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Postprint: Spatiotemporal Evolution of Summer Surface Urban Heat Island Effect in Typical Oasis Cities in Arid Regions Based on the FSDAF Model

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Abstract

Changes in the heat island effect of arid oasis cities caused by accelerated global urbanization and their associated eco-environmental problems have become one of the research hotspots in the fields of urban climate, environment, and ecology both domestically and internationally. Land surface temperature (LST) retrieved from remote sensing thermal infrared channels is a key parameter for monitoring and studying the Surface Urban Heat Island (SUHI) effect. However, constrained by the "spatiotemporal contradiction" of thermal infrared remote sensing data, currently there is no thermal infrared remote sensing data source with both high temporal resolution and high spatial resolution under a single spaceborne satellite sensor, thus limiting the conduct of high-precision surface urban heat island effect monitoring research within arid oasis cities. To address the above issues, taking Urumqi, a typical oasis city in arid regions, as the study area, using Landsat series images and MODIS land surface temperature products as the basic data sources, and based on the FSDAF (Flexible Spatiotemporal Data Fusion Method) spatiotemporal fusion model, we analyzed the spatiotemporal variation characteristics of the summer surface urban heat island effect in Urumqi against the background of urban expansion from 2001 to 2018, as well as the relationship between summer LST and urban surface parameters. The research results indicate that: (1) The summer heat island intensity (SUHI intensity, SUHII) in Urumqi shows an increasing trend across different suburban ranges. Within the smaller suburban range, SUHII1 increased from 1.24 ℃ in 2001 to 2.83 ℃ in 2018; within the larger suburban range, SUHII2 increased from 1.44 ℃ in 2001 to 2.88 ℃ in 2018; (2) Among the various land use types in the study area, bare land has the highest summer LST, while water bodies have the lowest; (3) The increase in surface albedo and impervious surfaces in the study area is positively correlated with the rise in urban summer LST,

while vegetation indices and vegetation coverage are negatively correlated with LST; (4) In arid oasis cities, the increase in vegetation area within the urban core helps alleviate the urban heat island effect, while an increase in vegetation only in the suburbs leads to further intensification of SUHII.

Full Text

Spatiotemporal Evolution of Summer Surface Urban Heat Island Effect in a Typical Oasis City of Arid Regions Based on the FSDAF Model

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Abstract

The urban heat island effect and associated ecological and environmental problems in oasis cities of arid regions, driven by accelerating global urbanization, have become a prominent research focus in urban climate, environment, and ecology. Land surface temperature (LST) retrieved from thermal infrared remote sensing channels is a critical parameter for monitoring surface urban heat island (SUHI) effects. However, constrained by the "spatiotemporal contradiction" of thermal infrared remote sensing data, current satellite-borne sensors cannot simultaneously provide high temporal and high spatial resolution thermal infrared data, limiting high-precision SUHI monitoring in oasis cities of arid regions. To address this issue, this study takes Urumqi, a typical oasis city in an arid region, as the study area. Based on MODIS LST products as the fundamental data source and Landsat imagery, we employed the Flexible Spatiotemporal Data Fusion Method (FSDAF) to analyze spatiotemporal variation characteristics of summer SUHI and its relationship with urban surface parameters. Results indicate that: (1) SUHI intensity (SUHII) showed an increasing trend across different suburban ranges. Within a smaller suburban area, SUHII increased from 1.24 °C in 2001 to 2.83 °C in 2018; within a larger suburban area, SUHII increased from 1.44 °C to 2.88 °C. (2) Among various land use types, bare land exhibited the highest summer LST, followed by construction land and vegetation, while water bodies showed the lowest temperatures. (3) Increases in surface albedo and impervious surface area were positively correlated with rising summer LST, whereas vegetation indices and fractional vegetation cover were negatively correlated. (4) In oasis cities of arid regions, increasing vegetation area within urban areas helps mitigate the urban heat island effect, whereas vegetation increase in suburban areas alone can intensify SUHI intensity.

Keywords: surface urban heat island; spatiotemporal fusion model; oasis city in arid area

Introduction

In recent years, the urban heat island effect has emerged as a significant ecological and environmental problem affecting urban residents' physical and mental health, air quality, water resource consumption, and sustainable urban ecosystem development. Compared with traditional meteorological station observations and numerical simulations for atmospheric heat island monitoring, satellite-borne and airborne thermal infrared sensors offer advantages of broad coverage and low data acquisition costs, making them widely used for surface urban heat island (SUHI) monitoring. However, due to technical bottlenecks in satellite thermal infrared sensor design and development, no single sensor currently exists that can simultaneously provide high temporal and high spatial resolution thermal infrared remote sensing data. For instance, commonly available high temporal resolution MODIS LST products have coarse spatial resolution (1000 m), while high spatial resolution Landsat series satellites have long revisit cycles (16 days). This "spatiotemporal contradiction" in remote sensing data not only leads to a lack of high spatiotemporal resolution data but also severely limits the application of remote sensing data in regional SUHI effect monitoring.

Spatiotemporal fusion models for land surface temperature have become an effective solution to this problem. These models primarily integrate high spatial resolution but low temporal resolution data with low spatial resolution but high temporal resolution data to generate high spatiotemporal resolution LST data. Previous studies have developed various models: Zhu et al. used the Spatiotemporal Adaptive Reflectance Fusion Model (STARFM) to combine MODIS LST and Landsat LST data, achieving prediction errors less than 1.5 K. Huang et al. constructed the Spatiotemporal Integrated Temperature Fusion Model (STITFM) by combining GEOS/SEVIRI LST and ASTER LST data, generating high spatiotemporal resolution LST data with root mean square error less than 2.5 K. Zheng et al. combined TsHARP and STITFM models to predict Landsat ETM and MODIS LST data, with root mean square errors below 2.5 K. Wei and Shan applied the FSDAF model using nonlinear radiative temperature decomposition to generate high spatiotemporal resolution LST data. Research demonstrates that the FSDAF model offers high computational efficiency, requires fewer input data sources, and produces high-precision LST predictions. Therefore, this study employs the FSDAF model to combine high spatial resolution Landsat LST data with low spatial resolution MODIS LST data, aiming to predict high spatiotemporal resolution LST data and analyze its relationship with urban surface parameters in arid oasis cities.

1 Study Area

Urumqi, the capital of Xinjiang Uygur Autonomous Region, is located in northwestern China (86°37 33 –88°58 24 E, 42°45 32 N–45°00 00 N). The northern part of the city comprises alluvial plains, while the southern region connects with the northern foothills of the central Tianshan Mountains. Both the northeastern and southwestern areas are mountainous, creating a three-sided mountainous enclosure [Figure 1: see original paper]. With an average elevation of approximately 800 m, Urumqi has a mid-temperate continental arid climate with annual precipitation of 145 mm. Seasonal differences are pronounced, with summer lasting from mid-May to mid-September, characterized by long duration, large diurnal temperature variation, and hot, dry conditions—making it a typical arid region oasis city.

As the largest oasis city in Central Asia' s arid region, Urumqi has experienced rapid economic development. From 2001 to 2018, GDP increased from 31.5 billion yuan to 309.9 billion yuan, while permanent population grew from 1.69 million to 3.5058 million. The surge in population, replacement of natural surfaces with impervious materials, and increasing urban heat emissions have gradually intensified urban thermal environmental problems.

2 Data Sources and Research Methods

This study combines Landsat LST and MODIS LST data using the FSDAF model to predict high spatiotemporal resolution LST data. Based on this dataset, we analyze spatiotemporal variations of summer SUHI in Urumqi from 2001 to 2018, focusing on relationships between SUHI intensity and urban surface parameters.

2.1 Landsat LST Data Acquisition

This study utilized Landsat TM and Landsat 8 data (path/row: 143/30, 143/31) with 30 m spatial resolution and 16-day temporal resolution. The thermal infrared band was resampled to 120 m. We employed the mono-window algorithm to retrieve Landsat LST data. Data were obtained from the U.S. Geological Survey (http://earthexplorer.usgs.gov/). Detailed steps for the mono-window algorithm retrieval follow Qin et al.' s methodology.

2.2 MODIS Land Surface Temperature Data Preprocessing

This study used MOD11A1 and MOD11A2 LST data, both with 1000 m spatial resolution, sourced from NASA' s Earth Observing System Data and Information System (https://earthdata.nasa.gov). These products are currently the most suitable for large-scale land surface temperature monitoring and have been widely applied in urban SUHI research. First, we converted MODIS data to the same coordinate system as Landsat data. Second, we performed geometric correction of MODIS data using Landsat LST as the reference to eliminate geometric errors between different sensors.

2.3 FSDAF Model Principle

The FSDAF model requires only a pair of high- and low-spatial-resolution remote sensing data at a known time and low-spatial-resolution data at a prediction time to effectively fuse and generate high-spatial-variability images at the prediction time. The model has been applied to LST spatiotemporal fusion research.

The FSDAF model calculates residuals using a thin plate spline function:

$$Eh0(x_{ij}, y_{ij}) = LST_{SP}(x_{ij}, y_{ij}) - LST_{TP}$$

$$LST_{SP}(x_{ij}, y_{ij}) = f_{TPS}(b(x_{ij}, y_{ij}))$$

The model prediction equation is:

$$LST(x_{ij}, y_{ij}) = LST_{t1}(x_{ij}, y_{ij}) + \sum_{k=1}^{n} W_k \times \Delta LST(x_k, y_k)$$

$$LST(x_{ij}, y_{ij}) = \varepsilon_{high}(x_{ij}, y_{ij}) + \Delta LST(c)$$

where (x_{ij}, y_{ij}) represents the high-spatial-resolution predicted data at prediction time t_m; $LST_{t1}(x_{ij}, y_{ij})$ is the high-spatial-resolution input data at base time t; W_k is the weight of the kth similar pixel; $\Delta LST(x_k, y_k)$ represents the change value from t to t_m at similar pixel (x_k, y_k); $\varepsilon_{high}(x_{ij}, y_{ij})$ is the residual between high- and low-spatial-resolution data; and $\Delta LST(c)$ is the change value of high-spatial-resolution LST data in category c from t to t_m.

The thin plate spline function for calculating residuals is:

$$\varepsilon_{high}(x_{ij}, y_{ij}) = m \times L(x_i, y_i) \times W(x_{ij}, y_{ij})$$

$$L(x_i, y_i) = \Delta L(x_i, y_i) - \sum_{j=1}^{m} LST_{t1}(x_{ij}, y_{ij})$$

$$LW(x_{ij}, y_{ij}) = Eh0(x_{ij}, y_{ij}) \times HI(x_{ij}, y_{ij}) + Ehe(x_{ij}, y_{ij}) \times [1 - HI(x_{ij}, y_{ij})]$$

where $L(x_i, y_i)$ represents the residual between high-spatial-resolution "observed data" and "predicted data" ; m is the number of sub-pixels in the low-spatial-resolution image; $\Delta L(x_i, y_i)$ is the change value of low-spatial-resolution image from t to t_m; $LW(x_{ij}, y_{ij})$ is the weight for residual allocation; $W(x_{ij}, y_{ij})$ is the normalized weight of $LW(x_{ij}, y_{ij})$; LST_{TP} is the temporally predicted LST at t_m; $Eh0(x_{ij}, y_{ij})$ is the temporal prediction error; $HI(x_{ij}, y_{ij})$ is the homogeneity coefficient; and $Ehe(x_{ij}, y_{ij})$ is the equal error within low-spatial-resolution pixels.

This study employs two steps: testing experiment and fusion processing. In the testing experiment, we used Landsat LST and MOD11A1 data from one month before summer 2001 as base input images (Table 1) to generate high-spatial-resolution "predicted data" for summer prediction time t_m using MOD11A1 data. We then validated accuracy using actually observed Landsat LST at prediction time. Three quantitative metrics were used: coefficient of determination (R^2), root mean square error (RMSE), and average absolute difference (AAD). If accuracy met requirements, we proceeded to fusion processing: using the same base images and replacing summer MOD11A1 data with MOD11A2 data (day-of-year: 169-176, 185-192, 193-200, 201-208, 209-216, 217-224, 225-232, 233-240, 241-248, 249-256) to predict high-spatial-resolution summer LST at 8-day temporal resolution. Finally, we averaged summer data across years to obtain the final summer LST dataset for 2001-2018.

2.4 Calculation of Surface Urban Heat Island Intensity (SUHII)

SUHII is defined as the temperature difference between urban and suburban areas. We calculated two SUHII indicators: SUHII1 (temperature difference between urban area and smaller suburban area comprising 100% of urban area) and SUHII2 (temperature difference between urban area and larger suburban area comprising 150% of urban area), following Peng et al.' s methodology.

$$SUHII_1 = LST_{urban} - LST_{rural\_100\%}$$

$$SUHII_2 = LST_{urban} - LST_{rural\_150\%}$$

2.5 Calculation of Urban Surface Parameters

To explore relationships between summer LST and urban surface parameter changes, we extracted four parameters: Enhanced Vegetation Index (EVI), Fractional Vegetation Cover (FVC), Impervious Surface Area (ISA), and surface albedo. EVI and NDVI are commonly used vegetation indices, with EVI being more effective for sparse vegetation monitoring in urban areas. EVI is calculated as:

$$EVI = 2.5 \times \frac{NIR - RED}{NIR + C_1 \times RED - C_2 \times BLUE + L}$$

where BLUE, RED, and NIR are reflectance bands from Landsat imagery; L is the soil background adjustment parameter; and C_1, C_2 are aerosol resistance coefficients.

FVC is another important indicator for assessing regional vegetation conditions. We extracted FVC using normalized spectral mixture analysis and linear spectral mixture analysis to reduce spectral differences among endmembers of different land use types. The calculation formula is:

$$FVC = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

where $NDVI_{max}$ and $NDVI_{min}$ are the maximum and minimum NDVI values for vegetation and bare soil, respectively.

Surface albedo significantly affects urban net radiation and energy balance. Mackey et al. found that lower urban surface reflectance corresponds to higher LST. We extracted albedo using the algorithm proposed by Liang:

$$\alpha_{short} = 0.356 \times BLUE + 0.130 \times RED + 0.373 \times NIR + 0.085 \times SWIR1 + 0.072 \times SWIR2$$

where α_{short} is shortwave albedo; BLUE, RED, NIR, SWIR1, and SWIR2 are Landsat band reflectances.

3 Results and Analysis

3.1 Definition of Urban and Suburban Areas

Defining urban and suburban boundaries is prerequisite for SUHII calculation. Using Landsat TM and Landsat 8 imagery, we applied Support Vector Machine (SVM) classification to extract land use information for the study area. To avoid high vegetation cover effects on urban area extraction accuracy, we selected cloud-free Landsat images from late summer or early autumn (September) when surface reflectance variation is minimal. Land use types were classified into vegetation, water, bare soil, and construction land. Classification accuracy for 2018 land use information exceeded 85% (Table 3), meeting subsequent research requirements.

Urban boundaries were delineated based on high-density, concentrated construction land. Suburban boundaries were established as buffer zones around urban areas: a smaller buffer (100% of urban area) and a larger buffer (150% of urban area). This approach enabled monitoring SUHI effects under different suburban extents [Figure 2: see original paper]. The final study area covered 50 km × 50 km.

3.2 Fusion of Landsat LST and MODIS LST Data

We first validated FSDAF spatiotemporal fusion performance through testing experiments. [Figure 3: see original paper] shows the "predicted LST" generated by the FSDAF model compared with actual high-spatial-resolution "observed LST" for validation. The overall spatial distributions were consistent. As shown in Table 4, R^2 ranged from 0.86 to 0.94, RMSE from 2.15 K to 2.59 K, and AAD from 2.38 K to 2.76 K, indicating that the FSDAF model generated high-precision predictions suitable for subsequent analysis.

We then applied the same base images (Landsat LST and MOD11A1) and replaced prediction time MOD11A1 data with summer MOD11A2 data (day-of-year: 169–176, 185–192, 193–200, 201–208, 209–216, 217–224, 225–232, 233–240, 241–248, 249–256) to predict high-spatial-resolution summer LST at 8-day intervals. After averaging across summer months, we obtained the final summer LST spatial distribution dataset for 2001–2018.

3.3 Analysis of Summer Heat Island Intensity and LST Changes

Summer LST in Urumqi showed distinct spatiotemporal patterns [Figure 4: see original paper]. Urban area expanded from 213.68 km^2 in 2001 to 304.88 km^2 in 2011 and 533.33 km^2 in 2018. With the "Urumqi-Changji Integration" strategy, rapid economic development shifted population and industries northward. Consequently, high LST values concentrated in central urban areas in 2001 but expanded northeastward and northwestward by 2018.

SUHII calculated using both indicators showed increasing trends [Figure 5: see original paper]. SUHII1 increased from 1.24 °C (2001) to 2.36 °C (2011) and 2.83 °C (2018). SUHII2 increased from 1.44 °C to 2.58 °C and 2.88 °C during the same period. Larger suburban extents yielded higher SUHII because suburban land cover is predominantly vegetation, and vegetation area proportion increases with suburban range. In arid oasis cities, while urban vegetation increase mitigates heat islands, suburban vegetation increase alone intensifies SUHII.

Mean summer LST varied by land cover type, ranking from highest to lowest as: bare soil > construction land > vegetation > water [Figure 6: see original paper]. Bare soil exhibited highest LST due to low soil moisture content and thermal inertia. Vegetation LST was lower because canopy transpiration effectively releases heat. Water bodies showed lowest LST due to strong heat storage capacity. Construction land LST decreased slightly with suburban expansion in 2001 but increased in 2018, reflecting rapid development of suburban towns.

3.4 Quantitative Relationship Between Summer LST and Urban Surface Parameters

We randomly sampled 500 points within urban and smaller suburban areas, and another 500 points within larger suburban areas (1000 points total). Pearson correlation analysis revealed relationships between LST and surface parameters (Table 5). Urban summer LST correlated negatively with EVI and FVC, indicating vegetation increase effectively reduces surface temperature and improves thermal environment. This negative correlation strengthened with suburban expansion because Urumqi' s east is forestland, south is grassland, and north is farmland. Conversely, LST correlated positively with ISA, with correlation strengthening in 2018 due to rapid impervious surface expansion in suburban towns. LST also correlated positively with albedo, and this correlation increased with suburban range because large suburban areas contain extensive bare soil with high albedo and low water content in this arid region.

4 Conclusion

This study generated high spatiotemporal resolution summer LST data for Urumqi from 2001–2018 using the FSDAF model and analyzed summer SUHI spatiotemporal variations. Key findings include:

1. FSDAF model predictions achieved high accuracy (R^2: 0.86–0.94, RMSE: 2.15–2.59 K), meeting research requirements.
2. SUHII showed increasing trends across different suburban ranges. SUHII1 increased from 1.24 °C to 2.83 °C, while SUHII2 increased from 1.44 °C to 2.88 °C between 2001 and 2018. Larger suburban extents produced more pronounced heat island effects.
3. Among land use types, bare land exhibited highest summer LST, followed by construction land and vegetation, with water bodies showing lowest temperatures.
4. Summer LST correlated positively with surface albedo and impervious surface area, and negatively with enhanced vegetation index and fractional vegetation cover.
5. In arid oasis cities, increasing vegetation within urban areas mitigates SUHI, whereas vegetation increase in suburban areas alone intensifies SUHI intensity.

Therefore, local greening departments should maintain suburban vegetation while increasing urban vegetation coverage to effectively mitigate urban heat island effects.

References

[1] Zhou X F, Chen H. Impact of urbanization related land use land cover changes and urban morphology changes on the urban heat island phenomenon[J]. Science of the Total Environment, 2018, 635: 1467-1476.

[2] Ren P, Zhang X, Liang H, et al. Assessing the impact of land cover changes on surface urban heat islands with high spatial resolution imagery on a local scale: Workflow and case study[J]. Sustainability, 2019, 11(19): 5188.

[3] Huang B, Wang J, Song H, et al. Generating high spatiotemporal resolution land surface temperature for urban heat island monitoring[J]. IEEE Geoscience and Remote Sensing Letters, 2013, 10(5): 1019-1023.

[4] Liu H, Weng Q. Enhancing temporal resolution of satellite imagery for public health studies: A case study of west Nile virus outbreak in Los Angeles in 2007[J]. Remote Sensing of Environment, 2012, 117: 57-71.

[5] Wu P, Shen H, Zhang L, et al. Integrated fusion of multi-scale polar-orbiting and geostationary satellite observations for the mapping of high spatial and tem-

poral resolution land surface temperature[J]. Remote Sensing of Environment, 2015, 156: 169-181.

[6] Zhu X, Helmer E H, Gao F, et al. A flexible spatiotemporal method for fusing satellite images with different resolutions[J]. Remote Sensing of Environment, 2016, 172: 165-177.

[7] Zheng M, Huang F, Zhang G. Land surface temperature data fusion of Landsat ETM and MODIS by combining TsHARP and STITFM mode[J]. Remote Sensing Technology and Application, 2018, 33(2): 275-283.

[8] Wei R, Shan J. Spatial and temporal fusion of urban land surface temperature image mapping[J]. Geomatics and Information Science of Wuhan University, 2018, 43(3): 428-435.

[9] Yang M, Yang G, Chen X, et al. Generation of land surface temperature with high spatial and temporal resolution based on FSDAF method[J]. Remote Sensing for Land and Resources, 2018, 30(1): 54-62.

[10] Qin Z, Karnieli A, Berliner P. A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region[J]. International Journal of Remote Sensing, 2001, 22(18): 3719-3746.

[11] Zhang Y, Balzter H, Liu B, et al. Analyzing the impacts of urbanization and seasonal variation on land surface temperature based on subpixel fractional covers using Landsat images[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2016, 10(4): 1344-1356.

[12] Peng S, Piao S, Ciais P, et al. Surface urban heat island across 419 global big cities[J]. Environmental Science & Technology, 2011, 46: 696-703.

[13] Dallimer M, Tang Z, Bibby P R, et al. Temporal changes in greenspace in a highly urbanized region[J]. Biology Letters, 2011, 7(5): 673-676.

[14] Zhou D, Zhao S, Zhang L, et al. Remotely sensed assessment of urbanization effects on vegetation phenology in China' s 32 major cities[J]. Remote Sensing of Environment, 2016, 176: 272-281.

[15] Cai Y, Zhang M, Lin H. Estimating the urban fractional vegetation cover using an object-based mixture analysis method and Sentinel-2 MSI imagery[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020, 13: 341-350.

[16] Yang F, Matsushita B, Fukushima T. A pre-screened and normalized multiple endmember spectral mixture analysis for mapping impervious surface area in Lake Kasumigaura Basin, Japan[J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2010, 65(5): 449-461.

[17] Wang J, Wu Z, Wu C, et al. Improving impervious surface estimation: An integrated method of classification and regression trees (CART) and linear spec-

tral mixture analysis (LSMA) based on error analysis[J]. GIScience & Remote Sensing, 2018, 55(4): 583-603.

[18] Mackey C W, Lee X, Smith R B. Remotely sensing the cooling effects of city-scale efforts to reduce urban heat island[J]. Building and Environment, 2012, 49: 348-358.

[19] Liang S. Narrowband to broadband conversions of land surface albedo I: Algorithms[J]. Remote Sensing of Environment, 2001, 76(2): 213-238.

[20] Knorn J, Rabe A, Radeloff V C, et al. Land cover mapping of large areas using chain classification of neighboring Landsat satellite images[J]. Remote Sensing of Environment, 2009, 113: 957-964.

[21] Li Z, Jin L, He Q, et al. Characteristics of temperature distribution and profiles in Urumqi City and its suburb[J]. Arid Land Geography, 2019, 42(6): 1273-1281.

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