How urban ecological land affects resident heat exposure: Evidence from the mega-urban agglomeration in China

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HIGHLIGHTS

- An index of resident heat exposure considering population distribution and ecological land accessibility is modeled.
- Urban ecological land diversity dominates the patterns of resident heat exposure.
- Spatial marginal mitigation effect of urban ecological land dominance increased by 234.97% in 2000–2020.
- Urban ecological transition can enhance the impact of landscape structure on resident heat exposure.
- The interaction between urban ecological land and natural-human factors gradually enhanced the drive for resident heat exposure.

GRAPHICAL ABSTRACT

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ABSTRACT

Resident heat exposure (RHE) is becoming more severe in the coming decades owing to rapid urbanization and climate change. Urban ecological land (UEL) provides important ecosystem services, such as mitigating the urban heat islands effect. However, the impacts of UEL on RHE remain poorly understood. This study quantifies the effects of UEL and its interaction with the natural-anthropogenic environment on RHE in the Guangdong-Hong Kong-Macao Greater Bay Area, a mega-urban agglomeration in China. The results showed a tight spatial-temporal coupling between the UEL and RHE: UEL transitioned from degradation-fragmentation in 2000–2010 to recovery-agglomeration in 2010–2020, while the RHE distribution evolved from intensification-expansion-inequity to mitigation-contraction-equity. The average explanatory power (q value) of UEL and its structure on RHE also increased by 75.99% and 70.79%, respectively. UEL patch diversity gradually dominated the RHE distribution, and the spatial marginal effect of UEL dominance increased by 234.97%. Moreover, RHE shifted from being dominated by UEL and anthropogenic heat emissions interactions to being jointly driven by UEL and natural-anthropogenic factors (especially the interaction of patch fragmentation with topography and...
1. Introduction

At present, more than 7.8 billion (55%) people live in urban areas (Klein and Anderegg, 2021), and this number is expected to increase to 10.9 billion by the end of the 21st century (UN DESA, 2019). The increased frequency, intensity, and duration of extreme heatwaves due to global climate change (Sanchez Rodriguez et al., 2018) have made urban resident heat exposure (RHE) a global threat to human health (Goldblatt et al., 2021; Li and Zha, 2020). However, urban ecological land (UEL) plays a significant role in mitigating RHE by providing shade, which reduces human exposure to heat and UV radiation (Knight et al., 2021; Tan et al., 2016) and serves as a “protective barrier” (Ha et al., 2022; Peng et al., 2016). Although UEL is beneficial in mitigating RHE (Knight et al., 2021), regional-scale RHE measurements and the mechanisms by which UEL interacts with environmental factors to influence RHE have not been fully understood. A comprehensive understanding of the spatial-temporal effects of UEL on RHE can help formulate sustainable urban landscape design to reduce threats from urban heat stress to human health (Bartesaghi-Koc et al., 2020).

Urban heat stress is a hot topic in urban geography, ecology, and environmental sciences. Previous studies commonly used a combination of metrics, such as heat exposure, to measure urban heat stress. Heat exposure refers to the physical level of thermal comfort (Bokwa et al., 2019; Dong et al., 2020) depending on the heat exchange between the body and the environment (Li and Zha, 2020), which can be “source-oriented” and “receptor-oriented” (Nazarian and Lee, 2021). The former focuses on the air or land surface temperatures (LST) affecting the human body’s response (Peng et al., 2016; Yu et al., 2019). Most previous studies primarily considered the thermal environment and its distribution based on remote sensing data at global, regional, and urban scales (Feng et al., 2020; Goldblatt et al., 2021). However, due to the importance of the well-being of urban residents, there has been a significant increase in “receptor-oriented” studies in recent years (Jones et al., 2015; Li and Zha, 2020). Such studies aimed to provide policy guidelines that help formulate human-centered thermal risk reduction strategies (Harrington and Otto, 2018). In particular, thermal comfort is a key parameter in the “receptor-oriented” measurement of heat exposure (Ashrae, 2004; Földvary-Licina et al., 2018), which refers to the subjective sensation or satisfaction of humans with the thermal environment (Djongyang et al., 2010; Feng et al., 2020; Mijani et al., 2020). Several numeric indices have been developed and utilized to estimate the “real feel” of the temperature, including the temperature-humidity index (THI) (Thom, 1955), the wet bulb-globe temperature index (WBGT) (Yaglou and Minard, 1957), the physiological equivalent temperature (PET) (Höppe, 1999), and the universal thermal climate index (UTCI) (Jendritzky et al., 2001) at a regional scale. These studies first quantified when, where, and to what extent people are exposed to urban heat and then assessed the impacts of heat exposure on human health. The results from these studies showed that the spatial-temporal patterns of populations and temperatures are significantly heterogeneous owing to intra-urban human movement, which is expected to cause more urban heat vulnerability and heat stress-related diseases in the future (Biardeau et al., 2020; Harrington and Otto, 2018).

The topic of urban heat and heat exposure and their driving mechanisms have received considerable attention lately for their potential to impact the health and well-being of urban residents. Previous studies have demonstrated that the heterogeneity in urban natural-human environments leads to spatial differences in heat and heat exposure (Hu et al., 2019; Kabano et al., 2021; Mijani et al., 2020). For example, studies combining quantitative models with multi-source data proposed that heat emissions from urban and transportation infrastructure construction and their impacts on the surface energy balance are some of the main reasons for the dramatic increase in RHE. This increase in RHE subsequently negatively impacts residents’ mental health and physical performance (Carrillo-Nique et al., 2022; Mijani et al., 2020). However, land patches with high vegetation coverage and continuous aggregation of UEL can mitigate the thermal environment (Coffel et al., 2017; Lin et al., 2020; Shih, 2017). Additionally, natural factors such as topography and precipitation can influence RHE by affecting humidity and vegetation cover (Harrington and Otto, 2018; Jones et al., 2015). For instance, relatively high elevation and topographically complex areas have well-preserved vegetation with higher UEL richness and diversity (Peng et al., 2016), resulting in lower RHE. However, the degree of direct influence of environmental and topographical factors on RHE may also vary with the stage of urbanization and the region (Ren et al., 2016). Therefore, UEL and natural-human factors may jointly drive the spatial-temporal pattern of RHE, and the effects are generally non-linear (Peng et al., 2012).

Despite the significant research progress in UEL and RHE in recent years, several limitations remain. First, matching thermal comfort levels with population distribution and accessibility in exploring regional spatial-temporal RHE patterns must be treated cautiously (Hu et al., 2019; Vahmani et al., 2019). Population distribution patterns and surface characteristics of urban agglomeration are not homogeneous (Lang and Knox, 2009; Wang et al., 2016a), resulting in significant spatial-temporal heterogeneity in RHE (Hu et al., 2019; Klein and Anderegg, 2021; Mijani et al., 2020). Limited observations on RHE at a certain time frame (segment) or space may therefore lead to biased conclusions (Yin et al., 2021), preventing decision makers from formulating effective policies to mitigate RHE (Gill et al., 2007; Wang et al., 2016b). Second, the air temperature or LST used alone essentially expresses the physical properties of the urban thermal environment (Biardeau et al., 2020; Jones et al., 2015), but subjective thermal comfort or the human body’s perception of the thermal environment further depends on other environmental factors such as wind speed and humidity (Lin et al., 2020; Peng et al., 2016; Shih, 2017). Therefore, a LST model coupled with other thermal comfort data is needed to improve the accuracy of RHE (Yin et al., 2021). Third, a few studies analyzed the impact of UEL on the thermal environment in an integrated manner from both spatial and temporal perspectives, especially at the regional scale (e.g., urban agglomeration). Finally, we have limited information on how the natural-human environment in urban agglomeration affects RHE.

In this study, taking China’s typical mega-urban agglomeration—the Guangdong-Hong Kong-Macao Greater Bay Area (GBA)—as the study area, we integrated the methods of remote sensing, spatial metrology, and fuzzy overlay to construct a modeling framework for UEL that impact RHE by putting humans at the center of the framework. We first determined UEL factors that controlled the RHE distribution and identified their spatial marginal effect on the RHE changes. We then quantified the interactive effects of the UEL structure and environmental factors on spatial-temporal patterns of RHE. Results from this study can provide important insight and a scientific basis for the design of human-oriented urban green infrastructures and ecological restoration strategies to improve the well-being of residents.

2. Materials and methods

2.1. Study area

Urban agglomeration is considered one of the most significant features of today’s urbanization (Fang and Yu, 2017). The Guangdong-Hong Kong-Macao Greater Bay Area (GBA; longitude,
111°12’E–115°35’E; latitude, 21°25’N–24°30’N) is a world-class mega-
urban agglomeration, with a total area of 56,000 km² (Fig. 1a). The
population of the GBA increased dramatically over the past 20 years,
from 50.0 million in 2000 to 72.77 million in 2020 (~5.16 % of China’s
total population). During that time, the urban main built-up area
(UMBA) also expanded by 118.20 % (Fig. 1b). The GBA has a subtropical
climate with long (approximately-six months) hot and rainy summers,
and an average annual temperature over 20 °C, which aggravates the
risk of urban heat. Rapid urbanization led to the fragmentation and
degradation of UEL (Yu et al., 2019). In this context, the interaction
between UEL and natural-human factors leads to nonlinear dynamic
changes in RHE. GBA provides a suitable case for exploring the spa-
tial–temporal effect of UEL on RHE.

2.2. Dataset

The data used in this study mainly included land cover/use data, LST
products, meteorological data, digital elevation model data, DMSP-OLS
nighttime lighting data, population grid data, and digital road maps
(Table 1). Thirty-meter resolution land cover/use data (including five
categories of forest land, grassland, water bodies, building land, and
other land) and 1-km annual average summer LST products of the study
area were obtained from previous studies (Feng et al., 2021a, b). UEL is a
fundamental element in urban ecosystems (Zhang et al., 2017), and
forest, grassland, and water bodies within the urban main built-up area
(UMBA) were identified as UEL in this study (Peng et al., 2016). The
UMBA refers to relatively concentrated areas of built-up land and
intensive land use (Feng et al., 2021b; Meng et al., 2018), which can be
seen as areas where urban residents are mainly active. We selected five
commonly used landscape indexes and five natural-anthropogenic fac-
tors as explanatory variables (Beusch et al., 2022; Coffel et al., 2017; Yao
et al., 2022). The landscape indexes include the UEL coverage rate
(PEL), patch density (PD), area-weighted mean shape index (SHP),
largest patch index (LPI), and Shannon diversity index (SHDI), repre-
senting the richness, fragmentation, shape complexity, dominance, and
diversity of the UEL patches (McGarigal et al., 2012), respectively, all of
which were calculated in Fragstats using a 1-km grid. Detailed informa-
tion on the landscape indexes is presented in the Supplementary
material. We also selected the slope (Sp), average annual precipitation
(PPT), nighttime lighting intensity (NTL), distance to the nearest road
(NRD), and land urbanization rate (LUR) as explanatory variables for
quantifying the interaction between UEL and RHE. The resolution of all
variables was resampled to a spatial resolution of 1 km, and subsequent
analyses were performed on a 1 × 1 km grid. See Table S1 for more
details on the data and metric calculations.

2.3. Methods

The model framework of UEL’s impact on RHE constructed is as
follows (Fig. 2).

(1) Remote sensing based thermal comfort calculation

The discomfort index (DI) was used to measure the degree of thermal
sensitivity of the human body (Thom, 1959). Xu et al. (2017) calculated
the level of thermal comfort by correcting the DI using the THI as:

\[
THI = 1.8T + 32 - 0.55 \times (1 - 0.01RH) \times (1.8T - 26)
\]

where \(T\) is air temperature (°C) and \(RH\) is relative humidity (%). How-
ever, it is difficult for THI to reflect the large-scale spatial features of
thermal comfort due to the limitation of meteorological observation
data (Feng et al., 2020). Feng et al. (2020) proposed a modified
temperature-humidity index (MTHI) to solve this problem:

\[
MTHI = 1.8 \times LST + 32 - 0.55 \times (1 - 0.01 \times \text{NDMI}) \times (1.8 \times LST - 26)
\]

where LST partially reflects the near-surface air temperature. The
normalized differential moisture index (NDMI) obtained from near-
infrared and short-wave infrared wavelengths and has been proven to
have a good correlation with RH (Benali et al., 2012; Xu et al., 2017).
More details are provided in Section S1.2 in Supplementary material. We
then normalized the MTHI to between 0 and 1 and used the mean-
standard deviation methods to classify thermal comfort into five
levels: more comfortable, comfortable, less comfortable, uncomfortable,
and more uncomfortable.

To verify the applicability of the MTHI, we calculated the PET in-
tensity based on the Radiation on the Human Body (RayMan) model
using data from meteorological stations as input. The validation results
(Table S2) showed that the MTHI obtained a statistically significant
correlation (average \(R^2 = 0.87 \pm 0.03\)) with PET. The MTHI is, there-
fore, representative of the thermal comfort level of the study area. In
addition, based on the relevant literature (Jones et al., 2015; Tuholske
et al., 2021), we defined daytime temperatures greater than 35 °C for
three consecutive hours as “hot” to verify whether the level of discom-
fort (less comfortable, uncomfortable) corresponds to the discomfort
human experience under heat stress. First, we divided the daily hourly
average temperature data collected from meteorological stations during
the study period (Table 1) into a 1 km × 1 km grid using bilinear
interpolation (Mora et al., 2017). Second, we calculated the correlation
coefficient between the MTHI and the probability of “hot” (i.e., the
proportion of hot days in summer) and found a high correlation (average
\(R^2 = 0.80 \pm 0.02\) (Table S3). In summary, all of the above validate the

Fig. 1. Location of the Guangdong-Hong Kong-Macao Greater Bay Area. Dynamic growth of (a) urban main built-up area (UMBA) and (b) population from 2000 to
Hong Kong.
correctness of the MTHI method for classifying heat stress. See the Supplementary material for the detailed procedure.

(2) RHE calculation

In a broad sense, RHE refers to the contact between an individual or group and the immediate thermal environment (Kuras Evan et al., 2017), which can be interpreted geospatially as the accessibility between a population and its thermal comfort (Nazarian and Lee, 2021). The RHE of this study is, therefore, a “human-centric” approach (Coffel et al., 2017; Hu et al., 2019; Klein and Anderegg, 2021). The modified Huff three-step floating set area method (Subal et al., 2021) is used in this study to model the spatial distance decay effect by combining the population distribution (demand) and MTHI (supply) considering a continuous approach to quantify RHE (Fig. 2b).

**Step 1:** Further distances from the non-thermal comfort zone were associated with lower weights and lower probability of interaction (Huff). Following this premise, Huff is calculated by:

\[
H_{ij} = \frac{\sum_{k} S_k W_k}{\sum_{k} \left( \sum_{j \in \{d_k \leq d_{\text{max}}\}} S_k W_k \right)}
\]

where \(S_k\) is the MTH value of the non-thermal comfort zone, \(d_{\text{max}}\) is the maximum distance, \(k\) is the non-thermal comfort zone located within the catchment \(i\) (\(d_k \leq d_{\text{max}}\)), and \(W_j\) and \(W_k\) are corresponding individual Gaussian distance weights for the distances between \(i\) to \(j\) and \(k\), respectively.

**Step 2:** The supply–demand ratio \(R_j\) is calculated as:

\[
R_j = \frac{\sum_i S_i H_{ij} D_i}{\sum_{i} \left( \sum_{j \in \{d_i \leq d_{\text{max}}\}} S_i H_{ij} \right)}
\]

where \(D_i\) is demand for each population location \(i\) within the catchment \(j\) (\(d_i \leq d_{\text{max}}\)).

**Step 3:** The RHE for each population \(i\) is calculated as:

\[
R_{HE_i} = \sum_{j \in \{d_i \leq d_{\text{max}}\}} H_{ij} R_j W_j
\]

Higher \(R_{HE_i}\) values are associated with a higher probability that the residents are exposed to areas with low thermal comfort levels and vice versa. See the Supplementary material for the detailed process.

Then, we used the Gini coefficient to measure the spatial equity of the RHE distribution in each city:

\[
Gini = 1 + \frac{1}{n} - \frac{2}{n^2} \sum_{i=1}^{n} \left( \frac{n-i+1}{n} \times G_i \right)
\]

where \(Gini\) is the Gini coefficient of RHE distribution, \(G_i\) is the sum of
RHE values of the i-th UMBA grid, $n$ is the number of UMBA grids, and $\mathcal{G}$ is the mean value of $G$. The range of the $Gini$ value is $0$–$1$; a higher value indicates an unequal RHE distribution.

$$ q = 1 - \frac{\sum_{h=1}^{h} N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SSW + ST} = \frac{N \sigma^2 - SSW}{N \sigma^2} = \frac{SSW}{N \sigma^2} \quad (7) $$

where $q$ is the explanatory power of UEL landscape structure and natural-anthropogenic factors on RHE, $N$ and $N_h$ are the number of sample units in the whole study area and its subregion, respectively, $\sigma_h$ and $\sigma^2$ are the variances of the samples in $h$ and the global RHE variance over the study area, respectively, $h = 1, 2, ..., N$, and $N$ is the number of subregions. The value range of $q$ is $[0,1]$, which means that the explanatory variable explains $q \times 100\%$ of the RHE.

To minimize the calculation uncertainty, we compared several common discretization methods (i.e., equal interval method, quantile classification method, and natural breaks method) and selected the discretization scheme with the maximum $q$ value. A comparison revealed that the quantile classification method had a higher probability of having the highest $q$ values (See the supplementary material for the detailed process). Therefore, this study used the quantile classification method to classify drivers into seven classes, ensuring that each class contains the same number of elements, a method that has also provided suitable results in previous studies (Cao et al., 2013; Hu et al., 2020).

The interaction detector compares the interaction $q$ values of the two factors with their respective $q$ values to determine whether their interaction attenuates or enhances the effect on RHE. The risk detector uses the $t$-statistic to determine if there is a significant difference in the mean attribute value (risk value) between explanatory variables. Detailed information on the Geodetector is presented in the supplementary material.

The spatial fuzzy overlay can integrate the heterogeneous and auto-correlated information prevalent in geospatial variables (Phillips et al., 2011; Song and Wu, 2021). In this study, we use the fuzzy membership function:

$$ f_x(X_1, X_2, ..., X_n) = g(\eta(X_1) \eta(X_2) ... \eta(X_n)) \quad (8) $$

where $X_i (i = 1, ..., m)$ is the UEL landscape structure factor and $m$ is its number, $\eta X_i$ is the average value calculated from the risk detector, $f_x(X)$ is the fuzzy number, and $g$ is the normalization function. The fuzzy number of relationships between variables is integrated using the AND operator, which can detect the least frequent geographic configurations.

$$ f_x(X_1 \cap X_2 \cap ... \cap X_n) = \min\{f_x(X_1), f_x(X_2), ..., f_x(X_n)\} \quad (9) $$

where $\cap$ represents the process of the spatial overlay and $X_1 \cap X_2 \cap ... \cap X_n$ is the interaction of UEL landscape structure factors. The spatial zone determined by the dominant UEL in interaction with $m$ factors was termed the control zone (Fig. 2c). The significant control proportion can be derived by counting the proportion of its area. The control proportion of the UEL landscape structure change on the RHE change is calculated using a $1 \times 1$ km grid and defined as the spatial marginal effect.

### 3. Results

#### 3.1. Spatial-temporal coupling pattern of UEL and RHE

Temporally, the area of UEL and its proportion to the total ecological land in the GBA both continuously increased from 2000 to 2020, with the area increasing from 914 km$^2$ to 1679 km$^2$ and the proportion increased from 3.48% to 6.54% (Fig. 3a). With the continued expansion of the UMBA, the proportion of UEL decreased from 16.51% in 2000 to 12.83% in 2015, whereas it increased by 344.03 km$^2$ in 2015–2020 with a growth rate of 25.76%. The RHE intensity increased and then declined, then decreased by 17.82% from 2010 to 2020.

The Gini coefficient for RHE in GBA showed a trend of increasing (2000–2010) and then decreasing (2010–2020) (Fig. 3a), suggesting that RHE experienced a transition from unequal distribution to equality. For each city, FS had the highest average Gini coefficient ($0.42 \pm 0.01$) (Fig. 3b), and the RHE spatial distribution inequality was significant, followed by the GZ, DG, ZS, and SZ with a concentrated and contiguous distribution of built-up land (Fig. 4a). However, the average Gini coefficient of RHE located in the other cities of GBA (e.g., HK, ZH, and MC) was relatively low (less than0.3), with less residential thermal inequality. Overall, it shows that the spatial equity of RHE distribution is lower for cities in the GBA.

The spatial pattern of RHE also showed a coupling relationship with the UEL distribution (Fig. 4). The RHE growth was mainly distributed in cities with substantial UEL degradation, fragmentation, population clustering, and increasing heat emissions. In 2000, the high RHE intensity areas were clustered in the periphery of GZ-FS and DG-SZ, where UEL patches were small in proportion, high in fragmentation, and low in dominance and diversity (Fig. 4a–e). However, the spatial coupling with the patch shape complexity was not observed (Fig. 4f). In 2010, the proportion of UEL in the UMBA decreased while the RHE intensity increased by 31.03% on average, expanded peripherally in GZ-FS. By 2020, the area of the UMBA expanded less, and the RHE distribution was essentially similar to that in 2010. However, as the proportion of UEL in the UMBA rebounded, the RHE intensity and polarization decreased, in which the “cold island” area in the periphery of the GZ-FS-ZS contiguous area and the center of DG-SZ expanded (Fig. 4a).

#### 3.2. Spatial-temporal effects of UEL on RHE

The explanatory power ($q$ value) of UEL for the RHE distribution increased significantly by an average of 75.59% from 2000 to 2020, in which the SHDI, LPI, and PD increased by 132.87%, 98.63%, and 88.54%, respectively. By counting the proportion of the significant control zone, it was found that the dominant factor of the RHE distribution shifted from LPI to SHDI; and the significant control zone area of SHDI within UMBA increased by 214.51% (Fig. 5a–c). Specifically, in 2000, the LPI and PEL controlled RHE in most areas, accounting for 34.69% and 14.44% of the UMBA area, respectively (Fig. 5a), which indicates that the size and dominance of UEL had a dominant effect on the RHE distribution. The dominant factors in 2010 were similar to those in 2000. However, the control zone proportion of the LPI and PEL over RHE decreased by 16.20% on average with the UMBA expansion and was mainly concentrated in DG-DG-SZ. In contrast, the area proportion of PD control significantly increased (mainly in FS-ZS). The impact of UEL fragmentation was highlighted in Fig. 5b. However, in 2020, the SHDI replaced the LPI as the dominant factor of RHE distribution, and the proportion of significant control zone rapidly increased to 16.20% and was distributed throughout the UMBA. However, the proportion decreased for all other factors, with LPI and PEL decreasing by 36.79% and 24.45%, respectively, mainly in FS and ZS (Fig. 5c).

The time scales were integrated to examine the spatial–temporal effects of the changes in UEL landscape structure on the RHE changes for 2000–2010 and 2010–2020 (Fig. 5d, e). Compared with 2000–2010, the explanatory power of the UEL landscape structure changes to RHE
increased by an average of 70.79 % from 2010 to 2020. This is mainly
due to the 62.72 %, 84.04 %, and 136.40 % increase of the effect of
SHDI, LPI, and PD, respectively. The spatial marginal effect of the UEL
on RHE was further calculated, and the dominant factor of the RHE
change was found to shift from the PEL to LPI with stage differences in
the effect ranking. The spatial marginal effect of UEL from 2000 to 2010
was ranked as PEL > SHP > SHDI > LPI > PD (Fig. 5d). The PEL
controlled the largest proportion (26.09 %) of the RHE change, indica-
ting that the spatial marginal effect of the patch scale on RHE was
significant. The RHE was mainly distributed in cities with rapid con-
struction land expansion, such as GZ, DG, and SZ. However, the spatial
marginal effect ranking of UEL shifted to LPI > PD > SHDI > SHP > PEL
by 2010–2020. The LPI had a considerable spatial marginal effect on
RHE, with the proportion of the significant control zone for its change
growing to 29.50 % (an increase of 234.97 %), especially in FS and SZ
(Fig. 5e).

Further analysis of the relationship between the changes in the UEL
factors and RHE at two stages within the UEL significant control zone
revealed that the differences between the positive and negative effects of
UEL on RHE quadratically declined over time (Fig. 6). From 2000 to 2010,
the RHE-mitigating effects of increasing LPI and SHDI were 1.28 and
1.88 times greater than the RHE-promoting effect of their decrease,
respectively, suggesting that increased UEL patch dominance and di-
versity contributed more to the RHE weakening (Fig. 6a). In contrast, for
PEL, PD, and SHP, the RHE mitigation effects from their increase were
45 %, 55 %, and 49 %, respectively, which were smaller than the RHE
promotion effects from their decrease. These results indicate that the
reduced area proportion, fragmentation, and irregular patches had
stronger effects than the same degree of improvement in the corre-
sponding UEL structure. However, this phenomenon changed from 2010
to 2020. The differences between the effects of increasing and
decreasing UEL landscape index on the RHE change significantly
decayed (Fig. 6b), indicating that the magnitude of the positive and
negative effects of UEL degradation and restoration were essentially the
same.

3.3. UEL and natural-anthropogenic environment interactions drive RHE

The three-time sections of 2000, 2010, and 2020 indicate that the
RHE spatial distribution gradually shifted from being dominated by the
interaction between UEL-anthropogenic factors to UEL-natural-
anthropogenic factors. In 2000, q(PEL ∩ NTL) was the largest (q =
0.71) and q(PEL ∩ NRD), q(LPI ∩ NTL), and q(SHDI ∩ NTL) were the next
closest (q = 0.70) (Fig. 7a). These results suggest that the interaction of
UEL patch area and dominance and diversity with anthropogenic heat
emissions interacted to influence RHE. The explanatory power of natural
factors (e.g., topography and precipitation) that interacted with UEL on
the RHE distribution was relatively small (all q values were less than
0.6). In 2010, the explanatory power of the interaction between UEL and
nature-human factors generally improved, with an average increase of
17.80 % (Fig. 7b), of which q(LPI ∩ NTL) and q(SHDI ∩ NTL) were larger
(0.87 and 0.82, respectively). Results showed that the interaction of UEL
patch dominance, diversity, and anthropogenic heat emissions domi-
nated the RHE distribution. Interactions among all the factors increased
in 2020, especially q(LPI ∩ NTL), q(LPI ∩ SLP), q(LPI ∩ PPT), and q
(SHDI ∩ NTL). These together explained more than 80 % of the RHE
distribution; UEL patch dominance with anthropogenic thermal emis-
sions, topography and precipitation, and the interaction of UEL patch
diversity with anthropogenic thermal emissions affected the RHE
(Fig. 7c).

From 2000 to 2010 to 2010–2020, the RHE change was dominated
by the interaction between UEL and anthropogenic factor change, while
the interaction between the UEL and natural factor change gradually
increased. From 2000 to 2010, q(SHDI ∩ LUR) and q(LPI ∩ LUR) were
greater than 0.65. The interaction between patch diversity, dominance, and built-up land expansion had a relatively high explanatory power for RHE changes (Fig. 7d). However, the interaction between UEL changes and natural-human factor changes increased significantly from 2010 to 2020, with average increases of 54.52%, 44.08%, and 35.17% for PPT, SLP, and NRD, respectively. The influence of UEL evolution with topography, precipitation, and road accessibility changes on RHE changes gradually became larger (Fig. 7e). However, the interactions of LPI and SHDI with LUR and NTL were still the dominant combination of spatial–temporal variation in RHE ($q > 0.70$), especially the $q(LPI \cap NTL)$, $q(SHDI \cap NTL)$, and $q(SHDI \cap LUR)$, which increased to 0.76, 0.74, and 0.73, respectively.

4. Discussion and implications

4.1. Discussion

This study demonstrates a strong spatial–temporal coupling between RHE and UEL. Most of the high RHE intensity regions were concentrated in the central UMBA with low UEL proportion and richness. In addition, the RHE growth was mainly distributed in cities with substantial UEL degradation, fragmentation, population clustering, and increasing heat emissions. From 2000 to 2010, the RHE distribution in the GBA showed contiguous expansion, especially in GZ-FS-ZS and SZ-DG. The rapid population growth and expansion of construction land in the UMBA occupied a large amount of UEL, thus weakening the mitigation effect of
Fig. 5. Spatial-temporal patterns of the determinant UEL landscape structure on RHE in (a) 2000, (b) 2010, (c) 2020, (d) 2000–2010, and (e) 2010–2020. The grids labeled in white indicate q values that are not statistically significant ($P > 0.01$) or with no urban ecological land in the UMBA. The abbreviations are listed in Table 1.
Urban construction and subsequent increase in impervious surfaces and anthropogenic heat emissions directly contribute to the resident’s probability of being exposed to high temperatures (Coffel et al., 2017; Park et al., 2021), while disparities in UEL supply (i.e., PEL) further rise in inequities in the RHE distribution (Zeng et al., 2022). Despite further urban population growth and agglomeration, the RHE intensity weakened and tended to contract with the ecological transition of the GBA during 2010–2020. This could be attributed to the ecological restoration in the GBA. For example, the implementation of greening initiatives such as urban forest agglomeration enhanced UEL richness, diversity, and nodal centrality (dominance) (Wong et al., 2017), mitigating the growth and spread of RHE while contributing to increased public access to “green” spaces (Declet-Barreto et al., 2016; Norton et al., 2015).

The UEL landscape structure significantly affects the spatial–temporal evolution of the RHE. The diversity and dominance of UEL controlled the spatial distribution of RHE, while the control zone proportions of patch area and complexity were significantly lower. These results are consistent with previous studies that reported abundant and aggregated UEL patches have stronger air renewal rates (Wesley and Brunsell, 2019), exerting more significant “cold island” effects. However, the rapid expansion of built-up land led to area degradation and reduced the complexity of UEL, reducing its ability to mitigate RHE (Declet-Barreto et al., 2016; Knight et al., 2021) and ultimately reducing the control zone proportions of PEL and SHP. The spatial marginal effect of UEL dominance changes on RHE changes also substantially increased, which was the opposite for area, fragmentation, and complexity. This suggests that the aggregated and continuous UEL have sustainable and steadily increasing RHE mitigation effects, and that increasing UEL dominance and diversity can nonlinearly enhance its spatial marginal effects (Hu et al., 2019; Lin et al., 2020; Meyfroidt et al., 2022). Since an increasing number of residents are paying attention to thermal comfort...
and ecological recreation space in their choice of residence (Djongyang et al., 2010; Jones et al., 2015; Li and Zha, 2020), the areas with high UEL aggregation are more likely to attract population (Harrington and Otto, 2018), effectively strengthening the spatial marginal effect of UEL patch dominance on RHE. However, with the urban agglomeration transition and ecological restoration, the positive or negative effects of UEL landscape structure deterioration and improvement on RHE tend to be equal.

This study further empirically supported an “inverted U-shaped” non-linear coupling (Feng et al., 2021a; Feng et al., 2021c, 2022) between the evolution of RHE and UEL and its natural-human environment (Fig. 8). Specifically, during rapid urban expansion and conflict with ecological spaces (e.g., 2000–2010), drastic urbanization (e.g., population concentration and urban sprawl) degraded a large amount of UEL; the patch diversity, therefore, decreased with a notable fragmentation trend. In addition, high anthropogenic heat emissions and infrastructure construction in commercial, industrial, and residential areas jointly lead to higher RHE intensity and spatial inequity (Peng et al., 2020). As the GBA enters the stage of coordinated governance between UEL and construction land (e.g., 2010–2020), the optimization of land use structure strengthens the role of natural factors, ultimately making RHE driven by both UEL and human-natural factors. For example, with the construction of satellite cities, some industrial development zones and residential areas have shifted to the nearby suburbs. Subsequently, the reduction of anthropogenic heat emissions from built-up areas and the construction of urban parks based on natural conditions (e.g., topography, precipitation) have contributed to RHE’s spatial contraction and equity. Furthermore, UEL restoration (increasing surface richness) in high construction density areas improved the diversity, dominance, and aggregation of UEL patches, thereby effectively reducing the RHE intensity.

4.2. Practice implications

Limiting the spatial expansion of RHE and reducing the UEL fragmentation, first, it is necessary to enrich the patch diversity and ensure the dominance of large patches. The spatial marginal effect of the UEL area on RHE also showed a significant decrease, suggesting that future UEL restoration should focus on size and comprehensive optimization of its landscape structure. For example, multiple satellite cities can be built around the central city to ensure the accessibility of UEL and the spatial equity of RHE while relieving residential pressure. Second, in urban agglomeration planning and construction, decision makers must harmonize the distribution of different land use types and populations to ensure the aggregation and dominance degree of UEL patches as much as possible. Such practices can maximize the spatial marginal effect on RHE changes. Third, the spatial layout of UEL and natural-anthropogenic factors should be reasonably configured according to the different development stages, especially considering the effects of natural conditions (topography and precipitation) on RHE in the future. Due to the spatial–temporal heterogeneity of geographic elements, adaptive urban green and ecological restoration strategies must also be subsequently developed based on the local relationships between the UEL landscape and RHE (Fig. 9). For example, in central cities such as GZ and SZ, the “cold island” and spatial margin effects of the UEL diversity and connectivity can be fully played by building multi-landscape pocket parks and urban greenways. Moreover, in peripheral cities with scattered patches, the ecosystem service functions and dominance of UEL can be effectively enhanced while reducing fragmentation by establishing regional country parks and natural reserves. For satellite cities, ensuring the dominance and diversity of UEL patches in the urbanization process should be the focus of landscape planning.

4.3. Limitations and prospects

This study provides important information for planning and developing RHE mitigation strategies. However, there are several limitations that still to be addressed. First, despite the great potential of remote sensing-based RHE monitoring (Feng et al., 2020; Patz et al., 2005; Peng et al., 2012), the limited spatial resolution is insufficient to accurately depict fine changes in local areas. In future work, data fusion techniques can be used to unify meteorological and remote sensing data to explore spatial–temporal evolution and mechanisms of RHE at multiple scales. Second, because this study is concerned with the synergistic effects of vegetation and water bodies as UEL on RHE, we unified the two as a whole and have yet to explore the differences in the effects of vegetation and water bodies. It is, therefore, necessary to investigate the effects of different UEL components and other drivers on RHE. Third, this study assesses “human-centric” RHE but does not consider population differences. Further analyses could incorporate demographic characteristics of the population, such as age, income, or education level, to promote equity and justice in urban planning and construction. Undeniably, a recent emerging method, the Geodetector calculation, is affected by data discretization methods. Therefore, further exploration of the differences

Fig. 8. Conceptual theoretical and driving mechanism diagram of the relationships between UEL and RHE owing to the mutuality of coupled human-natural systems. The UEL and natural-anthropogenic factor forces at different development stages can be illustrated with these simple “flower” diagrams, where the size on each axis indicates the contribution magnitude of each factor (in this illustration, the axes are not labeled with units). The abbreviations are listed in Table 1.
between Geodetector and other methods is needed to improve the accuracy and comprehensiveness of the results.

5. Conclusion

This study considered physiological heat stress and put humans at the center of the agenda to quantify the impact of UEL on the spatial pattern and temporal evolution of RHE in the GBA. The results showed that the proportion of significant control zones and the spatial marginal effect of UEL on RHE were spatially and temporally heterogeneous from 2000 to 2020. In addition, the patch diversity evolved into the dominant factor for the RHE distribution, while the spatial marginal effect of patch dominance on RHE gradually evolved to be the largest. The interaction of UEL with anthropogenic factors such as anthropogenic thermal emissions and urban construction controlled the RHE. In contrast, the interaction of UEL with natural-anthropogenic factors has gradually increased its effect on RHE. Therefore, future urban planning and thermal mitigation strategies should comprehensively consider the spatial–temporal dynamic relationship between UEL and natural-human elements. For example, implementing ecological restoration that combines with the environment to regulate regional RHE and its spatial pattern while focusing on enhancing the diversity and dominance of UEL patches.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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References


