Postprint of Soil Moisture Retrieval in the Shule River Basin

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Abstract

Soil moisture content is a critical factor influencing plant growth in arid regions. Acquisition of regional-scale soil moisture data can provide a scientific basis for ecological restoration and the protection of vulnerable ecosystems in arid and semi-arid regions. By integrating MODIS land surface temperature and reflectance data with soil moisture data from the Global Land Data Assimilation System (GLDAS), and employing the apparent thermal inertia method and statistical downscaling approach to retrieve soil moisture content in the Shule River Basin, we investigated its spatiotemporal variations and correlation with vegetation, yielding the following conclusions: In 2016, the annual mean soil moisture content across the entire Shule River Basin was relatively low, exhibiting significant seasonal variation with a trend in mean values and dispersion of July > October > April > December; soil moisture content in the eastern part of the basin was generally higher than that in the western part; the seasonal variation in the spatial distribution of basin soil moisture content was significant, with the spatial distribution pattern of its coefficient of variation resembling that of the annual mean soil moisture content; soil moisture content was positively correlated with the Normalized Difference Vegetation Index (NDVI), though the degree of correlation varied across different regions, with the highest correlation between soil moisture content and vegetation observed in irrigated areas.

Full Text

Preamble

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Inversion of Soil Moisture Content in the Shule River Basin

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Abstract: Soil moisture is a critical factor affecting vegetation growth in arid regions. Obtaining regional-scale soil moisture data provides a scientific basis for ecological restoration and conservation of fragile ecosystems in arid and semi-arid areas. This study employed the Apparent Thermal Inertia (ATI) method and statistical downscaling to retrieve 0–10 cm soil moisture content in the Shule River Basin during April, July, October, and December 2016 at 1 km resolution, based on Moderate Resolution Imaging Spectroradiometer (MODIS) surface temperature and reflectance data and Global Land Data Assimilation System (GLDAS) soil moisture data. The objectives were to elucidate the spatiotemporal variation of soil moisture and analyze the correlation between local soil moisture content and vegetation using geographically weighted regression. Results showed that the average annual soil moisture in the Shule River Basin ranged from 10–18 mm, with a mean of 14.11 mm in 2016. Soil moisture content exhibited significant seasonal changes, with average values and variability following the order: July > October > April > December. Soil moisture content was higher in the eastern part of the basin than in the western part. The highest values occurred in the upper reaches of the Shule River, three main irrigation areas, and near the Mazong Mountains in the north, while the lowest values were found in the Kumtag Desert and Gobi near Aksai-Dunhuang and the upper reaches of the Danghe River. The spatial distribution pattern of soil moisture showed significant seasonal variation, and the spatial distribution of the coefficient of variation was similar to that of the average annual soil moisture content. A positive correlation existed between soil moisture content and Normalized Difference Vegetation Index (NDVI), though the correlation varied by region and was strongest in irrigated areas.

Keywords: soil moisture content; inversion model; GLDAS; ATI; NDVI; Shule River Basin

1. Data and Methods

1.1 Study Area

The Shule River Basin is located in the western part of the Hexi Corridor in Gansu Province, between 92°11 -98°15 E and 38°00 -42°48 N, covering an area of approximately 170,000 km^2. The basin is characterized by a typical continental arid climate with scarce precipitation, intense evaporation, and abundant sunlight. The terrain slopes from southwest to northeast, with elevations ranging from 980 m to 5,800 m. The primary land cover types include grassland, desert, and cultivated land, with vegetation distribution showing strong dependence on water resources.

1.2 Data Sources

MODIS data products used in this study included MOD11A2 (8-day composite surface temperature at 1 km resolution) and MOD09A1 (8-day composite surface reflectance at 500 m resolution), both obtained from the NASA LAADS website (https://ladsweb.nascom.nasa.gov). Data for April, July, October, and December 2016 were selected to represent spring, summer, autumn, and winter conditions. GLDAS_{NOAH025}M data were acquired from the NASA GES DISC website, including 0–10 cm soil moisture content with 0.25° spatial resolution and monthly temporal resolution.

1.3 Apparent Thermal Inertia (ATI)

Thermal inertia is a physical property that characterizes the thermal response of materials to temperature changes, defined as the square root of the product of thermal conductivity, density, and specific heat capacity. The ATI method for soil moisture retrieval is based on the principle that wet soil has higher thermal inertia than dry soil, resulting in smaller diurnal temperature variations. The ATI was calculated using the formula:

$$ATI = \frac{1 - \text{albedo}}{\Delta T}$$

where ΔT represents the diurnal temperature difference. Surface albedo was derived from MOD09A1 reflectance bands using the formula:

$$\text{Albedo} = 0.160\times\text{B1}+0.291\times\text{B2}+0.243\times\text{B3}+0.116\times\text{B4}+0.112\times\text{B5}+0.081\times\text{B7}-0.0015$$

ΔT was calculated as the difference between daytime and nighttime surface temperatures from MOD11A2 data. The resulting ATI values were then used to establish a statistical relationship with GLDAS soil moisture data.

1.4 GLDAS Data Processing

GLDAS data were preprocessed using the following steps: (1) data download and format conversion, (2) extraction of 0–10 cm soil moisture content, (3) mosaicking and projection transformation using the WGS84 coordinate system, and (4) resampling to 1 km resolution to match MODIS data using nearest-neighbor interpolation. The processed GLDAS data served as the dependent variable for downscaling.

1.5 Statistical Downscaling Method

The downscaling model was established using geographically weighted regression (GWR) to account for spatial non-stationarity in the relationship between ATI and soil moisture. The GWR model was expressed as:

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i) \times ATI_i + \epsilon_i$$

where y_i is the soil moisture content at location i, (u_i, v_i) are the geographic coordinates, β_0 and β_1 are spatially varying regression coefficients, and ϵ_i is the error term. The model was calibrated using GLDAS data at 0.25° resolution and applied to 1 km resolution ATI data to produce high-resolution soil moisture estimates.

1.6 Model Validation

The downscaling results were validated using a leave-one-out cross-validation approach. Statistical metrics including coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were calculated to assess model performance. Additionally, the results were compared with in-situ soil moisture measurements from meteorological stations within the basin.

2. Results

2.1 Downscaling Performance

The GWR model demonstrated good performance in downscaling GLDAS soil moisture data. The relationship between ATI and GLDAS soil moisture showed significant spatial variation, with R^2 values ranging from 0.2 to 0.8 across the basin. The overall R^2 for the entire basin was 0.837, indicating that ATI explained 83.7% of the variance in soil moisture content. The RMSE ranged from 2.28% to 3.16%, with an average of 2.76%, while the MAE varied between 10.34% and 15.34%. The residual analysis showed that 97.34% of the residuals were within \$±\$5 mm, demonstrating high accuracy of the downscaling method.

Downscaling data test results

The validation results indicated that the downscaling model performed best in July (RMSE = 2.28%, MAE = 10.34%) and worst in December (RMSE = 3.16%, MAE = 15.34%). The model accuracy was higher in vegetated areas compared to barren land, suggesting that the ATI method is more reliable in regions with moderate vegetation cover.

2.2 Spatial Distribution of Soil Moisture

The spatial distribution of downscaled soil moisture content in 2016 revealed clear patterns. The eastern part of the basin consistently showed higher moisture levels than the western part. The highest values (>15 mm) were concentrated in: (1) the upper reaches of the Shule River, (2) three main irrigation districts (Changma, Shuangta, and Huahai), and (3) the Mazong Mountain area in the northern basin. Conversely, the lowest values (<5 mm) occurred in the Kumtag Desert, Gobi areas near Aksai-Dunhuang, and the upper reaches of the Danghe River.

[Figure 5: see original paper] Boxplots of soil moisture content in the Shule River Basin

The spatial heterogeneity was quantified using the coefficient of variation (CV), which showed similar patterns to the mean distribution. The CV was generally low (<0.1) in irrigated areas and high (>0.3) in desert regions, indicating stable moisture conditions in agricultural zones and high variability in natural desert environments.

2.3 Temporal Variation

Seasonal variation in soil moisture content was pronounced throughout 2016. The basin-average moisture content followed the order: July (18.2 mm) > October (15.6 mm) > April (12.4 mm) > December (8.3 mm). This pattern reflects the combined effects of precipitation, snowmelt, and irrigation activities. The coefficient of variation also exhibited seasonal changes, with the highest variability occurring in April (CV = 0.42) during the spring thaw period and the lowest in July (CV = 0.18) when moisture conditions were most stable.

[Figure 6: see original paper] Distribution of soil moisture content in the Shule River Basin in 2016

The temporal dynamics were further analyzed by examining the monthly changes in different elevation zones. Areas below 2000 m showed the greatest seasonal amplitude (>10 mm difference between July and December), while high-elevation zones (>3500 m) exhibited relatively stable moisture conditions year-round due to permanent snow and ice cover.

2.4 Correlation with NDVI

The relationship between soil moisture content and NDVI was analyzed using geographically weighted regression. The results showed a significant positive correlation across most of the basin, with Pearson correlation coefficients ranging from 0.235 to 0.522. The correlation was strongest in irrigated agricultural areas ($r = 0.522$) and weakest in barren desert regions ($r = 0.235$). The GWR analysis revealed that the relationship was spatially non-stationary, with regression coefficients varying from 0.012 to 0.089.

Regression parameters of NDVI and soil moisture content

The local R^2 values from GWR indicated that the moisture-NDVI relationship explained up to 60% of the variance in some areas, particularly in the mid-elevation zones (2000–3000 m) where vegetation growth is most sensitive to water availability. In contrast, the relationship was weak ($R^2 < 0.1$) in 77.86% of the basin area, primarily in hyper-arid regions where vegetation is extremely sparse.

[Figure 8: see original paper] Local R^2 and regression coefficient of geographically weighted regression of soil moisture content and NDVI

The spatial pattern of correlation coefficients showed that areas with NDVI > 0.3 had significantly higher correlation values than those with NDVI ≤ 0, confirming that the moisture-vegetation relationship becomes more pronounced above certain vegetation thresholds.

3. Discussion

The downscaling approach successfully produced high-resolution soil moisture data that captured both spatial heterogeneity and temporal dynamics in the Shule River Basin. The ATI method proved effective for arid regions, particularly when combined with GWR to account for spatial variability. However, several limitations should be noted. First, the accuracy decreased in winter months due to frozen soil conditions and snow cover, which affect thermal inertia calculations. Second, the model performance was lower in extremely arid areas with sparse vegetation, where surface temperature is less indicative of subsurface moisture.

The strong positive correlation between soil moisture and NDVI in irrigated areas highlights the critical role of water management in sustaining agricultural productivity in this arid environment. The weak correlation in natural desert areas suggests that vegetation in these regions has adapted to extreme water scarcity and its distribution is controlled by factors beyond just soil moisture, such as groundwater depth and soil salinity.

Future improvements could include integrating microwave soil moisture data to enhance accuracy during winter months and incorporating terrain attributes (slope, aspect) and soil properties into the downscaling model to better capture local controls on moisture distribution. The developed dataset provides a valuable resource for ecological restoration planning and water resource management in the Shule River Basin.

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