Spatial Pattern and Influencing Factors of Land Surface Temperature in the Western Sichuan Plateau Based on Geographical Detector: A Case Study of Xichang City (Postprint)

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Abstract

Taking Xichang City as a case study, this research selected Landsat series remote sensing images from 2010 and 2015. With the support of "3S" technology, the maximum likelihood method in supervised classification was employed, combined with high-resolution Google Earth imagery and GPS field validation data, to obtain land use information for Xichang City in 2010 and 2015. Land surface temperature of Xichang City in 2010 and 2015 was then retrieved using the atmospheric correction method, and field investigation and verification were conducted for high-temperature anomaly areas in the retrieval results. Finally, Geodetector was used to quantitatively analyze the explanatory power of nine influencing factors—slope, total radiation, aspect, elevation, annual average precipitation, annual average temperature, vegetation type, soil type, and land use type—on land surface temperature. The results indicate that: (1) Significant differences exist in the spatial distribution of land surface temperature. (2) The influences of different factors on land surface temperature vary, with elevation and annual average temperature having greater impacts, while total radiation has the smallest impact. (3) No single factor or single-nature factor influences land surface temperature; interactions exist among different influencing factors, and their effects on land surface temperature are mutually enhanced or nonlinearly enhanced. (4) Some influencing factors have significantly different effects on land surface temperature, and when the mean land surface temperature reaches its maximum, it corresponds to different ranges or types of influencing factors.

Full Text

1. Study Area

The study area, Xichang City, is located between 101°55 -102°22 E and 27°36 - 27°59 N in southwestern Sichuan Province, China. Situated in the central Anning River Valley, the region features a typical mountainous plateau landform with complex terrain. The total area of the study region is 2,655 km², characterized by high mountains, deep valleys, and a plateau basin. The elevation ranges from 1,184 to 4,152 m, with significant topographic relief. The area comprises 16.4% slope land and 78.9% mountainous terrain. The regional climate is subtropical monsoonal, with distinct wet and dry seasons. The average annual temperature is 17.5°C, average annual precipitation is approximately 1,000 mm, and the average annual sunshine duration is 2,421 hours. The region exhibits pronounced vertical climate zonality, with complex and diverse climate conditions.

2. Data and Methods

2.1 Data Sources

The primary data sources included Landsat series satellite imagery from 2010 and 2015, Google Earth high-resolution images, and GPS field verification data. The "3S" technology (Remote Sensing, Geographic Information Systems, and Global Positioning Systems) was employed for data integration and analysis. The Landsat imagery included TM and OLI_TIRS data. Additional ancillary data comprised a Digital Elevation Model (DEM), soil type maps, vegetation type maps, and meteorological data including total radiation, average annual precipitation, and average annual temperature.

2.2 Methods

2.2.1 Surface Temperature Retrieval The atmospheric correction method was used to retrieve land surface temperature (LST) from thermal infrared bands. The calculation formula is:

$$B(T_s) = I - L\uparrow - \tau \times (1-\varepsilon) \times L\downarrow$$

where $B(T_s)$ represents the blackbody radiance at surface temperature, I is the radiance measured by the sensor, $L\uparrow$ and $L\downarrow$ are atmospheric upwelling and downwelling radiance respectively, τ is atmospheric transmittance, and ε is land surface emissivity.

The NASA atmospheric correction website (http://atmcorr.gsfc.nasa.gov) was used to obtain atmospheric parameters. For the 2010 and 2015 data, atmospheric transmittance values were 0.90 and 0.93 respectively, upwelling radiance values were 0.60 and 0.45 W · m ^{2} · sr ^{1} · m ^{1}, and downwelling radiance values were 1.00 and 0.78 W · m ^{2} · sr ^{1} · m ^{1}.

Surface temperature was then calculated using:

$$T = \frac{K_2}{\ln\left(1 + \frac{K_1}{B(T_s)}\right)}$$

where T is the land surface temperature in Kelvin, and K_1 and K_2 are thermal constants. For Landsat 8 OLI_TIRS, $K_1 = 774.8853$ W · m ^{2} · sr ^{1} · m ^{1} and $K_2 = 1321.0789$ K; for Landsat TM, $K_1 = 607.76$ W · m ^{2} · sr ^{1} · m ^{1} and $K_2 = 1260.56$ K.

2.2.2 Land Use Classification Supervised classification using the maximum likelihood method was performed in ENVI 5.3 to extract land use information. ArcGIS 10.3 was used for spatial analysis and mapping. Field surveys conducted on July 14, 2010 and July 12, 2015 provided validation data with 130 and 41 sample points respectively. Classification accuracy was assessed using confusion matrices, with overall accuracy and Kappa coefficient calculated for both years.

2.2.3 Geographical Detector Method The geographical detector technique was employed to quantitatively analyze the influence of various factors on surface temperature distribution. This method includes factor detection, interaction detection, and risk detection. The factor detector quantifies the explanatory power of each factor using the q-statistic:

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

where q measures the degree of spatial stratified heterogeneity, h represents strata of the factor, N_h and N are the unit numbers in stratum h and the entire study area respectively, and σ_h^2 and σ^2 are the variances of surface temperature in stratum h and the entire area. The q-value ranges from 0 to 1, with higher values indicating stronger explanatory power.

Nine influencing factors were analyzed: slope (X), total radiation (X), aspect (X), elevation (X), average annual precipitation (X), average annual temperature (X), vegetation type (X), soil type (X), and land use type (X).

3. Results

3.1 Land Use Classification Accuracy

The classification results for 2010 and 2015 showed high accuracy. The 2010 classification achieved an overall accuracy of 98.09% with a Kappa coefficient of 0.97, while the 2015 classification achieved an overall accuracy of 82.18% with a Kappa coefficient of 0.78. The high accuracy indicates reliable land use data for subsequent analysis.

3.2 Surface Temperature Retrieval Results

The retrieved surface temperatures for 2010 and 2015 showed distinct spatial patterns. The average surface temperature was 23.7465°C in 2010 and 19.7704°C in 2015. Temperature distribution varied significantly across different land use types and elevations. High-temperature anomalies were verified through field investigations and Google Earth imagery comparison.

3.3 Factor Analysis

3.3.1 Factor Importance The q-values for each influencing factor are presented in . In 2010, the factors ranked by explanatory power were: X (total radiation) > X (average annual precipitation) > X (soil type) > X (slope) > X (elevation) > X (average annual temperature) > X (vegetation type) > X (aspect) > X (land use type). In 2015, the ranking was: X > X > X > X > X > X > X > X > X .

Total radiation and average annual precipitation consistently showed the highest influence on surface temperature distribution, while land use type showed the least influence.

3.3.2 Interaction Between Factors Interaction detection revealed that pairs of factors showed enhanced explanatory power when combined. The interaction results for 2010 and 2015 are presented in and respectively. The interactions were generally nonlinear, with q-values exceeding the sum of individual factor q-values in many cases, indicating synergistic effects.

Key interactions included: - Slope and total radiation (X X) showed the strongest interaction effect - Slope and precipitation (X X) also demonstrated significant interaction - Elevation and precipitation (X X) showed notable interaction effects

The interaction types were classified as: nonlinear enhancement (C > A + B), double-factor enhancement (C > A, B), or independent (C = A + B), where C represents the interaction q-value and A, B represent individual factor q-values.

3.3.3 Risk Detection Risk detection identified specific ranges or types of each factor associated with the highest surface temperatures. For different factors, the temperature-maximizing conditions varied:

- For elevation: 0–15° slope range showed temperatures of 23.8175°C (2010) and 18.9473°C (2015)
- For total radiation: 5,091–5,199 MJ · m ² range showed temperatures of 23.7707°C (2010) and 18.2195°C (2015)

- For aspect: South-facing slopes showed higher temperatures than north-facing slopes

The results indicate that the factor ranges associated with maximum surface temperature differ across factors and may vary between years.

3.3.4 Ecological Analysis The spatial distribution of surface temperature showed clear relationships with underlying surface characteristics. Areas with dense vegetation cover exhibited lower temperatures due to evapotranspiration cooling effects, while impervious surfaces in urban areas showed significantly higher temperatures. The vertical zonality of temperature was evident, with temperature decreasing as elevation increased. The analysis revealed that the combined effects of multiple factors create complex spatial patterns of surface temperature across the mountainous plateau landscape.

4. Discussion

The study demonstrates that surface temperature distribution in Xichang City is influenced by multiple factors with varying degrees of importance. Total radiation and precipitation emerge as the dominant factors, while land use type shows relatively minor direct influence but may have indirect effects through modification of surface properties. The significant interactions between factors highlight the complexity of surface temperature patterns in mountainous regions.

The geographical detector method proved effective for quantifying factor influences and interactions. The approach can inform urban planning and ecological management strategies, particularly for mitigating urban heat island effects and optimizing land use patterns in mountainous areas.

5. Conclusion

This study analyzed the spatial pattern of surface temperature and its influencing factors in Xichang City using Landsat imagery and geographical detector methods. Key findings include:

1. Surface temperature distribution showed significant spatial heterogeneity between 2010 and 2015, with average temperatures of 23.75°C and 19.77°C respectively.
2. Total radiation and average annual precipitation were the most influential factors, while land use type had the least direct influence.
3. Factor interactions generally enhanced surface temperature effects, with slope-total radiation and slope-precipitation interactions being particularly strong.
4. The factor ranges associated with maximum surface temperature varied by factor type, indicating complex nonlinear relationships.

The results provide valuable insights for understanding surface temperature patterns in mountainous plateau regions and can support sustainable urban development and ecological conservation efforts.

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