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Research on Soil Moisture Inversion of Agricultural Land in Wuchuan County Based on TVDI

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Abstract

Research conducted in the typical arid and semi-arid region of Wuchuan County, located at the northern foot of the Yin Mountains, utilized Landsat satellite imagery to establish the TVDI index based on the T_S-NDVI feature space. This study validates the accuracy of soil moisture estimation by comparing it with observed soil moisture values at 0 to 10 centimeters, thus enabling the spatial distribution mapping of soil moisture. The results that: (1) The determination coefficients (R^2) of the dry-wet boundary equations in the TS-NDVI feature space are 0.75 and 0.82, respectively, effectively expressing the arid conditions of the study area; (2) The regression coefficient (R^2) between the inverted TVDI and soil moisture at depths of 0~10cm reaches 0.68, demonstrating the feasibility of soil moisture inversion based on TVDI; (3) Soil moisture is lower in the desert grasslands in the eastern and northwestern parts of the study area, while it is higher in the mountainous forest areas in the southern and southwestern parts, as well as in the shaded areas of the mountain slopes. Inverting soil moisture based on TVDI can provide a scientific basis for agricultural layout and water resources management in arid and semi-arid regions.

Keywords

Arid and semi-arid regions, Soil Moisture, Temperature Vegetation Dryness Index, Wuchuan County.

1. Introduction

In arid and semi-arid regions, the scarcity of water resources is a significant issue, with soil moisture being a key factor limiting vegetation growth [1]. Due to the persistent drought in these areas, desertification is increasingly severe, imposing a heavy burden on agricultural production [2]. Therefore, real-time soil moisture monitoring through inversion techniques is of great practical significance and application value for agricultural production and ecological conservation in arid and semi-arid regions. Traditional methods for studying soil moisture, such as field measurement, gravimetric method, and oven-drying method, although providing data on soil moisture to some extent, are often limited by slow sampling speeds, complex operation procedures, high labor and material inputs, and poor timeliness of results [3]. These limitations result in low efficiency and may also introduce significant errors when conducting soil moisture detection over large areas. To overcome these challenges, remote sensing monitoring technology has been widely applied as an efficient means for large-scale soil moisture detection, mainly by utilizing changes in the T_S-NDVI (surface temperature-normalized difference vegetation index) feature space to invert soil moisture. This approach has gained widespread recognition among scholars for agricultural drought remote sensing monitoring [4-5]. Qi et al. [6] conducted a monitoring study on national drought conditions using the Temperature Vegetation Dryness Index (TVDI), finding that drought detection based on TVDI can effectively reflect trends in soil moisture changes. Wu et al. [7] investigated the application of the Temperature Vegetation Dryness Index (TVDI) in monitoring drought in complex mountainous areas, revealing its effectiveness in drought warning and monitoring in mountainous regions. Kang et al. [8] conducted an application study on drought monitoring in the karst mountainous areas of Guizhou using TVDI based on the NDVI-Ts feature space, finding a significant correlation between TVDI and soil moisture. Zhang et al. [9] analyzed the suitability of using NDVI and RVI combined with LST to construct TVDI for agricultural drought monitoring in the Weigan River-Kuqa River Delta Oasis in the northern margin of the Tarim Basin in Xinjiang, finding that RVI is suitable for soil moisture inversion in areas with high vegetation cover. At the same time, NDVI is more suitable for areas with medium to low vegetation cover. Cheng et al. [10] analyzed drought changes in grasslands in Inner Mongolia using TVDI based on the EVI-TS feature space, discovering that scarce precipitation significantly affects the degree of drought in non-desert grasslands. These studies consolidate and enrich the application of feature space methods in drought monitoring and sudden moisture inversion fields.

This study focuses on Wuchuan County, a typical area at the northern foot of the Yin Mountains, using Landsat satellite imagery as the data source. Utilizing the Google Earth Engine platform and Python 3.11 programming environment to construct the Temperature Vegetation Dryness Index (TVDI) based on the T_S-NDVI feature space. We have validated its accuracy using soil moisture data at 0~10cm and have inferred soil moisture in the study area. The aim has been to provide scientific evidence for agricultural layout and water resources management in arid and semi-arid regions as well as in the agro-pastoral ecotone of China.

2. Materials and Methods

2.1. Study Area

Wuchuan County, affiliated with Hohhot City, Inner Mongolia Autonomous Region, is located in the central part of Inner Mongolia Autonomous Region, at the northern foot of the Yin Mountains, north of the capital Hohhot City, with geographical coordinates ranging from 40°47′ N to 41°23′ N and from 110°31′ E to 111°53′ E (Figure 1). The county's total area is approximately 4885km^2, with terrain gradually becoming flat from south to north and elevations ranging from 1241~2338m. Wuchuan County has a temperate continental monsoon climate characterized by strong winds and significant diurnal temperature differences, with an annual average precipitation ranging from 250~400m. The main soil types are chestnut calcareous and grey-brown soil, characterized by loose texture and predominantly sandy grains, leading to frequent wind and sand activities. Principal crops include wheat, oats, buckwheat, and potatoes, while economic crops include sesame, rapeseed, and Codonopsis pilosula.

2.2. Data Sources and Pre-processing

The data utilized in this study comprised Landsat 8 OLI SR satellite imagery from 2020, obtained through the Google Earth Engine platform (https://earthengine.google.com/), with a spatial resolution of 30m. Due to high cloud cover in the study area, satellite images from one year before and after the target year's growing season (June to September) were selected. Cloudy pixels were removed using the Google Earth Engine platform, and the cloud-free composite image for the target year with minimal cloud cover was synthesized from cloud-free pixels. The Modified Normalized Difference Water Index (MNDWI) was also employed to remove water bodies from the satellite images. Furthermore, 30m SRTM elevation data from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov/) were utilized for spatial analysis. Land use data from the year 2020 were obtained from the Chinese Academy of Sciences Resource and Environmental Science and Data Center (https://www.resdc.cn/) to delineate agricultural land boundaries in the study area, with a spatial resolution of 30 meters. Soil moisture data at depths of 0~10cm during the 2020 growing season were derived from the global surface soil moisture (m^3m^{-3}) dataset [11] with a resolution of 1 kilometer, sourced from the National Tibetan Plateau Data Center (https://www.resdc.cn/), for accuracy validation of soil moisture inversion.

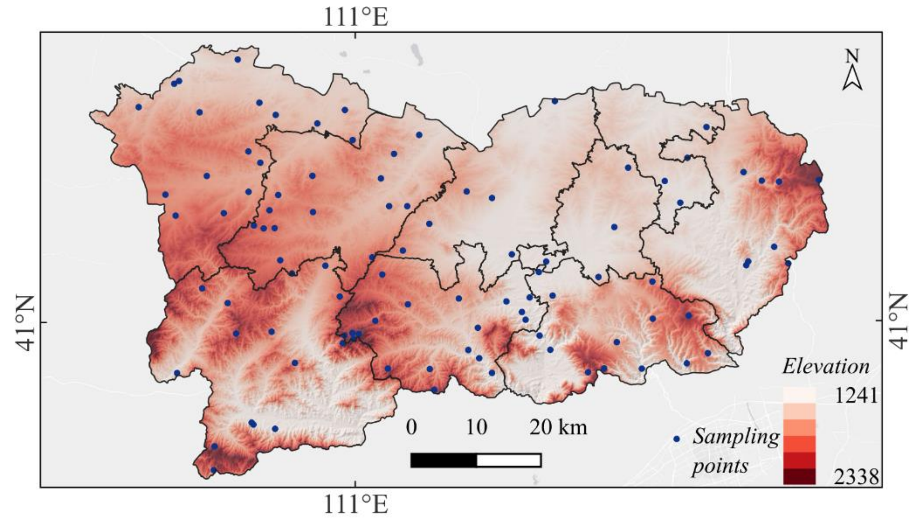

Fig. 1 Overview of the study area

2.3. Research Method

2.3.1. Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is widely used in remote sensing monitoring [12]. It is closely related to various aspects of vegetation, such as growth status, plant biomass, leaf area index, and vegetation coverage, making it one of the most used and practical tools for assessing vegetation conditions. Through NDVI, we can gain a more accurate understanding of vegetation distribution, density, and health. Its calculation formula is as follows:

$$NDVI = \left(\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}\right) / \left(\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}}\right)$$

The formula is as follows, where ρ_{NIR} represents the reflectance value at the near-infrared band, and ρ_{red} represents the reflectance value at the red band. NDVI values range from -1 to 1.

2.3.2. Land Surface Temperature

Land Surface Temperature (LST) serves as a critical parameter for characterizing surface drought conditions, reflecting not only the ground's heat status but also as a critical indicator for environmental issues such as climate change and land desertification [13]. The calculation formula is as follows:

$$LST = T / [1 + (\lambda T / \rho) ln\varepsilon] - 273.5$$

Where LST represents the land surface temperature in degrees Celsius, T denotes the sensor brightness temperature, λ is the central wavelength in the thermal infrared band (λ_{OLI}=11.9μm), ρ is a constant, and ε represents the surface emissivity.

2.3.3. Temperature Vegetation Dryness Index

The Temperature Vegetation Dryness Index (TVDI) is a method for inverting surface soil moisture in vegetated areas based on optical and thermal infrared remote sensing channel data [14]. The calculation formula is as follows:

$$T_{\mathrm{Smax}} = a + b \times NDVI$$

$$T_{\mathrm{Smin}} = c + d \times NDVI$$

$$TVDI = \frac{T_{\mathrm{S}} - T_{\mathrm{Smin}}}{T_{\mathrm{Smax}} - T_{\mathrm{Smin}}}$$

TVDI represents the Temperature Vegetation Dryness Index, and T_{Smax} and T_{Smin} represent the dry edge and wet edge equations, respectively. The dry edge corresponds to a TVDI value of 1, while the wet edge corresponds to 0. A smaller TVDI value indicates higher soil moisture content, while a more considerable TVDI value indicates lower soil moisture content.

3. Results and analysis

3.1. The TS-NDVI feature space and dry-wet edge equations

The Python 3.11 programming environment was utilized in this study, with land surface temperature as the dependent variable and normalized difference vegetation index (NDVI) as the independent variable x for regression analysis. This analysis successfully obtained the dry-wet edge equations for the Temperature Vegetation Dryness Index (TVDI). These equations were visually demonstrated in the subsequent triangular feature scatterplot (Figure 2). Specifically, the dry edge equation was expressed as T_{Smax}=36.1−9.1×NDVI, with a determination coefficient (R^2) of 0.75, indicating a strong correlation. This equation reveals the linear relationship between land surface temperature and normalized difference vegetation index when the surface temperature reaches its maximum value. Correspondingly, the wet edge equation was T_{Smin}=19.8−6.5×NDVI, with an even higher determination coefficient (R^2) of 0.82, demonstrating a closer linear relationship in describing the minimum surface temperature and normalized difference vegetation index.

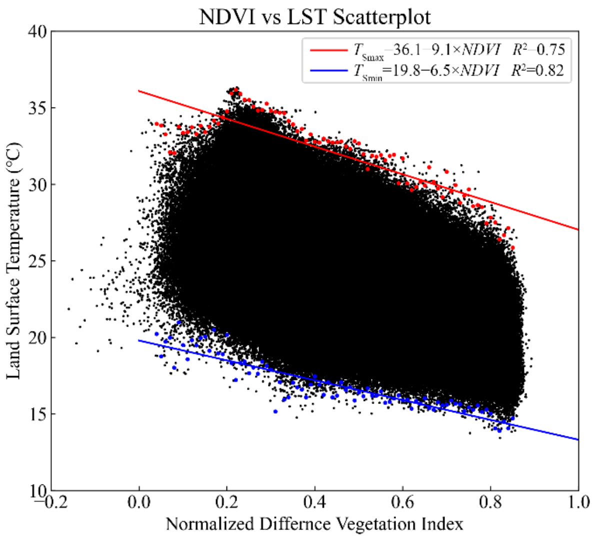

Fig. 2 Fitting of the dry-wet edge equations in the TS-NDVI feature space

3.2. Calculation of the TVDI index

Based on the derived dry-wet edge equations mentioned earlier, we further calculated the Temperature Vegetation Dryness Index (TVDI) for Wuchuan County (Figure 3). The analysis results indicate that the TVDI values for agricultural land in Wuchuan County fluctuate between -0.175 and 1.149, with an overall mean value of 0.528, which is relatively high. Spatially, areas with higher TVDI values are mainly concentrated in the eastern and northwestern parts of Wuchuan County, where deserts and grasslands predominate, exhibiting significant drought characteristics. Conversely, regions with lower TVDI values are primarily located in the southwestern part, characterized by dense distribution of forests and croplands, indicating better soil moisture and vegetation coverage and relatively lower levels of drought severity.

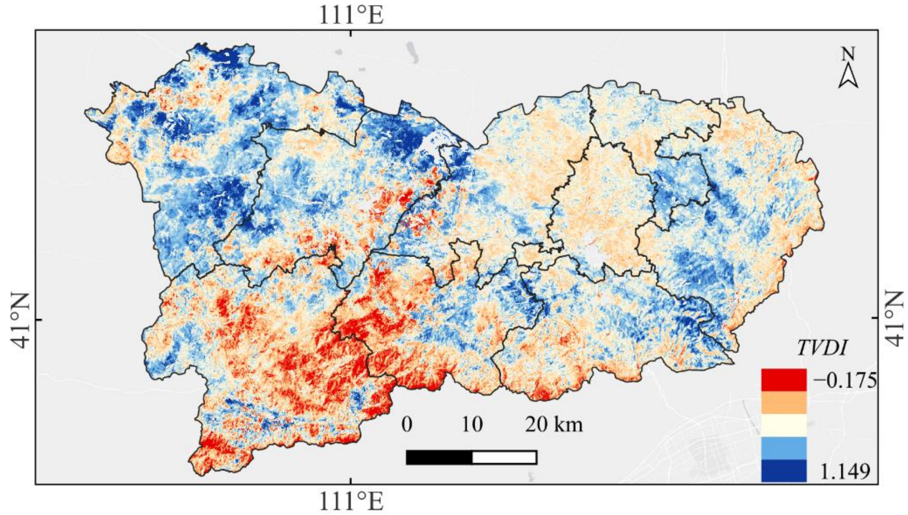

Fig. 3 spatial distribution of TVDI in Wuchuan County

3.3. Accuracy evaluation of soil moisture inversion based on TVDI

To further validate the accuracy of soil moisture inversion based on TVDI, 100 random sampling points were generated within the Wuchuan County area. Soil moisture and Temperature Vegetation Dryness Index (TVDI) were sampled and subjected to linear regression analysis at these points (Figure 3). During the analysis, the soil moisture (SM) at depths of 0~10cm was taken as the dependent variable y. In contrast, the corresponding soil moisture at TVDI points was taken as the independent variable x. The research results revealed a significant negative correlation between TVDI and soil moisture. An increase in TVDI values corresponded to a decrease in surface moisture content, while a decrease in TVDI values corresponded to an increase in surface moisture content. This negative correlation was more pronounced in arid and semi-arid regions, as the soil moisture conditions significantly affect vegetation growth and surface temperature. Through linear regression analysis, we obtained the regression equation $y=-0.103x+0.908$. This equation describes the linear relationship between TVDI and soil moisture and can be used to predict and estimate soil moisture content. The regression coefficient (R^2) reached 0.68, indicating that this linear model has a certain level of accuracy and reliability in explaining the relationship between TVDI and soil moisture.

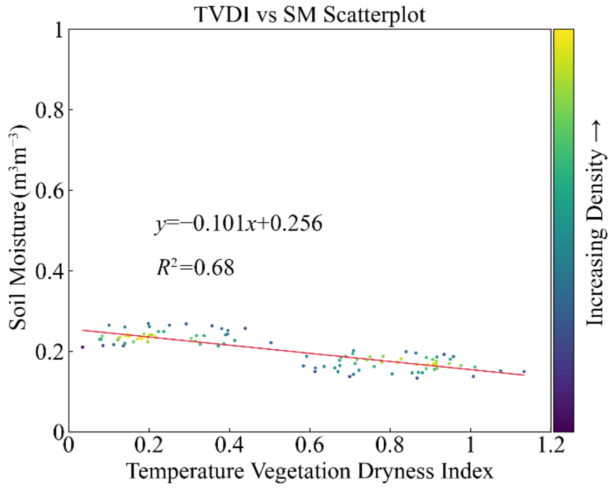

Fig. 4 linear regression relationship between TVDI and soil moisture

3.4. Soil moisture inversion based on TVDI

According to the regression equation mentioned earlier, the soil moisture at depths of 0~10cm in the study area was inverted, and the corresponding result map was obtained (Figure 4). The map shows that the soil moisture in the study area ranges from 0.140 to 0.276, with an average value of 0.203, indicating an overall dry state in the study area. Specifically, the soil moisture content in the desert and grassland areas in the study area's eastern, northwestern, and central parts is relatively low, showing pronounced drought characteristics. However, in the study area's southern and southwestern mountainous areas, the soil moisture content is relatively high, which may be related to factors such as terrain, vegetation coverage, and climatic conditions.

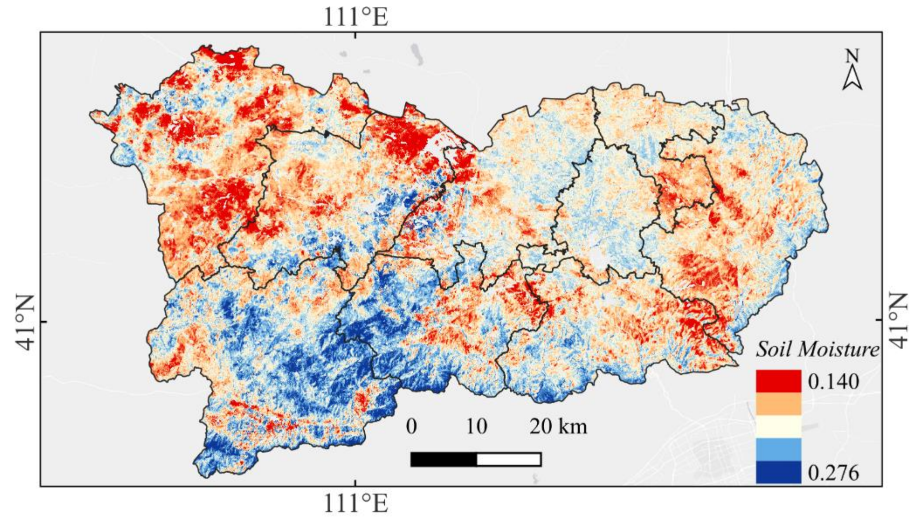

Fig. 5 spatial distribution of soil moisture in Wuchuan County

4. Discussion

Wuchuan County, located in the transitional zone between agriculture and animal husbandry at the northern foot of the Yinshan Mountains, typically represents arid regions. Therefore, conducting in-depth research on the distribution of soil moisture in this county is of immeasurable value for promoting the scientific development of agriculture in arid and semi-arid areas of China. This study successfully constructed the T_S-NDVI feature space and accurately inverted the Temperature Vegetation Dryness Index (TVDI). The determination coefficient of the dry edge equation reached as high as 0.75, and that of the wet edge equation even reached 0.82, fully demonstrating the high accuracy of TVDI inversion, which primarily reflects the surface drought conditions in the study area (Figure 2). During the soil moisture inversion process, 100 random sampling points were selected, and soil moisture data at depths of 0~10cm were taken as actual observation values, compared, and verified against the predicted values of TVDI. The results showed that the regression determination coefficient reached 0.68, indicating that it is feasible to invert soil moisture at depths of 0~10cm based on TVDI (Figure 4).

The desert grasslands in the eastern and northwestern parts of the study area exhibited lower soil moisture content, closely related to factors such as long-term drought, scarce precipitation, and climate warming, which have contributed to the degradation of desert grassland ecosystems (Figure 5). This finding is consistent with Weiskopf et al.'s study [16], which also pointed out that climate warming in arid regions is the leading cause of land desertification. In contrast, the soil moisture content in the southern and southwestern mountainous forest areas and the shaded slopes of the mountains is relatively high. This is mainly because these areas are usually moist and relaxed on the surface, providing favorable conditions for soil moisture retention, resulting in relatively higher soil moisture content than others.

5. Conclusion

This study, based on Landsat remote sensing imagery, constructed the Temperature Vegetation Dryness Index (TVDI) using the TS-NDVI feature space and regressed and inverted the spatial distribution of soil moisture in Wuchuan County by fitting it with 0~10cm soil moisture data. The following conclusions were drawn:

(1) Utilizing the TVDI model to invert the spatial distribution of 0~10cm soil moisture in Wuchuan County in 2020 and verifying the accuracy using ground-based soil moisture data from the same period yielded satisfactory results. The coefficient of determination (R^2) reached 0.68, demonstrating that TVDI can effectively infer soil moisture in arid and semi-arid regions.

(2) The desert grasslands in the eastern and northwestern parts of Wuchuan County exhibited lower soil moisture content. In contrast, higher soil moisture content was observed in the southern and southwestern mountainous forest areas and shaded slopes of the mountains. This provides important references for future agricultural layout and water resource management in these regions.

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