How to plan urban green space in cold regions of China to achieve the best cooling efficiency

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Abstract
With the acceleration of urbanization, the urban heat island (UHI) effect has intensified. Urban green space can retard the UHI effect. However, most existing studies have only focused on hot regions, while little attention has been given to cold regions that also have summer heat protection requirements. Furthermore, existing research has not classified urban green spaces according to the presence or absence of water, which can lead to inaccurate results. This paper takes four cities in cold regions of China as examples and studies the cooling effects of two different types of urban green space. The results indicate that in cold regions of China, green spaces containing water bodies have a stronger cooling effect than those without water. For green spaces without water, the cooling intensity is related to the background temperature and green space areas, while for green spaces containing water bodies, the area of the internal water body is the key influencing factor. Specifically, there is a threshold value of efficiency (TVoE) for the green space areas without water in cold region cities of China, which is approximately 0.52 ha, while there is no TVoE for the green space areas containing water bodies. Additionally, there is a TVoE for the water/land ratio of the green spaces containing water bodies of approximately 0.5. The methods and results of this study can provide a reference for future research and for urban planners and managers designing urban green spaces.

Keywords Urban heat island · Urban green space · Urban cold island · Threshold value of efficiency · Water/land ratio · Urban planning · Climate adaptation

Introduction
The Department of Economic and Social Affairs of the United Nations Secretariat (UN DESA) Population Division’s “World Urbanization Prospects (2018 Revision)” (United Nations 2018) reported that more people live in urban areas than rural areas globally. By 2050, 68% of the global population is expected to live in urban areas. At present, the level of urbanization in Asia is close to 50%, and this region has become the new focus of global urbanization. In China, the most populous country in the world, the urbanization rate reached 60.6% at the end of 2019, and this rate is predicted to rise to 75% by 2030 (Stanley 2019).

Rapid urbanization has brought significant changes in land use, and with the loss of green spaces, coupled with the substantial increase in the amount of heat released artificially, the urban climate has deteriorated significantly, and the urban environment has deteriorated seriously (Polli et al. 2016; Jaganmohan et al. 2016; Kaza 2013; Chrysoulakis et al. 2013). An important phenomenon is the generation of urban heat islands (UHIs). UHIs are urban areas that are warmer than surrounding non-urban areas (Manoli et al. 2019; Voogt and Oke 2003; Oke et al. 2017; Kalnay and Cai 2003). Their presence can increase water consumption and energy use, aggravate environmental pollution, and cause harm to human health (Sun et al. 2014; Santarnouris and Kolokotsa 2015; Akbari and Kolokotsa 2016; Wong et al. 2016; Zhou et al. 2018; Churkina et al. 2017). A considerable number of studies have demonstrated the significant cooling effect of urban green spaces, which can form urban cold islands...
(UCIs), improve people’s outdoor thermal comfort, and significantly reduce the environmental pressure generated by urban heat islands (Oke 1989; Fan et al. 2015; Kong et al. 2014; Li et al. 2016).

Many scholars have studied the cooling effect of urban green spaces. Studies have shown that the composition, configuration, shape and size of green space patches are important factors determining their cooling effect (Asgarian et al. 2015; Ren et al. 2016; Taleghani 2017). There are large differences in the cooling effect of different green space compositions and configurations. Trees can effectively block direct sunlight, and their cooling effect is significantly higher than that of surrounding herbs (Feyisa et al. 2014; Teresa et al. 2016) and a single-layer structure will produce a stronger cooling effect than a multi-layer green space structure (Volker and Kistemann 2015). Some studies have shown that the shape index of a green space plays an important role in its cooling effect. Cao et al. found that the irregular and belt-shape parks tend to have low cooling intensity (Cao et al. 2010). Yu et al. indicated that circular and square green spaces are significantly correlated with land surface temperature (LST) (Yu et al. 2017). Liang et al. found that the area of a green space is negatively correlated with the LST within a certain threshold; that is, within a certain threshold, the larger the green space area is, the lower the LST. (Weng et al. 2011) Mikami and Sekita found that if the green space area exceeds 20 ha, its cooling intensity will not increase with a further increase in area (Mikami and Sekita 2009). Moreover, Jaganmohan et al. concluded that increasing the spatial complexity of smaller green spaces has a negative effect on the cooling intensity but that increasing the spatial complexity of green spaces larger than 5.6 ha has a positive effect (Jaganmohan et al. 2016).

Yu et al. (2015, 2018) proposed the concept of the threshold value of efficiency (TVoE) to obtain the optimal scale of urban green space and deduced an idealized urban thermal security pattern model to optimize urban green space design (Yu et al. 2021a, b). Studies have shown that the TVoE is highly correlated with urban background climate conditions (Le et al. 2019; Yang et al. 2020; Fan et al. 2019) Le et al. found that the TVoE of green space in a tropical city (Hanoi) is 1 ha (Le et al. 2019). Yang et al. (2020) found that the TVoE of green space in a high-latitude city (Copenhagen) is 0.69 ha. Fan et al. investigated seven low-latitude Asian cities and showed that the TVoE of the cities ranged from 0.6 to 0.95 ha (Fan et al. 2019). Le et al. (2019) found that the TVoE in cities with a Temperate monsoon climate and a Mediterranean climate is generally approximately 0.5 ha. Therefore, it is necessary to conduct research based on specific climate regions with different background climatic conditions. The cold region is one of five climatic regions in China. It refers to the area where the average temperature of the coldest month is (-10) – 0 °C and the average number of days when the daily temperature is ≤ 5 °C is between 90 and 145 days. In summer, even in cities in cold regions, there are times when the temperature in the city is high. Therefore, it is necessary to pursue research in cold regions to explore how to plan urban green spaces in cold regions of China to achieve the best cooling efficiency. However, existing research has mainly focused on cities in hot regions or individual cities in cold regions or has merely taken individual parks as examples. Meanwhile, the number of studies on specific climatic regions is relatively low, and there is a lack of comprehensive research and comparative analysis in cold regions. These studies also have the defects of a small number of samples and a single type of green space. Additionally, existing research shows that water bodies also have strong cooling effects (Peng et al. 2020; Wu et al. 2020; Yu et al. 2020a). Water are heat sinks during all seasons which can slowly release heat energy into the air (Yu et al. 2020). Sun and Chen found that the mean cooling intensity and efficiency of water bodies are 0.54 °C/hm and 1.76 °C/hm/ha (Sun and Chen 2012). Studies have also found that the area and shape index of the water body are positively and negatively correlated with its cooling effect, respectively (Du et al. 2016; Wu and Ren 2019; Yu et al. 2015). Broadly speaking, urban green spaces include urban blue-green spaces and urban green spaces. Without considering the influence of water bodies, the research results can be inaccurate. Moreover, there are many uncertainties in existing research on green spaces containing water bodies, especially in terms of the threshold size and the optimal proportion of blue-green spaces (Yu et al. 2020c). Therefore, this article conducts a regional study on the cold regions of China, selects four cities as case studies, and divides the urban green spaces into two categories according to whether they contain water. And in this study, we tried to: (1) discuss the relationship between the UCI effect of urban green space and landscape indicators and background temperature; (2) on the basis of a more detailed classification of green space, investigate the optimal green space areas at regional scale (for cold regions in China) by analyzing and calculating the TVoE of the cooling effect of two different kinds of green space in each city; (3) specifically studies the optimal threshold of the proportion of blue-green spaces for green spaces containing water bodies. We hope this work can provide a valuable reference for urban planners and managers seeking to mitigate the impact of UHIs.

Methodology

Study area

To obtain a universal law, four cities in cold regions of China are selected for analysis, namely, Beijing, Tianjin, Xi’an, and Zhengzhou. The reasons for selection are as follows: (1) the selected cities are in cold regions of China, and there are requirements for heat protection in summer; (2) there are serious urban heat island effects in the selected cities; and (3) the selected cities can represent the general geographic characteristics of China’s cold regions in terms of
temperature, population density, urbanization rate, and urban structure. The populations and geographic details of these cities are shown in Table 1.

**Data collection and processing**

**Land surface temperature (LST) retrieval**

The same as ambient temperature, land surface temperature is also closely related to human health and thermal comfort (Li et al. 2013). Due to the large scale of the study areas, the limited number of weather stations and the data obtained from ground observations is of poor synchronicity, it is difficult to acquire ambient temperature data that can meet the research needs. Many studies have shown that there is good consistency between the change trend of LST retrieved from remote sensing data and the ambient temperature observed by meteorological stations, and the two data sources have a high correlation (Eliasson 1996; Abutaleb et al. 2015; Mohan et al. 2013; Hu et al. 2019). And many studies use LST to study the urban heat island effect in China (Yang et al. 2010; Gao et al. 2019; Tsou et al. 2017; Liu et al. 2019). Therefore, the difference in LST at different locations were used to study the urban heat island effect in this study. In addition, due to the high building density and building height of the built-up areas and the low sky-view factor in Chinese cities, buildings have strong heat storage performance and do not easily dissipate to the sky. Solar radiation heat is reflected in a building complex multiple times, directly affecting the LST and the outdoor thermal comfort of pedestrians in the area. Under the current situation of China’s built-up areas, the impact of building height on the thermal environment can be reflected in changes in LST. Moreover, although the temperature at night is important for quantifying the urban heat island effect, people basically stay at home at night, at this time, the outdoor thermal comfort has little effect on people. Therefore, this study selects the hottest summer day as the study time period.

1. Inversion methods and results

Previous studies have shown that reliable and accurate LSTs can be obtained by using the radiative transfer equation (RTE) algorithm (Churkina et al. 2017; Ren et al. 2016). Therefore, the RTE algorithm proposed by Jiménez-Muñoz et al. (Taleghani 2017) was chosen to calculate LST in this study.

The principle of the RTE involves estimating the impact of the atmosphere on the surface thermal radiation and then subtracting this part of the atmospheric impact from the total amount of thermal radiation observed by the satellite sensor to obtain the surface thermal radiation intensity. After that, LST can be obtained by converting this thermal radiation intensity. The RTE is calculated as follows:

\[
L_i = \left[\epsilon B(T_s) + (1-\epsilon) L_{\text{atm},i} \downarrow \right] \tau + L_{\text{atm},i} \uparrow
\]

where \(L_i\) is a radiance pixel value received by a satellite sensor, \(\epsilon\) is the surface emissivity, \(T_s\) is the LST, \(B(T_s)\) is the ground radiance, and \(\tau\) is the atmospheric transmittance. The atmospheric transmittance, atmospheric downward radiance, \(L_{\text{atm},i} \downarrow\) and upward radiance can be estimated (http://atmcorr.gsfc.nasa.gov/). Therefore, \(B(T_s)\) can be calculated by Eq. (2), and then the LST can be determined by Eq. (3):

\[
B(T_s) = \left[L_i - L_{\text{atm},i} \downarrow - \tau(1-\epsilon)L_{\text{atm},i} \downarrow \right] \epsilon
\]

\[
T_s = K_2 / \ln(K_1 / B(T_s) + 1)
\]

where \(K_1 = 774.89\) W/(m²·µm·sr) and \(K_2 = 1321.08\) K in Landsat-8 images. Landsat-8 satellite was launched by the National Aeronautics and Space Administration (NASA)

**Table 1 Overview of selected cities**

| City      | Area (km²) | Study area (km²) | Resident population (millions) | Urbanization rate | Location | Climate                       | Average temperature in summer (from June to August) (°C) |
|-----------|------------|-----------------|--------------------------------|-------------------|----------|-------------------------------|--------------------------------------------------------|
| Beijing   | 16,410.54  | 1378.04         | 21.53                          | 86.50%            | 39°56’N 116°20’E | Temperate monsoon            | 31                                                     |
| Tianjin   | 11,966.45  | 176.7           | 15.62                          | 83.15%            | 39°13’N 117°2’E | Temperate monsoon            | 32                                                     |
| Xi’an     | 10,752     | 977.44          | 10.20                          | 74.01%            | 34°15’N 108°55’E | Temperate monsoon            | 32                                                     |
| Zhengzhou | 7446       | 1017.29         | 10.35                          | 73.38%            | 34°75’N 113°65’E | Temperate monsoon            | 32                                                     |

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The study area is the main urban area of each city.
on 11 February 2013. The satellite carries two main payloads—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS)—which are currently used in various fields such as land planning, regional planning, land use, forest monitoring, and agricultural yield estimation (Hang and Rahman 2018; Zheng et al. 2022; Deng et al. 2019; Chen et al. 2021; dos Santos Luciano et al. 2021). Landsat-8 images with high resolution collected in summer 2019 were used as input data for the LST inversion (Table 2). The cloud content of the selected image data is less than 0.03%, which can clearly distinguish all kinds of feature information. During the imaging period, the weather conditions in each city were stable. There was no precipitation the previous day, the wind speed was low, and the overall thermal environment was not affected by rain or wind. This satisfies the research needs and offers good representative at the same time. Figure 1 shows the LST results.

2. Verification of the accuracy of LST results

Studies have shown that the accuracy of LST inversion results based on Landsat-8 TIRS can be verified with MODIS surface temperature products (Zhang and Zhang 2019; Feng et al. 2012, 2013). Obtaining the MODIS surface temperature product–MOD11A1 data, which are approximately half an hour apart from the Landsat-8 image data, can verify the validity of the LST inversion results. This verification method creates 20 random points for the inversion results in ARCGIS software, obtains the data of 2 different inversion results in each city at random points and compares their relations. If the two inversion results have similar trends and compare a strong correlation, the LST inversion based on Landsat-8 has high accuracy and can be used as a research data source. Otherwise, this indicates that the inversion accuracy is low and the inversion result is unreliable. The final result is shown in Fig. 2

Figure 2 shows that the two kinds of LST inversion results obtained from 20 random points in the four cities are highly consistent and highly correlated (R² = 0.94, 0.91, 0.92 and 0.94). Therefore, we believe that the LST inversion results used in this study are valid.

Land cover classification

In this study, ENVI software (Exelis Visual Information Solutions, USA) was used to classify the land cover of the four studied cities with a supervised classification method. The data source was the atmospherically corrected Landsat-8 images of each city from summer 2019 (Table 2).

Firstly, perform radiation calibration on the image to eliminate the error of the sensor itself and determine the accurate radiation value at the entrance of the sensor. Secondly, the actual surface albedo can be obtained through atmospheric correction. Finally, visual interpretation methods were used to select training samples for five types of land cover, namely, green space, cultivated land, construction land, water, and unused land. Green space refers to land covered by vegetation, which is mainly a mixture of grass, shrubs, and trees; cultivated land refers to land on which crops are grown; construction land refers to buildings and impervious land; water refers to rivers, lakes, and ponds; and unused land refers to land other than agricultural and construction land. The accuracy of the land cover classification results of the four cities were 83.6%, 86.9%, 85.2% and 88.8%.

Sample green space extraction

In previous studies on the cooling effect of urban green space, there were problems such as a small number of samples, only considering a single type of green space, and ignoring interference from other cooling factors. Due to the limited accuracy of land cover classification results, this study uses high-resolution Google Earth satellite images to select sample green spaces for each city based on the results of land cover classification. The selection principles are as follows: (1) the area of the green space is different; (2) the urban green space is classified and selected according to the presence or absence of internal water bodies; (3) there must be a certain distance between the sample green spaces to prevent mutual interference due to proximity; and (4) large external areas of water within 100 m of the green space are avoided because they can cause inaccurate data due to the influence of the external water (Fan et al. 2019). According to this principle, based on the results of the land cover classification and supplemented by high-resolution Google Earth images, the boundary of the sample green space vector was drawn in ArcGIS software (Esri, Redlands, CA, USA). After screening, in each city, 30 green spaces without internal water bodies and 20 green spaces with

| Table 2 | The information from Landsat 8 images |
|---------|--------------------------------------|
| City    | Landsat Scene ID                     | Acquisition date and time (GMT) |
| Beijing | LC81230322019229LGN00                | 03 Aug 2019; 02:42:10           |
| Tianjin | LC8123032019229LGN00                 | 19 Jul 2019; 03:30:28           |
| Xi’an   | LC81270362019225LGN00                | 21 Aug 2019; 02:18:29           |
| Zhengzhou | LC81240362019188LGN00              | 03 Aug 2019; 03:45:01           |
internal water bodies were selected. The specific locations of the green spaces selected in each city are shown in Fig. 3.

**UCI effect analysis**

In this study, as in the work by Yu, the UCI effect was defined as the difference in LST between a green space and its surrounding urban areas. Two indicators were selected to characterize the UCI effect of green space: the UCI intensity and the UCI extent. UCI intensity refers to the LST difference between the green space and the turning point of the first LST drop outside the patch. The UCI extent is the distance from the edge of the green space to the first turning point of cooling.
To calculate the UCI effect of each green space, we first calculated the average LST inside each selected green patch and then created different numbers of 30 m buffer zones for different types and sizes of green patches until the first turning point of cooling appeared. Finally, the UCI intensity and extent of each green space were obtained, and correlation analyses of the obtained results were carried out with Microsoft Excel software.

**Calculation of TVoE**

Yu et al. (2017) proposed the use of a TVoE to estimate the optimal green patch area. According to the “law of diminishing marginal utility,” before the TVoE is reached, as the area of green patches increases, the UCI effect of green patches also increases significantly. However, after the green patch area reaches or exceeds the TVoE, continuing to increase the patch area will produce a relatively insignificant increase in UCI intensity. Therefore, we believe that it is cost-effective to expand the patch area until the TVoE is reached. This paper used Excel software to conduct logarithmic regression analyses of the green patch areas and UCI intensity. The TVoE occurs where the slope of the obtained logarithmic function is 1.

**Selection of landscape indicators**

Previous studies have shown that the UCI effect of green space is correlated with various landscape indices, and the main influencing factors are the climate background, size,
shape and complexity of the green space (Estoque et al. 2017; Gunawardena et al. 2017; Kuang et al. 2015; Santamouris 2014). The present study started at the patch scale and landscape scale, selected the following indices, performed linear regression analysis, and explored the relationship between the indices and the UCI effect of green space: (1) background temperature (BGT): average temperature inside each green patch; (2) patch area (Area): the area of each green patch; (3) landscape shape index (LSI) and fractal dimension index (FRAC): describes the shape complexity of the green space (Yu et al. 2017, 2018, 2021a, 2021b; Liang and Weng 2010; Le et al. 2019; Yang et al. 2020; Fan et al. 2019). The calculation formula of the LSI is as follows:

$$LSI = \frac{0.25E}{\sqrt{A}}$$  \hspace{1cm} (4)

where \(E\) indicates the perimeter of the patch and \(A\) is the area of the patch. The LSI equals 1 for a circle and 1.13 for a square. The larger the LSI value is, the more complex the shape of the patch. And the FRAC is defined by the equation below:

$$FRAC = \frac{2 \ln (0.25P)}{\ln A}$$  \hspace{1cm} (5)

where \(P\) is the perimeter (m) of patch, \(A\) is the area (\(m^2\)) of the patch. \(1 \leq FRAC \leq 2\). FRAC approaches 1 for shapes with very simple perimeters and approaches 2 for shapes with complex boundaries.

These metrics were chosen based on the following considerations: (1) are the main factors in UCI effect of green spaces; (2) can express the spatial characteristics of green patches; (3) are important for both theory and practice; and (4) are easily obtained and calculated.
Results

The influence of landscape indices on UCI intensity and UCI extent

Basic information

The basic information for each city is shown in Table 3. The data were obtained by analyzing the Landsat 8 images shown in Table 2. For example, in Zhengzhou and Xi’an, the background temperature reached 38.23 °C and 37.38 °C. The recommended WBGT threshold according to ISO 7243 2017 is 32–33 °C if it is considered that people wear summer clothes (0.5 clo) in summer for comfort during outdoor leisure. When the WBGT value of the environment exceeds this value for a long time, safety protection measures should be taken to prevent the human body from suffering thermal damage. This shows that there are times when the temperature in the cities in cold regions in summer is higher than the WBGT value. Therefore, it is necessary to prevent heat in summer in cities in cold regions. As seen in Table 3, urban green space has a strong cooling effect. Among the four cities, the average cooling effect of urban green space was the highest in Beijing, reaching 3.84 °C, and the lowest in Zhengzhou, reaching 1.81 °C. Different types of urban green space have different degrees of cooling. The average cooling intensity of green spaces without water ranges between 1.36 and 1.80 °C. The green spaces containing water bodies have a stronger cooling effect than the green spaces without water, with an average cooling intensity of 2.50–2.86 °C. The difference between the cooling effects of the two different types of green space in Beijing, Tianjin, Xi’an, and Zhengzhou is 0.74, 0.99, 1.28, and 1.12 °C, respectively. The average cooling extent of green spaces with water ranges between 420 and 583.5 m, which is much higher than that of green spaces without water (from 174 to 219 m). Beijing and Xi’an have high NDVI (normalized difference vegetation index) values, and Tianjin has high urban relative humidity.

The influence of background temperature (BGT) on UCI intensity and UCI extent

Figure 4 shows the linear regression analysis results of the background temperature on UCI intensity and UCI extent for two different types of urban green space in each city. For green spaces without water, the BGT of the green space is negatively correlated with the UCI intensity—that is, the higher the average temperature inside the green space is, the worse the cooling effect of the green space. Beijing, Tianjin, and Zhengzhou have strong correlations between the BGT and the UCI intensity, with R^2 values of 0.32, 0.32, and 0.43.
respectively, while Xi'an has a weak correlation, with an $R^2$ of 0.17. For green spaces containing water bodies, there is no correlation between the BGT of green space and UCI intensity. In Beijing and Xi'an, the correlation between the BGT of the green space and the UCI intensity is extremely low, with $R^2$ values of 0.04 and 0.004, respectively, while Tianjin and Zhengzhou have strong negative correlations, with $R^2$ values of 0.51 and 0.37, respectively.

In cold regions, there is no correlation between the BGT of the green space and the cooling extent. For green spaces without water, Tianjin and Zhengzhou have strong correlations, with $R^2$ values of 0.37 and 0.27, respectively, while Xi'an has a weak correlation, with an $R^2$ value of only 0.17. There is almost no correlation between the BGT and the UCI extent in Beijing. For green spaces containing water bodies, Beijing and Zhengzhou are highly correlated, with $R^2$ values of 0.28 and 0.38, respectively, while Tianjin and Xi'an have almost no correlation.

The influence of patch area on UCI intensity and UCI extent

Figure 5 shows the linear regression analysis results of the patch area on UCI intensity and UCI extent for different types of green space in each city. As shown, the area of green spaces without water in each city is positively correlated with UCI intensity to varying degrees—that is, as the area of green space increases, the UCI intensity also increases ($R^2 = 0.24, 0.20, 0.32$, and 0.28 for Beijing, Tianjin, Xi'an, and Zhengzhou, respectively). There is no correlation between the area of green spaces with water and the UCI intensity in any city.

There is no correlation between the area of green space in each city and the UCI extent. Except for Beijing, the area of green spaces without water is positively correlated with the scope of UCI in each city ($R^2 = 0.14, 0.18$, and 0.22 in Tianjin, Xi'an, and Zhengzhou, respectively). The correlations between the area of green spaces with water and the
UCI extent are extremely low in Beijing and Tianjin, while those in Xi’an and Zhengzhou are positive ($R^2 = 0.25$ and 0.20, respectively).

The relationship between the shape complexity of green space and UCI intensity and UCI extent

In this study, the LSI and FRAC were selected to research the relationship between the shape complexity of green space and UCI intensity and UCI extent. The average LSIs and FRACs of the two different types of green space in the four cities are shown in Table 4. The linear regression results of the LSI and FRAC for each type of green space and UCI intensity and UCI extent are shown in Figs. 6 and 7, respectively. Table 4 shows that the average LSIs and FRACs of the two different types of green space in the four cities are not high, indicating that the shape complexity of the selected green space patches is low and the shape is basically close to a square.

Figures 6 and 7 show that there are no correlations between the LSI and FRAC of the two different types of urban green space, UCI intensity, and UCI extent in any city.

Analysis of TVoE

Figure 8 shows the logarithmic regression analysis results between the UCI intensity and the area of the two different types of green space in the four cities. The TVoEs of

| City        | Beijing | Tianjin | Xi’an  | Zhengzhou |
|-------------|---------|---------|--------|-----------|
| Average LSI of green spaces without water | 1.11    | 1.35    | 1.25   | 1.18      |
| Average LSI of green spaces containing water bodies | 1.12    | 1.29    | 1.17   | 1.16      |
| Average FRAC of green spaces without water | 1.03    | 1.06    | 1.03   | 1.03      |
| Average FRAC of green spaces containing water bodies | 1.02    | 1.05    | 1.04   | 1.03      |
green spaces without water in Beijing, Tianjin, Xi’an, and Zhengzhou are 0.53 ha, 0.57 ha, 0.55 ha, and 0.44 ha, respectively. Therefore, for cities in cold regions of China, the optimal patch area of green spaces without water is between 0.44 ha and 0.57 ha. The logarithmic regression result ($R^2$) for the UCI intensity of the green spaces with water in the four cities is close to 0, so it is considered that there is no TVoE.

Water has a high heat capacity and low thermal conductivity. The evaporation of water is the main cooling mechanism for water bodies. These characteristics of water lead to a significant reduction in sensible heat transfer capacity, which leads to a change in the heat transfer mode, the so-called “constant temperature effect”. The constant temperature effect helps to form a more stable climate, including lowering the maximum temperature and increasing the minimum temperature (ISO xxxx). Therefore, we believe that for green spaces containing water bodies, due to the influence of internal water bodies, there may not be a universal optimal green space patch area; however, we can further explore the relationship between the internal water-body area of green space and UCI intensity.

**Correlation analysis and TVoE of water area inside green space, UCI intensity, and BGT of green spaces**

Correlation analysis of water area inside green space, BGT, and UCI intensity of green spaces

Figure 9 shows that the proportions of the water areas in green space in the four cities have weak negative correlations with the BGT ($R^2 = 0.12, 0.14, 0.13$, and $0.13$, respectively). That is, as the proportion of water area increases, the BGT of the green space gradually decreases. The proportions of water area are positively correlated with the UCI intensities of green spaces ($R^2 = 0.24, 0.20, 0.27$, and $0.25$ for Beijing, Tianjin, Xi’an, and Zhengzhou, respectively); that is, the larger the proportion of water in the green space is, the stronger the cooling effect of the green space.

**TVoE of the water/land ratio**

To quantify the cooling effect of urban green spaces containing water bodies, this paper proposes a new quantitative
The water/land ratio refers to the ratio of the water area to the green area (including the green area and the area for a small number of buildings and road paving) in a single urban green patch. The calculation results of the TVoE of the water/land ratio of the green spaces containing water bodies are shown in Fig. 10, which are 0.42, 0.52, 0.50, and 0.55 for Beijing, Tianjin, Xi’an, and Zhengzhou, respectively.

TVoE of the water/land ratio of the green spaces containing water bodies are shown in Fig. 10, which are 0.42, 0.52, 0.50, and 0.55 for Beijing, Tianjin, Xi’an, and Zhengzhou, respectively.

Fig. 7 Correlation analysis between the FRAC, UCI intensity, and UCI extent of two different types of urban green space in each city: (a1), (a2): green spaces without water in Beijing; (a3), (a4): green spaces containing water bodies in Beijing; (b1), (b2): green spaces without water in Tianjin; (b3), (b4): green spaces containing water bodies in Tianjin; (c1), (c2): green spaces without water in Xi’an; (c3), (c4): green spaces containing water bodies in Xi’an; (d1), (d2): green spaces without water in Zhengzhou; (c3), (c4): green spaces containing water bodies in Zhengzhou. The P value of all cities <0.05.
Discussion

Relationship between landscape indicators and UCI intensity and UCI extent

The results of this study showed that in cold regions in China, for green spaces without water, the higher the BGT is, the lower the UCI intensity and the lesser the cooling effect, which is the same as Fan’s conclusion (Fan et al. 2019). For green spaces containing water bodies, different situations were observed in the four cities due to the cooling effect of the water inside the spaces. In Beijing and Xi’an, the correlation between the BGT of the green spaces containing water bodies and their UCI intensity is extremely low, while Tianjin and Zhengzhou have strong negative correlations. Therefore, we believe that there is
no correlation between BGT and UCI intensity in green spaces containing water bodies. We also found that the proportion of water bodies of green spaces in the four cities is weakly negatively correlated with the spaces’ internal temperatures and is positively correlated with the UCI intensity, which shows that the water bodies inside of the green spaces have a certain impact on the BGT and the cooling effect of the patch. This may be due to the “constant temperature effect” of water bodies. Researchers found that water bodies have a high heat capacity and low thermal conductivity which can reduce the maximum temperature and increase the minimum temperature (Weng et al. 2011). In conclusion, we conclude that water bodies can significantly reduce the UHI effect and that its UHI intensity is related to its area ratio, which are in common with previous researches (Feng and Shi 2012). Researchers should analyze green spaces with water separately in the future, and the TVoE of the water/land ratio will be discussed later.

Except for the green spaces without water in Beijing and the green spaces with water in Tianjin and Xi'an, the BGT of all of the green spaces in other cities is negatively correlated with the UCI extent. Therefore, the results indicate that there is no correlation between the BGT and the UCI extent for two different types of green space in cold regions of China. Most of the UCI extent of the green spaces without water in Beijing is 150 m; we think this may be related to the relatively large width of the urban roads in Beijing (Yuan et al. 2014). Paved roads have a lower specific heat capacity, absorb heat quickly, and dissipate heat slowly, which affects the cooling effects of green spaces. The lack of correlation between the BGT of green spaces with water and the UCI extent in Tianjin and Xi'an may be due to the influence of the water bodies inside the spaces. Studies have shown that by increasing the size of water bodies, the cooling intensity increases, while the cooling efficiency decreases (Sun and Chen 2012; Lin et al. 2015; Theeuwes et al. 2013). A lower cooling efficiency will affect the UCI extent.

Relationship between Area and UCI intensity and UCI extent

The area of green spaces without water in each city is positively correlated with UCI intensity to varying degrees, which is consistent with previous research results (Manoli et al. 2019; Bowler et al. 2010; Chang et al. 2007). There is no correlation between the area of green spaces containing water bodies and UCI intensity. However, the proportion of water bodies in the water-bearing green space is positively correlated with UCI intensity in each city, which is also similar to prior research results (Yu et al. 2017). This indicates that for the green spaces containing water bodies, the proportion of the area of the internal water body to the total area of the green space is an important factor affecting the cooling effect.

Except for Beijing, the area of green spaces without water in each city is positively correlated with the UCI extent to varying degrees. We also think this may due to the relatively large width of the urban roads in Beijing. The correlation between the area of green spaces containing water bodies in Beijing and Tianjin and the UCI extent is extremely low, while that in Xi'an and Zhengzhou is positive. This may be related to the higher BGT in Xi'an and Zhengzhou. Studies have shown that the higher the urban background temperature is, the stronger the cooling effect of urban water bodies (Feng et al. 2012, 2013). Therefore, in Xi'an and Zhengzhou, where the urban background temperature is relatively high, green spaces containing water bodies have a stronger cooling effect.

Relationship between LSI, FRAC and UCI intensity and UCI extent

There is no correlation between the LSI and FRAC of the selected green spaces in the four cities and UCI intensity or UCI extent. This is different from prior research results that the UCI effect is positively correlated with the complexity of the green space (Yu et al. 2017; Peng et al. 2016). In this study, we found most of the green spaces in cold regions of China are divided based on the square road network, and the overall green space landscape patch has a relatively regular spatial shape, lack of natural shape, heavy artificial traces, and insufficient complexity. Therefore, the research did not find a correlation between the complexity of green space and its cooling effect.

TVoE

In this study, we found that there is a TVoE for green spaces without water in cities in cold regions, which ranges from 0.44 ha to 0.57 ha. Therefore, it can be considered that the TVoE of green spaces without water in cold regions of China is approximately 0.52 ha. The same as Yang’s conclusion, we found that the TVoE is related to the average BGT of green spaces (Yang et al. 2020). For green space, the higher the BGT is, the lower the cooling effect. Therefore, it is necessary to increase the areas of individual green spaces to improve their cooling effect. Additionally, our study found that there is no correlation between the TVoE and the average NDVI of green spaces, which is different from the conclusion of Fan (Fan et al. 2019) that the TVoE of green spaces is highly correlated with the NDVI. The NDVI is affected by the vegetation and environmental and atmospheric conditions. Although the green spaces in cold
regions of China have a large amount of vegetation, the vegetation types inside a single patch are relatively limited in diversity and the vegetation health level is not high (Huang et al. 2018; Zhilin 2010). Therefore, there is no correlation between the NDVI and the TVoE.

Due to the influence of water bodies, for green spaces containing water bodies, none of the four cities has a TVoE for its area. Furthermore, considering that water is an important factor affecting the cooling effect of the entire green space, we continued to study the TVoE of the water/land ratio in the green spaces. We found that the water/land ratio of the green spaces containing water bodies in the four cities is positively correlated with the UCI intensity, with TVoEs of 0.42, 0.52, 0.50, and 0.55 for Beijing, Tianjin, Xi’an, and Zhengzhou, respectively. This result coincides with the conclusion of Feng et al. that when the proportion of water in a green space exceeds 30%, the green space has a higher cooling effect (Feng and Shi 2012).

**Guidance on urban planning and management**

Urban green space can play an important role in mitigating the UHI effect due to its cooling effect. This study confirms that green spaces containing water bodies have a stronger cooling effect than those without water bodies. In cold regions of China, as water resources are not abundant, there are few green spaces containing bodies of water. Therefore, water should be designed within green spaces. Previous studies have confirmed that the size of a green space is positively correlated with its cooling intensity; however, there is a TVoE—that is, when the area of green space exceeds this threshold, the cooling efficiency of green space will decrease. This study found that in cold regions of China, there is only a TVoE for green spaces without water, and the threshold ranges from 0.44 ha to 0.57 ha. However, the average area of the selected sample green space is 3.33 ha, which is obviously larger than the TVoE. This means that for green spaces without water in cold regions of China, designers should try to ensure that the area is approximately 0.52 ha to optimize the cooling efficiency of the green space. For green spaces containing water bodies, although there is no TVoE for their area, when the ratio of the internal water area to the area of the green space is 0.5, the cooling efficiency is the highest. Therefore, more emphasis should be placed on the area ratio of the various design elements inside the green space.

**Research limitations and future research directions**

First, this study analyzed the cooling effects of two different types of urban green space in cold regions of China. In future research, more cities and more sample green spaces can be selected, and higher-precision satellite images can be used to improve the accuracy of the research results. Second, every city is a unique, open and complex system with non-linearity and high uncertainty. Although cities in the same climate region have roughly the same background conditions, there are still internal differences and many factors that affect the cooling effect of urban green spaces—one of which is the presence of a water body. Additionally, scholars have identified anthropogenic indicators such as the height/density of building and the direction of street can impact the cooling effect and TVoE (Akbari and Kolokotsa 2016). Therefore, in future research, more factors that influence the UCI effect of urban green spaces need to be included for a comprehensive analysis. Generally, an urban water body is called an urban blue space. For urban spaces with both a water body and green space, in addition to external urban factors, the location and shape of the water body inside the green space will also affect the cooling effect of the entire green space. Determining how to quantify the cooling effect more accurately and proposing guiding opinions that can further guide the planning and design of urban green spaces are also key considerations for future research.

**Conclusion**

This paper mainly studies the cooling effects of urban green spaces in cold regions of China. Considering that a water body inside an urban green space may affect the cooling effect of the green space, we divided urban green spaces into two types for the present research. The following findings were made: (1) Green spaces containing water bodies have a stronger cooling effect than green spaces without water. (2) For green spaces without water, the BGT is negatively correlated with the UCI intensity, while its area is positively correlated with the UCI intensity to varying degrees; due to the differences in the internal climate and construction conditions of each city, the BGT and the area of this type of green space are not related to the UCI extent. (3) For green spaces containing water bodies, the cooling effect is different in different cities because of the water in green spaces and the different urban background conditions; the proportion of internal water area to the green space area is an important factor affecting the cooling effect of the entire green patch: as the water area inside the green space increases, the cooling effect of the green space increases. (4) In the cold regions of China, because the cities in this region are basically square road networks, the shape of urban green spaces there is not complex, so there is no relationship between the complexity of urban green spaces and their cooling effects. (5) There is a TVoE for the area of green spaces without water in cities in cold regions of China, ranging from 0.44 ha to 0.57 ha, while there is no TVoE for the area of green areas containing water bodies. Further research on the water area
inside the green spaces found that there is a TVoE for the water/land ratio of the green spaces containing water bodies for each of the four cities, which are 0.42, 0.52, 0.50, and 0.55 for Beijing, Tianjin, Xi’an, and Zhengzhou, respectively. In general, this research provides useful information for planners and managers of cities in cold regions of China and expands the research perspective of classifying green spaces.

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Authors’ contributions Bo Pang designed research, performed research, analyzed data, and wrote the paper. The remaining authors contributed to refining the ideas, carrying out additional analyses and finalizing this paper.

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Data availability The data that support the findings of this study available from the corresponding author upon reasonable request.

Declarations

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