Improving Spatial Representation of Soil Moisture by Integration of Microwave Observations and the Temperature-Vegetation-Drought Index Derived from MODIS Products

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ABSTRACT

The microwave observations of land surface soil moisture have been widely used for studying environmental change at large spatial scales. However, the coarse spatial resolution of the products limits their local-scale applications. In this paper, we developed a new method, which integrates the coarse spatial resolution soil moisture derived from microwave sensors and the temperature-vegetation- drought-index (TVDI) derived from the Moderate-resolution Imaging Spectroradiometer (MODIS) products, to spatially downscale soil moisture data from 25-km resolution to 1-km resolution. First, we assessed the quality of the remotely sensed soil moisture by comparing their values with field measured soil moisture at three temporal scales and two spatial scales. Second, we analyzed the robustness of the developed approach namely the PKU method by comparing its performance with the results of three published methods (i.e., the triangle-based method, the Merlin method, and the UCLA method) at the Magqu soil moisture monitoring network located in the northeastern Tibetan grasslands. The modeling results showed that by integrating the contextual information from the relatively fine spatial resolution MODIS products, spatial soil moisture representations were significantly improved. The PKU method produced the most accurate spatially disaggregated soil moisture among the four methods. In conclusion, the PKU method developed in this study is a practical and efficient approach for improving spatial representations of the coarse spatial resolution soil moisture data derived from microwave remote sensors. Within the PKU method, our refined method for estimating the parameters of the dry-edge outperforms the traditional method.

Keywords: Land surface soil moisture; Spatial downscaling; Microwave observations; MODIS; Tibetan Plateau

1. Introduction

Land surface soil moisture is a key variable in various hydrological and ecosystem models and for studying climate change, ecosystem dynamics, and crop yields (Chen et al., 2011; Entekhabi et al., 1999; Legates et al., 2011). For example, in hydrology, soil moisture is an important variable for understanding land surface hydrologic processes because it controls the partition of rainfall to subsoil drainage, surface runoff, and evaporation (Han et al., 2012; Mascaro and Vivoni, 2012; Ray et al., 2010). So, understanding the spatial and temporal dynamics of land surface soil moisture is crucial for understanding the role of hydrological cycle in climate systems (i.e., the feedbacks between hydrological cycle and climate change) and a variety of ecological and biogeochemical processes (Liu et al., 2012a; Oki and Kanae, 2006; Seneviratne et al., 2010). Therefore, accurate monitoring and assessment of land surface soil moisture are increasingly critical for the purpose of analyzing climate variability and change and their impacts on terrestrial ecosystems. Despite the importance of the information about land surface soil moisture, the accurate field measured soil moisture only exist in a limited number of field sites around the world.

Over the past two decades, remotely sensed soil moisture has become much more available while overcoming the limitations of traditional *in situ* point measurements (Anderson and Croft, 2009). In remote sensing of land surface soil moisture, satellite images derived from microwave remote sensors have been popular for investigating soil moisture. Microwave remote sensors offer an effective tool to measure land surface soil moisture over various spatial and temporal scales. The fundamental principle of microwave observations of soil moisture is the large contrast in dielectric properties of water and soil. Microwave remote sensors are favored in monitoring soil moisture not only because of their sensitivity to many land surface parameters (e.g., moisture, temperature, and roughness) but also because of their ability to directly measure land surface properties regardless of weather and sunlight conditions (Moran et al., 2004). Microwave observations of land surface soil moisture can be assigned into active (e.g., synthetic aperture radar) and passive (e.g., microwave spectroradiometers) microwave observations. The low temporal frequency and strong sensitivity of active microwave observations to vegetation cover and

surface roughness limits their applicability in measuring land surface soil moisture (Hosseini et al., 2015). A major limitation of land surface soil moisture data derived from passive microwave remote sensors is their coarse spatial resolution, which can mask the fine-resolution spatial variability of land surface soil moisture (Kim and Hogue, 2012).

In order to overcome the limitations of passive microwave observations of land surface soil moisture, many methods have been developed to spatially downscale or disaggregate the coarse spatial resolution soil moisture data (Merlin et al., 2008; Kim and Hogue, 2012). The above methods can be assigned into two types: (1) combining passive and active microwave remotely sensed soil moisture data to improve spatial soil moisture representations of the coarse spatial resolution soil moisture data (Liu et al., 2012b; Liu et al., 2012c); (2) integrating the coarse spatial resolution soil moisture data derived from microwave remote sensors and relatively fine spatial resolution optical remote sensing products for deriving the spatial variability of soil moisture at the fine spatial resolution (Chauhan et al., 2003; Choi and Hur, 2012; Piles et al., 2011; Zhao and Li, 2013). Data derived from optical remote sensors can provide detailed contextual information of land surface. In this type of methods, a downscaling factor, which is derived from optical remote sensing products, has been commonly used to represent the spatial variability of soil moisture within coarse spatial resolution remote sensing pixels.

Besides land surface soil moisture data derived from microwave sensors, land surface parameters derived from multispectral optical remote sensing data have been used for estimating land surface soil moisture since the early 1980s (Carlson et al., 1981; Carlson et al., 1990; Carlson et al., 1995; Leng et al., 2014; Patel et al., 2009; Rahimzadeh-Bajgiran et al., 2012). The normalized difference vegetation index (NDVI) is the most commonly used vegetation index (VI) to analyze the status of vegetation growth, and it is often referred to as a greenness index, which represents vegetation density and chlorophyll content of vegetation rather than the water status of a region. Therefore, in order to monitor water stress, there is a need for a more sensitive indicator than NDVI. Land surface temperature (LST) can be used as a proxy for estimating the status of water stress because the values of LST are high in dry conditions due to the lack of soil moisture. NDVI and LST in combination can provide critical information on the conditions of

vegetation and soil moisture (Gillies et al., 1997; Sandholt et al., 2002; Wan et al., 2004). Following this track, many studies have studied the emergence of a triangular or trapezoidal shape when plotting VI against LST (Carlson, 2007). The emergence of the LST/VI triangle is the result of the low sensitivity of LST to soil moisture variations over vegetated areas, and the increased sensitivity of LST to soil moisture variations in areas with bared soil (Sandholt et al., 2002). The focus of these studies has been the analysis of the biophysical properties encapsulated in the LST/VI scatter plot and making associations between these biophysical properties and the estimation of land surface soil moisture (Carlson et al., 1990; Gillies et al., 1997; Petropoulos et al., 2009).

Integrating microwave observations of soil moisture and optical remote sensing products is the most commonly used methods for disaggregating the coarse spatial resolution soil moisture data derived from microwave remote sensors. The LST/VI triangle-based models are the earliest and most commonly used methods. Based on the characteristics of the LST/VI feature space, Chauhan et al. (2003) first integrated passive microwave observations of soil moisture and optical remote sensing products by using a downscaling factor created based on the relatively high spatial resolution optical remote sensing data to improve the spatial variability of soil moisture within coarse spatial resolution pixels. The method was simple to be implemented and used widely since then (Choi and Hur, 2012; Piles et al., 2011; Ray et al., 2010). Merlin et al. (2009, 2010) developed a spatial downscaling method by using a semi-empirical soil evaporative efficiency model to integrate microwave observations of soil moisture and optical remote sensing products, and this model is more biophysically rigorous than the LST/VI triangle-based methods. However, because of requiring many field measured biophysical parameters, the Merlin method is not convenient to be implemented. Kim and Hogue (2012) developed the UCLA method, which used the soil wetness index (Jiang and Islam, 2003) derived from MODIS products as the downscaling factor to disaggregate the coarse resolution microwave observations of soil moisture. The above study showed that the UCLA method had similar performance with the Merlin method on spatially disaggregating the coarse spatial resolution land surface soil moisture in a semiarid region.

In this study, we developed a spatial downscaling approach namely the PKU method, which integrates

the coarse spatial resolution soil moisture data and the temperature-vegetation-drought-index (TVDI) derived from MODIS LST and MODIS VI to spatially disaggregate the coarse spatial resolution soil moisture data. We also assessed the robustness of the PKU method by comparing its performance on spatial downscaling with the results of three published methods (i.e., the LST/VI triangle-based method, the Merlin method, and the UCLA method). The reminder of the paper is organized as following. In Section 2, we describe the biophysical characteristics of the study area, *in situ* soil moisture measurement networks, and the remotely sensed soil moisture data used in this study. Section 3 presents the methods for assessing the uncertainties of the remotely sensed soil moisture and the four methods for spatially disaggregating microwave observations of soil moisture. The modeling results are presented in Section 4. Finally, we summarize the findings of this work and discuss the limitations of the spatial downscaling method developed in this study.

2. Study Area and Data

In the study, we ran modeling experiments covering the Magqu soil moisture and soil temperature monitoring network, which locates in the northeastern part of the Tibetan Plateau (33° 30′ - 34° 15′ N, 101° 38′ - 102° 45′ E) (Fig. 1). This is one of the three *in situ* reference networks for monitoring soil moisture and soil temperature on the Tibetan Plateau (Su et al., 2011). The objective of building these field monitoring networks is to validate satellite-based soil moisture products and to obtain an improved understanding of various land surface processes in high elevation regions (Dente et al., 2012). In the study area, the elevations of the field monitoring sites range between 3430 m and 3750 m above seal level. Grassland is the domninatnt vegetation type, and climate there is wet and cold and with dry winters and rainy summers. The *in situ* soil moisture monitoring network in Magqu was installed in July 2008 by the Chinese Academy of Sciences (CAS), China.

#Figure 1 is approximately here#

The *in situ* monitoring network at the Magqu station consists twenty sites in an area of approximately 40-km by 80-km. At the field sites, soil moisture and soil temperature at different depths (from 5 to 80 cm below surface) were recorded at 15-minute intervals. The geographic locations of the field sites were selected to monitor the area extensively at different altitudes and with different soil characteristics. Within the twenty sites, there are eleven sites installed in the valleys of the Yellow River and the Black River, three stations installed in the valleys between hills, four stations installed on hill slopes, and two stations installed in wetlands (Table 1). At these field sites, the capacitance EC-TM ECH2O probe with three flat pins of 5.2 cm length was used to measure the dielectric permittivity of the soil surrounding the pins and obtain volumetric soil moisture with a standard calibration equation. Measurement calibration has reduced RMSE between the volumetric soil moisture measured by the rings and that by the probes from 0.06 to 0.02 m³/m³ (Dente et al., 2012). In this study, we used the field measured soil moisture in Magqu from July 1st of 2008 to July 31st of 2010. The above soil moisture data were downloaded from the International Soil Moisture Network website (<http://www.ipf.tuwien.ac.at/insitu/>). Based on the analyses of local daily meteorological data, we only used soil moisture measurements in clear sky days in this study.

#Table 1 is approximately here#

Besides field measured soil moisture, we used the 30-year long time-series of microwave observations of soil moisture produced by Dorigo et al. (2012). The spatial and temporal resolutions of the product are 25-km and one-day, respectively. This product was created by fusing multisource active and passive microwave observations of soil moisture, covering the time period from November 1978 to December 2010. The source data of this product include remotely sensed data derived from the passive microwave remote sensors of the Scanning Multichannel Microwave Radiometer (SMMR) (1978-1987), the Special Sensor Microwave Imager (SSM/I) (1987-2007), the Tropical Rainfall Measuring Mission (TRMM) (1998-2008), and the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) (2002-2010) on board the NASA Earth Observing System (EOS) Aqua satellite. The data source of this

product also includes remotely sensed data derived from the active microwave remote sensors of the Scatterometers (SCAT) onboard the European Remote Sensing satellites (ERS-1/2) (1991-2006) and the Advanced Scatterometer (ASCAT) onboard the Meteorological Operational satellite program (MEtOp) (2007-2010).

The time-series of field measured soil moisture data used this study primarily covered the working periods of AMSR-E and ASCAT sensors (Dorigo et al., 2012). The soil moisture products derived from AMSR-E are expected to be more accurate than soil moisture products derived from other passive microwave remote sensors due to the relatively low microwave frequency and the high temporal and spatial resolution of the sensor (Draper et al., 2009). Microwave observations of land surface soil moisture are severely impacted by snow accumulation. With ground snow-cover, it is difficult to derive reasonable results of land surface soil moisture. According to the climate condition of the study area, we only used the remotely sensed soil moisture data covering the months of June, July, and August for the years 2008, 2009, and 2010. Moreover, in consideration of data availability and the quality of the remotely sensed soil moisture data, the microwave observations of soil moisture for the periods of June 2008, July 2009, and August of 2010 were not used in the study.

Besides the above soil moisture products, Aqua MODIS land products including MODIS vegetation index (MYD13A3) and MODIS land surface temperature (MYD11A1) (from July 2008 to July 2010) were downloaded from the NASA Reverb data portal (<http://reverb.echo.nasa.gov/reverb>). The spatial and temporal resolutions of the MYD13A3 dataset are 1-km and one-month, respectively. The MYD13A3 data layers include NDVI, enhanced vegetation index (EVI), and assessments of data quality. Compared to NDVI, EVI is more sensitive to regions with high density of biomass, and it can better reflect the status of vegetation growth. We used MODIS EVI to represent the status of vegetation growth in the study area. The spatial and temporal resolutions of the MYD11A1 dataset are 1-km and eight-day respectively. In the following experiments, MODIS LST and MODIS EVI were used to infer the spatial variability of soil moisture at a finer spatial resolution (1-km) than the original spatial resolution (25-km) of the remotely sensed soil moisture data.

3. Methodology

3.1. Uncertainty Analysis of the Microwave Observations of Soil Moisture

Remotely sensed data are commonly not free of errors. In this case, multiple procedures of collecting and processing microwave observations of soil moisture can introduce various errors and uncertainties in the final soil moisture products. Here, we used *in situ* measurements of soil moisture to evaluate whether the temporal and spatial variations in soil moisture were preserved in the final blended remote sensing products. Our study area included eight coarse spatial resolution pixels, and each pixel contained four to eight field monitoring sites. First, we conducted the temporal uncertainty analyses of the remotely sensed soil moisture. The spatially averaged of field measured soil moisture over the study area was used as ground reference for the validation of the remotely sensed soil moisture data. The comparisons between field measured and remotely sensed soil moisture were conducted at daily, biweekly, and monthly scales. If a field site has more than one qualified measurement per day, all values for that day were averaged. Then, we aggregated daily soil moisture to biweekly and monthly scales by taking averages of the daily data. Based on the above aggregated soil moisture data, we compared the consistency between field measured and remotely sensed soil moisture at daily, biweekly, and monthly scales.

Second, we conducted spatial uncertainty analyses of the remotely sensed soil moisture. The accuracy of the remotely sensed soil moisture was assessed by comparing pixel values with *in situ* measurements at site scale and pixel scale. For site-scale analysis, we directly compared the values of the field measured soil moisture with the corresponding pixel values to assess the representativeness of the pixel values. For pixel-scale analysis, we calculated the mean value of field measured soil moisture within the pixel and compared the mean of the field measurements with the pixel value. We also calculated the standard deviations of the *in situ* measurements within each pixel area. It should be stressed that there were some disadvantages in comparing field measured and remotely sensed soil moisture. For example, the spatial supports (i.e., the size of the measurement area) of *in situ* measurements and remotely sensed data had a big difference. Therefore, the above validation was inherently subject to some degree of uncertainty due

to the unavoidable support difference. In addition, differences in other factors, such as measurement depth and the time of measurements, could also affect the consistency between field measured and remotely sensed soil moisture. For both temporal and spatial uncertainty analyses, we used root mean square errors (RMSE) for measuring the difference between field measured and remotely sensed soil moisture.

3.2. Methods for Spatially Downscaling Microwave Observations of Land Surface Soil Moisture

Following the track of integrating land surface soil moisture data derived from microwave sensors and optical remote sensing products for spatially downscaling the coarse resolution soil moisture product, we developed the PKU method by integrating microwave observations of land surface soil moisture and the temperature-vegetation-drought-index (TVDI) derived from MODIS products. To assess the robustness of the PKU method, we compared the performance of the approach with the results of three published spatial disaggregation algorithms, including the LST/VI triangle-based method (Carlson et al., 1994), the Merlin method (Merlin et al., 2009, 2010), and the UCLA method (Kim and Hogue, 2012). Because we only used the above three spatial downscaling algorithms as the references of the PKU method, only the key equations of the three algorithms were provided in the Appendix A.

In the PKU method, we used the temperature-vegetation-drought index (TVDI) derived from MODIS LST and MODIS EVI to build a downscaling factor to improve the spatial variability of soil moisture within coarse resolution image pixels. The PKU method for spatially disaggregating the microwave observations of soil moisture is defined as

$$M_{MODIS} = M_{MRS} \left(\frac{1 - TVDI_{MODIS}}{1 - TVDI_{MRS}} \right) \quad (1)$$

where M_{MODIS} is the downscaled soil moisture at the spatial resolution of MODIS products (1-km),

M_{MRS} is the microwave observations of soil moisture at the spatial resolution 25-km, $TVDI_{MODIS}$ is the TVDI calculated using MODIS products. $TVDI_{MODIS}$ was empirically calculated by parameterizing the relationship between MODIS LST and MODIS EVI. $TVDI_{MRS}$ is the mean of $TVDI_{MODIS}$ within the

pixel area of microwave observations of soil moisture. The computation of $TVDI_{MODIS}$ from the LST/VI feature space is defined as (Patel et al., 2009; Sandholt et al., 2002)

$$TVDI_{MODIS} = \frac{T_{MODIS} - T_{MODIS(\min)}}{a + b \cdot EVI_{MODIS} - T_{MODIS(\min)}} \quad (2)$$

where T_{MODIS} is MODIS LST, $T_{MODIS(\min)}$ is the minimum MODIS LST within the LST/VI feature space, and EVI_{MODIS} is MODIS EVI. $a + b \cdot EVI_{MODIS}$ defines the dry-edge (i.e., limited water availability) of the LST/VI feature space, and a and b are the parameters of the dry-edge. Estimating the parameters of the dry-edge and the wet-edge (i.e., maximum evapotranspiration and thereby unlimited water access) in the LST/VI feature space is of critical importance in estimating land surface soil moisture.

The traditional approach to estimating the parameters of the dry-edge and the wet-edge is that using all pixel values of LST and VI in the study area and assigning the empirical data into small intervals based on the pixel values of VI. Then, by determining the maximum and minimum LST in each interval, plotting LST against VI of all intervals, and fitting linear regressions between the maximum LST and VI and between the minimum LST and VI, we can derive the parameters of the dry-edge and the wet-edge in the LST/VI feature space, respectively (Petropoulos et al., 2009).

$$T_{VI(i, \max)} = a + b \cdot VI_i \quad (3)$$

$$T_{VI(i, \min)} = a' + b' \cdot VI_i \quad (4)$$

where VI_i is the vegetation index of interval i , $T_{VI(i, \max)}$ and $T_{VI(i, \min)}$ are the maximum LST and the minimum LST of the interval i , respectively. The above two equations represent the dry-edge and the wet-edge in the LST/VI feature space, respectively. a , b , a' , and b' are parameters of the dry-edge and the wet-edge, respectively.

The above traditional method for estimating the parameters of the dry-edge and the wet-edge in the

LST/VI feature space has limitations in real-world applications. The assumptions of the traditional method are that the study area is large enough so that the soil water content can vary from the withering point of plants to the maximum soil water capacity, and the density of vegetation can vary from bared soil to full vegetation cover. In general, it is difficult to meet the above conditions at the local scale. In this study, we refined the traditional method to estimating the parameters of the dry-edge and the wet-edge in the LST/VI space in order to relax the limitations of the method (Fig. 2).

#Figure 2 is approximately here#

The refined algorithm proceeds as follows. First, according to the value range of VI in the study area, we evenly divide VI into 20 intervals and sub-divide each interval into five sub-intervals. Second, we calculate the maximum LST in each sub-interval, the mean values (T_{ave}) and the standard deviation (δ) of the maximum LST (T_{max}) in each interval. Third, if the maximum LST of a sub-interval is smaller than $T_{ave} - \delta$ of that interval, we remove the sub-interval and move back to the previous step. Finally, after the above iterations, we can derive the maximum LST (T_{ave}) of each interval. After the above steps, we conduct further refinements of the above dataset. We run linear regressions between T_{ave} and VI in each interval and calculate RMSE between predicted LST (T_{pre}) and remotely sensed LST. If T_{ave} of an interval is less than T_{pre} minus the two times of RMSE, then we remove that interval. Finally, after all of the above iterations, we can get the final empirical data of LST and VI used for estimating the parameters of the dry-edge and the wet-edge. By fitting the linear regressions between LST and VI, we can derive the parameters of the dry-edge. Finally, the wet-edge is defined as parallel to the x-axis with the y value corresponding to the x-axis that the value of VI equals one.

4. Results

3.1. Consistency between in situ Measurements and Remotely Sensed Soil Moisture

Land surface soil moisture is strongly time and space dependent, and it is constantly influenced by meteorological and terrain factors, such as precipitation, temperature, evaporation, and vegetation cover. The consistency between field measured and remotely sensed soil moisture were compared at daily, biweekly, and monthly scales (Fig. 3). At the three temporal scales, the values of the field measured soil moisture were all higher than the values of the remotely sensed soil moisture. The value difference (in term of RMSE) between field measured and remotely sensed soil moisture at daily and biweekly scales were smaller than the value difference at monthly scale. To be specific, the values of RMSE at daily, biweekly, and monthly intervals were 0.1035, 0.1030, and 0.1127, respectively. However, due to the high variability of soil moisture at daily and biweekly scales, measurements at the two temporal scales were less able to show the temporal trend of soil moisture than the monthly averaged soil moisture. We also calculated correlation coefficients between field measured and remotely sensed soil moisture, and the value of the correlation coefficient was also the highest at monthly scale. To be specific, the values of correlation coefficients at daily, biweekly, and monthly intervals were 0.6092 ($p < 0.01$), 0.5776 ($p < 0.01$), and 0.9434 ($p < 0.01$), respectively. In general, the original information about temporal variations in soil moisture was preserved in the final remotely sensed soil moisture data. Considering the uncertainties and errors of remotely sensed soil moisture at daily scale and averaging daily measurements could minimum the effects of measurement errors and noises in the data, we used the monthly averaged soil moisture as the final remotely sensed soil moisture data in the following spatial downscaling experiments. All of the daily soil moisture products covering the study area were averaged to the monthly values of soil moisture.

#Figure 3 is approximately here#

The spatial uncertainty analyses of the remotely sensed soil moisture data showed that at site scale and pixel scale, the value difference (in terms of RMSE) between field measured and remotely sensed soil moisture were both significant, especially at site scale (Table 2). This indicated that at both spatial scales, remotely sensed soil moisture could not reasonably reflect the spatial variability of soil moisture in the study area. The coarse spatial resolution soil moisture data can be utilized to analyze the spatial variability of soil moisture across pixels, and but they cannot give any information about the spatial variability of soil moisture within pixel areas. In addition, as discussed in Section 3.1, the differences in the spatial supports of measurements, measurement depth, and the time of measurements could affect the consistency between field measured and remotely sensed soil moisture.

#Table 2 is approximately here#

3.2. Estimations of the Parameters of the Dry-edge in the LST/VI Feature Space

We used the refined method of this study to estimate the parameters of the dry-edge and the wet-edge in the LST/VI feature space. We iteratively refined the empirical values of MODIS LST and MODIS EVI and fitted linear regressions between LST and EVI. As indicated in Figure 4, we can see that the linear regression parameters of the dry-edges in the LST/VI feature spaces were highly variable over the eight periods. Second, we compared the estimated parameters of the dry-edge by the traditional method and by the refined method (Table 3). The results indicated that the values of the regression parameters produced by the traditional method were highly variable over the periods. Moreover, the values of goodness-of-fit (R^2) produced by the refined method were significantly higher than the corresponding R^2 values produced by the traditional method. This indicated that in comparison with the traditional method, the refined method produced better estimates of the parameters of the dry-edges even in the condition that the values of soil water content did not cover from the withering point of plants to the maximum soil water capacity, and the density of vegetation did not cover from bared soil to full vegetation cover.

#Figure 4 is approximately here#

#Table 3 is approximately here#

3.3. Spatially Disaggregated Land Surface Soil Moisture by Four Methods

The robustness of the PKU method was evaluated by comparing its performance with the results of the LST/VI triangle-based method, the Merlin method, and the UCLA method. The RMSE values between the field measurements and the spatially disaggregated soil moisture by the four methods are shown in Table 4. The modeling results showed that the spatially disaggregated soil moisture by the PKU method had the lowest values of RMSE among the results produced by the four methods. The results produced by the LST/EVI triangle-based method had the highest values of RMSE over the eight monthly periods. The Merlin method and the UCLA method had relatively similar RMSE values over the periods. The RMSE values of the four methods also varied over the eight monthly periods. For the LST/VI triangle-based method, the temporal variability of the RMSE values (in terms of standard deviation) was the highest among the four methods. The RMSE values of the PKU method had the lowest variability over the eight periods. This indicated that the PKU method produced relatively stable spatial disaggregation results over time when comparing with the other three methods. In addition, the temporal profiles of the downscaled soil moisture averaged over the study area showed that the temporal profile of the downscaled results produced by the PKU method had better consistency with the temporal profile of the field measurements than the results produced by the other three methods (Fig. 5).

#Table 4 is approximately here#

#Figure 5 is approximately here#

Second, we calculated the cumulative distribution functions (CDFs) of the field measurements, the original remotely sensed soil moisture, the spatially disaggregated soil moisture by the four methods (Fig. 6). By plotting the CDFs over the eight periods, we intended to analyze how the four spatial downscaling methods influenced the spatial variability of the original coarse spatial resolution soil moisture data. The results showed that the values of the spatially disaggregated soil moisture were highly impacted by the values of the original remotely sensed data. The CDFs of the spatially disaggregated soil moisture were distributed around the values of the remotely sensed data. Moreover, in comparison with the CDFs of the original pixel values, the CDFs of the disaggregated soil moisture values were more similar to the shape patterns belonging to the CDFs of the field measurements. The results showed that the PKU method and the UCLA method significantly improved the spatial variability of the coarse spatial resolution soil moisture. For most of the eight monthly periods, the CDF shapes of the disaggregated soil moisture by the PKU method were the most similar to the CDF shapes of the field measurements. This indicated that the spatially disaggregated soil moisture by the PKU method had better representations of the spatial variability in soil moisture than the results produced by the other three downscaling methods.

#Figure 6 is approximately here#

The spatial patterns of the 1-km resolution spatially disaggregated soil moisture by the four spatial downscaling methods are shown in Figure 7. The modeling results showed that the spatial variability of soil moisture in the study area was enhanced by the four methods, especially by the PKU method and the UCLA method. As indicated by the results of the two methods, the spatial patterns of the spatially disaggregated soil moisture were fairly similar. The results produced by the two methods also captured the major characteristics of the spatial variability in soil moisture over the study area. The high values of soil moisture were mainly distributed along the river valley of the Yellow River, which ran through the middle of the study area (Fig. 1). Drier regions in the study area were also captured well in the disaggregated results by the PKU method and the UCLA method. The spatially disaggregated results by

the PKU method showed better spatial variability than the results produced by the UCLA method. In comparison with the results of the above two methods, the spatially disaggregated soil moisture by the Merlin method were less able to show the spatial variability in soil moisture over the study area. The spatially disaggregated soil moisture by the LST/VI triangle-based method was quite different from the real soil moisture conditions in the study area. For example, in most of the monthly periods, the values of soil moisture along the river valley of the Yellow River had lower values of soil moisture than the rest of the study area, and this was inconsistent with the real soil moisture conditions in the study area.

#Figure 7 is approximately here#

5. Discussion and Conclusions

The techniques of *in situ* measurements of land surface soil moisture are tedious and the cost of data collection is high. Moreover, the representativeness of *in situ* measured land surface soil moisture for large-scale applications is often questioned, and it is challenging to upscale field measured soil moisture to a larger spatial scale due to the spatial variability of soil moisture across heterogeneous space. The main advantage of remote sensing in monitoring land surface soil moisture, which is compared with field measurements, is that it can repeatedly monitor large-scale soil moisture at relatively low cost. Because of its high temporal resolution, passive microwave remote sensing of land surface soil moisture data are frequently used in studying environmental change at large spatial scales (Draper et al., 2009; Wagner and Scipal, 2000). Passive microwave remote sensors offer several advantages over other types of sensors. Besides the common advantages of microwave remote sensors, such as nearly all-weather working and direct relationship with land surface soil moisture, passive microwave sensors have a reduced sensitivity to land surface roughness and vegetation cover. However, passive microwave observations of land surface soil moisture with the spatial resolution of tens of kilometers limit their local-scale applications (Mascaro and Vivoni, 2012).

The primary objective of this study was to explore effective spatial downscaling methods to spatially disaggregate the coarse spatial resolution soil moisture derived from microwave remote sensors. Because of the limited number of stations for measuring land surface soil moisture in the world, the development of spatial disaggregation approaches, which are independent of *in situ* measurements, is significant for the applicability of the method in a wide range of geographic conditions (Kim and Hogue, 2012; Merlin et al., 2008). In this study, we developed a new spatial downscaling approach named the PKU method, which integrates the coarse spatial resolution soil moisture data derived from microwave remote sensors and the temperature-vegetation-drought-index (TVDI) derived from MODIS LST and MODIS EVI for spatially downscaling the coarse spatial resolution remotely sensed soil moisture data. Moreover, we assessed the robustness of the PKU method by comparing its performance on spatial downscaling with the results of three published methods. The comparisons were conducted in the Magqu soil moisture monitoring networks located in the northeastern part of the Tibetan grasslands. All of the four spatial downscaling methods assessed in this study belong to the type of spatial downscaling methods that using the relatively fine spatial resolution optical remote sensing products for improving the spatial variability of the coarse spatial resolution soil moisture data.

The results of the above modeling experiments showed that the newly developed microwave-optical synergistic approach was an efficient method for improving spatial soil moisture representations by using spatial contextual information from MODIS LST and MODIS EVI. The PKU method is also independent of field measurements. Therefore, it can be applied in geographic areas with limited or no field measured soil moisture. Moreover, the PKU method had advantages in representing the spatial variability of soil moisture in the study area and in the accuracy (in terms of RMSE values) of the spatially disaggregated soil moisture. The key difference between the PKU method and the UCLA method was that the soil wetness index was used in the UCLA method as the downscaling factor, and we used TVDI derived from MODIS products as the downscaling factor in the PKU method. Moreover, the calculation of MODIS TVDI is simple, and TVDI is also commonly used to estimate soil moisture (Patel et al., 2009). The Merlin method is theoretically solid because it relies on the theoretical and physical relationships between

remotely sensed data and land surface soil moisture. However, the implementation of the Merlin method requires many field measured biophysical variables, and this limits its applicability. Among the above four spatial disaggregation methods, the LST/VI triangle-based method had the lowest performance in spatially disaggregating the coarse spatial resolution soil moisture product.

There are several limitations in the PKU method. First, as with all disaggregation methods based on the LST/VI feature space, the errors and uncertainties in the spatially disaggregated soil moisture values by the PKU method may be greater over highly vegetated areas due to the sensitivity of LST to variations in soil moisture in the LST/VI feature space, and the LST/VI feature space tends to be much smaller over vegetated areas than over areas with bared soil (Gillies et al., 1997; Sandholt et al., 2002). This could potentially increase uncertainties of the spatially disaggregated soil moisture in these regions. Although in this study we only applied the PKU method in the semiarid region of the Tibetan grasslands, we will test the method for spatially disaggregating coarse spatial resolution soil moisture data over a variety of land cover types in the future. Second, within the PKU method, the estimated parameters of the dry-edge in the LST/VI feature space could involve errors. Although we refined the traditional method for estimating the parameters of the dry-edge, the value ranges of the soil water content and the density of vegetation in the study area could still affect the accuracies of the estimated parameters of the dry-edge in the LST/VI feature space. Finally, all of the above spatial disaggregation methods rely on the original soil moisture products derived from microwave remote sensors. Therefore, any error in remotely sensed soil moisture data can propagate to the final spatially disaggregated soil moisture. Consequently, these errors affect the consistency between the field measured and spatially disaggregated soil moisture.

In conclusion, although numerous confounding factors may affect the spatial and temporal variability of land surface soil moisture, the above computer modeling results have demonstrated that the PKU method newly developed in this study is an effective and efficient approach for spatially disaggregating the coarse spatial resolution land surface soil moisture data derived from microwave remote sensors. In addition, within the PKU method, our refined method for estimating the parameters of the dry-edge outperforms the traditional method.

Acknowledgements

This work was conducted with financial support from the National Basic Research Program of China (2012CB956303), National Science Foundation of China (41401215), and Shenzhen Oversea Talent Program of Technical Innovations (KQCX2014052114595626).

Appendix A. Supplementary material

Supplementary material associated with this article can be found, in the online version, at the website.

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Tables

Table 1. The basic information of the field sites in the Magqu soil moisture monitoring network.

Site ID	Location	Elevation (m)	Terrain	Land Cover	Soil Texture
1	33°53'N, 102°08'E	3431	River valley	Grass	N/A
2	33°40'N, 102°08'E	3449	River valley	Grass	N/A
3	33°54'N, 101°58'E	3507	Hill valley	Grass	N/A
4	33°46'N, 101°43'E	3504	Hill valley	Grass	N/A
5	33°40'N, 101°53'E	3542	Hill valley	Grass	N/A
6	33°53'N, 102°08'E	3431	River valley	Grass	Silt loam
7	33°53'N, 102°08'E	3434	River valley	Grass	Silt loam
8	33°46'N, 102°08'E	3513	Hill slope	Grass	Silt loam
9	33°37'N, 102°03'E	3448	Wetland	Grass	Silt loam
10	33°38'N, 102°03'E	3476	Hill slope	Grass	Silt loam
11	34°00'N, 102°16'E	3428	River valley	Grass	Silt loam
12	33°59'N, 102°21'E	3430	River valley	Grass	Silt loam
13	33°58'N, 102°36'E	3473	River Valley	Grass	Silt loam
14	33°54'N, 102°33'E	3434	River valley	Grass	Sandy loam
15	33°51'N, 102°34'E	3512	Hill slope	Grass	Silt loam
16	33°41'N, 102°28'E	3442	Wetland	Grass	Silt loam
17	33°37'N, 102°28'E	3441	River valley	Grass	Silt loam
18	34°01'N, 101°56'E	3519	River valley	Grass	Silt loam
19	33°55'N, 102°07'E	3432	River valley	Grass	Silt loam
20	33°51'N, 101°53'E	3752	Hill slope	Grass	Silt loam

Note: N/A stands for not available.

Table 2. The comparisons between field measurements and remotely sensed soil moisture at site scale and pixel scale.

Time Period	Comparisons at Site Scale	Comparisons at Pixel Scale
	RMSE	RMSE
2008/07	0.2251	0.2095
2008/08	0.2068	0.2031
2008/09	0.1862	0.1839
2009/06	0.1628	0.1452
2009/08	0.2160	0.1962
2009/09	0.2221	0.1963
2010/06	0.1692	0.1590
2010/07	0.2350	0.2158
Mean	0.2029	0.1886
SD	0.0270	0.0247

Note: RMSE means root mean square error. SD stands for standard deviation.

Table 3. The estimations of the parameters of the dry-edge in the LST/VI feature space by the traditional method and the refined method of this study.

Time Period	Traditional Method			Refined Method in This Study		
	Coefficient	Intercept	R ²	Coefficient	Intercept	R ²
2008/07	-15.52	312.97	0.46	-12.58	312.06	0.55
2008/08	-8.26	306.89	0.42	-11.55	308.63	0.61
2008/09	-13.98	307.12	0.68	-8.41	304.87	0.88
2009/06	-20.33	314.15	0.65	-24.06	315.67	0.82
2009/08	-10.69	307.74	0.60	-8.38	307.11	0.91
2009/09	-18.48	310.29	0.53	-22.13	311.90	0.71
2010/06	-5.85	303.80	0.30	-8.96	305.73	0.64
2010/07	-7.53	306.11	0.28	-7.82	306.75	0.61

Table 4. The accuracy assessments of the spatially disaggregated soil moisture in comparison with field measured soil moisture.

Time Period	LST/VI Triangle Method RMSE	Merlin Method RMSE	UCLA Method RMSE	PKU Method RMSE
2008/07	0.2343	0.2258	0.2250	0.2141
2008/08	0.2301	0.2076	0.2057	0.1975
2008/09	0.2229	0.1907	0.2025	0.1846
2009/06	0.1777	0.1684	0.1650	0.1632
2009/08	0.2375	0.2267	0.2239	0.2074
2009/09	0.2564	0.2274	0.2276	0.2105
2010/06	0.2572	0.2018	0.1990	0.1701
2010/07	0.2724	0.2368	0.2406	0.2285
Mean	0.2361	0.2107	0.2112	0.1970
SD	0.0288	0.0231	0.0235	0.0227

Note: RMSE stands for root mean square errors. SD means standard deviation.

Figures

Fig. 1. The geographic location of the study area and the field monitoring sites.

Fig. 2. The follow chart for estimating the parameters of the dry-edge in the LST/VI feature space using the refined method of this study.

Fig. 3. The time-series of field measurements and remotely sensed soil moisture averaged at daily scale (a), biweekly scale (b), and monthly scale (c) over the study area.

Fig. 4. The linear regressions between MODIS LST and MODIS EVI over the eight monthly periods using the refined method of this study.

Fig. 5. The temporal profiles of the field measured soil moisture (Field), the original remotely sensed soil moisture (MRS), and the downscaled soil moisture by the LST/VI triangle-based method (Triangle), the Merlin method (Merlin), the UCLA method (UCLA), and the PKU method (PKU) averaged over the study area.

Fig. 6. The cumulative distribution functions of the field measured soil moisture (Field), the original remotely sensed soil moisture (MRS), and the downscaled soil moisture by the LST/VI triangle-based method (Triangle), the Merlin method (Merlin), the UCLA method (UCLA), and the PKU method (PKU).

Fig. 7. The spatial patterns of the spatially disaggregated soil moisture by the four methods over the monthly periods. The subplots in the columns (a), (b), (c), and (d) are the spatially disaggregated soil moisture by the LST/VI triangle-based method, the Merlin method, the UCLA method, and the PKU method, respectively.