

Spatial Heterogeneity of Green Space Cooling Efficiency and Its Influencing Factors in the Beijing-Tianjin-Hebei Urban Agglomeration

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Abstract. The urban heat island effect exacerbates thermal environment risks in cities. As a key factor in mitigating heat islands, green spaces exhibit significant spatial differences in cooling efficiency. Taking the Beijing-Tianjin-Hebei urban agglomeration as the study area, this research constructed a 500 m grid-scale indicator system including NDVI, LST, and DEM based on Landsat 8 remote sensing data. The ordinary least squares (OLS) regression model was used to quantitatively assess the cooling efficiency (CE) of vegetation on land surface temperature and to analyze its spatial pattern and underlying mechanisms. The results show that CE generally presents a spatial differentiation pattern characterized by "high values in the northwestern mountainous areas and low values in the southeastern plains and built-up areas". Topographic gradient, vegetation cover structure, and urban form are the main regulating factors. This study provides a scientific basis for thermal environment management and ecological space optimization in the Beijing-Tianjin-Hebei region.

Keywords: Urban heat island effect, cooling efficiency, land surface temperature, NDVI, spatial heterogeneity

1. Introduction

With the interplay between global climate change and rapid urbanization, urban thermal environment issues have become increasingly prominent. The urban heat island (UHI) effect not only affects residents' thermal comfort but also exacerbates energy consumption, air pollution, and heat-related health risks, making it a critical environmental issue constraining sustainable urban development [1-3]. As an important component of urban ecosystems, vegetation can mitigate surface heat accumulation through evapotranspiration and shading effects, and is thus considered one of the effective measures to alleviate the urban heat island effect [4, 5]. Therefore, quantitatively identifying the contribution of green spaces to surface heat mitigation and their spatial differences is the scientific basis for urban ecological planning and thermal risk management.

In recent years, research on urban thermal environments based on remote sensing data has developed rapidly. In particular, the analytical framework using the Normalized Difference

Vegetation Index (NDVI) to characterize vegetation cover and Land Surface Temperature (LST) to reflect thermal environment conditions has been widely applied globally [6-8]. Meanwhile, multiple factors such as built environment structure and topography collectively influence heat transfer processes, resulting in significant spatial heterogeneity in the cooling effect of green spaces [9, 10]. Consequently, assessing the differences in vegetation cooling effects at a fine scale across different regions has become a key focus of current research.

Although numerous studies have focused on the overall thermal effect assessment at the city level, research exploring the cooling efficiency of green spaces at the regional scale, especially from an urban agglomeration perspective, remains relatively limited. Existing studies indicate that the cooling capacity of green spaces depends not only on vegetation conditions but also on external factors such as building density, topographic relief, and proximity to water bodies, leading to significant regional differences in cooling capacity. Therefore, it is necessary to construct a quantitative model that integrates multiple factors to reveal the driving mechanisms and regional differences in vegetation cooling effects.

The Beijing-Tianjin-Hebei urban agglomeration is one of the most densely populated and highly urbanized regions in China. In recent years, this region has experienced rapid land-use transformation, with significant expansion of built-up areas and increasingly prominent thermal risks. Additionally, the topography of the Beijing-Tianjin-Hebei region exhibits marked differences, with a large spatial gradient from piedmont slopes to plains, making it an important typical study area for identifying differences in green space cooling functions. However, compared to single-city scale studies, research on spatial differences in cooling efficiency at the overall Beijing-Tianjin-Hebei level remains insufficient, making it difficult to fully support regional ecological planning and refined governance needs.

Based on the above background, this study takes the Beijing-Tianjin-Hebei region as the research object, using remote sensing data to construct a 500 m grid-scale dataset of NDVI, LST, topography, and other variables. The Ordinary Least Squares (OLS) regression model is employed to quantify the cooling efficiency (CE) of vegetation on land surface temperature. By developing the spatial expression of CE, this study reveals the spatial pattern of the green space cooling effect in the Beijing-Tianjin-Hebei region and its potential influencing factors.

2. Study area and data sources

2.1. Study area overview

In fact, the Beijing-Tianjin-Hebei region lies in the northern part of the North China Plain and it is an important area for land development and economic growth in China where we can observe active construction and economic activities happening every year, and this makes it a key study area for us. The region spans 36°03'–42°37'N and 113°27'–119°50'E. It includes Beijing Municipality, Tianjin Municipality, and Hebei Province's major cities, so the spatial range is quite large and we should pay attention to this characteristic when we study the climate and environment in this area because it is important for our analysis. The total area is approximately 210,000 km². It has high population density and significant urbanization level, so it can be regarded as a typical large-scale composite urban agglomeration with complex structure, and this brings many challenges for the local environment and climate studies that we need to consider carefully [11, 12]. For physical geography, the northwest of Beijing-Tianjin-Hebei region has the Yanshan and Taihang mountains and hills, and the southeast changes into coastal plains where we can see flat terrain and this is suitable for

agriculture and industrial development. The topographic relief is different, so it creates diverse regional microclimatic environments.

This region is located in temperate monsoon climate zone. The summer is hot and humid, which means this is the period when surface heat accumulation can reach its maximum level and the temperature stays high for a long time, creating favorable conditions for the formation and development of urban heat island effect in the region. In fact, urban expansion in this region is rapid. Natural vegetation is replaced by impervious built-up areas, and this makes surface warming worse and the urban heat island effect becomes stronger, which is expected to influence the local climate and living environment in cities where population density is high and industrial activities are concentrated. Also, cities here differ greatly in development stage. They have different industrial layout and land use patterns, and this leads to spatially heterogeneous thermal environment characteristics that can vary from one district to another even within the same city, making it hard to use uniform mitigation strategies for all areas in Beijing-Tianjin-Hebei region. So we examine the relationship between green space cover and surface thermal environment at this scale, which can have good regional representativeness.

2.2. Data sources and description

We collected all remote sensing data used in this study through Google Earth Engine (GEE) platform [13-15]. GEE includes global multi-source remote sensing and geospatial data. Also it provides cloud computing environment, which can support efficient large scale data filtering, quality control as well as index calculation. This can be suitable for studies covering large areas such as the Beijing Tianjin Hebei urban agglomeration. It is worth noting that we constructed a dataset based on unified rasterization framework to ensure spatial consistency and comparability among different data types.

We use NDVI to describe vegetation cover. It can be calculated from Landsat 8 OLI surface reflectance data by combining red and near-infrared bands. Cloud detection and quality control can be applied to make sure NDVI values reflect real vegetation conditions. We obtain land surface temperature (LST) from Landsat 8 TIRS product for hottest summer months, and thermal infrared band inversion can be used to represent the intensity of surface thermal environment, while the data is atmospherically corrected and converted to uniform temperature unit for following modelling. Topographic information is extracted from high-resolution digital elevation model data (e.g., MERIT DEM) to capture elevation and topographic variation, so we can analyze the regulating effect of topographic differences on local thermal environment. It is worth noting that these data can compensate the limitation of pure remote sensing temperature information when considering micro-scale. The specific data sources are summarized in Table 1.

Table 1. Data sources

Data type	Data source platform	Specific dataset	Spatial resolution	Time range	Data purpose	Acquisition and processing method
Vegetation cover (NDVI)	Google Earth Engine	Landsat 8 OLI Surface Reflectance	30 m (resampled to 100 m)	Hottest summer months	Characterize vegetation cover status	Calculate NDVI in GEE, cloud/shadow removal, crop to study area

Table 1. (continued)

Land surface temperature (LST)	Google Earth Engine	Landsat 8 TIRS LST product	100 m (unified scale)	Hottest summer months	Characterize surface thermal environment	Extract LST in GEE, unify temperature units
Topographic data (DEM)	Google Earth Engine	MERIT DEM	90 m (resampled to 100 m)	Yearly	Analyze topographic differences	Acquire and project uniformly in GEE
Built environment data (building height)	Google Earth Engine	Global building height or GHSL data	100 m	Same period as NDVI	Describe spatial barriers of built environment	Rasterize and match with other variables
Water body data	Google Earth Engine	Global water body or land cover data	30–100 m	Same period as NDVI	Reflect potential impact of water body cooling capacity	Generate water body distance raster
Administrative boundaries	Official statistics/geographic data center	Provincial boundaries (Beijing-Tianjin-Hebei)	—	Latest	Crop study area	Import into GEE as mask

2.3. Data time range and spatial resolution

Summer is the main period with surface thermal risk in study area. We use remote sensing data from the hottest months of recent years as the analysis object, because this can help us examine vegetation cooling effects under extreme high-temperature conditions and this is expected to improve the reliability of our results. For spatial resolution, we first use original 30 m pixels of Landsat data. Then all data are resampled to a uniform 500 m grid scale, and it is worth noting that this step can balance data accuracy and model computational efficiency as we need. This scale can reflect local differences in built environment. At the same time, it covers a continuous area at the urban agglomeration scale, so this resolution should be suitable for the cross-city comparisons between different cities and this can provide support for our study.

2.4. Data preprocessing

To ensure accuracy and comparability of multi source remote sensing data in spatial analysis and modelling, we preprocessed raw data. Remote sensing images contain clouds and shadows. It is worth noting that this can cause low vegetation indices and biased temperature estimates. It interferes with authenticity of NDVI and LST and affects model fitting. So we used pixel level QA information to identify and remove clouds, shadows, and poor quality pixels, so the extracted surface information can reflect ground conditions. Because different datasets (e.g., NDVI, LST, DEM, building height) use different projection coordinates and pixel division methods, directly overlaying them can lead to spatial misalignment and area distortion and compromise variable matching and spatial regression analysis. Then we adopted a unified projection coordinate system and resampled all data to a consistent grid reference. It can guarantee accurate spatial

correspondence and improve reliability of subsequent statistics. Due to terrain, sensor noise, and cloud cover, some areas had missing pixels. Using incomplete data can result in insufficient training samples and break spatial continuity. So we filled small missing areas based on spatial neighbourhood or multi temporal information to restore a complete raster data structure, so input variables of the regression model can have consistent coverage. The model input variables—temperature, vegetation index, elevation, building height, etc.—differ in dimensions and numerical ranges. Without normalisation, contribution weights of variables can become unbalanced in regression optimisation, which hinders reliable quantification of the cooling effect. So we standardised (e.g., Z score) or normalised the variables to eliminate dimensional differences, so the regression coefficients can reflect influence strength of each variable on LST. At last, because the original remote sensing swaths cover an area larger than the study area. Working with the full swath can increase computational burden. Also it introduces irrelevant samples that interfere with model interpretation. So we masked all data with the Beijing Tianjin Hebei administrative boundary. This ensures a unified spatial range of samples and establishes an integrated dataset for the study area. It provides a foundation for subsequent regional scale comparisons and thematic mapping.

We preprocess the data to improve consistency of multi source remote sensing data. This can ensure accuracy of variable matching. Also, it can provide good data quality for quantitative estimation of cooling efficiency using OLS regression model [16, 17]. Also, the data has complete spatial coverage and consistent scale. This can help reveal the regional differences in surface thermal environment and the spatial patterns of vegetation cooling effects within Beijing -Tianjin- Hebei region.

3. Methodology and technical route

3.1. Technical route and analytical framework

We choose Beijing-Tianjin-Hebei region as study area. Based on remote sensing data, a unified raster database is built and we use multiple linear regression model to identify the cooling efficiency of vegetation on land surface temperature, which can help us understand the cooling effect, and results are visualized. It is worth noting that the technical route has four steps. These are data acquisition and preprocessing, indicator construction, model estimation for cooling efficiency, and CE (Cooling Efficiency) spatial mapping and analysis.

3.2. Indicator system construction

We build an indicator system to reflect green space status and thermal environment in study area and we also consider impacts from built environment and topography. The system includes NDVI, LST, DEM, building height, and water body distance [18, 19]. NDVI is calculated from Landsat 8 OLI data. It is worth noting that it can reflect vegetation cover degree and is the core variable for measuring vegetation cooling capacity. Higher NDVI values can indicate stronger evapotranspiration and shading effects. LST is obtained from Landsat 8 TIRS products. It can reflect intensity of regional thermal environment and is used as dependent variable in model. We select data from the hottest summer months. It can capture vegetation cooling effects under extreme conditions and this is important for our research. DEM is extracted from MERIT DEM data in GEE. It captures elevation information. Topographic changes can have important effects on local wind fields, sunshine conditions, as well as temperature distribution. So we include DEM as control variable in the model. Also, other auxiliary variables—such as surface albedo and land use type—can be added

according to research needs and it can improve model explanatory power [20]. All indicators are calculated and projected on GEE platform. This can ensure data consistency and comparability.

3.3. Indicator system construction

We know vegetation can cool the land surface. In this paper, we use the Ordinary Least Squares (OLS) regression model to examine this cooling effect, and we try to find the relationship between LST and multiple environmental factors including vegetation cover and albedo.

3.3.1. OLS Regression model

The basic form of the model is as follows:

$$LST_i = \beta_0 + \beta_1 NDVI_i + \beta_2 DEM_i + \varepsilon_i \quad (1)$$

where:

- LST_i : Land surface temperature of the i-th grid cell
- $NDVI_i$: Vegetation cover index
- DEM_i : Topographic elevation
- β_1 : Regression coefficient of NDVI, used to reflect the vegetation cooling effect
- ε_i : Random error term

The model is established across the entire Beijing-Tianjin-Hebei region and can reflect regional-scale differences in cooling effects.

3.3.2. Multicollinearity test

We first test variance inflation factor (VIF) for all independent variables before doing regression analysis, and it is worth noting that when $VIF > 5$ or > 10 the variables should be removed or combined and this can avoid bias in regression coefficients. Through stepwise screening, we try to ensure the variable independence. Also, the model estimation can be more reliable.

3.3.3. Definition of cooling efficiency (CE)

Based on reference studies, the absolute value of the regression coefficient of NDVI in the regression model is taken as the vegetation cooling efficiency (CE):

$$CE = |\beta_1| \quad (2)$$

Implications:

- A larger CE value indicates a more significant negative effect of NDVI on temperature, i.e., a stronger cooling effect per unit of vegetation cover.
- This indicator is comparable and can be used for horizontal comparisons across different regions.

3.4. Spatial mapping of cooling efficiency (CE)

We get the CE from regression model first. Then we map it to 100 m grid. If a whole region regression is used. Then the CE value is assigned to all grid cells to make a CE distribution map for the whole region. If we do regression for each city or functional zone, we can assign different values to different sub regions. In fact, this can show the spatial inequalities of cooling effects in the region.

Using a GIS platform, the CE is rasterized and thematic maps are generated to achieve a visual representation of the spatial characteristics of cooling efficiency.

4. Results

4.1. Spatial distribution characteristics of NDVI

We can see in Figure 1, from the NDVI (Normalized Difference Vegetation Index) map in Beijing-Tianjin-Hebei region, we can see the green space distribution has obvious spatial difference. In fact, red areas in figure show higher NDVI values. This means the vegetation cover is abundant. At the same time, blue areas represent lower NDVI values and it indicates sparse vegetation cover or open land.

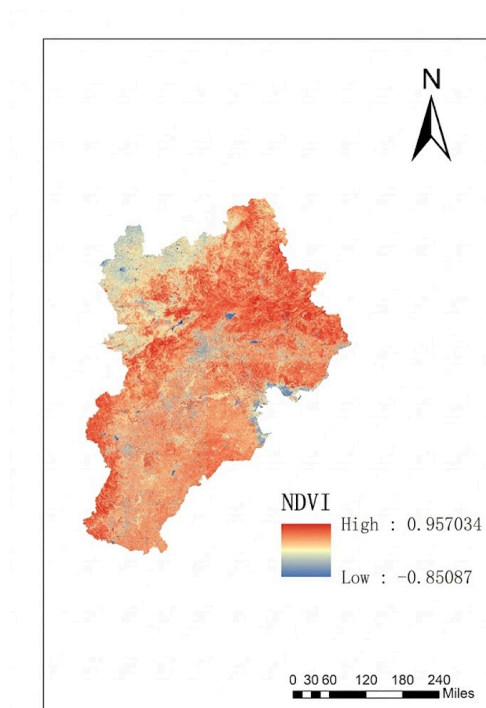


Figure 1. Spatial distribution of NDVI

Based on the NDVI distribution characteristics, we can see high values in this region are mainly found in the mountainous areas and forest-covered areas. Also, some peri-urban areas with abundant green space show high values. In fact, the maximum NDVI value is 0.957. It can indicate very high vegetation cover exists in some places, mainly in the mountainous areas and large-scale green belts. Low NDVI values are mostly located in the city centers and surrounding areas, especially industrial zones and densely built-up areas where vegetation cover is sparse, and this reflects the compression

effect of urbanization on the vegetation, and it is worth noting that this phenomenon is very common in the study area.

We find the minimum NDVI value is -0.85087. It indicates some water bodies or bare land exist, and vegetation cover there is almost zero. In fact, vegetation distribution in Beijing-Tianjin-Hebei region can be influenced by many factors, such as natural environment, the urbanization process, and land use type. High NDVI areas can be regarded as natural ecological areas with good vegetation cover, while low NDVI areas are expected to be concentrated in areas with high urbanization.

The NDVI distribution characteristic provides basic data for studying the cooling effect (CE) and urban heat island effect (LST) in the region. We can use this data to understand the temperature pattern and it is worth noting that areas with higher green space cover can play important role in mitigating the urban heat island effect. So rational planning is needed. Also, increasing green space area can optimize urban climate and is expected to improve environmental quality.

4.2. Spatial distribution characteristics of LST

We can see in Figure 2, from the spatial distribution map of LST (Land Surface Temperature) in the Beijing-Tianjin-Hebei region, surface temperature shows obvious spatial heterogeneity. According to the color gradient in the figure, red represents high-temperature areas, and blue represents low-temperature areas, showing the urban heat island effect and regional differences in temperature variation. High-temperature areas (red) are mainly distributed in city centers and their surrounding areas, while low-temperature areas (blue) are mainly concentrated in green spaces, lakes, and relatively open natural environments.

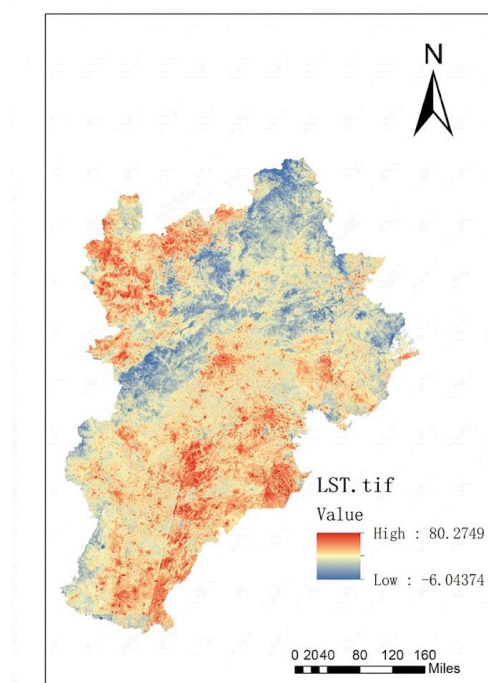


Figure 2. Spatial distribution of LST

We analyze the LST data in Beijing-Tianjin-Hebei region. The maximum value is 80.2749 and the minimum is -6.04374. It can be seen that the temperature difference is very large. In the urbanized areas around Beijing and Tianjin, the surface temperature is higher because there are

dense buildings and heavy traffic and this situation can form the urban heat island effect which is significant in these areas and can affect the local climate. In contrast, the natural areas and urban green spaces have lower surface temperature. Also, this can reflect the temperature-regulating effect of green spaces.

Spatial distribution shows that urbanization and green space cover can have different impacts on surface temperature. Green spaces and water bodies regulate local temperature. This can reduce heat island effect. So the surface temperature variation in region is influenced by multiple factors, including urbanization degree, green space cover, topographic features and water distribution and further analysis is needed for its relationship with cooling efficiency (CE). It is worth noting that understanding the spatial distribution characteristics of surface temperature can have practical significance for the urban environmental management and sustainable development when we consider climate change and urban planning.

4.3. Spatial distribution characteristics of DEM

As shown in Figure 3, The terrain distribution in the Beijing-Tianjin-Hebei region shows highland and lowland differences, and it is high in north and low in the south. Based on DEM (Digital Elevation Model) data analysis, the northern part has complex mountainous landscape with higher elevations reaching maximum 2849 meters, and we can see significant mountain characteristics there. The color gradient changes from red to blue, which reflects topographic height differences. In particular, the northern area has undulating terrain. It is worth noting that in the southern and coastal areas, the terrain is flat with lower elevations, and some areas can reach minimum -57 meters, indicating low-lying areas consisting of hills or plains.

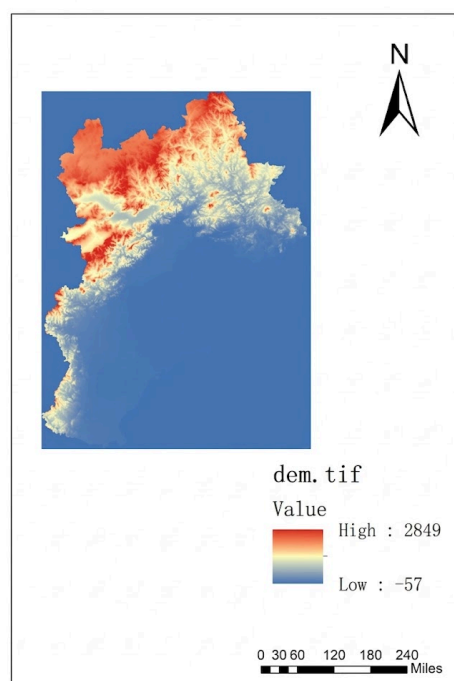


Figure 3. Spatial distribution of DEM

This topographic feature shapes the natural landscape of Beijing-Tianjin-Hebei region. It also influences the climate and ecosystem here. For example, high-altitude areas can have lower

temperatures because elevation rises and this plays important role in climate regulation and ecological restoration. Also, topographic differences have big impact on land surface temperature (LST) and cooling efficiency (CE), and it is worth noting that this is true in low-lying areas where small topographic relief can lead to more pronounced heat island effects during hot seasons. So topographic factors play an important role in the spatial distribution of cooling efficiency. They deserve further investigation in heat island effect research.

4.4. OLS regression results analysis

The following Table 2 shows the OLS regression results for the Beijing-Tianjin-Hebei region.

Table 2. OLS regression results for the Beijing-Tianjin-Hebei region

Variable	Coefficient[a]	Std. Error	t-statistic	Probability[b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Constant	-7419.01	26.69	-277.99	0	182.14274	-40.73	0	-----
DEM_WGS84	-0.0073	0.0040	-1.84	0.065	0.000832	-8.83	0	1.000005
NDVII	0.26	0.0027	95.61	0	0.018209	14.16	0	1.000005

We examine regression results. The coefficient of constant term is -7419.01 with $p < 0.01$. This suggests constant term in model can have negative effect on land surface temperature. For topographic variable DEM_WGS84, the coefficient is -0.0073. It indicates negative correlation between elevation and surface temperature. Although t-statistic is -1.84 with $p = 0.065$ and significance level is low, we can observe certain negative correlation trend, and it is worth noting that this may imply regulating effect of topographic relief on surface temperature can be limited especially in areas affected by urbanization.

NDVI is used as vegetation index and the coefficient is 0.26 and the t-statistic is 95.61 with $p < 0.01$. It indicates that increase of vegetation cover can reduce land surface temperature. In fact, green space cover plays key role in mitigating urban heat island effect. Also, this result shows green spaces are important in urban environmental regulation.

Also, VIF values of the model are close to 1. This means multicollinearity can be avoided. Regression results are reliable. We calculate robust standard errors to check robustness of model, and the robust Pr values for all variables are significant ($p < 0.01$). It indicates relationships between these variables and land surface temperature can be stable.

In fact, the OLS regression results we obtained show that land surface temperature in Beijing-Tianjin-Hebei region can be influenced by vegetation cover (NDVI) and topography (DEM), and we can see that vegetation cover has a stronger regulating effect on temperature than other factors. This result can be used as a reference for future work.

4.5. Spatial distribution characteristics of CE

In Figure 4, we can see the spatial distribution map of cooling efficiency (CE) in Beijing-Tianjin-Hebei region. The cooling effect has obvious spatial difference. In fact, the color gradient from red (high values) to blue (low values) can show the intensity in different areas, where red areas have strong cooling efficiency and blue areas have weak or almost no cooling effect, and this pattern is easy to observe.

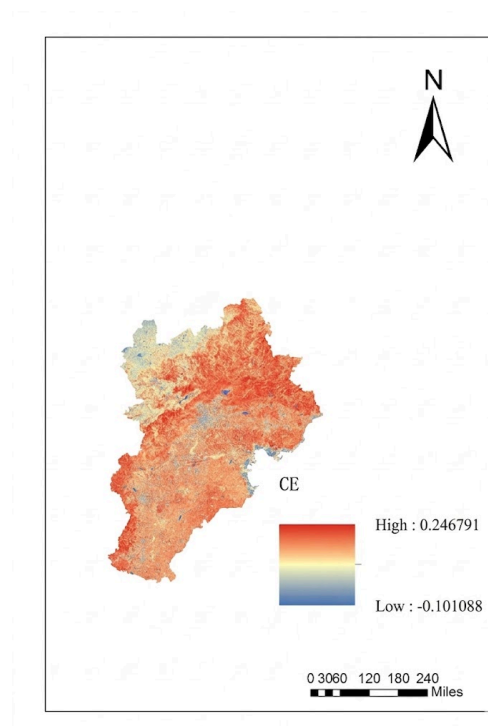


Figure 4. Spatial distribution of CE

We can see from the figure that the maximum CE value in Beijing-Tianjin-Hebei region is 0.246791 and the minimum is -0.101088. And this indicates there can be large spatial differences in cooling efficiency. High cooling efficiency areas are concentrated in green spaces and water bodies, while open natural areas have good performance. In contrast, low cooling efficiency areas are distributed in densely built-up urban areas. This includes industrial zones and commercial zones. In these areas, urban heat island effect is expected to be prominent and it results in low cooling efficiency because the built environment absorbs more heat and the release of heat is slow, which can lower the cooling efficiency.

In fact, high CE areas can be found in regions with rich greening, such as forests, lakes, parks and wetlands, which indicates that green spaces and water bodies can play a role to reduce surface temperature and improve cooling efficiency. But low CE areas are distributed in highly urbanized area and can be found in districts with many buildings. Cooling efficiency in these places is weak. Hardened surfaces such as buildings and roads in urbanization process can hinder the natural cooling mechanism, and this leads to higher surface temperatures.

The spatial distribution shows green spaces and water bodies play key role in regulating the urban heat island effect and it also indicates that increasing these areas during hot seasons can be significant for mitigating heat island effect. In fact, rational urban planning should be considered first. We can use greening strategies to enhance urban environmental quality and reduce heat island effect.

5. Conclusion

5.1. Analysis of the formation mechanism of spatial differences in green space cooling effect

Based on the above spatial statistical and mapping results of NDVI, LST, and cooling efficiency (CE) in the Beijing-Tianjin-Hebei region, it can be found that the three exhibit significant spatial heterogeneity at the regional scale: high NDVI areas are mainly concentrated in mountainous forest areas, ecological conservation zones, and some peri-urban green belts, while NDVI is relatively low in built-up areas and industrial agglomerations; high LST areas are mainly distributed in the built-up areas of Beijing, Tianjin, and central-eastern Hebei cities, while low LST areas are mostly located in mountainous regions and areas adjacent to water bodies [21, 22]. Furthermore, the spatial pattern of CE generally shows the characteristic of "higher in areas with a strong natural ecological background and lower in highly urbanized areas". The wide range of CE values indicates that the cooling effect of green spaces is significantly uneven in the Beijing-Tianjin-Hebei region. This result not only is consistent with the differences in underlying surface composition across the region but also suggests that the cooling effect of green spaces is regulated by the coupling of multiple factors, rather than being a simple linear response of a single vegetation indicator [23, 24].

From the perspective of formation mechanisms, the spatial differences in CE are first constrained by the topographic gradient and background climatic conditions [25]. The Beijing-Tianjin-Hebei region has a typical "northwest mountain – southeast plain/coastal" geomorphological differentiation pattern with a significant elevation gradient. Mountainous areas generally have lower background surface temperatures and more favorable wind field and turbulent exchange conditions, which facilitate heat diffusion and transport. At the same time, better hydrothermal conditions can maintain higher evapotranspiration capacity of vegetation, thereby enhancing the contribution of unit vegetation cover to surface cooling. In contrast, the built-up plains have small topographic relief, continuously distributed impervious surfaces, and more significant surface heat storage and accumulation, which may weaken the cooling effect of vegetation under a high thermal background. The above process provides a reasonable basis for explaining the overall differentiation of CE along the "mountain – plain – core urban area" gradient.

Vegetation cover and the vegetation-surface energy exchange process are the direct physical sources of CE differences. From the perspective of surface energy balance, vegetation mainly increases latent heat flux and reduces sensible heat flux through evapotranspiration, and reduces shortwave radiation entering the soil and impervious surfaces through canopy shading, thereby lowering surface temperature. In areas with high NDVI and good vegetation connectivity, evapotranspiration and shading effects can be fully exerted, manifesting as higher CE. In contrast, within built-up areas, green spaces are often fragmented and patchy, with a high proportion of surrounding impervious surfaces, and cold air is easily diluted by the surrounding thermal environment. Coupled with insufficient soil moisture and the limitation of evapotranspiration potential due to grass-dominated green space types, the overall CE is low [26, 27]. This coupled relationship of "green space structure – evapotranspiration potential – thermal background" is consistent with the spatial mapping characteristics shown in Chapter 4.

Urban morphology and anthropogenic heat emissions have a significant modulating effect on the cooling effect of green spaces. In high-density built-up areas, impervious surfaces have high heat capacity, strong daytime heat absorption, and slow nighttime heat release [28]. Anthropogenic heat emissions from traffic, industry, and air conditioning further raise the local thermal background. At the same time, street canyon effects and building clusters blocking wind worsen ventilation conditions and inhibit heat diffusion. In this situation, even if NDVI increases to a certain extent, the

corresponding cooling effect may be difficult to fully realize due to the "high thermal background and poor ventilation environment", thereby compressing CE. Furthermore, building height and density have a dual impact on radiation shading and turbulent exchange: shading helps reduce local surface heating, but excessive morphological resistance may weaken convective transport, thereby affecting the spatial expression of vegetation cooling effects. Therefore, the spatial differences in CE essentially reflect the combined effect of vegetation, urban morphology, and heat emissions.

Proximity to water bodies and surface moisture conditions can synergistically influence regional differences in CE [29, 30]. Water bodies change the near-surface thermal environment through evaporative cooling and humidity regulation, and may enhance the available water and evapotranspiration capacity of surrounding green spaces, making the "water body – green space" combination exhibit a more pronounced cooling effect within a certain range. Conversely, in areas where soil moisture is limited, vegetation evapotranspiration is subject to water stress, and the cooling effect of green spaces may be weakened, resulting in lower CE. Therefore, including water body distance (or a proxy variable for humidity) in the explanatory framework helps to improve the process-based understanding of CE spatial differences.

At the statistical level, the OLS regression results in Chapter 4 show a significant relationship between NDVI and LST. It should be noted that if the sign of the regression coefficient is inconsistent with the common expectation of a "cooling effect", priority should be given to checking variable orientation (e.g., standardization method), LST unit conversion, sample screening, and confounding factor control, and an explanation should be provided in the methods or appendix. On the other hand, the occurrence of locally negative or abnormal CE values does not necessarily mean "vegetation-induced warming", but more likely reflects effect attenuation under a high thermal background, boundary mixing effects caused by fragmented green spaces, or the combined effect of omitted variables and measurement errors. These uncertainties also provide directions for subsequent model improvement and mechanism validation.

In summary, the spatial differences in green space cooling efficiency in the Beijing-Tianjin-Hebei region are driven by multi-scale factors: at the macro level, they are influenced by the thermal environment base shaped by topography and background climate; at the meso level, they are dominated by the energy exchange capacity determined by vegetation cover and structure; at the micro level, they are modulated by urban morphology and anthropogenic heat emissions on the thermal background and ventilation conditions; meanwhile, water bodies and humidity conditions synergistically enhance or limit the evapotranspiration process. This mechanistic framework can well explain the co-differentiation of NDVI, LST, and CE presented in Chapter 4, and provides a process-based basis for subsequent green space system optimization and thermal risk management.

5.2. Research limitations and future prospects

Although this study constructed a remote sensing- and statistical model-based assessment framework for green space cooling efficiency in the Beijing-Tianjin-Hebei region and revealed the spatial heterogeneity of CE, several uncertainties and areas for improvement remain due to limitations in data, methods, and process variables, which need to be addressed in future work.

Temporal representativeness is limited, as we used data from summer high-temperature periods to characterise the thermal environment and vegetation response. While this effectively highlights cooling effects under extreme thermal backgrounds, CE may be influenced by short-term weather processes such as heatwaves, rainfall, and changes in cloud cover, making it difficult to capture multi-year average levels and interannual variability. Future studies should extend multi-year, multi-season, and multi-event window analyses to construct a "normal versus extreme" parallel CE

assessment system, which would help test the robustness of the conclusions and enhance their generalisability.

Uncertainties are inevitably introduced by multi-source data fusion and scale harmonisation. NDVI, LST, DEM, and built-environment data may differ in sources, temporal phases, and spatial resolutions. Resampling, projection unification, and quality control procedures can introduce scale effects and propagate errors. Moreover, LST inversion is sensitive to atmospheric correction, land surface emissivity, and cloud/aerosol conditions; even after cloud and shadow removal and quality screening, local errors may still affect the regression coefficients and the spatial representation of CE. Future studies are encouraged to introduce ground-based meteorological station observations or reanalysis data for cross-validation, and to report key parameter settings and error assessment results in the appendix, thereby enhancing reproducibility, transparency, and the credibility of the results.

The linear model form may insufficiently characterise spatial heterogeneity and non-linear processes. The OLS model is based on linear assumptions and requires independently and identically distributed residuals, whereas urban thermal environments often exhibit significant spatial autocorrelation and non-linear response characteristics. Furthermore, the cooling effect of green spaces may involve thresholds, diminishing marginal returns, and complex interactions with the built environment. Relying solely on a global linear model makes it difficult to fully explain micro-scale differences within cities. Future research should therefore introduce spatial econometric models (e.g., SLM or SEM), geographically weighted regression (GWR or MGWR), or machine learning methods to better capture spatial heterogeneity and non-linear relationships while maintaining interpretability, and cross-validate the results with OLS.

The coverage of influencing factors also needs to be expanded. The core explanatory variables in this study are NDVI and topographic factors. Although these effectively reflect the important roles of vegetation and topography in the thermal environment, urban thermal environments are also affected by factors such as impervious surface proportion, albedo, soil moisture, surface roughness, wind field conditions, and anthropogenic heat emissions. If these process variables are not adequately included, the regression coefficient of NDVI may "absorb" some of the effects of co-variables, affecting the physical interpretation of CE. Future work should supplement impervious surface area (ISA), the normalised difference built-up index (NDBI), albedo, soil moisture data (e.g., SMAP or CCI), and nighttime light data as proxies for human activity, and conduct variable contribution decomposition and sensitivity analysis to improve mechanistic explanation.

References

- [1] Gong, H., Cao, Y., Yao, J., Xu, N., & Zhang, Z. (2024). Factors influencing spatiotemporal changes in urban blue-green space cooling in the Beijing-Tianjin-Hebei urban agglomeration. *Land*, 13(9), 1423.
- [2] Impacts of coordinated development policies on urban heat islands in the Beijing-Tianjin-Hebei urban agglomeration, China, *Sustainable Cities and Society* (2024).
- [3] Xu, H., Li, C., Wang, H., Zhou, R., Liu, M., & Hu, Y. (2022). Long-term spatiotemporal patterns and evolution of regional heat islands in the BTH urban agglomeration. *Remote Sensing*, 14(10), 2478.
- [4] Exploring the multitemporal surface urban heat island effect and its driving relation in the Beijing-Tianjin-Hebei urban agglomeration. *Applied Geography* (2022).
- [5] Wang, Q., Wang, X., Zhou, Y., Liu, D., & Wang, H. (2022). Dominant factors and influence of urban characteristics on land surface temperature using random forest algorithm. *Sustainable Cities and Society*, 79, 103722.
- [6] Soltanifard, H. & Amani-Beni, M. (2025). The cooling effect of urban green spaces as nature-based solutions for mitigating urban heat: a systematic review (2014–2024). *Curr. Clim. Change Rep.*
- [7] Du, M., Li, N., Hu, T., Yang, Q., & Chakraborty, T. C. (2024). Daytime cooling efficiencies of urban trees derived from land surface temperature. *Environ. Res. Lett.*, 19, 044037.

- [8] Ni, N., Lou, D., Xu, D., & Wang, H. (2024). Measuring urban green space cooling effects using Landsat (NDVI/LST) and buffer analysis. *Int. J. Digit. Earth* (2024).
- [9] Qiu, X., Kil, S.-H., Jo, H.-K., Park, C., & Song, W. (2023). Cooling effect of urban blue and green spaces: Changsha case study. *Int. J. Environ. Res. Public Health*, 20(2613).
- [10] Abou Samra, R. M. (2025). How urban green spaces shape unequal cooling in urbanizing Egypt: Landsat + GEE analysis. *Earth Syst. Environ.*, 9, 605–624.
- [11] Wang, J., Zhou, W., Zheng, Z., et al. (2023). Interactions among spatial configuration aspects of urban tree canopy affect cooling effects. *Sci. Total Environ.*, 864, 160929.
- [12] Masoudi, M. & Tan, P. Y. (2021). Effects of land use on spatial pattern of urban green spaces and their cooling ability. *Urban Clim.*, 35, 100743.
- [13] Shah, A., Garg, A., & Mishra, V. (2021). Quantifying local cooling effects of urban green spaces (Bengaluru). *Landscape Urban Plan.*, 209, 104043.
- [14] Terfa, B. K., Chen, N. C., & Zhang, X. (2020). Spatial configuration and urban heat mitigation potential due to green spaces. *Remote Sens.*, 12(2876).
- [15] Wang, J., Zhou, W., Zheng, Z., Jiao, M., & Qian, Y. (2023). Significant effects of ecological context on urban trees' cooling efficiency. *ISPRS J. Photogramm. Remote Sens.*, 159, 78–89.
- [16] Sharmin, T., Chappell, A., & Lannon, S. (2024). Spatio-temporal analysis of LST, NDVI and SUHI using LCZ. *Energy Build. Environ.*
- [17] Chen, J.-K. et al. (2024). Quantifying dominant effects on diurnal LST cycles in urban zones. *Sustain. Cities Soc.*
- [18] Qiao, Y. et al. Examining urban water bodies' cooling effects using buffer & random forest. *Urban Clim.* (2025).
- [19] Na, N. et al. Remote sensing analysis of cooling radiation range of urban green spaces. *Mod. Agric. Res.*, 30, 107–110.
- [20] Li, Y. et al. Global analysis of greenspaces cooling benefits via Landsat. *Nat. Commun.* (2024).
- [21] Sharmin, T. et al. Global LST/NDVI/SUHI temporal dynamics — implications for heat mitigation. *Environ. Build.* 2024.
- [22] Chen, N.-C. et al. Urban thermal responses to 3D architectural pattern variation. *J. Clean Prod.*, 258 (2020).
- [23] Richards, D. R. et al. Differential air temperature cooling performance of vegetation types. *Urban For. Urban Greening* (2020).
- [24] Sun, F. Y. et al. Effects of 3D architectural patterns on surface temperature. *J. Clean Prod.*, 258 (2020).
- [25] Velastegui-Montoya, A. et al. Google Earth Engine: global analysis & future trends. *Remote Sens.*, 15 (2023).
- [26] Huang, Z. et al. Exploring urban green space & morphology influence on UHI using street view & satellite imagery. *Sci. Rep.*, 15: 23759 (2025).
- [27] Zhang, T. et al. Urban park cooling effects (PCI, PCG, PCA, PCE) measured with Landsat. *Glob. Change Biol.* 2025.
- [28] Na N. et al. Green space cooling mechanisms across multiple scales. *Int. J. Digit Earth* (2024).
- [29] Qiao, Y. et al. Water bodies & green space combined cooling under random forest. *Urban Clim.* 2025.
- [30] Du, M. et al. Comparative study of surface vs air cooling effectiveness. *Environ. Res. Lett.* 2024.