

Regulation of humid heat by urban green space across a climate wetness gradient

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Green spaces are a common strategy for adaptation to urban warming. Whereas they have been demonstrated to reduce air temperature, much less is known about their effect on air humidity. Because human heat stress is contributed by both temperature and humidity, it is important to quantify the relationship between the effects of both. Here, using mobile measurements in 15 cities, we show that the daytime temperature effect is negatively correlated with the humidity effect, resulting in an insignificant change in the wet-bulb temperature T_w or humid heat (daytime T_w difference between green space and built-up area $\Delta T_w = -0.01^\circ\text{C}$). A net reduction in humid heat was observed at night in intermediate (summer precipitation 180 to 570 mm) and wet climates (summer precipitation > 570 mm; mean $\Delta T_w = -0.35^\circ\text{C}$). A model simulation revealed that the nighttime T_w reduction resulted mostly from reduction in soil heat storage in vegetated land. These nuanced microclimate responses to urban vegetation caution against a one-size-fits-all solution to climate adaptation.

Urban overheating, as a result of global climate warming and local urban heat islands, is a serious threat to the health of urban residents. Most studies on urban climatic adaptation with green spaces focus on the temperature effect¹. Of the few studies that examine the humidity effect, the results are inconsistent regarding their effectiveness in reducing humid heat^{2–4}. Evaporation is a key mechanism underlying the temperature reduction by urban vegetation. Evaporation also increases air humidity. According to the data from urban climate model simulations, planting of street trees in Singapore⁵ and Hong Kong⁶ creates a stronger humidity effect than the temperature effect, with the result being a greater wet-bulb temperature T_w or an increase in humid heat (Supplementary Fig. 1a–d). These two cities are in the low-latitude wet climate. On the other hand, observational evidence for Salt Lake

City², Utah, USA, a city located in the dry climate, and for Würzburg, Germany⁷, and Shanghai, China⁸, two cities in a climate with intermediate wetness, indicates that the two effects roughly offset each other without significant changes in T_w (Supplementary Fig. 1e–g).

In a global modeling study, the urban dry island, the phenomenon whereby the urban vapor pressure e_a is lower than that of the adjacent rural land, is stronger in the dry climate than in the wet climate⁹. The authors of that study argue that this climate gradient exists because surface evaporation is water limited in the dry climate but is energy limited in the wet climate. On the basis of their reasoning, it may be proposed that in an energy-limited city, evaporative cooling and humification of green spaces is relatively weak in reference to built-up parcels. On the other hand, in the dry climate, evaporation of previous urban

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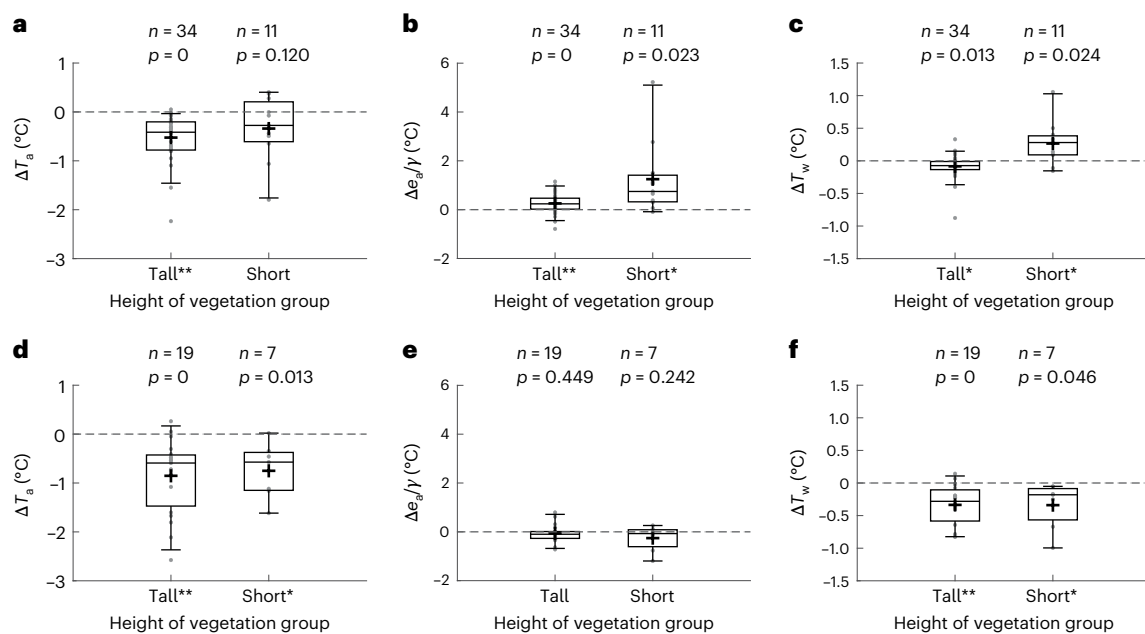


Fig. 1 | Effects of urban green space on air temperature, humidity and wet-bulb temperature in intermediate-wetness climate. a–c, Daytime. d–f, Nighttime. Panels show three different quantities as indicated by their y-axis labels (ΔT_a (°C) (a,d), $\Delta e_a/\gamma$ (°C) (b,e) and ΔT_w (°C) (c,f)). Data are presented for tall and short vegetation groups. Box-whisker plots indicate mean (plus), median

(line), 25th and 75th percentiles (box), and 5th and 95th percentiles (whiskers). Individual samples are shown as dots with each representing one green space. Results of two-tailed *t*-test are provided at the top of each figure (*n*, sample size; *p*, statistical significance). Confidence levels are shown as ***p* < 0.01 and **p* < 0.05 at the bottom.

ground and impervious parcels is negligible due to water limitation, but urban trees can sustain evaporation by drawing water from deep soil and therefore humidify the air, raising the possibility that green spaces in arid and semiarid cities may be counterproductive. However, high saturation vapor pressure deficit may increase the canopy resistance and impose a hydraulic limit on the transpiration potential of urban trees in the dry climate¹⁰. To resolve these inconsistencies, it is desirable to perform simultaneous measurement of the humidity and the temperature effects of urban green spaces and to assess their relative strengths across climate gradients.

In this study, we investigate the temperature and the humidity effects of urban green spaces using measurements made with smart sensors mounted on bicycles. These sensors measured simultaneously air temperature and air humidity. Radiation errors were minimized via ventilation forced by bicycle motion. A total of 114 green spaces (69 consisting of tall vegetation and 45 consisting of short vegetation) in 15 cities were sampled, spanning a summer precipitation range from 10 mm to 960 mm and a latitudinal range from 22° N (Hong Kong, China) to 61° N (Anchorage, Alaska, USA). The combined contribution of temperature and humidity to humid heat was quantified with the wet-bulb temperature T_w .

Temperature effect

We divide the cities into three wetness groups using 30-year mean summer (July–August) precipitation P_s . They are: dry cities ($P_s < 180$ mm), wet cities ($P_s > 570$ mm) and cities with intermediate wetness (P_s between 180 and 570 mm; Supplementary Fig. 2). The green space effects are quantified as the difference between a green space and its adjacent built-up neighborhood (green space minus built-up neighborhood) in air temperature (ΔT_a , °C), humidity ($\Delta e_a/\gamma$, °C) and wet-bulb temperature (ΔT_w , °C). The vapor pressure difference Δe_a is divided by the psychrometric constant γ so the humidity effect has the same dimension as temperature. Observations were made in the warm season. Data collected in daytime (sunrise to sunset) and nighttime (sunset to sunrise) were analyzed separately.

Urban green spaces reduce air temperature more at night than during the day. For cities in the intermediate-wetness category, the average daytime temperature reduction is 0.52 °C for tall vegetation and 0.34 °C for short vegetation (Fig. 1a). The average nighttime reduction is nearly doubled, at 0.85 °C and 0.75 °C for tall and short vegetation, respectively (Fig. 1d). Averaged across both vegetation types, the daytime temperature reduction is 0.48 °C, whereas the nighttime temperature reduction is 0.83 °C. These day-versus-night differences are statistically significant (*p* < 0.05). For cities in the wet climate, the average vegetation temperature reduction is 0.10 °C during the day and 0.59 °C at night (Supplementary Table 1; day-versus-night difference *p* < 0.01).

Tall and short vegetation within the same climate regime generally do not show a statistically significant difference in their temperature effect (Supplementary Table 2). For example, in the intermediate climate, tall vegetation reduces the daytime air temperature by nearly the same amount ($\Delta T_a = -0.52 \pm 0.46$ °C) as short vegetation (-0.34 ± 0.66 °C; tall-versus-short vegetation difference *p* = 0.31). One exception is the wet climate in the daytime. There, tall vegetation generates a stronger cooling than short vegetation. Tall vegetation reduces the daytime air temperature by 0.29 °C, whereas short vegetation actually increases air temperature by 0.21 °C (Fig. 2a,b); this difference is statistically significant (*p* < 0.01).

Humidity effect

The humidity effect of urban vegetation is less coherent than its temperature effect. Vegetation tends to make the air more humid during the day but drier at night than its adjacent built-up neighborhood (Figs. 1b,e and 2 and Supplementary Table 1), with a mean change $\Delta e_a/\gamma$ ranging from −0.44 °C (nighttime, tall vegetation, wet climate) to 1.25 °C (daytime, short vegetation, intermediate climate). One exception to this is short vegetation in the wet climate, which causes the daytime air to be drier, but the change signal ($\Delta e_a/\gamma = -0.34$ °C) is not statistically significant (*p* = 0.19). These short vegetation green spaces were in Guangzhou, China (Supplementary Table 3), and were drought stressed.

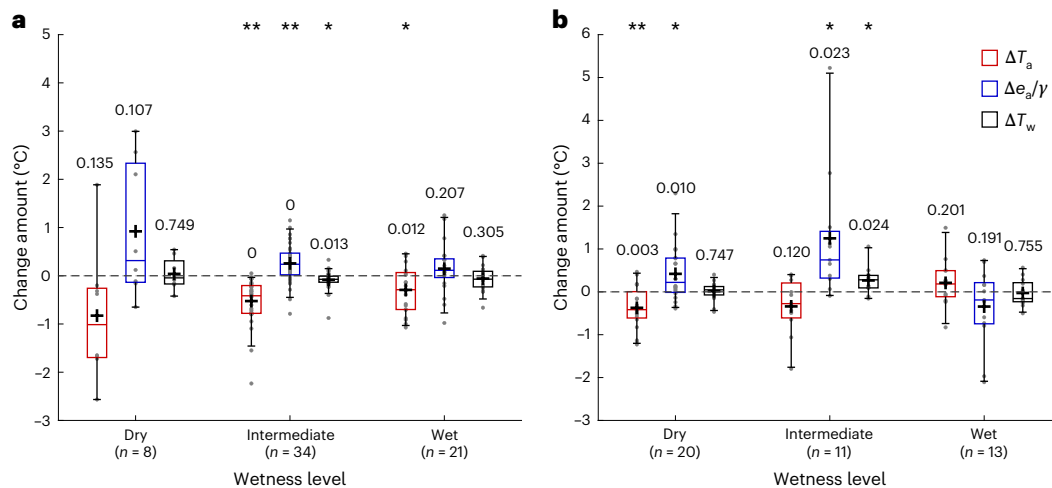


Fig. 2 | Daytime microclimatic effects of urban green space across the climate wetness gradient. a, Tall vegetation. b, Short vegetation. Box-whisker plots indicate mean (plus), median (line), 25th and 75th percentiles (box), and 5th and 95th percentiles (whiskers). Individual samples are shown as dots with

each representing one green space. Sample size (n) is provided at the bottom. Statistical significance of two-tailed t -test (p) is provided at the top of each box. Confidence levels are shown as $**p < 0.01$ and $*p < 0.05$.

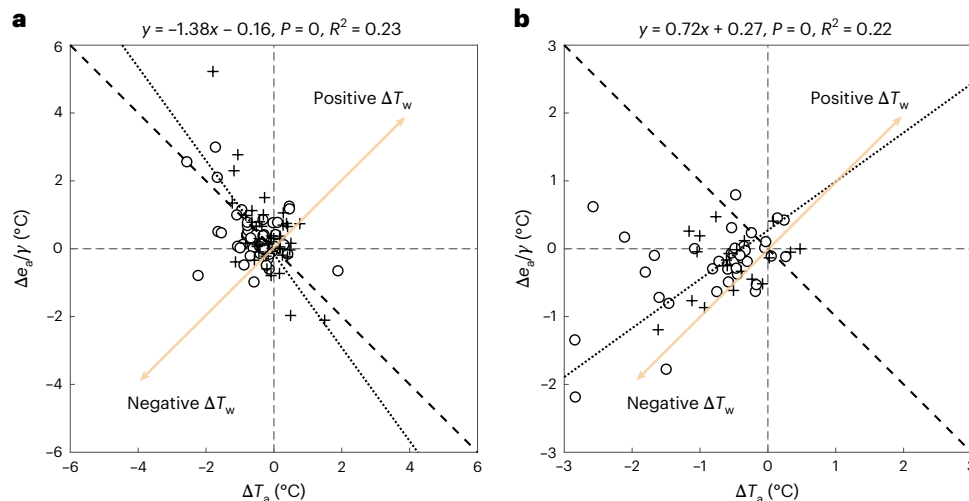


Fig. 3 | Relationship between temperature and humidity effects of urban green space. a, Daytime. b, Nighttime. Tall and short vegetation are shown as circles and plus signs, respectively. The black dotted line is the best-fit function with regression statistics and significance of a two-tailed t -test (p) shown. The black dashed line indicates the $-1:1$ relationship.

Relationship between temperature and humidity effects

Wet-bulb temperature is a thermodynamic measure of the combined heat stress arising from temperature and humidity. The difference in wet-bulb temperature (ΔT_w) between a green space and its neighboring built-up land is a linear combination of the temperature and the humidity effect

$$\Delta T_w = w\Delta T_a + w\frac{\Delta e_a}{\gamma} \quad (1)$$

where w is a positive and dimensionless scaling factor with a typical value of about 0.3 (Methods). In the $\Delta e_a/\gamma$ versus ΔT_a parameter space, the $-1:1$ line represents situations where the vegetation effect of temperature reduction on humid heat is exactly offset by the effect of humidity increase. The space below this line corresponds to net reduction of humid heat, and the space above corresponds to net increase.

In the daytime, a negative correlation between $\Delta e_a/\gamma$ and ΔT_a is observed, showing that vegetation reduction of air temperature is

generally accompanied by increase in air humidity (Fig. 3a; $p < 0.01$). The correlation is in the same direction as the full-compensation line, with a linear slope of -1.38 ± 0.23 (95% confidence bound), indicating that the temperature effect is mostly canceled by the humidity effect. When the data are grouped by vegetation type and climate regime, tall vegetation in intermediate cities has a significant effect on T_w ($p < 0.05$), but the mean change is small ($\Delta T_w = -0.08^\circ\text{C}$). In contrast to the daytime results, the nighttime correlation between $\Delta e_a/\gamma$ and ΔT_a is positive (Fig. 3b; $p < 0.01$). The nighttime data mostly fall below and in a direction almost orthogonal to the full-compensation line. The regression slope is 0.72 ± 0.17 . In other words, green spaces generally bring relief to humid heat at night. Both short and tall vegetation cause significant reductions in the nighttime T_w in intermediate and in wet cities (Supplementary Table 1; $p < 0.05$).

The vegetation effects are explained in part by the background climate wetness. For tall vegetation, the mean daytime ΔT_a changes from -0.83°C in dry cities to -0.52°C in intermediate cities, then to -0.29°C in wet cities (Fig. 2a). In other words, the cooling effect decreases when climate wetness increases. The humidification intensity also decreases

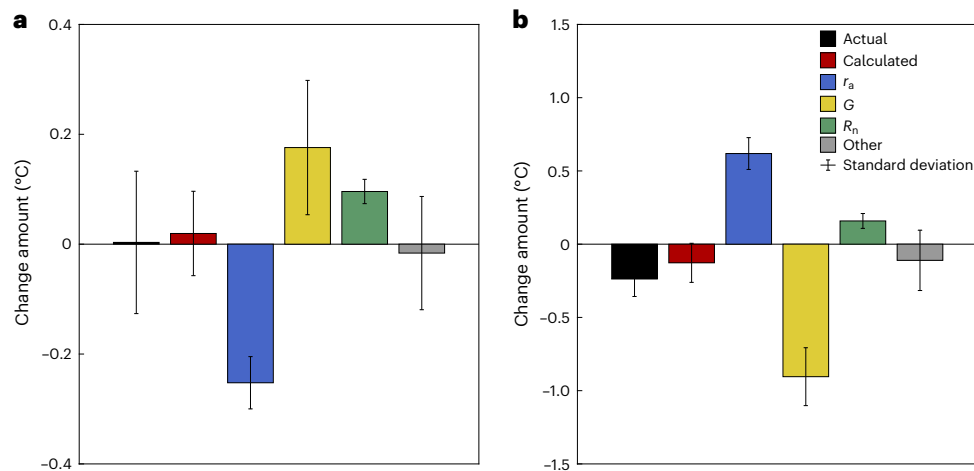


Fig. 4 | Attribution of vegetation effect on the wet-bulb temperature T_w . **a**, Daytime. **b**, Nighttime. Black bars denote actual change in T_w (green space minus built-up land). Red bars are calculated as the sum of component contributions, including contributions from changes in aerodynamic resistance r_a (blue bars), in soil heat storage G (yellow bars), in net radiation R_n (green bars)

and in other factors (grey bars). Component contributions represent the mean of 139 vegetation grids and are calculated with the terms on the right-hand side of equation (5). Error bars are $\pm$ one standard deviation of the regression coefficient multiplied by the mean difference of the corresponding variable.

with wetness, as $\Delta e_a/\gamma$ changes from 0.92 °C in dry cities, to 0.26 °C in intermediate cities and then to 0.15 °C in wet cities. These two trends offset each other, resulting in virtually no change to wet-bulb temperature ($\Delta T_w = 0.04$ °C in dry cities, -0.08 °C in intermediate cities and -0.06 °C in wet cities). Tall vegetation humidifies the daytime air more in dry cities ($\Delta e_a/\gamma = 0.92$ °C) than in wet cities ($\Delta e_a/\gamma = 0.15$ °C; dry-versus-wet city difference $p < 0.05$). For short vegetation, the dependence on climate wetness is not monotonic. In an inter-group t -test, we find that the air temperature and the humidity effects of short vegetation are different significantly between wet and dry climates ($p < 0.01$). Short vegetation humidifies but cools urban air in dry cities; it has the opposite effects in wet cities, reducing air humidity but increasing air temperature (Fig. 2b).

Mechanisms responsible for the vegetation effects

We used a mesoscale urban climate model to probe the mechanisms responsible for the observed vegetation effects (Methods). The model domain was the city of New Haven, Connecticut, USA, an intermediate-wetness city that had the most mobile measurements among all the cities. The green space effects were quantified as the difference in T_a , e_a and T_w between each vegetation grid or green space and the average results of built-up grids within the city boundary. The model was able to reproduce key observed patterns (Methods and Supplementary Figs. 3–6). In the model domain, all energy balance components and atmospheric forcing variables were calculated, allowing investigation of mechanisms underlying the green space effects that otherwise would not be possible with the mobile data alone.

The wet-bulb temperature is a measure of moist static energy (MSE) near the surface. According to a one-dimensional surface energy balance theory⁹, changes in the surface MSE can result from changes in diabatic heating of the surface-layer air and changes in dynamic mixing between the surface layer and the air layer above. Here diabatic heating consists of conduction heat released from or absorbed by the substrate (soil and buildings; heat storage term G , with positive values indicating absorption and negative values indicating release) and net absorption of radiation energy (R_n). A multi-linear regression was used to quantify the contribution from changes (green space minus built-up land) in each of these variables to the total change in T_w (Fig. 4). In the daytime, green spaces had slightly lower the aerodynamic resistance r_a than built-up areas (mean $\Delta r_a = -0.7$ s m⁻¹), allowing MSE to dissipate

more efficiently to the upper boundary layer and causing a reduction in T_w . But less heat was conducted into the substrate in green spaces than in built-up land ($\Delta G = -46$ W m⁻²), resulting in an increase in humid heat, which largely offsets the role of mixing. At night, these patterns were reversed. There was a marked reduction in the heat released from the substrate in green spaces than in built-up land ($\Delta G = 36$ W m⁻²), resulting a large reduction in humid heat (-0.91 ± 0.20 °C). Dynamic mixing over green spaces was still more efficient than over built-up areas ($\Delta r_a = -117$ s m⁻¹), but because the air above the surface layer had higher MSE than the air in the surface layer in the nighttime boundary layer, more efficient mixing means that more MSE would be brought down to the surface layer, resulting in higher humid heat in green spaces ($+0.62 \pm 0.11$ °C). However, the role of heat storage was more important than the role of dynamic mixing; this is the main reason that explains a net reduction in humid heat at night ($\Delta T_w = -0.23 \pm 0.11$ °C).

Summary and discussion

In summary, the differential form of the wet-bulb equation (equation (1)) is a useful framework for isolating the roles of temperature and humidity in green space regulation of humid heat. These two roles tend to cancel each other during the day and reinforce each other at night (Figs. 1c,f and 3). So far, researchers have investigated evaporation and shading as vegetation cooling mechanisms^{1,11}. Our analysis reveals reduction in the substrate heat storage as another mechanism that underlies the climate benefit of a green space. The wet-bulb equation can also be used for evaluation, using published data, of the net climate effect of other climate interventions, such as street trees^{7,12} and urban irrigation¹³, on humid heat.

The climate wetness gradient in the daytime ΔT_w mirrors the observed pattern of the daytime urban wet-bulb island. The urban wet-bulb island, defined as the T_w difference between a city and its adjacent natural land, can be decomposed into a temperature (or urban heat island) and a humidity (or urban dry island) component⁹. Both the urban heat island and the urban dry island components are muted in the wet climate and are more intense in the dry climate, similar to the microclimate effects of green space shown in Fig. 2. This climate gradient exists because evaporation is energy limited in the wet climate and water limited in the dry climate⁹. The same mechanism may be invoked to explain the climate gradients of ΔT_w and $\Delta e_a/\gamma$. We suggest that in wet cities, there is enough water in the exposed soil to sustain evaporation of a built-up neighborhood, so comparatively speaking, its

adjacent green space can only produce weak cooling and humidification. In dry cities, the microclimate effects of green spaces are much stronger because built-up neighborhoods are severely water limited. In an observational study, urban vegetation produces a larger nighttime temperature reduction in six arid and semiarid cities than in two cities in the intermediate and the wet climates¹⁴.

The climate benefit of green spaces—as measured by the wet-bulb temperature—is significant at night ($\Delta T_w = -0.35^\circ\text{C}$, $p < 0.01$) but is not significant during the day ($\Delta T_w = -0.01^\circ\text{C}$, $p = 0.73$). This pattern is at variance with the accepted view that the cooling benefit of vegetation should occur in daylight hours due to high rates of plant transpiration and is generally negligible at night. Although they reduce air temperature significantly, green spaces offer little relief to the daytime humid heat. This is because evaporation is the primary mechanism of the daytime temperature reduction, but evaporation also increases air moisture. In some modeling studies, the humidifying effect of urban vegetation is stronger than its effect on temperature, causing a net increase in the daytime wet-bulb temperature (Supplementary Fig. 1). According to our urban climate model simulation, vegetated land stores less heat during the day and releases less heat at night than built-up land, in agreement with the established principle of urban surface energy balance¹⁵. Energy release from soil, vegetation and built structures is a source of diabatic heating at night. Our model calculation showed that reduction of this heating source in vegetated land lowered moist static energy, reducing the surface-layer air T_w by $0.91 \pm 0.20^\circ\text{C}$ at night. A full climate adaptation strategy may require that green infrastructure be used in combination with other approaches, such as installation of reflective roof and pavement. By reflecting solar radiation away from the cityscape, the diabatic heating of the surface-layer air is reduced, with a result being a lower T_w during the daytime⁹.

Human mortality occurs when T_w exceeds the threshold of about 27°C (refs. 3,9,16,17). The observed T_w reduction of 0.35°C seems small in comparison to this threshold. However, if the T_w probability distribution is shifted by this amount, the likelihood of T_w exceeding the threshold should be significantly lowered due to the sensitivity of the tail end of a distribution to the mean change¹⁸. As an example, a small change of 0.33°C in T_w changes the at-risk population in the western Maritime Continent by about 2% (ref. 9).

An open question is whether our results, which were obtained under normal thermal conditions, are applicable to extreme conditions. In heatwaves, plants, especially short vegetation with shallow roots, may lose some of their evaporating cooling power^{19,20}. But because reduction of T_w is accomplished primarily by the change to soil heat storage, we suggest that ΔT_w should be insensitive to vegetation health status. Observations in the wet climate offer partial support for this argument. There, short vegetation in urban green spaces (in Guangzhou, China) suffered drought stress. During the observation period (April 2021), the monthly rainfall was 50% below the climate mean, but these green spaces still reduced the nighttime T_w by $0.23 \pm 0.28^\circ\text{C}$ ($p < 0.05$; Supplementary Table 1). Dead grass and organic mulch do not evaporate much water, but they are still preferred over concrete because they can bring relief to nighttime humid heat via reduction in soil heat storage.

Averaged across all the cities, the temperature reductions are 0.49°C and 0.78°C by tall vegetation and 0.19°C and 0.53°C by short vegetation in the daytime and at night, respectively. These values are lower than the mean values revealed by the meta-analysis of other published results (0.9°C by tree parks in the wet and intermediate climates²¹, 3.0°C by green vegetation across diverse geographic zones¹ and 1.8°C by tree canopies over a wide aridity range¹¹). Several factors may have contributed to these differences. Our observations were conducted in all-sky conditions, whereas some other studies emphasize the maximum cooling power by choosing clear-sky and low-wind conditions to do observation^{2,8,22–24}. Unlike the practice of using only an impervious surface for ref. 8, some of our urban

reference neighborhoods were inhabited by trees, which could mute the temperature effect of a nearby green space. Our green spaces were in public land without irrigation, whereas some observations in those meta-analyses may have been affected by irrigation. Finally, radiative interference with stationary sensors may have played a role. The temperature sensors used in most published studies were protected by a radiation shield to avoid heating from direct sunlight, but because they relied on passive ventilation by natural wind, heating of the radiation shield itself could still lead to a warm bias of the air temperature reading. The warm bias increases with solar radiation and surface albedo and decreases with wind speed^{25–27}. Experiments at exposed sites indicate that without active ventilation, the measured temperature is biased high by 2°C in low-wind conditions^{28,29} and by about an average of 1°C in the summer months³⁰. The warm bias is probably less if the measurement takes place in a tree park, where the tree canopy provides additional protection against solar heating of the sensor, than at an open reference site. In our case, the sensor heating bias was small (0.05°C to 0.07°C) because bicycle motion promoted active ventilation of the sensor (Supplementary Figs. 7 and 8). Other researchers have reported that air temperature in urban green spaces consisting of tall vegetation is lower than in those consisting of short vegetation, by 1.0 to 2.4°C in Tel Aviv, Israel^{22,31} (dry climate), 1.3°C in Indiana, USA¹², and 0.9°C in Beijing, China³² (intermediate climate), and 1.6°C in Singapore³³ and 1.6°C in Hong Kong²³ (wet climate). These differences are larger than our tall-versus-short difference in temperature reduction (0.27°C in the daytime and 0.25°C at night). We hypothesize that radiation errors are a factor contributing to this discrepancy.

The wet-bulb temperature has been increasingly employed to indicate humid heat stress^{9,34–37}. In addition to temperature and humidity, wind and solar radiation also influence human heat stress. The aggregated impact of these factors are measured by compound indices, such as the Universal Thermal Climate Index³⁸ and the Physiological Equivalent Temperature³⁹. In particular, solar radiation can be a large heat source to the human body. In this regard, green spaces made of tall trees can provide shades to directly relieve heat stress in daylight hours. Likewise, building shadows in built-up neighborhoods with a small sky-view factor may partially offset the stress due to higher temperatures. In the current study, the role of solar radiation was omitted because our primary goal is to investigate the combined effect of temperature and humidity on humid heat. Our main conclusion, that urban green spaces provide relief to humid heat at night, is not influenced by this omission because solar radiation does not play a role at night.

Methods

Mobile sensor

The mobile measurement was made with Smart-T sensors mounted on moving bicycles. The sensor's temperature–humidity sensing element was housed in a radiation shelter (Supplementary Fig. 9). The sensor used the cyclist's smartphone to record data and for geolocation. Its time response was 9.7 s for temperature and 18.5 s for humidity, corresponding to a spatial resolution of about 40 m for temperature and 70 m for humidity at a typical bicycle traveling speed of 4 m s^{-1} (Cao et al.⁴⁰). Its performance was characterized with an indoor test and two outdoor tests. These tests showed that the sensor had accuracy and precision comparable to other research-grade instruments.

A goal of the indoor test was to determine the sensor's reproducibility. We compared 30 Smart-T sensors with three commercial HOBO units (model MX2302A, Onset Computer Corporation) in a sealed room with stable temperature and humidity (Supplementary Fig. 10). Air around these sensors was thoroughly mixed with fans. The mean bias (Smart-T minus HOBO, 5-min average) was -0.10°C for temperature and $+3.4\%$ for relative humidity. The reproducibility, measured as one standard deviation of variations among the 30 Smart-T sensors, was 0.04°C for temperature and 0.25% for relative humidity.

In the first outdoor test, a Smart-T sensor was compared with a commercial fast-responding temperature–humidity sensor (6 mm diameter, model I-Met XQ2, InterMet Systems Inc.) protected by a ventilated radiation shield. They were mounted on a moving bicycle. The measurement was made along a 10-km-long road under full sunlight (solar radiation 320 W m^{-2}). The Smart-T showed smaller variations due to its longer response times but otherwise tracked the I-Met time series quite well (Supplementary Fig. 7). The mean temperature bias was small ($+0.05^\circ\text{C}$, Smart-T minus I-Met), indicating that the radiation error of Smart-T in sunlight was negligible as long as it was in motion. (Radiation interference with the I-Met sensor was negligible because of its small thermal inertia and because of ventilation.)

The second outdoor test was carried out at an air quality monitoring site in New Haven, Connecticut, USA, where temperature and humidity were monitored with a standard National Oceanic and Atmospheric Administration (NOAA) weather station. A Smart-T sensor was brought to the site periodically, both during the day and at night, for comparison with the NOAA reference, in the warm season of 2023. The overall agreement was excellent ($R^2 > 0.95$; Supplementary Fig. 8). In stationary mode, the mean difference (Smart-T minus NOAA) was $+0.10^\circ\text{C}$ at night (number of observations $n = 43$) and $+0.91^\circ\text{C}$ during the day ($n = 74$), indicating a small sensor bias of 0.10°C and a mean radiation error of 0.81°C . When the Smart-T was deployed in mobile mode, the mean daytime difference was much reduced (to $+0.17^\circ\text{C}$; $n = 17$). These results confirm that ventilation caused by sensor motion substantially reduced the Smart-T radiation error.

Sites

Observations were made along selected street transects in 15 cities from 2019 to 2022 (Supplementary Fig. 2). The biking routes were paved side streets except in Anchorage, Alaska, USA and North Platte, Nebraska, USA, where some sections of the route were unpaved gravel and dirt road. The average trip duration was 35 min and the average travel distance was 10 km. Each biking transect was sampled 1 to 33 times (mean number of replicates 5.4 during the day and 5.8 at night). Observation days were selected randomly with no preference for sky conditions except that rainy days were avoided. Warm-season (March to September for cities south of 35°N and April to September for cities north of 35°N) data were selected for analysis. We divided the cities into three wetness groups using summer precipitation (P_s), including dry cities ($P_s < 180 \text{ mm}$), intermediate-wetness cities ($180 \text{ mm} \leq P_s \leq 570 \text{ mm}$) and wet cities ($P_s > 570 \text{ mm}$). These thresholds coincide roughly with dry, temperate and boreal and tropical climate zones in the Köppen climate classification⁹.

Each biking transect traversed at least one green space and at least one built-up neighborhood. An example is given in Supplementary Fig. 11. Delineation of green spaces and reference built-up neighborhoods were based on Normalized Difference Vegetation Index (NDVI) and impervious surface fraction (IMP) and consisted of three steps. First, an NDVI map was derived from a warm-season clear-sky Sentinel-2 satellite image for each city. The original image resolution was 10 m. A 100-m moving window was applied to remove local extremes and to enhance homogeneity. A land parcel was provisionally designated as green space if vegetation was relatively homogeneous and its mean NDVI exceeded a preset threshold (0.2 in dry cities, 0.3 in intermediate cities and 0.4 in wet cities). A parcel was considered provisionally as built-up if its mean NDVI was lower than 0.2 and was located within 15 min biking time from the closest green space. Second, the selected parcels were visually inspected and cross checked against high-resolution Google Earth images and IMP maps to confirm that they were correctly classified. Third, boundaries of the confirmed parcels were drawn manually with the help of Google Earth images. These shape files were then used to screen the mobile data for calculating spatial averages for each green space and built-up neighborhood. Across the whole dataset, the average IMP is 19% for green spaces and 85% for

built-up references. The IMP was broadly consistent across the three climate zones (18%, 15% and 27% for green spaces and 93%, 83% and 83% for built-up references in the dry, intermediate and wet climates, respectively).

The green space dimension in the direction of travel ranged from 50 m to 6,340 m (with a median value of 440 m), and its dimension measured in the direction perpendicular travel (mean distance between every point on the bicycle transect and the closest side edge) ranged from 8 m to 512 m (with a median value of 39 m). Determination of vegetation type was based on visual inspection of Google Earth images, assisted by a global land-use product⁴¹. Green spaces with dominant tree canopy cover were defined as tall vegetation and those with grass and crop as short vegetation. Several studies show that green spaces consisting mostly of tall vegetation (trees) can reduce air temperature more than those consisting of short vegetation (grass)^{12,22,32,33,42} implying the hypothesis that tall vegetation is the preferred choice for urban climate adaptation. Our simple classification (tall versus short) can be used to test this hypothesis. Additionally, it recognizes two important climate attributes: tall vegetation is aerodynamically rougher and generally darker (having lower albedo) than short vegetation. The two classes correspond roughly to the two major functional types (Forest and Grassland) in the unified NOAA (National Centers for Environmental Prediction - Oregon State University - Air Force - Hydrology Lab) land surface scheme embedded in the Weather Research and Forecasting (WRF) mesoscale model. We measured a total of 114 green spaces, 69 of which were marked as tall vegetation and 45 as short vegetation. Supplementary Table 3 provides detailed characterization of these green spaces and their neighboring built-up parcels, including NDVI, IMP, local climate zone, sky-view factor⁴³ and satellite visuals.

The reader should keep several factors in mind when comparing the results in this study with those in the published literature. Our method of delineating green spaces and built-up references is similar to those deployed in several mobile surveys^{8,24,44,45}. It differs from some studies that deployed stationary sensors^{7,10,12,46–49}. In those studies, the vegetation effect was quantified for individual trees or small tree clusters, usually using measurements at an impervious surface or an urban lawn as the reference. In the present case, the built-up references were predominantly street canyons, some of which were inhabited by street trees. Furthermore, the green spaces in our dataset were land parcels with a clear patch boundary; scattered or small clumps of trees were not used as green spaces.

Several authors have examined the association between cooling efficiency and morphological traits of urban plants, with some finding species difference¹⁰ whereas others detect no influence¹². This aspect is omitted in the present study. Most of the green spaces in the tall category in this study consist of multiple tree species. Our research design is suitable for quantifying their aggregated effect. Investigating morphological influence of individual species would require a different observational strategy, such as simultaneous measurements of air temperature and humidity within and immediately outside the crown of a single street tree or a cluster of trees of the same species⁷. Readers interested in information about species in the green spaces in the US cities can consult the TreeMap database⁵⁰ using the coordinates provided in Supplementary Table 4.

Analysis of observational data

The microclimate effects of a green space were quantified as relative differences in temperature, vapor pressure and wet-bulb temperature in reference to that observed in an adjacent built-up neighborhood (green space minus built-up neighborhood). Data collected in the built-up neighborhood within 1 min or beyond 15 min from the closest green space were discarded. The lower time limit allowed the sensor to fully respond to the step change after it had existed the green space, and the upper time limit was imposed to minimize temporal changes during travel between the green space and in the reference built-up

neighborhood. These differences were further averaged over replicated trips. Data analysis was conducted separately for daytime and nighttime data. No correction was made to temporal changes in background temperature and humidity during the trip. Most trips were made outside morning and evening transitional periods. According to an urban mobile study⁸, temporal variations in air temperature around midday and midnight are on the order of 0.3 °C over 45 min or 0.1 °C over 15 min.

The green space effect on the wet-bulb temperature ΔT_w is decomposed linearly into a temperature component and a humidity component. The wet-bulb equation is given by

$$T_a - T_w = \frac{(e_w^* - e_a)}{\gamma} \quad (2)$$

with e_w^* denoting the saturation vapor pressure at T_w and γ the psychrometric constant. Differentiating equation (2), we obtain equation (1), where the positive and dimensionless scaling factor w is given by

$$w = (1 + \Delta_w/\gamma)^{-1} \quad (3)$$

where Δ_w is the slope of the saturation vapor pressure at T_w . A typical value of w is 0.3.

Modeling microclimate effects of urban green spaces

We performed diagnostic analysis with data generated by an urban climate model. The goal was to establish a mechanistic understanding on how urban vegetation regulates the wet-bulb temperature. We used the WRF model version 4.0 coupled with a single-layer urban canopy model. The model domain was centered at New Haven, Connecticut, USA (Supplementary Fig. 3), a city with the most mobile observations. New Haven belongs to the intermediate-wetness group ($P_s = 308$ mm). The parent domain has a size of 357 km by 357 km and a grid spacing of 3 km. Nested in this domain is an inner domain with a size of 151 km by 151 km and a grid spacing of 1 km. A total of 40 atmospheric levels were used in the vertical direction. We chose the following schemes for physical parameterizations: the Purdue Lin scheme for microphysics, the Dudhia scheme for shortwave radiation transmission, the RRTM scheme for longwave radiation transmission, the Janjic Eta scheme for the surface layer, the Bougeault–Lacarrère scheme for the planetary boundary layer and the unified Noah LSM for land surface modeling. The simulation was conducted for the period from 5 July to 30 July 2023. The first 24 h were used as spin-up and were excluded from the analysis.

We analyzed the modeling results for grids in a sub-region in the inner domain that roughly coincides with the extent of the city (red box, Supplementary Fig. 3). The green space effects were quantified for each vegetation grid in reference to the average of all urban and built-up grids in the sub-region. Data were averaged separately for daytime (10 a.m. to 3 p.m. local time) and nighttime (8 p.m. to 1 a.m. local time). The day–night separation roughly matches the mobile measurement times in New Haven. Grids that belong to the five MODIS forest land cover types were grouped as tall vegetation, and those belonging to Woody Savannas, Grasslands and Croplands were grouped as short vegetation. The model was able to reproduce sub-day and inter-day variations in temperature ($R^2 = 0.68$) and humidity ($R^2 = 0.69$; Supplementary Fig. 4). The simulated microclimatic effects of green spaces are in agreement with the observed patterns. Specifically, green spaces reduced air temperature and increased air humidity in the daytime and reduced both air temperature and humidity at night, with a larger reduction in the wet-bulb temperature at night than during the day (Supplementary Fig. 5). These changes are comparable in magnitude to the observations (Fig. 1). According to the model simulation, changes in humidity and air temperature were negatively correlated during the day and positively correlated at night (Supplementary Fig. 6), again in agreement with the observed pattern (Fig. 3).

The diagnostic analysis was performed with the modeled net radiation (R_n), the soil/building heat storage flux (G) and the aerodynamic resistance r_a . We used the standard micrometeorological sign convention: R_n is positive if the surface gains radiation energy and negative otherwise, and G is positive if heat is gained by the substrate (soil and buildings) and negative if heat is released from the substrate to the surface-layer air. The aerodynamic resistance is not a standard model output; it was calculated using the following diagnostic relationship,

$$r_a = \frac{\rho c_p (T_{q,a} - T_{q,b})}{H + \lambda E}, \quad (4)$$

where $T_{q,a}$ and $T_{q,b}$ are equivalent temperature at the screen height (2 m above the ground) and the blending height (70 m; first model vertical layer), respectively. Equivalent temperature T_q is given by the sum of T_a and e_a/γ at the corresponding height. H is sensible heat flux, λE is latent heat flux, ρ is air density and c_p is specific heat of air at constant pressure. According to the theory described in Zhang et al.⁹, changes in T_w are contributed by changes in diabatic heating (R_n and G) of the surface-layer air and dynamic mixing between the surface-layer air and the air above, the latter of which can be characterized by changes in r_a . A three-variable linear regression was used to quantify the contribution of each change to the change in T_w , as

$$\Delta T_w = a \Delta r_a + b \Delta G + c \Delta R_n + d \quad (5)$$

where a , b , c and d are regression coefficients, and Δ denotes the difference in a variable between a vegetation grid and the mean of the urban grids. The first three terms on the right-hand side of equation (5) represent the contribution to the wet-bulb temperature change from changes in aerodynamic mixing (term 1), in heat storage (term 2) and in net radiation (term 3), respectively. The intercept coefficient d can be interpolated as the contribution from other factors unaccounted for by the one-dimensional energy balance theory of Zhang et al.⁹, such as horizontal advection of moist static energy and nonlinear interactions between diabatic heating and dynamic mixing. The actual contribution from a variable is the product of the regression coefficient and the mean difference of that variable between all vegetation grids and the urban grids. The uncertainty is given as one standard deviation of the regression coefficient multiplied by the mean difference of the variable. The results are given in Fig. 4 in the main text.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The satellite NDVI data are available at <https://scihub.copernicus.eu/dhus/#/home>. The global land cover data (FROM-GLC) are available at <http://data.starcloud.pcl.ac.cn>. ESA Worldwide Land Cover Mapping data are from <https://esa-worldcover.org/en>. Global Local Climate Zone maps can be downloaded from <https://www.wudapt.org/>. Precipitation assessment uses ERA-5 reanalysis data product, available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview>. TreeMap database is available at <https://apps.fs.usda.gov/lcms-viewer/treemap.html>. The mobile microclimate data are available via figshare at <https://doi.org/10.6084/m9.figshare.27165168> (ref. 51). Imagery data for green space and built-up neighborhood delineation are available via figshare at <https://doi.org/10.6084/m9.figshare.26533303> (ref. 52).

Code availability

The MATLAB code used to produce the figures in this paper is available via figshare at <https://doi.org/10.6084/m9.figshare.27165168> (ref. 53).

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Author contributions

X.L. designed the research. Y.Y. performed data analysis. C.C. assessed the quality of instruments. Y.Y., C.C., I.B., C.D., G.D., J.H., L.H., X.H., N.K., J.L., H.L., K.T., C.Y. and K.Z. contributed to data collection. X.L. and Y.Y. drafted the paper.

Competing interests

The authors declare no competing interests.

Additional information

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be downloaded from <https://www.wudapt.org/>. Precipitation assessment uses ERA-5 reanalysis data product, available at <https://cds.climate.copernicus.eu/cdsapp#!dataset/reanalysis-era5-land?tab=overview>. The mobile microclimate data is available at <https://figshare.com/s/9d03a3b2260c75622f8d>. Imagery data for greenspace and built-up neighborhood delineation is available at <https://figshare.com/s/2cb7289c1e4854f82ff4>.

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Supplementary Table 1: Summary of greenspace microclimate effects. T_a , air temperature (°C); $\Delta e_a/\gamma$, ratio of vapor pressure to the psychrometric constant (°C); T_w , wet-bulb temperature (°C); n , number of greenspaces; p : statistical significance of two-tailed t-test for group mean change; *, significantly different from zero at $p < 0.05$; **, significance at $p < 0.01$. Error range is ± 1 standard deviation of spatial replicates.

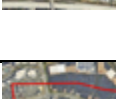
Dry	Daytime			p
Intermediate	Tall ($n = 8$)	ΔT_a	$-0.83 (\pm 1.39)$	0.135
		$\Delta e_a/\gamma$	$0.92 (\pm 1.41)$	0.107
		ΔT_w	$0.04 (\pm 0.33)$	0.749
	Short ($n = 20$)	ΔT_a	$-0.37 (\pm 0.49)^{**}$	0.003
		$\Delta e_a/\gamma$	$0.42 (\pm 0.66)^*$	0.010
		ΔT_w	$0.01 (\pm 0.20)$	0.747
	All ($n = 28$)	ΔT_a	$-0.50 (\pm 0.84)^{**}$	0.004
		$\Delta e_a/\gamma$	$0.56 (\pm 0.93)^{**}$	0.004
		ΔT_w	$0.02 (\pm 0.24)$	0.635
	Nighttime (N/A)			
	Tall ($n = 34$)	ΔT_a	$-0.52 (\pm 0.46)^{**}$	0.000
		$\Delta e_a/\gamma$	$0.26 (\pm 0.41)^{**}$	0.000
		ΔT_w	$-0.08 (\pm 0.19)^*$	0.013
	Short ($n = 11$)	ΔT_a	$-0.34 (\pm 0.66)$	0.120
		$\Delta e_a/\gamma$	$1.25 (\pm 1.54)^*$	0.023
		ΔT_w	$0.27 (\pm 0.33)^*$	0.024
	All ($n = 45$)	ΔT_a	$-0.48 (\pm 0.52)^{**}$	0.000
		$\Delta e_a/\gamma$	$0.50 (\pm 0.92)^{**}$	0.000
		ΔT_w	$0.00 (\pm 0.27)$	0.981
	Tall ($n = 19$)	ΔT_a	$-0.85 (\pm 0.76)^{**}$	0.000
		$\Delta e_a/\gamma$	$-0.06 (\pm 0.36)$	0.449
		ΔT_w	$-0.34 (\pm 0.31)^{**}$	0.000
	Short ($n = 7$)	ΔT_a	$-0.75 (\pm 0.57)^*$	0.013
		$\Delta e_a/\gamma$	$-0.26 (\pm 0.52)$	0.242
		ΔT_w	$-0.34 (\pm 0.36)^*$	0.046
	All ($n = 26$)	ΔT_a	$-0.83 (\pm 0.71)^{**}$	0.000
		$\Delta e_a/\gamma$	$-0.12 (\pm 0.41)$	0.161
		ΔT_w	$-0.34 (\pm 0.32)^{**}$	0.000
Wet	Daytime			p
Wet	Tall ($n = 21$)	ΔT_a	$-0.29 (\pm 0.49)^*$	0.012
		$\Delta e_a/\gamma$	$0.15 (\pm 0.52)$	0.207
		ΔT_w	$-0.06 (\pm 0.25)$	0.305
	Short ($n = 13$)	ΔT_a	$0.21 (\pm 0.56)$	0.201
		$\Delta e_a/\gamma$	$-0.34 (\pm 0.89)$	0.191
		ΔT_w	$-0.03 (\pm 0.31)$	0.755
	All ($n = 34$)	ΔT_a	$-0.10 (\pm 0.56)$	0.304
		$\Delta e_a/\gamma$	$-0.04 (\pm 0.72)$	0.745
		ΔT_w	$-0.05 (\pm 0.27)$	0.327
	Tall ($n = 17$)	ΔT_a	$-0.70 (\pm 0.93)^{**}$	0.007
		$\Delta e_a/\gamma$	$-0.44 (\pm 0.74)^*$	0.025
		ΔT_w	$-0.44 (\pm 0.68)^*$	0.016
	Short ($n = 12$)	ΔT_a	$-0.42 (\pm 0.52)^*$	0.017
		$\Delta e_a/\gamma$	$-0.15 (\pm 0.40)$	0.225
		ΔT_w	$-0.23 (\pm 0.28)^*$	0.017
	All ($n = 29$)	ΔT_a	$-0.59 (\pm 0.78)^{**}$	0.000
		$\Delta e_a/\gamma$	$-0.32 (\pm 0.63)^*$	0.012

	ΔT_w	$-0.35 (\pm 0.55)^{**}$	0.002
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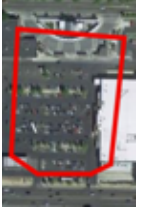
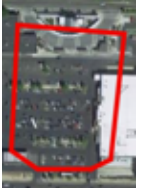
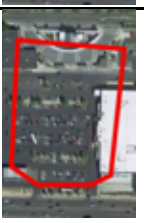
Supplementary Table 2: P value from two-sample t-test between tall and short vegetation groups

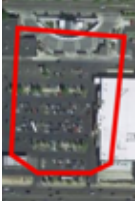
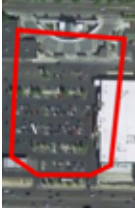
	ΔT_a	$\Delta e_a/\gamma$	ΔT_w
	Daytime		
Dry	0.204	0.205	0.813
Intermediate	0.308	0.001	0.000
Wet	0.009	0.050	0.753
	Nighttime		
Intermediate	0.751	0.299	0.978
Wet	0.348	0.223	0.310

Supplementary Table 3 Morphological attributes of greenspace and adjacent reference built-up land.
NDVI: normalized difference of vegetation index; IMP: impervious surface fraction; SVF: sky view factor.
Values in parentheses are for built-up reference.

City	ID	Type	NDVI	IMP	Urban SVF	Greenspace image	Urban image
San Lorenzo, USA	1	Grass	0.32 (0.09)	19 (83)	0.7 - 1		
San Lorenzo, USA	2	Tree-grass Mixture	0.37 (0.11)	10 (96)	0.7 - 1		
San Lorenzo, USA	3	Grass	0.26 (0.11)	42 (96)	0.7 - 1		
Los Angeles, USA	4	Grass	0.35 (0.09)	9 (86)	0.7 - 1		
Los Angeles, USA	5	Grass	0.37 (0.12)	12 (89)	0.7 - 1		
Los Angeles, USA	6	Grass	0.4 (0.12)	19 (89)	0.7 - 1		
Los Angeles, USA	7	Grass	0.35 (0.12)	23 (86)	0.7 - 1		
Los Angeles, USA	8	Grass	0.34 (0.10)	17 (89)	0.7 - 1		
Los Angeles, USA	9	Grass	0.44 (0.08)	19 (99)	0.7 - 1		
Los Angeles, USA	10	Grass	0.33 (0.09)	34 (99)	0.2 - 0.6		

			0.38 (0.10)				
San Francisco, USA	11	Tree Canopy		10 (92)	0.2 – 0.6		
			0.36 (0.10)				
San Francisco, USA	12	Grass		12 (92)	0.2 – 0.6		
			0.35 (0.12)				
San Francisco, USA	13	Tree Canopy		8 (92)	0.2 – 0.6		
			0.2 (0.13)				
San Francisco, USA	14	Tree-grass Mixture		21 (99)	0.7 - 1		
			0.44 (0.15)				
Provo, USA	15	Grass		37 (96)	0.2 – 0.6		
			0.49 (0.15)				
Provo, USA	16	Grass		27 (96)	0.2 – 0.6		
			0.6 (0.16)				
Provo, USA	17	Grass		18 (96)	0.2 – 0.6		

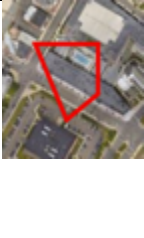
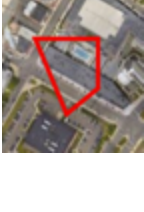
Logan, USA	18	Tree-grass Mixture	0.62 (0.19)	10 (98)	0.7 - 1		
Logan, USA	19	Tree-grass Mixture	0.64 (0.15)	10 (92)	0.2 - 0.6		
Logan, USA	20	Crop	0.51 (0.24)	6 (73)	0.6 - 0.9		
Logan, USA	21	Tree Canopy	0.51 (0.14)	25 (100)	0.7 - 1		
Logan, USA	22	Grass	0.41 (0.17)	21 (99)	0.7 - 1		
Logan, USA	23	Grass	0.36 (0.17)	9 (99)	0.7 - 1		
Logan, USA	24	Crop	0.5 (0.14)	12 (98)	0.7 - 1		
Logan, USA	25	Crop	0.58 (0.16)	6 (99)	0.7 - 1		

Logan, USA	26	Grass	0.59 (0.15)	14 (73)	0.7 - 1		
Logan, USA	27	Tree-grass Mixture	0.6 (0.14)	31 (98)	0.7 - 1		
Logan, USA	28	Crop	0.37 (0.13)	10 (98)	0.7 - 1		
London, UK	29	Tree-grass Mixture	0.25 (0.16)	22 (96)	0.6 - 0.9		
London, UK	30	Tree-grass Mixture	0.39 (0.04)	11 (100)	0.3 - 0.6		
London, UK	31	Tree-grass Mixture	0.39 (0.08)	14 (99)	0.3 - 0.6		
North Platte, USA	32	Crop	0.57 (0.16)	3 (91)	0.7 - 1		
North Platte, USA	33	Crop	0.59 (0.34)	1 (57)	0.7 - 1		

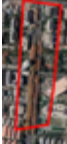
North Platte, USA	34	Grass	0.6 (0.25)	1 (60)	0.7 - 1		
North Platte, USA	35	Crop	0.63 (0.31)	2 (60)	0.7 - 1		
North Platte, USA	36	Tree-grass Mixture	0.6 (0.27)	3 (60)	0.7 - 1		
North Platte, USA	37	Tree-grass Mixture	0.54 (0.27)	9 (60)	0.7 - 1		
Anchorage, USA	38	Tree-grass Mixture	0.47 (0.17)	15 (66)	0.7 - 1		
Anchorage, USA	39	Tree Canopy	0.26 (0.14)	9 (87)	0.7 - 1		
Anchorage, USA	40	Tree Canopy	0.73 (0.13)	2 (78)	0.7 - 1		
Anchorage, USA	41	Tree Canopy	0.44 (0.15)	14 (80)	0.7 - 1		

Anchorage, USA	42	Tree-grass Mixture	0.58 (0.16)	9 (66)	0.7 - 1		
Anchorage, USA	43	Tree-grass Mixture	0.41 (0.16)	9 (66)	0.7 - 1		
Anchorage, USA	44	Tree Canopy	0.57 (0.13)	3 (78)	0.7 - 1		
Anchorage, USA	45	Tree Canopy	0.5 (0.14)	12 (66)	0.7 - 1		
Anchorage, USA	46	Tree Canopy	0.51 (0.13)	6 (78)	0.7 - 1		
Washington DC, USA	47	Tree Canopy	0.74 (0.26)	5 (90)	0.5 - 0.8		
Washington DC, USA	48	Tree Canopy	0.5 (0.23)	24 (90)	0.5 - 0.8		
Washington DC, USA	49	Tree-grass Mixture	0.37 (0.23)	56 (90)	0.5 - 0.8		

Washington DC, USA	50	Tree-grass Mixture	0.37 (0.23)	30 (90)	0.5 - 0.8		
Washington DC, USA	51	Tree-grass Mixture	0.56 (0.24)	18 (90)	0.5 - 0.8		
Washington DC, USA	52	Grass	0.5 (0.23)	20 (90)	0.5 - 0.8		
Washington DC, USA	53	Tree Canopy	0.66 (0.23)	6 (90)	0.5 - 0.8		
New Haven, USA	54	Tree Canopy	0.77 (0.34)	6 (93)	0.5 - 0.8		
New Haven, USA	55	Tree Canopy	0.73 (0.34)	9 (94)	0.3 - 0.6		
New Haven, USA	56	Tree-grass Mixture	0.56 (0.34)	24 (93)	0.5 - 0.8		

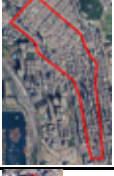
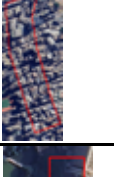
New Haven, USA	57	Tree Canopy	0.54 (0.40)	7 (67)	0.6 - 0.9		
New Haven, USA	58	Tree-grass Mixture	0.45 (0.28)	35 (93)	0.6 - 0.9		
New Haven, USA	59	Grass	0.47 (0.25)	31 (93)	0.6 - 0.9		
New Haven, USA	60	Tree Canopy	0.55 (0.24)	15 (93)	0.6 - 0.9		
New Haven, USA	61	Tree Canopy	0.67 (0.41)	10 (67)	0.6 - 0.9		
New Haven, USA	62	Tree Canopy	0.81 (0.24)	4 (85)	0.7 - 1		
New Haven, USA	63	Tree-grass Mixture	0.62 (0.25)	14 (93)	0.6 - 0.9		
New Haven, USA	64	Tree Canopy	0.85 (0.25)	3 (93)	0.6 - 0.9		

			0.42 (0.25)				
New Haven, USA	65	Grass		22 (86)	0.7 - 1		
			0.62 (0.34)				
New Haven, USA	66	Tree-grass Mixture		4 (93)	0.5 - 0.8		
			0.46 (0.16)				
North Branford, USA	67	Grass		0 (84)	0.5 - 0.8		
			0.57 (0.16)				
North Branford, USA	68	Tree Canopy		2 (84)	0.5 - 0.8		
			0.47 (0.16)				
North Branford, USA	69	Crop		3 (84)	0.5 - 0.8		
			0.45 (0.16)				
North Branford, USA	70	Tree Canopy		10 (84)	0.5 - 0.8		
			0.48 (0.16)				
North Branford, USA	71	Tree-grass Mixture		10 (84)	0.5 - 0.8		
			0.57 (0.35)				
Nanjing, China	72	Tree-grass Mixture		46 (77)	0.5 - 0.7		
			0.35 (0.33)				
Nanjing, China	73	Crop		21 (88)	0.5 - 0.7		

Nanjing, China	74	Tree Canopy	0.49 (0.23)	44 (93)	0.2 - 0.4		
Nanjing, China	75	Tree-grass Mixture	0.53 (0.33)	39 (88)	0.5 - 0.7		
Nanjing, China	76	Tree Canopy	0.74 (0.45)	4 (60)	0.5 - 0.8		
Nanjing, China	77	Grass	0.51 (0.33)	38 (88)	0.5 - 0.7		
Nanjing, China	78	Crop	0.46 (0.33)	36 (88)	0.5 - 0.7		
Nanjing, China	79	Tree Canopy	0.62 (0.33)	16 (88)	0.5 - 0.7		
Hangzhou, China	80	Tree Canopy	0.5 (0.26)	4 (57)	0.7 - 1		
Hangzhou, China	81	Tree Canopy	0.40 (0.22)	4 (57)	0.7 - 1		
Hangzhou, China	82	Crop	0.57 (0.30)	7 (57)	0.7 - 1		

Hangzhou, China	83	Crop	0.58 (0.30)	15 (57)	0.7 - 1		
Hangzhou, China	84	Crop	0.56 (0.30)	13 (57)	0.7 - 1		
Hangzhou, China	85	Crop	0.46 (0.17)	29 (82)	0.5 - 0.7		
Hangzhou, China	86	Tree Canopy	0.68 (0.27)	6 (81)	0.2 - 0.4		
Hangzhou, China	87	Crop	0.35 (0.24)	12 (85)	0.5 - 0.8		
Hangzhou, China	88	Tree Canopy	0.5 (0.24)	6 (85)	0.5 - 0.8		
Hangzhou, China	89	Grass	0.4 (0.18)	35 (82)	0.5 - 0.7		
Hangzhou, China	90	Grass	0.35 (0.20)	27 (81)	0.2 - 0.4		

Hangzhou, China	91	Grass	0.41 (0.18)	45 (81)	0.2 - 0.4		
Hangzhou, China	92	Tree Canopy	0.40 (0.19)	38 (83)	0.5 - 0.7		
Hangzhou, China	93	Tree Canopy	0.41 (0.11)	42 (92)	0.3 - 0.6		
Hangzhou, China	94	Grass	0.30 (0.19)	39 (94)	0.7 - 1		
Hangzhou, China	95	Crop	0.32 (0.20)	31 (81)	0.2 - 0.4		
Hangzhou, China	96	Grass	0.40 (0.19)	28 (81)	0.2 - 0.4		
Hangzhou, China	97	Tree-grass Mixture	0.39 (0.19)	30 (81)	0.2 - 0.4		
Hangzhou, China	98	Crop	0.37 (0.20)	31 (95)	0.5 - 0.7		

Hong Kong, China	99	Tree Canopy	0.38 (0.08)	53 (99)	0.2 - 0.4		
Hong Kong, China	100	Tree Canopy	0.24 (0.07)	55 (93)	0.2 - 0.4		
Hong Kong, China	101	Tree Canopy	0.29 (0.08)	25 (99)	0.2 - 0.4		
Hong Kong, China	102	Tree-grass Mixture	0.37 (0.06)	46 (99)	0.2 - 0.4		
Guangzhou, China	103	Tree Canopy	0.57 (0.30)	29 (72)	0.5 - 0.7		
Guangzhou, China	104	Tree Canopy	0.49 (0.40)	18 (71)	0.5 - 0.7		
Guangzhou, China	105	Tree Canopy	0.40 (0.13)	16 (100)	0.6 - 0.9		
Guangzhou, China	106	Tree Canopy	0.35 (0.14)	38 (100)	0.6 - 0.9		
Guangzhou, China	107	Tree Canopy	0.32 (0.13)	35 (100)	0.6 - 0.9		

Guangzhou, China	108	Tree Canopy	0.34 (0.16)	27 (99)	0.6 - 0.9		
Guangzhou, China	109	Tree-grass Mixture	0.42 (0.29)	50 (90)	0.5 - 0.7		
Guangzhou, China	110	Tree Canopy	0.47 (0.18)	19 (99)	0.6 - 0.9		
Guangzhou, China	111	Crop	0.37 (0.29)	34 (83)	0.2 - 0.4		
Guangzhou, China	112	Tree Canopy	0.56 (0.29)	19 (83)	0.2 - 0.4		
Guangzhou, China	113	Tree-grass Mixture	0.34 (0.29)	25 (83)	0.2 - 0.4		
Guangzhou, China	114	Tree-grass Mixture	0.47 (0.29)	8 (83)	0.2 - 0.4		

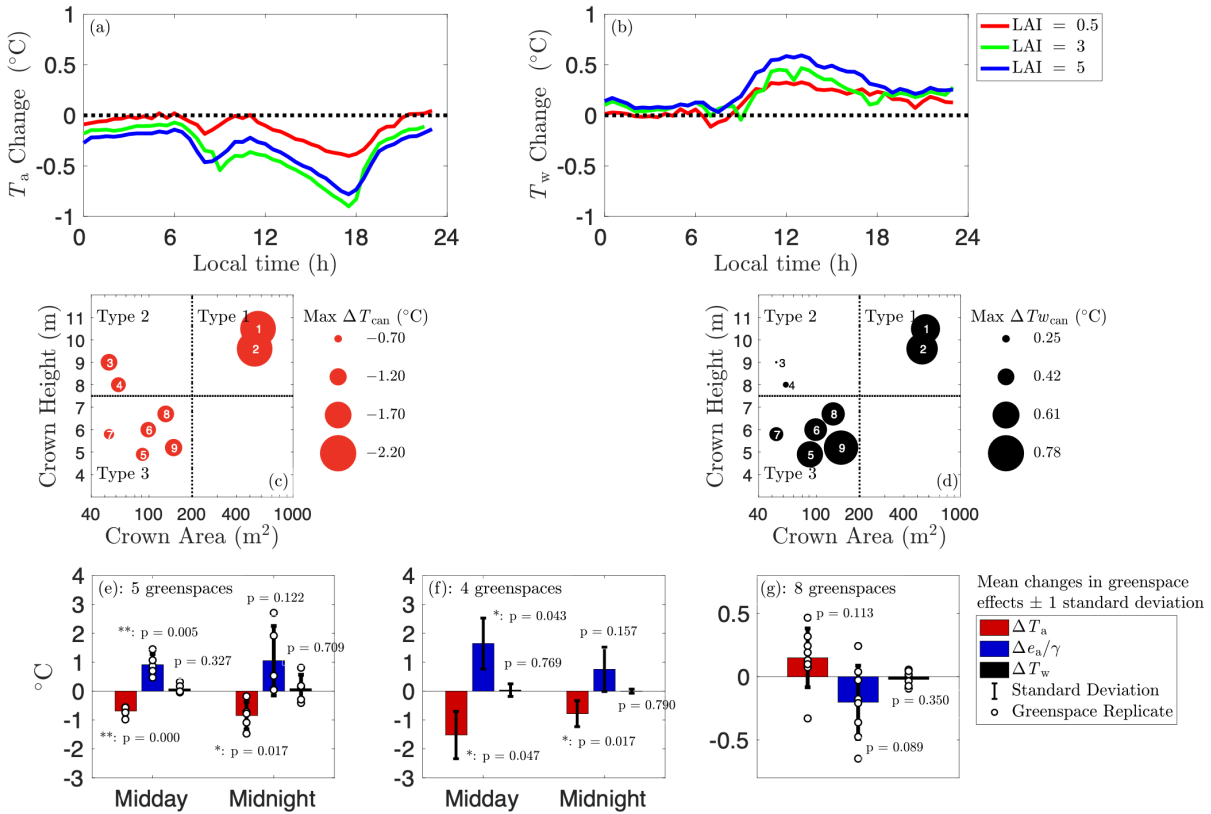
Vegetation type is based on visual inspection of Google Earth images. NDVI is warm season value based on Sentinel-2 satellite observations. Cropland was identified using FROM-GLC10 global landcover data 2017 (<https://data-starcloud.pcl.ac.cn/resource/1>). IMP is based on ESA Worldwide Land Cover Mapping 2021 (<https://esa-worldcover.org/en>). SVF is the value of the dominant local climate zone (LCZ) of the built-up neighborhood. LCZ classification data: <https://www.wudapt.org>. SVF values associated with LCZs from Stewart¹. High-quality images for the greenspaces and the built-up references can be accessed from <https://figshare.com/s/deb7b987e38d335eff20>. Greenspace and urban images were obtained from Google Earth.

Supplementary Table 4: WGS84 coordinates of central point of each greenspace listed in Supplementary Table 3.

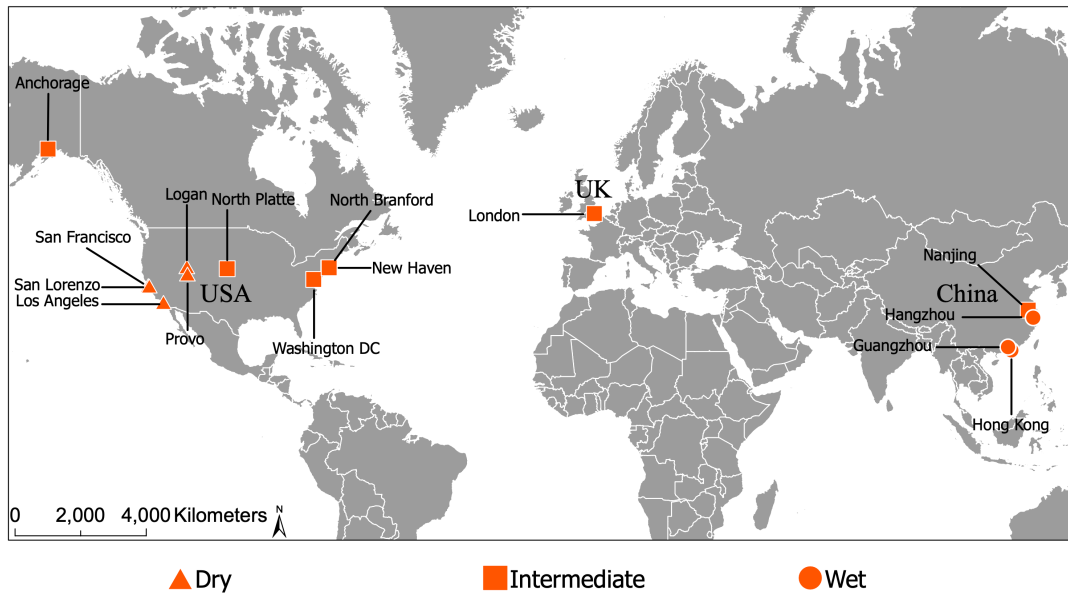
ID	Latitude	Longitude
1	37.68753	-122.16093
2	37.69412	-122.14605
3	37.67819	-122.13854
4	34.22348	-118.57187
5	34.27634	-118.55539
6	34.27618	-118.54913
7	34.25078	-118.54999
8	34.25439	-118.53283
9	34.24359	-118.52696
10	34.26000	-118.52682
11	37.76896	-122.48203
12	37.74883	-122.49788
13	37.78781	-122.48104
14	37.83703	-122.48347
15	40.23585	-111.64760
16	40.23427	-111.64482
17	40.24702	-111.63991
18	41.71728	-111.84887
19	41.72306	-111.84638
20	41.76893	-111.84013
21	41.72655	-111.84324
22	41.77799	-111.83065
23	41.77497	-111.82844
24	41.76806	-111.82694
25	41.79624	-111.82697
26	41.78489	-111.82264
27	41.74175	-111.82307
28	41.77310	-111.82111
29	51.52832	-0.22774
30	51.50700	-0.17207
31	51.53127	-0.15580
32	41.13915	-100.82468
33	41.08850	-100.79658
34	41.11542	-100.77896
35	41.09063	-100.77706
36	41.11960	-100.77665
37	41.11915	-100.76942
38	61.16665	-149.87754
39	61.17003	-149.87108
40	61.20200	-149.85200
41	61.18271	-149.85724
42	61.17961	-149.84591

43	61.16719	-149.84118
44	61.16150	-149.78665
45	61.19208	-149.82722
46	61.19229	-149.80686
47	38.94445	-77.04939
48	38.92123	-77.03629
49	38.92150	-77.02682
50	38.92147	-77.02318
51	38.93827	-77.01033
52	38.92415	-77.01180
53	38.94969	-77.00488
54	41.34069	-72.96098
55	41.31723	-72.95648
56	41.32003	-72.93873
57	41.35128	-72.92412
58	41.30793	-72.92678
59	41.31380	-72.92717
60	41.31375	-72.92357
61	41.36540	-72.91560
62	41.39872	-72.91386
63	41.30462	-72.91782
64	41.32952	-72.90449
65	41.30260	-72.90335
66	41.29659	-72.88267
67	41.33745	-72.81779
68	41.33132	-72.81470
69	41.34053	-72.80311
70	41.30602	-72.77083
71	41.30169	-72.76088
72	32.01072	118.71946
73	32.21636	118.71987
74	32.05704	118.77522
75	32.20768	118.71861
76	32.05774	118.84310
77	32.20373	118.72030
78	32.22644	118.72945
79	32.22049	118.74004
80	30.29551	119.76192
81	30.27098	119.77053
82	30.36960	119.86860
83	30.37649	119.87628
84	30.38492	119.88121
85	30.28835	119.93999
86	30.22442	120.09112
87	30.39575	119.99079
88	30.36697	120.00620

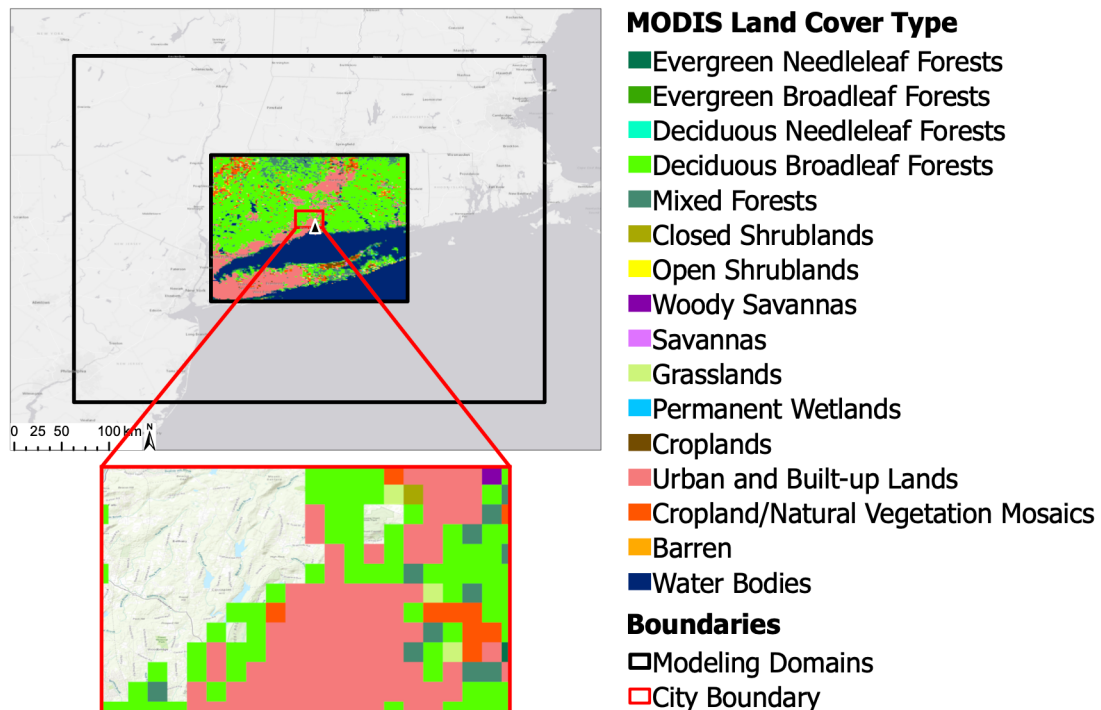
89	30.29138	120.01278
90	30.32203	120.07198
91	30.32418	120.10150
92	30.38995	120.11530
93	30.29563	120.12788
94	30.24755	120.19426
95	30.31454	120.28800
96	30.33210	120.29050
97	30.34962	120.29370
98	30.32332	120.30482
99	22.33088	114.15717
100	22.27812	114.16698
101	22.30012	114.17055
102	22.28187	114.18884
103	23.09971	113.29374
104	23.11219	113.30083
105	23.08333	113.30416
106	23.08499	113.31057
107	23.08628	113.31333
108	23.12415	113.31914
109	23.10660	113.31985
110	23.12235	113.33419
111	23.08506	113.35130
112	23.09387	113.35990
113	23.07548	113.36203
114	23.08935	113.37329



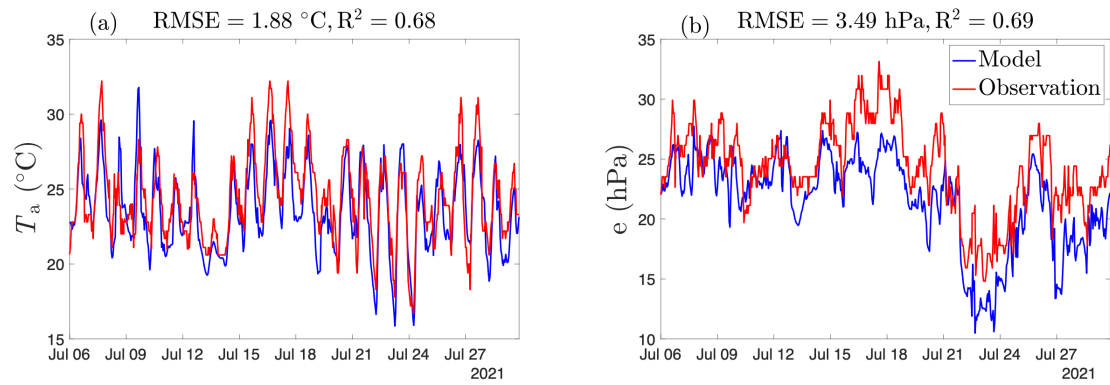
Supplementary Figure 1: Response of air temperature and wet-bulb temperature to urban vegetation. **a** & **b**: Change in air temperature and wet-bulb temperature caused by street vegetation in Singapore (data source: Meili et al.²). Vegetation cover (tree and grass) is 25%. Vegetation density is set to three levels of leaf area density (LAI); **c** & **d**: Response of daily maximum air temperature and wet-bulb temperature (d) to planting of street trees in Hong Kong, China (data source: Huang et al.³). Numbers stand for different tree species; **e**: Mean changes in air temperature, humidity and wet-bulb temperature caused by urban greenspaces in Salt Lake City, USA (data source: Gómez-Navarro et al.⁴). Error bars are ± 1 standard deviation of 5 replicates; **f**: Mean changes in air temperature, humidity and wet-bulb temperature in urban parks in reference to those observed over a concrete surface in Shanghai, China (Wang et al.⁵). Error bars are ± 1 standard deviation of 4 replicates; **g**: Mean differences in daily mean air temperature, humidity and wet-bulb temperature between tree canopies and a reference weather station at an exposed location in Würzburg, Germany (Rahman et al.⁶). Error bars are ± 1 standard deviation of 8 replicates. Significance of two-tailed t-test for mean changes (p) is provided in **e**, **f**, and **g**, with ** denoting $p < 0.01$ and * denoting $p < 0.05$. Individual data points are shown as dots in **e** and **g**. For **f**, only group mean and standard deviation are available from Wang et al.



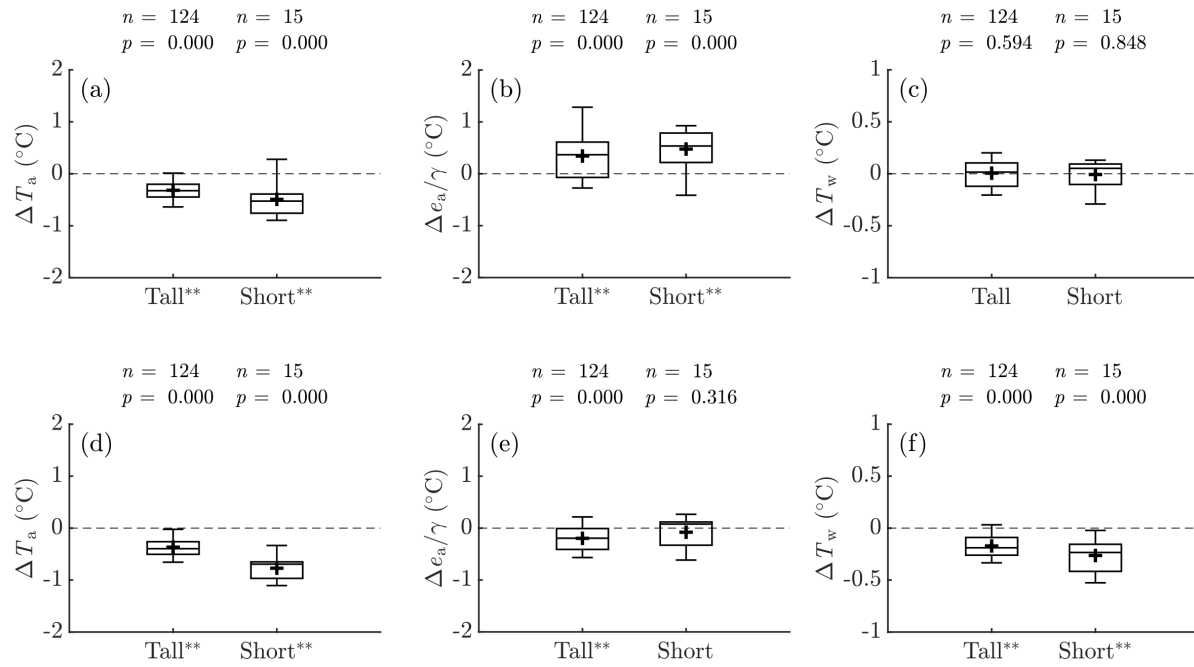
Supplementary Figure 2: Map showing cities where mobile data were collected. Triangle: dry cities (summer precipitation $P_s < 180$ mm); Square: intermediate wetness cities ($180 \leq P_s \leq 570$ mm); Circle: wet cities ($P_s > 570$ mm). Basemap was obtained from Environmental Systems Research Institute, Inc (Esri).



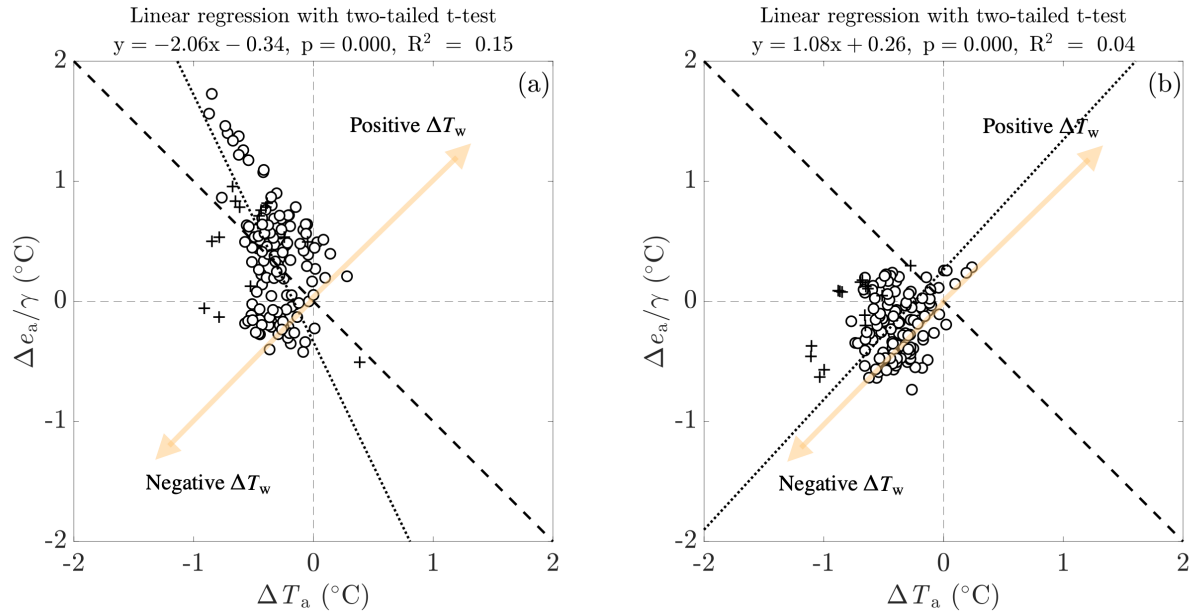
Supplementary Figure 3: Domains and the analysis extent for the WRF showcase at New Haven. MODIS Land cover types are displayed for Domain 2 (nested domain; black box) and approximate city boundary (red box). The black triangle marks the weather station at Tweed New Haven Airport. Grids in the grey area within the city boundary have elevation greater than 100 m and are excluded from the analysis. Basemap was obtained from Environmental Systems Research Institute, Inc (Esri). MODIS landcover map was obtained from NASA.



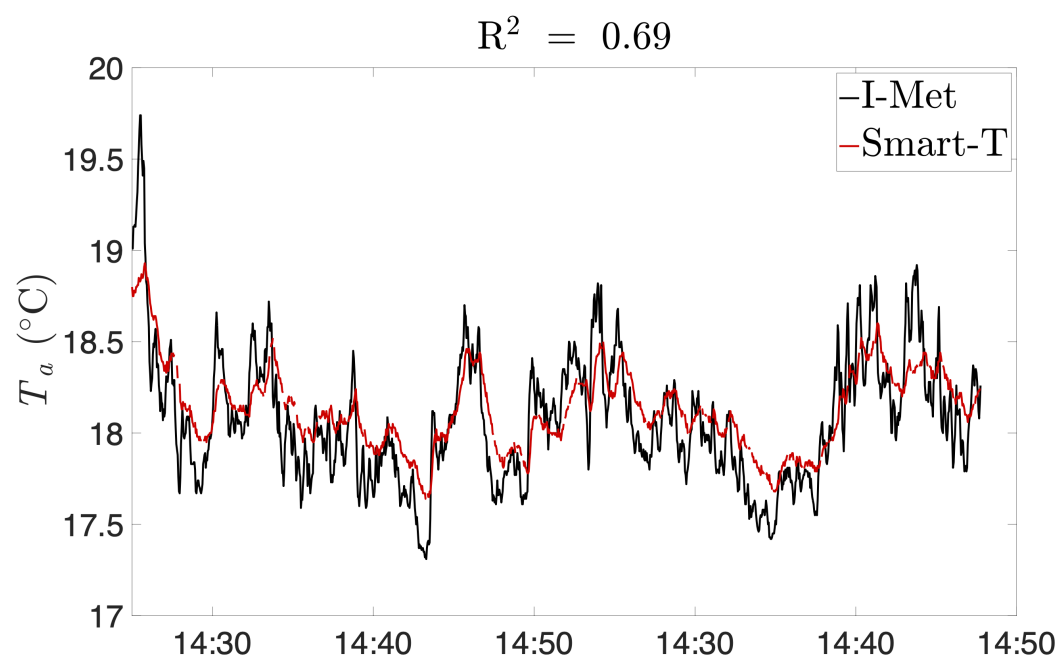
Supplementary Figure 4: Evaluation of (a) modeled temperature and (b) vapor pressure with in-situ observations at Tweed New Haven Airport (black triangle in Supplementary Figure 3). For each figure, root mean squared error (RMSE) and coefficient of determination (R^2) between modeling results and observations are provided.



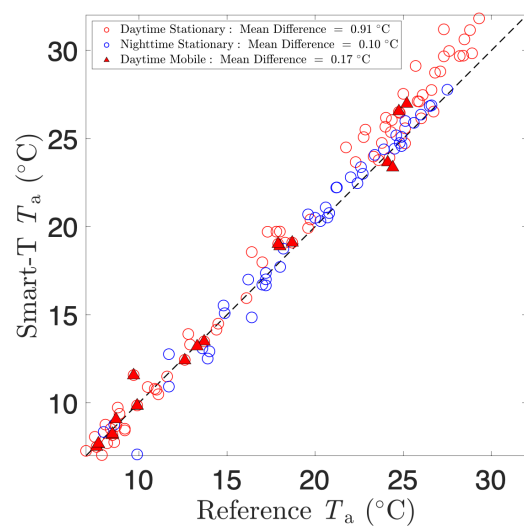
Supplementary Figure 5: Effects of urban greenspace on air temperature (ΔT_a), humidity ($\Delta e_a/\gamma$), and wet-bulb temperature (ΔT_w) in intermediate wetness climate. Same as Figure 1 but for modeling results. **a, b, and c:** daytime. **d, e, and f:** nighttime. Data are presented for tall and short vegetation groups. Each sample represents a modeling grid. Box-whisker plots indicate mean (plus), median (line), 25 and 75 percentiles (box), and 5 and 95 percentiles (whiskers). Results of two-tailed t-test are provided at the top of each figure (n : sample size; p : statistical significance). Confidence levels are shown as ** ($p < 0.01$) and * ($p < 0.05$) at the bottom.



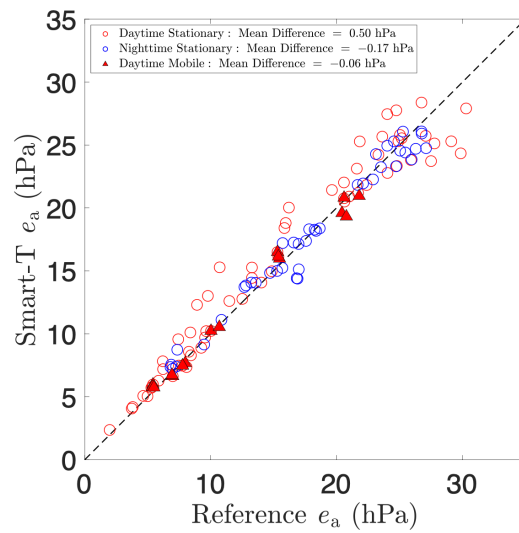
Supplementary Figure 6: Relationship between temperature and humidity effects of urban greenspace. Same as Figure 3 but for modeling results. **a:** daytime. **b:** nighttime. Tall and short vegetation are shown as circles and plus signs, respectively. The black solid line is the best-fit function with regression statistics and significance of a two-tailed t-test (p) shown. The black dashed line indicates the $-1:1$ relationship.



Supplementary Figure 7: Comparison between temperature measurements from a Smart-T sensor and an I-Met sensor.

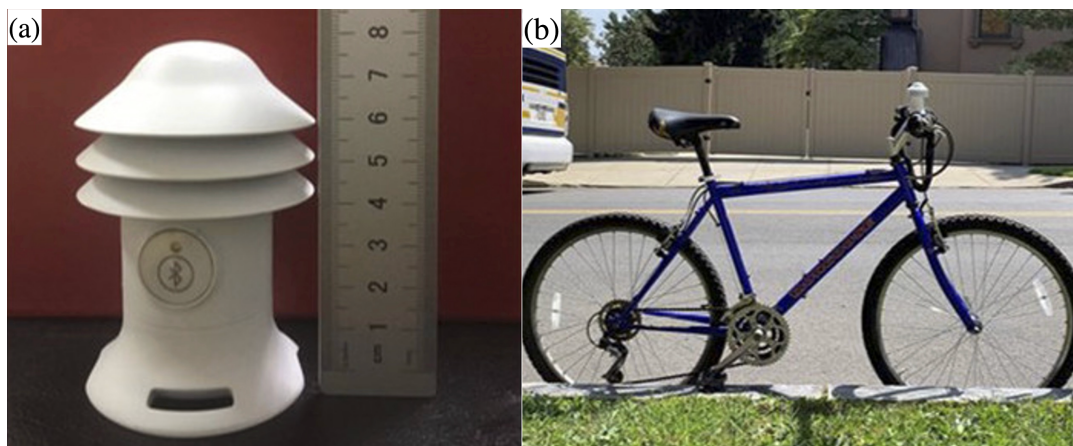


(a)



(b)

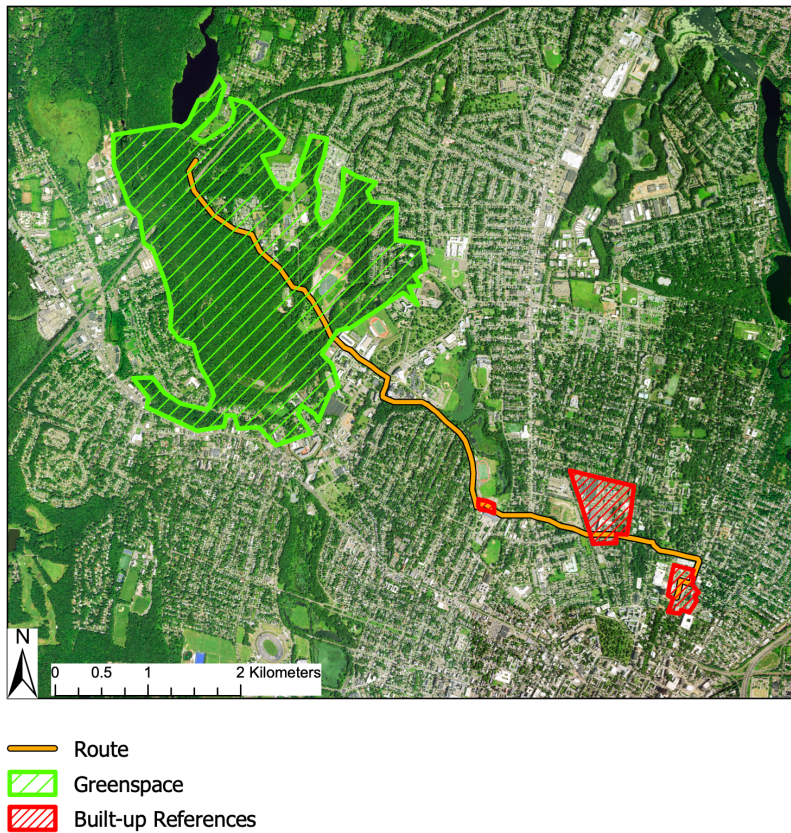
Supplementary Figure 8: Comparison between measurements from a Smart-T sensor and a NOAA reference sensor. **a:** temperature comparison. **b:** humidity comparison (vapor pressure). Black dashed line indicates 1:1. Data points are 1 min averages.



Supplementary Figure 9: (a) Photographs of a Smart-T unit and (b) a Smart-T unit mounted on a bicycle. Figure adapted from Cao et al.⁷



Supplementary Figure 10: Photograph of an indoor test setup for Smart-T performance evaluation. The three larger units are HOBO sensors. The other smaller units are Smart-T sensors.



Supplementary Figure 11: A biking transect in New Haven, USA. Aerial base map was marked with the biking transect (orange line), a greenspace (West Rock Park; green area), and three built-up reference neighborhoods (red areas). Aerial image was obtained from the US Department of Agriculture.

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