DOWNSCALING OF AMSR2 SOIL MOISTURE CONTENT USING MULTI-SATELLITE LAND SURFACE VARIABLES WITH REGRESSION KRIGING

Ae-Sook Suh[1], Sunghwa Choi[1] , Dae-Sun Kim[2], Kyounghye Nam[2] , Nari Kim[2] , Daeyun Shin[1], Yang-Won Lee[2]
[1]K-Water, 200 Sintanjin-ro, Daedeok-gu, Deajeon 34350, South Korea
Email: assuh@partner.kwater.or.kr
[2]Pukyong National University, 45 Yongso-ro, Nam-gu, Busan 48513, South Korea

KEY WORDS: Soil moisture, Downscaling, Satellite image, Regression kriging

ABSTRACT: Soil moisture is a primary state variable of hydrology and the water cycle over land. To solve the problem of limited spatial resolution of soil moisture data retrieved from microwave satellite sensors, this study presents the downscaling by spatial statistical methods combined with various land surface variables. Regression kriging, which is known as the most elaborated downscaling technique, was employed to the downscaling of daily soil moisture content retrieved by AMSR2 (Advanced Microwave Scanning Radiometer 2) at the resolution of 10 km for the period between April and October, 2013-2014. The downscaled result at the resolution of 2 km showed quite good consistencies with the original data, which means the spatial patterns and the data properties were well preserved even after downscaling. Our approach can also apply to other hydrological factors such as rainfall and evapotranspiration and can be a viable option for overcoming the problem of limited spatial resolution in satellite images and numerical model dataset.

1. INTRODUCTION

Soil moisture is a primary state variable of hydrology and the water cycle over land. Recent remote sensing technologies have enabled microwave satellite sensors to monitor soil moisture for wide area irrespective of weather conditions. AMSR-E (Advanced Microwave Scanning Radiometer - Earth Observing System) instrument on board the Aqua satellite which was launched in 2002 provided global daily 25-km soil moisture data, and MIRAS (Microwave Imaging Radiometer with Aperture Synthesis) instrument on board the SMOS (Soil Moisture and Ocean Salinity) satellite which was launched in 2009 produces global daily 25-km soil moisture data. Also, AMSR2 (Advanced Microwave Scanning Radiometer 2) instrument on board the GCOM-W1 (Global Change Observation Mission-Water 1) satellite which was launched in 2012 succeeds the role of AMSR-E and provides global daily 25-km and 10-km data. NASA (National Aeronautics and Space Administration) has launched SMAP (Soil Moisture Active Passive) satellite in 2015. It has an active radar and a passive radiometer for producing global daily 3-km and 36-km soil moisture data, respectively, but owing to the failure of the radar, only 36-km data is available now.

The spatial resolution of 10 to 36 km is not sufficient for regional-scale applications for hydrology and meteorology although the temporal resolution is quite appropriate. To solve the problem of limited spatial resolution of soil moisture data retrieved from microwave satellite sensors, this study presents the downscaling by spatial statistical methods combined with various land surface variables. To date, statistical methods such as multiple regression and machine learning have been employed for downscaling of soil moisture. However, the inevitable residuals (that is, the part which cannot be explained by the statistical models) bring about differences between the original and the downscaled data in terms of the spatial distribution pattern, so the consistencies between them may not be maintained. To overcome the drawback, a novel method named regression kriging has been proposed by combining multiple regression and kriging interpolation (Hengl et al., 2004). Downscaling by the regression kriging can produce a high-resolution data which is spatially consistent with the original data through the correction of residuals. Rainfall datasets such as TRMM (Tropical Rainfall Measuring Mission) have been downscaled using the regression kriging (e.g., Park, 2013), but downscaling of soil moisture dataset using this novel method has not been reported yet.

In this study, we carried out the downscaling of AMSR2 soil moisture data using multi-satellite land surface variables with the regression kriging. The database for LST (land surface temperature), RR (rising rate of LST in daytime), NDVI (normalized difference vegetation index), NDWI (normalized difference water index), TVDI (temperature vegetation dryness index), and SA (surface albedo) was built using the satellite images from MODIS (Moderate Resolution Imaging Spectroradiometer) and COMS (Communication, Ocean and Meteorological Satellite). The low-resolution soil moisture data from AMSR2 on the 10-km grid was downscaled on the 2-km grid using the land surface variables. The spatial consistencies before and after downscaling can be measured by comparing the pixel values of the low-resolution grid with the upscaled block means of the high-resolution grid. Our results showed a favorable data consistency with the correlation coefficient of 0.974. The downscaled soil moisture data can be used in many regional-scale applications for hydrology and meteorology.

2. DATA AND METHODS

2.1 Land Surface Variables

We built a database for the six land surface variables: LST, RR, NDVI, NDWI, TVDI, and SA. We used COMS LST product because the hourly temperatures are necessary for calculation of RR using the LST at 9 AM and 12 PM, respectively:

$$\mathrm{RR} = \frac{(LST)_{12\mathrm{PM}} - (LST)_{9\mathrm{AM}}}{3(\mathrm{hours})} \tag{1}$$

NDVI was obtained from the Terra and Aqua MODIS products (MOD13A2 and MYD13A2), and time-series correction for the 8-day NDVI was conducted to avoid the low-peak problem (Figure 1). NDWI was calculated using the reflectance of 857-nm and 2130-nm bands extracted from the MODIS 8-day product for surface spectral reflectance (MOD09A1). SA was obtained from the shortwave black-sky albedo in the 16-day MODIS product (MCD43B3). TVDI was derived from the NDVI–LST space in Figure 2:

$$\mathrm{TVDI} = \frac{(LST)_{\mathrm{day}} - (LST)_{\mathrm{day\_min}}}{(LST)_{\mathrm{day\_max}} - (LST)_{\mathrm{day\_min}}} \tag{2}$$

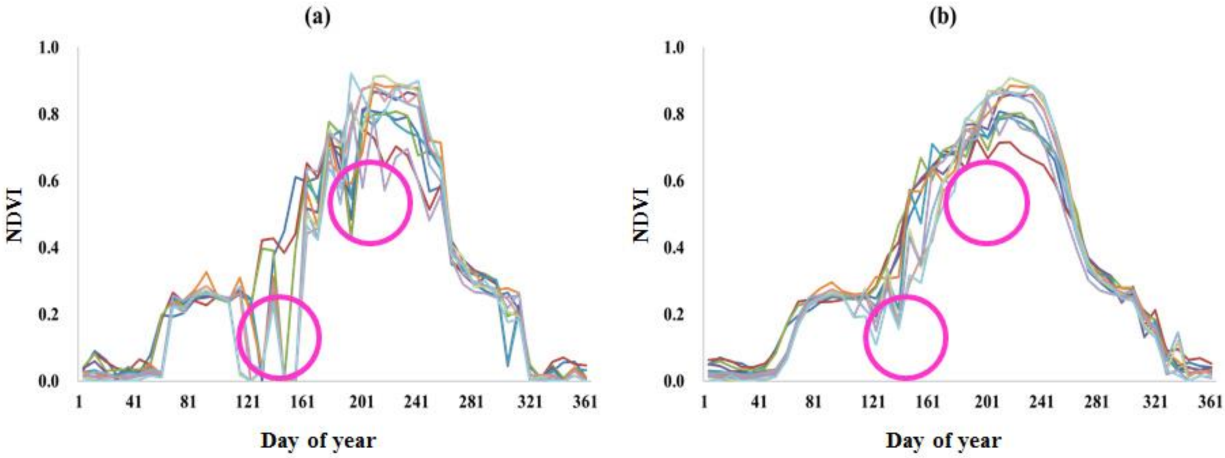

Figure 1. Effects of time-series correction for MODIS NDVI: (a) before correction and (b) after correction.

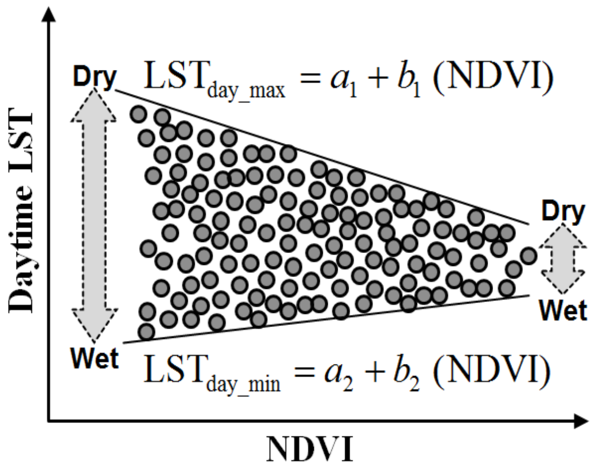

Figure 2. Principle of TVDI

Missing values in the land surface variables were filled by spatial and/or temporal mean values. The database for LST, RR, and TVDI was built on the daily basis in accordance with the temporal resolution of the AMSR2 soil moisture. Also, NDVI, NDWI, and SA dataset were temporally interpolated to daily values using the cubic spline technique.

2.2 Regression Kriging

Figure 3 illustrates the general process of downscaling by regression kriging, which consists of regression estimates at low resolution, residual kriging from low to high resolution, regression estimates at high resolution, and the downscaled result by the residual correction at high resolution (Hengl et al., 2004; Immerzeel et al., 2009).

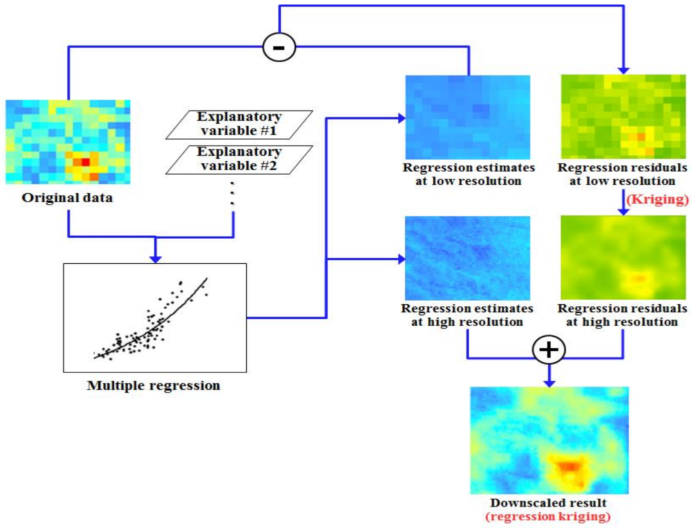

Figure 3. Process of downscaling by regression kriging

3. RESULTS

AMSR2 daily soil moisture data at the resolution of 10 km for the period between April and October, 2013-2014 was collected to match up with the land surface variables. Multiple regression models were built for each month to take account of possible seasonal variations. Regression estimates on the 10-km grid were derived from the monthly models, and the regression residuals on the 10-km grid were spatially interpolated to the 2-km grid using the kriging (Cressie, 1985). Then, the regression estimates on the 2-km grid were derived and added to the interpolated residuals on the 2-km grid, which resulted in downscaled soil moisture at the resolution of 2 km (Figure 4 and 5). The spatial consistency before and after downscaling in terms of the correlation coefficient was 0.974 (Figure 6).

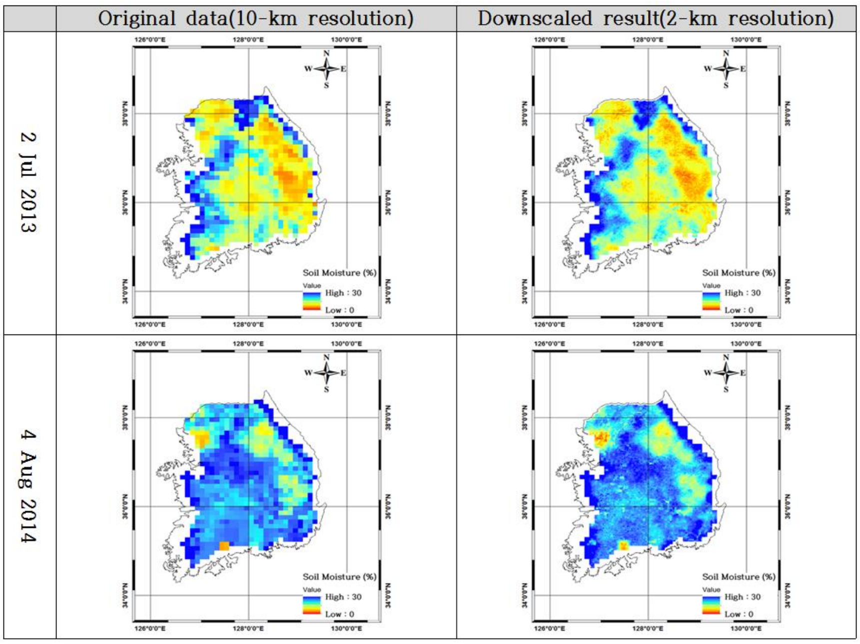

Figure 4. Downscaled result of AMSR2 soil moisture content (July and August)

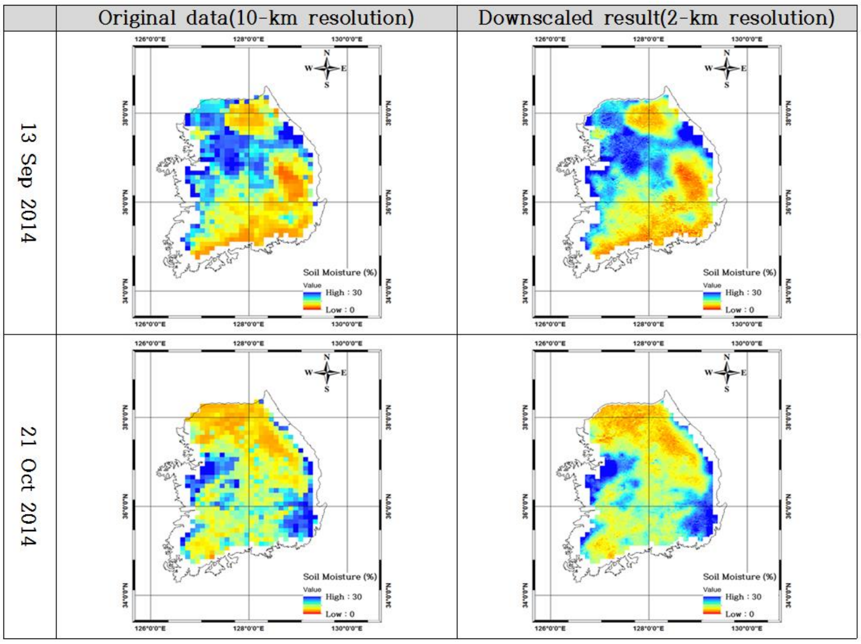

Figure 5. Downscaled result of AMSR2 soil moisture content (September and October)

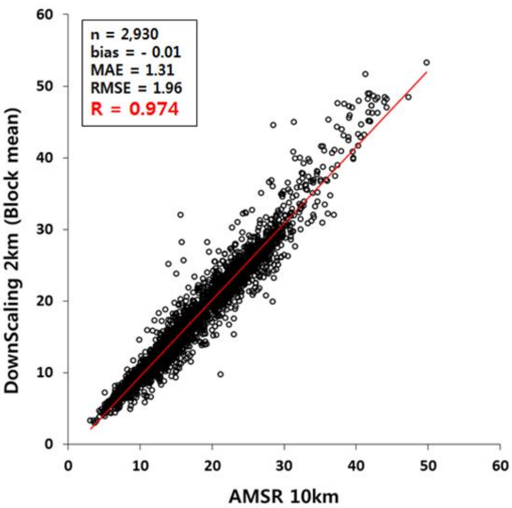

Figure 6. Measure of spatial consistency before and after downscaling

4. CONCLUSIONS

This study presented the downscaling of AMSR2 soil moisture data using various land surface variables with the regression kriging. The downscaled result from 10-km to 2-km resolution showed quite good spatial consistencies, which means the spatial patterns and the data properties were well preserved even after downscaling. Our approach can also apply to other hydrological factors such as rainfall and evapotranspiration and can be a viable option for overcoming the problem of limited spatial resolution in satellite images and numerical model dataset.

REFERENCES

Cressie, N. (1985). "Fitting variogram models by weighted least squares." Mathematical Geology, Vol. 17, No. 5, pp. 563-586.

Hengl, T., Heuvelink, G.B.M., and Stein, A. (2004), "A generic framework for spatial prediction of soil variables based on regression-kriging." Geoderma, Vol. 122, No. 1-2, pp. 75-93.

Immerzeel, W.W., Rutten, M.M., and Droogers, P. (2009). "Spatial downscaling of TRMM precipitation using vegetative response on the Iberian Peninsula." Remote Sensing of Environment, Vol. 113, pp. 362-370.

Park, N.W. (2013). "Spatial downscaling of TRMM precipitation using geostatistics and fine scale environmental variables." Advances in Meteorology, Article ID 237126.