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Deriving temporally continuous soil moisture estimations at fine resolution by downscaling remotely sensed product

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A R T I C L E I N F O

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A B S T R A C T

Land surface soil moisture (SSM) has important roles in the energy balance of the land surface and in the water cycle. Downscaling of coarse-resolution SSM remote sensing products is an efficient way for producing fine-resolution data. However, the downscaling methods used most widely require full-coverage visible/infrared satellite data as ancillary information. These methods are restricted to cloud-free days, making them unsuitable for continuous monitoring. The purpose of this study is to overcome this limitation to obtain temporally continuous fine-resolution SSM estimations. The local spatial heterogeneities of SSM and multiscale ancillary variables were considered in the downscaling process both to solve the problem of the strong variability of SSM and to benefit from the fusion of ancillary information. The generation of continuous downscaled remote sensing data was achieved via two principal steps. For cloud-free days, a stepwise hybrid geostatistical downscaling approach, based on geographically weighted area-to-area regression kriging (GWATARK), was employed by combining multiscale ancillary variables with passive microwave remote sensing data. Then, the GWATARK-estimated SSM and China Soil Moisture Dataset from Microwave Data Assimilation SSM data were combined to estimate fine-resolution data for cloudy days. The developed methodology was validated by application to the 25-km resolution daily AMSR-E SSM product to produce continuous SSM estimations at 1-km resolution over the Tibetan Plateau. In comparison with ground-based observations, the downscaled estimations showed correlation ($R \geq 0.7$) for both ascending and descending overpasses. The analysis indicated the high potential of the proposed approach for producing a temporally continuous SSM product at fine spatial resolution.

1. Introduction

Land surface soil moisture (SSM) has vital importance in both the energy balance of the land surface and the water cycle (Seneviratne et al., 2010; Ochsner et al., 2013). A fine spatial resolution SSM dataset is one of the crucial input parameters for catchment-based hydro-ecological modeling (Li et al., 2015), drought and flood forecasting (Chakrabarti et al., 2014), weather and climate prediction (Koster et al., 2011), and crop growth monitoring (Tubiello et al., 2002). Ground-based measurement methods such as gravimetric measurements (Robock et al., 2000), electrical resistivity measurements (Samouëlian et al., 2005), and time domain reflectometry (Noborio, 2001) can yield accurate in situ soil moisture data at different depths. These techniques make the acquisition of simultaneous regional-scale measurements of soil moisture feasible given the advent of wireless sensor networks (Jin et al., 2014; Ge et al., 2015) and the Cosmic-ray Soil Moisture Observing System (Zreda et al., 2012). However, the implementation of dense networks of instruments across large areas to obtain continuous SSM measurements is generally restricted because of financial and practical limitations. Furthermore, in situ measurements cannot characterize the large-scale variability attributable to the high spatial and temporal heterogeneities of SSM (Kang et al., 2017).

Remote sensing techniques are characterized by the advantages of large information capacity, huge observation scope, and high speed; thus, they have become the principal means of earth observation at regional, continental, and global scales. With the development of remote sensing techniques, satellite microwave observations acquired by active and passive sensors have increasingly been applied to retrieve

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SSM via the physically based relationship between the soil dielectric constant and water content. Many satellite-based active and passive microwave sensors have been launched (Jackson et al., 2010; Jensen et al., 2011), including the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), Advanced Synthetic Aperture Radar (ASAR), Advanced Scatterometer, Soil Moisture and Ocean Salinity (SMOS), Advanced Microwave Scanning Radiometer 2 (AMSR-2), and Soil Moisture Active Passive (SMAP) instruments. Several related SSM products have also been made available, such as the AMSR-E Land Parameter Retrieval Model (Owe et al., 2008) and the SSM products from the Advanced Scatterometer (Naeimi et al., 2009), SMOS (Kerr et al., 2002), and SMAP (Entekhabi et al., 2010). Unfortunately, all of the above SSM products have coarse spatial resolution of the order of tens of kilometers. To monitor SSM at fine spatial resolution over large areas, the spatial resolution of existing SSM products must be downscaled (Atkinson, 2013; Malbéteau et al., 2017).

Various methods have been developed to downscale microwave-derived SSM products. These methods can be classified broadly into the following two categories based on the type of input data: a combination of active and passive microwave data (Wagner et al., 2008), and a combination of visible/infrared and microwave data. The change detection method (Njoku et al., 2002; Wagner et al., 2008), SMAP baseline algorithm (Das et al., 2011), and a Bayesian merging method (Zhan et al., 2006) have been proposed for merging radar (active) and radiometer (passive) data. However, because of the fine resolution of visible/infrared remote sensing data, it has become popular to combine them with coarse SSM remote sensing data in a downscaling procedure (Piles et al., 2011). General statistical methods (Wilson et al., 2005), machine learning methods (Ahmad et al., 2010; Srivastava et al., 2013), data assimilation (Sahoo et al., 2013a,b; Yang et al., 2016; Chen et al., 2017), universal triangle/trapezoidal models (Merlin et al., 2013, 2015), and geostatistical methods (Thattai and Islam, 2000; Chen et al., 2014) have been developed to obtain SSM by employing fine spatial resolution visible/infrared data. The idea behind these methods is to establish either statistical correlation or a physically based model between SSM and ancillary variables. A systematic review of the techniques for downscaling satellite remotely sensed SSM data and their potential for application was presented by Peng et al. (2017). However, some problems that remain in the downscaling process must be addressed, such as local heterogeneity, discontinuous downscaled estimations, and the enhancement of model representativeness.

Because SSM commonly has high spatial heterogeneity, global models might be inadequate in capturing its local variability. Strong surface heterogeneity would decrease the spatial correlation and increase the error in downscaled estimations. However, nonstationary models have been developed to deal with high spatial heterogeneity (Harris et al., 2010). For example, Jin et al. (2017) proposed the use of geographically weighted area-to-area regression kriging (GWATARK) to downscale the AMSR-2 SM product, which is a technique that integrates geographically weighted regression (GWR) and area-to-area kriging (ATAK).

Although the high accuracy of downscaled results has indicated the potential of combining visible/infrared data to estimate SSM at fine spatial resolution, one of the major limitations of the technique is the requirement for full-coverage visible/infrared data. However, the visible/infrared remotely sensed products generally cannot provide full coverage on a daily basis due to the cloud disturbance; thus, it is not possible to obtain continuous SSM estimations by employing visible/infrared data in downscaling procedures. Several reconstruction methods (Roy et al., 2008; Rakwatin et al., 2009; Chen et al., 2016) have been proposed to derive continuous satellite visible/infrared observations; however, limited research has been conducted on obtaining temporally continuous downscaling estimations (e.g., Sahoo et al., 2013a,b; Djamai et al., 2016). In addition to downscaling, some researchers (Zhao et al., 2013; Leng et al., 2014) focus on the SSM retrieval models to obtain continuous SSM estimations from the combination of optical/infrared data and ancillary data (e.g. meteorological data, hydrologic data). In recent studies (Leng et al., 2016, 2017), a practical algorithm that uses the real temporal information of diurnal changes of satellite-derived land surface variables (e.g. LST, solar radiation) has been developed and applied in different biophysical and atmospheric conditions.

Most of the abovementioned methods assume the model between SSM and the ancillary variables is scale-invariant and they downscale SSM directly from the coarse-resolution dataset to the target fine resolution. The established downscaling model might not simulate the relationships at different resolutions effectively, and it might perform better under the condition of a smaller scale factor than a larger scale factor (e.g., from 25 to 1 km, the scale factor is 25). In addition to the ancillary variables at the coarse and target fine resolutions, data are also available at several intermediate resolutions that could provide further information to explain the SSM. For example, there are multiscale satellite products of both land surface temperature (LST) and normalized difference vegetation index (NDVI), which are two ancillary variables used often in SSM downscaling (Chauhan et al., 2003; Colliander et al., 2017), as well as multiscale soil texture information that could influence the pattern of SSM distribution (Reichle et al., 2010; Hengl et al., 2014). The use of multiscale ancillary information in the downscaling process is considered beneficial, and the stepwise method is an alternative approach with which to narrow the scale factor in each implementation of the downscaling and to make the best use of multiscale ancillary data.

To overcome the three weaknesses outlined above, this paper presents a methodology for the acquisition of continuous SSM at fine resolution, which considers local spatial heterogeneity of SSM, temporal discontinuity of SSM estimations, and multiscale ancillary information. This process is implemented via two principal steps. Because of its potential for addressing the local spatial heterogeneity problem, the GWATARK method is used on cloud-free days (Jin et al., 2017). Based on the GWATARK method, stepwise downscaling is implemented by combining multiscale ancillary variables with SSM. The coarse-resolution SSM data are downscaled through intermediate scales to the target fine resolution. On cloudy days, the GWATARK-estimated SSM and SSM data from another source are combined to estimate SSM at the target fine resolution. Then, the continuous downscaled estimations can be obtained. The proposed methodology was applied to improve the spatial resolution of the 25-km-resolution AMSR-E SSM product for both ascending and descending overpasses by integrating soil texture, LST, and NDVI information as ancillary variables. Fine-resolution (1 km) SSM estimations were acquired for the region of the Tibetan Plateau (TP), which includes two ground-based monitoring networks.

The structure of the rest of this paper is organized as follows. Section 2 describes both the study area and the data used. The downscaling methodology is described in Section 3. The downscaled results and their validation are presented in Section 4. Finally, several conclusions are drawn in Section 5.

2. Study area and data description

2.1. Study area

The study area comprised the TP in eastern Asia (26.5°–40.0°N, 73.4°–104.4°E), which is the highest plateau in the world (Zeng et al., 2015) (Fig. 1). It has average elevation of over 4000 m above sea level and it encompasses an area of approximately $2.5 \times 10^6\ km^2$ (Qin et al., 2013). In order to both investigate the mechanism of soil–vegetation–atmosphere interactions and validate satellite SSM products, several soil moisture networks have been established on the TP (Su et al., 2011; Yang et al., 2013). These include two soil moisture and temperature measurement system (SMTMS) networks at Maqu and Naqu, which provide representations of different land surface conditions and climates. In the north-eastern fringe of the TP, the Maqu area is the largest