Urban ecological land and natural-anthropogenic environment interactively drive surface urban heat island: An urban agglomeration-level study in China

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ABSTRACT

The surface urban heat island effect (SUHI) that occurs during rapid urbanization increases the health risks associated with high temperatures. Urban ecological land (UEL) has been shown to play an important role in improving urban heat stress, however, the impact of UEL interactions with the natural-anthropogenic environment on SUHI at the urban agglomeration-scale is less explored. In this study, the Google Earth Engine and GeoDetector were applied to characterize the spatiotemporal patterns of UEL and SUHI in the Guangdong-Hong Kong-Macao Greater Bay Area from 2000 to 2020 by extracting major built-up urban areas and quantifying the impacts of UEL and its interactions with the natural-anthropogenic factors on SUHI. The results show that the evolution of the UEL landscape structure exhibits clear spatiotemporal coupling with SUHI. Specifically, the UEL underwent a dispersion and degradation process in 2000–2015 and a convergence and restoration process in 2015–2020, the SUHI correspondingly transitioned from intensification and continuity to mitigation and contraction. The UEL landscape structure showed a notable impact on the SUHI reduction, and the dominance and richness of the patches explained an average of 19.95% and 16.03% of the SUHI, respectively. Moreover, the interaction between UEL and land urbanization rate and anthropogenic heat release had a dominant effect on SUHI, but this effect significantly declined from 2015 to 2020. With the implementation of ecological restoration projects, the interaction of UEL with topography rapidly increased and the SUHI gradually dominated by the joint interaction of UEL and natural-anthropogenic factors. A synthesis of the varying effects of several factors showed that the dynamic relationship between the development stages of the urban agglomeration’s regional system and SUHI may conform to the Environmental Kuznets Curve. SUHI reduction strategies should therefore comprehensively optimize the rational allocation of UEL landscape structures and natural-human elements to promote the well-being of residents.

1. Introduction

Urban heat islands (UHIs) are defined by higher temperatures in urban areas than in surrounding suburbs (i.e., rural areas) (Oke, 1973; Voogt and Oke, 2003). Since the Anthropocene, dramatic urbanization has led to profound changes in ecological space and landscape structures, which has disturbed the balance between the Earth’s surface radiation and energy (Foley et al., 2005; Oke, 2006) and introduced a wide range of negative impacts on the urban environment, including heat stress and health problems for city dwellers (Brunekreef and Hoffmann, 2016; Deng et al., 2018), biodiversity reduction (Peng et al., 2016), and global warming (Tonne et al., 2021). Urban ecological land (UEL) is a combination of natural or semi-natural ecosystems within a city that contains both vegetation and water bodies (Chen et al., 2014; Hunter et al., 2019). The optimization of ecological land layout is a nature-based solution to promote ecosystem services (Leal Filho et al., 2018) and maintain urban ecological security (Grimm et al., 2008; Ren et al., 2019), especially for regulating urban microclimates (Nowak and
Greenfield, 2012). The impact mechanism by which the UEL and related UHI factors interact is therefore important for promoting livable urban development, improving human well-being.

The global average surface temperatures could increase by approximately 1.4–5.8 °C by 2100 and urban dwellers could be increasingly exposed to extreme heat waves in the future (Jones et al., 2015; Liu et al., 2020). Numerous international organizations (e.g., World Health Organization), programs (e.g., United Nations’ Sustainable Development Goal 11: Sustainable Cities and Communities), and scientific projects have keenly focused on the relationship between human systems and the urban thermal environment (Georgescu et al., 2014; Sanchez Rodriguez et al., 2018). An urban agglomeration is defined as a spatially organized, economically connected, and highly integrated urban cluster, and has become the most prominent feature of global urbanization in the 21st century (Fang and Yu, 2017). In urban agglomeration areas, UHIs have expanded from a single city to entire regions owing to the formation of contiguous metropolitan areas, which has led previously isolated high-temperature areas to gradually connect and form regional UHIs (Du et al., 2016). This phenomenon is highly prominent in the Guangdong–Hong Kong–Macau Greater Bay Area (GBA) (Yu et al., 2019) where development has been accompanied by intense UEL degradation and restoration (Feng et al., 2021). However, the impact of ecological land structure changes in urban agglomerations on spatiotemporal UHI changes has not been extensively explored (Chapman et al., 2017).

Surface UHI (SUHI) refers to the difference of land surface temperature (LST) between an urban area and its surrounding natural environment (Weng, 2009; Yu et al., 2019), which contributes to understanding the spatial thermal patterns in urban environments and the impact of surface biophysical characteristics on UHI formation (Buyantuyev and Wu, 2010). Many studies have concluded that in urban landscapes, certain land cover types (e.g., water bodies, forests, grasslands, other green spaces) introduce significant cooling effects and are therefore considered “cold islands” (Oke, 1973; Peng et al., 2020). The proportion of green space or water bodies positively correlates with their cooling effect (Terfa et al., 2020). In the past few years there has been a trend in the related research, which is to use ecological land including water bodies and green spaces as an overall research object to study its impact on urban heat islands. For example, Peng et al. (2016) regarded forest, farmland, urban green space, and water bodies as UEL, and found that the cooling efficiency becomes more notable when the coverage of UEL exceeds 70% of the total land area. UEL basically mitigates SUHIs by weakening the thermal transfer between neighboring urban areas (Dai et al., 2018; Yao et al., 2019), especially as the overall cold island effect of UEL (e.g., forests, water bodies) becoming more pronounced as the connectivity of isolated heat islands in urban agglomerations gradually increasing (Lin et al., 2020; Yu et al., 2019). Additionally, vegetation and water bodies commonly coexist in urban environments (Hu et al., 2020a,b) and have shown significant synergistic cooling effects on SUHI during the daytime in summer (Gunawardena et al., 2017). Therefore, it should be paid more attention to the potential effect of UEL on urban heat island taking the green spaces and water bodies as a whole and explore the driving mechanisms of SUHI.

Understanding the influence factors of SUHI lays the foundation for formulating strategies of mitigation and adaptation to enhance human well-being (Yu et al., 2019). Scholars have advocated for quantitative and in-depth studies that incorporate more natural and anthropogenic factors (Ward et al., 2016; Yu et al., 2020). Some of them focus on surface biophysical parameters, which refer to the amount of different land cover/use types and their indicators (Chen et al., 2014; Peng et al., 2016; Ward et al., 2016), such as the normalized difference vegetation index, normalized difference water index, and normalized difference built-up index (Yu et al., 2020). Landscape configuration factors which are usually quantified by landscape metrics also attracted some attention. For cities with limited ecological space, an efficient UEL arrangement has become increasingly important to achieve the best cooling effect (Connors et al., 2013; Yang et al., 2020). For instance, Peng et al. (2018) argued that the landscape morphology and diversity of urban green spaces influenced seasonal LST variations, and Lin et al. (2020) and Shih (2017) emphasized that the cold island effect is relatively stronger in UEL patches with regular shapes, good connectivity, and aggregation. Finally, many researchers believe that SUHI mostly results from the coupling of nature and socio-economics, for which natural factors (e.g., elevation, wind speed, precipitation) and human factors (e.g., urban expansion, population concentration, anthropogenic heat emissions, road construction) have a significant impact (Peng et al., 2018). Topography controls urban vegetation growth by changing the light, moisture, and soil nutrient conditions, which affects SUHI (Grassein et al., 2014; Yang et al., 2020) and is the major cause of spatial SUHI heterogeneity (Ren et al., 2016). Moreover, urban sprawl and population activities can indirectly increase the SUHI intensity by reducing vegetation and increasing roads, buildings, and energy consumption (Buyantuyev and Wu, 2010; Connors et al., 2013). Mathematical analysis models (e.g., correlation analysis, stepwise regression, principal component analysis, random forest, logistic regression) are widely used to identify the key drivers of SUHI (Shafizadeh-Moghadam et al., 2020; Ward et al., 2016; Yu et al., 2019). While statistical methods are effective, the majority of existing studies mostly focused on the effects of a single factor and the determination of nonlinear spatial relationships between multiple factors, and their interactions remains poorly understood (Ren et al., 2016).

UHI research has received substantial attention and made notable progress in recent decades however, the following limitations remain. First, most SUHI studies separately examined the cooling effects of urban green space and water areas, while ignoring the synergistic effect of UEL. Water and green areas are generally interspersed within cities, and comprehensive studies of ecological land are important to reduce errors caused by the mutual influence of their cooling effects (Sun et al., 2020). In addition, due to the subtropical climate characteristics of the GBA, the water networks and vegetation are interspersed and densely distributed (Sun et al., 2020; Yu et al., 2020), green spaces and water bodies extensively exist in a single analysis grid and the cooling effect of either may be overestimated (Yang et al., 2017). Second, numerous studies have focused on diurnal or seasonal SUHI differences (Chen et al., 2014; Peng et al., 2018), whereas few have quantified the temporal effects of UEL landscape structures and their interactions with natural-anthropogenic factors (Peng et al., 2016; Shafizadeh-Moghadam et al., 2020). Third, the SUHI pattern evolution in regional thermal environments cannot be resolved from a single-city perspective and related problems should be addressed at a larger scale (Yu et al., 2019). Taking the entire GBA as the research area, this study characterized the spatiotemporal patterns of UEL and SUHI in the major built-up urban areas from 2000 to 2020 and quantified the effects of UEL and its interaction with natural-anthropogenic factors on SUHI using the Google Earth Engine (GEE) and long-term multisource data. The results provide important insight and scientific basis for the ecological planning and heat mitigation strategies of urban agglomerations.

2. Study area and dataset

2.1. Study area

The GBA is located in southern China and consists of 11 cities, namely Guangzhou, Dongguan, Huizhou, Shenzhen, Foshan, Zhongshan, Zhuhai, Jiangmen, Zhaqoing, Hong Kong, and Macau (Fig. 1), with a total area of 56,611 km². As one of the most economically developed and densely populated urban agglomerations in the world, the GBA had a resident population of 772.7 million and gross domestic product (GDP) of over 11 trillion RMB in 2019, accounting for 5.2% and 11.7% of China’s total population and GDP, respectively. Most of the GBA is located south of the Tropic of Cancer and has a subtropical ocean monsoon climate with abundant rainfall and heat occurring in the same season. The annual average temperature is approximately 21.4–22.4 °C.
Especially in summer, the GBA is hot and rainy and high-temperature disasters frequently occur. Despite the outstanding achievements in economic development, there remain numerous environment problems in the GBA. In particular, imperfect ecological network construction and a high degree of urbanization have left inhabitants more vulnerable to UHI effects (Peng et al., 2020). The combination of climate change and rapid urbanization has further increased the probability of the GBA being exposed to heat-related disasters (Ward et al., 2016). The GBA was required to impose a number of eco-engineering measures in recent years to alleviate the environmental risks. Understanding the mechanisms of the UEL’s influence on SUHI will therefore not only guide relevant UEL planning, but also provide a reference for ecological sustainability in other metropolitan areas worldwide.

2.2. Variables and data sources

2.2.1. SUHI

The 8-day 1-km MOD11A2 daytime LST products were used to calculate the daytime SUHI in the study area, which are available from LAADS Web (https://ladsweb.nascom.nasa.gov). Due to low density of monitoring sites and the changeable weather in the GBA limit the precision of the traditional method (Lin et al., 2020; Liu et al., 2017; Yu et al., 2019), making remote sensing data with low economic cost, large spatial coverage and short revisiting times one of the most commonly used methods for investigating the SUHI (Du et al., 2016; Peng et al., 2018). These LST products adopt a universal split-window algorithm by optimizing the observation angle and range of water vapor column contents, and have been widely applied in SUHI studies (Meng et al., 2018). During data processing, the process of joint, tailor, and projection transformation were completed using the MODIS Reprojection Tool (MRT), then multiplied by a scale factor of 0.02 to obtain the real LST. To avoid the impact of clouds, the LST is only retrieved for clear-sky (cloud cover is < 5%), thus the LST product has a large amount of gap (missing values), which can be mitigated by averaging the LST products (Li et al., 2018). In addition, due to the subtropical climate characteristics of the GBA, SUHI is notable in spring, summer, and autumn (Liu et al., 2017). We finally acquired 1058 MOD11A2 LST products from March to November every five years in 2000–2020 and averaged these products to portray the SUHI patterns. Nevertheless, it is calculated that the average proportion of missing pixels in LST data for the 11 cities in the GBA from 2000 to 2020 is 0.18% (Table A1), so we filled gaps using a linear regression method (Liu et al., 2020).

2.2.2. Driving factors

We selected a total of 12 driving factors from three perspectives: Landscape structure of UEL, natural and human elements, respectively (Table 1). Six commonly used landscape metrics were selected as explanatory variables: percent cover of ecological land (PEL), patch density (PD) the area-weighted mean shape index (SHAPE), largest patch index (LPI), aggregation index (AI), and Shannon diversity index (SHDI) (Buyantuyev and Wu, 2010; Connors et al., 2013; Peng et al., 2018; Yang et al., 2020). PEL refers to the area percentage of UEL patches in the total landscape area, representing their richness. PD is the number of landscape patches per unit area, which reflects patch fragmentation. SHAPE is a direct measure of the patch shape complexity. LPI is the area percentage of the largest patch in the total landscape area, which characterizes patch dominance. AI measures the aggregation of UEL, and SHDI is used to describe diversity at the landscape level. Urban vegetation and water bodies are combined as UEL based on the Opinions on the Delineation and Strict Observance of the Red Line of Ecological Protection (http://www.gov.cn/zhengce/2017-02/07/content_5166291.htm). UEL and construction land data were obtained from the 30-m resolution GBA land cover/use dataset (1990–2019) created by Feng et al. (2021) with five land categories: forestland, grassland, water bodies, construction land, and other land. The dataset is constructed based on Landsat satellite images combined with the random forest algorithm, and yields a relatively high overall accuracy of 0.93 ± 0.05. We applied this method to create land cover/use data for 2020 with an overall accuracy of 0.95 ± 0.05, as verified by the original field survey. The landscape metrics were calculated based on Fragstats software at the category level using a 1-km grid size (McGarigal et al., 2012).

In addition, topography (elevation and slope), development intensity...
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(population distribution and construction intensity), anthropogenic heat release, and traffic conditions also may have significant impacts on SUHI (Chapman et al., 2017; Leal Filho et al., 2018; Ren et al., 2016). DMSP-OLS nighttime lighting data have been shown to be a proxy variable for anthropogenic heat release (Peng et al., 2018; Yang et al., 2017). Therefore, the elevation (DEM), slope (Sp), population density (POP), nighttime lighting intensity (NTL), land urbanization rate (LUR), and distance to nearest road (NRD) were selected as the natural-anthropogenic explanatory variables. All factors had a spatial resolution of 1 km and temporal resolution of 5 years in 2000–2020.

3. Methods

The approach used in this study is as follows (Fig. 2). (1) Extract the urban main built-up area (UMBA) in the GBA from 2000 to 2020 based on the 30-m resolution land cover/use dataset, impervious surface distribution density (ISDD) method, and city clustering algorithm (CCA). (2) Investigate the spatial–temporal SUHI evolution process at the yearly scale. (3) Quantify the time-series effect of UEL and its interaction with natural-anthropogenic factors on SUHI using GeoDetector.

3.1. UMBA extraction

The accuracy of the UMBA definition affects the SUHI computation (Meng et al., 2018). The UMBA is extracted using the ISDD method proposed by He et al. (2018). This algorithm is based on the density of construction land at a certain distance to a central pixel. Equation (1) was used to determine the density of the construction land distribution of a pixel related to its surrounding area at a certain radius.

$$\text{Density}_b(r) = \frac{\sum_{i=1}^{n} B_i \left(1 - \frac{D_i^2}{r^2}\right)}{\sum_{i=1}^{n} \left(1 - \frac{D_i^2}{r^2}\right)}$$

where $\text{Density}_b(r)$ is the construction land density of a pixel’s surrounding region within a defined radius, $b$ is the central pixel, $B_i$ the value of the $i^{th}$ pixel within radius $r$ (construction land pixel $= 1$; non-construction land $= 0$), $D_i$ is the distance between the $i^{th}$ pixel and central pixel, and the summation refers to all pixels within a circle with radius $r$. Patches with areas < 900 m$^2$ were excluded owing to pixel limitations of the land cover/use dataset (30 × 30 m). The CCA algorithm (Rozenfeld et al., 2008) was then used to extract the pixels within the UMBA (Fig. A1) from all of the construction land pixels.

3.2. SUHI intensity calculation

SUHI is calculated as the difference in mean LST between the UMBA and suburb boundary area. Some scholars (Meng et al., 2018; Peng et al., 2012) concluded that the calculated SUHI effect was significant when the suburban area is 150% of the urban area. Therefore, the elevation (DEM), slope (Sp), population density (POP), nighttime lighting intensity (NTL), land urbanization rate (LUR), and distance to nearest road (NRD) were selected as the natural-anthropogenic explanatory variables. All factors had a spatial resolution of 1 km and temporal resolution of 5 years in 2000–2020.

![Fig. 2. Flow chart for the current study. UMBA: urban main built-up area, ISDD: impervious surface distribution density, CCA: city clustering algorithm, SUHI: surface urban heat island.](image-url)
extracted UMBA as the urban area and 150% of its suburban area
(surrounding rural area). The SUHI intensity ($\Delta T$) is given as:

$$\Delta T = T_{\text{Urban}} - T_{\text{Boundary}} \quad (2)$$

where $T_{\text{Urban}}$ is the mean LST of the UMBA and $T_{\text{Boundary}}$ is that of the boundary area.

### 3.3. GeoDetector

GeoDetector is a statistical method for detecting spatial variations and revealing their driving forces (Wang et al., 2010), and has been widely used in SUHI studies in recent years (Hu et al., 2020a; Ren et al., 2020). The principle assumes that if an independent variable significantly affects a dependent variable, the spatial distribution of the independent and dependent variables should be similar (Fig. 3). The most prominent advantage of GeoDetector over other methods is that it can detect the relationship between drivers and geographical phenomena without requiring linear assumptions, so its calculation processes and results will not be influenced by collinearities of multiple variables (Hu et al., 2020a). GeoDetector consists of four modules: factor, interaction, ecological, and risk detector (Wang et al., 2016), the first three of which are mainly used in this work. The factor detector uses the q value to quantify the impact of the factors, which is given as:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{\sum_{h=1}^{L} N_h \sigma_h^2 + \sum_{h=1}^{L} \sigma_h^2} = 1 - \frac{SSW}{\text{SST}} \quad (3)$$

where $q$ is the power of the determinant, $N$ and $N_h$ are the number of sample units in the entire region and sub-region, respectively, where $h = 1, 2, \ldots, L$ is the number of secondary regions, $\sigma_h$ and $\sigma^2$ are the variance of the samples in sub-region $h$ and global SUHI variance over the entire study region, respectively, and $SSW$ and $SST$ are the within sum of squares and total sum of squares, respectively. The value range of $q$ is [0,1], which means that the selected driving factor explains $q \times 100\%$ of SUHI (Wang et al., 2016).

The ecological detector is used to compare whether factor $X1$ has a significantly greater influence or contribution than factor $X2$ and is measured using the statistical index $F$:

$$F = \frac{N_{X1}(N_{X2} - 1) SSW_{X1}}{N_{X1}(N_{X2} - 1) SSW_{X2}} = \frac{SSW_{X1}}{SSW_{X2}} = \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{\sum_{h=1}^{L} \sigma_h^2}$$

where $N_{X1}$ and $N_{X2}$ represent the number of factors $X1$ and $X2$ in the samples, $SSW_{X1}$ and $SSW_{X2}$ are the within sum of squares in the subregion generated by factor layers $X1$ and $X2$, respectively, and $L1$ and $L2$ represent the number of $X1$ and $X2$ subregions. The null hypothesis is defined as $H_0: SSW_{X1} = SSW_{X2}$. A rejected $H_0$ at a given significance level indicates that it is statistically significant.

The purpose of the interaction detectors is to identify the interactions between different factors ($X$), namely, whether factors $X1$ and $X2$ interact to increase or decrease the explanatory power of SUHI or whether the effects of these factors on SUHI are independent. We first calculate the $q$ values of two factors ($X1$ and $X2$) and then overlay the two factors and calculate their $q$ value ($q(X1 \cap X2)$). The relationship between the two factors can be divided into five categories (Table 2). The Spearman correlation coefficient ($\rho$) is also used to determine the direction of the influencing factors on SUHI.

### 4. Results

#### 4.1. Spatiotemporal patterns of UEL and SUHI

The UEL in the GBA showed a continuous growth trend from 2000 to 2020 (Fig. 4a), with the area and proportion of total ecological land increasing from 914 km² and 3.48% to 1679 km² and 6.54%, respectively. However, the rapid expansion of UMBA from 5537 km² to 12,083 km² (1.41-fold increase compared with that of UEL) led to a gradual reduction of the proportion of UEL in the UMBA from 16.51% to 13.90%, which reached a minimum of 12.83% in 2015. In addition, the average SUHI also fluctuated from 1.80 °C to 1.88 °C and was strongly coupled to the UEL in the time-series. The average SUHI of the UEL was significantly lower than that of the non-UEL, and the difference decreased with UEL degradation in 2000–2015 (from 1.02 °C to 0.78 °C), and increased by 1.04 °C with UEL restoration in 2015–2020 (Fig. 4b).

<table>
<thead>
<tr>
<th>Interaction categories</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhance</td>
<td>$q(X1 \cap X2) &gt; q(X1) + q(X2)$</td>
</tr>
<tr>
<td>Bi-enhance</td>
<td>$q(X1 \cap X2) &gt; q(X1) \cap q(X2)$</td>
</tr>
<tr>
<td>Enhance, nonlinear</td>
<td>$q(X1 \cap X2) &gt; q(X1) + q(X2)$</td>
</tr>
<tr>
<td>Weaken</td>
<td>$q(X1 \cap X2) &lt; q(X1) + q(X2)$</td>
</tr>
<tr>
<td>Weaken, uni-enhance</td>
<td>$q(X1 \cap X2) &lt; q(X1) \cap q(X2)$</td>
</tr>
<tr>
<td>Weaken, nonlinear</td>
<td>$q(X1 \cap X2) &lt; q(X1) + q(X2)$</td>
</tr>
<tr>
<td>Independent</td>
<td>$q(X1 \cap X2) = q(X1) + q(X2)$</td>
</tr>
</tbody>
</table>

![Table 2](image-url)

**Fig. 3.** Principle of GeoDetector and the impact of interactions between $X1$ and $X2$ on SUHI.
4.2. Influence of the UEL on SUHI

The factor detector was used to calculate the determinant power (q) of UEL on SUHI for 1990–2020, with all driving factors statistically significant at the 1% level (Table 3). In addition, the q values and correlation coefficients (ρ) were significant for all factors and there were statistically significant differences among 73.33% of the factors. The UEL landscape factors can be ranked as follows based on the q value of their spatial heterogeneity: LPI > PEL > AI > SHAPE > SHDI > PD, all of which showed a significant negative correlation with SUHI.

LPI and PEL were found to be the dominant factors in the spatial SUHI pattern, the average q value of LPI (19.95%) was slightly higher than that of PEL (16.03%), and the proportion of statistically significant differences was 100% (Table A2). This indicates that larger areas and percentages of the UEL patches were associated with stronger cooling effects. The mean q values of AI, SHAPE, SHDI, and PD were 11.72%, 11.16%, 8.69%, and 7.81%, respectively, whereas the differences between the factors were relatively small (30% of statistically significant differences), which suggests that the UEL aggregation, shape complexity, diversity, and fragmentation were negatively correlated with SUHI. In terms of trends, the q values of LPI and PEL decreased by 23.77% and 24.02% from 2000 to 2015, respectively, and then increased by 9.28% and 9.34% from 2015 to 2020, which is consistent with the degradation-restoration process of the UEL patches. The q values of AI, SHAPE, SHDI, and PD decreased by 2.45%, 25.00%, 17.75%, and 4.27% from 2000 to 2015, respectively, which indicates that the UEL degradation limited the cooling effect of the landscape structure. With the rapid restoration of UEL in 2015–2020, the q values of SHAPE, SHDI, and PD rapidly increased by 18.28%, 9.35%, and 28.62%, respectively, while AI remained stable.

The reduction effect of the UEL landscape index on SUHI also changed dynamically due to the different index values (Fig. 6). SUHI decreased nonlinearly with increasing LPI and PEL levels (Fig. 6a, 6b), indicating that a greater proportion and dominance of the patches achieved a more significant SUHI cooling effect. SUHI values also showed a fluctuating decrease with increasing PD and SHAPE levels (Fig. 6c, 6d) with a clear threshold (generally between levels III and V) for the cooling effect of the UEL fragmentation and shape complexity. SUHI values significantly decreased with increasing AI and SHDI levels (Fig. 6e, 6f) and SUHI seems to rise again when AI and SHDI are about to reach their highest value. In summary, the SUHI was not linearly decreased with increasing levels of PD, SHAPE, AI, and SHDI, indicating that the increase of patch density, aggregation, shape complexity and diversity is not robust to the improve cooling effect of UEL.

4.3. Interactive effects of UEL and natural-anthropogenic factors on SUHI

The interaction effect of UEL and natural-anthropogenic factors on SUHI was calculated using the interaction detector. Each pair of factors was found to be larger than the q value of each individual factor and smaller than the sum of the two factors’ q values (Fig. 7). This indicates that the interaction relationships between UEL and natural-anthropogenic factors on SUHI were bivariate enhanced. The main factors that influenced SUHI gradually changed from UEL-anthropogenic factor interaction (2000–2015) to UEL-natural-anthropogenic factor interaction (2015–2020).

The interaction of PEL and LPI with LUR and NTL maximized the q value. The richness and dominance of the UEL patches together with the land urbanization and human activity intensity controlled SUHI, whereas the interaction of anthropogenic factors with AI, SHAPE, SHDI, and PD was relatively small. The interaction between UEL and human factors also decreased from 2000 to 2020, and the average interaction effects with POP and NRD decreased continuously by 43.82% and 28.11%, respectively. Meanwhile, q(SHAPE ∩ POP), q(PD ∩ POP), q
Fig. 5. Distribution pattern of urban ecological land (UEL), surface urban head island (SUHI), and urban main built-up area (UMBA) in the Guangdong-Hong Kong-Macao Greater Bay Area during 2000–2020.
Table 3
Determinant power (%) and correlation coefficient ($\rho$) of urban ecological land on surface urban heat island. Both the $q$ values and $\rho$ were statistically significant at the 1% level the abbreviations are listed in Table 1.

<table>
<thead>
<tr>
<th>Year</th>
<th>PEL</th>
<th>PD</th>
<th>SHAPE</th>
<th>LPI</th>
<th>AI</th>
<th>SHDI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$q$</td>
<td>$\rho$</td>
<td>$q$</td>
<td>$\rho$</td>
<td>$q$</td>
<td>$\rho$</td>
</tr>
<tr>
<td>2000</td>
<td>18.26</td>
<td>-0.39</td>
<td>6.94</td>
<td>-0.23</td>
<td>12.06</td>
<td>-0.34</td>
</tr>
<tr>
<td>2005</td>
<td>16.28</td>
<td>-0.33</td>
<td>9.22</td>
<td>-0.28</td>
<td>12.26</td>
<td>-0.33</td>
</tr>
<tr>
<td>2010</td>
<td>16.58</td>
<td>-0.32</td>
<td>7.69</td>
<td>-0.26</td>
<td>11.73</td>
<td>-0.32</td>
</tr>
<tr>
<td>2015</td>
<td>13.88</td>
<td>-0.25</td>
<td>6.65</td>
<td>-0.23</td>
<td>9.04</td>
<td>-0.28</td>
</tr>
<tr>
<td>2020</td>
<td>15.17</td>
<td>-0.28</td>
<td>8.55</td>
<td>-0.27</td>
<td>10.69</td>
<td>-0.30</td>
</tr>
</tbody>
</table>

Fig. 6. Average SUHI with different urban ecological land landscape metrics levels. The abbreviations are listed in Table 1.
SHAPE ∩ NRD), and \( q(Al ∩ NRD) \) decreased by 53.68%, 46.18%, 46.86%, and 28.67%, respectively, demonstrating significantly reduced interactions of the population distribution, UEL shape complexity, fragmentation, as well as road construction and UEL complexity and aggregation on SUHI. Moreover, \( q(LPI ∩ LUR) \), \( q(PEL ∩ LUR) \), \( q(PEL ∩ NTL) \), and \( q(LPI ∩ NTL) \) decreased by 5.91%, 8.96%, 12.80%, and 5.65%, respectively, and the cooling effect of the percentage and maximum patch dominance of UEL within a certain area interacting with the construction land density and human activity intensity on SUHI significantly weakened.

The interactions of Al and LPI with DEM and Sp were relatively strong, indicating that the aggregation and dominance of the UEL patches and topography jointly controlled SUHI, whereas the interaction of topography with PEL, SHAPE, SHDI, and PD was relatively small. The average interaction effect of UEL with DEM and Sp also increased by 45.71% and 33.61%, respectively. The interaction of UEL with DEM and Sp decreased by an average of 6.40% and 4.97% from 2000 to 2015, and \( q(PD ∩ DEM) \), \( q(SHDI ∩ DEM) \), \( q(PD ∩ Sp) \), and \( q(SHDI ∩ Sp) \) decreased by 10.28%, 9.53%, 9.85%, and 7.69%, respectively. This implies a reduced cooling effect from the interaction of topography with UEL shape complexity, elevation with UEL richness, and slope with maximum UEL patch dominance on SUHI. However, the interaction between UEL and DEM and Sp respectively increased by an average of 55.67% and 40.59% during 2015–2020. The increase rates of \( q(PD ∩ DEM) \), \( q(SHDI ∩ DEM) \), \( q(PD ∩ Sp) \), and \( q(SHDI ∩ Sp) \) were 69.09%, 59.44%, 49.11%, and 44.19%, respectively, which implies that the interaction between topography and UEL fragmentation, diversity, and complexity significantly enhanced the control of SUHI. Nevertheless, the mean \( q \) values of UEL with LUR (31.03%) and NTL (31.74%) were essentially equal to those of DEM (33.67%) and Sp (32.38%); thus the UEL-natural and anthropogenic interaction jointly dominated the SUHI spatial pattern.

5. Discussion and implications

5.1. Discussion

Collectively, high-SUHI zones mainly concentrated in areas of low elevation and low UEL richness and dominance with high urban development intensity. The SUHI in the GBA showed a trend of concentrated contiguity, significant increasing and outward expansion from 2000 to 2015, especially in FS-GZ-DG megalopolis, which is similar to the findings of Du et al. (2016) and Yu et al. (2019). Population concentration and urban expansion dramatically increased anthropogenic heat emissions while occupying a large amount of UELs, leading to a reduction in the dominance and richness of patches and further weakening the mitigation effect of UEL on SUHI (Peng et al., 2018; Yang et al., 2020). However, SUHI showed a slow growth trend and spatial contraction towards central FS and northern DG from 2015 to 2020. The increased UEL dominance can be attributed to the GBA’s extensive ecological restoration and urban greening measures carried out during that time (Feng et al., 2021). For example, the GBA issued five specific plans for ecological protection and restoration (including 2014) (Table A3), all of which emphasized the need to promote the construction of urban green spaces and wetland parks. In addition, the implementation of many ecological restoration projects increased the coverage of green and blue underlying surface, which can effectively reduce the temperature of the surrounding environment and alleviate
the SUHI (Shih, 2017; Xue et al., 2019; Yao et al., 2019).

In general, UEL has a mitigating effect on SUHI intensity by transforming incoming solar radiation into latent heat through evapotranspiration and reducing the release of sensible heat by providing shade (Chen et al., 2014; Gunawardena et al., 2017; Shih, 2017; Sun et al., 2020). However, there are significant differences in the cooling effect of its landscape structure (Fig. 6), which is consistent to the conclusions of Peng et al. (2016) and Yang et al. (2020). For instance, higher PEL and LPI values were associated with more significant UEL cooling effects. In urban environments, pollutants such as dust and other industrial particulate matter (e.g., PM2.5) can settle on plant leaf surfaces and limit leaf stomatal conductance, photosynthesis rate, and transpiration rate, thereby affecting the evaporative cooling effect of UEL (Naiddo and Chirkoot, 2004; Ren et al., 2016). Larger continuous, regular shaped UEL patches have stronger air renewal rate and purification function than several dispersed small patches (Yu et al., 2020), regulating latent and sensible heat exchange through intensive transpiration and shading effects, and therefore have more significant cooling effect (Wesley and Brunsell, 2019). In addition, the higher level of PD and SHAPE, the more complex the UEL patch edge, and it has a longer cooling distance, which facilitates the material-energy flow between the UEL and urban environment, making its mitigation effect on SUHI more obvious (Xie et al., 2013). Due to the fact that the cooling distance is generally confined, it directly limits the cooling potential at the edges of the UEL patches in the high level of PD and SHAPE (Yao et al., 2019). The cooling effect of AI and SHDI also showed an overall enhancing trend with increasing levels mainly because the increase in patch aggregation and diversity of UEL promotes the connectivity and heat energy exchange between the vegetation patch and their surroundings (Wesley and Brunsell, 2019) to provide more shade for the surrounding area and more effective in mitigating anthropogenic disturbances, and ultimately reduces the SUHI (Naeem et al., 2018). Consequently, the spatial pattern of UEL landscape was an important factor affecting the association between surface energy transfer and SUHI.

Our study found that the SUHI intensity of the GBA initially increased with urban expansion and population growth and then decreased. It is different from previous studies which suggested that SUHI linearly positively correlates with urban built-up area or population size (Connors et al., 2013; Liu et al., 2020), this fluctuating trend may be related to the interaction of UEL with natural-anthropogenic factors. Specifically, the conversion of UEL to impermeable surfaces in the GBA from 2000 to 2015 was accompanied by UEL degradation and high proportion of industries (>30%) (Feng et al., 2021), resulting in a rapid increase and gradual contiguous SUHI under LUR and NTL domination (Table A4), which is constant to the results of Yu et al. (2020). This is attributed to the fact that impervious surfaces absorb and store more heat (Meng et al., 2018), and that high-rise buildings and dense urban environments trap short-wave radiation, enhance energy transfer efficiency, and block air (especially cooled air) into city blocks (Ward et al., 2016; Xie et al., 2013; Yu et al., 2019), which together with large anthropogenic heat emissions result in higher LST (Feng et al., 2018). The SUHI intensity during this phase was therefore relatively significant in an interactive environment interface with a high percentage of built-up land, anthropogenic heat emissions, and low UEL richness and dominance (Fig. 8). The interaction between DEM and UEL was one of the main determinants of the significant reduction of SUHI in 2015–2020, and the SUHI intensity was relatively low in high-elevation mountainous areas (e.g., forests) (Fig. 8). During this stage, the layout of UEL and human activities (e.g., human renovation of urban forests and rivers) was optimized based on natural conditions, thus the interaction between UEL and natural-anthropogenic factors became dominant. For example, the GBA has accelerated the UEL restoration in areas of low altitudes, high population and prevented the surface from absorbing energy from energy sources such as downtown, industrial areas, residential centers, and others by constructing urban ecological corridor (Yu et al., 2019; Bi et al., 2020), which has been shown to weaken the impacts of anthropogenic factors (Table A4) and strongly mitigate SUHI (Shafizadeh-Moghadam et al., 2020). In addition, elevation and slope controlled the growth of urban vegetation growth through changing light, moisture and soil nutrients, and contributed to the reduction of SUHI with the construction of transportation infrastructure and the implementation of anthropogenic projects (Table A3), such as Ecological Red Line.

Combining the above analyses, we hypothesized that the functional relationship between development stage of urban agglomeration (X-axis) and SUHI (Y-axis) may be similar to the Environmental Kuznets Curve (Fig. 9) under the influence of the mutual of human and natural system. Specifically, the temperature was mainly influenced by natural factors due to the weak human activity (Venter et al., 2021) and the adaptation of human system to natural system during the initial development stage, so the SUHI spatial pattern was dominated by interactions between the UEL and natural factors. During the rapid development stage (corresponding to 2000–2015), it was accompanied by the intensification of human activities and the incursion of human system on natural system, led to a massive degradation of UEL and a significant increase in the SUHI (Figs. 4 and 5). The anthropogenic factors began to play a dominant role in the SUHI formation (Table A4), while the influence of UEL weakened (Table 3). Therefore, the interactions between UEL and human factors have become the dominant forces in the continued growth of SUHI (Fig. 7). When the urban agglomeration entered an advanced development stage, the human and natural systems integrated in harmony with each other due to the improvement of people’s awareness of environmental protection and the implementation of the government’s ecological protection policy (Yang et al., 2020), thus the importance of natural factors were enhanced again (Akbari and Kolokotsa, 2016; Kuang, 2019). The role of single factors eventually decreased in this phase and the interaction between UEL and natural-anthropogenic factors began to dominate the SUHI. These changes have been shown to effectively reduce urban temperatures (Gilbert et al., 2016) and result in gradual SUHI mitigation.

5.2. Implications

Previous studies have shown that the cooling effects of UEL on SUHI is largely unknown given the presence of the natural-anthropogenic factors (Gunawardena et al., 2017). This study explored the impact of UEL on urban heat islands considering urban agglomeration as a coupled human and natural territorial system (CHANS) mainly based on the methodology of geography (An et al., 2020). The integrated analysis perspective of surface elements in geography has been carried out throughout the study. First, the synergistic effect of water and green spaces on SUHI has been processed. Secondly, we put UEL in the certain natural and human geographic environment of urban agglomeration to examine the impact of their interactions on SUHI. This study found that the interaction between UEL and natural-anthropogenic factors was bivariate enhanced, and evolutionary relationship between human and natural systems in urban agglomeration can be characterized by an Environmental Kuznets Curve. The results indicate the positive impact of the balance and harmony of natural and human geographic elements in the urban agglomerations on the reduction of SUHI.

Practically, urban agglomeration can achieve the best cooling effect by optimizing the UEL space. The cooling effects of PEL and LPI values on SUHI were remarkable and robust. First, when designing UEL landscapes to reach maximum SUHI cooling, it is important to ensure the effective size and integrity of UELs through maximizing connectivity between patches (e.g., by creating ecological corridors) and reducing gaps between patches. Second, the distribution characteristics of SUHI identified in our study suggest GBA should infill UEL patches in FS-GZ-DG with high population density and concentrated built-up land, and design more green infrastructure networks (e.g., the creation of a new park and the planting of street trees and grassy areas) in combination with topographic and road, provide greater access to cooler
Fig. 8. Average SUHI for PEL, LPI with LUR/NTL (2000–2015) and DEM (2020) interactions at different levels (I: low, VII: high). The inner ring represents PEL/LPI and the outer ring represents LUR/NTL/DEM. The Roman numerals represent to the level of the landscape metrics, and the numbers represent to the average SUHI. The abbreviations are listed in Table 1.
environments. Third, the relationship between UEL and environment factors suggest a need to combine vegetation and water bodies, natural and anthropogenic factors at a macro perspective to formulate strategies for alleviating SUHI under stringent land availability constraints. Policymakers should seize the characteristics of urban agglomerations at different development stages and rationally configure UEL and natural-anthropogenic elements to reduce the heat stress of urban residents. For example, more grid-like forest and water networks can be laid in SZ and ZS based on topography to organically connect UEL patches with parks, roads, and urban built-up areas, thus weakening the concentrated and contiguous high-SUHI areas.

5.3. Limitations and future directions

There are some limitations in this study. First, we selected representative potential drivers mainly from the CHANS perspective, but the factors that affect SUHI are diverse in terms of different fields such as biological factors or atmospheric physical parameters. Therefore, the interaction of other factors with UEL on SUHI needs to be considered in order to reveal the driving mechanism more comprehensively. Moreover, although it is promising to examine the impact of green space and water networks can be laid in SZ and ZS based on topography to organically connect UEL patches with parks, roads, and urban built-up areas, thus weakening the concentrated and contiguous high-SUHI areas.

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Second, notwithstanding the value of landscape metric in spatial pattern recognition (McGarigal et al., 2012; Peng et al., 2018), some of its problems such as relatively vague concepts, high correlation among metrics, and strong scale sensitivity (Arnot et al., 2004; Li and Wu, 2004; Xia et al., 2020) have not been totally addressed. More researches can attempt to optimize the portrayal of landscape structure by capturing spatial information on the dynamics of UEL using other indicators such as the location centrality index (LCI) (Liu et al., 2021) and proximity expansion index (PEI) (Jiao et al., 2018). Finally, we proposed the theoretical hypothesis of Environmental Kuznets Curve, but a special study and quantitative methods (e.g., urban growth stage evaluation model (Yun and Nam, 2021)) are required to verify the functional relationship between urbanization stages and SUHI.

6. Conclusion

This study innovatively applied remote sensing techniques and Geodetector to quantitatively characterize the UEL landscape and its interaction with natural-anthropogenic factors on the spatial heterogeneity of SUHI in the GBA from 2000 to 2020. The results show that the evolution of the UEL landscape structure and SUHI exhibit notable spatiotemporal coupling, and the richness and dominance of UEL patches, urban construction, anthropogenic heat emissions, and their interactions dominate SUHI. The dominant effects on SUHI gradually change to interactions between UEL and natural-anthropogenic factors. Urban landscape design and planning should therefore reasonably optimize the spatial layout of UEL and natural-anthropogenic elements, such as infilling UEL patches in areas with high population density and concentrated built-up land, and designing more ecological networks in combination with topography, roads and built-up areas to achieve a harmonious coexistence of natural and social economic systems and reduce the regional UHIs in urban agglomerations.

Author contribution

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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