Efficacy of Possible Strategies to Mitigate the Urban Heat Island Based on Urbanized High-Resolution Land Data Assimilation System (u-HRLDAS)

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Abstract

Summer heat waves are a significant public health threat in China. This paper took Wuhan (one of the four hottest furnace cities in China) as an example to explore several strategies for mitigating the surface urban heat island (UHI), measured by the land surface temperature, including green roofs, cool roofs, bright pavements, and altered urban building patterns. The offline urbanized High-Resolution Land Data Assimilation System (u-HRLDAS) was used to conduct 1-km resolution numerical simulations, which also accounts for the effects of Wuhan’s abundant lakes on UHI evolution, with a dynamic lake model. The diurnal cycle and spatial distribution of simulated UHI were analyzed under different mitigation strategies. Results show that considering lake effects reduces daytime (nighttime) UHI intensity by about 1.0 K (0.5 K). Green roofs and cool roofs are more effective in mitigating daytime UHI than bright pavements. The maximum UHI reduction is about 2.1 K at 13:00 local time by replacing 80 % of conventional roofs with green roofs. The UHI mitigation efficiency increases with larger fractions of green roofs, and increased albedo of roofs and roads. In contrast to green roofs, cool roofs and bright pavements are ineffective during nighttime, changing the urban building pattern to mitigate UHI is effective throughout the
1. Introduction

The urban heat island (UHI) is a well-known phenomenon where the temperature in a city is higher than that in surrounding rural regions (Oke 1995; Rizwan et al. 2008; Kusaka et al. 2012). The UHI magnitude is important to thermal comfort and stress for city residents (Aflaki et al. 2017; Deilami et al. 2018), and is often responsible for death during summer heatwaves (Burke et al. 2018; Ward et al. 2016). The UHI effects have been intensifying with rapid urbanization (Aoyagi et al. 2012; Koomen and Diogo 2017; Mohajerani et al. 2017; Gaur et al. 2018) under changing climates, leading to numerous studies investigating UHI’s spatiotemporal variation (Cao et al. 2016; Gao et al. 2018; Peng et al. 2011), the driving factors of urban heat effect (Cao et al. 2016; Mohajerani et al. 2017; Yao et al. 2018a), and mitigation strategies at different scales and different regions (Aflaki et al. 2017; Kyriakodis and Santamouris 2018; Li et al. 2014; Sharma et al. 2018).

The UHI for a specific region depends on the unique characteristics of regional climatic and geographic conditions (Mohajerani et al. 2017; Yang et al. 2015). Chinese cities have been experiencing strong heat effects recently. For example, the city of Wuhan, often referred to as one of China’s four hottest-furnace cities with 10 million residents (Shen, H. et al. 2016), experienced extreme heatwaves in the summer of 2013, with 26 “hot days” (with daily maximum air temperature exceeding 35°C). The average mortality in Wuhan during “hot days” was 50.7% higher than “non-hot days” during 1998 to 2006 summer (Yang et al. 2013). Since excessive thermal stress is a great threat to human life, it is important to take active strategies that will mitigate increasing deterioration of urban thermal environments (Sharma et al. 2016, 2018).

There are several ways to mitigate the UHI (Mohajerani et al. 2017), such as replacing conventional roofs and roads with reflective materials, making the environment green, and water-related strategies. Green roofs can mitigate warming and provide cooling benefits by reducing energy consumption (Lazzarin et al. 2005; Santamouris 2014). Cool roofs, where a conventional roof is replaced by higher-albedo materials, are also an effective strategy to mitigate the UHI (Li et al. 2014; Santamouris 2013). Similarly, bright pavements can reflect a higher portion of solar radiation than conventional roads (Aflaki et al. 2017; Ramírez and Muñoz 2012; Zhao et al. 2017), and urban-design characteristics related to urban green distributions and urban form also influence the UHI (Dai et al. 2018; Li, W. et al. 2017; Adachi et al. 2014; Kusaka et al. 2016).

Although some studies focused on investigating and comparing various different mitigation strategies in the USA (Zhao et al. 2017) and Canada (Wang et al. 2015), there is limited research on China, and most of those studies only investigated one or two strategies, which are insufficient for urban heat mitigation research. For example, Liu et al. (2018) investigated green roofs and cool roofs in the Chengdu-Chongqing metropolitan region; Wang et al. (2016) only studied the white roofs in Beijing-Tianjin-Hubei metropolitan area. The mitigation strategies based on urban building patterns traditionally received less attention compared with the strategies based on materials and vegetation in Chinese cities. Besides, mitigation studies in Wuhan are essentially absent, even though Wuhan is extremely hot in summer. This study focuses on Wuhan and explores the effectiveness of the following common UHI mitigation strategies: green roofs, cool roofs, bright pavements, and changing urban building patterns.

Assessing the model’s fidelity is an important step
for studying UHI mitigation with numerical simulations. This problem is further complicated by the presence of lakes in cities, because some studies have calculated the UHI intensity (UHII) excluding water bodies (Haashemi et al. 2016; Imhoff et al. 2010) while others include them (Wang et al. 2015; Zhang et al. 2010). Considering the abundant lakes in Wuhan, it is important to estimate the effect of including water body in the UHI calculation. This study’s primary objectives are to understand the extent to which lakes affect the UHI calculation in Wuhan, and how well the above-mentioned UHI mitigates strategies. To achieve this, numerous simulations were conducted with an offline urban canopy model coupled to a dynamic lake model. Regional high-resolution land-use data and remotely-sensed land surface temperature (LST) were used to improve the model and to evaluate its performance. The rest of this paper is organized as follows: Section 2 presents the study area, models, and analysis methods; the results and discussion are shown in Section 3; and Section 4 presents the conclusions.

2. Materials and methods

2.1 Study region

Metropolitan Wuhan (113°41′E–115°05′E, 29°58′N–31°22′N) (Fig. 1c), the capital city of Hubei Province (Fig. 1b), covers an area of 8494 km$^2$ and has a population of more than 10 million. It is located in the subtropical zone with a humid monsoon climate, plentiful rainfall, and abundant sunshine. By the definition in the “Chinese national standard QX/T 152-2012: Definition of climatic season”, the Wuhan summer lasts for more than 130 days (Chen et al. 2015). There are 166 lakes located in Wuhan. The Yangtze River, the largest river in China, flows through the city (Fig. 1c). The total water area of 2217.6 km$^2$ makes Wuhan the city with the most water coverage among all China’s major cities (Duan and Niu 2018).

2.2 u-HRLDAS model and numerical experiment design

We used the offline urbanized High-Resolution Land Data Assimilation System (u-HRLDAS) as our principal UHI modeling tool, which is based on HRLDAS (Chen et al. 2007) and couples the Noah
land model (Chen and Dudhia 2001) with a single-layer, urban canopy model (SLUCM, Kusaka et al. 2001). One advantage of offline u-HRLDAS, compared to the fully-coupled Weather Research and Forecasting (WRF)-Urban model (Chen et al. 2011), is that it demands much less computational power and can be employed easily to study UHI (Meng et al. 2013; Monaghan et al. 2014). As a new addition to u-HRLDAS for this study, a lake model, based on Community Land Model version 4.5 (Oleson et al. 2013), with further improvements made by Gu et al. (2015), was coupled to u-HRLDAS to assess the water bodies’ impacts. Then different UHI mitigation strategies were explored with various u-HRLDAS simulations.

The u-HRLDAS simulation was executed independently for each model grid (i.e., no horizontal exchange between grids). For each urban grid, SLUCM simulates the portion of man-made impervious surfaces, and Noah simulates the vegetation-covered portion (parks, lawns). The merged LST of each urban grid is the weighted average of simulated LST for man-made and natural surfaces by urban fraction ($urban_{frac}$) in the following equation:

$$LST = urban_{frac} \times LST_{urban} + (1 - urban_{frac}) \times LST_{rural},$$  

(1)

where the $LST_{rural}$ (K) is derived by Noah, and the $LST_{urban}$ (K) is calculated by SLUCM according to the following:

$$LST_{urban} = Ta + SH(Rhoo \times Cpp \times Chs),$$  

(2)

where $Ta$ (K) is the 10-m air temperature used to drive u-HRLDAS; $Rhoo$ (kg m$^{-3}$) is air density; $Cpp$ (J K$^{-1}$ kg$^{-1}$) is the heat capacity of dry air; $Chs$ (m s$^{-1}$) is the surface exchange coefficient for heat and moisture. $SH$ (W m$^{-2}$) is sensible heat flux calculated by Eq. (3).

$$SH = SH_{roof} \times frac_{roof} + SH_{wall} \times frac_{wall} + SH_{road} \times frac_{road} + AH,$$  

(3)

where $AH$ (W m$^{-2}$) is anthropogenic heat. $SH_{roof}$, $SH_{wall}$, and $SH_{road}$ are sensible heat flux of roof, wall and road respectively, and $frac_{roof}$, $frac_{wall}$, $frac_{road}$ are weighting coefficient of roof, wall, and road.

The surface energy balance can then be formulated as:

$$Rn + AH = SH + LH + G,$$  

(4)

where $Rn$ (W m$^{-2}$) is net radiation, $LH$ (W m$^{-2}$) and $G$ (W m$^{-2}$) are latent, and ground heat fluxes respectively.

The simulation domain (Fig. 2) covers Wuhan and its surrounding areas with 1-km grid spacing (159 × 159 grid cells). Canopy layer UHI (CUHI), based on air temperature, and surface UHI (SUHI), based on LST, are two popular heat indexes, revealing different
UHI characteristics. CUHI are strongest with tall buildings and narrow streets and are relatively small during the daytime. SUHI has a complex spatial pattern, mainly due to building geometry and surface thermal properties (Oke et al. 2017; Voogt and Oke 2003). Lacking dense observations of air temperature in Wuhan, 1-km LST from MODIS (Moderate-resolution Imaging Spectroradiometer) is used to assess model simulations. MODIS LST is effective for overcoming difficulties associated with the lack of in-situ observations over large areas (Shen, H. et al. 2016; Yao et al. 2018b).

In summer of 2013, from 23 July to 18 August, there were 26 “hot days” exceeding 35°C (all days except 4 August). The daily maximum air temperature exceeded 39°C during 11–14 August. Strong, extreme heat is a great threat to public health (Habeeb et al. 2015). Based on the availability of high-quality MODIS LST, we selected 1–15 August 2013 as our analysis period. u-HRLDAS simulations were driven by atmospheric forcing conditions from the 3-hourly 0.1° China Meteorological Forcing Dataset (CMFD, Yang et al. 2010), which has widely been used for land-surface modeling (e.g., Zhang et al. 2016). Using CMFD, the model is spun up from 1 January 2010 to 31 July 2013, a sufficient length for simulating temperatures in urban canyons (temperature of roofs, roads, and walls) to reach equilibrium (Chen et al. 2011).

In u-HRLDAS, the default land-use and land-cover (LULC) dataset is based on 500-m MODIS LULC from the WRF pre-processing system, which has only one generic urban category (i.e., category-32 for high-density residential area). This dataset also has problems with capturing correct fine-scale landscape features in Wuhan. For instance, it shows a discontinuous Yangtze River (the blue-colored water area within the yellow rectangle in Fig. 2a). Therefore, we used the 30-m GlobeLand30-2010 and Landsat 8 data for 31 July 2013 to improve the description of regional LULC in Wuhan.

The GlobeLand30-2010 was upscaled to 1 km to obtain the impervious surface percentage (ISP) and lake percentage in each 1-km grid. When the lake percentage in each grid is more than 50 %, the grid is marked as lake. The urban land use is then divided into three categories according to ISP: low-density residential with ISP 0.15–0.7, high-density residential with ISP 0.7–0.9 and commercial areas with ISP > 0.9. Meanwhile, the forest data in GlobeLand30-2010 were used to correct the WRF default MODIS data. The GlobeLand30-2010 represents the LULC in 2010, but our simulated year is 2013. There is a big gap between the two years from the impervious percentage based on Landsat 8 in 2010 and 2013 (Shen, Y. et al. 2016). To capture the urbanization from 2010 to 2013, and avoid the errors introduced by remotely sensed data mosaic, the 30-m Landsat data on 31 July 2013, covering the main Wuhan region, was used to update the urban land use in each 1-km grid. The updated LULC dataset was marked as ULULC.

As seen in Fig. 2, the ULULC (Fig. 2b) shows an expanded and more detailed urban area, fixes the discontinuity problem of Yangtze River traversing the city (the yellow rectangle in Fig. 2b), and has more accurate descriptions of the lakes.

In the baseline control simulation (hereafter CNTL), the roof height was set to 8, 15, and 25 m, respectively, for low-density residential, high-density residential and commercial. The irrigation parameterization (Yang et al. 2016) was used in u-HRLDAS to represent lawn and tree irrigation practices in Wuhan. Also, the urban fraction was calculated from 30-m Landsat data and then aggregated to the 1-km modeling grid. The method proposed by Hu et al. (2014) was selected here to quantitatively compare MODIS LST (MOD11A1 and MYD11A1) with u-HRLDAS LST. More detailed parameter configurations in CNTL are listed in Table 1.

An additional 11 simulations (listed in Table 2) were designed to assess the impacts of UHI calculation by including water areas and various UHI mitigation strategies for Wuhan. Then the SUHI based on u-HRLDAS LST in the simulations with different settings were analyzed in this study.

The LAKE run was conducted by coupling the aforementioned lake model to the u-HRLDAS. The lake model is a one-dimensional mass and energy balance scheme with 20–25 model layers, including up to 5 snow layers on the lake ice, 10 water layers, and 10 soil layers on the lake bottom. The lake scheme is independent of u-HRLDAS. To further quantify the impacts of water areas, the NOIRRI and NOIRRI_LAKE simulations were conducted similar to CNTL and LAKE but without irrigation effects. The lake areas are empty in CNTL and NOIRRI because of the absence of the lake model. In Lake and NOIRRI_LAKE runs, the lake grids’ surface temperature is calculated by the lake model (Oleson et al. 2013; Gu et al. 2015). The irrigation process affects all the vegetation in urban grids because the irrigation is turned on in CNTL and LAKE.

A large percentage of green roof fraction is needed to achieve noticeable effects (Sharma et al. 2016);
thus, the GR05 and GR08 were conducted with the hypothesis that buildings in Wuhan are uniformly covered by 50% or 80% of green roofs. When the green roofs are implemented, the Eq. (3) will be changed to Eq. (5).

\[
SH = SH_{roof} \cdot \text{frac}_\text{roof} \cdot (1 - \text{frac}_\text{gr}) + SH_{gr} \cdot \text{frac}_\text{roof} \cdot \text{frac}_\text{gr} + SH_{wall} \cdot \text{frac}_\text{wall} + SH_{road} \cdot \text{frac}_\text{road} + AH,
\] (5)
where \( \text{frac\_gr} \) is fraction of green roofs and \( \text{SH\_gr} \) is sensible heat flux of green roofs.

Imran et al. (2018) and Wang et al. (2016) changed the albedo of the urban roof from 0.3 to 0.85, and the values of 0.5 (CR05) and 0.7 (CR07) were chosen for cool roofs in our experiments. The albedo of concrete pavement can be as high as 0.7 with the incorporation of slag or white cement (Ramírez and Muñoz 2012); therefore, BP05 and BP07 were conducted similarly to CR05 and CR07 but for road. When cool roofs and bright pavements are employed, the net radiation in Eq. (4) will be changed due to the albedo of cool roofs and bright pavements. In addition, Table 3 lists the surface parameters of green roofs, cool roofs and bright pavements.

The following two scenarios (density-driven building structure changing and height-driven building structure changing) were designed to test the mitigation performance of changing the urban building structure. In our simulation, the total building volume stays the same as the current one, which provides the convenience to compare with CNTL simulation.

The built-up density varies greatly in different city zones. Li, X. et al. (2017) reported that the UHI depends on building height and building density, so we conducted the experiment SPD (Spatial Pattern changes of Density) in which the building density was altered primarily. For SPD, the total urban area in the domain was calculated, and the average urban area was then allocated to each urban grid, i.e., urban density is the same across the original urban grids. Because all grids of each urban land use type were assigned the same urban building height in the u-HRLDAS, the urban building height was also changed to keep the total building volume consistent with the current volume. This structure is essentially the “density-driven building structure changing”. The spatial distribution of urban building heights and urban fraction in SPD are shown as Fig. 3b and 3e.

According to the overall urban planning for Wuhan in 2030 (http://gtghj.wuhan.gov.cn/), the current fraction of high-rise buildings in Wuhan is much lower than other Chinese megacities (e.g., Beijing, Shanghai), and the future city planning will likely increase building heights. Therefore, the SPH (Spatial Pattern changes of Height) case is designed such that, primarily, the urban building height was raised. To keep the total building volume unchanged, the impervious fraction was reduced by 20 % in each urban grid while the building height increased by 20 %. This structure is essentially the “height-driven building structure changing”. Figure 3 demonstrates the urban fraction and urban building height in each grid in CNTL, SPD, and SPH.

### 2.3 Definitions of UHII, EUHII and ELST

To analyze the temporal evolution of UHII, a method used in previous studies (Shen, H. et al. 2016; Zhou et al. 2013) was selected:

\[
\text{UHII} = T_1 - T_2. \tag{6}
\]

Here, \( T_1 \) (K) is the averaged LST in the area within the third ring road, as shown with dark-red line in Figs. 2a and 2b or in Fig. 1c, and \( T_2 \) (K) is the averaged LST for the area within the Wuhan administrative boundary line, shown with black line in Figs. 2a and 2b or in Fig. 1c, but without the third ring road in Wuhan. In the LAKE and NOIRRI_LAKE run, the UHII was calculated, including water bodies. In other simulations, the water bodies were not considered.

In temporal analysis, to describe the efficacy of each mitigation strategy in UHI, the effect of UHII (EUHII) was used to represents the change in UHII.

\[
\text{EUHII} = \text{UHII\_miti} - \text{UHII\_cntl}, \tag{7}
\]

where \( \text{UHII\_cntl} \) represents the UHII in the CNTL run and \( \text{UHII\_miti} \) represents the UHII in simulations using various mitigation strategies. Negative EUHII values mean a UHII reduction for a given mitigation strategy while positive values mean an enhancement.

Besides, in spatial analysis, the effect of LST (ELST) was used to describe the impact of each miti-
igation strategy on LST compared with the CNTL run.
ELST is calculated as follows:

\[ ELST(i, j) = LST(i, j)_{\text{miti}} - LST(i, j)_{\text{cntl}}, \]  

where \( LST(i, j)_{\text{cntl}} \) and \( LST(i, j)_{\text{miti}} \) are the LST of location \((i, j)\) in CNTL and other simulations with mitigation respectively.

3. Results and discussion

3.1 Evaluation of u-HRLDAS simulated LST based on land areas

In qualitative evaluation, Figs. 4 and 5 show that the spatial distribution pattern of simulated LST in the CNTL run is very similar to the observed daytime and nighttime LST from MODIS. There are biases between MODIS LST and simulated LST, but for most grids, the bias is less than 4 K in the daytime (Fig. 4) and less than 2 K in the nighttime (Fig. 5). This result is consistent with, or better than, previous studies. For instance, Monaghan et al. (2014) showed that the simulation bias of Houston, which is around 5 K in the daytime, is strongly related to vegetation types. The night bias patterns are more homogeneous. Vahmani and Ban–Weiss (2016) also showed that the night bias is more homogenous than daytime bias in Los Angeles.

The quantitative evaluation, as shown in Table 4, indicates the RMSE during daytime and nighttime is less than 4 K and 2 K, respectively. In other studies, Monaghan et al. (2014) showed that the daytime RMSE is about 3.5 K to 9 K, and the nighttime RMSE is 1.5 K to 3.5 K, depending on land type. Vahmani and Ban–Weiss (2016) introduce albedo and vegetation fractions in WRF-Urban, using remotely sensed data in Los Angeles, and the improved simulation RMSE is about 4.3 K during the daytime and 1.8 K at nighttime. The evaluation statistics, shown in Table 4, are better than in previous studies, likely due to the introduction of an urban fraction in each urban grid, the modification of urban building heights, and the improved descriptions of urban land use. In addition, the simulated accuracy differences among cities may be affected by the different basic climatology in each city. Given these verifications, the control u-HRLDAS simulation (CNTL) can serve as a baseline simulation in our investigation of UHI and its mitigation strategy for Wuhan.

Fig. 3. The spatial distribution of urban building height used in CNTL (a), SPD (b) and SPH (c) run, and the spatial distribution of urban fraction used in CNTL (d), SPD (e) and SPH (f) run.
Fig. 4. The evaluation of CNTL simulation during the daytime (a and b are LST based on MODIS, averaged from 1–15 August 2013 for local time 10:30 and 13:30; c and d are similar to a and b, but they are based on CNTL run; e and f describe the bias between simulated LST based on CNTL run and MODIS LST. The black points in each sub-figure represent the urban grids, which are the urban land types represented by 31, 32 and 33 in Fig. 2b. The white areas are the lake areas. Unit: K).
Fig. 5. The evaluation of CNTL simulation during the daytime (a and b are LST based on MODIS, averaged from 1–15 August 2013 for local time 22:30 and 01:30; c and d are similar to a and b, but they are based on CNTL run; e and f describe the bias between simulated LST based on CNTL run and MODIS LST. The black points in each sub-figure represent the urban grids, which are the urban land types represented by 31, 32 and 33 in Fig. 2b. The white areas are the lake areas. Unit: K).
3.2 Impacts of water areas on the UHI calculation

Table 5 lists the evaluation statistics by comparing simulated water LST with MODIS LST. The overall RMSE is around 2–3 K, which is a reasonable range.

Figure 6 shows the spatial distribution of mean LST in CNTL and LAKE run. Obviously the lake surface temperature is lower than its surrounding grids, and including the lake model fills the blank lake grids.

To explore the effects of including water bodies on UHI intensity calculation, Fig. 7a confirms that considering water bodies reduces UHII and shows the daytime UHII in LAKE is about 1 K lower than that in CNTL, while the nighttime UHII is about 0.5 K lower. The same difference exists between NOIRRI_LAKE and NOIRRI (Fig. 7a). However, Yao et al. (2018b) shows that including water bodies in UHII calculation overestimates summer-daytime and underestimates summer-nighttime UHII by 0.28 K and 0.16 K, respectively (averaged for 31 cities in China). One plausible reason for this discrepancy is that the Wuhan Metro area includes ample lakes in both urban and surrounding rural areas. The lakes’ locations and the water temperature’s diurnal variation characteristics are the possible reasons for changes in the UHII; therefore, the effects of water bodies on UHI may differ among different cities. As shown in Fig. 7b, the lake LST’s diurnal variation is relatively small compared to the LST diurnal variation over other land-cover types (as shown in Fig. 7c). Therefore, including the lake areas in UHII calculation may affect the UHII variations.

The temperature of different regions (T1 and T2) in different simulations shows a similar diurnal cycle tendency (Fig. 7c). All of them are unimodal, and the LST reaches its maximum around 13:30, while the minimum appears around 4:30. In the region within the third ring road of Wuhan (LST is marked as T1), the LST in CNTL is higher about 2 K than in LAKE at around noon; meanwhile, the LST in NOIRRI is higher than that in NOIRRI_LAKE. In the region outside the third ring road, but within the Wuhan administrative boundary line (the LST is represented by T2), the difference of T2 in CNTL and LAKE is about 1 K at around noon, which is lower than the difference of T1 (2 K). At nighttime, including water bodies in LAKE (or NOIRRI_LAKE) increases T1 and T2 compared with CNTL (or NOIRRI), but the T2 increase is higher than the T1 increase, which reduces UHII calculated by T1 minus T2 (Fig. 7a). It is obvious that the temperature difference between

| Land use type | Rural* | Urban* | Rural* | Urban* |
|---------------|--------|--------|--------|--------|
| Time          | local 10:30 | local 13:30 | local 22:30 | local 01:30 |
| RMSE (K)      | 3.7    | 3.7    | 2.7    | 3.1    |

Note: the “urban” contains the land use type 31, 32 and 33 in Fig. 2b, the “rural” used here contains all the others except for the “urban” land use type and the “lake” land use type in Fig. 2b.

| Local time     | 10:30 | 13:30 | 22:30 | 01:30 |
|----------------|-------|-------|-------|-------|
| RMSE (K)       | 2.8   | 3.1   | 2.2   | 2.6   |

Fig. 6. The spatial distribution of LST in CNTL (a) and LAKE (b) run, averaged from 1–15 August 2013 (Unit: K).
daytime and nighttime in LAKE and NOIRRI_LAKE is smaller than in CNTL and NOIRRI. This is caused by the small diurnal cycle range of lake LST (Fig. 7b). However, UHII’s diurnal variation tendencies are similar in these four different runs. Besides, the slope denoting “the change rate” of T2 and T1 is not the same at specified time point (Fig. 7c). For example, the T2 slope is different from T1 at local time 17:30; therefore, some suddenly changed points exist in the diurnal variation of UHII (Fig. 7a). Including water bodies in the above UHII calculation for Wuhan has a non-negligible effect on the UHI strength but has little effect on UHI’s diurnal cycle tendency.

Including water bodies in UHI strength calculations is particularly important for a city like Wuhan with abundant lakes. However, in the following discussions, considering that urban heat mitigation strategies only work for urban grids, and excluding lake areas can simplify the computation and discussion, we will focus on analyzing impacts of various UHI mitigation strategies using u-HRLDAS simulations that only include land areas.

3.3 Impacts of green roofs, cool roofs, and bright pavements on UHI strength

Green roofs show prominent UHI mitigation performance (Fig. 8), especially during the daytime. The albedo of the green roofs is set to 0.2 (Table 3) in the GR08 and GR05 simulation, which is lower than traditional roofs (0.3 is set in the CNTL simulation); thus, the net radiation increases during the daytime, as shown in Figs. 9a and 9b. The evaporation of soil water and the transpiration of vegetation convert more radiation to latent heat flux (Figs. 9a, b), so the sensible heat flux decreases and, subsequently, the UHII is lower than CNTL (Fig. 8). The roof temperature of each layer in green roofs is lower than in conventional roofs (Fig. 10a). The diurnal variation tendency of roof temperatures in green roofs is smoother than in traditional roofs (Fig. 10a). With the insignificant evapotranspiration, and the absence of solar radiation, the nighttime changes of latent

Fig. 7. (a) The diurnal variations of UHII in CNTL, LAKE, NOIRRI, and NOIRRI_LAKE. (b) The diurnal variations of mean LST over lake grids. (c) LST diurnal variation in the region within the third ring road of Wuhan (marked as T1) and the LST in the region without the third ring road, but within the Wuhan administrative boundary line (marked as T2), averaged from 1–15 August 2013 (Unit: K).

Fig. 8. The EUHII diurnal variation under different mitigation strategies, averaged from 1–15 August 2013 (Unit: K).
Fig. 9. The diurnal variation of mean surface heat flux changes regarding impervious areas in urban grids, averaged from 1–15 August 2013 (a presents the surface heat flux in GR05 minus them in CNTL, b, c, d, e and f are similar to a, but for GR08, CR05, CR07, BP05 and BP07 respectively. LH: latent heat flux. SH: sensible heat flux. G: ground heat flux. RN: net radiation).
heat flux and sensible heat flux is small (Figs. 9a, b), causing a negligible cooling efficacy of temperature (Fig. 8). The decreased daytime LST is consistent with Li et al. (2014), Sharma et al. (2016) and Yang et al. (2016). The highest EUHII (in both GR08 and GR05) occurs around 13:00 local time, which also agrees with the green-roof study for Chicago (Sharma et al. 2016). There is a slight reduction (less than 0.2 K) in nighttime UHII. This result agrees with studies for Chicago (Sharma et al. 2016) and Washington, DC (Li et al. 2014), but differs from a slight nighttime warming effect in Phoenix, Houston (Yang et al. 2016), and California (Georgescu 2015). Many factors may contribute to the varying efficacy of employing green roofs, such as the albedo, soil moisture, thermal capacity, thermal conductivity, local climate, and specific building characteristics (Santamouris 2014; Smith and Roebber 2011).

During the period between sunrise (05:30) and sunset (19:00), the net radiation in the CR and BP scenario is lower than in CNTL (Figs. 9c–f), because a larger portion of the incoming solar radiation is reflected by cool roofs or bright pavements compared with conventional materials, decreasing sensible heat fluxes (Figs. 9c–f). Subsequently, the CR05, CR07, BP05, and BP07 produce lower LST in urban grids, leading to lower UHII (Fig. 8). Similarly, the temperature of each layer in cool roofs is lower than that in the CNTL simulation (Fig. 10b). Bright pavement is not as effective at lowering urban heat as altering roof materials (Fig. 8). Previous studies indicated that the effects of bright pavement depend on location (Santamouris et al. 2012; Yang et al. 2015). The weak efficiency of bright pavement in Wuhan may be because most roads inside the city are easily influenced by building shadows. As shown in Figs. 9c–f, increasing roof albedo reduces net radiation more compared with the bright-pavement experiment. The maximum of CR-induced change of net radiation reaches about 130 W m⁻² in CR07 and about 65 W m⁻² in CR05, but the maximum net radiation changes due to the bright pavement is about 50 W m⁻² in BP07 at local time 12:00 and about 25 W m⁻² in BP05. The cooling effects of CR07 (Fig. 8) exceed 1.8 K at 12:30. Santamouris (2014) indicates that, with a roof albedo increase of 0.1, the 2-m temperature will be reduced by about 0.10 to 0.33 K. In our study, when the roof albedo changes from 0.3 to 0.5 (CR05) and 0.7 (CR07), the maximum UHII reductions are about 0.9 K and 1.8 K, respectively, which are stronger than that of Santamouris (2014). This is reasonable because LST is more sensitive to surface property changes than 2-m temperature. At nighttime, with the absence of solar radiation and weak atmospheric turbulence, the heat flux changes due to the cool roofs and bright pavement are very small (Figs. 9c–f), which may reduce UHII slightly (Fig. 8).

From the spatial distribution of ELST, high-coverage green roofs (GR08) are the most effective at reducing LST by more than 1.2 K in most urban grids (Fig. 11b). High-albedo cool roofs (CR07) show ELST between −0.8 to −1.2 K in most urban areas (Fig. 11d). The ELST of medium-coverage green roofs (GR05) is about −0.4 to −1.2 K (Fig. 11a) while the ELST
of medium-albedo cool roofs (CR05) is about −0.4 to −0.8 K (Fig. 11c) in the center urban region of the domain. Bright pavement is less effective at reducing LST lower than 0.4 K (Figs. 11e, f). The temporal analysis in Fig. 8 indicates that employing a higher fraction of green roofs, and higher albedo of roofs and roads, can effectively mitigate UHI. This agrees with studies in Chicago (Sharma et al. 2016), Washington (Li et al. 2014), and Melbourne (Imran et al. 2018). Although the ELST by modifying pavement characteristics shows little spatial heterogeneity within the city (Figs. 11e, f), the effects of green roofs and cool roofs show a strong heterogeneity (Figs. 11a–d), partially based on urban category. The most effective LST mitigation is for the commercial urban-category with a reduction of 1.29 K in GR08 and of 1.01 K in CR07, as shown in Fig. 12. But for the low-density residential, the LST reduction of different strategies are lower than 0.5 K. This may be related to several factors, such as lower roof coverage in low-density rather than commercial areas. Therefore, the ELSTs of using green and cool roofs are related to urban categories.

Moreover, for the same urban land-use category, different strategies show different performances (Fig. 12). For example, in high-density residential areas, the ELSTs of green roofs (−0.51 K and −0.84 K) and cool roofs (−0.39 K and −0.79 K) are higher than for bright pavement (−0.08 K and −0.16 K). The ELST of using bright pavement is similar for different urban land-use categories, likely because the road is shaded easily by surrounding buildings. The boxes representing green roofs are longer than others over each urban category in Fig. 12, implying more daily variation. The main difference among simulated days is the weather condition. Therefore, significant daily variations with green roofs are most likely caused by changes in weather conditions. Other mitigation strategies do not seem to vary much from weather conditions during the simulated period. This is because the evaporative
cooling strength of green roofs depends on changes in precipitation, radiation, temperature, and humidity (Yang et al. 2016).

In other studies, Wang et al. (2015) compared the effects of different UHI mitigation strategies for Toronto, Canada. The cool pavement, cool roof, and vegetation strategies are investigated in that paper, and the results indicated that different strategies show different performances, which agrees with our results. Zhao et al. (2017) suggested cool roofs as the preferred strategy for UHI mitigation compared to green roofs, street vegetation, and reflective pavement in the United States and southern Canada. The UHI mitigation intensity may depend on specific city and model simulations, which may be due to different model simulation settings, the study scale, and local climate conditions.

3.4 Impacts of the urban building pattern on UHI strength

Because the UHI is intimately related to urban forms (Sobstyl et al. 2018; Zhou et al. 2017), the impacts of changing urban-building patterns on UHI intensity are tested here. Compared to the CNTL run, the SPD run reduces UHII by 1.2–2.6 K, while the SPH run reduces UHII by 0.4–0.9 K throughout the day (Fig. 13a). Figure 13b reveals that the LST reduction of SPD is more than 1.6 K in the center urban region of Wuhan, which is much more effective than the mitigation strategies represented in Fig. 11. In SPH, the LST reduction is higher than 0.8 K in most urban grids (Fig. 13c). In contrast to mitigation strategies that are only effective in reducing daytime UHII (Fig. 8), changing the urban-building pattern is effective both during the daytime and nighttime.

For SPD (moving buildings from dense districts to sparse districts), the vegetation spaces in the original dense built-up areas in the center region of Wuhan are now increased. For example, the vegetation fraction in high-density residence and commercial regions increase because of reduced urban fraction in SPD (Fig. 3e) compared with CNTL simulation (Fig. 3d). In these regions, the upward solar radiation and longwave radiation decrease (Figs. 14c, e) with less impervious areas (Fig. 3e) in SPD. However, more vegetation fraction increases latent heat fluxes during the daytime (Figs. 15c, e). The maximum increase of latent heat flux is about 150 W m$^{-2}$ in high-density residence, and about 300 W m$^{-2}$ in commercial region, accompanied by decreased sensible heat fluxes ranging from about 100 W m$^{-2}$ and 200 W m$^{-2}$ for high-density residence and commercial regions, respectively, in SPD (Figs. 15c, e). This results in a reduction of LST in Fig. 13b. Notably, when moving buildings from dense to sparse areas, the SPD ELST becomes positive in those sparse areas (Fig. 13b) due to increased impervious fractions.
The LST is low in original sparse built areas (Fig. 6a) with a relative lower impervious fraction before changing the urban building density (CNTL run), so a moderate LST increase would not bring discomfort in these areas. These grids, with increasing temperatures, are located in low-density residential areas. Both the upward solar radiation and upward longwave radiation increase in the low-density residential areas (Fig. 14a). The urban fraction of some grids in the low-density residence in SPD (Fig. 3e) is higher than in CNTL (Fig. 3d); hence, the latent heat flux decreases (Fig. 15a) due to reduced vegetation fractions in these grids. The average sensible heat flux of low-density residence in SPD increases and its maximum is about 25 W m$^{-2}$, which increases LST in some grids (Fig. 13b).

For SPH (raising building heights with increases vegetation fraction), the radiation is simultaneously affected by a decreased impervious surface (Fig. 3f), and an increased shadow area induced by the building height changes (Fig. 3c). In each urban land-use type, the simulated results reveal that the upward solar radiation decreases during the daytime, and the upward longwave radiation decreases throughout the day (Figs. 14b, d, f). These changes lead to net radiation changes in all urban grids because the downward shortwave and longwave radiation stay intact. In each type of urban land-use category, latent heat fluxes increase during the daytime due to a 20% increase of the vegetation fraction in each urban grid; sensible heat fluxes decrease (Figs. 15b, d, f) and subsequently cool the city (Figs. 13a, c). The maximum reduction of sensible heat flux is about 10 W m$^{-2}$, 40 W m$^{-2}$, and 60 W m$^{-2}$ for the low-density residence, high-density residence and commercial areas, respectively.

In addition, there are some fluctuations in the diurnal variation of shortwave radiation changes around noontime (Fig. 14). The fluctuations appeared due to the variations of radiation curve slopes in each case at specific time points. For example, the diurnal variation tendencies of the upward shortwave radiation are similar over low-density residence in CNTL, SPD and SPH (Fig. 16), but the radiation change tendencies (SPD minus CNTL or SPH minus CNTL) are dissimilar (Figs. 14a, b) because of the different slopes of the radiation curves. The different slopes of the upward radiation curves indicate the radiation change rates vary among CNTL, SPD, and SPH, likely from different effects of shadowing and reflection of urban morphology among these simulations.

In the SPH run, raising the building height leads to increased building shadow and modified radiation budgets. The changes of the building shadow affect road and wall radiation. The net solar radiation of the impact of shadowing in SPH is lower than that in the CNTL simulation (Fig. 17). The maximum decrease of the net solar radiation is about 45 W m$^{-2}$ around noon local time (Fig. 17).

The expansion of the shadow region, the decrease of the roof areas in urban parts, and the changes of impervious surface fraction collectively result in cooler urban grids in SPH than in CNTL. From the above analysis, changing the urban building structure, such as an SPH-like scenario, is efficient for a city like Wuhan to mitigate urban heat.
Fig. 14. The diurnal variation of mean surface energy changes over all the grids of each urban land type, averaged from 1–15 August 2013 (a, c and e are the surface energy in SPD minus them in CNTL over low-density residence, high-density residence and commercial region respectively. b, d and f are similar to a, c and e, but for SPH simulation. SWUP means upward shortwave radiation; LWUP represents upward longwave radiation).
Fig. 15. The diurnal variations of mean surface heat flux changes over all the grids of each urban land type (a, c and e are the surface heat flux in SPD minus them in CNTL over low-density residence, high-density residence and commercial region respectively. b, d and f are similar to a, c and e, but for SPH simulation. G_SH means the mean sensible heat flux over all the grids of specified urban land types, and the value used here does not represent the impervious part but the whole urban grids. G_LH is similar to G_SH, but for latent heat flux. All those results are averaged from 1–15 August 2013).
4. Conclusions

With the goal of providing practical guidance for urban planners and policymakers to make the city more habitable, this study combines satellite data and model simulations to explore the effectiveness of different strategies to mitigate surface UHI, measured by LST, for Wuhan, and the main findings are:

1) Considering lake effects reduces the UHII by about 1 K (0.5 K) during the daytime (nighttime), but does not significantly affect UHI’s diurnal cycle tendency.

2) Employing green roofs, cool roofs, and bright pavements reduce UHII, but their efficacy at nighttime is negligible. By contrast, changing urban building patterns can mitigate UHI throughout the day.

3) Using green roofs and cool roofs is more effective than using bright pavements, and their mitigation efficacy increases with larger fractions of green roofs and higher albedo in roofs or roads. Using 80 % green roofs can reduce LST more than 1.2 K in most urban areas, and the maximum reduction of UHII is more than 2 K about 13:00. Cool roofs with albedo of 0.7 produce a maximum cooling efficacy, with EUHII changes of about 1.8 K at 13:00, and the average ELST in most urban areas is about 0.8–1.2 K.

4) The effects of green roofs and cool roofs depend on urban land-use categories, and the effects of green roofs also depend on weather conditions.

5) The height-driven building-structure changes (i.e., raising the building height, and meanwhile changing the fraction of the impervious surface in each grid to keep the total building volume intact) can reduce the surface UHI intensity by 0.4–0.9 K, and the density-driven building-structure changes (i.e., uniformly distributing building density uniformly and the building height are modified to make the total building volume unchanged) reduce UHI by 1.2–2.6 K.

This study shows the efficacy of various strategies to mitigate daytime and nighttime UHI for Wuhan. The most effective mitigation strategy is modifying the urban building density, which is perhaps the most difficult to implement for a mature city. However, it can provide meaningful guidance for the urban designer for expanding the city extent. Using green roofs is more effective than changing building heights during the daytime, but the effect of changing building heights is more effective for reducing nighttime UHI.

Based on this study, mitigating UHI effects in Wuhan in future urban development can be achieved by increasing the fractions of high-rise buildings and homogenizing city building densities. For daytime UHI mitigation, both green roofs and cool roofs are effective. Without considering the aesthetic, installation costs, conservation potential, and other reasons in practical applications, 80 % green roofs is a better choice than cool roofs with albedo as 0.7, though cool roofs are more easily implemented.

This study provides some initial results regarding the impacts of changing urban building patterns on
UHI mitigation by demonstrative design, but more analysis of other factors, such as the exact locations of buildings, ventilation corridors, and green spaces, like parks and lawns on UHI, should be investigated in future studies.

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