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Combined Effects of Artificial Surface and Urban Blue-Green Space on Land Surface Temperature in 28 Major Cities in China

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Abstract: The two most common land cover types in urban areas, artificial surface (AS) and urban blue-green space (UBGS), interact with land surface temperature (LST) and exhibit competitive effects, namely, heating and cooling effects. Understanding the variation of these effects along the AS ratio gradient is highly important for the healthy development of cities. In this study, we aimed to find the critical point of the joint competitive effects of UBGS and AS on LST, and to explore the variability in different climate zones and cities at different development levels. An urban land cover map and LST distribution map were produced using Sentinel-2 images and Landsat-8 LST data, respectively, covering 28 major cities in China. On this basis, the characteristics of water, vegetation, and LST in these cities were analyzed. Moreover, the UBGS (water or vegetation)–AS–LST relationship of each city was quantitatively explored. The results showed that UBGS and AS have a competitive relationship and jointly affect LST; this competition has a critical point (threshold). When the proportion of UBGS exceeds this value, UBGS replaces AS as the dominant variable for LST, bringing about a cooling effect. In contrast, when AS dominates LST, it causes a warming effect. The critical points between AS and water and between AS and vegetation in 28 major cities in China were 80% and 70%, respectively. The critical point showed an obvious zonal difference. Compared with cities in subtropical and temperate climate regions, the critical point of arid cities is higher, and UBGS exhibited better performance at alleviating the urban thermal environment. The critical point of cities with higher development levels is lower than that of cities with lower development levels. Even areas with relatively low AS coverage are prone to high temperatures, and more attention should be paid to improving the coverage of UBGS. Our research results provide a reference for the more reasonable handling of the relationship between urban construction, landscape layout, and temperature control.

Keywords: urban blue-green space; land surface temperature; cooling effect; artificial surface; China

1. Introduction

Ongoing rapid urbanization has led to the evolution of urban landscape patterns and processes [1–5], resulting in changes in the types of urban surface cover, which in turn has led to changes in the thermodynamic properties of urban surfaces, and given rise to the urban heat island (UHI) effect and other ecological consequences [6–9]. Importantly, over 1000 cities around the world are suffering from the UHI phenomenon [10].

The UHI effect introduces a series of hazards to the urban climate and to residents’ health, such as accelerating the formation of photochemical smog, generating haze, and causing air quality deterioration [11–13], as well as increasing urban energy consumption [14–16], causing various heat-sensitive diseases and even death [17–20]. Therefore, finding a method to alleviate the high temperatures of urban summer has become a current research hotspot in multi-disciplinary fields, such as urban thermal environmental effects, climate change, and urban natural disasters [21–24].
In addition to air temperature [25,26], land surface temperature (LST) is the most widely recognized indicator of the characteristics of the UHI, as it can be used to collect data on a wide range of thermal conditions with the help of satellite images [27]. The launching of various Earth observation satellites provides an effective means for constructing fine land cover maps with a large scale and long-term time series. On this basis, a large number of related studies have proven that the distribution of LST under different land covers has spatial heterogeneity [28–33]. Urban blue-green space (UBGS) is defined as containing both urban green vegetation and water bodies [34,35]. Studies have found that vegetation can reduce the solar radiation absorbed by the ground through shading, photosynthesis, evapotranspiration, and air flow shielding [36–38]. Water lowers the ambient temperature due to its high specific heat capacity and radiation properties (transmission, absorption, reflection of the long-wave part of the radiation spectrum, and atmospheric reverse radiation) [39].

Within the UHI zone, UBGS is a cold spot that has a significantly lower temperature than the surrounding ambient temperature, which can effectively alleviate the high urban temperature. This phenomenon is known as the urban cooling island (UCI) effect [40–42]. When UBGS and AS are distributed in the same region, it is generally accepted that the impact of these two land cover types on LST leads to a competitive phenomenon (the cooling effect of UBGS and the warming effect of AS) and that differences in competition (i.e., the net effect) determine the change in LST [43–45]. To date, the response of this competitive effect to the ratio of AS in metropolitan regions and its impact on the development of a city’s effective measures to mitigate the UHI effect has not received adequate attention. Therefore, this study assumes that there is a threshold (critical point) between UBGS and AS in the competition to affect LST according to the proportion of each factor (Figure 1). It has been shown that the positive effect of AS on LST gradually increases as the proportion of AS increases, while the negative effect of UBGS gradually weakens [46]. When the proportion exceeds the critical point, it overtakes UBGS and becomes the dominant factor of LST, whereas UBGS dominates LST.

Previous studies have attempted to explore the impact of the proportion of UBGS on LST in certain cities. For example, Li et al. [47] reported that a 10% increase in green area coverage could lead to a 0.86 °C drop in the surface temperature in Beijing. Similar results were also found by Kong et al. [48] in Nanjing, and Xiao et al. [49] in Vienna. Roy et al. [50] used long-term Landsat series data to study the relationship between LST and urban growth in Bangladesh’s Chattogram metropolitan area, and discovered that in order to minimize the LST and UHI impacts caused by land cover changes, a certain proportion of vegetation and water body presence should be guaranteed for every 0.25 km² rectangular urban unit. Although Myint et al. [43] and Liu et al. [51] studied the competitive effects of urban impervious surfaces and vegetation on LST, the cooling effect of water bodies has been neglected. However, the urban landscape is a mixture of multiple land cover types. In a given region, LST is not only affected by a certain land cover type, but by the intricate interaction of various land cover types [52–55]. Therefore, this study was initiated based on the two major types of land cover with a warming effect (AS) and cooling effect (UBGS) on LST to find the critical point affecting LST, so as to provide a reference for alleviating the high urban temperature problem by optimizing the proportion of these two types of land covers. In addition, it should be noted that the influence of the ratio of AS to UBGS on the local microclimate varies significantly with different climatic conditions and urban development levels [56–58]. Previous studies have mostly focused on a specific city, which is not conducive to summarizing the general laws of the UBGS–AS–LST relationship.
Figure 1. Concept graph showing the combined effect of UBGS (green) and AS (blue) on LST at various AS proportions. In the figure, when the proportion of AS is low, the cooling impact of UBGS is better established than the heating impact of AS, and UBGS is the dominant variable; when the proportion of AS exceeds the critical point, this is reversed.

Taking this into account, we originally chose 28 representative urban areas in China as the study area, which have different levels of economic development and are located in different climate zones. Then, Sentinel-2 high spatial resolution satellite imagery (10 m) and Landsat-8 Operational Land Imager and Thermal Infrared Sensor (Landsat-8 OLI/TIRS) data covering 28 major cities in China were used to produce detailed urban land cover and LST distribution maps, respectively. On this basis, the characteristics of the water body, vegetation, and LST in these cities were analyzed, and the UBGS–AS–LST relationship of each city was quantitatively explored from the perspective of competition. The specific objectives of this study were as follows: (1) to examine the proportion of UBGS and the distribution of LST in the study area, and to understand the overall AS–UBGS–LST relationship; and (2) to investigate the AS–UBGS–LST relationship under different climatic backgrounds and economic development levels. In general, this study aimed to provide an understanding of the potential mechanism of urban AS and UBGS jointly affecting LST, which could be beneficial to urban UHI mitigation decisions, especially during the summer daytime.

2. Study Area

China is the most populous developing country, and its land area ranks third in the world (approximately 9.6 million km²). Moreover, China’s vast territory makes it
diversified in climate types and rich in plant species. According to the Köppen–Geiger climate classification [59], China traverses five climatic zones, as displayed in Figure 2A: (1) the tropical climate zone (fundamentally jungle and tropical rainstorm tropical jungle); (2) the subtropical climate zone (principally expansive evergreen-leaved backwoods and blended timberland); (3) the temperate and sub-frigid zone (predominantly deciduous wide-leaved woods, coniferous woodland, and blended woodland); (4) the arid climate zone (essentially coniferous woods, grassland, and shrubs); and (5) the frigid climate zone (mainly alpine grassland meadow shrubs). In addition, since the reform, the process of urbanization in mainland China has accelerated; some vegetation areas have been occupied by urban construction, and the intensity in different cities varies greatly. Such differences between natural and human factors have resulted in significant differences in urban landscapes, making it an ideal research area to study the combined effects of UBGS and AS on LST.

Figure 2. (A) Locations of China’s 28 major cities, with markings of different sizes and colors representing cities at different development levels. In addition, the base map shows five climatic zones in China. (B–E) Land cover maps of four agent cities extracted from the Esri 2020 Land Cover dataset: Beijing, Zhengzhou, Wuhan, and Nanchang. (F–I) Their corresponding LST distribution maps.

In total, 28 significant metropolitan regions in China were selected, including 23 provincial capitals, four municipalities, and one extraordinary financial zone. All these urban areas have encountered China’s fast urbanization process and witnessed changes in the metropolitan environment and micro- and macro-climate. These cities are mainly located in three climate zones, which are widely distributed in China (subtropical climate zone, temperate and sub-frigid climate zone, and arid climate zone). We also sought to study further the discrepancy of the UBGS–AS–LST relationships among cities at different development levels. According to the list of city levels, we divided the 28 cities into first-tier cities, new first-tier cities, second-tier cities, and third-tier cities [60].
3. Data and Methods

3.1. Land Cover Mapping: The Esri 2020 Land Cover Dataset

The ESRI 10 m Land Cover 2020 map was derived from ESA Sentinel-2 images with a resolution of 10 m. It combines land use and land cover (LULC) predictions from 10 categories throughout the year to produce a representative snapshot of 2020. The map was generated by Impact Observatory’s deep learning AI land classification model, trained with a massive dataset of billions of human-labeled image pixels developed by the National Geographic Society [61]. The model achieves an overall accuracy of 86% with the validation set (https://www.arcgis.com/home/item.html?, accessed on 1 August 2021). The global map was produced by applying this model to the Sentinel-2 2020 scene collection of the Microsoft Planetary Computer, and processing over 400,000 Earth observations (https://livingatlas.arcgis.com/landcover/, accessed on 1 August 2021). The output provides a 10-class map of the surface, including water, vegetation type, bare surface, crops, and built area. In our exploration, we characterized the land class of vegetation by blending the trees, grass, flooded vegetation, and scrub/shrubs. Water and built areas were defined as urban blue space (water) and artificial surface (AS), respectively. We calculated the total proportion of UBGS and AS in each city to examine the differences between cities with different climate zones and different development levels.

3.2. LST Retrieval from Landsat-8 Images

In order to map the LST distribution of the 28 cities, we acquired all accessible Landsat-8 OLI/TIRS images that cover the 28 cities from June to August over the last five years (2017–2021), with a maximum cloud cover of 30% (Table S1). All Landsat-8 images were downloaded from the United State Geological Survey Earth Explorer website (http://earthexplorer.usgs.gov/, accessed on 1 July 2021).

Since it is difficult to acquire near-real-time atmospheric profile data when the satellite passes through the research region, we adopted a method that required only the normalized vegetation index (NDVI) and the top of the atmosphere (TOA) spectral radiance to retrieve LST [62]. The TOA spectral radiance and reflectance of the Landsat-8 OLI/TIRS images can be obtained from the parameter information in the header file. Using ENVI software, a moderate spectral resolution atmospheric transmittance algorithm and computer model (MODTRAN)-based fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) model was utilized to perform radiation calibration and atmospheric correction on Landsat-8 OLI/TIRS images [63]. Thus, by adopting the conversion formula, the spectral radiance values of the Landsat-8 thermal infrared bands were converted to at-sensor brightness temperatures, under the assumption of uniform emissivity [64]:

\[ T_{sensor} = \frac{K_2}{\ln(K_1/L_\lambda + 1)} \]

where \( T_{sensor} \) is the effective at-sensor brightness temperature in kelvin (K), \( L_\lambda \) is the TOA spectral radiance in W/(m\(^2\)·sr·µm), and \( K_1 \) and \( K_2 \) are the calibration constants. For Landsat-8 TIRS, \( K_1 \) is 774.89 W/(m\(^2\)·sr·µm) and \( K_2 \) is 1321.08 K for band 10 (http://landsat.usgs.gov/Landsat8_Using_Product.php, accessed on 1 July 2021).

The \( T_{sensor} \) values acquired above were referenced to a black body, which is highly unique to the properties of real objects. Along these lines, it was important to correct the spectral emissivity, and the LST based on the satellite brightness temperature (\( T_{sensor} \)) was determined using the following equation [65]:

\[ \text{LST} = \frac{T_{sensor}}{1 + (\lambda \times T_{sensor}/\alpha) \ln(\varepsilon)} \]

where LST is the LST in K, \( T_{sensor} \) is the black body temperature and also the satellite brightness temperature in K, \( \lambda \) is the wavelength of the emitted radiance in meters, and \( \alpha = 1.438 \times 10^{-2} \text{ mK}; \varepsilon \) is the surface emissivity.
For $\varepsilon$, water (NDVI < 0) was assigned a value of 0.9925, urban artificial surface and uncovered soil (0 \leq \text{NDVI} < 0.15) were allocated a value of 0.923 [66], and vegetation (NDVI > 0.727) was allotted a value of 0.986 [67]. Otherwise, there was a corresponding relationship with the NDVI through the following equation [68]:

$$
\varepsilon = 1.0094 + 0.047 \ln(\text{NDVI})
$$

(3)

The NDVI was derived as follows:

$$
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
$$

(4)

where RED is the red band and NIR is the near-infrared band.

In this investigation, we used the average LST of the past five years to generate the final LST map for each city based on the following considerations: (1) This study covers a wide area and a variety of climate types. The use of a single image will lead to some cities being affected by meteorological conditions (e.g., rain and cloudy) with redundant Landsat-8 images. (2) Cloud pollution exists in Landsat-8 images to a greater or lesser extent, and the cloud removal of a single image will cause the loss of the LST value.

3.3. Urban Area Extraction

In accordance with the strategy proposed by Zhou et al. [69], we extracted the urban areas of 28 cities. We originally created an exhaustive building intensity (BI) map from the land cover map of every city utilizing a 1 $\times$ 1 km moving window. Then, with a limit of 50%, the BI map was isolated into high- and low-intensity built-up patches [70]. Finally, high-intensity built-up building patches were assembled to obtain a minimal metropolitan region. The urban areas of the 28 major cities ranged from 443.26 km$^2$ (Yinchuan) to 3777.54 km$^2$ (Beijing). The urban area extraction results of four agent cities in China (Beijing, Zhengzhou, Wuhan, and Nanchang) are displayed in Figure 2B–E.

3.4. Investigation of the AS–UBGS–LST Relationship

In accordance with Myint et al. [43], we set up a progression of 360 $\times$ 360 m sample grids inside each urban area. This framework scale finds a balance between ensuring land cover subtleties and breaking down their effect on LST. On this basis, by overlaying the LST distribution map and land cover map on the grid layer, we can calculate the average LST of each grid and the proportion of each land cover type in each urban area. In this study, we investigated the grid cells (pure grid cells) containing only AS, water, and vegetation to exclude the impact of other land cover types on LST [51]. The chosen grid samples were separated into 10 groups according to the proportion of AS, i.e., 0–10% (Group I), 10–20% (Group II), . . . , and 90–100% (Group X).

Figure 3A delineates the grouping results for the grid cell samples from Wuhan, for instance. Here, we arbitrarily chose a grid cell sample in each group to show the structure of the land cover, as displayed in Figure 3B. Then, we further separated each group into 50 intervals on average according to the proportion of AS. Since the number of grid cell samples in each interval might be unique, we only took one of the grid samples, whose proportion of AS was the median of the interval, as an agent of each interval (Figure 3C). This guaranteed an equal number of grid cell samples in each group, which confirmed the inter-group comparability of the subsequent regression results. This ensured that the same number of grid cell samples were in each group and guaranteed that the results of subsequent regression were comparable between groups.
Furthermore, we established regression models for each group. The proportion of UBGS (water or vegetation) to AS of the grid cells in each group was taken as the independent variable, while the average LST was taken as the dependent variable, and the variable with the largest regression coefficient was viewed as the dominant variable influencing the LST of the group. Since each grid contains three types of land cover, AS, water, and vegetation, there was a multicollinearity phenomenon when their proportions were included in the regression model together. To alleviate this problem, we used the hierarchical regression model (HRM) [71] by adjusting the third independent variable, and examined the AS–water–LST and AS–vegetation–LST relationships.

HRM is a bi-layer linear regression model [72,73]. The first layer consists of control variables and a dependent variable, and the second layer is established by inserting independent variables utilizing the “enter” technique, as displayed in the following:

$$LST_i = \alpha_i UBGS_i + \beta_i AS_i + \epsilon_i$$  \hspace{1cm} (5)$$

where $\alpha_i$ is the coefficient of UBGS (water or vegetation), $\beta_i$ is the coefficient of AS, and $\epsilon_i$ is the intercept of group no. $i$ ($i = I, II, \ldots, X$). Here, the regression coefficient estimates the extent of the impact of UBGS and AS on LST. On the premise of the conceptual graph in Figure 1, when the proportion of AS is low (e.g., Group I, no. $n$), if $\alpha_1 > \beta_1, \ldots, \alpha_n > \beta_n$, UBGS is considered to be the dominant variable. Otherwise, when the proportion of AS is high (e.g., group no. $(n + 1)$, no. $X$), if $\alpha_{n+1} < \beta_{n+1}, \ldots, \alpha_X < \beta_X$, AS is viewed as the dominant variable. In this vein, $10^\circ N\%$ is the critical point of the competitive effect of AS and UBGS on LST within the city.

4. Results
4.1. Characteristics of the AS, UBGS, and LST within the 28 Major Urban Areas in China

As shown in Table S2, the overall AS, water, and vegetation proportions and LST values of 28 major cities in China were calculated on the urban scale, and the results were
further counted according to the climate zone and development level (Figure 4). The overall proportion of AS, water, and vegetation in these urban areas ranged from 44.99% (Harbin, HB) to 76.90% (Shanghai, SH), from 0.75% (Urumqi, UQ) to 23.33% (Wuhan, WH), and from 3.65% (Shanghai, SH) to 29.02% (Fuzhou, FZ), respectively, and the LST over the urban areas ranged from 27.17 °C (Shenzhen, SZ) to 38.67 °C (Urumqi, UQ).

According to Figure 4A, the overall proportion of water in subtropical cities was 10.58% ± 4.19%, higher than that in temperate zones (2.67% ± 0.45%) and arid zones (2.21% ± 1.13%); the proportion of AS in temperate cities (62.69% ± 2.71%) was higher than that in subtropical zones (58.81% ± 4.20%) and arid zones (60.94% ± 1.85%), while the total proportion of vegetation in arid zone cities was the highest (18.15% ± 4.07%). Meanwhile, it can be observed that the boxes of AS, water, and vegetation in subtropical cities were longer than those in temperate and sub-frigid and arid zones, indicating that the corresponding values were more volatile. The box of AS in the arid zone city was the shortest, and the data were the most concentrated, while the box of water and vegetation in the temperate and sub-frigid zone city was the shortest, and the data were the most
concentrated. In addition, the median LST of the subtropical cities was 0.36 °C and 1.12 °C higher than that of temperate and sub-frigid and arid zone cities, respectively (Figure 4B). Temperate cities had the shortest LST cabinets, and the temperature fluctuations between cities were small.

Figure 4C shows that the proportion of AS in first-tier cities (67.25% ± 4.17%) and new first-tier cities (62.15% ± 6.33%) is significantly higher than that in second-tier cities (58.29% ± 2.23%) and third-tier cities (59.30% ± 2.75%). The new first-tier cities had the highest proportion of water (8.16% ± 5.20%), followed by first-tier cities (6.37% ± 2.74%) and second-tier cities (6.10% ± 3.76%), and the third-tier cities had the lowest proportion of water (5.67% ± 4.58%). The third-tier cities had the highest proportion of vegetation (17.85% ± 5.76%), followed by second-tier cities (17.55% ± 4.67%) and first-tier cities (15.66% ± 7.75%), and the proportion of vegetation in the new first-tier cities was the smallest (11.06% ± 5.49%). The box plot of water in first-tier cities was the shortest and the proportion of water area was the most concentrated, while the box body of AS in the new first-tier cities was the longest, reflecting the great differences in urban construction among the new first-tier cities. The vegetation box in the third-tier cities was the shortest, and the greening levels between urban areas were relatively close. In terms of the median LST, first-tier cities (33.57 °C) and new first-tier cities (34.27 °C) had a higher LST than second-tier (32.72 °C) and third-tier cities (32.89 °C) (Figure 4D). First-tier cities had the longest LST box, and the temperature difference between the cities fluctuated greatly. This is related to the large latitude spacing of these four cities across China. Overall, we found that the cities with a higher development level had a higher proportion of AS and a correspondingly higher LST.

Figure 5 shows UBGS (water/vegetation) proportions and the homologous LST along the proportion slopes of AS within the 28 major urban areas. It can be observed that with the increase in AS increments, the extent of water and vegetation decreased nonlinearly in many urban areas, while it decreased linearly in a few urban areas (e.g., CC, HB, and TY). However, in some cities, such as CS, FZ, HT, KM, NC, NJ, SJZ, and YC, as the proportion of AS increased, the vegetation curve showed a slight increment in a few regions, and the AS coverage rate in these areas was 10–40%; thus, they might profit from metropolitan greening arrangements and developments. Furthermore, there was a nonlinear positive connection between the proportion of AS and LST in most cities (except SH, WH, and TY).
4.2. Combined Effects of AS and UBGS on LST

Figure 6A,B demonstrates the overall HRM outcomes for the 28 urban areas. It can be observed that as the percentage of AS increased, the influence of water and vegetation on LST steadily declined, while the influence of AS gradually strengthened, which was in accordance with the findings of previous studies [44,46]. Obviously, AS and UBGS had a significant competition effect on LST: when the percentage of AS in an area was relatively low, the influence of UBGS on LST was more significant than that of AS. Moreover, although there were small fluctuations, the influence of AS on LST gradually increased with the increase in the AS percentage, and when the percentage reached a certain value (critical point), AS supplanted UBGS and became the dominant land cover type affecting LST. These outcomes confirmed the originally proposed conjecture of this review. The critical point where AS competes with water was 80% AS (Figure 6C, $R^2 = 0.45$, $p < 0.05$), while the critical point of competition between AS and vegetation was 70% AS (Figure 6D, $R^2 = 0.40$, $p < 0.05$).

4.3. Critical Points of Cities with Different Climatic Zones and Development Levels

In this section, we quantified the differences among the AS and UBGS competitive critical points in the 28 cities across the three climatic zones (Figure 7) and four stages of development (Figure 8). Although the outcomes for arid, first-tier, and third-tier cities fluctuated, possibly due to their smaller sample sizes, the competition phenomenon and the critical point remained.
In terms of climate zones, we found that the competition critical points of AS and water in cities in subtropical, temperate, and arid zones increased successively, with values of 70% (Figure 7A, $R^2 = 0.52$, $p < 0.05$), 80% (Figure 7B, $R^2 = 0.44$, $p < 0.05$), and 90% (Figure 7C, $R^2 = 0.39$, $p < 0.05$), respectively. The critical points of AS and vegetation had similar patterns in cities in subtropical, temperate, and sub-frigid, and arid regions, with values of 60% (Figure 7D, $R^2 = 0.46$, $p < 0.05$), 70% (Figure 7E, $R^2 = 0.41$, $p < 0.05$), and 80% (Figure 7F,
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\[ R^2 = 0.34, \ p < 0.05 \], respectively. In terms of the urban development level, the critical points of AS and water in first-tier cities, new first-tier cities, second-tier cities, and third-tier cities were 70% (Figure 8A, \( R^2 = 0.42, \ p < 0.05 \)), 80% (Figure 8B, \( R^2 = 0.48, \ p < 0.05 \)), 80% (Figure 8C, \( R^2 = 0.49, \ p < 0.05 \)), and 90% (Figure 8D, \( R^2 = 0.39, \ p < 0.05 \)), respectively; the critical points of AS and vegetation were 70% (Figure 8E, \( R^2 = 0.38, \ p < 0.05 \)), 70% (Figure 8F, \( R^2 = 0.43, \ p < 0.05 \)), 60% (Figure 8G, \( R^2 = 0.48, \ p < 0.05 \)), and 80% (Figure 8H, \( R^2 = 0.30, \ p < 0.05 \)), respectively. Overall, the critical point of cities with a low development level was higher than that of cities with a high development level.

5. Discussion
5.1. Significance and Implications of the Critical Point

Previous studies have confirmed that blue-green spaces play a cooling role in cities. The water body has a large specific heat capacity, low thermal conductivity, and radiance [74]. In addition, it absorbs less heat than impervious surfaces and buildings since it has fewer surfaces that absorb and store energy under solar radiation [75]. Vegetation cools cities by evaporating water, storing carbon dioxide (CO\textsubscript{2}), and providing shade [76]. On the other hand, AS mainly refers to roads, parking lots, and buildings, which are large in size, absorb sunlight, and release heat, creating the UHI effect [77].

Many studies have reported the impact of various land cover types on LST. For example, Lemus-Canovas et al. [78] found that green urban areas in Barcelona’s metropolitan area had temperatures up to 2.5 °C lower than those in urban areas. Adams and Dove [79] found a 35 m wide river caused an ambient temperature reduction of 1–1.5 °C. However, most of these studies assessed the impact of a certain land cover type on LST. In fact, land cover types in urban areas are diverse, and the combined effects of land cover types on LST are complex. This study considered the types of land cover that have warming and cooling effects on LST and explored the impact of this effect on LST along the gradient of the AS ratio from the perspective of competition, which can help us to understand more clearly the potential mechanism of how UBGS and AS jointly affect LST. In addition, previous studies focus mostly on single cities, which is not conducive to the comparison of results. This study quantitatively investigated the UBGS–AS–LST relationship in 28 major cities in China. This not only helps to summarize the general law of this joint effect in multiple regions, but it also reflects its changing trend in different climatic zones and its relationship with the level of urban development. Concurrently, in the context of global urban warming, the critical point we obtained has important practical significance for balancing urban construction and temperature regulation. For example, our results showed that when the AS coverage of an area exceeds 70% or 80%, high-temperature events were easily triggered, and some targeted measures, such as adjusting the spatial layout of AS, are necessary to make up for the insufficient cooling efficiency of UBGS. In the process of urbanization, increasing amounts of water and vegetation are inevitably transformed into AS, which in turn leads to the UHI effect; however, an in-depth understanding of the combined effect of land cover on LST can raise concerns over dense urban construction. Furthermore, taking the AS ratio (not to exceed the critical point) as a warning line for urban high-intensity construction areas will effectively prevent the further rise of LST during the daytime in summer.

It is worth noting that the critical points have spatial differences. For cities with a humid climate and abundant rainfall, measures can be taken to protect the existing water area and water quality and expand the vegetation area to cool down. For cities with a mild climate and less rainfall, planting trees and grass seems to be a reasonable choice for cooling. In addition, the critical point of subtropical cities and first-tier cities is lower, and more attention should be paid to the reasonable space matching of UBGS and AS in urban construction to avoid the large-scale contiguous occurrence of AS. Indeed, in cities with a high level of development, the available land in the city is limited and land resources are costly. Importantly, it is impractical to over pursue UBGS coverage. More attention should be given to various cost-effective means, such as careful urban overall planning [80], road cooling [81–83], urban green roofs [84–86], and building materials cooling [87,88], etc.
We also found that the critical points of water and vegetation are 80% and 70%, respectively, which means that in most cities, water is a more powerful source of cooling than vegetation. This phenomenon was also detected by Wang and Murayama [89] and Chen et al. [33]. However, considering the climatic conditions and practical operability, increasing vegetation coverage is a more universal and feasible cooling method for these cities. In addition, different types of urban vegetation provide different cooling effects. In view of the large number of studies proving that trees have a stronger cooling effect than grass and shrubs, we prefer to plant more trees in cities affected by high temperatures [51,90]. Alternatively, urban vegetation can be designed at multiple levels, combining layers of shrubs and small trees under a larger canopy to make it more “forest-like” for better cooling [91].

5.2. Impact Factors for the Critical Point

The transformation of land cover types will lead to changes in the characteristics of the underlying urban surface regarding albedo, emissivity, specific heat capacity, and thermal conductivity, as well as a variety of heat balance processes, such as radiation flux, thus affecting the urban thermal environment [92]. Krishna [93] and Yang et al. [94] demonstrated that this change is not consistent across different climatic zones. At the same time, different urbanization levels have different effects on LST [95,96]. Therefore, this study investigated the UBGS–AS–LST relationship from two aspects: climate background and urban development level. The urban background climate often determines the local landscape pattern and main vegetation types. We found that the critical point along the proportion gradient of AS is higher in arid cities, which means that less blue-green space is required to offset the warming effect of AS, and urban areas are easier to warm up under a humid climate. This is mainly due to the obvious decrease in urban convective efficiency under humid climate conditions, resulting in local warming. In rainy and humid climate areas, the convective effect can increase the average daytime temperature of urban areas by approximately 3 °C [97]. In addition, the surface roughness has an important influence on the urban LST. Different surface cover types have different roughness. The roughness of the forest is greater than that of the grass; therefore, it is easier to cause the turbulent movement of the atmosphere, which helps the surface heat to diffuse into the atmosphere, thereby reducing the surface temperature. The urban vegetation in humid areas is mostly wooded areas, with a rough surface and high convective heat dissipation efficiency. In contrast, the convection efficiency of cities in these areas has decreased by 58%, causing the UHI effect [97]. In semi-arid areas, plants are mostly low-lying grasslands, while the urban landscape surface is rougher and has higher heat dissipation efficiency, which will inhibit the UHI effect and even cause the UCI effect [97]. In addition, the arid climate zone is an area with a small population density in China, with low anthropogenic heat emissions.

The main characteristics of urbanization are the expansion of AS and the agglomeration of the population. The urban structure and artificial buildings alter the atmospheric convection effect and reduce the efficiency of heat transfer from the ground to the atmosphere. In addition, buildings, sidewalks, and other building structures store more heat than vegetation and soil, which directly leads to an increase in LST in urbanized areas [98,99]. The higher the level of urbanization, the greater the population density, and the more heat generated by human and production activities, which also promotes urban warming [100,101]. This is also consistent with our finding that cities with higher levels of urbanization have lower critical points.

5.3. Limitations and Uncertainties

This study has certain limitations. Firstly, this study only investigated the combined effects of UBGS and AS on LST and lacked the corresponding air temperature for comparison. This is mainly due to the inability of remote sensing data to capture latent heat flux [102]. This may have had an impact on the accuracy of the study’s findings. Secondly, although we used pure pixels when analyzing the UBGS–AS–LST relationship, various
land cover types in urban areas are diverse, and mixed pixels are more common. Adjacent pixels and other adjacent land cover types will also cause some abnormal results due to heat flow to the surrounding area; for example, the negative coefficients of individual AS and the positive coefficients of some UBGS appeared in HRM [51]. Thirdly, although we analyzed the UBGS–AS–LST relationship of 28 major Chinese cities as a whole, and considered different climate zones and economic development levels, the basis for city selection may not be sufficient. Differences between cities in the same climate zone or level of economic development, as well as possible differences in results from urban topography, were ignored. In addition, the shape and depth of water bodies, as well as the height and health of vegetation, were not considered in this study, and the effects of some climatic and anthropogenic elements, such as wind speed and direction, the density and height of buildings, street direction, and anthropogenic emissions, were also ignored [103–105]. Lastly, with the development of technology and the application of data, relevant research results will continue to improve in the future.

6. Conclusions

This study revealed the combined effect of UBGS and AS on LST in 28 major urban areas in China from the perspective of competition and discussed the differences of the combined effect in various climatic zones and cities at various stages of development. The main results are as follows:

(1) There is indeed a critical point in the proportional gradient of UBGS in each city. When the proportion of UBGS exceeds this value, UBGS will substitute AS and become the leading variable in LST, causing a cooling effect; otherwise, AS will dominate LST, resulting in a warming effect.

(2) The overall results for 28 major cities in China show that the critical points between AS and water and between AS and vegetation are 80% and 70%, respectively, meaning that water is a more powerful source of cooling than vegetation in most cities.

(3) The critical point has obvious zonal differences. In comparison to cities in subtropical, temperate, and sub-frigid climatic zones, the critical point of cities in arid climate zones is higher, which means that these cities have better performance in alleviating the urban heat island effect.

(4) The critical points between cities of different development levels are quite different. Overall, the critical point of economically developed cities is lower than that of less developed cities, which means that these cities have less temperature flexibility, and even relatively low AS coverage rates are prone to heat island effects.

Supplementary Materials: The following can be downloaded at: https://www.mdpi.com/article/10.3390/rs14030448/s1, Table S1. Landsat-8 OLI/TIRS images of the 28 major cities in China used in this study. Table S2. The total proportions of AS, water, and vegetation in the urban areas of 28 major cities in China and their corresponding average LST.

Author Contributions: Conceptualization, L.C.; data curation, L.C., X.C. and X.W.; formal analysis, L.C.; funding acquisition, X.W. and X.L.; methodology, X.C. and X.W.; software, L.C., C.Y. and X.L.; supervision, X.W.; writing—original draft, L.C.; writing—review and editing, X.W. and X.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (Grant No. XDA23040402); National Natural Science Foundation of China (Grant No. 41571202, 41171426); Natural Science Foundation of Hubei Province, China (Project No. 2014CFB330).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.
Data Availability Statement: Data associated with this research are available online. The Esri 2020 Land Cover dataset is available for download at https://livingatlas.arcgis.com/landcover, accessed on 1 August 2021. The Landsat 8 dataset is available for download at http://earthexplorer.usgs.gov/, accessed on 1 July 2021.

Acknowledgments: We would like to thank the handling editor and the anonymous reviewers for their careful reading and helpful remarks.

Conflicts of Interest: The authors declare no conflict of interest.

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