ESTIMATING HI-RESOLUTION SOIL MOISTURE DATA USING THE *HP* MODEL COUPLED WITH LANDSAT-8 AND SMAP DATASETS

Xinyi Miao[1], Yong Wang[1,2,3], Yuanyuan Yang[1,3], and Hong Li[4]

[1]School of Resources and Environment
University of Electronic Science and Technology of China (UESTC)
2006 Xiyuan Avenue, West Hi-tech Zone, Chengdu, Sichuan 611731, China
hisumyee@foxmail.com

[2]Department of Geography, Planning, and Environment
East Carolina University, Greenville, North Carolina 27858, USA

[3]Center for Information Geoscience, UESTC
2006 Xiyuan Avenue, West Hi-tech Zone, Chengdu, Sichuan 611731, China

[4]Department of Information Management Systems
East Carolina University, Greenville, North Carolina 27858, USA

ABSTRACT

Coupled with Landsat-8 and SMAP brightness temperature datasets and using the *HP* model, an algorithm to estimate soil moisture in November of 2015 at Zoige alpine wetland, China was developed. The algorithm was verified using soil moisture data downloaded at NASA Earthdata web site. The spatial patterns of two datasets were similarly to each other with the maximum value occurring near the center but the minimum value in the eastern region. The spatial correlation coefficient of both datasets was 0.6832. The preliminary findings should be very encouraging in the pursuing to produce soil moisture data with high spatial resolution.

Index Terms—Brightness temperature of SMAP, Landsat 8, Soil moisture, Zoige Alpine wetland.

1. INTRODUCTION

Soil moisture modulates the energy cycle through exchanges of energy between the atmosphere and land surface [1]. Soil moisture and soil freeze or thaw state are key factors to determine the methane emission (CH_4) at the land surface. The traditional manual measurement of soil moisture (e.g., the tensiometer method) is time-consuming and arduous. It cannot provide the timely information of the large region. Thus, numerous satellite-based methods are developed for soil moisture estimation [2,3].

Currently, soil moisture is measured at variable spatial scales ranging from point to satellite footprint in tens of kilometers by tens of kilometers, and at various temporal resolutions. Measurement networks of *in situ* sensors can have high measurement accuracy but are very sparsely spaced. The Soil Moisture Active and Passive (SMAP) project is a wide-swath L-band soil moisture mission that has the potential to estimate soil moisture over a wide range of vegetation conditions and at fine spatial resolution. Unfortunately, the radar sensor of the SMAP mission malfunctioned shortly after the operation of SMAP in space. Consequently, the SMAP mission is depending on the microwave radiometer for the soil moisture measurement at coarse spatial resolution. Furthermore, the availability of high-resolution soil moisture product is very limited globally. This is especially true in Zoige alpine wetland where natural environments are harsh. The wetland is vast spatially.

Knowing the soil moisture is very significant for this fragile wetland ecosystem such that one can better understand the wetland and better protect it. Fortunately, other operational satellite sensors (e.g., the Landsat-8) provide soil moisture information. Thus, the goal of this study is to merge the Landsat and SMAP L-band radiometer datasets to estimate soil moisture data at fine spatial resolution.

2. STUDY AREA AND DATA

2.1 Study area

The Zoige wetland is located in the source regions of the Yangtze River and the Yellow River, roughly within 102º5' E and 103º23' E in longitudes, and 33º4' N and 33º50' N in latitudes. The average elevation is ~3,500 m above the mean sea level. The region due to its high altitude has frigid continental monsoon climate. The mean annual temperature ranges from 0.6 to 1.1 ºC, and the mean annual precipitation ranges from 654 to 780 mm. The precipitation mainly falls as rain between May and September accounting for more than 80% of the annual precipitation.

2.2 Datasets

Landsat 8 data of Zoige alpine wetland are downloaded from United States Geological Survey (USGS) EarthExplorer. The data are used to calculate the land surface temperature, and normalized difference vegetation index. The SMAP brightness temperature acquired on 2 November 2015 are downloaded from the US/NASA web site at https://search.earthdata.nasa.gov/search. The Level 1C data are georeferenced and radiometrically calibrated. The spatial resolution is 9 km × 9 km. To evaluate the derived soil moisture and in lack of ground soil moisture measurements at fine spatial resolution, we download the soil moisture data at the same NASA web site. The spatial resolution of the data is 9 km × 9 km. With this intermediate step in accuracy assessment, one should have confidence about the estimated soil moisture data that have the finest spatial resolution of 30 m by 30 m.

3. METHODOLOGY

The *HP* semi-empirically developed from the Q/H model [4] is one of the most widely used semi-empirical models. The model is a function of surface roughness coefficient *Hp* and polarization mixing coefficient *Q*, which can be described as

$$R_p = 1 - e_p = \left[(1-Q)\cdot r_p + Q\cdot r_p\right]\cdot H_p \quad (1)$$

where R_p is surface effective reflectivity. e_p is smooth surface reflectivity. Subscript *p* stands for the polarization of the model. H_p stands for the influence surface roughness poses to effective reflectivity. *Q* and H_p are constants between 0 and 1. Since *Q* can be ignored in low frequency band (e.g., L-band [5]), *Q* is set as zero. Thus, (1) is rewritten as

$$R_p = H_P \cdot r_p \quad (2)$$

which is also called *HP* model. With the analysis of the estimated database using the advanced integral equation model (AIEM), the Fresnel reflectivity r_p in different polarization can be expressed as a power function [6] or

$$r_h = r_v^A \quad (3)$$

where *A* is a constant and can be obtained by parameter fitting. Combining (2) and (3), one obtains

$$\frac{R_v^A}{R_h} = \frac{H_v^A}{H_h} = H_{index} \quad (4)$$

The difference of the exponential of roughness coefficients H_v and H_h ($(\frac{R_v}{r_v})^B - (\frac{R_h}{r_h})^C$) has a strong correlation with H_{index}. The relationship can be expressed as

$$f(H_{index}) = (\frac{R_v}{r_v})^B - (\frac{R_h}{r_h})^C \quad (5)$$

B and *C*, and the expression for function, $f(H_{index})$ can be obtained using the optimization method. With the combination of (2), (4), and (5), the soil dielectric constant ε in bare soil can be implicitly expressed as

$$f(\frac{R_v^A}{R_h}) = (\frac{R_v}{r_v})^B - (\frac{R_h}{r_h})^C \quad (6)$$

where R_h and R_v is effective reflectivity of rough surface under *H* and *V* polarizations, respectively. Fresnel reflectivity r_p under *H* and *V* polarizations can be written as

$$r_v = \left|\frac{\varepsilon\cdot\cos\theta - \sqrt{\varepsilon - \sin^2\theta}}{\varepsilon\cdot\cos\theta + \sqrt{\varepsilon - \sin^2\theta}}\right|^2 \quad (7)$$

$$r_h = \left|\frac{\cos\theta - \sqrt{\varepsilon - \sin^2\theta}}{\cos\theta + \sqrt{\varepsilon - \sin^2\theta}}\right|^2 \quad (8)$$

where θ stands for the radar incidence. R_v and R_h can be obtained from the ratio of the brightness temperature and land surface temperature. The brightness temperature is available from the SMAP data. The land surface temperature comes from Landsat-8 TIRS data.

The soil moisture is affected by the surface vegetation cover. One way to remove the influence is to use the NDVI data. As the initial step in this study, the soil moisture data in later fall season is studied. In that time of a year, the vegetation coverage should be minimum. The mean NDVI value derived from Landsat-8 data in November for the study area is 0.1 or less. Thus, the vegetation influence on the soil moisture estimation is ignored (for the purpose to simplify the estimation process). Thus, the soil moisture under the bare land [7] is only considered. ε can be expressed [7] as

$$\begin{aligned}\varepsilon = &\left(a_0 + a_1 \cdot S_s + a_2 \cdot C_c\right) + \left(b_0 + b_1 \cdot S_s + b_2 \cdot C_c\right) \cdot m_v \\ &+ \left(c_0 + c_1 \cdot S_s + c_2 \cdot C_c\right) \cdot m_v^2\end{aligned} \quad (9)$$

where a_i, b_i, and c_i (i=0, 1, 2) are constants. They at central frequency of 1.4GHz [7] are shown in the Table 1. m_v is the volumetric soil moisture content. According to the Harmonized World Soil Database (HWSD) v1.1, sand content, S_s and clay content, C_c, are set as 0.74 and 0.1, respectively. The data were downloaded at http://westdc.westgis.ac.cn, the Cold and Arid Regions Sciences Data Center at Lanzhou, China.

Table 1, Complex coefficients of Hallikainen model [7] at the central frequency of 1.4 GHz. In each cell, the 1st value is real part, and 2nd one imaginary part.

a_0	a_1	a_2
2.862, 0.356	–0.012, –0.003	0.001, –0.008
b_0	b_1	b_2
3.803, 5.507	0.462, 0.044	–0.341, –0.002
c_0	c_1	c_2
119.006, 17.753	–0.500, –0.313	0.633, 0.206

4. RESULTS

4.1 Model parameterization

Based on the SMAP satellite parameters, the AIEM was used to generate estimated data in order to establish the linkage of r_v and r_h. The range of soil dielectric constants ranged from 2.5 to 40 with an interval of 2.5. The fitting result was shown (Figure 1). R^2 value was 0.9999. The root means square error (RMSE) was 0.0014. Thus, A in (3) was 0.5889.

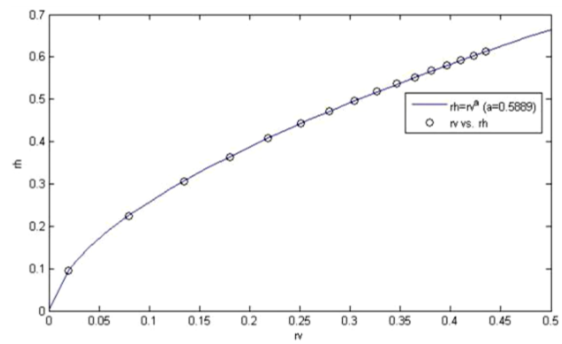


Figure 1. The estimated relationship of r_h and r_v.

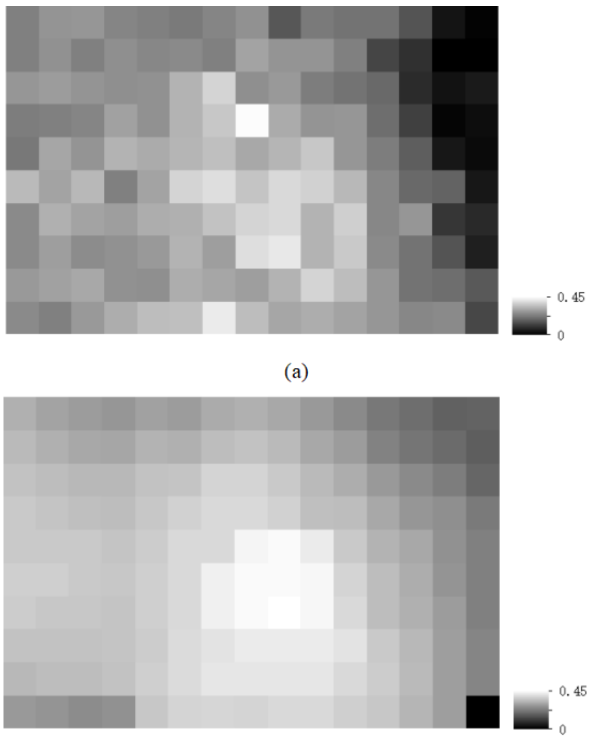
B and C, and the expression for function $f(H_{index})$ were obtained using the optimized method. B and C were 0.4 and 0.8, respectively. The expression $f(H_{index})$ was

$$\begin{aligned}&\left(\frac{R_v}{r_v}\right)^{0.4} - \left(\frac{R_h}{r_h}\right)^{0.8} \\ &= 0.8643 H_{index}^{\ 3} - 4.062 H_{index}^{\ 2} + 6.541 H_{index} - 3.359\end{aligned} \quad (10)$$

R^2 of (10) was 0.9441, and the $RMSE$ was 0.01975.

4.2 Estimated hi-resolution soil moisture data

Once all parameters in (9) were solved, the estimation of soil moisture was ready. Figure 2a was the volumetric soil moisture content for an area of 90 km (high) by 135 km (wide). Each pixel was 9 km by 9 km initially. The soil moisture varied from 0.0567 to 0.4108. As stated previously, even though fine-resolution soil moisture data can be estimated, the esitmation of soil moisture data at 9 km by 9 km was for the purpose of the accuracy assessment. Since no *in situ* or fine resolution of soil moisture data were available, the soil moisture content data downloaded from NASA was considered as truth (e.g., Figure 2b). In comparison of Figure 2a and 2b, spatial patterns might be similar. The maximum value of each dataset occurred near the center, but the minimum value in the eastern region. Quantitatively, the spatial correlation coefficient of both images was 0.8287. The mean value of the absolute difference of both datasets was 0.0349.



(b)

Figure 2. (a) Estimated soil moisture data at the study area, and (b) soil moisture extracted from US/NASA dataset.

5. CONCLUDING REMARKS

As an initial step to estimate soil moisture at fine spatial resolution using optical and SMAP datasets, the soil moisture data of Zoige alpine wetland, China were obtained by using the *HP* model coupled with SMAP radiometer and Landsat-8 datasets. To simplify the estimation procedure, the vegetation impact on the soil moisture was ignored. Thus, the late fall season (e.g., November of 2015) was chosen. In comparison of the estimated soil moisture dataset and an external dataset, spatial patterns of both datasets might be similar, and their spatial correlation coefficient was 0.6832. The findings were very encouraging in the pursuing to produce hi-resolution soil moisture data in wetlands at remote alpine areas.

6. ACKNOWLEDGMENTS

This work was sponsored by the National Natural Science Foundation of China under grants 41471361, 41771401, and 61601090 to the University of Electronic Science and Technology of China (UESTC), and the Fundamental Research Funds for the Central Universities under grant ZYGX2015J115 of UESTC. Landsat data were downloaded from the USGS web site, https://earthexplorer.usgs.gov/. The SMAP brightness temperature and soil moisture datasets were downloaded from the US/NASA web site at https://search.earthdata.nasa.gov/search.

7. REFERENCES

[1] N. N. Das, D. Entekhabi, E. G. Njoku, “An algorithm for merging SMAP radiometer and radar data for high-resolution soil-moisture retrieval,” *IEEE Transactions on Geoscience and Remote Sensing*, 49(5): 1504-1512, 2011.

[2] Z. Y. Tong, and W. C. Zhang, “Progress of soil moisture monitoring by remote sensing,” *Bulletin of Soil and Water Conservation*, 4, 032, 2007.

[3] G. P. Petropoulos, G. Ireland, and B. Barrett, “Surface soil moisture retrievals from remote sensing: Current status products & future trends,” *Physics and Chemistry of the Earth, Parts A/B/C*, 83, 36-56, 2015.

[4] J. R. Wang, P. E. O'Neill, T. J. Jackson, and E. T. Engman, “Multifrequency measurements of the effects of soil moisture, soil texture, and surface roughness,” *IEEE Transactions on Geoscience and Remote Sensing*, (1), 44-51, 1983.

[5] J. P. Wigneron, L. Laguerre, and Y. H. Kerr, "A simple parameterization of the L-band microwave emission from rough agricultural soils," *IEEE Transactions on Geoscience and Remote Sensing*, 39(8):1697-1707, 2001.

[6] P. Guo, “Passive microwave soil moisture retrieval based on SMAP configuration,” Doctoral dissertation, University of Chinese Academy of Science, 2013.

[7] M. T. Hallikainen, F. T. Ulaby, M. C. Dobson, M. A. El-Rayes, and L. K. Wu, “Microwave dielectric behavior of wet soil-part 1: Empirical models and experimental observations,” *IEEE Transactions on Geoscience and Remote Sensing*, (1), 25-34, 198, 2001.