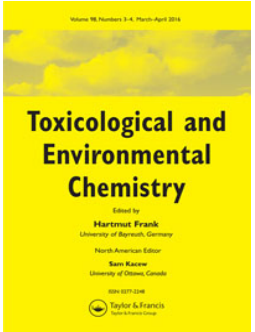

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Assessing the effect of scaling methods on retrieval of soil moisture based on MODIS images in arid regions

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ABSTRACT

Knowledge of spatial distributions of soil moisture, particularly at large spatial scales, is critical for many practical reasons. Unlike point-scale measurements, remote sensing provides an efficient way to estimate soil moisture over large areas. By resampling MODIS images with different scaling techniques, the impacts of those scaling methods on accuracy of soil moisture retrieval from MODIS data was first investigated using *in situ* soil moisture measurements. A soil moisture retrieval model was then constructed to obtain and analyse the spatial pattern of soil moisture in the Xinjiang Uygur Autonomous region of China in 2007. The following results were obtained. (1) With the process of spatial scale increases, the value of goodness-of-fit of the model change is relatively large, showing a strong randomness. (2) With resampling scales for 2 and 4 km when compared with measured data, correlation coefficient showed apparent fluctuation. With increased scale sampling, random changes in the model appeared to fluctuate less. Comparison of six different scaling methods, the results indicated that soil moisture retrieval model showed better correlation and higher accuracy of fitting under the scaling method of 2 km, respectively, followed by 1 and 16 km. (3) In order to test the accuracy of the retrieval model, the distribution of soil moisture was analysed by using of satellite image of the study area and retrieval of *in situ* soil moisture data, the data demonstrated high consistency with fieldwork. Evidence thus indicates that 2 km $\times$ 2 km is a significant level for retrieval distribution of soil moisture in the study area. The results also provide some reference for land-use planning and policy-making of sustainable utilisation of land resources.

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Soil moisture; MODIS; scaling; spatial distribution; remote sensing retrieval

Introduction

Soil moisture is a key state variable for understanding large-scale climate patterns and land surface–atmosphere interactions (Seneviratne et al. 2010). However, there is a

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significant mismatch in spatial scales between point measurements of soil moisture and large-scale hydrometeorological processes. In addition, for operational purposes such as drought monitoring, information on soil moisture at large spatial scales is necessary. Owing to limited practical conditions, soil moisture data captured by traditional methods just represents point data. Hence these data lack spatial continuity. It is difficult to collect spatial-temporal information on a large geographical scale, which cannot satisfy the necessity of operational monitoring. In recent years, the retrieval of quantitative remote sensing offered an important way to assess soil moisture on a large geographical scale (Kuang et al. 2008). Remote sensing technology has been found to play an important role for soil moisture monitoring, but there are two problems that need to be considered: (1) there is not a suitable special soil moisture remote sensing retrieval model for arid and semi-arid areas; (2) the matching problems between measured data of soil moisture and different spatial resolution of the satellite remote sensing images. Therefore, it is necessary to construct a soil moisture assessment model to examine different scale remote sensing images affected by soil moisture retrieval.

The spatial variation of soil moisture is a complex process, which is affected by natural, social and economic factors (Chen, Verburg, and Xu 2000). In the field of soil moisture research, the scale of the study area is an important factor (Southworth, Munroe, and Nagendra 2004), because soil moisture presents varying characteristics in different geographical scale-scale (Holling 1996). Through the study of combined soil moisture and scale effect together, three problems still need to be solved: (1) how to transform spatial soil moisture data between different scales effectively (Marceau and Hay 1999); (2) which scale is the best scale to observe soil moisture changing (Meng and Wang 2005); (3) what are the difference soil moisture at varying geography scale (Zhang and Zhou 2012)?

Several investigators examined these issues (Chen and Verburg 2000; Deng and Zhan 2004; Zhang et al. 2006; Southworth, Munroe, and Nagendra 2004) where a grid scale sequence was constructed using an average polymerisation method. The raster data are an important mode for soil moisture data spatial analysis, simulation and application (Herrmann et al. 2015). However, in reality spatial data is continuous and heterogeneous. When the rasterisation of spatial soil moisture was processed selecting the proper polymerisation method according to data distribution characteristic was necessary. In this study, Xinjiang Uygur Autonomous region with a large spatial scales arid region was examined. The raster data with spatial distribution of soil moisture was transformed to different geographic scales, and corresponding soil moisture retrieval models were built by Multi-logistic regression method (Chen and Nuo 2014). The objective of the current investigation was to analyse the dependency rules between soil moisture and geographic scale and obtain better understanding of soil moisture dynamics in relation to different geographic scales.

Material and methods

Study area

The study area was located between 73°40′∼96°23′E and 34°25′∼49°10′N, on both sides of the Tarim River and the edge of the Gurbantunggut Desert in Xinjiang Uygur Autonomous region of China in July 2007 (Figure 1). This area is one of the farthest away from the sea. The northern Xinjiang belongs to the temperate continental arid climate zone,

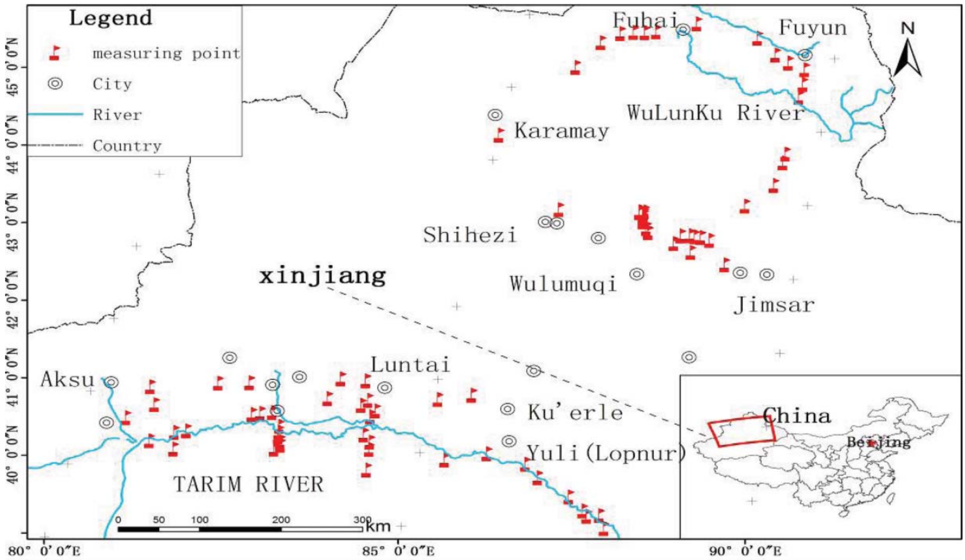

Figure 1. The distribution map of land synchronisation measuring point.

while the southern Xinjiang belongs to the warm temperate continental arid climate zone. The study area which belongs to the classical continental arid climate is located with mountains on the eastern, southern and northern sides, and temperature changes drastically. In recent years, desertification which was produced by unreasonable land utilisation constituted a serious issue. Measuring of the soil moisture began in July 2007, and lasted approximately one month.

Experiment design

MODIS product

Terra (EOS AM-1) is a multi-national NASA scientific research satellite in a Sun-synchronous orbit around the Earth (Tollinge-Rová, Pavelka, and Technicke 2008). It is the flagship of the Earth Observing System (EOS). The MODIS (Moderate-Resolution Imaging Spectroradiometer) dataset was selected as the satellite image data source. MODIS, which was installed on Terra, was one of the most important spectroradiometers, and data has been broadcasted to the whole world directly for free. There are 36 optical channels which range from 0.4 to 14 μm. The resolutions of MODIS images are 250 m, 500 m and 1000 m, respectively, and its scanning width is 2330 km. The satellites transit the sky of the study area at 0:30 p.m. and 12:30 a.m. (Beijing time) respectively. In this study, image dataset (MODIS 1B) at 12:30 a.m. was chosen to reduce the effect of clouds. MODIS 1B datasets were received by the National Meteorological Satellite Centre. The MODIS 1B dataset with 1 km resolution was 16 bit data, and geographical calibration preprocessing was completed prior to those satellite images being used. The seventh band data of MODIS was selected for soil moisture retrieval (Huo et al. 2010), and resolution was 1 km.

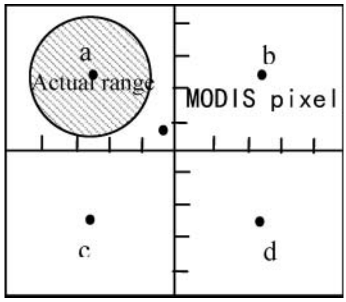

Figure 2. Actual range in one pixel.

Soil moisture collection

Figure 1 shows the locations of the observation areas in the study area. In each observation area, there were 21 measure points which are shown in Figures 2 and 3. Figure 2 demonstrates the situation with all 21 measure points in one MODIS pixel region, and Figure 3 illustrates the situation with all 21 measure points in different MODIS pixel regions. It is reasonable to assume that all measure points are in one pixel region. To achieve this effect, the actual measurement processes are as follows: (1) according to the time of the satellite going through the sky above the study area, the measure actions were also arranged from 10:30 a.m. to 16:00 p.m.; (2) the observation area needs to be selected at least more than 1 km^2 with uniform land cover, and the central point coordinate of the observation areas may be found in the MODIS images, furthermore, the global positioning system (GPS) technology might help to make the actual measure region in one MODIS image pixel; (3) the four 100 m long measuring ropes were used to indicate the direction of the east, west, south and north directions from the observation area central point (each soil sample along the measure lines was extracted from the soil at 20 m intervals from the central point with a 10-20 cm depth under the ground surface, then, the oven drying method was used to calculate the measure of the actual soil moisture, i.e. soil samples were baked to a dry state with a constant temperature of 100 to 105 °C, and moisture contents were achieved by comparison between weight of soil samples before and after drying); 4) the mean value of the 21 measured points (including the central point of the survey area) data represents the actual soil moisture value of the surface of the corresponding pixel in the MODIS images. As the surface soil moisture, which was retrieved

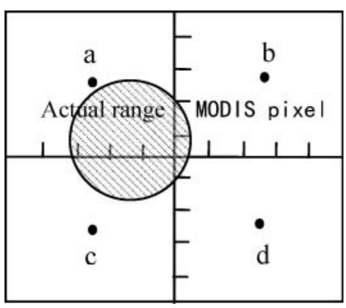

Figure 3 . Actual range in several pixels.

by satellite remote sensing images, is a comprehensive value, therefore it is reasonable to presume that the mean measured soil moisture value represents the actual soil moisture value in one pixel of the MODIS images.

The limitation factors which may lead to observation error were clouds, wind speed, plants, observation time and scale of the observation area. When one selects the observation area, it is worthwhile noting that the larger areas (more than 1 km^2) with uniform plant cover with no clouds and no wind (Huo et al. 2008) were preferred.

Methodology

The most popular method for scale transformation is K-nearest Neighbour (KNN) classification algorithm. This method was developed from a theoretical background, and is one of the simplest for machine learning. The KNN algorithm may be depicted as follows: (1) sample A belonging to a feature space; (2) there are several k nearest neighbour samples. If most of these k samples belong to the same classification, then sample A also belongs to the same classification. In KNN, the unknown-sample's classification depends on its neighbor's classification. Hence, KNN is suitable to sample classification, which is located at the intersection or overlaps the region.

The remote sensing image resampled by the ENVI software was the first step (shown in Figure 4); the images were then transformed to different scales by KNN. The beginning scale was 1 km × 1 km; the terminal scale was 32 km × 32 km; interval scales were 1 km, 2 km, 4 km, 8 km, and 16 km, respectively. The dependency of soil moisture and scale was analysed by DPS software (Tang and Feng 2007). Finally, the relationship between different scale transformation methods was analysed and the soil moisture retrieval model was built in the study area.

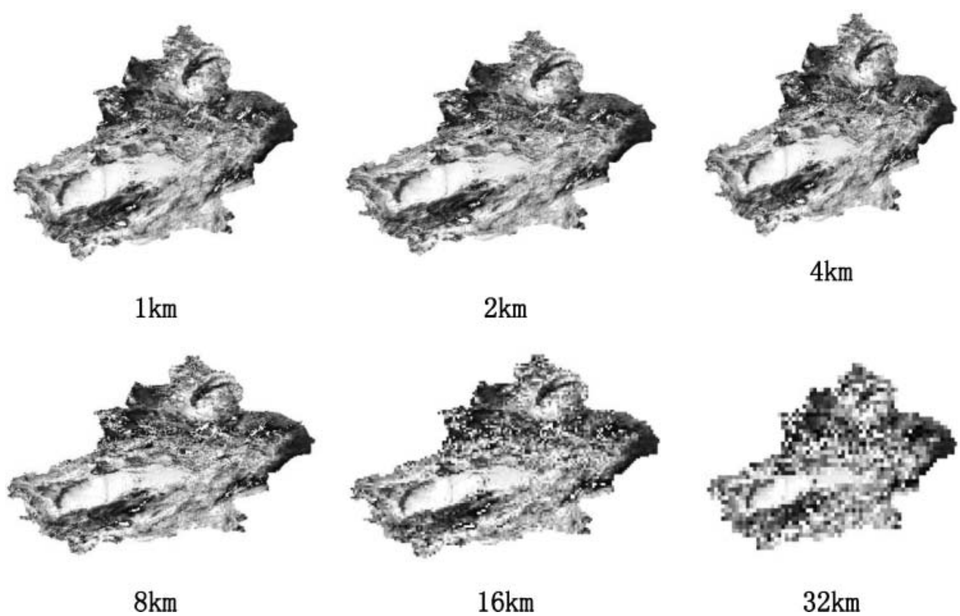

Figure 4. Different scale remote sensing image sampling.

Table 1. Correlation analysis results.

R	Measured values	1 km	2 km	4 km	8 km	16 km
Measured values	1					
1 km	−0.28	1				
2 km	−0.68	0.19	1			
4 km	−0.48	0.07	0.67	1		
8 km	−0.15	−0.18	0.27	0.30	1	
16 km	−0.28	−0.09	0.37	0.39	0.49	1
32 km	−0.14	−0.16	0.22	0.38	0.28	0.43

Results

Table 1 shows data at different scales in the study area in July 2007. With changes of grid size, correlation between the field measure and retrieval values with different scale remote sensing images displayed different trends. In general, the relationship between field measure and retrieval values with different scales showed negative correlation; the absolute value of correlation was highest at 2 km (−0.68) scale, the smallest value present at 32 km (0.14).

These results may be attributed to the following: the influencing factors of soil moisture in different spatial and temporal scales are variable, resulting in temporal and spatial variability of the soil moisture exerting significant changes with size scales (Blöschl and Sivapalan 1995; Entekhabi and Eagleson 1989; Shu, Liu, and Si 2008; Metselaar and De Jong van Lier 2011). Entin et al (2000) suggested that the size scales of temporal and spatial variability of the soil moisture may be divided into two components: (1) large-scale was controlled by the climate changes which was mainly determined by the pattern of rainfall and evaporation; and (2) small-scale was predominantly related to the structure of soil, topography, vegetation and roots. The spatial correlation scale of about 500 km was found by large-scale studies. The investigations in the Idaho Grassland showed that as spatial scale (range) increases, the spatial variability of soil moisture in the random component of the measurement error decreases, and the climatic factors which controlled by the soil type and elevation rises (Seyfried 1998; Zhang et al. 2015). For the earlier reasons, the scales approximately 2 and 4 km displayed a relatively high level of correlation. The scale about 1 km showed a small correlation, the reason may be due to the relatively large differences in terrain factors; and scales above 8 km may be attributed to measured area not represented by actual representation scales.

The observation scale depends on technology development, and actual demand in ideal conditions. The observation scale, and analogue scale and process scale need to be similar. Because of observation technology and analogue level limitation, in the actual situation results are different. Hence the best correlation and most suitable scale need to be selected to diminish this limitation. A principle and law of observation at one scale may be useful or similar at another scale, because sometimes it needs to be amended. The observation and simulation of the process are always carried out in laboratories or on a small scale in a short time; however these results were usually utilised to simulate the situation at large scale in long time series which is not reflective of realistic conditions. Large scale information or models need to be applied on small scale areas to verify data are accurate. Although, the result of resampling remote sensing image is different at different scales, the retrieval direction is the same. According to the analysis results, it might be noted that 2 km scale is the best observation scale in Xinjiang for resampling MODIS image, and the 1 and 4 km scale are second choice. These three scales' (1, 2, or 4 km) images are selected

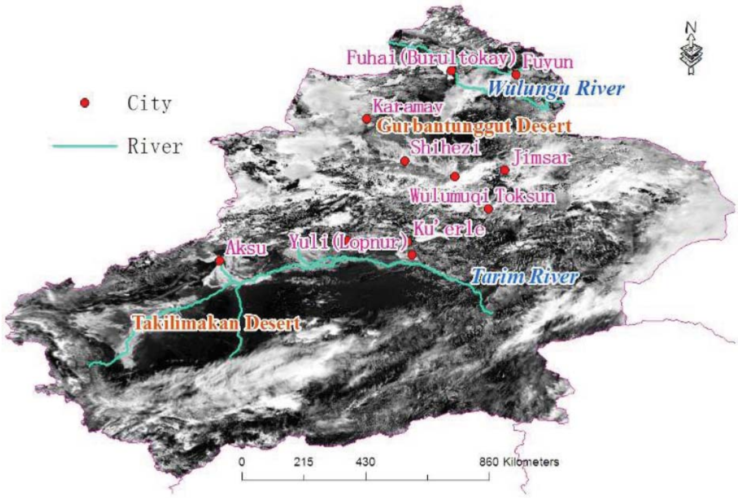

Figure 5. The spatial distribution of soil moisture.

to construct the multiple regression model by using DPS software (Tang and Zhang 2013). The formula is shown in the following:

$$M = 239.27 - 0.09b1 - 0.45b2 - 0.05b3 \tag{1}$$

where, M means the soil moisture of the model, $b1$, $b2$, and $b3$ are the resampled images at 1, 2, and 4 km scales, respectively. For examination, Equation (1) was used in Xinjiang province, the retrieval results are shown in Figure 5. The colour from light to dark displays soil moisture value from high to low.

At 2 km scale, the soil moisture spatial distribution resampled result correlates with reality; the lowest soil moisture area is the Takilimakan desert hinterland and Gurbantunggut desert. Takilimakan desert is located at the central Tarim basin. It is the biggest desert in China, and it is also one of the tenth biggest deserts globally. Its length is about 1000 km in an east-western direction; the width 400 km in a south-northwest direction; the area is 330,000 km^2. The average annual precipitation is lower than 100 mm; the lowest precipitation is 4–5 mm; while the average evaporation capacity is 2500–3400 mm. Gurbantunggut desert is located at the centre of the Junggar Basin, it is the second biggest desert in China. The area covers approximately 48,800 km^2. These two deserts have the lowest soil moisture values, which are shown as dark colour in Figure 5. Around these deserts, there are some cities, including Aksu, Karamay and Shihezi, which have high soil moisture values and shown in light colour in Figure 5.

In some areas, the retrieval result did not correspond with the practical situation. The reason would be that there was self-correlation between soil moisture and region spatial distribution, and it produced errors in scale transformation. This situation illustrates scale transformation plays an important role in retrieval processes.

Conclusions

The distributions of soil moisture were analysed by spatial scale transformation from MODIS image dataset in Xinjiang Uygur Autonomous region. The soil moisture retrieval models at different scales were then constructed by multivariate logistic regression. The following conclusions were determined.

1. Based on the MODIS 1B dataset, the relationship between retrieval values from the remote sensing image datasets and fieldwork measured values of soil moisture, were determined at six spatial scales from 1 km × 1 km to 32 km × 32 km, respectively. Data showed that there are apparent differences of soil moisture retrieval at different scales.
2. When the spatial scale increased, the correlation demonstrated a strong randomness in this processing. When the scale was 2 and 16 km, the values of R showed significant fluctuations. When the scale rose, the changes occurred less frequently. For the six scales, the 2 km scale is the most suitable scale for retrieval of soil moisture in the study area; 1 and 4 km the second best scales.
3. In order to test the accuracy of the retrieval model, the MODIS images were used to retrieve soil moisture in the study area. The retrieval results are consistent with fieldwork measured findings. In addition, the retrieval results might prove useful for local agricultural planning and land resource utilisation.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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