative analysis suggests that previous studies have overestimated the CE of urban trees, especially at night when trees' activities are weak.

4.3. Implications and uncertainties

This study presents a global-scale quantitative analysis of urban trees' cooling efficiency by using multisource remote sensing data. The results highlight the positive effect of increasing FTC on reducing daytime urban LST, which is consistent with the findings from previous local studies (Zhou *et al* 2017, Wang *et al* 2019, 2020). More importantly, it is found that, though with distinctive daytime CE, urban trees pose an ambiguous effect on nighttime LST. This implies that increasing FTC is not an effective way to mitigate the nocturnal UHI effect, and other measures are needed for relieving nocturnal urban thermal stress (Zhou *et al* 2014, Huang and Wang 2019, Yang *et al* 2019). Besides, our results reveal that urban trees' CE is closely related to climatic conditions, and trees tend to have a stronger cooling effect in cities with a higher temperature and/or less humidity. This means that the same percentage increase in FTC can achieve more cooling benefits in dry and hot cities.

Several uncertainties need to be addressed here. Firstly, besides the fraction of coverage, urban LST can be affected by other aspects of trees such as the spatial configuration and canopy height, the composition of species, and even the analysis scales (Jiao *et al* 2017, Zhang *et al* 2019, 2021). A systematic analysis of all these factors can better capture the effect of trees on LST, but relies on more comprehensive and higher resolution remotely sensed data. Secondly, the CE of urban trees is not only dependent on climatic conditions, but may also be related to soil properties, planting conditions, and human management, and future studies need to combine all requisite data for further analysis.

5. Conclusions

Increasing FTC has long been recognized as an effective way to mitigate the UHI effect, but there is a lack of global-scale quantitative analysis of the CE of urban trees based on remotely sensed data. Therefore, this study presents a comprehensive analysis of the spatiotemporal patterns of CE in 510 global cities by using multi-source satellite observations. The method of quantifying CE is improved from previous studies by constructing a multiple linear regression model, which can suppress the influence of other factors such as topographic relief and anthropogenic heat.

The results show that the increase of FTC in urban regions can significantly reduce daytime LST, with an annual average daytime CE of 0.063 °C %⁻¹ across global cities. However, the effect of urban trees on LST is relatively weak at night, with a global average annual nighttime CE of only 0.007 °C %⁻¹. More importantly, CE shows obvious spatial heterogeneity, with generally higher values in hot and arid cities located in regions such as northwestern China, southwestern United States, and the Middle East, suggesting that higher cooling gains can be achieved by increasing FTC in these cities. The spatial pattern of CE is closely related to urban climatic conditions (e.g. temperature and humidity). An increase in temperature and a decrease in humidity can enhance VPD and promote transpiration of tree leaves, which in turn causes an enhancement of CE of urban trees. In terms of seasonal variations, CE generally shows a pattern of being highest in summer and weakest in winter, which fits well with seasonal characteristics of trees' own growth state. Overall, the study fills the knowledge gap of how urban trees influence LST across global cities, and provides important information for UHI mitigation from the perspective of tree planting.

Data availability statement

The global artificial impervious area (GAIA) dataset is publicly available at http://data.ess.tsinghua.edu.cn /gaia.html. Global fractional tree cover is derived from the Copernicus Global Land Service (CGLS) dataset, which is publicly available at https://land.copernicus.eu/global/products/lc. The climatic variables are derived from the global subdaily station dataset (HadISD), which is publicly available at https://catalogue.ceda.acuk/uuid/32eff53 af32442d1a347da2cc45bb9db. The biome boundaries are derived from the global terrestrial ecoregions defined by the WWF, which are publicly available

www.worldwildlife.org/publications/terrestrialat ecoregions-of-the-world. The global surface water dataset is provided by the European Commission's Joint Research Centre, and is publicly available at https://global-surface-water.appspot.com/download. The global nighttime light intensity is derived from the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) dataset, which is publicly available at https://eogdata.mines.edu/products/vnl/. The Moderate Resolution Imaging Spectroradiometer (MODIS) and the Global 30 Arc-Second Elevation (GTOPO30) datasets are publicly available at https://earthdata.nasa.gov/. In addition, all of abovementioned datasets (except the HadISD climatic variables and the WWF biomes) are also publicly available from the Google Earth Engine platform (https://code.earthengine.google.com/).

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgment

This research was supported by the China Postdoctoral Science Foundation (Nos. 2021TQ0245 and 2021M702470).

References

- Buchhorn M, Lesiv M, Tsendbazar N-E, Herold M, Bertels L and Smets B 2020 Copernicus global land cover layers—collection 2 *Remote Sens.* 12 1044
- Chen C, Li D and Keenan T F 2021 Enhanced surface urban heat islands due to divergent urban-rural greening trends *Environ. Res. Lett.* **16** 124071
- Chinchilla J, Carbonnel A and Galleguillos M 2021 Effect of urban tree diversity and condition on surface temperature at the city block scale *Urban For. Urban Green.* **60** 127069
- David T S, Ferreira M I, Cohen S, Pereira J S and David J S 2004 Constraints on transpiration from an evergreen oak tree in southern Portugal *Agric. For. Meteorol.* **122** 193–205
- Drake J E *et al* 2018 Trees tolerate an extreme heatwave via sustained transpirational cooling and increased leaf thermal tolerance *Glob. Change Biol.* **24** 2390–402
- Dunn R J H, Willett K M, Thorne P W, Woolley E V, Durre I, Dai A, Parker D E and Vose R S 2012 HadISD: a quality-controlled global synoptic report database for

selected variables at long-term stations from 1973–2011 *Clim. Past* **8** 1649–79

- Gong P *et al* 2020 Annual maps of global artificial impervious area (GAIA) between 1985 and 2018 *Remote Sens. Environ.* **236** 111510
- Grimm N B, Faeth S H, Golubiewski N E, Redman C L, Wu J, Bai X and Briggs J M 2008 Global change and the ecology of cities *Science* **319** 756–60
- Grossiord C, Buckley T N, Cernusak L A, Novick K A, Poulter B, Siegwolf R T W, Sperry J S and McDowell N G 2020 Plant responses to rising vapor pressure deficit *New Phytol.* 226 1550–66
- Gunawardena K R, Wells M J and Kershaw T 2017 Utilising green and bluespace to mitigate urban heat island intensity *Sci. Total Environ.* **584** 1040–55
- Huang X and Wang Y 2019 Investigating the effects of 3D urban morphology on the surface urban heat island effect in urban functional zones by using high-resolution remote sensing data: a case study of Wuhan, Central China ISPRS J. Photogramm. Remote Sens. 152 119–31
- Jiao M, Zhou W, Zheng Z, Wang J and Qian Y 2017 Patch size of trees affects its cooling effectiveness: a perspective from shading and transpiration processes *Agric. For. Meteorol.* 247 293–9
- Kalnay E and Cai M 2003 Impact of urbanization and land-use change on climate *Nature* **423** 528
- Kuusinen N, Stenberg P, Korhonen L, Rautiainen M and Tomppo E 2016 Structural factors driving boreal forest albedo in Finland *Remote Sens. Environ.* **175** 43–51
- Li X, Zhou W, Ouyang Z, Xu W and Zheng H 2012 Spatial pattern of greenspace affects land surface temperature: evidence from the heavily urbanized Beijing metropolitan area, China *Landsc. Ecol.* **27** 887–98
- Li Y, Zhao M, Motesharrei S, Mu Q, Kalnay E and Li S 2015 Local cooling and warming effects of forests based on satellite observations *Nat. Commun.* **6** 6603
- Liu X *et al* 2020 High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015 *Nat. Sustain.* <u>3 564–70</u>
- Liu Y, Huang X, Yang Q and Cao Y 2021 The turning point between urban vegetation and artificial surfaces for their competitive effect on land surface temperature *J. Clean. Prod.* **292** 126034
- Loughner C P, Allen D J, Zhang D-L, Pickering K E, Dickerson R R and Landry L 2012 Roles of urban tree canopy and buildings in urban heat island effects: parameterization and preliminary results *J. Appl. Meteorol. Climatol.* **51** 1775–93
- Lukeš P, Stenberg P and Rautiainen M 2013 Relationship between forest density and albedo in the boreal zone *Ecol. Modell.* **261** 74–9
- Maimaitiyiming M, Ghulam A, Tiyip T, Pla F, Latorre-Carmona P, Halik Ü, Sawut M and Caetano M 2014 Effects of green space spatial pattern on land surface temperature: implications for sustainable urban planning and climate change adaptation *ISPRS J. Photogramm. Remote Sens.* 89 59–66
- Meili N, Manoli G, Burlando P, Carmeliet J, Chow W T L, Coutts A M, Roth M, Velasco E, Vivoni E R and Fatichi S 2021 Tree effects on urban microclimate: diurnal, seasonal, and climatic temperature differences explained by separating radiation, evapotranspiration, and roughness effects *Urban For. Urban Green.* **58** 126970
- Pekel J-F, Cottam A, Gorelick N and Belward A S 2016 High-resolution mapping of global surface water and its long-term changes *Nature* **540** 418–22
- Peng -S-S, Piao S, Zeng Z, Ciais P, Zhou L, Li L Z X, Myneni R B, Yin Y and Zeng H 2014 Afforestation in China cools local land surface temperature *Proc. Natl Acad. Sci. USA* 111 2915–9
- Peters E B, McFadden J P and Montgomery R A 2010 Biological and environmental controls on tree transpiration in a suburban landscape J. Geophys. Res. Biogeosci. 115 G04006

- Sailor D J 2011 A review of methods for estimating anthropogenic heat and moisture emissions in the urban environment *Int. J. Climatol.* **31** 189–99
- She Y, Liu Z, Zhan W, Lai J and Huang F 2021 Strong regulation of daily variations in nighttime surface urban heat islands by meteorological variables across global cities *Environ. Res. Lett.* **17** 014049
- Susca T, Gaffin S R and Dell'Osso G R 2011 Positive effects of vegetation: urban heat island and green roofs *Environ*. *Pollut*. **159** 2119–26
- Tan J *et al* 2010 The urban heat island and its impact on heat waves and human health in Shanghai *Int. J. Biometeorol.* **54** 75–84
- Trinder J and Liu Q 2020 Assessing environmental impacts of urban growth using remote sensing *Geo. Spat. Inf. Sci.* 23 20–39
- Vrieze S I 2012 Model selection and psychological theory: a discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) *Psychol. Methods* 17 228
- Wang C, Wang Z H and Yang J 2018 Cooling effect of urban trees on the built environment of contiguous United States *Earth's Future* 6 1066–81
- Wang C, Wang Z-H, Wang C and Myint S W 2019 Environmental cooling provided by urban trees under extreme heat and cold waves in U.S. cities *Remote Sens. Environ.* 227 28–43
- Wang H, Wang X, Zhao P, Zheng H, Ren Y, Gao F and Ouyang Z 2012 Transpiration rates of urban trees, Aesculus chinensis J. Environ. Sci. 24 1278–87
- Wang J, Zhou W, Jiao M, Zheng Z, Ren T and Zhang Q 2020 Significant effects of ecological context on urban trees' cooling efficiency ISPRS J. Photogramm. Remote Sens. 159 78–89
- Will R E, Wilson S M, Zou C B and Hennessey T C 2013 Increased vapor pressure deficit due to higher temperature leads to greater transpiration and faster mortality during drought for tree seedlings common to the forest–grassland ecotone *New Phytol.* 200 366–74
- Wujeska-Klause A and Pfautsch S 2020 The best urban trees for daytime cooling leave nights slightly warmer *Forests* **11** 945
- Xu G, Zhou Z, Jiao L and Zhao R 2020 Compact urban form and expansion pattern slow down the decline in urban densities: a global perspective *Land Use Policy* **94** 104563
- Yan C, Guo Q, Li H, Li L and Qiu G Y 2020 Quantifying the cooling effect of urban vegetation by mobile traverse method: a local-scale urban heat island study in a subtropical megacity *Build. Environ.* **169** 106541
- Yang Q, Huang X and Tang Q 2019 The footprint of urban heat island effect in 302 Chinese cities: temporal trends and associated factors *Sci. Total Environ.* **655** 652–62
- Yang Q, Huang X, Yang J and Liu Y 2021 The relationship between land surface temperature and artificial impervious surface fraction in 682 global cities: spatiotemporal variations and drivers *Environ. Res. Lett.* 16 024032
- Yang W, Luan Y, Liu X, Yu X, Miao L and Cui X 2017 A new global anthropogenic heat estimation based on high-resolution nighttime light data *Sci. Data* 4 170116
- Yu Z, Xu S, Zhang Y, Jørgensen G and Vejre H 2018 Strong contributions of local background climate to the cooling effect of urban green vegetation *Sci. Rep.* **8**
- Zhang Y, Middel A and Turner B L 2019 Evaluating the effect of 3D urban form on neighborhood land surface temperature using Google Street View and geographically weighted regression Landsc. Ecol. 34 681–97
- Zhang Z, Li X and Liu H 2021 Biophysical feedback of forest canopy height on land surface temperature over contiguous United States *Environ. Res. Lett.* (https://doi.org/ 10.1088/1748-9326/ac4657)
- Zhen-Feng X U, Ting-Xing H U, Li Z, Yuan-Bin Z, Jun-Ren X and Kai-Yun W 2010 Short-term gas exchange responses of Betula utilis to simulated global warming in a timberline ecotone, eastern Tibetan Plateau, China Chin. J. Plant Ecol. 34 263

Zhou D, Xiao J, Bonafoni S, Berger C, Deilami K, Zhou Y, Frolking S, Yao R, Qiao Z and Sobrino J 2018 Satellite remote sensing of surface urban heat islands: progress, challenges, and perspectives *Remote Sens.* 11 48
Zhou D, Zhao S, Liu S, Zhang L and Zhu C 2014 Surface urban heat island in China's 32 major cities: spatial patterns and drivers *Remote Sens. Environ.* **152** 51–61

 Zhou W, Wang J and Cadenasso M L 2017 Effects of the spatial configuration of trees on urban heat mitigation: a comparative study *Remote Sens. Environ.* 195 1–12