A Preliminary Exploration of the Cooling Effect of Tree Shade in Urban Landscapes

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A preliminary exploration of the cooling effect of tree shade in urban landscapes

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ABSTRACT

Mitigating urban heat island (UHI) effects, especially under climate change, is necessary for the promotion of urban sustainability. Shade is one of the most important functions provided by urban trees for mitigating UHI. However, the cooling effect of tree shade has not been adequately investigated. In this study, we used a simple and straightforward method to quantify the spatial and temporal variation of tree shade and examined its effect on land surface temperature (LST). We used the hillshade function in a geographic information system to quantify the spatiotemporal patterns of tree shade by integrating sun location and tree height. Relationships between shade and LST were then compared in two cities, Tampa, Florida and New York City (NYC). We found that: (1) Hillshade function combining the sun location and tree height can accurately capture the spatial and temporal variation of tree shade; (2) Tree shade, particularly at 07:30, has significant cooling effect on LST in Tampa and NYC; and (3) Shade has a stronger cooling effect in Tampa than in NYC, which is most likely due to the differences in the ratio of tree canopy to impervious surface cover, the spatial arrangements of trees and buildings, and their relative heights. Comparing the cooling effects of tree shade in two cities, this study provides important insights for urban planners for UHI mitigation in different cities.

1. Introduction

Urban heat island (UHI) effect as a result of urbanization, has become a major problem for the sustainable development of modern societies (Alavipanah et al., 2015; Giorgio et al., 2017; Murgante et al., 2011; Kim, 1992). UHI dynamics are critical for the pursuit of sustainable urban development as they can lead to increased water consumption and energy use (Akbari et al., 2001; Alavipanah et al., 2015; Kundu et al., 2017; Spera et al., 2016; White et al., 2002), elevated environmental pollution (Stone, 2005), and detrimental effects on human health and comfort in both big and small cities (Alavipanah et al., 2015; Fanger, 1970; Huang et al., 2015; Hwang et al., 2011; Tan et al., 2010). About 27% of cities and 65% of urban population is currently experiencing warmer temperature (0.6 °C) than the world average (Estrada et al., 2017), as the impacts of climate change in cities can be exacerbated by UHI effects (Campbell, 1996; Huang et al., 2015; Tan et al., 2015). These phenomena threaten the sustainability of future urban development to support growing populations. As most of the world’s population already reside in cities, it is important and urgent to examine how urban regions can become more sustainable under global climate change (Campbell, 1996). In this regard, mitigating UHI effects is necessary for the promotion of urban sustainability, especially under climate change (Akbari et al., 2001).

Mitigating UHI effects has important economic and environmental implications for most of the cities around the world. A wide variety of strategies have been implemented ranging from the altering land configuration (Zhou et al., 2011), through using more reflective roofs (Costanzo et al., 2016; Qi et al., 2019), to planting trees (Li et al., 2017; Yan et al., 2020). Planting trees in urban areas is a significant strategy to mitigate UHI effects through evapotranspiration and shade (Alavipanah et al., 2015). While the cooling effect of evapotranspiration has been studied (Metselaar, 2012; Qi et al., 2013), shade has seldom been examined. Shading is one of the most important functions provided by urban trees to cool urban regions in summer (Armson et al., 2017).
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2013; Environmental Protection Agency, 2020). Tree shade can directly lower surface temperature by reducing the storage and convection of heat of land surface by reducing the incident solar radiation at urban surfaces such as buildings and roads (Akbari et al., 1997; Berry et al., 2013; Morakinyo et al., 2016). By blocking solar radiation from directly striking buildings, tree shade can reduce energy consumption for cooling and as a result, it can also reduce carbon dioxide emission in urban areas (Akbari et al., 1997, 2001; Akbari, 2002; Armson et al., 2012; Balogun et al., 2014; Berry et al., 2013; Heisler, 1986; Hwang et al., 2017; Middel et al., 2016; Morakinyo et al., 2016; Simpson, 2002), while there is lack of studies at larger scale such as city scale. Tree shade varies both spatially and temporally. Tree structure, together with the diurnal changes in solar geometry, contributes to the spatiotemporal variation of shade. Typically, trees with bigger crowns provide more shade than smaller ones, while tree height determines the spatial extent (length) of shade. Moving sun lead to the temporal change of shade. Spatiotemporal variation of tree shade plays an important role in the difference of surface temperature, because the spatial and temporal patterns of tree shade affect the solar radiation or energy received by dry exposed surface. Examining the cooling effect of tree shade in a city requires the quantification of tree shade in both space and time. However, there is no effective method to quantify the spatiotemporal patterns of tree shade due to the difficulties in measuring tree height for an entire city. It may due to this reason that previous studies mainly focused on single point of time at small spatial scale.

Remote sensing methods, such tree canopy and sky view factor (Gál et al., 2009; Lee et al., 2013; Li et al., 2018; Li and Ratti, 2018), have been used to quantify tree shade at city scale. However, tree canopy only captures the 2-dimensional cover of tree crowns, which cannot accurately represent the distribution of shade as it lacks the vertical dimension needed to estimate the spatial extent of shade. Sky view factor can be used to estimate the amount of shade cast by buildings and street trees by calculating their fraction in a planar surface (Hwang et al., 2011; Lee et al., 2013; Lin et al., 2012). Compared to tree canopy, sky view factor improves the estimation of shade because it considers the amount of sunlight that is blocked from the ground. Nevertheless, sky view factor cannot fully capture the variance of shade as it does not consider the movement of the sun. As a result, neither tree canopy nor sky view factor can quantify the temporal patterns of tree shade.

The cooling effect of tree shade may also vary from city to city due to the differences in cities’ landscape. First, the amount and duration of shade can vary between cities due to their geographic location (Murmson, 2020). Furthermore, the spatial arrangement of land cover, especially that of trees and buildings, determines where in the city can enjoy tree shade. The spatial arrangement of land cover varies between cities as a result of both natural environment and socio-economic decisions (Spronken-Smith and Oke, 1998; Zhou et al., 2017). For example, many trees are planted in strips in front of commercial buildings in Las Vegas, Nevada while trees are more clustered in Phoenix, Arizona (Myint et al., 2015). Similarly, cities with high density of buildings may leave little space for planting trees, while less compacted cities would have more potential green space. Besides, high-rise buildings are less likely being covered by tree shade except the bottom few stories. Therefore, the cooling effect of tree shade can vary between cities. To promote efficient UHI mitigation strategies for cities, we need to understand how and why the cooling effect of tree shade changes between cities.

Current research lacks the quantification of spatiotemporal variation of tree shade and the comparison between cities is also needed to develop efficient UHI mitigation strategies for different cities. Therefore, our research aims to quantify the spatial and temporal pattern of tree shade and compare its cooling effect in different cities. More specifically, we quantified the spatial and temporal patterns of tree shade at a city scale in two cities in the U.S. (New York City, New York and Tampa, Florida). We then compared the cooling effect of tree shade between the two cities by examining the relationship between shade and land surface temperature (LST). We hope this pilot study can contribute to the better understanding of the cooling effect of tree shade and help future studies to better quantify the spatiotemporal patterns of tree shade.

2. Materials

2.1. Study area

The two cities selected in this study differ with respect to their climate and urban landscape (Fig. 1). Tampa, Florida (27.9°N, 82.5°W) has a humid subtropical climate with relatively wet and hot summer, while New York City (NYC, 40.7° N, 74.0° W) has a humid continental climate with warm summer (Kottek et al., 2006). These two cities also have very different urban landscape (Table 1). NYC has a high density of buildings of which a large proportion are high-rise buildings (MacFadden et al., 2012). In contrast, Tampa is characterized by lower buildings and larger tree canopy cover. Using these two cities allows us to examine how the cooling effect of tree shade is affected by the urban structure.

2.2. Data

2.2.1. Land surface temperature (LST)

LST is a key parameter related to surface energy and balance at local and global scale. Although surface temperature can be computed in atmospheric weather models and measured at weather stations, accurate retrieval of LST from thermal infrared remote sensing could provide explicit wall-to-wall measurement of LST. LST from thermal infrared remote sensing has a long history that can be traced back to the early 1960s. After almost six decades, we have been in a good position to simulate and quantify the process in atmospheric and on ground surface both from theory and experiments, and thus to efficiently retrieve LST (Prata et al., 1995). Remotely sensed LST has been used extensively to examine the UHI effects of different land use and land cover types (e.g. Hamoodi et al., 2019; Zheng et al., 2019), the cooling effects of vegetation cover (Li et al., 2015) and spatial configuration (Zhou et al., 2017). Among the vast amount of thermal infrared remote sensing data, Landsat has been the most popular due to its long-term temporal coverage (from early 1970s) and suitable spatial resolution (Sano et al., 2007). The presented study also used Landsat products to retrieve LST.

Landsat 5 thematic mapper (TM) products (both optical and thermal) were downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov). Landsat 5TM data were acquired around 10:30 local time. The land surface reflectance images were derived after applying the atmospheric correction routines of MODIS (the Second Simulation of a Satellite Signal in the Solar Spectrum, done by U.S. Geological Survey, USGS) to the original Landsat TM images. The thermal infrared product provides thermal infrared data at wavelengths from 10.4 μm to 12.5 μm and was used to estimate LST. We calculated LST using the radiative transfer equation algorithm (Fu and Weng, 2016; Sobrino et al., 2004, 2006; Weng and Fu, 2014). Radiative transfer equation algorithm calculates LST by simulating the correction of the atmospheric and emissivity effects on the satellite thermal
infrared data. Parameters are integrated in the algorithm, including land surface emissivity, blackbody radiance given by the Planck’s law, and atmospheric parameters including the downwelling atmospheric radiance, the upwelling atmospheric radiance, and the total atmospheric transmissivity between the surface and the sensor. Details of the radiative transfer equation algorithm can be found in Yu et al. (2018). Landsat 5 TM data for Tampa and NYC were acquired on April 30, 2011 and August 28, 2010 respectively (Table 2). The solar altitude for the two cities was very similar on these two days, that solar altitude was only \( \sim 1-2 \)° higher in NYC than that in Tampa. LST was also close in the two cities on the selected days. LST ranged from 289.58 K to 316.94 K in NYC, while LST was between 290.37 K and 322.03 K in Tampa.

### 2.2.2. Spatial pattern of land cover and tree height

Land cover map and normalized Digital Surface Model (nDSM) were used to obtain tree canopy cover and tree height, respectively. The spatial distribution of land cover and nDSM were derived from point cloud Light Detection and Range (LiDAR) data (Fig. 2). Land cover was generated using object-based image classification methods that utilized aerial imagery, LiDAR, and ancillary data (Landry et al., 2013; MacFaden et al., 2012; O’Neil-Dunne et al., 2013, 2014). nDSM represents the absolute height by subtracting digital terrain model from digital surface model, which is obtained from the last and first return of point cloud LiDAR respectively. Tree height was extracted from nDSM which overlapped with tree cover indicated by the land cover map. The spatial resolutions of tree canopy cover and tree height for Tampa and NYC were 0.31 m and 0.70 m, respectively. Tree canopy cover and mean tree height were 33% and 9.5 m for Tampa and 22% and 9.04 m for NYC, respectively. All remote sensing data were acquired under a clear sky condition and projected to the associated local coordinate system (Florida West State Plane NAD83 for Tampa and New York Long Island State Plane NAD83 for NYC) and subset to the study areas.

### 3. Method

To explore and compare the cooling effect of shade cast by trees in NYC and Tampa, we adopted the idea of shaded relief (hillshade) to quantify the spatiotemporal pattern of tree shade. The cooling effect of tree shade was then examined by investigating the relationship between LST and shade in the two cities.

#### 3.1. Shade quantification

We used the hillshade function in ArcGIS (ESRI, 2020. ArcGIS

| Table 1 | Basic information about urban settings of Tampa and NYC (Landry et al., 2013; MacFaden et al., 2012). |
|---------|--------------------------------------------------|
|         | Population (km\(^2\)) | Population (km\(^{-2}\)) | Households | Tree canopy cover | Impervious surface cover |
| Tampa   | 335,709                 | 2,960.2                    | 135,955    | 29%                | 36%                        |
| NYC     | 8,175,133               | 27,012.5                   | 3,109,784 | 20%                | 58% \(^1\)                  |

\(^1\) 20% are buildings.
Table 2: Research data used to examine the effects of shade in Tampa and New York City: land surface temperature, land cover (O’Neil-Dunne et al., 2014), and normalized Digital Surface Model (nDSM).

| Description | Data source | Acquisition Date | Spatial resolution (m) |
|-------------|-------------|------------------|-----------------------|
| Land Surface Reflectance | USGS | 04/30/2011 (Tampa); 08/28/2010 (NYC) | 30 |
| Thermal infrared | USGS | Jan 2011-Feb 2011 (Tampa); Jan 2010-Feb 2011 (NYC) | Same as above |
| Land cover | Data for New York City was provided by O’Neil-Dunne from University of Vermont | 04/14/2010-05/01/2010 (NYC) | 30 |
| nDSM | Same as above | Similar as above | Similar as above |

The effects of shade at a pixel scale were examined by comparing the relationship between percent of shade and land surface temperature (LST) through correlation and regression analysis. The cooling effect of tree shade on temperature at 10:30 am was used as a response variable. It would be ideal to examine the cooling effect of shade with surface temperature data at other time of a day such as early afternoon. However, due to the limitation of data availability, we can only focus on the cooling effect of tree shade on temperature at 10:30 am.

We first analyzed the pairwise correlation between tree shade cover at different time and LST using Pearson Correlation analysis. Pearson correlation coefficient ranges from -1 to 1, indicating the extent of correlation between the two variables (Benesty et al., 2009).

We also used decision tree regression analysis to compare the relative importance of tree shade at different time on LST and to examine the interactions between tree shade and land cover types (Kazemitabar et al., 2017). Decision tree builds a regression model in the form of a tree structure. It breaks down the dataset into small clusters. The result is a tree with decision nodes and leaf nodes. The decision nodes display the rules splitting response variables (in our case LST) into subsets, and each leaf node shows the means of response variables of the clusters. A cost complexity was used to control the tree size and to avoid overfitting. The optimum cost complexity value (0.01) was chosen after experiments prior to data analysis. The most important explanatory
variable will be displayed in the first decision layer and the secondary important variables will be shown in the following layers. The decision rules of the regression tree can also be used to interpret the interactions between tree shade at a different time and land cover (including tree, grass, and impervious surface) and their effects on LST (Kazemitabar et al., 2017). The R square value of the decision tree regression represents the amount of variance of LST that can be explained by tree shade or the combination of tree shade and land cover. The difference of the regression trees (e.g. R square values and decision rules) can be used to compare the cooling effects of tree shade between the two cities.

4. Results

4.1. Spatiotemporal patterns of tree shade and LST

4.1.1. Spatiotemporal variation of shade

For both NYC and Tampa, the spatial pattern of shade by hillshade function varies in space. Shade clustered in some regions in both cities, while scattered in other regions (Fig. 4). In Tampa, tree shade concentrated at the north part of the city, overlapping with the natural conservation site. Tree shade can also be found in neighborhoods contributed by trees in yards and along streets. Some areas such as the two airports by Tampa Bay did not have any shade (Fig. 4). In NYC, shade seems more spread out. Temporal variability of tree shade was also captured by the hillshade function as the cover and direction of shade all changed from sunrise to sunset. Fig. 5 gives an example about the details of temporal variation of shade derived using hillshade function. The shade of different ground objects regardless of height and size have been captured, indicating the efficiency of hillshade function.

To examine the accuracy of shade quantification using the hillshade function, we compared the simulated shade cast by both trees and buildings (11:00 on 04/30/2011) with actual shade obtained from photos taken on ground (Fig. 6, photos were taken at 11:00, 10/21/2017 at University of South Florida, Tampa, Florida). As the sun’s
4.2. Effects of tree shade on LST

Statistical analysis revealed both similarities and differences of the cooling effects of tree shade on LST between the two selected cities. In general, tree shade negatively correlated with LST in both Tampa and NYC. The correlations between LST and tree shade, however, were generally stronger in Tampa than in NYC. Furthermore, as indicated by the decision tree regression analysis, the interaction between tree shade and land cover was different between the two cities. Detailed results are presented below.

4.2.1. Correlation between LST and tree shade

Correlation between tree shade and LST was negative \( p < 0.01 \) and from 07:00 to 10:00 in both cities (Table 3). Generally, tree shade has a stronger correlation with LST in Tampa than in NYC. Pearson correlation analysis also showed significant relationship between LST and land cover (Table 4). While tree canopy cover and grass/shrub were negatively correlated with LST, impervious surface had a positive correlation with LST in both cities.

4.2.2. The effect of interactions between tree shade and land cover on LST

Decision tree regression analysis with both shade and land cover types showed that, in general, tree shade and land cover had a slightly stronger cooling effect in Tampa than in NYC as indicated by \( R^2 \) (Fig. 7). In details, tree shade and land cover explained \(~53\%\) and \(~43\%\) of the variance of LST in Tampa and NYC, respectively. In Tampa, while tree shade at 07:30 was the main factor in influencing LST, the cooling effect was the strongest in areas with high tree canopy cover \( (> = 78\%) \) and the weakest in areas with high impervious surface cover \( (> = 41\%) \). Impervious surface cover exerted the strongest positive effect on LST in NYC, but this warming effect was lessened to some degree by tree shade at 7:30 \( (> = 81\%) \) and tree canopy cover \( (> = 86\%) \).

5. Discussion

Shading is one of the most important cooling effects provided by urban trees. Understanding the cooling effect of tree shade can provide critical insights into UHI mitigation strategies. Particularly, examining the cooling effect of shade cast by urban trees at the scale of a city is needed for whole-city UHI mitigation strategies. This study quantified tree shade with a hillshade function for Tampa and NYC and analyzed the cooling effect of shade using statistical analyses.

5.1. Quantification of tree shade

The lack of quantification of spatial and temporal pattern of tree shade represents a real and important hurdle to understanding its cooling effect in urban areas. This study provided a reliable and accurate quantification of the spatiotemporal pattern of tree shade using hillshade function with nDSM derived from LiDAR data. Following the idea of shade simulation for a single tree (Simpson, 2002), the hillshade function was able to accurately estimate the amount of shade by directly simulating the exact path of sunlight using both sun location and tree height. Compared to existing methods such as tree canopy cover and sky view factor methods (Berry et al., 2013; Li et al., 2018; Li and Ratti, 2018; Simpson, 2002), the hillshade function can capture the spatial distribution of shade at an any given time. Shade characterized by tree canopy cover only considers the area under tree crowns (Li et al., 2018), which fails to capture the actual distribution of shade. Sky view factor method also ignores the movement of the sun, and thus fails to obtain the temporal pattern of tree shade. Given the availability of LiDAR data at a city scale, we were able to extend the quantification of the spatiotemporal pattern of tree shade from plot- (Berry et al., 2013; Simpson, 2002) or street-scale (Li et al., 2018; Li and Ratti, 2018) to the whole city, which makes it possible to examine the cooling effect of tree shade at the city scale and to compare the cooling effects of tree shade between cities.

5.2. Cooling effect of tree shade

Tree shade showed significant cooling effect in both Tampa and NYC (Table 3). Tree shade covering ground objects can block direct-impact sunlight. Consequently, man-made materials covered by shade absorb less solar energy than those exposed to sunlight. The more shade cast on the surface, the lower the surface temperature would be. Our results also indicated that tree shade at 07:30 was the most important in regulating LST in both cities (Fig. 7). As surfaces absorb shortwave solar radiation and emit longwave radiation, the surface temperature begins to rise when the incoming shortwave radiation becomes greater than longwave emission (June et al., 2018; Masson, 2000). The increase in surface temperature can be attributed to both the status of shade (Armson et al., 2012) and thermal inertia of ground objects (Ait-Mesbah et al., 2015; Armson et al., 2012), which is usually the highest in the first few hours after sunrise when heat absorption is the highest (Hoyano et al., 1999). Therefore, whether a surface ground is shaded or not in early morning (in our case tree shade at 07:30) plays an important role in determining the amount of solar energy it absorbs and consequently, its effect on surface temperature in the morning.

The cooling effect of tree shade is also affected by urban landscape. The interaction between tree shade and land cover led to different cooling effect on LST in different cities (Fig. 7). NYC has a high density of high-rise buildings and relatively low tree canopy cover. Most of the green spaces are located in parks. Meanwhile, the density of buildings is lower in Tampa and the city also has relatively higher tree canopy cover. Most of the trees in Tampa are found in parks, natural reserved area, and residential areas close to buildings. Impervious surfaces normally have higher thermal inertia and lower moisture availability than trees (Buyantuyev and Wu, 2010; Martinkauppi et al., 2015; Ryu and Baik, 2012). The large thermal inertia of impervious surface means a high capability to absorb and store heat of shortwave radiation during daytime (Ryu and Baik, 2012), so that impervious surfaces contribute the most to the UHI effects. Shade cast by the clustered trees in NYC is
Fig. 4. Shade distribution at 10:30 in Tampa (a) and NYC (b). The figures illustrate hillshade for both cities. A value of 0 (blue) stands for shade (100%) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).
restricted to small areas, which is insufficient to prevent most of the solar radiation from reaching impervious surface. The rate of increase in surface temperature was thus largely controlled by the amount of impervious surface that was not covered by tree shade in NYC. Moreover, heat storage is intensified by the street canyons in NYC as a result of multiple reflection of incoming shortwave radiation and outgoing longwave radiation. In Tampa, on the other hand, more buildings can be covered by tree shade cast by urban trees distributed throughout the city. Additionally, trees are less clustered and are usually placed around buildings in Tampa, resulting in a stronger cooling effect of tree shade on urban surface temperature (Berry et al., 2013; Heisler, 1986; Simpson, 2002).

In addition to the spatial arrangement of trees and impervious surface, the relative height of trees to buildings can also alter the cooling effect of tree shade. For instance, many high-rise buildings in NYC are free of tree shade on their upper floors and roofs, which leads

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Fig. 5. Examples showing estimated hillshade on University of South Florida campus in Tampa, Florida from 8:00 to 19:00 with an interval of one hour on 4/30/2011.
to higher heat levels in summer. Existing research seldom considered tree height as a critical factor in determining the cooling effects of tree shade. However, these results support assertions by Li et al. (2018), who suggested that tall trees are more useful than small trees in reducing wall surface temperature because their shade can cast onto building walls (Li et al., 2018). Comparing the cooling effects of tree shade between Tampa and NYC with a distinct tree-building height distribution, we suggested that tree height would affect heat storage by changing shade length in both cities. Tree height should be considered into urban forest management. For instance, selecting tree species with tall and large crowns and maintaining mature trees should be prioritized as they are more helpful in reducing surface temperature.

By comparing the cooling effects of tree shade in two cities, our results also revealed that city-scale urban structure, especially the spatial arrangement and the relative height of trees to buildings have significant influence on the cooling effect of tree shade. Therefore, appropriate UHI mitigation strategies should be developed with the consideration of the local characteristics of urban settings (Kim et al., 2018).

Despite the importance of tree shade in regulating land surface temperature in most urban areas, cities with different structures should implement different strategies to mitigate UHI. Space is limited in highly developed cities such as NYC to increase tree cover, especially on the ground, while less developed cities such as Tampa are less restricted by this problem. For a city such as New York City to gain comparable shade advantage as Tampa, it will be crucial to utilize the roofs of high-rise buildings to their advantage, as installation of green roof or cool roof can significantly alleviate UHI effect. Additionally, cities with more ground impervious surface (e.g. parking lots) may need more trees with extending crowns to lower LST. Urban planners should also carefully choose tree species as other factors such as water availability and soil conditions may all affect tree growth in urban areas.

5.3. Limitations

There are several limitations of this study which should be addressed in future research. First, compared to LST at 10:30, analysis using LST data acquired at different time of the day would offer a more complete picture of the cooling effect of tree shade. Although MODIS

Table 3
Pearson correlation coefficients between LST (K) and tree shade (%) from 07:00 to 10:00 at 30 min interval in Tampa, Florida and New York City (NYC), New York.

|       | Tree Canopy | Grass/Shrub | Impervious surface |
|-------|-------------|-------------|--------------------|
| Tampa | −0.50 ²     | −0.60 ²     | −0.60 ²            |
|       | −0.60 ²     | −0.60 ²     | −0.60 ²            |
|       | −0.60 ²     | −0.60 ²     | −0.60 ²            |
|       | −0.60 ²     | −0.60 ²     | −0.60 ²            |
| NYC   | −0.48 ²     | −0.50 ²     | −0.50 ²            |
|       | −0.50 ²     | −0.50 ²     | −0.50 ²            |
|       | −0.50 ²     | −0.50 ²     | −0.50 ²            |
|       | −0.50 ²     | −0.50 ²     | −0.50 ²            |

1 Column headers are shade simulated from 07:00 to the acquisition time of LST (10:00) at 30 min interval.
2 Correlation is significant at the 0.01 level (2-tailed).

Table 4
Pearson correlation coefficients between LST (K) and land cover (%) in Tampa, Florida and New York City (NYC), New York.

|       | Tree Canopy | Grass/Shrub | Impervious surface |
|-------|-------------|-------------|--------------------|
| Tampa | −0.64 ¹     | −0.14 ¹     | 0.60 ¹             |
|       | −0.53 ¹     | −0.26 ¹     | 0.61 ¹             |

¹ Correlation is significant at the 0.01 level (2-tailed).

Fig. 6. Simulated shade at 11:00 on 4/30/2011 compared to real shade (inserted photos) on 10/21/2017 at 11:00 on the campus of University of South Florida, Tampa, Florida.
offers LST data at four times of the day, the coarse spatial resolution (~1 km) makes it unsuitable for the analysis with tree shade in cities. Additionally, due to the 120 m spatial resolution of the Landsat LST data, pixels are very likely to contain thermal characteristics of mixed ground objects. LST at finer scale would improve investigating cooling effect of tree shade. Meanwhile, this study analyzed the effect of tree shade on a single day in two cities. A time-series of LST of multiple cities may reveal important daily/seasonal patterns and interactions between LST and tree shade and urban structure which were not discussed in our study. At the same time, tree shade used in this study was simulated at discrete time steps due to lack of resources. The examination of cooling effect of tree shade can be improved by combining the coverage and duration of tree shade. In addition, tree shade quantification method in our study can only capture tree shade over ground objects while tree shade covering vertical surfaces such as building walls was not included in our analysis. Finally, while this study focuses on tree shade only and strived to isolate the effects of shade cast by trees, shade cast by buildings may still exert a level of influence surface temperature where building shade are in close proximity to tree shade. 

While this study focused on one critical cooling factor: tree shade,

![Regression tree between tree shade quantified from 07:00 to 10:30 at 30 min intervals and land cover (tree, grass/shrub, and impervious surface) and land surface temperature (LST) in Tampa (a) and NYC (b). Branches are labeled with classification criteria. Values in leaf nodes (ellipses) are mean LSTs of the corresponding branches.](image-url)
we admit that there are many other biophysical factors influencing the spatial and temporal variation of LST. The effects of different biophysical factors have been continuously analyzed including but not limited to land use land cover type (Buyantuyev and Wu, 2010; Fu and Weng, 2016), landscape configuration (Estoque et al., 2017), canopy structure (cover, height, and density; Armson et al., 2012; Heisler, 1986; June et al., 2018; Yu et al., 2018), tree species (Armson et al., 2013), evapotranspiration (Qiu et al., 2013), and geometry (Yang et al., 2015).

Our study highlighted the importance of tree shade, which has been seldom analyzed. Efficient UHI mitigation strategies would benefit from a comprehensive understanding of the effects of different factors. Therefore, it is worthwhile to examine other properties such as shade of building and other biophysical factors of trees (e.g. leaf area) whose cooling effect have not been sufficiently analyzed. Future research can also benefit mitigating UHI by partitioning and quantifying the contribution of different biophysical properties.

6. Conclusions

Examining the cooling effect of tree shade at a city scale provides both an avenue to improve the understanding of the ecosystem services of urban forest and to aid the development of efficient UHI mitigation strategies. Due to the structural complexity of urban environment, analysis based solely on small plots at a single point of time tends to be location- and temporal-dependent. Understanding the effect of tree shade on LST is required to develop efficient UHI mitigation strategies.

In this study, we uncovered the cooling effects of tree shade in two U.S. cities, Tampa, Florida and NYC, New York, with different geographic locations and urban settings. Evidence from the analyses presented in this study indicate the following:

- The hillshade function which accounts for the sun location can improve the quantification of the spatiotemporal pattern of tree shade.
- Shade cast by urban trees can lower LST in both cities. Tree shade at 07:30 was the most important factor in controlling LST at 10:30 local time. The effect of tree shade at 07:30 on LST in Tampa was intensified by tree canopy cover. In NYC, impervious surface cover was identified as the most important factor in controlling LST while tree shade remained significant in regulating LST.
- The difference of cooling effect of tree shade in Tampa and NYC is mostly due to the differences in the ratio of tree canopy cover to impervious surface cover, the spatial arrangement of trees and buildings, and their relative heights. While this study has been successful in unravelling important aspects of tree shade-LST relationship, it is important on future research to build on this exploratory study by using higher resolution data – temporal and spatial – to further illuminate the effects of shade on LST.

This study allows us to better understand the cooling effects of tree shade in urban environments through a city-wide accurate simulation of tree shade at a fine temporal scale. The comparison of the cooling effects of tree shade between the two cities provides important insights for urban planners to moderate urban climate and implement different tree management strategies for different cities. The findings of this study also allow further explorations of the mechanisms behind the observed spatiotemporal patterns in UHI.

CRediT authorship contribution statement

Quyan Yu: Conceptualization, Methodology, Formal analysis, Writing - original draft. Wenjie Ji: Conceptualization, Methodology, Writing - review & editing. Ruiliang Pu: Software, Validation, Writing - review & editing, Supervision. Shawn Landry: Software, Resources, Data curation, Writing - review & editing. Michael Acheampong: Methodology, Writing - review & editing. Jarlath O’Neill-Dunne: Resources, Data curation, Writing - review & editing. Zhibin Ren: Writing - review & editing. Shakhatwat Hosen Tanim: Writing - review & editing.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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