Surface Soil Moisture Retrieval From Optical/Thermal Infrared Remote Sensing

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Introduction

The water held in the top few centimeters about 0 to 5 cm of the soil, namely surface soil moisture (SSM), plays a significant role in various domains of science such as agriculture, hydrology, meteorology and ecology.

However, the spatial resolution of microwave SSM products is too coarse for regional and local applications. Most of the current optical/thermal infrared SSM retrieval models cannot estimate the quantitative volumetric soil water content directly without establishing empirical relationships between SSM measurements and satellite derived proxies of SSM.

In addition, geostationary satellites would have a great opportunity to develop more practical and precise methods to retrieve SSM. Due to allowing for much more frequent observations than polar orbiting satellites, geostationary satellites can provide 48-96 images per day with a fixed observation angle for a given pixel, which is most likely to benefit the understanding of terrestrial water and energy budgets. Furthermore, as geostationary meteorological observations provide more cloud-free observations due to their high temporal resolution, it may give us a great opportunity to develop more practical and precise methods to retrieve SSM.

In this study, after optimizing the model by accounting for the influence of FVC, SSM is estimated directly from Chinese geostationary meteorological satellite FY-2E data with a high spatial resolution of 5 km.

Study area and dataset

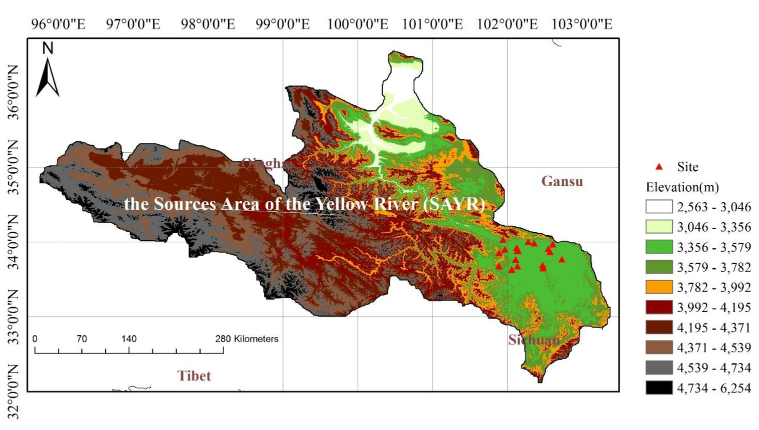
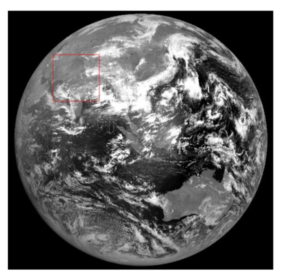


Figure 1. The DEM of the source area of the Yellow River (SAYR)



FY-2E data

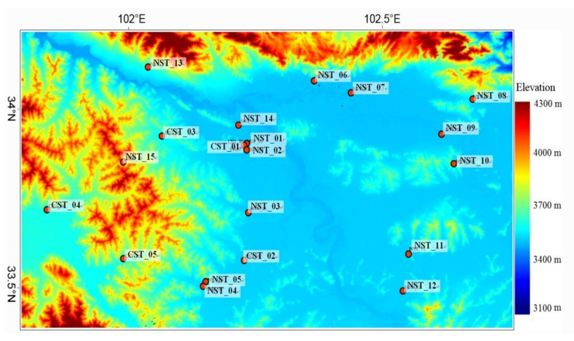
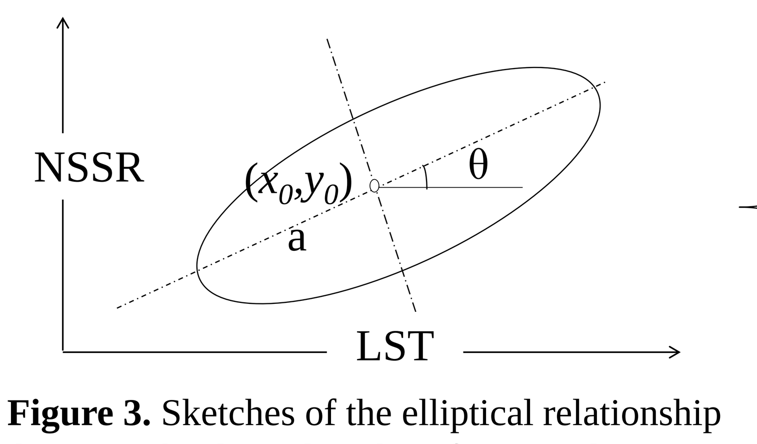


Figure 2. DEM of the soil moisture monitoring network operated by CARRERI and ITC

Methods

Based on a great elliptical relationship between the diurnal LST and NSSR as shown in Figure 1, the novel SSM retrieval model was improved as expressed[1-2]:

$$SSM = n_1 \times y_0 + n_2 \times a + n_3 \times ln\theta + n_0$$



- SSM - daily average SSM (m3/m3)
- y0 - the ellipse center vertical coordinate
- a - semi-major axis
- θ-rotation angle
- n_i (i = 0, 1, 2, 3) - the model coefficients simulated from CoLM.

Figure 3. Sketches of the elliptical relationship between the diurnal cycles of LST and NSSR.

LST and NSSR are estimated from FY-2E data[3-4].

LST

$$T_S = a_0 + (a_1 + a_2 \frac{1-\varepsilon}{\varepsilon} + a_3 \frac{\delta\varepsilon}{\varepsilon^2}) \frac{T_{IR1} + T_{IR2}}{2} + (a_4 + a_5 \frac{1-\varepsilon}{\varepsilon} + a_6 \frac{\delta\varepsilon}{\varepsilon^2}) \frac{T_{IR1} - T_{IR2}}{2}$$

Based on the generalized split-window algorithm[5]

NSSR

$$S_n = R_s^{\downarrow} - R_s^{\uparrow} = (1 - r)R_s^{\downarrow}$$

$$R_S^{\downarrow} = G \times \cos(SZA) \times d_r \times \tau$$

$$d_r = 1.00011 + 0.034221\cos(\alpha) + 0.00128\sin(\alpha) + 0.000719\cos(2\alpha) + 0.000077\sin(2\alpha)$$

Atmospheric transmittance is estimated by water vapor content for the FY-2E VIS band.

$$WVC = C_1 + C_2 \times \frac{\tau_{IR2}}{\tau_{IR1}}$$

$$\frac{\tau_{IR2}}{\tau_{IR1}} = \frac{\varepsilon_{IR1}}{\varepsilon_{IR2}} \times \frac{\sum_{k=1}^{N}(T_{IR1,k} - \overline{T_{IR1}})(T_{IR2,k} - \overline{T_{IR2}})}{\sum_{k=1}^{N}(T_{IR1,k} - \overline{T_{IR1}})^2}$$

FVC

based on dimidiate pixel model and MODIS NDVI product (MOD13Q1)

$$FVC = (NDVI - NDVI_{soil}) / (NDVI_{veg} - NDVI_{soil})$$

NDVI is normalized difference vegetation index; $NDVI_{soil}$ is minimum NDVI where is without vegetation covered, $NDVI_{veg}$ represents maximum NDVI of fully covered by vegetation. With noise ineluctably, 0.5% and 99.5% cumulative probability are taken as $NDVI_{soil}$ and $NDVI_{veg}$ respectively.

Results

It has been found that FVC has a great effect on soil moisture. In this study area, vegetation varies a lot at different time. In figure 4, it shows FVC on 8th Oct. 2010 over the study area.

In figure 5, a correlation coefficient (R) of 0.620, a root mean square error (RMSE) of 0.146 m^3/m^3 and a bias of 0.038 m^3/m^3 are found between in-situ measurement and FY-2E-derived SSM from original model. While it reveals a better relationship between FY-2E-derived SSM from improved model and ground measurement with a R of 0.845, a RMSE of 0.064 m^3/m3 and a bias of 0.017 m^3/m^3.

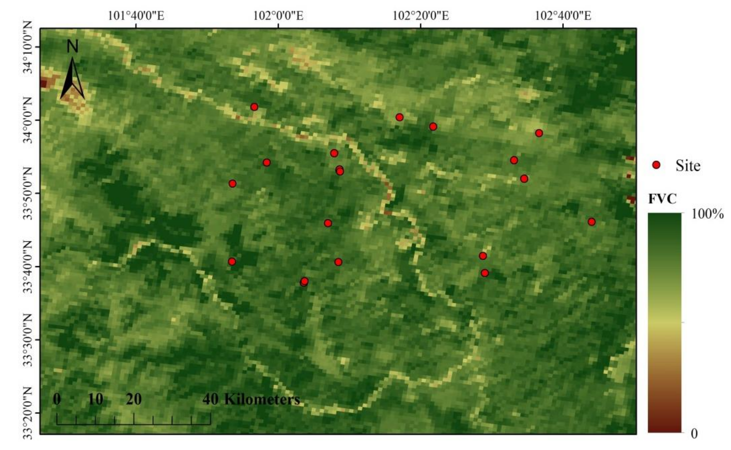


Figure 4. FVC on 8th Oct. 2010 in Maqu

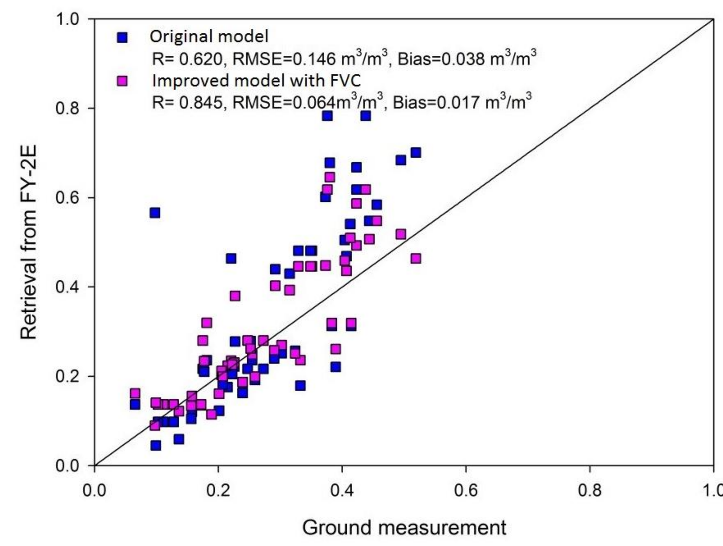


Figure 5 validation with ground measurements

To study the result further, the error has been analysed. At station NST_04 where is wetland grass has lower estimations than ground measurement in table 1. In Table 2, it reveals that the lower accurate LST result in worse FY-2E-derived SSM. When the difference value between LST retrieval and ground surface temperature is high on 15 Sep., the SSM retrieval error is large with 0.3 m^3/m^3.

Date	Ground measurement (m^3/m^3)	Retrieval $_{\text{by original model}}$ (m^3/m^3)	Retrieval $_{\text{improved model}}$ (m^3/m^3)
20 Jul.	0.829	0.464	0.785
28 Jul.	0.733	0.618	0.587
3 Sep.	0.461	0.104	0.113
8 Oct.	0.415	0.313	0.319

Table 1 Validation with ground measurement at NST_04 site

Date	LST at 11 a.m. (K)			Daily average SSM (m^3/m^3)		
	Retrieval	Ground measurement	Difference between retrieval and true value	Retrieval	Ground measurement	Difference between retrieval and true value
20 Jul.	293.14	286.25	6.89	0.657	0.730	-0.073
28 Jul.	299.49	289.45	10.04	0.557	0.673	-0.116
3 Sep.	295.83	281.85	13.98	0.241	0.507	-0.266
15 Sep.	297.01	283.55	13.46	0.202	0.503	-0.301

Table 2 LST and SSM Retrieval and ground measurement at NST_15

Conclusions

In this study, the original model has been improved by accounting for the influence of FVC, which is based on a dimidiate pixel model and MODIS NDVI product. Ultimately, a preliminary validation was conducted using the ground measurements. In order to provide more accurate SSM, high accuracy FVC, LST and NSSR are still needed. In addition to the point scale validation, cross comparison with other existing SSM products will be conducted in the future studies.

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