Soil Water Content Model of Inner Mongolia Based on GNSS ZTD and Meteorological Elements

Yong Wang[1], Zesheng Lou[1], Yumei Sun[2], and Xuan Wang[3]

[1]Tianjin Chengjian University
[2]Shijiazhuang Institute of Railway Technology
[3]Henan Polytechnic University

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Abstract

Soil water content is an important indicator of drought in agriculture and animal husbandry, and has an important impact on climate and ecology. The change trend of soil water is of great significance for regional soil erosion and climate change research. Thus, soil water content should be investigated using other existing data. In this study, the existing Global Navigation Satellite System (GNSS) zenith tropospheric delay (ZTD) and humidity, sunshine, and evaporation data in Inner Mongolia was used to investigate soil water content inversion. The correlation between each element and soil water content was analyzed. Noises was observed in the soil water content and GNSS ZTD data and wavelet transform was used to eliminate the noises. After denoising, the correlation between soil water content data and each element was improved, and the correlation between soil water content and humidity is the best. The average correlation between the two experimental points is 0.645. Negative correlations are observed between soil water content and sunshine and evaporation, and their average correlations are -0.561 and -0.547, respectively. The correlation between soil water content and GNSS ZTD data is the smallest, with an average correlation of 0.271. Then, a soil water content model was constructed on the basis of the correlation between each element and soil water content, and its reliability was verified. The verified error statistics show that the NMWJ station model in the experimental area has the highest accuracy, with the accuracy of 90.1%, whereas the HLAR site model has the lowest accuracy, with 69.1%. The average accuracy of each station in the study area is 81.35%. The soil water content model based on multivariable elements can provide reference for the research on the change trend of soil water content.

Introduction

Soil water content is an important indicator used to measure the level of soil drought in agriculture and animal husbandry, and has an important impact on climate, ecology, and hydrology. Analyzing the change trend through soil water content monitoring can predict the future changes, and has important significance for the effective allocation of water resources and sustainable use of water and soil resources, ecological environment protection, and drought monitoring in agriculture and livestock industries.

At present, monitoring methods of soil water content mainly include traditional physical monitoring methods, soil water content inversion based on Global Navigation Satellite System reflectometry (GNSS-R), soil water content inversion based on space remote sensing, and soil water content simulation based on mathematical statistical model calculation. Traditional physical monitoring has many soil layers, large depth, and high precision. However, it requires large manpower, material resources, and financial resources to manually collect samples in the field, thereby making it difficult to monitor soil water content in a large range and long-term. Therefore, traditional physical monitoring is mostly used to calibrate the precision of soil water content inversion by other methods. Soil water content retrieval based on GNSS-R has high accuracy but requires considerable manpower and material resources to set up stations in the measurement area and cannot ensure long-term continuous observation in the field(Larson et al.,2010). Soil water retrieval based on space remote sensing mainly includes optical and microwave remote sensing (Bowers & Hunks, 1965; Schmugge, Gloersen,Wilheit, & Geiger, 1974; Lee & Anagnostou, 2004; Narayan, Lakshmi, & Jackson, 2006; Zhao et al.,2009; Wang & Lou, 2019). Optical remote sensing is vulnerable to weather, whereas microwave remote sensing is vulnerable to vegetation coverage, surface roughness, and interference (Zhang & He, 2017; Zhou, 2018). The first soil water content monitoring satellite is the SMOS satellite (Mladenova et al.,2011). However, it cannot accumulate data and cannot be used for long-time series change trend research. Existing mathematical statistical and conceptual class models are generally applied to small spatial scales, and they require few parameters and computation. Although the physical mechanism model has high accuracy, it requires many complicated soil parameters and meteorological data, making it unsuitable for large-scale monitoring of farmland surface soil moisture (Fasinmirin, Olufayo, & Oguntunde, 2008; Li, Ma, & Du,2010).

These methods for obtaining soil water content data have problems, and continuous long-time series of soil water content monitoring data cannot be obtained. Therefore, a new soil water content monitoring method should be developed to obtain long-time series of soil water content data and provide support for the change trend of soil water content. Transpiration and evaporation are important factors affecting soil water consumption (Rana & Katerji,2000; Nakhaei & Simuunek,2014). Soil water forms water vapor after evaporation and transpiration, and a correlation is found between water vapor and soil water (Wang, Liu, Bernhofer, & LAPC.,2017).GNSS ZTD is mainly related to air pressure, temperature, and water vapor content, and the changes in air pressure and temperature in the same area are small in a short time period. Therefore, the change in GNSS ZTD is mainly affected by the change of water vapor, indicating that soil water and GNSS ZTD are correlated (Wang & Lou, 2019). GNSS ZTD is used as the condition for soil water inversion in this study.

The soil water content inversion in this study can provide reference for the missing data of remote sensing microwave inversion of soil water content, and GNSS data have been accumulated for more than 20 years. The inversion of soil water content in long-time series can be conducted using this method to provide reference for the research on the change trend of soil water content.

1 Research Data and Data Processing

1.1 Research Area

Inner Mongolia, an autonomous Region of northern China, is located 126° 04' east longitude, 97° 12' west longitude, 37° 24' south latitude, and 53° 23' north latitude, with a total area of 1.183 million square kilometers. It is one of the regions with the most abundant grassland resources in China. Approximately 90% of the available natural grasslands in China have been degraded in varying degrees, and the proportion of Inner Mongolia's degraded grassland has exceeded 70%. Grassland desertification area is increasing, and the ecological environment is continuously deteriorating, thereby limiting the development of grassland animal husbandry, affecting the income of farmers and herdsmen, and directly threatening the national ecological security (Pierre et al.,2011). Precipitation in Inner Mongolia is small and uneven, and the distribution of water resources in regions and time scales is extremely uneven. The grassland ecosystem is mainly affected by water resources (Ruppert et al.,2015).

1.2 Soil Moisture Active Passive (SMAP) Soil Water Data

SMAP soil water content data are obtained from (https://search.earthdata.nasa.gov/), and the original data are the 9-km grid data. In this study, GNSS site coordinates are used as the center to extract the surrounding 18-km soil water content data for averaging. The data used are the 2016 data with a time resolution of 2 times/day. The average data are processed into daily average data with a data unit of mm/cm^3. The time series of soil water content at the two stations of the study area is show in Fig. 1.

1.3 GNSS ZTD and Meteorological Data

Meteorological data, including 0-cm surface temperature, sunshine, relative humidity, evaporation, and other elements, are obtained from the China Meteorological Sharing Website (http://data.cma.cn/). The data of all elements are the daily data in 2016. The data acquisition location of this experimental site is shown in Figure 2.

GNSS ZTD data are obtained from the China Mainland Tectonic Environment Monitoring Network (FTP: 60.30.77.19/Continuous Basic Product/Trouble). The data are based on 2016 with a time resolution of 2 h. Average refers to the daily average, and the unit is expressed in mm. Fig. 3 shows the GNSS ZTD time-series changes of the two experimental stations (note: the abscissa in Fig. 3 is the day of year).

As shown in Fig. 2, the acquisition site of meteorological data and the coordinate matching site of GNSS data are selected for research and analysis to ensure the consistency of data in time and space.

2 Research Methods

2.1 Principle of Wavelet Transform

As shown in Fig. 3, the GNSS ZTD sequence has evident noises. All data are denoised through wavelet denoising to improve the correlation between each element and soil water content. Wavelet transform has high resolution and can reduce the influence caused by noises and reveal the relationship between GNSS ZTD change and soil water content.

Wavelet transform is a time-frequency analysis method of signals, and has multiresolution characteristics and can characterize the local characteristics of signals in time and frequency domains. Wavelet transform produces an inner product with analysis signal (T) at different scales (A) after a certain function called basic wavelet (τ) is shifted:

$$\mathrm{Wf}\left(a,\tau\right)=\left\langle f\left(t\right),\Psi_{a,t}(t)\right\rangle=\frac{1}{\sqrt{a}}\int_{R}\Psi^{*}\left(\frac{t-\tau}{a}\right)dt,(1)$$

where a $>$ 0 is the scale factor used to scale the basic wavelets ψ a and τ (t), τ reflects the displacement, and its value can be positive or negative, and a and τ are continuous variables. Thus, this formula is also called the continuous wavelet transform. At different scales, wavelet duration widens with the increase in value, amplitude inversely decreases, and wave shape remains unchanged [Zhang, 2011.].

Common wavelet functions include Morlet, Marr, DOG, Haar, and orthogonal wavelets. Each wavelet has its own characteristics. DbN wavelet system with tightly supported standard orthogonal wavelet is selected to achieve denoising and reconstruction.

2.2 Multivariate Linear Regression Model

The change in soil water content is affected by many factors. Two or more influencing factors are needed as independent variables to explain the change in dependent variables. Under the correlation of linear relationship, two or more independent variables versus one dependent variable are studied through multiple linear regression analysis, and the mathematical formula showing this quantitative relationship is called a multiple linear regression model. A phenomenon is frequently associated with multiple factors. Predicting or estimating dependent variables through the optimal combination of multiple independent variables is more effective and practical than predicting or estimating with only one independent variable. Let Y be the dependent variable and x1, x2, x3 … be the independent variables. Then, the multiple linear regression model is expressed as:

$$y=b_0+b_1x_1+b_2x_2+\ldots+b_kx_k,\ (2)$$

where b_0 is a constant term, and b_1, $b_2 \ldots b_k$ are the regression coefficients.

3 Experiment and Analysis

3.1 Correlation Comparison of Soil Water Content with Meteorological Elements and GNSS ZTD

External environment factors, such as humidity and sunshine (radiation), and internal factors, such as evaporation and transpiration of meteorological elements, can affect soil water content. Therefore, humidity, sunshine, evaporation, GNSS ZTD, and soil water content are selected for correlation analysis.

As shown in the correlation of the original data in Table 1, the correlation between soil water content and 0-cm surface temperature is accidental. Only three stations pass the correlation significance test, and their correlations are small and cannot prove the correlation between soil water content and 0-cm surface temperature. Soil water content is correlated with humidity, evaporation, sunshine, but the correlation s small. As shown in Figs. 1 and 3, the low correlation coefficient is because of the observed noises between GNSS ZTD and soil water content and meteorological element data. Noise affects the correlation between soil water content and various elements, thereby affecting the construction of this model. Therefore, the data are denoised.

In this study, wavelet denoising is selected, and GNSS ZTD and soil water content data are decomposed through wavelet transform and reconstructed after removing the noise layer. The comparisons of Figs. 1 and 4 and Figs. 2 and 5show that abrupt changes and elimination are observed occurred in the time series after denoising the soil water content and GNSS ZTD data through wavelet transform. As shown in Table 1, the correlation between soil water content data and each element is improved after denoising, indicating that noise affects the correlation of data and wavelet decomposition reconstruction can eliminate noises.

As shown in Table 1, the correlation between the soil water content of NMWJ station and GNSS ZTD data is abnormal. The correlations between soil water content and GNSS ZTD are 0.198 and 0.127 before and after denoising, respectively, but their significance is $0.04<0.05$. A statistical correlation between the soil water content and GNSS data is found through significance test. GNSS ZTD can be used to construct a soil water content model. The noise layer of GNSS ZTD at this site contains real data information after small-scale decomposition and is removed through wavelet denoising, resulting in reduced correlation.

3.2 Construction of Soil Water Content Model for Different Elements

The relative air humidity and GNSS ZTD (water vapor) may be duplicated because soil water is transported to the atmosphere through transpiration and evapotranspiration. As shown in Table 2, the two elements pass the significance test and are statistically correlated. Therefore, different models are constructed, and their reliability are tested.

3.2.1 Construction of Meteorological Element Model

Only meteorological elements are used to build the soil water content model on the basis of the correlation analysis in Table 1. The model is built with soil water content as dependent variable and humidity, sunshine, and evaporation as independent variables, in which the average relative humidity is expressed in percentage data. These percentage data are converted into numerical data, that is, humidity numerical data = humidity data $(\%)\times 0.01$. The discontinuous part of the soil water content data is missing. The data are noncontinuous to ensure accuracy. The first 85% of the data are selected to build the model, and the remaining 15% of the data are used to test the reliability of the model.

Table 3 shows the constant term and each factor coefficient of the soil water content model constructed in terms of humidity, sunshine, and evaporation. As shown in Table 3, the evaporation coefficient is smaller than that of the coefficients of other factors, proving that the proportion of evaporation in the model is small and mainly plays a limited role. By contrast, the humidity coefficient is large and is the main factor in the model.

Fig. 6 shows the comparative analysis of the soil water content models constructed using meteorological elements of humidity, sunshine, and evaporation and the true value of soil water content. As shown in Fig. 6, the model can be used for soil water content inversion, but the reproduction accuracy of some stations is extremely low. The soil water content models of the three stations in Figs. 6(a), (d), and (f) are consistent with the change trend of the true value of soil water content. As shown in Figs. 6(b), (c), and (f), the inversion change trends of the three stations are relatively different from the actual change trend, and the inversion accuracy is relatively low. As shown in Table 6, the error of each experimental station of the model constructed by this method can be observed. As shown in Fig. 6 and Table 6, the model built using humidity, sunshine, and evaporation is accidental, and some stations have large errors. Therefore, soil water content inversion cannot be conducted.

3.2.2 Model Construction Using Sunlight, Evaporation, and GNSS ZTD

Humidity factors are removed because humidity is correlated with GNSS ZTD, and GNSS ZTD is used rather than relative average humidity to build a soil water content model. The accuracy of the model is verified.

Table 4 shows the constant term and factor coefficients of the soil water content model constructed using sunshine, evaporation, and GNSS ZTD. Table 4 shows that the evaporation coefficient of the model is small, which is the same with the result in Section 3.2.1, proving that evaporation plays a limited role in the model. However, GNSS ZTD and sunshine have large factor coefficients, proving that they play a leading role in the model.

As shown in Fig. 7, the inversion effect of soil water content using sunshine, evaporation capacity, and GNSS ZTD is poor. The change trends of inversion soil water content in Figs. 7(a) and (f) are basically the same with the actual change trend of soil water content. The differences between the inversion soil water content trend change of other experimental stations and the actual change trend of soil water content are large. The analysis in Fig. 7 combined with Table 6 shows that the error of soil water content generated using this method is large. Therefore, this model cannot be used for the inversion of soil water content.

3.2.3 Model Construction Combining GNSS ZTD, Humidity, and Other Elements

Table 5 shows that humidity and GNSS ZTD have larger coefficients in the model compared with the two other elements. Therefore, the two elements play a leading role in the model construction, and sunshine and evaporation are the constraints.

As shown in Fig. 8, the soil water content model integrating GNSS ZTD with humidity, sunshine, and evaporation can be used to retrieve the actual and inversion values of soil water content because the change trend is basically the same. The analysis in Fig. 8 and Table 6 show that the inversion accuracy of this model is immensely improved compared with the two other models in this study.

As shown in Figs. 8(c) and (e), the change trend of soil water content retrieved by the two stations using this model is basically consistent with the actual value of soil water content. As shown in Table 6, the inversion accuracy is obviously improved compared with the two other models. As shown in Figs. 8(a), (b), (d), and (f), a small difference is found between the three models of soil water content inversion. The correction effect of the model constructed by combining meteorological elements and GNSS ZTD is insignificant compared with the two other models. As shown in Table 6, the accuracy of RMSE reduction of the model constructed by merging meteorological elements and GNSS ZTD is improved compared with the other models. The HLAR station model in Fig. 8(b) has a large error compared with the actual value and has poor inversion accuracy. The statistics in Table 6 show that the RMSE of the this station is 0.0508, and its accuracy is 69.1%. This condition is because the correlation between GNSS ZTD and soil water content is small, but the coefficient of the model built using GNSS ZTD is large, thereby causing large errors. The inversion accuracies of other stations in the study area exceed 80%, and the inversion accuracy of the NMWJ station reaches 90.1%. The average accuracy of the six experimental stations is 81.35%.

The inversion result of soil water content with meteorological elements and GNSS ZTD is more consistent with the actual change of soil water content compared with the inversion models of soil water content with only meteorological elements and using sunshine, evaporation, and GNSS ZTD. The inversion data change of the model with meteorological elements and GNSS ZTD data is basically consistent with the actual change. As shown in Table 6, the RMSE of the model integrating meteorological elements and GNSS ZTD is reduced compared with the RMSEs of the two other models, proving that the inversion model integrating meteorological elements and GNSS ZTD data has higher accuracy and better reliability. This condition is because of the following reasons: humidity and GNSS ZTD are correlated with soil water content and play a leading role in the model, humidity ranges from 0 to 1(0%–100%), and GNSS ZTD is not used to build the model. Thus, the accuracy of the model built in Section 3.2.1 is limited. However, humidity has a high correlation with soil water content. Thus, the accuracy of the model constructed by eliminating humidity in Section 3.2.2 is low.

4. Conclusion and Prospect

In this study, the correlation between meteorological elements, GNSS ZTD, and soil water content is analyzed, and an inversion model of soil water content is established. The conclusions are provided as follows:

(1) Relative average humidity, sunshine (radiation), and evaporation have good correlation with soil water content. Average relative humidity is positively correlated with evaporation, whereas sunshine and evaporation are negatively correlated with soil water content.

(2) Meteorological elements and GNSS ZTD are used to build the model, humidity and GNSS ZTD play a dominant role in the model, and sunshine and evaporation play a constraint role.

(3) The soil water inversion model using meteorological elements and GNSS ZTD data has high precision of 90%, and the average precision in the research area is 81.35%.

The soil water content data used in this study are SMAP satellite data. Although the accuracy of the SMAP satellite data is relatively reliable, they still have a gap with the actual data. The study area used in this paper is Inner Mongolia, China, with relatively single vegetation coverage. In the later period, the measured data of soil water content are analyzed and discussed, the inversion of soil water content in different vegetation coverage areas and different climatic types is conducted.

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Conflicts of Interest: The authors declare no conflict of interest.

Data Availability Statement

In this paper, soil water data is from https://search.earthdata.nasa.gov; meteorological data is from http://data.cma.cn/ and ZTD data is from FTP: 60.30.77.19/continuous basic product / problem.

These data are free and there are source descriptions in the paper. Thank National Aeronautics and Space Administration,Crustal Movement Observation Network of China,China Meteorological Data Network for providing data for this study.

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