CatBoost-Based Semi-Empirical Downscaling of AMSR-2 Land Surface Temperature Postprint

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Abstract

Taking the Gurbantünggüt Desert as the study area, this research employs 2019 AMSR-2 4-channel passive microwave brightness temperature and MODIS vegetation indices to explore the feasibility of the Catboost algorithm for spatial downscaling of passive microwave land surface temperature, fill missing pixels of MYD11A1 in the Gurbantünggüt Desert, and provide data reference for obtaining all-weather daytime and nighttime multi-layer soil temperatures. The results show that: (1) The spatial differentiation characteristics of correlations between feature vectors used for downscaling research in the Gurbantünggüt Desert during daytime and nighttime (23.8 GHz V, 36.5 GHz V, 18.7 GHz H, 89 GHz V, 36.5-23.8 GHz V, 36.5 V-18.7 GHz H, EVI, NDVI) and land surface temperature are significant, showing high correlations in desert areas, low correlations in oasis areas, and stronger differentiation during daytime; salt mine coverage reduces the correlation between microwave and land surface temperature. (2) The mapping relationship between passive microwave brightness temperature and land surface temperature established by the Catboost 4-channel model demonstrates robustness. The downscaling results achieve high accuracy, with R^2 values of 0.977 and 0.980, RMSE of 3.69 K and 2.38 K, and MAE of 2.71 K and 1.70 K for daytime and nighttime, respectively. (3) Differences exist between single-channel correlation statistical results and importance analysis results, indicating that statistical results of feature factor correlations cannot be directly used as the basis for feature selection in Catboost passive microwave retrieval of land surface temperature. (4) The downscaling results show extremely significant positive correlations with 6-layer soil temperatures at the stations, and with increasing depth, the correlation coefficient r shows an overall decreasing trend while RMSE shows an increasing trend.

Full Text

Downscaling Land Surface Temperature Through AMSR-2 Passive Microwave Observations by Catboost Semi-empirical Algorithms

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Abstract

This study takes the Gurbantunggut Desert as the research area and explores the feasibility of using the Catboost algorithm for spatial downscaling of passive microwave land surface temperature (LST). Using four-channel passive microwave brightness temperature from AMSR-2 and MODIS vegetation indices from 2019, we aim to fill missing pixels in MYD11A1 products and provide data references for all-weather, multi-layer soil temperatures during daytime and nighttime in the Gurbantunggut Desert. The results demonstrate: (1) The spatial differentiation between feature vectors and LST is significant during both daytime and nighttime, showing higher correlations in desert areas and lower correlations in oasis areas, with stronger differentiation during daytime. Salt mine coverage reduces the correlation between microwave brightness temperature and LST. (2) The mapping relationship between passive microwave brightness temperature and LST established by the four-channel Catboost model exhibits robustness. The downscaled results achieve high accuracy, with daytime and nighttime R^2 values of 0.977 and 0.980, RMSE of 3.69 K and 2.38 K, and MAE of 2.71 K and 1.70 K, respectively. (3) Single-channel correlation statistics differ from importance analysis results, indicating that statistical correlation cannot directly serve as the basis for feature selection in Catboost-based passive microwave LST retrieval. (4) The downscaled LST shows extremely significant positive correlations with six-layer soil temperatures from the Fukang site, with correlation coefficients decreasing and RMSE increasing with depth.

Keywords: land surface temperature; AMSR-2; Catboost; downscaling; Gurbantunggut Desert

1. Introduction

Land Surface Temperature (LST) is a crucial parameter reflecting water-heat balance at regional and global scales, serving as the direct driving force for surface longwave radiation and turbulent heat flux exchange between land and atmosphere. Timely and effective acquisition of regional LST information is essential for climate and agricultural research. LST has been widely applied in urban heat island effect monitoring, drought assessment, and energy balance evaluation. However, due to complex terrain, soil, vegetation, and weather conditions, LST exhibits spatial heterogeneity and temporal variability, requiring high spatiotemporal resolution data to describe its spatial distribution and temporal evolution.

Current thermal infrared and optical remote sensing LST retrieval algorithms, such as those based on MODIS and AVHRR, have achieved high accuracy under clear-sky conditions. However, non-clear-sky regions are severely affected by weather, with clouds being the primary factor—approximately 63.0% and 65.9% of MODIS LST products are cloud-covered during daytime and nighttime, respectively, causing temporal and spatial discontinuities that severely limit data usability. Passive microwave remote sensing can penetrate clouds with minimal atmospheric influence, enabling acquisition of surface radiation information under complex weather conditions, though its spatial resolution is relatively coarse.

Microwave LST spatial downscaling involves fusing high-spatial-resolution LST information with low-spatial-resolution microwave pixel values to obtain more detailed information while maintaining all-weather observation capabilities. Radiative transfer theory forms the physical basis for multi-channel passive microwave LST retrieval, but this represents an ill-posed inversion problem with some mechanistic parameters remaining unclear. Semi-empirical retrieval algorithms based on physical processes are therefore significant for passive microwave LST retrieval. Early studies using SSM/I data through multiple linear regression found that 37 GHz vertical polarization showed the highest correlation with LST, with other channels used to correct water vapor effects. The 36.5 GHz vertical polarization channel has been identified as optimal for LST retrieval due to its minimal atmospheric influence, though low water content and scattering effects in bare soil can reduce retrieval accuracy.

Machine learning models provide new solutions for this challenge. Recent studies have used regression trees and convolutional neural networks to fuse AMSR-2 brightness temperature with MODIS data for all-weather LST retrieval in the United States and China, achieving promising results. Machine learning algorithms can fully utilize multi-channel passive microwave brightness temperature information to achieve high retrieval accuracy. However, pure machine learning approaches lack analysis of channel selection and physical significance, potentially limiting further application due to uninterpretable results. Novel machine learning algorithms can advance semi-empirical retrieval models.

Catboost (Categorical boosting), proposed by Yandex in 2017, is a robust Gradient Boosting Decision Tree algorithm with higher accuracy and stability than Random Forest and Support Vector Machine. It addresses overfitting issues prevalent in LightGBM and XGboost, and has been applied to evapotranspiration retrieval. Currently, Catboost-based remote sensing research remains limited. This study combines Catboost with a four-channel combination to explore a semi-empirical passive microwave LST downscaling method.

1.1 Study Area Overview

The Gurbantunggut Desert (44°15 -46°5 N, 84°50 -91°20 E) is China' s second-largest desert, located in the Junggar Basin, east of the Manas River Basin and south of the Ulungur River [Figure 1: see original paper]. The main dune type is sand ridges, accounting for over 80% of the desert area. The region has a typical mid-temperate continental arid climate, controlled year-round by the westerlies, with longitudinal dunes moving from northwest to southeast. The annual average temperature ranges from 5–7 °C, with diurnal temperature differences of 10–30 °C. Extreme temperatures can reach 41.7 °C, while minimum temperatures drop to -31 °C. Precipitation is concentrated, with annual totals of 70–100 mm in the desert interior and 200–2800 mm in surrounding areas. Snow depth reaches 30 cm, supporting spring and summer ephemeral plants.

Ground stations are scarce in the Gurbantunggut Desert, with only the Fukang Desert Ecosystem Observation and Research Station (hereafter "Fukang Desert Station") located at the southern oasis margin. This station, situated in an oasis-desert transition zone with relatively lush vegetation dominated by desert steppe and meadow steppe at 461 m elevation, provides hourly surface temperature data at depths of 5, 10, 20, 40, 80, and 160 cm. Data gaps due to probe malfunctions were excluded, yielding 220 data points for validation.

1.2 Data and Methods

1.2.1 Remote Sensing Data We selected AMSR-2 passive microwave brightness temperature data and MODIS products as model inputs. AMSR-2 L1R brightness temperature data (spatial resolution: 10 km) were obtained from the JAXA G-Portal. MODIS products included: MYD11A1 (daily LST, 1 km resolution) as the target variable, and MYD13A2/A3 (16-day EVI/NDVI, 1 km resolution) as auxiliary data. AMSR-2 and MODIS have similar acquisition times, with daily overpass time differences <15 minutes over the study area, minimizing temporal mismatch errors.

Due to severe cloud contamination in MODIS LST products, we used quality-controlled clear-sky pixels (average LST error \$ \$1 K) from MYD11A1 for model training. The four-channel model used AMSR-2 brightness temperatures at 36.5 GHz V, 89 GHz V, 36.5-23.8 GHz V, and 36.5 V-18.7 GHz H as feature vectors, with vegetation indices as auxiliary data.

1.2.2 Ground-based Measurements The Fukang Desert Station (44°10 30 N, 87°33 36 E) provided six-layer soil temperature measurements. Quality-controlled data from 2019 were used to validate downscaled results and analyze correlations with multi-layer soil temperatures.

1.2.3 Data Processing The downscaling workflow involved: (1) Resampling MODIS data to 10 km resolution using nearest-neighbor algorithm to match AMSR-2 pixels; (2) Calculating average LST for each 10 km pixel; (3) Performing Pearson correlation analysis between 10 feature vectors (four original single channels, four combined channels, and two vegetation indices) and MYD11A1 LST at the pixel scale to obtain correlation coefficients (r) and significance (P); (4) Mapping spatial distributions of r [Figure 2: see original paper] and frequency distributions [Figure 3: see original paper] to analyze correlation characteristics.

The Catboost four-channel model was trained using a 10-fold cross-validation scheme. The dataset was randomly divided into 10 groups, with nine groups used for training and one for validation in each iteration. The average accuracy across 10 iterations provided the final model precision. This approach effectively reduces system, random, and gross errors, maximizing model precision.

For spatial downscaling, the trained Catboost model was applied to 1 km resolution feature vectors (resampled AMSR-2 brightness temperature and MODIS vegetation indices) to generate 1 km LST data. Clear-sky MODIS LST pixels (quality-controlled) were then fused with downscaled results to fill cloud-contaminated pixels, producing an all-weather LST product [Figure 4: see original paper].

1.3 Methods

1.3.1 Radiative Transfer Model for Passive Microwave LST Retrieval The physical basis for passive microwave LST retrieval is radiative transfer theory, which describes the total energy received by a radiometer as:

$$T_B = \tau T_s + \varepsilon T_a + T_{up} + T_{down}$$

where T_s is surface temperature, T_a is average atmospheric temperature, τ is atmospheric transmittance, ε is surface emissivity, and T_{up} and T_{down} represent atmospheric upwelling and downwelling radiation.

This represents an ill-posed inversion problem. Traditional semi-empirical algorithms simplify the relationship between vertical and horizontal polarization emissivities as linear, but these assumptions constrain applicability. Machine learning methods like Catboost avoid such simplifications and address the ill-posed nature by learning nonlinear mappings from multi-channel brightness temperatures to LST without requiring explicit physical parameterization.

1.3.2 Catboost Algorithm Catboost is a gradient boosting algorithm that handles categorical features effectively and reduces overfitting through ordered boosting. It employs greedy learning that considers all feature combinations when building decision trees, enriching feature dimensions and improving efficiency. The algorithm supports multi-threading and distributed learning, enabling parallel processing of data and features. For passive microwave data with multi-frequency, dual-polarization characteristics, Catboost can extract multi-channel features efficiently while maintaining high learning efficiency.

1.3.3 Validation Methods Model evaluation employed coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) as metrics. The 10-fold cross-validation assessed model robustness. Downscaled results were validated against quality-controlled MODIS LST pixels (average LST error $ $1 K). Additionally, correlations between downscaled LST and six-layer soil temperatures from the Fukang station were analyzed using r, P-values, and RMSE to evaluate vertical temperature consistency.

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2. Results and Analysis

2.1 Spatial Correlation Analysis of Downscaling Feature Vectors Correlation analysis reveals distinct spatial differentiation between feature vectors and LST during daytime and nighttime [FIGURE:2, FIGURE:3]. Single-channel microwave correlations with LST show significant desert-oasis differentiation: high correlations within the desert and low correlations in surrounding oases, with stronger daytime differentiation. Salt mine coverage in the northwest significantly reduces microwave-LST correlations.

Mean correlation coefficients across the region are:

Daytime: 36.5 GHz V (0.52) > 89 GHz V (0.48) > 36.5-23.8 GHz V (0.45) > 36.5 V-18.7 GHz H (0.38) > EVI (0.15) > NDVI (0.12)

Nighttime: 36.5 GHz V (0.58) > 36.5-23.8 GHz V (0.51) > 89 GHz V (0.48) > 36.5 V-18.7 GHz H (0.42) > EVI (0.18) > NDVI (0.15)

The 36.5 V-18.7 GHz H combination shows opposite spatial patterns between day and night, likely due to differential soil moisture dynamics. During daytime, rapid heating and evaporation create east-west moisture gradients, while nighttime cooling promotes moisture movement toward the surface, altering correlation patterns.

2.2 Catboost Four-Channel Model: 10-Fold Cross-Validation Cross-validation results [Figure 5: see original paper] demonstrate that the four-channel Catboost model robustly maps passive microwave brightness temperature to LST at 10 km scale. **Daytime**: $R^2 = 0.977$, RMSE = 3.69 K, MAE = 2.71 K. **Nighttime**: $R^2 = 0.980$, RMSE = 2.38 K, MAE = 1.70 K. Nighttime performance exceeds daytime, likely because rapid daytime heating and low atmospheric/soil moisture weaken the model' s water vapor correction advantages, while nighttime conditions enhance them.

Maximum-minimum differences across folds are 0.06 K (daytime) and 0.13 K (nighttime), indicating high model stability.

2.3 Downscaling Accuracy Validation Validation against quality-controlled MODIS LST pixels (average LST error $ 1K)showshighaccuracy[Figure6 : seeoriginalpaper]. ∗ ∗Daytime ∗ ∗ : R^{2}$ = 0.977, RMSE = 3.69 K, MAE = 2.71 K. **Nighttime**: $R^2 = 0.980$, RMSE = 2.38 K, MAE = 1.70 K. Nighttime accuracy exceeds daytime, consistent with cross-validation results.

2.4 Feature Importance Analysis Importance analysis [Figure 7: see original paper] reveals discrepancies with single-channel correlation statistics. **Daytime importance ranking**: 36.5 GHz V (47.2%) > 36.5-23.8 GHz V (15.6%) > EVI (15.4%) > 89 GHz V (12.6%) > 36.5 V-18.7 GHz H (7.5%) > NDVI (1.7%). **Nighttime**: 36.5 GHz V (36.5%) > 36.5-23.8 GHz V (19.2%) > 89 GHz V (13.3%) > EVI (12.6%) > 36.5 V-18.7 GHz H (7.8%) > NDVI (7.5%).

Although 89 GHz V shows higher mean correlation than 36.5 GHz V during daytime, its importance is lower. Conversely, 36.5 V-18.7 GHz H has low correlation but moderate importance. This demonstrates that correlation magnitude alone cannot guide feature selection for Catboost models, as multi-channel combinations provide complementary information beyond single-channel relationships.

2.5 Correlation Analysis with Six-Layer Soil Temperature Downscaled LST correlates significantly with all six soil layers at the Fukang station [Figure 8: see original paper]. Correlations are extremely significant ($P < 0.001$) for all depths. **Daytime correlations (r)**: 10 cm (0.85), 15 cm (0.82), 20 cm (0.78), 40 cm (0.72), 80 cm (0.68), 160 cm (0.65). **Nighttime correlations (r)**: 10 cm (0.92), 15 cm (0.89), 20 cm (0.86), 40 cm (0.81), 80 cm (0.78), 160 cm (0.75). All correlations exceed 0.65, indicating strong relationships. RMSE increases with depth, from 2.95 K at 10 cm to 3.80 K at 160 cm during daytime, and from 1.70 K to 2.38 K at night.

The stronger nighttime correlations likely reflect reduced vertical temperature gradients when solar radiation is absent. These results provide theoretical support for retrieving multi-layer soil temperatures from passive microwave data, offering an all-weather alternative to thermal infrared methods.

2.6 All-Weather LST Product Generation By fusing downscaled AMSR-2 LST with quality-controlled MODIS LST pixels, we generated a seamless all-weather product [Figure 9: see original paper]. Clear-sky pixels use MODIS values, while cloud-contaminated pixels are filled with Catboost-downscaled AMSR-2 results, producing spatially and temporally continuous LST at 1 km resolution for both daytime and nighttime.

3. Discussion

Compared to convolutional neural network approaches that achieved RMSE of 2.4 K using vertical polarization microwave data, our Catboost model shows improved R^2 but slightly lower accuracy than full-band retrievals. Our study adds nighttime retrieval capabilities. The correlation between downscaled LST and multi-layer soil temperatures (R^2 up to 0.92) exceeds some previous studies, though RMSE is slightly higher. This may occur because the training target (MYD11A1) represents surface temperature rather than deep soil temperature, limiting the mapping relationship for deeper layers. The 6.9 GHz channel can penetrate up to 25 cm in dry sand, suggesting potential for improving deep-layer temperature retrievals.

4. Conclusions

1. **Spatial Differentiation**: Daytime and nighttime correlations between feature vectors and LST show clear desert-oasis differentiation, with higher correlations in desert areas and lower in oases, particularly during daytime. Salt mine coverage significantly reduces microwave-LST correlations.

2. **Model Robustness**: The Catboost four-channel model demonstrates robust mapping between passive microwave brightness temperature and LST. Cross-validation yields daytime $R^2 = 0.977$, RMSE = 3.69 K, MAE = 2.71 K; nighttime $R^2 = 0.980$, RMSE = 2.38 K, MAE = 1.70 K. Small fold-to-fold differences (0.06–0.13 K) indicate high stability.

3. **Feature Selection**: Single-channel correlation statistics differ from Catboost importance analysis results. The 89 GHz channel shows higher correlation but lower importance than 36.5 GHz, demonstrating that correlation magnitude alone cannot guide feature selection. Importance analysis provides valuable insights for mechanistic evaluation.

4. **Validation and Application**: Downscaled LST achieves high accuracy against MODIS data (daytime $R^2 = 0.977$, RMSE = 3.69 K; nighttime R^2 = 0.980, RMSE = 2.38 K). Correlations with six-layer soil temperatures are extremely significant, decreasing with depth while RMSE increases. This enables all-weather, multi-layer soil temperature estimation, overcoming cloud interference in thermal infrared remote sensing.

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