THE METHOD OF DECOMPOSING THE PASSIVE MICROWAVE SOIL MOISTURE USING OPTICAL INFORMATION

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KEY WORDS: soil moisture; passive microwave; MODIS; TVDI; soil evaporation

Abstract: The water held in the top few centimeters of the soil is a key variable in many hydrological, geological, climatological and ecological processes. Different types of remote sensing systems are currently used to infer soil moisture at different spatial and temporal scales, each with its specific characteristics and limitations. Selecting 1km resolution optical data MODIS and 25km resolution passive microwave data AMSR-E 2 level of soil moisture product, the authors used NDVI-Ts feature space to remove the vegetation effect, and decompose the passive microwave soil moisture through a soil evaporation model. At last the authors got the 1km resolution soil moisture. Through building scatter diagram, it could be found that the relevance between the inversion result and 1km Vegetation Drought Index (TVDI) reached 0.569. At the same time, the author computed the 25m resolution relative soil moisture by using TM image and measured points, and resampled to 1km resolution. The scatter diagram showed a significant relationship. The correlation coefficient was 0.355. The quantitative results of the study still need further validation and improvement.

INTRODUCTION

Soil moisture is a key parameter in controlling the water thermal energy interchange between land surface and atmosphere, and an important component of the water circulation in a land-surface ecosystem. Soil moisture is also very important to geological-based industries, such as mining, construction, transportation and so on.

Point-based observation of soil moisture cannot represent the hydrological parameters under meteorological model, therefore unable to meet the requirement of application. Different from the conventional observation, remote sensing observation is able to obtain the soil moisture of a large area, with a high degree of efficiency. In the last 20 years, the method of remote sensing monitoring of soil moisture mainly involves surface temperature, radar back scattering coefficient, microwave brightness temperature, and other remote sensing parameters.

Compared to thermal infrared and radar data, microwave brightness temperature can invert the surface soil moisture with higher precision. Passive microwave data are sensitive to soil moisture information and have a return cycle of 1 to 3 days; however due to its low spatial resolution (25km-40km), it's mainly applicable to macro-scale study. Satellite-borne visible light and thermal infrared data can reach medium to high resolution (100m-1km), but their sensitivity to soil moisture is less than satisfactory because of the weather. A number of current studies apply the integration of passive microwave data and optical data, aiming to improve the temporal and spatial resolution at the same time, while obtaining reliable soil moisture data.

These methods mainly comprise three thoughts: method based on topography and soil information; method based on integrating passive microwave and high resolution active microwave data, and optical data; and method based on integrating passive microwave data and optical data through land surface modeling.

This paper applies the method proposed by Merlin, incorporating the specifics of the study area and making revisions on the model's parameters: by integrating the 1km resolution optical data MODIS and 25km resolution passive microwave data AMSR-E Class-2 soil moisture product; and applying NDVI-Ts feature space, removing



the influence of vegetation, incorporating the bare soil evapotranspiration model, and disassembling the passive microwave soil moisture data of the study area; hence obtaining 1km resolution soil volumetric moisture content; then together with TVDI, conducting comparison of the results.

STUDY AREA AND DATA

A. Introduction of the Study Area

The test site is located at the upstream of Guanting Reservoir, in the southwestern part of Yanqing County, Beijing. At longitude 115°47' to 115°54' east and latitude 40°25' to 40°30' north, the site situates northern China's largest and Beijing's only wetland birds natural reserve, the Wild Duck Lake Wetland Natural Reserve.

B. Data

1) Passive Microwave Soil Moisture

AMSR-E, carried by Aqua which was one of the EOS satellite series, was launched in 2002. This paper selects and uses its Class-2 soil moisture product of June 4th, 2010. Its data value is soil volumetric moisture content, with the unit being % and the spatial resolution being 24km.

2) Optical Data

Of the MODIS data, the 16 day composite vegetation index MOD13A2 is used, as well as the daily surface temperature product MYD11A1 and the MODIS classification product MCD12Q1. Also being used is the image of Landsat 5 TM with orbital of 124/32 and passing on June 4th, 2010.

3) Meteorological data

Meteorological data is obtained from the uninterrupted measurement by the weather station which is installed at 2m height in the study area's Wild Duck Lake.

4) Test Data

The test data is the relative soil humidity measured by soil moisture-salinity thermometer in the study area on June 4th, 2010.

METHODOLOGY

The implementation of the experiments outlined in this paper comprises four sections: 1) Establishing NDVI-Ts feature space by using the optical data; 2) NDVI-Ts feature space is used to remove the influence of the vegetation in the study area; to obtain the soil surface temperature, and to calculate the soil transpiration efficiency; 3) using bare soil evapotranspiration model, the soil transpiration efficiency and the surface soil moisture are tied together; 4) to establish a scale transformational relation, and to use the soil transpiration efficiency to break down the passive microwave soil humidity information.

C. Establishing NDVI-Ts Feature Space

NDVI-Ts feature space reflects that the soil humidity is positively related to vegetation growth, and negatively related to surface temperature. Sandholt has utilized NDVI-Ts feature space to establish the TVDI methodology, by which the extracted water forces the indicator to estimate the surface soil moisture.

$$\mathbf{TVDI} = \frac{TS - TS_{main}}{TS_{main} - TS_{main}} \qquad (1)$$

In the above formula, Ts_{min} is the lowest surface temperature for a certain NDVI value, representing the warm edge; Ts_{max} is the highest surface temperature for a certain NDVI value, representing the cold edge; Ts represents the surface temperature of any pixel.

D. Calculating Soil Transpiration Efficiency

Soil transpiration efficiency is calculated by MODIS surface temperature T_s and NDVI. Within small scale, soil transpiration efficiency is of high correlation with near surface soil moisture. Soil transpiration efficiency EF is employs the method proposed by Nishida.

$$\text{EF} = \frac{T_{max} - T_{soll}}{T_{max} - T_{min}} \quad (2)$$

In Formula (2), T_{max} is the highest soil surface temperature of the area having the least soil moisture, and is derived by extrapolating the cold edge of the $T_s/NDVI$ feature space, namely temperature T_s when NDVI is 0 on the cold edge. T_{min} is the lowest soil surface temperature of the area having the highest soil moisture, which can be

approximately equal to the air temperature T_{α} or water surface temperature. $T_{\sigma\sigma il}$ is the soil surface temperature, calculated from MODIS data T_{σ} and NDVI.

$$T_{soul} = \frac{T_s T_{uag}f}{1 - f} \quad (3)$$

Wherein f is vegetation coverage, which is calculated from NDVI. T_{veg} is the land surface temperature T_s when the vegetation coverage is maximum.

$$f = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \qquad (4)$$

E. Relation between Soil Moisture and Soil Transpiration Efficiency

Some researches show that the transpiration efficiency is most constant during daytime, during which time the soil humidity situation can be reflected with greater ease. As the soil transpiration efficiency is mainly affected by meteorological conditions, soil texture and other factors, we take into account these temporal and spatial factors, and adopt the method raised by Komatsu by establishing relationship between soil transpiration efficiency EF from MODIS and the near surface soil moisture θ .

$$EF = 1 - e^{(-\theta/\theta_c)}$$
(7)
$$\theta_c = \theta_{c0} (1 + \gamma/r_{ah})$$
(8)

 $\theta_{c,C}(\% \text{ vol/vol})$ and $\gamma(s/m)$ are soil relevant parameters. r_{cc} is the bare soil's aerodynamic impedance (m/s), and is related to kinetics transmission roughness $z_{0m}(m)$ and wind speed u(m/s) measured at certain height. Empirical parameter $\theta_{c,C}$ is mainly relevant to the soil texture, and has a typical range of variation of 1-4%. The higher the $\theta_{c,C}$, the slower the soil transpires. From (7) we arrive the following:

 $\boldsymbol{\theta} = -\boldsymbol{\theta}_c \ln \left(\mathbf{1} - \boldsymbol{EF} \right) \tag{9}$

F. Relationship with Downscaling

Expression of scaling starts from second-order Taylor's algorithm expansion to arrive Formula (10), in which EF_{25leve} is the data value by re-sampling EF_{Modis} from the MODIS calculation to 25km. θ_{25km} is the soil volumetric moisture content at spatial resolution of AMSR-E 25km, and \mathbb{I} is such at 1km spatial resolution.

$$\Theta = f(EF_{25km}) + \binom{\partial \theta}{\partial EF} (EF_{MODIS} - EF_{25km}) + \frac{1}{2} \binom{\partial^2 \theta}{\partial EF^2} (EF_{MODIS} - EF_{25km})^2$$
(10)

Let $\Delta \mathbb{E} F = \mathbb{E} F_{Modis} - \mathbb{E} F_{2.5km}$, then:

$$\Theta = \theta_{25km} + \left(\frac{\partial \theta}{\partial EF}\right) \Delta EF + \frac{1}{2} \left(\frac{\partial^2 \Theta}{\partial EF^2}\right) \Delta EF^2$$
(11)

Substituting Formula (9) into Formula (11), we arrive at Formula (12):

$$\Theta = \Theta_{25\text{km}} + \frac{\Theta_c \Delta EF}{1 - EF_{25\text{km}}} + \frac{\Theta_c \Delta EF^2}{2(1 - EF_{25\text{km}})^2}$$
(12)

PRACTICAL APPLICATIONS

A. Establishing MODIS Imaging NDVI-Ts Feature Space

We use the test area's MODIS surface temperature on June 4th, 2010 and the 16-day composite NDVI product data. The calibrated surface temperature and vegetation index are used to establish NDVI-Ts feature space. The step precision of NDVI is set to be 0.01. Taking the largest and the smallest value of all surface temperature that NDVI corresponds to, and performing linear fit upon the derived largest and smallest value of land surface temperature, we obtain the results of vegetation temperature T_{weg} , the lowest temperature T_{min} and the highest soil humidity

 T_{max}

	T _{max}	T_{\min}
Fitted Equation	Y=-15.541X+322.28	Y=- 10.779X+306.94
\mathbf{R}^2	0.8648	0.5226

 Table 1: The results of cold edge and warm edge of MODIS image

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B. Establishing TM Imaging NDVI-Ts Feature Space

Single window algorithm is used to invert TM image surface temperature. The same method is applied to establish NDVI-Ts feature space, and to estimate the relative soil humidity in the study area.

Table 2: The fitted results of cold edge and warm edge of TM image

	T _{max}	T _{min}
Fitted Equation	Y=-26.661X+318.03	Y=-8.5587X+298.14
\mathbf{R}^2	0.948	0.901

Using formula (13) to arrive at the relative soil humidity in the study area:

$$RSM = RSM_{w} - TVDI * (RSM_{w} - RSM_{D})$$
(13)

In the above formula, RSM represents a certain pixel's relative soil water content; RSM_w is the relative soil water content (maximum) corresponding to the warm edge; RSM_D is the relative soil water content (minimum) corresponding to the cold edge. The relative humidity of the warm edge is set to be 100% or 1, while the relative humidity of the cold edge is obtained through the empirical relationship (14) that is proposed by Xin.

$$RSM = 101.75 + 1.71 * Ts/NDVI$$
 (14)

C. Estimating the Aerodynamic Impedance

Calculation of aerodynamic impedance \mathbf{r}_{ac} is performed by formula (15) which is proposed by Thom and Oliver.

The formula has been tested and verified by A.Sarwar and R.Bill in the Indus Valley to sufficiently meet the requirement of estimation. In the formula, z is the reference height (m) for measuring wind speed, and \mathbb{Z}_{0} is the kinetics surface roughness length (m).

$$r_{ac} = 4.72 \left\{ \ln \left(\frac{z}{z_0} \right) \right\}^2 / (1 + 0.54u)$$
(15)

D. Integrated Model Parameters

Wind speed **u** is obtained by the 2m high weather station in the study area on June 4th, 2010 upon AQUA's passing.

From the China Region Soil Database that is established by Beijing Normal University's College of Global Change and Earth System Science, we obtain the composition ratio of sand and clay among surface soil. Using the empirical parameters mentioned by Komatsu, the weighting function is set up to arrive at $\theta_{\alpha \theta}$.

$$\theta_{c0} = \text{Sand}\% * 1/100 + \text{Clay}\% * 4/100$$
 (16)

Because the weather station measures wind speed at a height of 2 meters, the result is not representative of the entire forest. Taking into account the data of the types of land use, the forest land area and the bodies of water are removed, so that the inversion results are only limited to the area of low vegetation and bare soil.

Table 3 shows a part of the parameters that need to be confirmed in the model.

Table 3: The model parameters

Parameter	Value	Unit	Source of Reference
u	3.8	s/m	Weather station
θ_{c0}	1-4	% v/v	Komatsu (2003)
γ	100	-	Komatsu (2003)
z _o	0.005	m	Liu (2007)
Sand%	0-100	%	Shangguan (2011)
Clay%	0-100	%	Shangguan (2011)
T _{max}	322.28	K	Modis image
T _{veg}	301.64	K	Modis image
T _{min}	304.16	K	Modis image
NDVI _{min}	0.2	-	Modis image
NDVI _{max}	0.9	-	Modis image

RESULTS

A. Analysis of the Results

Upon calculation of the model, the 1km soil volumetric moisture content in the study area can be obtained. The value of soil volumetric moisture content in the study area is in the range of 7%-11%. The inversion result of the soil moisture is mainly controlled by the data value distribution of AMSR-E's soil moisture product.



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Figure 1: The AMSR-E soil moisture in the study area



Figure 2: The result of 1km soil volumetric moisture content in the study area

B. Verfication of the Results

Because the soil volumetric moisture content from the model is of 1km spatial resolution, its precision cannot be verified by using a limited number of spot measured moisture data. Due to the lack of reliable soil moisture sampling points that are of actual measurement and uniform distribution, the author uses TDVI's distribution tendency and data values to compare with the inversion results. From TVDI (Figure 3) and soil moisture (Figure 2), one can see that soil moisture values tend to be lower in area of higher TDVI value, and vice versa. From the scatter diagram constructed by TDVI and soil moisture data, it shows that the two are in an obvious and stable correlation, illustrated by Figure 4.



Figure 3: The 1km TVDI in the study area



Figure 4: The scatter diagram of volumetric soil moisture and TVDI

By re-sampling the relative soil humidity data from 25m spatial resolution to 1km spatial grid, and comparing it with the 1km soil volumetric moisture content in the study area, the correlation coefficient is 0.3551, which shows relatively significant relation between the two (Figure 5).



Figure 5: The scatter diagram of volumetric soil moisture and relative soil moisture

DISCUSSION & CONCLUSIONS

This paper uses passive microwave data, optical data and auxiliary data of soil, together with the inversion of soil moisture to achieve improvement in both spatial resolution and time resolution. However the following uncertainties remain in the data model's parameters used in this paper:

(1) Previous researchers have set $\theta_c 0$ to be a fixed value, while $\theta_c 0$ in this paper changes with soil texture parameters accordingly. When establishing the weight, the empirical parameters proposed by Komatsu are cited, therefore leaving some uncertainties.

(2) Because the passive microwave soil moisture in this statistics model is the mean value of the pixels, it has a controlling influence over the range of variation of the model. Due to the error that passive microwave data carries, the inversion result is to be affected.

But since the research uses the MODIS data and passive microwave data, both of which have excellent time resolution, long time series inversion results can be obtained when sufficing the research of parameter changes under medium scale, therefore it possesses excellent practicality in terms of obtaining ecological parameters' annual trend and within-the-year changes.

FUNDING

National Science and Technology Support Program of China (No. 2012BAH29B03) National Science and Technology Key Project of China (No. E0306/1112) National Natural Science Foundation of China, Key Project (No. 40930530) The CAS/SAFEA International Partnership Program for Creative Research Teams (No. KZZD-EW-TZ-09) National Natural Science Foundation of China (No. 41130744/D0107, No. 41171335/D010702) Natural Science Foundation of Beijing (No. 8101002)

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