Spatiotemporal variation of land surface temperature and its driving factors in Xinjiang, China Postprint

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Abstract

Land surface temperature (LST) directly affects the energy balance of terrestrial surface systems and impacts regional resources, ecosystem evolution, and ecosystem structures. Xinjiang Uygur Autonomous Region is located at the arid Northwest China and is extremely sensitive to climate change. There is an urgent need to understand the distribution patterns of LST in this area and quantitatively measure the nature and intensity of the impacts of the major driving factors from a spatial perspective, as well as elucidate the formation mechanisms. In this study, we used the MOD11C3 LST product developed on the basis of Moderate Resolution Imaging Spectroradiometer (MODIS) to conduct regression analysis and determine the spatiotemporal variation and differentiation pattern of LST in Xinjiang from 2000 to 2020. We analyzed the driving mechanisms of spatial heterogeneity of LST in Xinjiang and the six geomorphic zones (the Altay Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, Turpan-Hami (Tuha) Basin, and Pakakuna Mountain Group) using geographical detector (Geodetector) and geographically weighted regression (GWR) models. The warming rate of LST in Xinjiang during the study period was 0.24°C/10a, and the spatial distribution pattern of LST had obvious topographic imprints, with 87.20% of the warming zone located in the Gobi desert and areas with frequent human activities, and the cooling zone mainly located in the mountainous areas. The seasonal LST in Xinjiang was at a cooling rate of 0.09°C/10a in autumn, and showed a warming trend in other seasons. Digital elevation model (DEM), latitude, wind speed, precipitation, normalized difference vegetation index (NDVI), and sunshine duration in the single-factor and interactive detections were the key factors driving the LST changes. The direction and intensity of each major driving factor on the spatial variations of LST in the study area were heterogeneous. The negative feedback effect of DEM on the spatial differentiation of LST was the strongest. Lower latitudes, lower vegetation coverage, lower levels of precipitation, and longer sunshine duration increased LST. Unused land was the main heat source landscape, water body was the most important heat sink landscape, grassland and forest land were the land use and land cover (LULC) types with the most prominent heat sink effect, and there were significant differences in different geomorphic zones due to the influences of their vegetation types, climatic conditions, soil types, and human activities. The findings will help to facilitate sustainable climate change management, analyze local climate and environmental patterns, and improve land management strategies in Xinjiang and other arid areas.

Full Text

Preamble

Spatiotemporal Variation of Land Surface Temperature and Its Driving Factors in Xinjiang, China

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Abstract

Land surface temperature (LST) directly affects the energy balance of terrestrial surface systems and influences regional resources, ecosystem evolution, and ecosystem structures. Xinjiang Uygur Autonomous Region, located in the arid northwest of China, is extremely sensitive to climate change. There is an urgent need to understand the distribution patterns of LST in this region, quantitatively measure the nature and intensity of major driving factors from a spatial perspective, and elucidate the underlying formation mechanisms. In this study, we used the MOD11C3 LST product developed from Moderate Resolution Imaging Spectroradiometer (MODIS) data to conduct regression analysis and determine the spatiotemporal variation and differentiation patterns of LST in Xinjiang from 2000 to 2020. We analyzed the driving mechanisms of spatial heterogeneity of LST in Xinjiang and its six geomorphic zones (the Altay Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, Turpan-Hami (Tuha) Basin, and Pakakuna Mountain Group) using geographical detector (Geodetector) and geographically weighted regression (GWR) models. The warming rate of LST in Xinjiang during the study period was 0.24°C/10a, and the spatial distribution pattern exhibited obvious topographic imprints, with 87.20% of the warming zone located in Gobi desert areas and regions with frequent human activities, while cooling zones were mainly situated in mountainous areas.

Seasonal LST in Xinjiang decreased at a rate of 0.09°C/10a in autumn, while showing warming trends in other seasons. Digital elevation model (DEM), latitude, wind speed, precipitation, normalized difference vegetation index (NDVI), and sunshine duration were identified as key factors driving LST changes in both single-factor and interactive detections. The direction and intensity of each major driving factor on spatial LST variations were heterogeneous across the study area. The negative feedback effect of DEM on spatial LST differentiation was the strongest. Lower latitudes, lower vegetation coverage, lower precipitation levels, and longer sunshine duration increased LST. Unused land was the primary heat source landscape, water body was the most important heat sink landscape, and grassland and forest land were the land use and land cover (LULC) types with the most prominent heat sink effects, with significant differences observed across geomorphic zones due to influences of vegetation types, climatic conditions, soil types, and human activities. These findings will facilitate sustainable climate change management, support analysis of local climate and environmental patterns, and improve land management strategies in Xinjiang and other arid regions.

Keywords: geographically weighted regression (GWR); source-sink effect; Xinjiang land surface temperature; MOD11C3; climate change; geographical detector (Geodetector)

1 Introduction

Land surface temperature (LST) is an essential parameter for assessing energy exchange between the Earth' s surface and atmosphere. It directly affects the energy balance of terrestrial surface systems and visually reflects regional and global climate change (Tian et al., 2022). As a core element of the climate system, LST is a critical tool for studying and detecting environmental changes (Townshend et al., 1994). LST evolves through complex energy transfer and transformation processes, and its spatial and temporal differentiation is controlled by numerous geo-environmental factors influencing water-heat balance, which in turn affects resource environments and ecosystem structures (Sfîcă et al., 2023), making it vital for agriculture, hydrology, and ecology (Anderson et al., 2008; Zhang et al., 2009; Li et al., 2013). As a key factor in surface physical processes at global and regional scales, analyzing spatial and temporal pattern divergence and spatial heterogeneity of LST is essential for understanding regional climate change processes and driving mechanisms (Xi et al., 2023).

Currently, LST research widely focuses on the urban heat island effect (Ren et al., 2021; Yang et al., 2021; Sfîcă et al., 2023), crop sowing date predictions for agriculture (Zeng et al., 2015; Zhang et al., 2015), drought monitoring (Khan et al., 2018; Hu et al., 2020), soil freeze-thaw analysis (Yue et al., 2021), and human activity intensity research (Portela et al., 2020; Chen et al., 2022a). Although LST is a general term for soil temperature on the surface and at different depths, obvious spatial differences in topography, climatic environment, and underlying surface attributes can cause diverse LST distribution patterns and regional formation mechanisms (Wu et al., 2022). Numerous investigations have analyzed LST change characteristics in China and other regions from perspectives of temporal and spatial changes, mutation characteristics, influencing factors, and climate change response mechanisms (Huang et al., 2016; Tian et al., 2022; Zhang et al., 2022). A consensus exists that LST shows a significant upward trend in response to climate change (Ren et al., 2021). However, due to different research areas and periods, spatial and temporal pattern differentiation and variation ranges differ, and driving mechanisms for spatial LST differentiation have not been fully elucidated. In particular, the warming and cooling effects of different underlying surfaces and complex geomorphic zones remain unclear. Spatial heterogeneity of LST is also related to spatial scale; the smaller the scale, the more complex the mechanisms (Ren et al., 2021). At macro scales, latitude determines solar radiation duration and heat amount, whereas longitude characterizes land-sea location and continental influence on local climate formation (Zhang et al., 2023). Topography is an important parameter for characterizing surface geomorphology at small and medium scales (Tian et al., 2022) and is multifaceted, with complex mountain-basin geomorphic features increasing spatial heterogeneity. Additionally, due to obvious differences in heat budget processes such as radiation, absorption, reflection, and transpiration, LST effects on underlying surfaces and feedback mechanisms exhibit significant spatial and temporal differentiation (Wang et al., 2015; Yu et al., 2020; Chi et al., 2021). Various meteorological factors participate in energy exchange between land surface and free atmosphere, and different thermodynamic cycle ranges in this process also affect LST (Tian et al., 2022). Previous LST studies used correlation coefficient methods to determine characteristics of various influencing factors' effects on LST changes (Portela et al., 2020). However, correlation analysis cannot clarify each driving factor' s contribution to spatial LST heterogeneity nor express joint control by multiple factors. When considering numerous factors that may affect LST distribution patterns, a suitable method is required to quantitatively analyze spatial heterogeneity of driving factors and synergy or antagonism between factors to reveal LST differentiation rules and genetic mechanisms. The geographical detector (Geodetector) model is a new tool for measuring, mining, and analyzing spatial heterogeneity that can objectively reflect each driving factor' s priority and joint effects in geographical phenomena (Wang and Xu, 2017). The geographically weighted regression (GWR) model (Brunsdon et al., 1996) enables local spatial regression modeling of relationships between independent and dependent variables, revealing spatial heterogeneity of driving factors. The complementary advantages of these models help explore response mechanisms of LST distribution in relation to its driving factors from multiple perspectives.

Xinjiang Uygur Autonomous Region in Northwest China is a vast territory encompassing oasis, alpine, and dry-hot desert areas (Chen et al., 2022a) and represents an important oasis distribution area in global arid regions (Pan et al., 2021). As the main gathering place for human activities, oases in arid areas play a decisive role in determining agricultural structure rationality, crop growth suitability, and grassland phenology (Zhang et al., 2016; Fu et al., 2017). Additionally, as important cold and heat sources, glacier-frozen soil distribution and development and snow cover ablation/accumulation in alpine frozen and dry-hot desert areas have apparent regulatory effects on regional energy balance processes (Hachem et al., 2012). Desert ecosystem stability is also affected by LST changes (Brenning et al., 2012; Hachem et al., 2012; Zhang et al., 2019). Differences in water, air, and heat conditions of local underlying surfaces in these areas form significantly different microclimates (Mao et al., 2017), resulting in differences in system heat balance and water volume, which make inter-annual and seasonal LST changes in Xinjiang highly distinct.

This study quantitatively characterized spatial and temporal LST differentiation in Xinjiang from 2000 to 2020 using monthly MOD11C3 LST product developed from Moderate Resolution Imaging Spectroradiometer (MODIS) data. Dominant driving factors were identified using the Geodetector model, and spatial heterogeneity of driving factors was analyzed in combination with the GWR model.

The objectives of this study are: (1) to elucidate inter-annual and seasonal variation characteristics of LST in Xinjiang; (2) to explore main driving factors affecting spatial LST differentiation in Xinjiang; (3) to examine response patterns of main driving factors to spatial LST heterogeneity in each geomorphic zone of Xinjiang; and (4) to quantitatively analyze contribution degree of each LULC type to LST in Xinjiang combined with source-sink theory. This will help explain eco-geographic pattern evolution in arid regions multi-dimensionally, providing scientific reference data to help cope with climate change, harmonize human-land relations, and facilitate regional sustainable development.

2.1 Study Area

Xinjiang Uygur Autonomous Region (73°20 -96°25 E, 34°15 -49°10 N; Fig. 1 [Figure 1: see original paper]) is located in northwestern China. Xinjiang exhibits rich landform types from north to south, including the Altay Mountains, Junggar Basin, Tianshan Mountains, Turpan-Hami (Tuha) Basin, Tarim Basin, Pamir Plateau, Karakoram Mountains, Kunlun Mountains, and Altun Mountains. The Pamir Plateau, Karakoram Mountains, Kunlun Mountains, and Altun Mountains are collectively referred to as the Pakakuna Mountain Group (Ning et al., 2020). The "three mountains" (Altay Mountains, Tianshan Mountains, and Pakakuna Mountain Group) and "two basins" form a closed terrain area. The deep inland position and distance from the ocean make it difficult for maritime airflow to reach the region, resulting in a typical temperate continental arid climate with abundant sunshine, cold winters, and hot summers. The annual average temperature ranges from 6.46°C to 9.23°C, and average annual precipitation is 199.60 mm. Climate differences create complex oasis-mountain-desert-basin ecosystems with landform types such as desert, mountain forest, grassland, alpine meadow, and extremely high mountain glaciers (including snow). Although Xinjiang is vast, the land underutilization rate is approximately 61.02%, making it susceptible to climate change. Differences in light radiation and energy balance across landform types cause vertical and horizontal LST differentiation.

2.2 Data Sources

This study used monthly MODIS-based MOD11C3 LST product data from 2000 to 2020 to explore spatiotemporal LST differentiation characteristics. Precipitation (mm), sunshine duration (h), digital elevation model (DEM; m), normalized difference vegetation index (NDVI), wind speed (m/s), population density (persons/km^2), and land use and land cover (LULC) data were used for attribution analysis of LST spatial heterogeneity (Table 1). We extracted topographic and locational factors such as slope (°), aspect, latitude, and longitude based on DEM data. All data were unified to the WGS-84 coordinate system and UTM projection, and resampled to 5 km × 5 km using the BILINEAR method, except for LULC.

Two types of MODIS data were used. The first was MOD11C3 LST product data derived from MODIS Terra global daily surface temperature/emissivity data (https://www.nasa.gov/). The product format was Hierarchical Data File (HDF), and the MODIS Reprojection Tool (MRT) was used for batch processing of mosaicking and reprojection. MOD11C3 contains daytime and nighttime LST data, and an arithmetic average method was used to obtain seasonal and annual LST. The second type was MOD13Q1 NDVI data (https://www.nasa.gov/). We synthesized MOD13Q1 NDVI data with a 16-day temporal resolution to monthly NDVI data using the maximum value composite method to reflect vegetation distribution across Xinjiang' s geomorphic zones at temporal and spatial scales.

The spatially interpolated dataset of average meteorological conditions in China (https://www.resdc.cn/) was based on daily observations from 2400 stations nationwide, with 1 km spatial resolution. We selected precipitation, wind speed, and sunshine duration data from this dataset. Population density data were downloaded from WorldPop (https://www.worldpop.org/), which provides current long time-series data with high accuracy and reliability that has been widely cited in research. The LULC dataset from the Resource and Environment Science and Data Center (https://www.resdc.cn/) contains data for 2000, 2010, and 2020. Referring to classification standards from China' s Current Land Use Situation Remote Sensing Database combined with actual conditions in the study area, LULC types were grouped into six categories: forest land, cultivated land, grassland, water body, construction land, and unused land. Based on DEM data (http://www.gscloud.cn/) and geomorphic spatial distribution data (https://www.resdc.cn/), actual boundaries of landforms such as mountains (groups) and basins were further revised to provide basic data for exploring spatiotemporal LST differentiation in various geomorphic zones of Xinjiang.

2.3.1 Trend Analysis

The univariate linear regression equation provides a reasonable straight line expressing the relationship between climate and time variables (Zheng et al., 2021). Using regression analysis, we conducted trend analysis of LST at each grid from 2000 to 2020, analyzing spatial variation characteristics of LST during 2000–2020 at annual and seasonal scales. The formula is as follows:

$$\text{Slope} = \frac{n \times \sum_{i=1}^{n} i \times \text{LST}_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} \text{LST}_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where Slope (°C/10a) represents the LST trend per decade (indicating the rate of change); n is the total number of years; and LST (°C) is the land surface temperature in the ith year (i = 1, 2, ···, n). When Slope > 0, the LST sequence increases with time, and vice versa. The greater the absolute Slope value, the more pronounced the trend.

2.3.2 Significance Test

The significance test describes the possibility of equation fitting differences due to sampling error, which can be used to verify and describe the fitting effect of LST and time. The F-test evaluates the significance of the LST change rate, representing the credibility of the change trend. The greater the F value, the better the fitting effect and the more pronounced the LST change trend. The formula is as follows:

$$F = \frac{U/m}{Q/(n-m-1)}$$

where U is the sum of squared errors; m is the number of years; and Q is the sum of regression squares. After reclassifying significance test results and superimposing the change rate layer, the change trend was divided into six categories as described in Table 2 .

2.4 Geodetector Model

The Geodetector model can detect driving factors of spatial heterogeneity in response variables and the influence of interactions between driving factors on response variables. Based on this, we selected 11 driving factors—longitude, latitude, DEM, slope, aspect, precipitation, sunshine duration, wind speed, NDVI, population density, and LULC—to build an index system, and used the Geodetector model to explore causes of spatial differentiation in annual LST in Xinjiang. The factor detection model tested each factor’ s explanatory power on spatial LST differentiation patterns, while the interactive detection model identified coupling modes between factors and their influence on LST spatial differentiation (Table 3). The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{\text{SSW}}{\text{SST}}$$

where q is the explanatory power of each independent variable on LST spatial heterogeneity, with greater values indicating stronger explanatory power; L is the stratification of LST (or its driving factors), i.e., classification or partitioning; N and N are the number of units in layer h and the whole region, respectively; σ ^{2} and σ^2 are LST variances in layer h and the whole region, respectively; and SSW and SST are the intra-layer variance and total variance of the area, respectively.

Factors affecting LST changes are diverse, with complex process mechanisms including both natural and human factors. Among natural factors, topographic and geographical location factors such as DEM, latitude, longitude, slope, and aspect affect solar radiation balance at different heights and directions. Climatic factors such as wind speed, sunshine duration, and precipitation directly affect total solar radiation received by the surface. NDVI is essential for characterizing surface vegetation coverage, and vegetation transpiration significantly impacts the surrounding environment. Human factors were characterized by population density and LULC in this study, both objectively describing human activity influence on surface heat distribution. Population density reflects human aggregation degree, which transforms the natural environment. Under human activity influence, LULC type changes cause variations in underlying surface physical and chemical properties, thereby enhancing or weakening reflected solar radiation and affecting LST distribution.

2.5 GWR Model

Traditional global regression assumes regression parameters remain unchanged in space, ignoring spatial heterogeneity between geographical relationships. The GWR model is a spatial regression model based on local smoothness that obtains local regression coefficients according to different geospatial division units, effectively estimating data with spatial autocorrelation and reflecting spatial heterogeneity of driving factors across regions (Han et al., 2020). This study used GWR to explore main driving factor influences in each geospatial unit and differences in direction and intensity of each action. The formula is as follows:

$$Y_e = \beta_0(u_e, v_e) + \sum_{k=1}^{P} \beta_k(u_e, v_e) x_{ek} + \varepsilon_e$$

where Y is the dependent variable value at grid e; β_0 is the intercept; (u , v) are grid e coordinates; β_0(u , v) is the constant term for grid e; P is the number of independent variables; β (u , v) is the regression coefficient of the kth independent variable (k = 1, 2, ···, P) for grid e; x   is the value of the kth independent variable for grid e; and is random error. Driving factors were normalized to avoid outlier and extreme value influences on results.

2.6 Source-Sink Effect on LST

Each LULC type acts as a heat source or sink within a certain area, and heat source/sink landscape (HSI) identification can be used to identify the source-sink effect of each LULC type. We calculated HSI values using previously reported LST classification with five LST levels: low LST, secondary low LST, medium LST, secondary high LST, and high LST (Wu et al., 2022). Based on HSI, we calculated the contribution index (CI) to assess each heat source or sink landscape' s contribution to LST. The formulas are as follows:

$$\mathrm{HSI} = \left(\frac{S_{ahi}}{S_a}\right) / \left(\frac{S_{hi}}{S}\right)$$

where HSI is heat source and sink landscape identification; S (km^2) is the area of high and secondary high LST zones in LULC type a; S (km^2) is the total area of LULC type a; S (km^2) is the total area of high and secondary high LST zones in the study area; and S (km^2) is the total study area. When HSI > 1.00, the LULC type is defined as a heat source landscape; when HSI < 1.00, it is a heat sink landscape; and when HSI = 1.00, the LULC type shows flow effect.

$$\mathrm{CI} = \sum_{s=1}^{n} (T_s - T) \times S_s$$

where T (°C) is the average LST of each LULC type showing sink effect (or source effect); T (°C) is the average LST of the total study area; and S (km^2) is the area of each LULC type showing sink effect (or source effect) in the study area.

3.1.1 Spatiotemporal Variation Characteristics of Annual LST in Xinjiang

LST spatial patterns in Xinjiang showed apparent topographic imprints. LST was affected by underlying surface type, topography, and geomorphology, resulting in low values in mountain regions and high values in basin regions (Fig. 2 [Figure 2: see original paper]). Overall, Xinjiang' s annual average LST showed a fluctuating upward trend from 2000 to 2020, varying from 8.53°C to 10.26°C, with large inter-annual fluctuations and periodic differences (Fig. 3 [Figure 3: see original paper]). The multi-year average annual LST in Xinjiang was 9.45°C. Annual average LST in 2007, 2013, and 2015 exceeded 10.00°C, with the highest value in 2013 (10.26°C) caused by atmospheric circulation anomalies that resulted in hot events with broad coverage, high intensity, and long duration (Liu et al., 2021). Additionally, the subtropical high in 2013 was significantly stronger than during the same period, making the Tuha Basin the most significantly affected high-temperature area (Dong et al., 2022), where the highest annual average LST reached 19.53°C in 2013. The lowest annual average LST in Xinjiang occurred in 2012 (8.53°C), primarily due to an abnormally cold winter and long cumulative duration of shallow temperature events (Chen et al., 2022b).

The rate of change for annual LST in Xinjiang was 0.24°C/10a, showing an annular desuperheating zone surrounded by plains and mountains (Fig. 2b). This warming trend (0.24°C/10a) was not only higher than global LST (0.18°C/10a; Li et al., 2020) but also higher than China' s average (0.21°C/10a; Tian et al., 2022). LST in Xinjiang was primarily characterized by non-significant increasing during 2000-2020 (Fig. 2c). Areas passing the F-test ($P < 0.05$) accounted for only 10.36% of the total area, whereas significant warming areas comprised 8.57% and highly significant warming areas occupied 1.27%. These areas were primarily in the southwest Tarim Basin, Tuha Basin, Ili River Valley (western Tianshan Mountains), and Harketawu Mountains (southwestern Tianshan Mountains).

3.1.2 Spatiotemporal Differentiation Characteristics of Annual LST in Geomorphic Zones

Spatially, the highest multi-year average annual LST in geomorphologic zones was 23.06°C (Fig. 2a). The mid-latitude Tuha Basin had the highest annual average LST (regional average of 20.06°C) in 2017, followed by the Tarim Basin (regional average of 18.03°C) in 2013, with high-value areas predominantly beside deserts. Low-value areas were primarily located in the three mountain systems. Although the Pakakuna Mountain Group has low latitude, its high DEM resulted in the lowest multi-year average annual LST of -21.06°C. The Tianshan Mountains have abundant underlying surfaces including Gobi desert, forest lands, and grasslands. The lowest multi-year average annual LST in the Tianshan Mountains was -21.92°C and the highest value (19.05°C) was adjacent to the Tarim Basin. Although the Tianshan Mountains have higher latitude than the Pakakuna Mountain Group, their multi-year average annual LST was higher (regional average of 5.77°C). The Altay Mountains have the highest latitude, with a multi-year average annual LST of -1.35°C, the lowest among the six geomorphic zones (Fig. 4 [Figure 4: see original paper]).

Among the six geomorphological zones (Table 4), the annual LST change rate in the Tuha Basin was 0.44°C/10a, making it the fastest warming area in Xinjiang, followed by the Tarim Basin (0.32°C/10a), whereas the Pakakuna Mountain Group had the smallest increase rate (0.13°C/10a). In Xinjiang, 87.20% of warming areas were concentrated in Gobi Desert and areas with frequent human activities. The warming rate in some Tuha Basin areas reached 0.96°C/10a. Cooling areas were primarily located in pre-mountain basins and oasis plain areas with high vegetation coverage. The Pakakuna Mountain Group was the dominant cooling area, with some regions showing a fast cooling rate of -1.55°C/10a;

the Tianshan Mountains had a fast cooling rate of -0.94°C/10a in some areas, particularly the Yulduz Basin (Central Tianshan Mountains) and Bogda Mountains (eastern Tianshan Mountains). Warming area for each geomorphic zone exceeded cooling area. Cooling areas in the Pakakuna Mountain Group (26.82% of its total area) and Tianshan Mountains (14.84%) accounted for large proportions. Warming area proportions in the Tuha Basin and Altay Mountains exceeded 97.19%. After testing significance of LST change rates, 39.36% of the Tuha Basin showed significant ($0.01 \leq P < 0.05$) and 4.04% showed highly significant ($P < 0.01$) warming or cooling. Only 0.11% of the Altay Mountains showed significant ($0.01 \leq P < 0.05$) warming or cooling.

In summary, LST in Xinjiang showed a warming trend with high heating intensity over a wide area. Warming trends in basin regions were more significant than in mountainous regions. The Tuha Basin and Tarim Basin were the most stable geomorphic zones for warming. Cooling trends mainly appeared in mountainous areas; however, many significant warming areas were located west of the Tianshan Mountains.

To further explore LST variation characteristics at different latitudes and longitudes in Xinjiang, we selected 87.30°E (passing through the Pakakuna Mountain Group, Tarim Basin, Tianshan Mountains, Junggar Basin, and Altay Mountains) and 43.30°N (passing through the Ili River Valley, Tianshan Mountains, Bogda Mountains, and Barkol Mountains (eastern Tianshan Mountains)) to analyze latitudinal and longitudinal LST differentiation (Fig. 5 [Figure 5: see original paper]). These longitude and latitude lines cross main geomorphic zones and can reflect LST variation characteristics across different geomorphic zones.

LST distribution followed latitudinal zonal law (Fig. 5a). For every degree of latitudinal increase from south to north, LST decreased by 0.38°C. However, DEM significantly weakened latitudinal zonal characteristics of LST in each geomorphic zone. From south to north, average LST of the Pakakuna Mountain Group along 87.30°E was -1.25°C, average LST in the Tianshan Mountains reached 7.75°C, and that in the Altay Mountains decreased to -3.00°C. High values were distributed in the two basins, with LST in the Junggar Basin lower than in the Tarim Basin (which is at lower latitude). Although the Tianshan Mountains have higher latitude than the Pakakuna Mountain Group, LST was higher in some regions, possibly due to significant warming effects in the Tianshan Mountains (Zhang et al., 2023). The LST decline rate on southern Tianshan slopes was lower than on northern slopes, primarily because southern slopes are sunnier, at lower latitude, and have lower vegetation coverage. LST significantly increased from west to east (Fig. 5b); for every degree of longitudinal increase, LST increased by 0.67°C. LST in the middle of the Ili River Valley reached approximately 10.53°C, whereas the lowest LST in the middle Tianshan Mountains was -3.47°C. In the Bogda Mountains and Barkol Mountains, the lowest LST was -2.49°C due to influence from surrounding Gobi Desert and vegetation coverage. LST in lower DEM areas of the Bogda and Barkol Mountains could reach 17.25°C, whereas in the middle Tianshan Mountains it was significantly lower than in the Bogda and Barkol mountainous areas at the same latitude.

LST gradually decreased from valley bottoms to mountain tops, and spatial variation of certain terrain and underlying surface properties also reduced latitudinal zonality of ground temperature. Further exploration of correlation between LST and DEM revealed that vertical decline law of LST restricted its distribution (Table 5). The correlation between LST and DEM in Xinjiang was stronger than in China' s first geomorphic partitioning step (Tian et al., 2022). The negative correlation between LST and DEM in the Pakakuna Mountain Group was strongest, with a correlation coefficient reaching -0.91, followed by the Altay Mountains (-0.87). Vertical decline rates of LST in each mountainous zone are shown in Table 5. Although the northernmost Altay Mountains have lower DEM and high latitude, they have large differences in solar radiation acquisition capacity, thus exhibiting the largest vertical LST decline rate, with LST most significantly affected by elevation. Although the Pakakuna Mountain Group has high absolute elevation and large undulation, its lower latitude provides abundant solar radiation, thus weakening vertical LST dependence. It is evident that latitudinal and altitudinal LST dependence was significant in each geomorphic zone. LST distribution associated with solar radiation had latitudinal zonal characteristics; however, DEM and subsurface characteristics strengthened LST spatial heterogeneity by affecting local surface thermal properties, resulting in spatial differentiation patterns with lower or higher temperatures at the same latitude.

3.2 Spatiotemporal Variations of Seasonal LST in Xinjiang

Seasonal LST variations in Xinjiang have led to significant differences in vegetation phenology, snow freezing and thawing, and glacier ablation (Shi et al., 1991); thus, this analysis is crucial for ecosystem and water resource regulation. The multi-year average LST in Xinjiang was 11.97°C in spring and 9.34°C in autumn. Spatial distribution patterns of LST in spring and autumn were similar (Fig. 6 [Figure 6: see original paper]). Low-temperature areas (below zero) were in alpine regions with average DEM higher than 4329 m in the three mountain systems. The multi-year average LST in Xinjiang in summer was 24.95°C, with low-temperature areas only located in the Pakakuna Mountain Group and Hantengri Peak (in the Tianshan Mountains). In winter, the multi-year average LST in Xinjiang was -9.04°C, with higher values in the south and lower values in the north when bounded by the Tianshan Mountains. Only a small high LST area was found in the southern hinterland of the Tarim Basin.

Of LST changes across four seasons in Xinjiang, only autumn experienced cooling at 0.09°C/10a, while other seasons showed warming trends, with the largest change rate in spring (0.49°C/10a), followed by winter (0.48°C/10a) (Table 6). In spring, warming area in Xinjiang (accounting for 88.74% of total area) was 7.8 times larger than cooling area. The Tianshan Mountains and Pakakuna Mountain Group were geomorphological zones with the slowest warming rate and largest cooling area, whereas warming rates in the Altay Mountains and

Junggar Basin exceeded 0.85°C/10a. Warming trends in the Altay Mountains, eastern Tianshan Mountains, and southern Xinjiang showed high significance.

In summer, warming area in Xinjiang decreased to 83.32% of total area, of which 67.41% showed significant warming and the fastest warming rate was 0.64°C/10a in the Tarim Basin. A highly significant cooling zone appeared in the economic zone on northern Tianshan slopes and along the Tarim Basin, which are areas of rapid economic development in Xinjiang. Significant vegetation coverage increase due to artificial intervention reduced surface albedo, increased soil moisture, and produced an important cold zone, confirming that LULC type transformation and physical property changes caused by vegetation coverage and human activity changes were closely linked to LST changes (Huang et al., 2016).

Warming area reached its minimum in autumn, with 60.87% of Xinjiang showing cooling, and most regions exhibiting non-significant warming or cooling. The Altay Mountains had the fastest cooling rate (-0.42°C/10a), and only the Tuha Basin and Pakakuna Mountain Group were in warming conditions. In winter, warming area increased to 84.16% of Xinjiang' s area, with most cooling areas in the Tianshan Mountains and Pakakuna Mountain Group still dominated by insignificant warming or cooling. At this time, the warming rate of the Altay Mountains increased to 0.88°C/10a, followed by the Junggar Basin and Tarim Basin. Overall, LST changes in most parts of Xinjiang fluctuated sharply with seasons, and all geomorphic zones except the Pakakuna Mountain Group followed Xinjiang's seasonal LST change rate, reflecting their climatic sensitivity and indicative nature to a certain extent.

3.3.1 Dominant Factor Identification Using the Geodetector Model

Previous studies have indicated spatial differences in LST changes in Xinjiang (Kang et al., 2022). To address this, possible driving factors related to LST changes were identified. All 11 selected factors passed confidence tests and showed significant relationships with LST distribution patterns in Xinjiang. Factor detection results showed that topographic factors contributed most to LST spatial differentiation, followed by natural factors (Fig. 7a [Figure 7: see original paper]). Among them, DEM, wind speed, and latitude had the most prominent explanatory power, with q values of 0.698, 0.503, and 0.392, respectively. Generally, higher DEM means thinner air, and long-wave radiation received by the ground indirectly restricts vertical heat transfer through conversion of surface latent heat and heat energy (Wan et al., 2012). Wind speed indirectly affects LST changes through dynamic effects of surface heat (Zhou et al., 2014). Excessive wind speeds generated at higher LST result in air absorbing and removing heat from the surface more rapidly. Faster air movement that absorbs and removes surface heat (Garratt, 1994) leads to faster surface temperature decrease. If wind speed is low, decreases in surface heat are weakened or disappear, and surface temperature increases significantly. When wind speed increases, turbulent mixing intensity increases, and mixing of high and low temperature air results in more uniform LST spatial distribution (Ampatzidis and Kershaw, 2020). Latitude influence on LST shows that higher latitude means smaller solar elevation angle, longer solar radiation path through the atmosphere, and greater light and heat weakening and dispersion.

Additionally, effects of precipitation, slope, and sunshine duration on LST distribution were prominent, with q values of 0.288, 0.280, and 0.221, respectively. Precipitation affects LST through evaporative cooling, heat transfer, and groundwater recharge (Xi et al., 2023). Precipitation is usually accompanied by cloud formation that blocks direct solar radiation and reduces surface solar energy input and surface temperature. Slope is the core factor describing microtopography, affecting LST by controlling local-scale solar radiation and prevailing wind direction angles; higher latitude increases microtopographic factor influence on solar radiation (Zeng et al., 2005). Sunshine duration directly affects solar radiation reception time and is an important LST factor. More ground sunshine means greater solar radiation, faster ground temperature increase, and higher LST. The q value of LULC was 0.199, with influence second only to natural factors, because LULC spatial distribution is related to surface cold and hot environment spatial patterns (Wei et al., 2021). Although human-dominated change areas exist in the economic belt on northern Tianshan slopes and some southern Xinjiang cities, the Gobi desert area is too large, limiting human activity impacts on LST.

Interaction detection results showed that explanatory power of combined driving factors was stronger than single factors, and LST spatial heterogeneity in Xinjiang was enhanced through two-factor enhancement or nonlinear enhancement between factors (Fig. 7b). Interaction between DEM and other factors was most prominent, with q values greater than 0.700, further highlighting DEM' s strong influence on LST. Interactions of DEM with precipitation (q = 0.888), latitude (0.885), sunshine duration (0.836), and NDVI (0.848) had the strongest power to explain LST spatial heterogeneity, indicating that spatial differences in precipitation, latitude, and underlying surface vegetation coverage were main reasons for enhanced spatial LST differentiation at the same DEM in Xinjiang. Explanatory power of interactions between wind speed and other factors on LST spatial differentiation was second to DEM. Two-way interaction between wind speed and aspect had the lowest explanatory power for LST spatial divergence (q = 0.508). In single-factor detection, q values of slope and population density were 0.005 and 0.024, respectively, which were significantly enhanced after interactions with DEM and wind speed. Aspect affects solar radiation reception at different DEM and heat distributions. The LST change rate on southern Tianshan slopes was lower than on northern slopes because southern slopes receive more solar radiation. Simultaneously, slope affected wind speed distribution—when airflow passes over slopes, terrain blocking accelerates or decelerates airflow. Xinjiang is sparsely populated, with human activities concentrated in plain oasis areas and inland river basins at low DEM. Frequent, high-intensity human activities directly affect surface material and energy exchange in populated areas. Therefore, LST changes were mainly affected by

DEM and human activities in these areas. Meanwhile, continuous urban expansion and industrial energy consumption from human activities have transformed farmland, natural vegetation, and water bodies into impervious surfaces such as asphalt, concrete, and buildings, which continuously release large amounts of heat. Generated waste heat and smoke also strengthen atmospheric insulation and inversion effects (Qiao et al., 2019). All these factors directly or indirectly affect surrounding heat budget balance, increase heat island effects, and influence local air convection and turbulence intensity in cities (Grimmond and Oke, 1999), which can enhance interaction intensity between population density and wind speed and affect LST.

3.3.2 Attribution Analysis Using the GWR Model

Spatial LST differentiation in each geomorphic zone was significant. The mountain-scale elevation of the Pakakuna Mountain Group exceeded other mountainous areas, but correlation between LST and DEM was weakest. In middle latitudes of the Tianshan Mountains, average annual LST was higher than in lower latitudes of the Pakakuna Mountain Group, and average annual LST in middle latitudes of the Tuha Basin was higher than in lower latitudes of the Tarim Basin (Fig. 5). In contrast, interior Tianshan Mountains exhibited low LST at the same latitude. Although topography profoundly impacted LST distribution, it cannot fully explain LST spatial heterogeneity, raising questions about whether spatially heterogeneous correlations exist with remaining factors. To address this, this study selected driving factors including DEM, wind speed, latitude, precipitation, NDVI, and sunshine duration, which provided more powerful explanations for LST spatial heterogeneity according to Geodetector model results. The GWR model was introduced to identify spatial differences in direction and intensity of main driving factors (Fig. 8 [Figure 8: see original paper]).

GWR model regression coefficients indicated each driving factor was spatially non-stationary and showed characteristic variability (Table 7). The negative feedback effect of DEM on LST spatial differentiation played a dominant role across Xinjiang and geomorphological zones, with the strongest negative feedback in the Altay Mountains, Junggar Basin, and Tuha Basin. Latitude had negative feedback effects on LST spatial differentiation across the study area, with each geomorphological zone following the rule: higher latitude means stronger negative feedback effect. The Pakakuna Mountain Group absorbs more solar radiation due to its low latitude; therefore, latitude plays a positive role in LST differentiation of this geomorphological zone. Precipitation and NDVI had significant negative effects on LST differentiation. Interaction strength of precipitation and NDVI differed across geomorphic units, with the most prominent negative effect on LST differentiation in the Tuha Basin. Annual precipitation and mean NDVI in the Tuha Basin were 2.3 mm and 0.06, respectively, and aridity, low precipitation, and sparse vegetation coverage of neighboring deserts contributed to LST increase.

Overall, wind speed negatively affected LST in the study area, with intensity second only to DEM. Wind speed in the Tarim Basin and Pakakuna Mountain Group had prominent cooling effects on LST, whereas wind speed in the Tuha Basin and Junggar Basin showed weak positive correlation with LST. Basin interiors are typically surrounded by mountains, forming relatively closed terrain. Cold air inversion in the Tarim Basin and through-valley rapid formation due to narrow tube effects of topography increased near-surface wind speed in the Tarim Basin bordering the Pamir Plateau and Tianshan Mountains, and rapid air flow carried away surface heat, resulting in lower LST. However, inside the Tuha Basin, due to terrain closure, higher wind speed created stronger airflow that increased heat removal. Because mountains provide blocking, heat is difficult to transmit to the atmosphere through convection and radiation, resulting in higher LST (Bogren and Gustavsson, 1991; de Wekker et al., 1998). Furthermore, southeast-down northwest airflow enters the Tuha Basin in a dry, hot environment after turning, and dry high-temperature winds brought by increased wind speed also increase LST (Hu, 2004). Some studies have indicated that spatial distribution relationships between LST and wind speed are season-related, with wind speed positively correlated with LST in summer (e.g., Yu, 2017).

Among all driving factors, only sunshine duration influence on LST was positive, with only LST change in the Tuha Basin weakly negatively correlated with sunshine duration. Lower latitudes of the Pakakuna Mountain Group and Tarim Basin are geomorphic zones receiving the longest solar radiation duration; sunshine duration had the strongest positive feedback effect. Annual average LST of the Tarim Basin was lower than that of the Tuha Basin, partly due to low terrain in the Tuha Basin (140–1117 m) and weaker cooling effects of precipitation and NDVI than in the Tuha Basin. However, this was also due to negative feedback and cooling effects of wind speed in the Tarim Basin, second only to those in the Pakakuna Mountain Group. Although sunshine duration had negative feedback effects on Tuha Basin LST, its influence was far less than other factors, weakening control intensity of latitudinal zonality on Tuha Basin LST.

In general, DEM was the main factor determining LST spatial differentiation in Xinjiang. Low latitude, low vegetation coverage, less precipitation, and long sunshine duration were conducive to warming; however, not all geomorphological zones followed this trend. Periodic and local differences existed in LST spatial heterogeneity caused by wind speed. Regional LST spatial heterogeneity was formed by combined influence of various driving factors. Whether spatial differentiation exists in seasonal LST across geomorphological zones requires further investigation.

3.4 Source-Sink Effect on LST in Xinjiang

Spatial LST distribution and thermal environmental characteristics in the study area were primarily due to combined effects of small regional topography and underlying surface properties. LULC has different physical properties such as reflectivity, roughness, and humidity, which affect energy and material exchange between ground and atmosphere, thereby altering climate (Chi et al., 2021). The source-sink concept is an important ecological process/pattern concept (Wu et al., 2022). Promoting geographical phenomenon generation is called a source, while inhibiting geographical phenomenon development is called a sink. Energy cycles between the two can reflect ecological process differences to a certain extent (Wu et al., 2022). Underlying surface heterogeneity is strong in arid areas, with numerous LULC changes (Mao et al., 2017), reflecting human activity influence on LST distribution. In natural ecology, land cover better reflects vegetation influence on LST (Chen et al., 2022a). Therefore, introducing source-sink theory to explore heat source and sink effects of different LULC types in surface thermal environments can provide references for alleviating urban heat islands, protecting and planning ecosystems, and restoring vegetation and water bodies to promote sustainable development in arid areas.

This study calculated source-sink effect identification results for different LULC types based on LST in the study area from 2000 to 2020 (Fig. 9a [Figure 9: see original paper] and b). Due to LULC type complexity and large uncertainty in LST changes of converted LULC types with small area in each geomorphic zone, only detailed analysis of LULC source-sink effects in each geomorphic zone in 2020 was conducted (Table 8). Simultaneously, CI values of different LULC types to LST were calculated. Positive CI values indicate warming amount per square kilometer, and vice versa (Fig. 9c [Figure 9: see original paper]). Results showed unused land was the most stable heat source in Xinjiang, and source-sink effects and contribution indices of different LULC types differed across geomorphological zones.

Only unused land (with HSI $>$ 1.00) had source effects on LST changes in Xinjiang during 2000–2020. In contrast, cultivated land, forest land, grassland, water body, and construction land (with HSI $<$ 1.00) had sink effects on LST changes. Unused land accounted for an average of 61.02% of Xinjiang' s total area during 2000–2020. These areas usually lack human activities or vegetation coverage, and their bare surfaces have low reflectivity, absorbing more solar radiation and converting it to heat (Qu et al., 2014). These areas are the main geothermal resource producers in Xinjiang. In 2010, 20,443 km^2 and 45,663 km^2 of grassland and water body were converted to unused land, respectively, resulting in 6.61°C/km^2 warming in unused land in 2010. From 2010 to 2020, 153,200 km^2 of unused land was converted to grassland, cultivated land, and other LULC types showing typical heat-sink effects, which reduced warming produced by unused land to 3.29°C/km^2. The area proportion of unused land in the Tarim Basin in 2020 was as high as 84.95%, making it the main heat source of LST in this geomorphic zone, with LST increase of 0.56°C/km^2. Although unused land area in the Tianshan Mountains was small, it had a prominent source effect, with LST increase of 1.24°C/km^2 in unused land.

Water body had the smallest HSI value, and its heat sink effect was most prominent as a dominant cooling type. However, water body only decreased LST by 0.02°C/km^2, while its heat sink effect decreased due to area reduction. Maximum cooling effect of water body was 0.70°C/km^2 in the Pakakuna Mountain Group. Surfaces of forest land and grassland with high vegetation coverage can absorb part of solar radiation, and transpiration consumes large amounts of heat. Simultaneously, vegetation has high specific heat capacity and heat conduction ability, storing and releasing large amounts of heat. Forest land and grassland provide shade, reducing surface heat input (Bonan, 2008). Because water body area in Xinjiang is much smaller than grassland and forest land areas, the cooling effect is weaker. Therefore, grassland and forest land were the most prominent LULC types with heat sink effects in Xinjiang. In 2020, LST was reduced by 0.48°C/km^2 in grassland.

Grassland and forest land in some geomorphic zones showed heat source effects. For example, the Altay Mountains, Tuha Basin, and Pakakuna Mountain Group with low vegetation coverage showed heat source effects, while remaining geomorphic zones exhibited heat sink effects. Cooling effects of forest land and grassland in the Tianshan Mountains were highest, decreasing LST by 0.15°C/km^2 and 0.94°C/km^2, respectively. In arid areas, vegetation is usually a heat source rather than heat sink during non-growing periods (Li et al., 2004). Dry environments lead to higher soil thermal conductivity, facilitating heat conduction. During non-growth periods, vegetation absorbs and stores large amounts of heat, converts solar radiation to heat during the day, and releases stored heat at night, resulting in relatively high LST. In 2020, 28.99% of construction land increase came from unused land. Increased impervious surface area from conversion of cultivated land and grassland to construction land can enhance heat island effects (Dong, 2012; Zeng, 2015). In contrast, conversion of large unused land areas such as deserts and bare land to construction land results in cooling. Although the same is true for construction land expansion, transformation of different LULC types by human activities has different positive and negative effects. With socioeconomic development, human activities such as land reclamation and agricultural planting have expanded cultivated land and increased related heat sink effects. The heat sink effect of cultivated land is primarily related to agricultural irrigation area and crop growth status, with the most prominent effect in the Junggar Basin. Studies have shown water-saving irrigation can improve water-use efficiency and increase net heat sink (Zhang et al., 2022). The heat sink effect of cultivated land may also impact climate and ecosystems, affecting temperature distribution and precipitation patterns, as well as biodiversity, soil moisture, and crop growth. Therefore, agricultural planning and land-use management must consider and rationally utilize cultivated land' s heat sink effect.

In summary, LULC source-sink effects in Xinjiang had particular regulatory impacts on LST. Due to influences of vegetation types, soil types, climatic conditions, and human activities, significant LST differences existed across geomorphic zones. Unused land is the most common LULC type in Xinjiang and makes the largest contribution to LST increase. Reasonable transformation through human activities can moderately reduce unused land' s heat source effect. Water body is the most important heat sink landscape, greatly affecting water ecosystems and biodiversity. Although melting glacier snow as a heat sink is conducive to mountain water conservation functions and downstream water security, long-term glacier snow reduction is not beneficial for ecosystem balance. The heat sink effect on land is primarily produced by crop vegetation; however, the heat sink effect of some vegetation in arid areas is related to growth period. Grassland and forest land are the main land cover types with the most prominent heat sink effects. In addition to strict forest cutting control, it is necessary to prohibit shrubland and grassland reclamation and attach importance to desert biodiversity function and value, which is more valuable than extensive and backward utilization methods such as reclamation and grazing. Whether cultivated land acts as heat source or sink is affected by many natural factors, management methods, and agricultural activities. For example, improving water resource utilization efficiency in arid areas can effectively enhance cultivated land' s heat sink effect, maintain soil and vegetation temperature in winter, and prevent freezing disasters. However, excessive heat sink effects can lead to soil drought and water evaporation. Therefore, cultivated land and agricultural production management must comprehensively consider and balance various factors to maximize positive roles of heat source and sink effects and reduce negative impacts. Additionally, human activity impacts on ground temperature cannot be ignored. When anthropogenic vegetation destruction leads to increased secondary unused land, vegetation degradation and conversion of forest land to grassland or bare land with low vegetation coverage can cause regional warming. Therefore, understanding and studying these factors' impacts on source-sink effects will aid rational planning and management, reduce adverse environmental and ecosystem effects, and ensure regional ecological security.

4 Conclusions

This study analyzed spatial and temporal differentiation patterns of LST in Xinjiang from 2000 to 2020. The Geodetector and GWR models were used to determine mechanisms driving LST spatial differentiation at different scales. The main conclusions are as follows:

(1) During the study period, the multi-year average LST in Xinjiang was 9.45°C, showing an overall warming trend (0.24°C/10a) with vast warming area. The Tuha Basin and Tarim Basin were the most stable geomorphologic zones in terms of warming. Mountainous areas were identified as primary cooling zones, but several significant warming zones in the western Tianshan Mountains were also identified. DEM played a prominent role in LST changes. LST was characterized by latitudinal zonation under solar radiation influence, and the underlying surface strengthened its spatial heterogeneity by influencing local surface thermal properties.

(2) Significant seasonal LST variations existed in the study area. Among the four seasons, only autumn showed cooling at 0.09°C/10a. Other sea-

sons all showed warming trends, with the fastest warming rate in spring (0.49°C/10a), followed by winter (0.48°C/10a). Seasonal variability in all geomorphic zones was consistent with Xinjiang' s LST except for the Pakakuna Mountain Group, reflecting their climatic sensitivity and indicative nature to a certain extent.

(3) LST spatial distribution in Xinjiang was dominated by topographic and locational factors, followed by natural factors. DEM, wind speed, and latitude contributed significantly. Interactions among factors had greater effects on LST spatial differentiation than single factors. Interaction strength between DEM and other driving factors was greatest. Specifically, interactions of DEM with precipitation ($q = 0.888$), latitude (0.885), and NDVI (0.848) better explained LST spatial heterogeneity, emphasizing DEM' s strong influence.

(4) Obvious spatial heterogeneity existed in direction and strength of driving factor effects on LST spatial differentiation in Xinjiang. Only sunshine duration was positively correlated with LST spatial differentiation, and DEM' s negative feedback effect was strongest. Low latitude, low vegetation coverage, less precipitation, and long sunshine duration favored LST increase. Driving factors for each geomorphological zone were subject to atmospheric circulation at different spatial and temporal scales, with cyclic and local differences in processes coupled with unique local circulation system formation, resulting in seasonal variations in driving mechanisms.

(5) LULC type source-sink effects in Xinjiang had regulatory effects on LST, with significant differences in influences across geomorphologic zones due to vegetation types, climatic conditions, soil types, human activities, and other factors. Unused land was the most common LULC type in Xinjiang and contributed most to LST increase, whereas water body was the most important heat sink, and the heat sink effect on land was primarily generated by crop vegetation. Grassland and forest land were the main LULC types with the most prominent heat sink effects, but these were related to growth period in arid zones.

Analysis of spatiotemporal LST evolution and its driving mechanisms in Xinjiang helps quantitatively determine factors driving LST spatial heterogeneity and investigate their spatial relationships. The source-sink effects of different LULC types on LST in Xinjiang were also explored to provide references for understanding climate change and planning sustainable oasis development in arid regions. Based on attribution analysis of LST spatial differentiation at inter-annual scale, LST changes were affected by numerous factors and some geomorphological zones had unique mechanisms of action. Therefore, it is necessary to consider whether differences exist in LST response mechanisms at different time scales. Furthermore, in geographical studies, results are affected by analysis unit size. Due to sparse vegetation and small population in Xinjiang, human activities are relatively weak; if scale is too large, the study may not reflect human factor impacts on LST. In future research, analysis of LST spatial distribution characteristics and causes based on multiple time scales (such as seasonal, monthly, and daily) should be conducted. Attempts can be made to analyze relationships between LST and natural and socioeconomic factors based on study units with different underlying surfaces and grain sizes.

Conflict of 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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