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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 pose a great threat to public health in China. This paper took Wuhan (one of the four hottest furnaces 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 the use of green roofs, cool roofs, bright pavements, and alternations in urban building patterns. The offline urbanized High-Resolution Land Data Assimilation System (u-HRLDAS) was employed to conduct 1-km resolution numerical simulations, which also accounts for the effects of abundant lakes in Wuhan 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 the daytime (nighttime) UHI intensity by about 1.0 K (0.5 K). Employing green roofs and cool roofs are more effective in mitigating daytime UHI than the use of 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 the green roofs, cool roofs and bright pavements which are ineffective in nighttime, changing urban building pattern to mitigate the UHI is effective throughout the day. “Height-driven building structure changing” (raising the building height, and meanwhile changing the fraction of 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 “density-driven building structure changing” (distributing building density uniformly and the building height are modified to make the total building volume unchanged) reduces UHI by 1.2-2.6 K. These results showed new insights in mitigating the urban heat islands for a mega city like Wuhan and provides a practical guideline for policymakers to offer a more habitable city.

**Keyword:** urban heat island mitigation, lake, green roof, cool roof, bright pavement, urban design.
1. Introduction

The urban heat island (UHI) is a well-known phenomenon where the temperature in cities 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 residents in cities (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 changed climate, leading to numerous studies investigating the spatiotemporal variation of UHI (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 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 the four China’s hottest-furnace cities with 10 million residents (Shen et al. 2016a), 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). Given the great threat of excessive thermal stress to human life, it is important to take active strategies to mitigate increasingly deteriorated urban thermal environments (Sharma et al. 2016; Sharma et al. 2018).

There are several ways to mitigate the UHI (Mohajerani et al. 2017), such as replacing conventional roofs and roads by 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 road (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 et al. 2017a; Adachi et al. 2014; Kusaka et al. 2016). Although some studies focused on investigating and comparing various different mitigation strategies in USA (Zhao et al. 2017) and Canada (Wang et al. 2015), there are limited researches regarding to China and most of them only investigated one or two strategies which are insufficient for urban heat mitigation research. For example, Liu et al. (2018) investigated the green roofs and cool roofs in 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 pattern traditionally received less attention compared with the strategies based on materials and vegetation in Chinese cities. Besides, the mitigation studies in Wuhan are essentially absent, despite the fact Wuhan is extremely hot in summer. In order to fill the gap in examining the UHI mitigation for Wuhan, this study focus on Wuhan and exploring the effectiveness of the following common UHI mitigation strategies: green roofs, cool roofs, bright pavements, and changing urban building pattern.

Assessing the fidelity of modeled UHI is an important step to study 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 body (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. The primary objectives of this study are to understand the extent to which lakes affect the UHI calculation in Wuhan, and the effectiveness of the above-mentioned UHI mitigate 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 concludes this
2. Materials and methods

2.1 Study region

The metropolitan region of 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 km² 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 summer in Wuhan 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 km² 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 easily employed 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 the 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 impacts of water bodies. 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 weighted average of simulated LST for man-made and natural surfaces by urban fraction ($urban\_frac$) in the following equation:

$$LST = urban\_frac \cdot LST\_urban + (1 - urban\_frac) \cdot LST\_rural$$  \hspace{1cm} (1)

where the $LST\_rural$ (K) is derived by Noah, and the $LST\_urban$ (K) is calculated by SLUCM according to the following:

$$LST\_urban = Ta + SH / (Rhoo \cdot Cpp \cdot Chs)$$  \hspace{1cm} (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).

$$SH = SH\_roof \cdot frac\_roof + SH\_wall \cdot frac\_wall + SH\_road \cdot frac\_road + AH$$  \hspace{1cm} (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
\( \text{frac}_\text{roof}, \text{frac}_\text{wall}, \text{frac}_\text{road} \) 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 the Wuhan and its surrounding areas with a 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 in 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 has been shown to be effective in overcoming difficulties associated with the lack of in-situ observations over large areas (Shen et al. 2016a; 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). Daily maximum air temperature exceeded 39 °C during 11-14 August. Strong extreme heat brings great threat to public health (Habeeb et al. 2015). Based on 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 simulated temperature 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). This dataset also has problems to correctly capture 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 et al. 2016b). 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 region of Wuhan 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 description of 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. The MODIS albedo for 28 July 2013 on Wuhan downtown areas was used to specify the albedo of roof, wall and road in SLUCM. 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. It is noteworthy that the lake areas are empty in CNTL and NOIRRI because of the absence of lake model. In Lake and NOIRRI_LAKE runs, the surface temperature of lake grids is calculated by the lake model (Oleson et al. 2013; Gu et al, 2015). The irrigation process affects all the vegetation in urban grids due to 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).

$$SH = SH_{roof} * frac_{roof} (1 - frac_{gr}) + SH_{gr} * frac_{roof} * frac_{gr} + SH_{wall} * frac_{wall} + SH_{road} * frac_{road} + AH$$  \tag{5}$$

where $frac_{gr}$ is fraction of green roofs and $SH_{gr}$ is sensible heat flux of
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 urban building structure. In our simulation, the total building volume stays the same as the current, which provides the convenience to compare with CNTL simulation.

The built-up density varies greatly in different city zones. Li et al. (2017b) 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. 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 Fig. 3e.

According to the overall urban planning for Wuhan in 2030 (http://gtghj.wuhan.gov.cn/zl/zq2030/show.asp?id=100671&cid=2229), the current fraction of high-rise buildings in Wuhan is much lower than other megacities (e.g., Beijing, Shanghai) in China, and the future city planning will likely increase building heights. Therefore, the SPH (Spatial Pattern changes of Height) case is designed such that the urban building height was raised primarily. 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 temporal evolution of UHII, a method used in previous studies (Shen et al. 2016a; Zhou et al. 2013) was selected:

\[ U_{\text{HII}} = T_1 - T_2 \]  

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 strategies in UHI, the effect of UHII (EUHII) was used to represents the change in UHII.

\[ EUHII = UHII_{miti} - UHII_{cntl} \] (7)

where \( UHII_{cntl} \) represents the UHII in the CNTL run and \( UHII_{miti} \) 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 mitigation strategies on LST compared with CNTL run. ELST is calculated as follows:

\[ ELST(i, j) = LST(i, j)_{miti} - LST(i, j)_{cntl} \] (8)

where \( LST(i, j)_{cntl} \) and \( LST(i, j)_{miti} \) 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 shows 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 the bias for most grid is less than 4 K in the daytime (Fig. 4) and less than 2 K in the nighttime (Fig. 5). This result is consistent or better than previous studies. For instance, Monaghan et al. (2014) showed that the simulation bias of Houston is around 5 K in the daytime and it is strongly related to vegetation types and 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.

In quantitative evaluation, as shown in Table 4, 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 fraction in WRF-Urban using remotely sensed data in Los Angeles and the improved simulation RMSE is about 4.3 K in daytime and 1.8 K in nighttime. The evaluation statistics shown in Table 4 are better than in previous studies, likely due to the introducing of urban fraction in each urban grid, the modification of urban building height, and the improved description 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.
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 of the lake grids.

To explore the impacts 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 comprises ample lakes in both urban areas and surrounding rural areas. The location of the lakes and the diurnal variation characteristics of water temperature are the possible reasons which change the UHII, therefore, the impacts of water bodies on UHI may differ among different cities. As shown in Fig. 7b, the diurnal variation of lake LST is relatively small, compared to the diurnal variation of LST 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 the similar diurnal cycle tendency (Fig. 7c). All of them are unimodal and the maximum LST reaches at around 13:30, while the minimum appears at 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 administrative boundary line of Wuhan (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). In nighttime, the including of water bodies in LAKE (or NOIRRI_LAKE) increases T1 and T2 compared with CNTL (or NOIRRI), but the increase of T2 is higher than the increase of T1, which causes the reduction of UHII calculated by T1 minus T2 (Fig. 7a). It is obvious that the temperature difference between 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, the diurnal variation tendencies of UHII 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 slope of T2 is different from the slope of T1 at local time 17:30, therefore some sudden changed points exist in the diurnal variation of UHII (Fig. 7a). In above, including water bodies in the UHII calculation for Wuhan has a non-negligible effect on the UHI strength but has a little effect on the diurnal cycle tendency of UHII.
Including water bodies in defining UHI strength is particularly important for a city like Wuhan with abundant lakes. However, in the following discussions, considering that the urban heat mitigation strategies only work for urban grid 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 the strength of UHI

Green roofs show prominent urban heat island mitigation performance (Fig. 8) especially in 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 in daytime shown in Figs. 9a and 9b. The evaporation of soil water and the transpiration of vegetation covert more radiation to latent heat flux (Figs. 9a and 9b), and the sensible heat flux decreases and subsequently the UHII is lower than CNTL (Fig. 8). Roof temperature of each layer in green roofs is lower than in conventional roofs as shown in Fig. 10a. The diurnal variation tendency of roof temperature in green roof is smoother than in traditional roofs (Fig. 10a). With the insignificant evapotranspiration and the absence of solar radiation, the nighttime changes of latent heat flux and sensible heat flux is small (Figs. 9a and 9b), causing a negligible cooling efficacy of temperature (Fig. 8). The decrease of 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) is achieved at 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 it 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, leading to a decrease in 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 impacts of bright pavement have a strong dependency on location (Santamouris et al. 2012; Yang et al. 2015). The weak efficiency of bright pavement in Wuhan may be caused by the majority of roads inside the city being 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 the roof albedo increases 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 reduction is about 0.9 K and 1.9 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. In 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 result in a small reduction of UHII (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 has a weaker efficiency with reducing LST lower than 0.4 K.
(Figs. 11e and 11f). Combing the temporal analysis in Fig. 8, it can be concluded 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 and 11f), the effect 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 the lower roof coverage in low-density than that in commercial area. Therefore, the ELST of using green and cool roofs are related to the urban categories.

Moreover, for the same urban land-use category, different strategies show different performance (Fig. 12). For example, in high-density residential areas, the ELST of green roofs (-0.51 and -0.84 K) and cool roofs (-0.39 and -0.79 K) are higher than that for bright pavement (-0.08 and -0.16 K). The ELST of using bright pavement is similar for different urban land-use categories, likely due to the road being easily shaded 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 condition. Other mitigation strategies do not seem to vary much with 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 performance, which agrees with our results. Zhao et al. (2017) suggested cool roofs as the preferred strategy for UHI mitigation in comparison 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 the different model simulation settings, the study scale, and the local climate condition.

3.4 Impacts of the urban building pattern on the strength of UHI

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 the UHI intensity are tested here. Compared to the CNTL run, the SPD run reduces UHI by 1.2-2.6 K while the SPH run reduces UHI by 0.4-0.9 K throughout the day (Fig. 13a). Fig. 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 compared with 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 the mitigation strategies only being effective in reducing daytime UHII (Fig. 8), changing urban-building pattern is effective for both in 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 region increase due to the reduction of 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 and 14e) with less impervious areas (Fig. 3e) in SPD. However, more vegetation fraction increases latent heat fluxes during daytime (Figs. 15c and 15e). 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 decrease in 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 and 15e). This results in a reduction of LST in Fig. 13b. Notably, when moving buildings from dense areas 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 relative lower impervious fraction before changing the urban building density (CNTL run), so the moderate increase of LST would not bring discomfort in these areas. These girds with increasing temperature are located in the low-density residence. Both
the upward solar radiation and upward longwave radiation increase in the low-density residence (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 the reduction of vegetation fraction in these grids. The averaged sensible heat flux of low-density residence in SPD increase and its maximum is about 25 W m$^{-2}$, which cause the increase of LST in some grids (Fig. 13b).

For SPH (raising building heights with increases vegetation fraction), the radiation is simultaneously affected by the decrease of the impervious surface (Fig. 3f), and the increase of the 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 in daytime, and the upward longwave radiation decreases throughout the day (Figs. 14b, 14d and 14f). These changes lead to the net radiation changes in all urban grids, because the downward shortwave and longwave radiation stay intact. In each type of urban land-use categories, latent heat fluxes increase during daytime due to the 20% increase of vegetation fraction in each urban grid; sensible heat fluxes decrease (Figs. 15b, 15d and 15f) and subsequently cools the city (Figs. 13a and 13c). 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 regarding to the slopes of radiation curves 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 tendency of the radiation changes (SPD minus CNTL or
SPH minus CNTL) are dissimilar (Figs. 14a and 14b) because of the different
slopes of the radiation curves. The different slopes of the upward radiation
indicate the change rates of the radiation varies among CNTL, SPD and SPH,
likely as result of different effects of shadowing and reflection of urban
morphology among these simulations.

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

The expansion of the shadow region, the decrease of the roof areas in
urban part, and the changes of impervious surface fraction collectively result in
cooler urban grids in SPH than in CNTL. From the above analysis, changing
urban building structure such as a scenario like SPH is efficient for a city like
Wuhan to mitigate urban heat.

4. Conclusions
With the goal to provide practical guidance for urban planners and policymaker to make the city more habitable, this study combines satellite data and model simulations to explore the effectiveness of different strategies to mitigate the 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) in daytime (nighttime), but does not significantly affect diurnal cycle tendency of UHI.

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

3) Using green roofs and cool roofs are 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 at about 13:00. Cool roofs with albedo of 0.7 produce its maximum cooling efficacy by the changes of EUHII about 1.8 K at 13:00, and the averagely ELST in most urban areas is about 0.8-1.2 K.

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

5) Height-driven building-structure changes (i.e., raising the building height, and meanwhile changing the fraction of 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) reduces 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 to modify the urban building density, which is perhaps the most difficult to implement for a mature city. However, it can provide a meaningful guideline for the urban designer towards expanding the city extent. Using green roofs is more effective than changing building heights in daytime, but the effect of changing building heights is more effective to reduce 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. In daytime UHI mitigation, both green roofs and cool roofs are effective. Without considering the aesthetic, install cost, conservation potential and other reasons in the practical application, 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.
Acknowledgments

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<th>High-density residence</th>
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Table 2 Design of u-HRLDAS numerical experiments

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<th>Run name</th>
<th>Model setup</th>
<th>Objectives</th>
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<td>LAKE</td>
<td>Same as CNTL, but lake model was adopted.</td>
<td>Assess the impact of lakes on the strength of UHI, compare CNTL with LAKE and NOIRRI with NOIRRI_LAKE.</td>
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<td>NOIRRI_LAKE</td>
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<tr>
<td>GR08</td>
<td>Same as CNTL, but with 80% roofs are replaced by green roofs</td>
<td></td>
</tr>
<tr>
<td>CR05</td>
<td>Same as CNTL, but with the roof albedo set as 0.5 for all urban categories</td>
<td></td>
</tr>
<tr>
<td>CR07</td>
<td>Same as CNTL, but with the roof albedo set as 0.7 for all urban categories</td>
<td>Investigate possible scenarios of changing urban building pattern to mitigate UHI.</td>
</tr>
<tr>
<td>BP05</td>
<td>Same as CNTL, but with the road albedo set as 0.5 for all urban categories</td>
<td></td>
</tr>
<tr>
<td>BP07</td>
<td>Same as CNTL, but with the road albedo set as 0.7 for all urban categories</td>
<td></td>
</tr>
<tr>
<td>SPD</td>
<td>Same as CNTL, but the &quot;building height&quot; and &quot;urban fraction&quot; are set as the value in Fig.3b and 3e respectively</td>
<td></td>
</tr>
<tr>
<td>SPH</td>
<td>Same as CNTL, but the &quot;building height&quot; and &quot;urban fraction&quot; are set as the value in Fig.3c and Fig. 3f respectively</td>
<td></td>
</tr>
</tbody>
</table>
Table 3 The surface parameters of green roofs, cool roofs and bright pavements

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Green roofs</th>
<th>Cool roofs</th>
<th>Bright pavements</th>
</tr>
</thead>
<tbody>
<tr>
<td>albedo</td>
<td></td>
<td>0.2</td>
<td>0.5/0.7</td>
<td>0.5/0.7</td>
</tr>
<tr>
<td>emissivity</td>
<td></td>
<td>0.93</td>
<td>0.9</td>
<td>0.95</td>
</tr>
<tr>
<td>Saturated soil moisture</td>
<td>m³m⁻³</td>
<td>0.439</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wilting-point soil moisture</td>
<td>m³m⁻³</td>
<td>0.084</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LAI</td>
<td></td>
<td>1.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4 RMSE of the CNTL run calculated from observed MODIS LST.

<table>
<thead>
<tr>
<th>Land use type</th>
<th>Rural*</th>
<th>Urban*</th>
<th>Rural*</th>
<th>Urban*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>local 10:30</td>
<td>local 13:30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE(K)</td>
<td>3.7</td>
<td>3.7</td>
<td>2.7</td>
<td>3.1</td>
</tr>
<tr>
<td>Time</td>
<td>local 22:30</td>
<td>local 01:30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE(K)</td>
<td>1.6</td>
<td>1.8</td>
<td>1.6</td>
<td>1.9</td>
</tr>
</tbody>
</table>

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.
Table 5 RMSE of LST at water bodies when compared with MODIS LST

<table>
<thead>
<tr>
<th>Local time</th>
<th>10:30</th>
<th>13:30</th>
<th>22:30</th>
<th>01:30</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE(K)</td>
<td>2.776</td>
<td>3.075</td>
<td>2.169</td>
<td>2.552</td>
</tr>
</tbody>
</table>