How does the ambient environment respond to the industrial heat island effects? An innovative and comprehensive methodological paradigm for quantifying the varied cooling effects of different landscapes

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**ABSTRACT**

Local landscape patterns in cities can substantially alter surrounding land surface temperature (LST) and affect the surface urban heat island effect. Previous studies have confirmed that some urban functional areas produce pronounced local heat/cold island effects in cities; however, the mitigating of this effect from the perspective of surrounding landscapes has not been investigated in depth. Additionally, different types of industrial plants have not been individually studied across multiple cities as major contributors to the local heat island effect. Therefore, based on 17 mega plants in various cities in the Northern Hemisphere, this study explores the impact of surrounding landscapes on the surface industrial heat island (SIHI) effect, proposes cooling metrics from a new landscape patch perspective, and quantifies the impact of different patch configurations on the SIHI using Extreme Gradient Boosting regression models and Shapley Additive exPlanations. The primary results are as follows: 1) Regarding to the footprint of the SIHI effect, the coverage of impervious surfaces dominates the ambient LST pattern. Industrial plant types and latitudes are moderately influencing factors. 2) In terms of the cooling effect, landscape patch size and width relative to industrial plant size has a pronounced impact on the LST cooling speed. Besides, various land cover types have distinct relative cooling thresholds for patch area and distance from the plants. The influence of patch attributes on LST cooling speed is determined by the distinct land cover type. 3) What is prominent is that the patches of water bodies with larger relative footprints often exhibit higher cooling speeds. This study aims to provide guidelines for urban planners in assessing the local thermal environment and mitigating further urban warming.

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1. Introduction

Over the past few decades, human society has experienced rapid urbanization. In this context, numerous climatic and ecological issues have occurred (Chen et al. 2017; Tam, Gough, and Mohsin 2015; Xiong et al. 2012; Zeng et al. 2015). Surface urban heat island (SUHI) is among the major problems that have resulted from rapid urbanization. It is a phenomenon where atmospheric boundary /surface temperatures in an urban core are higher than those in the surrounding rural areas or suburbs (Oke 1982). As an essential feature of SUHI, land surface temperature (LST) can effectively reflect and evaluate changes in the thermal environment due to the urban landscape (Esteoque, Murayama, and Myint 2017; Peng et al. 2021; Zhao et al. 2020). Furthermore, anthropogenic heat emissions from some functional areas within cities can exacerbate the SUHI effect (Feng et al. 2019; Boehme, Berger, and Massier 2015; Mohammad and Goswami 2021). This local heat effect within cities has aggravated air pollution, increased energy consumption, and endangered human health (Schafer et al. 2021; Henao, Rendon, and Salazar 2020; Ngarambe et al. 2021; Li et al. 2019). Mitigating the negative effects of local heat islands is one of focal areas among urban researchers.

The surface industrial heat island (SIHI) effect, the heat island effect within cities, occurs when the LST of industrial lands is higher than its surrounding areas. Its existence has been evidenced in previous studies (Meng et al. 2022; Liu et al. 2021; Mohan et al. 2020). There have been numerous findings demonstrating that SIHI plays a dominant role in SUHI effects (Khamchiangta and Dhakal 2019) and has pronounced impact on the urban environment (Wan,
Shen, and Choi 2017; Zhang et al. 2017; Pearsall 2017). Nevertheless, it is unknown whether there are differences in the extents and intensities of SIHI impacts in different cities, and whether different types of industrial plants cause the same SIHI. Recent studies have evaluated the temporal variations and spatial patterns of SIHI effects (Meng et al. 2022; Mao, Xie, and Fu 2020), and explored the effects of the internal configurations of industrial plants on SIHI (Liu et al. 2021; Rao et al. 2018). Nevertheless, distinctions among the SIHI by various plants and the reasons for these differences have not been explained in detail.

Recently, various metrics have been proposed to quantify the local heat island/cold island effect generated by plants and blue-green landscapes. For example, Meng et al. (2022) measured the warming effect of SIHI based on land cover types, microclimatic backgrounds, and buffer-based surroundings. Cheng et al. (2015) and Feyisa, Dons, and Meilby (2014) proposed maximum area, maximum distance, cold island intensity, and cooling efficiency to quantify the cold island effect of the parks. Peng et al. (2021) linked maximum perspective to the cumulative impact from spatial continuity to assess park cooling effects. However, these studies have focused on the influence of surrounding landscapes as uniform entities, ignoring the influences of their heterogeneities and distances on the island effects. Although the object of the study remains constant, changes in the composition and configuration of surrounding landscapes can lead to different warming/cooling effects, which are difficult to detect using previous metrics.

Assessing the relationship between local thermal environment and landscape heterogeneities at fine-scale has been a key issue in landscape ecology (Ossola et al. 2021; Gao et al. 2022). Based on the landscape patch scale, the cooling effect and additional fine-scale variation of LST can be identified (Kowe et al. 2021; Xu et al. 2022). Landscape patches are often explored as units of temperature mitigation in urban thermal environment studies. However, only a few studies have considered the effect on LST changes due to the location of the landscape patches in relation to the target to be mitigated (i.e. the source of the LST anomaly).

In this study, the cooling effect of surrounding landscape patches was quantitatively explored based on 17 mega plants and using an explainable Extreme Gradient Boosting (XGBoost) tree algorithm that combined two perspectives. The specific aims of this study were: 1) to introduce new metrics for describing LST mitigation speed by individual landscape patches; 2) to demonstrate the pronounced cooling effect of surrounding landscapes on SIHI and detect the effects of geographical locations, seasons, and plant types on SIHI; and 3) to quantitatively evaluate the mitigation effect of surrounding landscape patches on SIHI, and determine a relevant threshold range.

2. Materials and methods
2.1 Study area and data sources
Table A1 lists the eight thermal power plants and nine nuclear power plants selected for this study. The Northern Hemisphere is the hemisphere north of the Earth’s equator, and covers most of Earth’s land mass. It is also home to a large population and where most economically developed countries are concentrated. Thermal and nuclear power plants in 17 large industrial areas located on various plains in the Northern Hemisphere were selected for comparison (Figure 1). In this study, a mega plant is defined as a plant with a total nameplate capacity of power generation that exceeds 4000 MW, or a nuclear power plant with a nameplate capacity of cross power for a single nuclear reactor exceeding 980 MW, which is also used as a plant selection criterion. Additionally, this study considered the internal pattern (Liu et al. 2021), climate type, and geographic location as plant selection criteria. The industrial zones selected for this study were located as far from their urban centers as possible to avoid additional effects on the SIHI effect from the larger and more extensive heat generated in the commercial and residential areas of the city (Li et al. 2011).

The Landsat 8 Operational Land Imager-Thermal Infrared Sensor (OLI-TIRS) satellite images were obtained from the United States Geological Survey. Images from 1 January 2017 to 31 December 2020 in various seasons (i.e. summer, winter, and transition season) and with distinct targets (i.e. no clouds in the plant and surrounding area) in each study area (Table A2) were selected for the acquisition of LST and surface biophysical metrics (Table 1). Additionally, in this study, both the spring and fall seasons were referred to as transitional seasons owing to the
similarity between their features. Land cover data were generated by applying the training sample set to Sentinel-2 images using a random forest classifier (Gong et al. 2019). The 10 original land cover types of the land were combined into five land cover types: cropland, forest, grassland, water, and impervious surface. Additionally, the vector boundary data of each industrial area were artificially determined based on empirical knowledge and visual interpretation, and corrected based on Baidu Maps (https://map.baidu.com/).

### 2.2 Land surface temperature retrieval

The atmospheric correction and radiometric calibration of the remote sensing images in each band were performed using the ENVI 5.3 software. In this study, the radiative transfer equation method was used for

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**Table 1. Landscape patch metrics and their descriptions in this study.**

| Metrics | Abbreviation | Description |
|---------|--------------|-------------|
| Industrial zone metrics | | |
| LST around the industrial zone | LST$_{industrial}$ | LST of the patch around the industrial zone |
| Distance in patch | DIP | Length of the line segment extending from the center of the plant through the center of the patch and bordered by the patch boundaries |
| Distance from the industrial zone | Distance$_{industrial}$ | Distance from a defined edge of the zone boundary to the point of interest |
| Surface biophysical metrics | | |
| Normalized difference vegetation index | NDVI | \( \text{NDVI} = (\rho_{\text{NIR}} - \rho_{\text{RED}}) / (\rho_{\text{NIR}} + \rho_{\text{RED}}) \) |
| Normalized difference built-up index | NDBI | \( \text{NDBI} = (\rho_{\text{SWIR1}} - \rho_{\text{NIR}}) / (\rho_{\text{SWIR1}} + \rho_{\text{NIR}}) \) |
| Modified normalized difference water body index | MNDWI | \( \text{MNDWI} = (\rho_{\text{Green}} - \rho_{\text{SWIR1}}) / (\rho_{\text{Green}} + \rho_{\text{SWIR1}}) \) |
| Area and edge metrics | | |
| AREA | | Area of the patch |
| Perimeter | PERIM | Perimeter of the patch |
| Radius of gyration | GYRATE | Average distance between each cell in the patch and the centroid of the patch |
| Shape metrics | | |
| Shape index | SHAPE | Perimeter of the patch divided by the square root of patch area |
| Perimeter-area ratio | PARA | Patch perimeter to area ratio |
| Fractal dimension index | FRAC | Two times the logarithm of the perimeter divided by the logarithm of the area |
| Contiguity index | CONTIG | Mean contiguity value of cells in the patch is subtracted by 1 and divided by the sum of the template values is subtracted by 1 |
| Neighboring metrics | | |
| Edge contrast index | ECON | Sum of the segment lengths of the patch perimeter multiplied by corresponding contrast weights, divided by total patch perimeter, and multiplied by 100 |
| Euclidean nearest-neighbor distance | ENN | Distance to the same type of the nearest neighboring patch |

\( \rho \) represents the band of Landsat 8.
LST retrieval in each study area in different seasons (Sobrino, Jimenez-Munoz, and Paolini 2004), and was found to be effective in characterizing the SUHI effect (Yu et al. 2017; Cao et al. 2019). The first step of radiative transfer was calculated using Equation 1 below.

\[ L = \left[ eL_T + (1 - \varepsilon)L_{\text{atm}}^{\text{up}} \right] \tau + L_{\text{atm}}^{\text{down}} \]  

(1)

where \( L_T \) is the blackbody radiance obtained via Planck’s Law, \( \varepsilon \) is the land surface emissivity, and \( L \) is the top of atmospheric radiance or at-sensor radiance. Additionally, \( L_{\text{atm}}^{\text{up}} \) and \( L_{\text{atm}}^{\text{down}} \) are the upwelling and downwelling atmospheric radiance, respectively, and \( \tau \) is the total atmospheric transmissivity between the sensor and the surface.

The radiative brightness of a blackbody in the Thermal Infrared Sensor band was determined using Equation 2 below:

\[ L_T = \frac{L - L_{\text{atm}}^{\text{down}} - \tau(1 - \varepsilon)L_{\text{atm}}^{\text{up}}}{\tau \varepsilon} \]  

(2)

Finally, the LST was calculated according to Equation 3 below (Sobrino, Jimenez-Munoz, and Paolini 2004):

\[ T = \frac{k_2}{\ln \left( \frac{k_1}{k_2} + 1 \right)} - 273.15, \]  

(3)

where \( k_1 \) and \( k_2 \) are two calibration constants for Landsat 8 band 10: \( k_1 = 774.89 \text{ W/(m}^2\text{s} \mu\text{m}) \) and \( k_2 = 1321.08 \text{ K} \).

### 2.3 Modeling the cooling effect of landscape patches surrounding plants

This study defines SIHI as the LST of an industrial plant being higher than surrounding environment within a 3 km buffer zone. Industrial plant scale and patch scale were applied to this study, where plant scale refers to the surrounding landscape as a uniform entity from the plant perspective and bordered with buffers to explore the overall effect of SIHI. Patch scale refers to landscape patches as the basic unit from the perspective of the landscape around the plants and explores the cooling effect of each patch on the SIHI. To determine whether landscapes around each plant cause pronounced LST cooling effects and the extent of the SIHI effect, and to compare the differences between the various SIHI, the study was initially explored at the plant scale. Next, to investigate the quantitative influence of landscape patches on heat sources in industrial areas and their driving factors, this study was conducted at the patch scale.

#### 2.3.1 Modeling cooling effect at the plant scale

Owing to the Landsat 8 image resolution (30 m), 100 × 30 m buffer zones were established with the industrial area as the center. The distance from the buffer to the industrial zone boundary was used as the horizontal coordinate and the average LST of each buffer was used as the vertical coordinate to determine the range of warming effects caused by each plant (Peng et al. 2021). Selecting an excessively wide buffer zone for a study area can lead to a poor fitting effect between LST and distance (Peng et al. 2021). Therefore, the study selected appropriate distances and fitted them to the corresponding average LST with a cubic polynomial (Park et al. 2019), and obtained a plant-scale SIHI fitting curve. The appropriate distance of the 17 industrial zones’ warming effects depended on the point where the first order derivative of the curve function was zero. When the curve reached this inflection point, the change in difference of LST was no longer apparent (Yu et al. 2018).

Next, to eliminate the effect of variations in LST caused by plants in different cities and varying times, this study modified the SIHI fitting curve. The study calculated the mean LST (LST_{out}) of the area with a non-significant cooling effect (i.e. the area after the inflection point of the curve) demonstrated in the SIHI curve. Meanwhile, the difference between the average LST within each buffer and LST_{out} was defined as the dependent variable (ΔLST) of the new SIHI curve. Finally, the distance from the buffer zone to the industrial zone boundary was used as the independent variable to build the relationship between the ΔLST and distance at plant scale (Figure 2a).

#### 2.3.2 Modeling cooling effect at the patch scale

Because there is no pronounced pattern in the configuration and composition of the landscape around industrial areas, this study investigated the cooling effects of the landscapes on SIHIs mainly at the patch scale. Additionally, because LST is less sensitive to changes in factory size (Liu et al. 2021), the study
assumed that individual mega plant sizes do not substantially influence cooling effects in surrounding landscapes. To quantify this phenomenon, we determined the temperature mitigation speed (TMS) to explain the patch temperature mitigation phenomenon due to SIHIs. As shown in Figure 2b, TMS is the ratio of the difference between the $LST_{max}$ and $LST_{min}$ within the patch to the distance in patch (DIP; Equation 4). This is expressed visually by constructing a line that passes through the center of the industrial area and the center of the patch. The length of the line segment connecting the boundaries of the patch was defined as the DIP. Variables $LST_{min}$ and $LST_{max}$ represent the minimum and maximum LST within the patch, respectively. Furthermore, to eliminate tiny patches, the rules for the selection of patches (Peng et al. 2020; Wu et al. 2020) were as follows: 1) patch size should be greater than 900 m² owing to the spatial resolution of LST (30 m); and 2) DIP should be greater than 30 m to exclude the influence of too narrow patches on TMS.

$$TMS = \frac{LST_{max} - LST_{min}}{DIP}$$  \hspace{1cm} (4)

TMS indicates the magnitude of the cooling speed of the individual patch to LST. Therefore, the more pronounced the temperature variation within the patch (within a fixed DIP), the larger the absolute value of TMS. When TMS was greater than zero, larger values indicated that the patch was more effective in cooling the SIHI. When TMS was 0 or negative, smaller values indicated that the patch was less effective in cooling the SIHI or was affected by other heat sources. Furthermore, some larger patches (e.g. water and forests) can span large distances from the plant boundary. We hypothesized that the parts of these large patches near the plants were more influential on the SIHI effect. Therefore, the patches were divided using buffer zones (i.e. cutting line) which were delineated based on ΔLST curve at the the plant scale (Figure 2b).

### 2.4 Factors impacting the cooling effects

Considering the characteristics of patches and their location attributes, five types of landscape patch metrics were constructed based on previous studies (Table 1). Based on a combination of the foundation of previous studies and with the needs of this study (Chen and Zhang 2017; Sekertekin and Zadbager 2021; Asgarian, Amirji, and Sakieh 2015; Baker, Hughes, and Landman 2015; Azhdari, Soltani, and Alidadi 2018; Qiu et al. 2021), five types of landscape patch metrics were screened. Industrial zone metrics are aimed at exploring the locations of individual patches relative to the plants and the characteristics of their influence on SIHI radiation. Surface biophysical metrics were used in this study to distinguish the same land cover patches. They have been proved to be an effective approach toward quantifying the radiometric characteristics of surface components (Sun et al. 2018; Chen and Zhang 2017). Area and edge metrics were used to characterize patch area and perimeter, where patch area (e.g. areas of forests and water bodies) was found to influence the heat dissipation process of the SUHI effect (Peng et al. 2021). Shape metrics describe the patch shape complexity and connectivity. The patch shape can affect the radiation and change rate of LST to some extent (Estoque, Murayama, and Myint 2017). Neighboring
metrics were used to explore whether the patches were influenced by surrounding patches, leading to changes in TMS. Additionally, we hypothesized that all heat generating sources other than plants were on impervious surfaces; therefore, the Edge Contrast Index (ECON) was defined in this study as the degree of contiguity between other types of patches and impervious surfaces.

2.5 Patch cooling model based on explainable XGBoost

In this study, XGBoost was used to establish patch cooling regression models under different land cover types and to interpret the model with Shapley Additive exPlanations (SHAP). This method enabled both the exploration of qualitative findings of different patches’ cooling effects and the examination of changes under the influence of distinct factors at different thresholds. XGBoost is an algorithm for parallel tree learning that can excel in handling sparse data (Chen and Guestrin 2016). An advantage of XGBoost is that the use of residuals to learn is likely to yield accurate predictions. The basic principle of boosting is combining a series of weakly based prediction models, usually regression trees, into a single strong learner (Xia et al. 2017). In many LST related studies, the decision tree-based XGBoost algorithm outperforms other algorithms, such as K-nearest neighbor, random forests, and support vector machine, owing to its remarkable decision making, fast computational speed, and portability (Li et al. 2020; Stojic et al. 2019; Xu et al. 2021; Zhang et al. 2020). XGBoost regression models have exhibited good simulation ability in land cover change detection, landscape ecological analysis, and LST driving factors analysis (Georganos et al. 2018; Batunacun, Wieland, and Nendel 2021). The model in this study was used to detect the relationship between landscape patch attributes and TMS due to its high accuracy, high scalability, and the practical needs of this study. The model was adjusted using a grid search method with five-fold cross-validation (Chen et al. 2019; Stojic et al. 2019). The patch dataset was randomly divided into a validation set (20%) and training set (80%). After tuning and training the XGBoost model, the model accuracy was evaluated using the explained variance, which led to the selection of the final model.

SHAP was used to illustrate the constructed XGBoost model and the quantified influence of the characteristics of the landscape patches on TMS (Lundberg and Lee 2017). SHAP interprets the Shapley value based on cooperative game theory (Stojic et al. 2019) as an additive feature attribute approach, which interprets the predicted value of the model as the sum of the attribute values of each input feature. SHAP is a tree integration algorithm that recursively tracks the proportion of all possible subsets flowing to each leaf node of the tree, thereby making SHAP considerably less complex for model interpretation. In this study, SHAP values were used to describe the positive or negative effect and magnitude of features of landscape patches on TMS. SHAP dependency plots and summary plots were established to visualize the quantitative impact and contribution of each patch metric. SHAP summary plots measure the importance of each metric to the patch cooling efficiency by calculating the sum of the SHAP values of each metric and sorting based on this sum. SHAP dependency plots show details by displaying each SHAP value and sample value of a specific feature. They can show how each sample of a single metric affects the model, as well as the interaction of two metrics in the model.

3. Results

3.1 Evidence of the cooling effects from the landscape patches around the mega plants

As shown in Figure 3, there was a pronounced cooling effect of the landscape around all large 17 plants. The surrounding patches demonstrated substantial changes in LST owing to plant production activities. The surface thermal anomalies generated by the plants were gradually cooled by the surrounding patches with increasing distance from the factory boundaries. The maximum change in ΔLST for all power plant curves was 10.71°C (Hongyanhe Nuclear Power Plant), and the average change was 2.908°C. The maximum radius of influence of the SIHI effect was 1300 m, the minimum was 300 m, and the average distance of influence was 660 m. Additionally, the average ΔLST of the thermal power plant curves was 2.172°C, and that of the nuclear power plant curves was 3.589°C. The trend of the ΔLST variation curves
was the same among the different cities. These curves are consistent with the diagram of the difference in ΔLST at the industrial zone scale shown in Figure 2a.

From the spatial scale, to thoroughly explore the reasons behind the two trends of the ΔLST change curve, land cover maps, and thermal infrared remote sensing images of various plants were studied and compared. Surrounding landscapes of the 17 plants were divided into two categories: 1) landscapes adjacent to the plant had almost no impervious surfaces, and there were no thermal interferences from human activities (Figure 4a; and Figure 2) landscapes adjacent to the plant had additional impervious surfaces (Figure 4b,c). In terms of the first type of curve, as the distance from the plant boundary increased, the decline rate changed from fast to slow, and the trend showed an “L” shape. The average radius of influence of the thermal effect was 540 m, and the average ΔLST of the curve was 3.055°C. The landscape around the second type of plant was divided into two types: 1) plants located in large industrial parks (Figure 4b; and Figure 2) plants where adjacent landscapes included towns (Figure 4c). The ΔLST variation curve of such plants showed that as the distance from the plant boundary increased, the decline speed changes from slow to fast, and the trend shows a “τ” shape. The average radius of influence of thermal effects was 883 m, and the average variation curve of ΔLST was 2.64°C.

From the time scale, the average ΔLST of the summer curve was 4.23°C, the average of the transition season curve was 2.99°C, and the average of the winter curve was 1.50°C. Additionally, the comparison of different seasonal curves revealed that in most cities, the cooling effect of surrounding landscapes was more pronounced in summer, followed by the transition season, with the least pronounced effect in winter.

### 3.2 Cooling effects in diverse types of landscape patches

To explore whether individual patch metrics have distinct cooling effects in varying land cover types, patches were divided into five subsets according to land cover type. According to the results presented in Section 3.1, the winter data of six plants that did not conform to the SIHI change pattern were removed.
and a 500 m buffer zone was established as a cutting line for large landscape patches (Figure 2b). Considering landscape patches as units, XGBoost regression was used to explore the impact of patch metrics on TMS. The F-test indicated significant differences in TMS among various land cover types (p < 0.01). Next, an XGBoost regression model was constructed for each land cover type. Table 2 shows that the percentage of explained variance by the five regression models did not substantially differ, but was slightly lower for grass and slightly higher for water and impervious surfaces. Figure 5 shows each patch metric and its SHAP value.

DIP and AREA had large effects on TMS in each model, and the contribution of patch area to TMS decreased slightly but tended to be stable. LST_{industrial} was also observed to have a positive correlation with TMS. This result reveals that the TMS of the patch will be affected by the local LST. Although NDVI, NDBI, and MNDWI showed varying characteristics in the five models, biophysical parameters contributed little to the model. Furthermore, the model showed that the shape metric has a weak effect on TMS.

In the forest and grassland models, the contribution of PERIM was more prominent than in other models, but did not show distinctive positive or negative correlation. GYRATE of impervious surfaces shows that plants or other human activities with a wide range of influence have a positive impact on TMS. GYRATE of water shows similar results to that of the water area. In addition, Distance_{industrial} for land cover types except water bodies are negatively correlated with TMS, and the contribution of this metric to each model is only moderate. While the model selects patches within a 2 km buffer zone, only some patches play a role in alleviating plant thermal pollution, and the Distance_{industrial} of non-alleviating patches have a negative effect on the contribution of this metric.

### 3.3 Patch influencing factors of cooling effects

#### 3.3.1 Influence of patch geometric on cooling effects

Figure 6 shows the impact of landscape area on the five models and the relationship between DIP and AREA. In general, the influence trends of AREA on TMS in the five models are similar. With an increase in patch area, SHAP gradually increases to stability. In this process, the SHAP value of patches with constant area will decrease with the increase of DIP. When the AREA of the five SHAP

| Table 2. Percentage of explained variance of TMS. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| TYPE            | Cropland        | Forest          | Grassland       | Water           | Impervious      |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Percentage of explained variance of TMS | 55.85% | 54.70% | 48.49% | 57.49% | 57.52% |

Figure 4. Examples of land cover maps and LST spatial distribution maps of landscapes around the plants with different curve trends: (a) no impervious surfaces around the plant (Yangjiang Nuclear Power Station); (b) other small plants around the studied plant (Fangchenggang nuclear power plant); and (c) towns around the plant (Zouxian Power Station); (d), (e), and (f) are the LST spatial distribution corresponding to (a), (b), and (c), respectively.

Figure 5. Examples of landscape patches with different curve trends: (a) no impervious surfaces around the plant (Yangjiang Nuclear Power Station); (b) other small plants around the studied plant (Fangchenggang nuclear power plant); and (c) towns around the plant (Zouxian Power Station); (d), (e), and (f) are the LST spatial distribution corresponding to (a), (b), and (c), respectively.
dependency plots: cropland, forest, grassland, impervious surface, and water exceed 5400, 9000, 5400, 11,700, and 3600 m², respectively, SHAP becomes positive. This is because the cooling effect of small patches is limited and is overpowered by the surrounding thermal environment. It is notable that when the patch area exceeds 18,000, 96,000, 64,000, 15,000, and 291,000 m², respectively, SHAP tends to be stable.

The threshold range of water was the largest (3600–29,100 m²) because the cooling effect of water is stable owing to the biophysical characteristics, which can provide stronger cooling effects than other land cover types (Peng et al. 2020).

Impervious surfaces have thermal interferences resulting from human activities. Therefore, our study selected only water bodies for exploration. The SHAP

Figure 5. SHAP summary plots of five land cover types. Each line represents a feature, and each point represents a landscape patch. The colors show the size of each feature value. All the features are arranged along the y-axis from top to bottom according to their contribution to LST mitigation speed. The horizontal distribution of points shows that a given feature contributes to a higher or lower prediction along the x-axis. The plus and minus signs indicate that the features positively and negatively affect the model output, respectively.
dependency plots of GYRATE for water have the same trend as those for AREA. With increasing GYRATE in the patch, the SHAP value gradually increases until it stabilizes (Figure 7). Additionally, when GYRATE is above 80, its influence on TMS is positive. Owing to the definition of GYRATE, an increase in patch area leads to an increase in the range of influence of the patch. However, there were also cases where the ranges of influence of patches with different areas were similar. Figure 7(a,b) show that patches with a larger range of relative impact tend to have a high TMS.

3.3.2 Influence of patch location on cooling effects

Figure 8 shows that the low Distance\text{\textit{\textsc{industrial}}} values of cropland, forest, grassland, and impervious surfaces lead to high SHAP, and notably positive SHAP values below 570 m, 420 m, 750 m, and 50 m, respectively. The relief distances for the distinct types of patches are ranked as impervious < forest < cropland < grassland because each land cover type shows unique moisture, radiation, and thermal properties (Du et al. 2016b; Mohajerani, Bakaric, and Jeffrey-Bailey 2017). Additionally, as Distance\text{\textit{\textsc{industrial}}} increases, this influence decreases. When Distance\text{\textit{\textsc{industrial}}} is larger than the respective threshold, its influence is always near zero, indicating it has negligible effect on TMS. Notably, the effective Distance\text{\textit{\textsc{industrial}}} reflected by the results of the SHAP dependency plots of the five land cover types is less than the average mitigation distance previously observed (Figure 3). This is because the purpose of the SHAP result is to determine the distance required to alleviate the thermal pollution of the plant through the SHAP value. The patches on the right side of the vertical red dashed line do not prove that they are not contributing to thermal pollution mitigation.

4. Discussion

This study combines the industrial plant perspective with the surrounding landscape patch perspective
and proposes a new method for measuring the cooling effect of the landscape around large urban heat sources. It shows that there is a clear SIHI around nuclear and thermal power plants, and the ΔLST and trend of the SIHI curves are the same as those from previous studies (Meng et al. 2022; Mohan et al. 2020; Rao et al. 2018). In terms of SIHI impact range, the results of this study are similar to those of Rao et al. (2018) based on Wuan city in China, but both are clearly smaller than the SIHI impact range reported by Meng et al. (2022) for industrial parks. This is because the latter study area is an industrial park containing several industrial plants, where the combined heat island effect footprint of each plant is higher than that of individual plants. Similar to previous urban local heat/cold island effect studies (Cheng et al. 2015; Peng et al. 2021), the fitting curve trend and curve turning point (i.e. the response range radius of the SIHI phenomenon) were a little different (Figure 4). The reason could partly be that there were different landscape configurations around each plant, and the same landscape played varying roles at different distances from the plant, resulting in the landscape heterogeneity of the LST near the plant.

In this study, most landscape cooling effects of a particular plant in different seasons show similar curve trends. This seasonality was comparable to previous research on the SIHI and SUHI effect (Hu, Dai,
and Guldmann 2020; Yao et al. 2020; Meng et al. 2022). However, the winter curves of six cities (i.e. Belchatow coal-fired power plant, Kawagoe Power Station, Zouxiann Power Station, Dangjin Coal Fired Power Complex, Cattenom Nuclear Power Plant, and Brown’s Ferry Nuclear Plant) did not conform to the trend of other seasonal curves. These curves were different from other seasonal curves even outside the range of influence of SIHI (i.e. response distance to 3000 m). Notably, each of these curves was for the plants from middle and high latitudes. The reason may be that cities with different latitudes and climates alter the urban temperature owing to the seasonal changes of their surface physical properties (Hu et al. 2019).

Similar to the explained variance of XGBoost models for LST driving laws in the current study (Yu et al. 2020), the percentage of explained variance of the XGBoost models based on different land covers can adequately reflect that the selected primary drivers can explain TMS in our study. In contrast to other LST studies (He et al. 2021; Li et al. 2016), this study did not focus on exploring the drivers of intra-city LST, and therefore the study did not put other drivers (e.g. economic factors, demographic factors) into the regression model, which contributed to the lower variance explained by the model. Additionally, a higher explained variance can be found for impervious surfaces. This is because the heat capacity of impervious surface materials such as concrete, granite, and marble is one-quarter that of water (Chatzidimitriou and Yannis 2015). Meanwhile, human activity on impervious surfaces and the low thermal conductivity of impervious surfaces affect the heat transfer in adjacent areas, resulting in LST on impervious surfaces that are less susceptible to other factors.

Under the landscape patch perspective, patch geometry can largely affect the LST cooling speed. Previous studies showed that the cooling effect of urban landscapes is spatially nonlinear (Du et al. 2016; Yu et al. 2017). In this study, with an increase in patch area, SHAP did not increase after reaching the peak, but had a slight downward trend. This was because many of the selected plants were in far proximity from urban areas, resulting in land cover types with large areas within the 2 km buffer zone of the plant (Figure 4). This resulted in the larger patches having DIPs that exceeded the effective distance for temperature mitigation.

In urban land cover and LST studies, water bodies have a stronger and more stable cooling effect due to their biophysical characteristics compared to other land cover types (Brans et al. 2018; Cheng et al. 2019; Peng et al. 2020; Yang et al. 2020). Similarly, water patches play an essential role in cooling efficiency in this study. However, the Distance_{industrial} of the water is not strongly correlated with SHAP, which may be because the heat released by the plant exceeds the limit that the water can absorb, resulting in the heat island effect of the water. Lai et al. (2019) and Wu et al. (2020) also showed that when the impervious surface proportion around the water is high, the cold island effect produced by the water may be offset by the heat emitted by the surrounding environment.

4.1 Influence of plant types on the surface industrial heat island effect

Owing to diverse types of plants requiring high temperature environments, production processes, and equipment, there is a slight difference in the surrounding warming effect (Mao, Xie, and Fu 2020; Rao et al. 2018). Meanwhile, this distinction responds differently for diverse types of plants (Liu et al. 2021). To further explore the impact of plant type on the SIHI effect, the buffer zone was divided into two groups for different plant types: serious thermal pollution area (0–1 km) and sub-serious thermal pollution area (1–2 km, Figure 9). Distinct plant types are regarded as groups of dummy variables. Three landscape patch metrics in separate buffer areas were selected to conduct Pearson correlation analysis on plant types (Table 3).

Notably, ECON had significantly little correlation with plant type within 1 km of the buffer radius, but had a pronounced negative correlation with plant type within 1–2 km of the buffer radius. The larger the ECON, the more the non-impervious landscape patches were adjacent to the impervious surface, which can affect the cooling efficiency of the landscape patches. Additionally, Figure 9 shows that the impervious surface around the thermal power plant did not change with buffer distance, while the impervious surface around the nuclear power plant decreased substantially (10.4%).
with increasing distance. This phenomenon can also be confirmed by the comparison of curves of different plants in Figure 3. The curve trends of the two types of plants were comparable within 1 km, but the curve trends of nuclear power plants were relatively regular beyond 1 km. Additionally, the correlation coefficient between plant type and TMS shows that there is no pronounced difference in LST efficiency according to plant type for landscape patch mitigation in this study. Pearson correlation analysis of the plant type, area and edge metrics, and shape metrics also failed to pass the significance test.

In this study, the patch cooling effect does not vary with the type of power plant and the influence of SIHI on the surrounding environment varies with the surrounding landscape’s heterogeneity. This is because the heat transfer process from the plant to the ground surface is similar irrespective of the change in plant type. Meanwhile, the cooling effect of the surrounding landscape patches was changed according to their own properties or the received LST (Brans et al. 2018; Du et al. 2016a; Peng et al. 2020; Yu et al. 2017), which is not directly related to the plant type. Additionally, the SIHI intensity of the plant on the surrounding environment does not show direct correlation with the type of plant, but rather, different SIHIs are generated due to the varying intensities of plant activities.

### Table 3. Pearson’s correlation between selected landscape metrics and industrial zone type.

|                    | TMS | Distance | ECON |
|--------------------|-----|----------|------|
| Serious thermal pollution area | /   | /        | -0.083*** |
| Sub-serious thermal pollution area | /   | /        | -0.326*** |

*ECON is calculated from all non-impervious surface landscapes.

*** Represents significance at the 0.01 level.

### 4.2 Limitations

This study proposes a method for quantitatively measuring the cooling effects of landscapes around industrial plants. This method combines the interpretable XGBoost tree algorithm with the landscape patch attributes to consider the influences of individual patches on the thermal environment, and can provide important suggestions on how to design landscapes to mitigate the SUHI effect caused by large urban heat sources.

However, this study also had some limitations. First, the spatial resolution of remote sensing images affects the research results (Peng et al. 2021). In future research, higher spatial resolution should be used to explore urban landscape and temperature. Next, due to data limitations, this study only selected two types of plants: thermal and nuclear power plants. If more types of plants are added to compare their abnormal thermal changes, the temperature cooling effect of surrounding landscape patches may be different. Third, although the study explains and compares the SIHI effect in different seasons, the study had to select a single image as a proxy for each season at each plant due to the limitations of satellite images. This led to uncertainty in the results on the seasonality of the SIHI. Meanwhile, the specific pattern of the patch cooling effect with respect to latitude or climate zone was not obtainable due to the limitation of the number of plant samples. Therefore, the effects of individual seasons, latitudes, or climatic zones were not studied in detail in this study, and the effects of natural conditions on SIHI can be further explored in future. Additionally, this study lacked air temperature observation data to enhance air temperature cooling...
effects in the landscapes surrounding the plants. Meteorological data may be helpful to support a more complete study of the SIHI effect and the cooling effect in the surrounding landscape patches. Finally, this study did not consider the internal pattern and work intensity of the plants. The work intensity of plants and their interior landscapes affect the surrounding LST (Liu et al. 2021). However, this study aimed to explore the cooling effect of the SIHI from the perspective of surrounding landscapes. Thus, we only studied the contribution of patch LST (i.e. LST\textsubscript{industrial}) to TMS. The exploration of the driving law of plant internal landscapes is recommended for future research.

5. Conclusions

Accurately measuring the cooling effects of landscape patches around large urban heat sources can provide a scientific basis for alleviating the SUHI effect at a fine scale. This study measured the effect of SIHI in multiple cities and different types of industrial plants, which filled the gap of previous studies on SIHI for a single city or single type of plants, using 17 mega plants in various cities in the Northern Hemisphere as examples. Based on the regression analysis performed using XGBoost and the SHAP interpretation method, this study established new patch heat metrics and quantitatively explored the complex relationships between the patch attributes and patterns around the plants and the efficiency of reducing heat pollution. By combining the plant perspective with the surrounding landscape patch perspective for the first time, the influence of surrounding landscape patch attributes on plant thermal pollution was revealed. From the plant perspective, there was a pronounced cooling effect in the landscape around the plant. The SIHI effects were greatly affected by the surrounding impervious surfaces. The trend of the winter SIHI effects curve in the middle and high latitudes differed from that of other effects. From the surrounding landscapes perspective, the effect of patch individual attributes on LST mitigation speed was determined by distinct land cover type. The size and width of patches relative to plants (i.e. AREA and DIP) had remarkable effects on the rate of temperature variation. The patch cooling effect of various land cover types was affected by the location relative to the plants (i.e. Distance\textsubscript{industrial}), and the thresholds were different. The surface biological metrics and shape metrics of the landscape patches had little effect on the mitigation speed.

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Data availability statement

Supporting data are available upon request by contacting the corresponding author, and are accessible at https://earthexplorer.usgs.gov and http://data.ess.tsinghua.edu.cn.

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