Collaborative soil moisture inversion with multi-source remote sensing data

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Key Words: Soil moisture inversion; Multi-source remote sensing collaboration; VWC model; Water cloud model; BP neural network

Abstract

Soil moisture is a key variable in the global water cycle, carbon balance and energy conversion, and is crucial for hydrological control, meteorological forecasting and crop growth. Pengyang County in Ningxia is a typical region with fragile ecology. In this paper, we utilize Sentinel 1 SAR data and Landsat 8 optical imagery to synergistically invert soil moisture in Pengyang County by combining the advantages of optical and microwave remote sensing. The study calculates the vegetation water content through the VWC model, and uses the water cloud model to eliminate the influence of vegetation on the radar signal to obtain the soil backscattering coefficient with the removal of the influence of vegetation. Finally, the BP neural network model was utilized to invert the soil moisture in Pengyang County. The results show that the VH-polarized SAR data are more sensitive to the vegetation structure and moisture content, which is more suitable for soil moisture inversion in this region, and the NDMI has the highest sensitivity to the vegetation moisture content, which contributes more to the soil moisture estimation. The inversion results of the BP neural network model have a high correlation with the measured values, which indicates that the method can effectively invert the soil moisture in Pangyang County. The results of the study can provide a reference for soil moisture monitoring in the region, and provide a basis for decision-making in ecological protection, water conservation and comprehensive regional management.

1. Introduction

Soil Moisture (SM) plays an important role in the global water cycle, carbon balance and energy exchange, and is of great significance in hydrological management, climate prediction and agricultural production. The traditional methods of obtaining soil moisture information based on monitoring stations or drying and weighing methods, although with high accuracy, are unable to meet the needs of large-scale and time-series monitoring. With the continuous development of remote sensing technology, the combination of traditional measurement methods, remote sensing technology and model simulation has significantly compensated for the limitations of the traditional way. Therefore remote sensing technology has become an important method for soil hydrology research.

Optical inversion methods can effectively reflect vegetation conditions with high spatial resolution, but they are easily affected by bad weather. Various optical inversion methods need to utilize optical data to obtain surface vegetation information or surface temperature first, and weather conditions such as cloudy weather can seriously affect the accuracy of information extraction. In addition, the depth of optical remote sensing inversion of soil moisture is very limited because of the short wavelength of optical sensors, and most of the methods can only invert soil moisture at the millimeter level, which cannot meet the needs of actual soil moisture products. Microwave remote sensing is developing rapidly in the field of soil moisture monitoring, both active microwave remote sensing and passive microwave remote sensing have the ability to monitor soil moisture, but each of them has certain disadvantages. The inversion method of passive microwave remote sensing is simpler but the spatial resolution is limited. Active microwave remote sensing has a higher spatial resolution, but this method has limitations in monitoring large areas over long periods of time. Soil moisture inversion methods using a single data source have certain shortcomings, and combining the advantages of multiple types of sensors to invert soil moisture is a popular research topic nowadays. Many scholars have carried out synergistic inversion studies of visible and thermal infrared within the optics, Fei et al. (Wang and Zhang 2010)combined SAR and visible spectral remote sensing data to extract the soil and vegetation water content in arid oasis areas. Liu et al.(Liu, Xu et al. 2021) constructed a regression convolutional neural network model for soil moisture inversion in agricultural fields using Sentinel multi-source data, aiming to improve the inversion accuracy. Zhang et al.(Zhang, He et al. 2023) proposed a synergistic inversion method based on the water cloud model and Oh model to invert soil moisture in winter wheat-covered farmland using Sentinel-1/2 multi-source remote sensing data. GuoJiao et al. (Guo, Bai et al. 2022) took the winter wheat planting area in Guanzhong Plain as the research object and constructed a one-dimensional regression convolutional neural network model for soil moisture inversion with a correlation coefficient of 0.917 by utilizing radar and multispectral remote sensing data to reduce the effect of vegetation cover on the inversion accuracy.

Currently. There are three main methods to invert soil moisture using the synergistic method of multi-source remote sensing data. The first method is based on improving the model of active microwave vegetation effect analysis, this method is improved by calculating the vegetation index to obtain the vegetation water content, the advantages are more obvious, the simulation process is obvious, and the inversion accuracy is higher, but the disadvantage is that it needs to measure the vegetation water content data to be corrected as auxiliary data. The second method is to monitor soil moisture through the changes of active microwave remote sensing data, this method is simpler to calculate, less demanding on auxiliary data, but when using a single vegetation index, the stability is weaker, there will be a certain lag, the data requirements are higher. The third method is the intelligent algorithm model, this method has good real-time and high calculation rate, and can be very good you and the nonlinear relationship between the influence factors.

Pengyang County, Ningxia Hui Autonomous Region, is located in an inland area with a relatively arid climate and low precipitation, resulting in more obvious soil moisture changes, and this climatic condition makes soil moisture monitoring and analysis more direct and obvious. At the same time, the land use in Pengyang County is varied, which provides many data samples for the study of soil moisture and helps to establish a more accurate model. In addition, the local vegetation cover is relatively low and the bare ground surface is easier to obtain remote sensing data, which improves the accuracy of soil moisture monitoring. The moderate hilly and plain landscapes in the area have a good influence on the distribution and flow of soil moisture on the surface, which also facilitates soil moisture research. Considering the arid climate, diverse land use, vegetation cover status, topography and light conditions in Pengyang County, it was found to provide an ideal environment for soil moisture studies. Therefore, the selection of Pengyang County as a soil moisture research site is appropriate and promises to provide valuable data and scientific basis for the development and application of soil moisture monitoring technology.

2. Study Area and Data

2.1 Study Area

Pengyang County is located in the southern part of China's Ningxia Hui Autonomous Region, at the eastern foot of the Liupan Mountains and the upper reaches of the Jing River, with geographic coordinates of longitude 106°31′-107°12′E and latitude 35°16′-35°54′N, as shown in Figure 1. The main climate is continental monsoon climate, with precipitation mainly concentrated in the summer period, a large temperature difference between day and night, and plenty of light. Pengyang County has a variety of soil types, rich vegetation types, and rich and varied topography and geomorphology. In addition, the economy of the region is mainly based on agriculture.

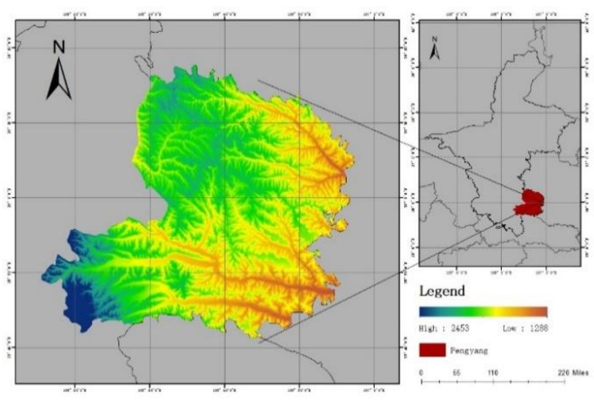


Figure 1. Research Area

2.2 Experimental data and pre-processing

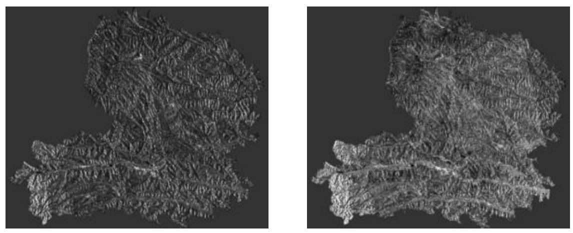
2.2.1 Sentinel-1 SAR : The Sentinel-1 satellite (Sentinel-1) is a cooperative initiative of the European Space Agency (ESA) and the European Union (EC) for the Global Monitoring for Environment and Security (GMES) program project and consists of two satellites. Specific imaging parameters are shown in Table 1.

Imaging Mode	Resolution (Meters)	Width (Kilometers)
SM	5 x 5	80
IW	5 x 20	250
EM	20 x 40	400
WV	5 x 5	20

Table 1. Sentinel-1 SAR Different Imaging Modes

With a resolution of up to 5 m and a width of up to 400 km, and with dual-polarized data, Sentinel I has easy access to data, which can be downloaded free of charge from ESA's website, and has been widely used for research in the field of agriculture. In this paper, we use the Ground Distance Multiview product GRD of the IW model.

In this study, SNAP software was used as a tool to perform a systematic preprocessing process on the acquired image data. The preprocessing steps include accurate orbit correction to correct positional errors in the data, thermal noise removal through advanced algorithms to improve image quality, radiometric calibration to calibrate the radiance of the image, coherent spot filtering using Refined Lee algorithm to reduce speckle noise, topographic correction using the Distance Doppler method to correct for the effect of topography on the image, and finally decibelization for better display and analyze the data. Together, these pre-processing measures ensure the accuracy and reliability of our subsequent analysis.



(a) (b)

Figure 2. Sentinel-1 SAR data preprocessing

(a) VV; (b) VH

2.2.2 Landsat 8 : Landsat 8, a joint project of NASA and the U.S. Geological Survey (USGS), represents the latest development in the Landsat family of land satellites, building on the advances of Landsat 7 with a number of enhancements. Landsat 8 has a significant performance improvement over the ETM+ sensor on board the earlier Landsant 7. The OLI sensor on board Landsat 8 has significantly improved its performance, with the addition of the deep blue and short-wave infrared (SWIR) bands, which provide scientists with a richer set of data, as well as the modification of the near-infrared (NIR) bands, which have been narrowed down to exclude the effects of water vapor on the quality of the images, and the panchromatic band. The panchromatic band has also been adjusted to make it easier to distinguish between vegetation and non-vegetation. In terms of temperature measurement, Landsat 8's TIRS sensor can provide us with more accurate surface temperature data by virtue of its wavelength advantage and advanced split-window algorithm, which is very important for climate change research, environmental monitoring and urban planning.

In this paper, we use Landsat 8 OLI data downloaded from Geospatial Data Cloud Platform, and the image selection time is July 31, 2021, which is basically the same as the acquisition time of Sentinel-1 SAR data. ENVI5.3 professional remote sensing image processing software is used to pre-process Landsat 8, which mainly includes radiometric calibration, FLAASH atmospheric correction, cropping, and so on.

2.3 measured data

Source: National Tibetan Plateau/Third Pole Environmental Data Center.
The dataset was carefully compiled by the China Meteorological Administration (CMA), covering data from 1648 observation points, which are based on a 10-layer soil moisture baseline. During the construction process, the researchers not only utilized the mandatory ERA5_Land meteorological data, but also fully considered a variety of covariates including leaf area index (LAI), land cover types (Land types), topography (DEM), and a variety of soil properties and characteristics. Ultimately, through advanced machine learning techniques, these data are integrated and transformed into information with practical applications. The data can be used for hydrological, meteorological, and ecological data analysis and modeling, especially critical for soil moisture applications that require high quality and resolution.

3. Inversion of soil moisture parameters based on water cloud modelling

3.1 Water cloud model

Water cloud models are valuable tools for estimating biophysical parameters from remotely sensed radar data. Svoray et al. (Svoray and Shoshany 2010) emphasized the importance of estimating pasture biomass in semi-arid regions and proposed modifications to the water cloud model to address issues related to sparse vegetative cover and soil background effects. Graham et al.(Graham and Harris 2002) introduced methods for estimating crop- and band specific water cloud model parameters that enhance the portability of the model. In addition, Graham et al.(Graham and Harris 2003) provided a comprehensive review of water cloud models detailing the formulation and development of spatial values of biophysical parameters derived from radar data. Kweon et al.(Kweon, Hwang et al. 2012) developed a soil moisture inversion technique for vegetated fields using an improved water cloud model, combining parameter estimation with a radiative transfer model to improve accuracy. Huang et al.(Huang , Chi et al. 2012)used optical image data and multipolarized radar data with a water cloud model to monitor soil moisture and effectively eliminate vegetation effects. both Liu et al.(Liu and Shi 2015) and Liu et al.(Liu and Shi 2016) demonstrated the application of a water cloud model to global scatterometer observations to estimate vegetation parameters and recover soil moisture at appropriate settings. In addition, Rawat et al.(Rawat and Singh 2022) focused on retrieving surface roughness in cropped regions using a modified water cloud model and SAR data. Bai et al.(Bai, Zheng et al. 2022)simulated Sentinel-1A observations and constrained the water cloud model on a regional scale using a discrete scatterometer model. These studies emphasized the versatility and effectiveness of the water cloud model in various remote sensing and biophysical parameter estimation applications. Despite the simplicity and utility of the model in describing radar scattering mechanisms in vegetated crop cover areas, it is important to note that the model ignores the structure and complexity within the vegetation canopy. As a result, there may be some error in areas covered by tall vegetation such as forests and tall crops. In these areas, a more sophisticated model or a combination of other remote sensing data and ground observations may be needed to improve the accuracy of the estimates.
The principle of the water cloud model is based on three core assumptions: (1) the vegetation is considered as a horizontal and uniformly distributed cloud, with water molecules uniformly distributed on the top of the vegetation canopy and on the soil surface; (2) the effect of multiple scattering between the soil surface and vegetation is ignored; and (3) only three variables, namely, vegetation water content, soil moisture, and vegetation height, are considered in the model. Based on these assumptions, the water cloud model decomposes the signal (backscattering coefficient) received by the synthetic aperture radar (SAR) sensor into two components: soil scattering (from the signal that passes through the vegetation and enters the soil) and vegetation reflection (from the signal that is reflected from the vegetation). The water cloud model expression is specified below:

$$\sigma^0=\sigma^0_{veg}+\gamma^2\cdot\sigma^0_{soil} \tag{1}$$

$$\sigma^0_{veg}=A\cdot m_{veg}\cdot cos(1\text{-}r^2) \tag{2}$$

$$r^2=e^{(-2\cdot B\cdot m_{veg}\cdot sec\,\theta)} \tag{3}$$

Where σ^0=Total surface backscattering coefficients obtained by microwave sensors
σ^0_{veg}=Backward scattering coefficient of vegetation
σ^0_{soil}=Soil backscattering coefficient
r^2=Two way attenuation factor of microwave signal through vegetation layer
m_{veg}=Vegetation water content
A, B=empirical parameter
θ=Radar incidence

3.2 Inversion of vegetation water content

3.2.1 Vegetation index: The vegetation index is a measure of vegetation growth through the use of satellite sounding data.
(1) Normalised Vegetation Index
NDVI is a widely used vegetation index that can be calculated by measuring the spectrum in the visible and near-infrared bands with the following expression.(Sims and Gamon 2003)

$$NDVI=\frac{R_{RIN}\text{-}R_{RED}}{R_{RIN}+R_{RED}} \tag{4}$$

Where R_{RIN}=Near-infrared reflectance
R_{RED}=Infrared reflectance

(2) Normalised mid-infrared near-infrared difference index
NDMI is a new vegetation moisture index proposed by Gao(Penuelas, Pinol et al. 2010), which is characterised by comparing the reflectance in the near-infrared and mid-infrared bands, and the NDMI index can respond in time when the moisture in the vegetation layer changes.

$$NDMI=\frac{R_{NIR}\text{-}R_{MIR}}{R_{NIR}+R_{MIR}} \tag{5}$$

Where R_{NIR}=Near-infrared reflectance
R_{MIR}=Short-wave infrared reflectance

(3) Normalised water body index
In 1996, Mcfeeters proposed the Normalised Water Body Index (NDWI)(McFEETERS 1996), which can more accurately reflect the characteristics and conditions of a water body by comparing the reflectance in the green and near-infrared bands.

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$$NDWI=\frac{R_{GREEN}-R_{NIR}}{R_{GREEN}+R_{NIR}} \tag{6}$$

Where R_{GREEN}=Green Band Reflectance
R_{NIR}=Near-infrared reflectance

3.2.2 Calculation of vegetation canopy water content: The VWC empirical formula was used to estimate the vegetation water content by first calculating the vegetation indices such as NDVI, NDMI and NDWI using different bands of optical remote sensing satellites, and then describing the relationship between the vegetation water content and vegetation indices through the empirical formula to get the vegetation water content data needed for the study. (Bai, Zheng et al. 2022)The empirical equations between vegetation water content and NDVI, NDMI and NDWI are as follows.

$$VWC=1.9134*NDVI^2-0.3215*NDVI \tag{7}$$

$$VWC=2.15*NDMI+0.32 \tag{8}$$

$$VWC=1.44*NDWI^2+1.36*NDWI+0.34 \tag{9}$$

The result of vegetation water content in the study area calculated by the empirical formula is shown in Figure 3, which is a necessary parameter in the water cloud model, and the surface soil backscattering coefficient removing the influence of vegetation can be obtained after the processing of the water cloud model, which can effectively inhibit or attenuate the influence of the vegetation layer on the radar backscattering coefficient, and thus greatly improve the accuracy of the study result

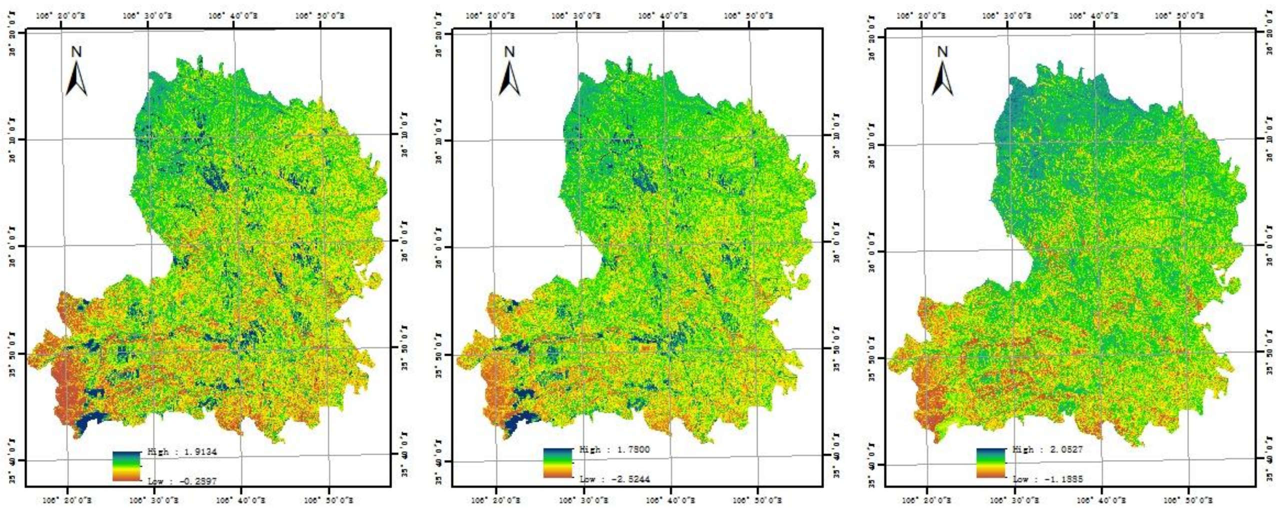


Figure 3. Vegetation water content in the study area

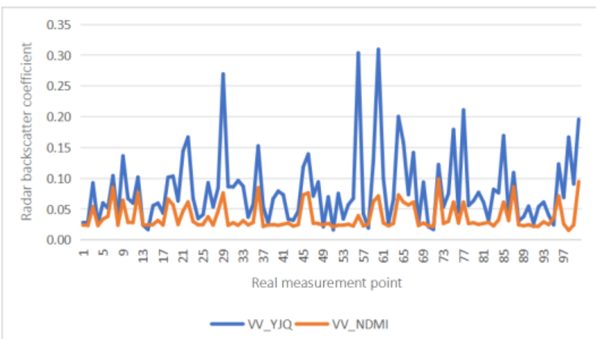
(a) VWC_NDVI; (b) VWC_NDMI; (c) VWC_NDWI

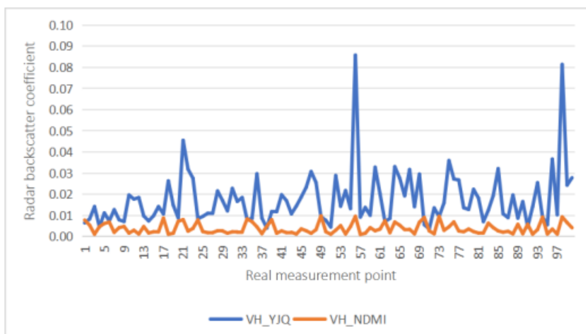
3.3 Soil backscattering coefficient

The backward scattering coefficient of a surface object received by a radar sensor consists of two main components, one is the backward scattering coefficient of the bare soil surface, and the other is the backward scattering coefficient of the vegetation-covered area. The soil backward scattering coefficient is calculated as follows:

$$\sigma^0_{soil}=\frac{\sigma^0_{tot}-AM_V\cos\Theta(1-e^{-2BM_V\sec\Theta})}{e^{-2BM_V\sec\Theta}} \tag{10}$$

Soil backscattering coefficients excluding the effect of vegetation layer were obtained for different parameter combinations, including six combinations of VV_NDVI, VH_NDVI, VV_NDWI, VH_NDWI, VV_NDMI and VH_NDMI.





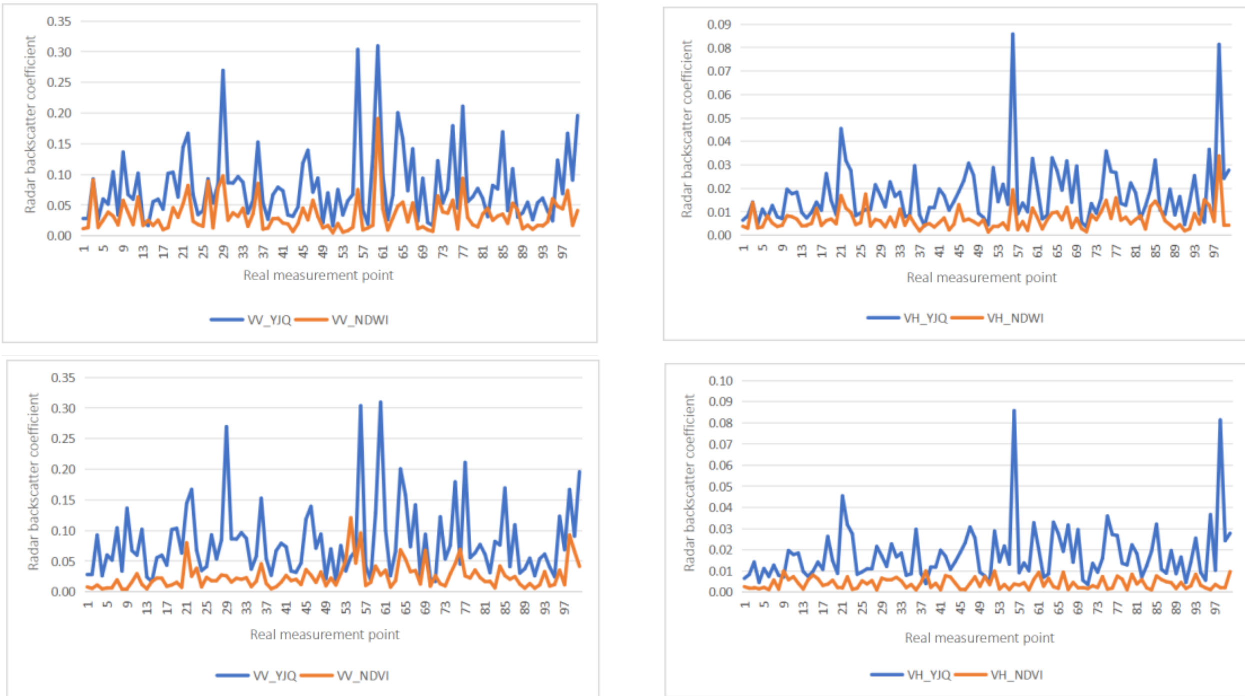


Figure 4. Soil backscattering coefficients after removal of vegetation effec

The radar backscatter coefficients for both VV and VH polarizations were reduced after removing the influence of vegetation, and the reduction values were mainly related to the vegetation cover and water content. The average contribution of the vegetation layer to the radar backward scattering coefficient is 0.17 dB for VV polarization and 0.27 dB for VH polarization, and the average contribution of the vegetation layer to the radar backward scattering coefficient is 0.27 dB for VH polarization. In the Sentinel-1 SAR data, only in terms of the backward scattering coefficients of the radar signals attenuated by the different polarizations through the vegetation, the radars of both the VV and the VH polarizations are attenuated by the VH polarization through the vegetation. The attenuation of VH polarization is more obvious, indicating that VH polarization radar information is more sensitive to vegetation, and VH polarization is more suitable for soil moisture inversion and more sensitive to vegetation structure and moisture content than VV polarization. Compared with VV polarization, VH polarization is more affected by vegetation, and the moisture content and structural changes of vegetation cause different reflection characteristics of SAR signals, which makes VH signals perform better in soil moisture inversion. In Landsat 8 optical imagery, NDMI has high sensitivity to vegetation moisture content analysis and contributes more to soil moisture estimation, making it more suitable for soil moisture inversion. In this regard, the effect of the presence of vegetation on radar backscatter information cannot be ignored. Vegetation cover increases the attenuation and scattering of radar waves, which in turn reduces the soil backscattering coefficient. Therefore, when using SAR data for soil moisture inversion, it is important to consider the influence of vegetation and select appropriate polarization directions and processing methods to minimize the interference of vegetation.

In summary, using Sentinel-1 SAR data and Landsat 8 optical imagery, combined with water cloud modeling, the effect of vegetation moisture can be effectively removed and the soil backscattering coefficient can be estimated more accurately. This is of great significance for applications such as soil moisture monitoring, crop growth assessment and water resource management.

4. Soil moisture inversion based on neural network

4.1 Constructing BP Neural Networks

BP neural network is a multi-stage feed-forward neural network, which can transmit the signal to the target position and reverse the error, this network is the most widely used in the field of artificial neural applications, of which “feed-forward” is the most frequently used category. When determining the parameters of the radar system, the backscattering coefficient is directly affected by the surface roughness and incidence angle, and especially has a close relationship with the soil moisture content. In order to effectively recover soil moisture, the correlation between the backscatter coefficient and soil moisture must be established to better control the performance of the radar system. The input parameters need to be obtained from the output parameters, so there must be an uncertainty between the backscatter information obtained from the radar and the soil moisture. However, building a scientific model for measuring soil moisture can reduce this uncertainty and establish a more accurate relationship between the two. Artificial neural networks are an effective method that can be used to investigate the relationship between microwave backscattered signals and soil moisture. By analyzing the characteristic parameters of specific bands as well as other auxiliary data, the soil moisture content can be inferred and thus an accurate inversion of soil moisture can be achieved. A neural network algorithm is utilized to construct a prediction model by collecting input and output sample data in order to achieve an accurate inversion of soil moisture.

The BP neural network model used in this paper was programmed and implemented in MATLAB 2021 according to the research requirements. In the study of soil moisture inversion in Pengyang County, Ningxia Hui Autonomous Region, the input variables of the BP artificial neural network were selected as radar backscattering coefficients (VV, VH polarization) and soil backscattering coefficients after removing the influence of vegetation. The output variables were measured soil moisture data in the study area. In this study, a total number of 100 samples were extracted, the ratio of training set to validation set was 4:1, the maximum number of iterations was 1000, the number of nodes in the implicit layer was 7, and the objective was 0.0001, and the training was repeated in order to get the best fitting effect.

4.2 Model Evaluation

In this paper, three accuracy evaluation indexes, namely, coefficient of determination, Root Mean Squared Error (RMSE) and Mean Absolute Error, were used to accurately verify the inverted soil moisture data.
The model accuracy of the BP neural network inversion of soil moisture is shown in Table 2. From the inversion accuracy, it can be seen that the coefficient of determination between the inverted soil moisture and the measured soil moisture after BP neural network inversion is 0.7220, the root mean squared error is 0.0310, and the mean absolute error is 0.0230, which is at a high level of confidence, and there is a high correlation between the predicted value and the measured value of the soil moisture. Overall, the BP neural network model can predict soil moisture better, and the error distribution is also more concentrated, and the correlation between the predicted and actual values is higher. The above indicates that the model has some generalization ability and can predict the input sample data more accurately.

R^2	RMSE	MAE
0.7220	0.0310	0.0230

Table 2. Soil moisture inversion accuracy

4.3 Model Application

The BP neural network model obtained from the above training has good generalization ability and can carry out soil moisture inversion more accurately. The model was used to carry out soil moisture inversion in the study area, and the inversion results obtained are shown in Figure 4. From the inversion results, it can be seen that the main colors in the figure are green and yellow, indicating that the soil moisture content is between 0.3 and 0.6, which shows that the soil moisture content in the area is roughly at a medium level. There are a small number of light blue areas which have higher soil moisture content of around 0.7. Similarly, there are some areas shown in white color indicating soil moisture content between 0.2 and 0.3 and these areas have low soil moisture content. The northeastern region of the map, i.e., the green and light blue areas (0.5-0.7) corresponds to low-lying or flat areas, which are less geologically hazardous and more prone to waterlogging, and which have higher soil moisture content. The southwestern region, i.e., the yellow and light green area (0.3-0.5), corresponds to high slopes or steep hills, where geohazards are more likely to occur, water is lost quickly after rainfall, and soil moisture content is low. The middle area, where yellow and green color alternates (0.4-0.6), corresponds to the area with moderate slope and medium rainfall, and the soil moisture content is medium. According to the survey data, drought was the main disaster in Pengyang County, Ningxia between 1983 and 2010, and the ecosystem was extremely fragile, with a forest cover of 3% and a watershed management level of 11%. From 2004, the implementation of policies such as returning farmland to forest, afforestation, and so on, the management of 26 sub-watersheds and 538 square kilometers over the decades, the degree of soil erosion management increased to 76.3%; completed 770,000 acres of reforestation of fallow land, and reforestation of barren mountains and ravines of 940,000 acres, and the county's forested preservation area increased to 1.8 million acres, and the forest coverage rate increased from 26.7% to 31.5% in 2016, which was far more than the 16.9% of the region's forest coverage rate. Through the implementation of these strategies, the content of organic matter in the soil has been successfully enhanced, the soil structure has been optimized, the rate of water evaporation has been further reduced, and the phenomenon of soil erosion has been effectively mitigated, significantly enhancing the water retention capacity of the soil.

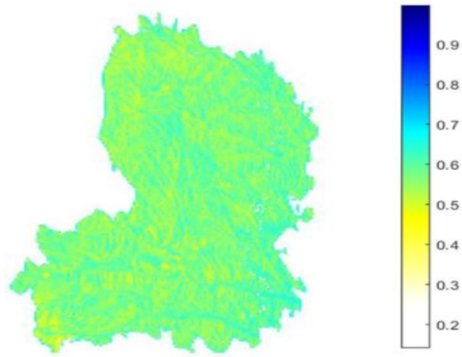


Figure 5. Neural network inversion results

5. Conclusion and outlook

5.1 Findings

Soil moisture is a key element of the global water cycle, carbon balance and energy exchange, and is crucial for hydrological management, climate prediction and agricultural production. In this study, we used Pengyang County in Ningxia as the study area to synergistically invert the spatial and temporal distribution characteristics of soil moisture using Sentinel 1 synthetic aperture radar (SAR) data and Landsat 8 optical image data. The main research contents and conclusions are as follows
(1) Calculate the vegetation index using optical images and combine with the VWC model to get the vegetation water content. Apply the water cloud model to eliminate the influence of vegetation cover on the radar backscattering coefficient, and obtain the soil backscattering coefficient with the influence of vegetation layer removed. The contribution of the vegetation layer to the radar backscattering coefficient under different parameter combinations was analyzed to determine the optimal parameter combinations and vegetation indices suitable for inverting soil moisture in Pengyang County. The results show that VH polarization is more sensitive to vegetation structure and moisture content than VV polarization, which is more suitable for soil moisture inversion; NDMI has the highest sensitivity to vegetation moisture content and contributes more to soil moisture estimation.
(2) Construct a BP neural network model to invert soil moisture. The results of model validation showed that the coefficient of determination was 0.7220, the root mean square error (RMSE) was 0.0310, and the mean absolute error (MAE) was 0.0230, which indicated that there was a high correlation between the model predicted values and the measured values, and the confidence level was high.
(3) The BP neural network model was used to invert the spatial and temporal distribution characteristics of soil moisture in Pengyang County. The results showed that the overall soil moisture in Pengyang County is at a medium level.
This study effectively inverted the spatial and temporal distribution characteristics of soil moisture in Pengyang County

through the synergistic remote sensing technology and neural network model, revealed the influence of vegetation cover, soil properties and other factors on soil moisture, and provided a scientific basis for water resource management and agricultural production in the area.

5.2 Prospects and shortcomings

(1) Due to the difficulty in acquiring research data and my limited research level, the soil moisture inversion model established in this paper needs to be further improved, and there is much room for optimizing the accuracy of soil moisture inversion.
(2) The aim of this paper is to collaboratively invert soil moisture through multi-source data, but it fails to achieve a long time series inversion on the time scale, therefore, in the future, it can be extended on the time series in order to better monitor the non-growing season or complex weather conditions, and to improve and optimize the model so that it can cover a larger area.

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