The Index Optimization Method in Neural Network for Soil Moisture Inversion

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Keywords: Soil moisture, Remote sensing, Back propagation neural network, Modified temperature vegetation dryness index.

Abstract. Soil moisture, an important evaluation index in the field of environmental studies, plays a vital role in the exchange process between global surface and atmosphere. Although its content just takes a small percentage of freshwater resources, it is involved in the surface evapotranspiration process, moisture exchange process and many other cyclic processes. Temperature vegetation dryness index (TVDI) is a major mean that is based on optical and thermal infrared remote sensing to inverse soil moisture. However, its inversion accuracy is affected by soil background and the resolution of the thermal infrared data. Aiming at solving the problem of limited conditions of the data and complicated mathematical relations in modeling, ASTER NIR/TIR data is used in this study, and normalized differential vegetation index (NDVI) is replaced by the modified soil-adjusted vegetation index (MSAVI). Then, piecewise linear model is used to downscale the resolution of land surface temperature (LST), and modified temperature vegetation dryness index (MTVDI) is gained. Finally, back propagation (BP) neural network is established to calculate soil moisture. The result shows that the precision root mean square error (RMSE) of the two-parameter optimization model is higher than that of the none optimization model and single parameter optimization model. Improving the precision of soil moisture inversion by optimizing the input parameters of the neural network is feasible.

Introduction
Soil moisture refers to the moisture content in the impermeable layer of earth[1], and it plays a vital role in energy cycle, water cycle, and biogeochemical cycle[2]. Especially in arid and semi-arid, low rainfall and high evapotranspiration areas, soil moisture directly affects the vegetation growth[3]. Therefore, it is of great significance to monitor it on a large scale. Traditional methods are mostly based on point scale, which have a great precision on monitoring the soil moisture. However, it is difficult to carry out large-scale observation[4]. Nowadays, with the thriving of computer science, the efficiency of remote sensing related research has been greatly improved. Remote sensing has become the major means of land observation, having provided much power and potential to the national development. New possibility is lying in the studying of neural network.

This study established MTVDI-BP neural network to inverse soil moisture. Then by adjusting and modifying parameters in the model, discussion on parameter optimization and accuracy improvement was made. By analyzing the index optimization method in neural network for soil moisture inversion, this study may provide technical support for the study of hydrology, ecology, agriculture and meteorology.

Study Area and Data Acquisition and Preprocessing
The Heihe River basin covers an area of 142,90km^2 with a total 821km length of the main stream. It is from the Zou Lang Nan Shan mountain and Leng Long Ling at the north foot of Qilian mountain, which gets a range of east longitude from 98 to 102 degrees, northern latitude from 37.83 to 42.67 degrees. The study area and land utilization are shown in Figure 1.
In this study, ASTER data was gained by integrated remote sensing experiment on hydrological and ecological processes in the Heihe River Basin on August 2, 2012. Its product level is L1A with a spatial resolution of 15m (visible near-infrared band) and 90m (thermal infrared band). ASTER data was then preprocessed, such as radiometric calibration, atmospheric correction, geometric correction and image cropping.

![Figure 1. Study area and land utilization.](image)

**Indicator System and Research Method**

This research optimized two parameters in Ts-NDVI model and MSAVI was utilized to replace NDVI. Piecewise-linear regression model was adopted to downscale the LST data to calculate TVDI/MTVDI. The neural network was established where its inputs are the various indices and output is soil moisture. The structure of the neural network is shown in Figure 2. TVDI, MTVDI1, MTVDI2 and MTVDI3 are gained by NDVI-LST, NDVI- downscaled LST, MSAVI-LST and MSAVI- downscaled LST respectively.

![Figure 2. Structure of the neural network.](image)

**Land Surface Temperature Inversion**

Split window algorithm for ASTER data proposed by Mao Kebiao et al. can be used to inverse LST data. Band 13 and band 14 of ASTER were chosen in the algorithm, because these two bands have the minimal impact on the atmosphere. Besides, this algorithm only needs three necessary parameters to calculate the LST data, which are emissivity, atmospheric transmissivity, and brightness temperature.

**Land Surface Temperature Downsampling**

Kustas found out that LST and NDVI have a relatively stable mathematical relation under the same scale, so he proposed DisTrad algorithm which utilized this relation to spatially downscale the surface temperature data. Based on the premise that there was a stable relation between surface temperature and vegetation index, Agam used vegetation coverage instead of NDVI to improve DisTrad method and proposed TsHARP algorithm[5].
This study adopted TsHARP algorithm to downscale LST (90m) to LST (15m), which is based on NDVI (15m) data. In this process, NDVI (15m) was converted to 90m resolution, and by taking 0, 0.25 and 0.55 as thresholds, the piecewise linear relationship between NDVI and LST was established. The downscaling process is shown in Figure 3. And the downscaling formulas (1) to (4) are as follows.

\[ LST_{90} = f(NDVI_{90}) \]  
\[ \Delta LST_{90} = LST_{90} - LST_{90} \]  
\[ LST_{15} = f(NDVI_{15}) \]  
\[ LST_{15} = LST_{15} + \Delta LST_{15} \]  

In the formulas, \( LST_{90} \) and \( LST_{15} \) are the estimated value; \( \Delta LST_{90} \) and \( \Delta LST_{15} \) are residual errors under 90m and 15m resolutions; \( LST_{15} \) is the land surface temperature under 15m resolution; \( f(NDVI) \) is the linear relation of NDVI and LST[6], as in (5).

\[ LST = f(NDVI) = a + b \times NDVI \]  

Where \( a \) and \( b \) are intercept and slope. The relations are shown in Figure 4.
Modified Soil-Adjusted Vegetation Index

Temperature vegetation dryness index (TVDI) is normally established by the feature space of NDVI and LST. Then a certain threshold value is taken to calculate the extreme value of LST, and the dry and wet edges are fitted to get the index. Modified soil-adjusted vegetation index (MSAVI) can increase the dynamic range of vegetation and weaken the influence of soil properties[7], as in (6).

\[
MSAVI = \frac{(2\rho_{nir} + 1 - \sqrt{(2\rho_{nir} + 1)^2 - 8(\rho_{nir} - \rho_{red})})}{2}
\]  

Where \(\rho_{nir}\) and \(\rho_{red}\) are the reflectivity of band3 (near-infrared) and band1 (red) of ASTER. In this study, downscaled LST (15m) data was gained by TsHARP algorithm. Then, feature space is established by NDVI and MSAVI to calculate soil moisture.

Modified Temperature Vegetation Dryness Index

In the soil moisture inversion study, the scholars analyzed the relations between MSAVI and LST and found that there is a significant negative correlation between the two within some limits, which can reflect the soil moisture distribution by establishing feature space. Their relation formulas (7) to (9) are as below.

\[
TVDI = \frac{T_s - T_{s_{\text{min}}}}{T_{s_{\text{max}}} - T_{s_{\text{min}}}}
\]

(7)

\[
T_{s_{\text{max}}} = a_1 + b_1 \times MSAVI
\]

(8)

\[
T_{s_{\text{min}}} = a_2 + b_2 \times MSAVI
\]

(9)

Where \(T_s\) is surface temperature; \(T_{s_{\text{max}}}\) and \(T_{s_{\text{min}}}\) are equations of the wet and dry side fitted by MSAVI and LST respectively; \(a\) and \(b\) are slope and intercept. With the increasing value of TVDI, the land surface became drier. Therefore, TVDI can reflect the distribution of soil moisture[8]. The fittings of TVDI/MTVDI are shown in Figure 5.

Figure 5. The fittings of TVDI/MTVDI.

Result and Discussion

Optimization Results and Effects

As shown in figure 4, MSAVI has a better fitting effect on dry edges than NDVI does. Besides, the downscaling process has effects on the fitting. The dry edge R2 of none downscaling LST (90m) model increased from 0.73 to 0.83, while the dry edge R2 of downscaled LST (15m) increased from...
The wet edge of downscaled LST (15m) by NDVI increased from 0.52 to 0.56, and by MSAVI from 0.34 to 0.41.

The Results of Soil Moisture Inversion

Based on the algorithm and processes mentioned above, this study adopted 53 samples as model training samples and 20 samples as model verification samples. The layer of the BP neural network is 3, with 1 node in input layer, 5 nodes in hidden layer, and 1 in output layer. This study chose tansig function, or hyperbolic tangent function, as a activation function for input and hidden layer; linear function as a activation function for output layer. The soil moisture result is shown in Figure 6.

Precision Validation

With the support of ground data, the verification results of the model sample are shown as follows: as for TVDI-BP neural network, the mean absolute error (MAE) is 0.0671, and root mean square error (RMSE) is 0.0815; as for MTVDI1-BP neural network, MAE is 0.0460 and RMSE is 0.0594; for MTVDI2-BP, MAE is 0.0517 and RMSE is 0.0661; for MTVDI3-BP, MAE is 0.0395 and RMSE is 0.0409, as in Figure 7. The results show that the optimization is helpful for improving the accuracy of BP neural network soil moisture inversion.

Study Analysis

In this study, the middle reaches of the Heihe River is the study area. Aiming at the deficiency of TVDI model in the influence of soil background and spatial resolution, the input parameters were optimized in two aspects: replacing NDVI by MSAVI; adopting TsHARP algorithm to downscale LST. Then BP neural network algorithm with optimized parameters was adopted to inverse soil moisture. Proved by ground experimental data, the index optimization methods have a much higher precision in the neural network soil moisture inversion. The higher LST resolution has better effects on the fitting results of the model. Besides, in the process of soil moisture inversion by TVDI/MTVDI-BP neural network, downscaling improved the inversion results: two-parameter optimization is with a
highest inversion accuracy, and none optimization is the lowest. Therefore, the optimization method has a good applicability in BP neural network for soil moisture inversion.

This paper mainly discussed the effect of the parameter optimization, which only focused on the optical scope. So how to carry out the synergy work with other data resources and combine their advantages needs to be studied further.

![Figure 7. Verification results of the model sample.](image)

Acknowledgment

Funding Technology Foundation for Selected Overseas Chinese Scholar in Sichuan Province (10900-19BZ08-014); The National Students Training Program for Innovation and Entrepreneurship (201810616069).

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