Land Surface Temperature Simulation and Its Impacts in Complex Mountainous Areas: A Case Study of Daqing Mountain, Inner Mongolia (Postprint)

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Abstract

Land Surface Temperature (LST) is an important factor affecting plant distribution and ecosystem processes. This study utilizes the Weather Research and Forecasting (WRF) model to simulate high spatiotemporal resolution LST in the Daqingshan Nature Reserve, validates the accuracy of the simulation results through comparison with meteorological station observations and MODIS LST values, and analyzes the relationship between LST and environmental factors through comprehensive influencing factor analysis and single influencing factor analysis. Comprehensive influencing factor analysis is conducted based on regional simulated LST and regional environmental factors; single influencing factor analysis first fixes other environmental factors and then analyzes the relationship between LST and a single environmental factor. The results show that: the correlation coefficients between simulated values and observations from three stations all exceed 0.97 (P<0.001), and the spatial correlation with MODIS LST is 0.73 (P<0.05), indicating that WRF has good applicability in mountainous areas. Through comprehensive influencing factor analysis, the correlation between annual mean LST and elevation is the strongest (R>0.97), followed by 2 m air temperature and 2 m water vapor mixing ratio (R>0.8), while correlations with vegetation coverage and slope are relatively weak (R>0.3), and other factors have minimal influence. Through single influencing factor analysis, in the four seasons of spring, summer, autumn, and winter, the rates of LST decrease with increasing elevation are 0.83 K · (100 m)-1, 0.79 K · (100 m)-1, 0.80 K · (100 m)-1, and 0.32 K · (100 m)-1, respectively; for every 10° increase in slope, LST increases by -0.05 K, 0.17 K, -0.14 K, and 0.02 K in spring, summer, autumn, and winter, respectively; for every 10% increase in vegetation coverage, LST increases by 0.31 K and 1.41 K in summer and winter, respectively, with no

effect in other seasons; the influence of aspect on seasonal average LST in all four seasons follows the order: south > southwest > southeast > west > east > northwest > northeast > north; annual mean LST shows a logarithmic relationship with 2 m water vapor mixing ratio and an exponential relationship with 2 m air temperature. The research results can provide fundamental data for the management of the Daqingshan Nature Reserve and also offer a reference method for mountain research.

Full Text

Simulation of Land Surface Temperature in Complex Mountainous Terrain and Its Influencing Factors: A Case Study in Daqingshan, Inner Mongolia

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Abstract

Land surface temperature (LST) is a critical parameter influencing plant distribution and ecosystem processes. This study utilized the Weather Research and Forecasting (WRF) model to simulate high spatiotemporal resolution LST in the Daqingshan Nature Reserve and analyzed variations in mountainous influencing factors. The accuracy of WRF-simulated LST was verified against meteorological station observations and MODIS LST values, and the relationship between LST and environmental factors was examined using both comprehensive and single-factor analysis methods. Comprehensive factor analysis evaluates relationships based on regional WRF LST and environmental variables, while single-factor analysis isolates the effect of individual factors by holding others constant. Results showed that correlation coefficients between simulated and observed values exceeded 0.97 ($P < 0.001$), with spatial correlation against MODIS LST reaching 0.73 ($P < 0.05$), demonstrating WRF's strong applicability in mountainous regions. Comprehensive analysis revealed that annual mean WRF LST correlated most strongly with elevation ($R > 0.97$), followed by 2 m air temperature and 2 m water-air mixing ratio ($R > 0.8$), while vegetation coverage and slope showed weaker correlations ($R > 0.3$). Single-factor analysis indicated that LST decreased with elevation at rates of 0.83 $K \cdot (100m)^{-1}$, 0.79 $K \cdot (100m)^{-1}$, 0.80 $K \cdot (100m)^{-1}$, and 0.32 $K \cdot (100m)^{-1}$ in spring, summer, autumn, and winter, respectively. LST increased by 0.14 K, 0.17 K, -0.14 K, and 0.02 K for every 10° increase in slope across the four seasons. For every 10%

increase in vegetation coverage, LST increased by 0.31 K and 1.41 K in summer and winter, respectively, but showed no correlation in spring and autumn. Seasonal mean LST across aspects followed the order: south > southwest > southeast > west > east > northwest > northeast > north. The 2 m water-air mixing ratio increased logarithmically with LST, while 2 m air temperature increased exponentially with LST. These findings provide foundational data for managing the Daqingshan Nature Reserve and offer a methodological reference for mountain environment studies.

Keywords: WRF model; land surface temperature; environmental factors; Daqingshan of Inner Mongolia

Introduction

Land surface temperature (LST) is a crucial parameter in land-atmosphere interactions, directly reflecting how soil thermal conditions respond to climate change [citation]. LST has become one of the most important environmental variables in scientific research, playing vital roles in urban remote sensing [citation], cryosphere remote sensing [citation], hydrological engineering, climate change, and land use studies [citation]. The primary methods for obtaining LST include station observations, remote sensing, and model simulation. While station observation data are accurate and reliable, stations in complex mountainous areas are sparsely distributed, making it difficult to obtain continuous spatiotemporal distributions using conventional observations. Remote sensing based on thermal infrared spectra can provide high spatiotemporal resolution data, but due to satellite transit times, return cycles, and cloud cover, it is difficult to obtain continuous high-temporal-resolution data in areas above mid-latitudes [citation]. Compared with remote sensing data, model simulation can resolve issues of low spatiotemporal resolution, though simulation accuracy depends heavily on model selection and internal mechanisms.

The Weather Research and Forecasting (WRF) model transforms low-spatiotemporal-resolution meteorological data into regional high-resolution data by simulating atmospheric physical processes and chemical changes, and WRF simulations are not affected by cloud cover. Different WRF schemes account for various atmospheric dynamics and surface characteristics and processes, making them key to numerical simulation [citation]. WRF features a more complete dynamical framework and multi-source parameterization schemes capable of simulating weather phenomena in different geographic regions. Previous studies have demonstrated that land surface processes strongly influence temperature simulation [citation], and improving underlying surface accuracy can enhance meteorological element simulation under complex terrain conditions. For instance, integrating high-precision land use and soil type data better simulates near-surface temperature and wind field variations in oases and gobi regions [citation]. Wang et al. [citation] found that increasing spatial resolution significantly reduced precipitation simulation errors in the Yarlung Zangbo River source area. Numerous studies have shown that changes in underlying surface information such as land use, elevation, and vegetation cover are important factors causing regional LST variations [citations]. While these studies have revealed the impacts of underlying surface changes on regional LST to some extent, they have not analyzed the effects of single geomorphic factors (e.g., elevation, slope, aspect, and land use type) on LST. Xiao et al. [citation] noted that due to large topographic relief and high spatial heterogeneity in mountainous areas, LST retrieval research has mostly focused on flat regions with minimal topographic influence, making it difficult to obtain long-term LST data for mountainous areas.

The Daqingshan National Nature Reserve in Inner Mongolia is located in a semi-arid typical grassland region and represents the most complete ecosystem and concentrated biodiversity in the Yinshan Mountains [citation]. The reserve's complex natural geography creates substantial spatiotemporal differences in LST, providing an excellent study site. Minimal human disturbance in the nature reserve facilitates analysis of LST variation patterns under mountainous geomorphic conditions. This study explores WRF's capability for spatiotemporal downscaling in complex mountainous terrain, enabling selection of appropriate physical parameterization schemes and comparison with station characteristics. Given the intertwined influences of multiple factors such as geomorphology and land use type, this research examines variation patterns between LST and individual factors, providing a methodological reference for studying LST impacts in other complex geomorphic environments and delivering foundational data for Daqingshan reserve management.

Study Area and Methods

Study Area

The Daqingshan National Nature Reserve (hereafter "Daqingshan Reserve") is located in the Yinshan Mountains of central-western Inner Mongolia, within the jurisdictions of Hohhot, Baotou, and Ulanqab cities, geographically positioned at 109°47 ~112°17 E, 40°34 ~41°14 N. The region experiences a mid-temperate continental semi-arid monsoon climate with annual mean temperatures of 3~5 °C and annual precipitation of 320~450 mm. Daqingshan is a fault-block mountain oriented east-west with asymmetric north-south topography—steep southern slopes and gentle northern slopes. Soil types are primarily mountainous chestnut soil, mountainous typical brown soil, mountainous leached brown soil, and mountainous meadow steppe soil. Dominant vegetation includes trees such as *Betula platyphylla*, *Populus davidiana*, and *Larix gmelinii var. principis-rupprechtii*; shrubs including *Ostryopsis davidiana*, *Rosa xanthina*, and *Spiraea salicifolia*; and herbs such as *Sanguisorba officinalis*, *Aster altaicus*, *Scutellaria scordifolia*, *Artemisia lavandulaefolia*, and *Leymus chinensis*.

Data Sources

Elevation data were obtained from the Shuttle Radar Topography Mission (SRTM). Land use data featured 21 categories. Meteorological station data for model validation were obtained from the National Meteorological Science Data Center (http://data.cma.cn). The NCEP FNL reanalysis data from the U.S. National Centers for Environmental Prediction, with $0.25° \times 0.25°$ resolution, served as WRF driving data. These data integrate extensive meteorological observations and numerical simulations, including upper-air pressure, temperature, humidity, wind direction, and wind speed. MODIS LST data were obtained from NASA's Terra (MOD11A2) and Aqua (MYD11A2) products, comprising daytime (LST_{Day_1km}) and nighttime (LST_{Night_1km}) LST data, quality control layers, and imaging time layers. Data were extracted using the MODIS Reprojection Tool.

WRF Model Configuration

The simulation employed two-layer nested grids centered at 111°E, 40.8°N. The outer domain had a horizontal resolution of 9 km with 199×199 grid points, while the inner domain covering the entire Daqingshan Reserve had a resolution of 3 km with 1 grid points. To avoid errors from physical parameterization schemes, short-term pre-tests were conducted with different scheme combinations to determine the optimal configuration (Table 1). The Noah-MP land surface scheme comprehensively considers interactions among soil, vegetation, and hydrological processes, accurately simulating key variables such as soil temperature, moisture, heat flux, and water flux [citation]. The MM5 surface layer scheme, designed for surface-atmosphere interactions, performs well for large-scale weather phenomena and climate change simulation and is often used with the YSU boundary layer scheme [citation]. The YSU scheme simulates turbulent and convective processes in the boundary layer, making it suitable for moderate to large-scale meteorological phenomena like medium-scale convection. Zhang et al. [citation] evaluated four PBL schemes in WRF for complex terrain and found the YSU scheme produced the smallest temperature simulation errors.

The simulation started at 00:00:00 on January 1, 2020, with a one-month spin-up period excluded from analysis. The outer and inner domain integration time steps were 45 s and 15 s, respectively, with continuous integration through December 31, 2021. Output intervals were set to every 3 h for the outer domain and every 1 h for the inner domain to compare with meteorological station data. To match MODIS LST timing, simulation results were output at 10:30, 13:30, 22:30, and 01:30.

Data Processing and Model Evaluation

Since MODIS LST represents daily averages, simulated LST was expanded to daily averages for evaluation. For spatial comparison with MODIS LST in the target area, simultaneous temporal data were selected. Simulated LST at

10:30, 13:30, 22:30, and 01:30 was averaged and compared with corresponding MODIS LST. MODIS LST was derived using the split-window algorithm at ~1 km resolution. The 8-day composite products (MOD11A2/MYD11A2) from July 20, 2021, and August 12, 2021, were selected. Non-zero pixels and cloud-contaminated areas were removed using quality control layers, retaining high-quality pixels with emissivity errors < 0.02. Imaging time layers were used to select appropriate time windows.

MODIS LST digital numbers were converted to Kelvin using: MODIS LST = $0.02 \times$ DN (where DN is the pixel value).

Model evaluation employed mean deviation error (MDE), root mean square error (RMSE), and Pearson correlation coefficient (R). The formulas are:

Mean Deviation Error: MDE = 1n i
RMSE = 1n i

where Pi and Qi represent simulated and observed values, respectively; n represents the number of samples.

Analysis of Influencing Factors

This study analyzed relationships between mountainous LST and influencing factors including land use, elevation, slope, aspect, vegetation coverage, 2 m air temperature, and 2 m water-air mixing ratio. Both comprehensive and single-factor methods were used. Comprehensive factor analysis examined relationships between regional WRF LST and all environmental factors through regression. Single-factor analysis isolated effects by fixing other environmental factors at constant values (Table 2) while analyzing the relationship between LST and a specific factor.

Results

Accuracy Assessment of WRF Simulations

Comparisons with meteorological station observations showed that simulated values at Hohhot and Tumed Left Banner stations had mean deviations of -0.74~2.43 K, while Wuchuan station simulations were 0.14 K lower than observed. The mean deviation across all stations ranged from -0.14~2.43 K, with root mean square errors of 2.72~4.14 K. The main error sources were overestimation at low elevations and underestimation at high elevations. For example, on July 20, 2021, Hohhot station was 2.9 K higher than observed; Tumed Left Banner was 3.9 K higher; Wuchuan was 5.5 K lower. Overall, WRF LST showed excellent temporal consistency with observations, with correlation coefficients exceeding 0.97 ($P < 0.001$) at all stations. LST generally peaked in July and reached minima in January, with WRF LST closely tracking observed seasonal patterns (Figure 2).

Validation Against MODIS LST

Instantaneous Image Comparison Spatial patterns of WRF LST closely matched MODIS LST at all four times (Figure 3), with similar high and low temperature regions. Some discrepancies occurred: at 10:30, simulated values were high in low-elevation construction land in the west but low elsewhere; at 13:30, values were high in construction land and high-elevation central reserve areas; at 22:30 and 01:30, nighttime simulations were generally high. Spatial differences at all four times followed normal distributions, with smaller mean deviations but larger variance during daytime, and larger mean deviations but smaller variance at night. Mean deviations were 0.97 K at 10:30, 1.65 K at 13:30, -6.05 K at 22:30, and -1.29 K at 01:30 (Figure 4).

Daily Mean Comparison MODIS and WRF daily mean LST showed clear spatial differences on different dates but correlations were consistently significant ($P < 0.001$), confirming MODIS LST reliability. Differences were concentrated in western and central areas. WRF LST was generally lower than MODIS in July but higher in August. The largest mean difference occurred on July 20, 2021 (-6.05 K), while August 12 showed the largest standard deviation. Simulations overestimated temperatures in construction land and high-elevation areas during daytime on July 20 but underestimated them elsewhere. Difference distribution curves for both dates followed normal distributions, with WRF LST variations highly consistent with MODIS LST, indicating good overall simulation performance (Figures 5 and 6).

Analysis of Environmental Factors

Comprehensive Factor Analysis Correlations between seasonal mean WRF LST and environmental factors varied by season (Table 3). In spring, summer, and autumn, LST correlated best with elevation ($R > 0.92$) and 2 m air temperature ($R > 0.97$), moderately with 2 m water-air mixing ratio ($R > 0.60$), and weakly with vegetation coverage and slope ($R < 0.33$). In winter, LST correlated well with elevation ($R > 0.97$) and 2 m air temperature ($R > 0.97$), but weakly with water-air mixing ratio, vegetation coverage, and slope ($R = 0.62$). Annually, LST showed the strongest correlation with elevation ($R > 0.97$), followed by 2 m air temperature and water-air mixing ratio ($R > 0.8$), and weakest correlations with vegetation coverage and slope ($R > 0.3$). LST was positively correlated with 2 m air temperature and water-air mixing ratio, and negatively correlated with elevation, vegetation coverage, and slope.

Single Factor Analysis Under single-factor conditions, seasonal mean LST decreased with elevation at rates of $0.83\ \mathrm{K \cdot (100m)^{-1}}$, $0.79\ \mathrm{K \cdot (100m)^{-1}}$, $0.80\ \mathrm{K \cdot (100m)^{-1}}$, and $0.32\ \mathrm{K \cdot (100m)^{-1}}$ in spring, summer, autumn, and winter, respectively (Figure 7). LST increased with slope in summer and winter (0.14 K and 0.17 K per 10°, respectively) but decreased in spring and autumn (-0.14 K and 0.02 K per 10°, respectively). Vegetation coverage increases raised LST by 1.41 K and 0.31 K per 10% in summer and winter, respectively, with no correlation in spring and autumn. Seasonal mean LST across aspects ranked: south > southwest > southeast > west > east > northwest > northeast > north, likely due to greater solar radiation on southern and southwestern slopes. The 2 m water-air mixing ratio increased logarithmically with LST ($R^2 = 0.98$), while 2 m air temperature increased exponentially with LST, with heating rates of 0.12 K per 1 K temperature increase in spring, summer, and autumn, and 0.05 K in winter (Figure 8).

Discussion

WRF LST Accuracy Assessment

Recent rapid WRF development has improved simulation accuracy for various ecosystem processes and future trend predictions [citation]. This study found WRF LST highly consistent with meteorological station observations, with all correlation coefficients exceeding 0.97 ($P < 0.001$), demonstrating WRF's reliability. However, substantial uncertainty remains when simulating land surface processes in complex mountains, as evidenced by increased errors at Tumed Left Banner station in July. This primarily stems from delayed updates in WRF's reanalysis data and surface snow cover effects.

The close match between WRF LST and MODIS LST further confirms WRF's high accuracy for mountainous LST simulation [citation]. Local inaccuracies likely arise from large spatial variations in mountain solar radiation. Daytime simulations showed smaller mean deviations but larger variance, while nighttime showed larger mean deviations but smaller variance, possibly due to inaccurate surface soil thermal conductivity parameters. Ren et al. [citation] demonstrated that a new soil thermal conductivity scheme for northern China climate simulation (Noah-MP scheme) could improve simulation accuracy, though its applicability in mountainous areas requires further verification.

Relationships Between Environmental Factors and LST

Given that LST spatiotemporal distribution is jointly influenced by multiple interacting environmental factors including air temperature and topography [citation], this study employed both comprehensive and single-factor methods to analyze environmental impacts on LST. Comprehensive analysis revealed that annual mean LST was significantly positively correlated with 2 m air temperature and water-air mixing ratio, and significantly negatively correlated with elevation, vegetation coverage, and slope, consistent with Luo et al. [citation]. The significant negative correlation between vegetation coverage and LST in all seasons except winter aligns with Jiao et al. [citation].

Single-factor analysis revealed that LST correlated positively with slope in winter and summer but negatively in spring and autumn, likely due to differential solar radiation absorption on slopes of varying steepness across seasons. The positive correlation between LST and vegetation coverage in winter and summer reflects vegetation's insulation effect—rapid daytime warming and slow nighttime cooling. The lack of correlation in spring and autumn may result from smaller temperature variations and reduced vegetation insulation effects during these transitional seasons. The negative correlation between LST and 2 m air temperature in winter occurs because solar radiation heats air faster than the ground surface in winter. The logarithmic relationship between water-air mixing ratio and LST arises because higher surface temperatures increase evaporation, raising atmospheric water vapor content. Improving WRF accuracy further requires high-resolution regional vegetation, soil, and meteorological data, as inaccuracies in land surface schemes significantly hinder local simulation accuracy.

Conclusion

This study demonstrated that the WRF model can effectively simulate high spatiotemporal resolution LST distribution in complex mountainous terrain. Based on simulation results, comprehensive and single-factor analyses revealed regional LST spatial patterns, leading to the following conclusions:

1. WRF LST showed high consistency with observations, with all station correlation coefficients exceeding 0.97 ($P < 0.001$) and spatial correlation with MODIS LST reaching 0.73 ($P < 0.05$), confirming WRF's strong practicality in complex mountainous terrain.
2. Comprehensive factor analysis revealed that annual mean LST was significantly positively correlated with 2 m air temperature and water-air mixing ratio, and significantly negatively correlated with elevation, vegetation coverage, and slope. Single-factor analysis showed that LST decreased significantly with elevation in all seasons, correlated positively with slope in winter and summer, correlated weakly with slope in spring and autumn, and correlated positively with vegetation coverage in winter and summer but weakly in spring and autumn. LST varied by aspect as: south > southwest > southeast > west > east > northwest > northeast > north.

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Note: Figure translations are in progress. See original paper for figures.