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A new continuous fusion method of remote sensing data

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Abstract. Remote sensing soil moisture is one of the important indexes for monitoring agricultural drought in large scale farmland area. The time series length and update speed of remote sensing data have been the important factors restricting their application. Because of the difference between the sensor and the inversion method, remote sensing data from different sources cannot be directly compared and analysed. Therefore, data fusion becomes a hotspot of research interest and key issue in the application of remote sensing data nowadays. Based on cumulative distribution matching principle, Lagrange interpolation can establish this correlation between any quantile on different cumulative probability distribution curves. Based on the above, a continuous fusion algorithm of multi-source remote sensing soil moisture is built in this study. Using this new fusion method, SMOS and CCI data are fused to real-time remote sensing soil moisture data product with long time series. The verification application result in Songnen plain indicates that this Lagrange interpolation continuous fusion method can improve the fusion accuracy of multi-source remote sensing soil moisture significantly. The low-value region of the cumulative probability distribution curve is the key data segment to characterize agricultural drought. According to this continuous fusion method, fused SMOS and CCI are almost completely coincident at each quantile in the low-value region of the curve. This remote sensing fusion data combining the advantages of CCI and SMOS provides reliable data support for the next study of agricultural drought evaluation.

1. Introduction

Remote sensing soil water is an effective means of rapid detection of large-scale agricultural drought change. However, these remote sensing data have different spatial and temporal resolution and time series length due to different platforms, sensors and inversion methods. Satellite data of the same surface feature released by different sources cannot compare the absolute value size directly. And the data by different satellite sources also cannot be used directly for continuous analysis. Data fusion of different sources can improve the data spatial/temporal resolution, extend the time series, remote sensing inversion accuracy. This method is the development direction of application research on remote sensing data at present. The concept of data fusion, was firstly born in the United States, is defined as the different sources of data to carry out the detection, correlation, analysis and combination of a multi-level all-round blend process [1]. Data fusion was first applied in military field. With the popularization and application of remote sensing technology, multi-source remote sensing data fusion has been applied in many fields. According to the purpose of fusion, fusion can be divided into: remote sensing image enhancement, improve the remote sensing image geometric correction precision, replace or remedy a defect/missing data [2], and improve the precision of remote sensing image classification, etc. The principle of remote sensing data fusion is the cumulative distribution function matching method (cumulative distribution fusion, the CDF). CDF method was first put forward by Calheiros in 1987 [3], is then used to correction radar, remote sensing observation precipitation data [4,5], etc. In remote sensing soil water fusion research, CDF matching method with linear regression algorithm is firstly used to the correction of SMMR remote sensing data of soil water by Reichle. This research reduced the data deviation, and the data after correction was been fused by land surface models furtherly [6]. In another study, a 29-years' time series satellite soil water data produced by different passive microwave data using the CDF method [7]. In 2010, this CDF method with linear regression algorithm also applied in the fusion from AMSR-E and ASCAT data to Noah simulation results, and good fusion results were obtained [8]. Lots of studies and researches show that using the cumulative distribution function of remote sensing data from different sources is one of the effective methods to improve the remote sensing data of soil water. The CDF method can improve the precision of remote sensing data of soil water by several remote sensing data from different sources or simulation model data. For remote sensing data, the change of the relative dynamic analysis is more important than the absolute value. This CDF matching method cannot change the relative changes of remote sensing data, also can adjust the data value range close to the true value as a whole [8]. To sum up, CDF is a useful principle method for data fusion. And the essence algorithm of CDF plays a decisive role in fusion precision.

Songnen plain as an important commercial grain production base in China has been significantly affected by drought in recent years. In this study, a new algorithm of data fusion has been put forward based on the CDF matching principle with SMOS and CCI remote sensing soil moisture data. And this new method has been applied and verified in the farmland scope of Songnen plain. The result of this research show that, this new method has improved the precision of the fusion of multi-source remote sensing data, so as to further enhance the practical application value of remote sensing of soil water.

2. SMOS and CCI data

SMOS satellite was launched in 2009 to monitor global soil moisture content and salinity of ocean waters. The L-band is insensitive to the surface roughness and vegetation cover, which is very suitable for extracting soil moisture data. The SMOS soil moisture data is obtained by radiative transfer model based on the L-band bright temperature data [9,10]. A large number of relevant studies have proved that SMOS soil water product has high accuracy in areas with high vegetation coverage [11], which is a significant advantage over other soil moisture products. The soil moisture data of SMOS used in this paper is obtained from the soil water data set of the L3 class of SMOS satellite from January 2010 to March 2016 published by BEC (http://www.smos-bec.icm.csic.es/smos_products), the expert centre in Barcelona, Spain. SMOS data is near-real time soil moisture product, which is significant in agricultural drought assessment.

The European Space agency launched the ESA-CCI (European Space agency, Climate Change Initiative) program in 2010, to generate the global soil moisture including passive, active and fused products. This project is to produce a set of the most complete and consistent global soil moisture data based on several active and passive microwave sensors. The time series of CCI was from 1979 to 2013, which provided the possibility for long-term dynamic analysis of global soil moisture [12].CCI data, as a set of multi-satellite integrated soil moisture data products with a long time series, has been widely concerned since its release and has been verified and applied in many regions of the world [13]. The latest version data of ESA CCI has been carried out in this research. This CCI data covers 35 years.

3. Data fusion method

3.1. *Principle of remote sensing data fusion*

The cumulative distribution function (CDF) is the sum of the probability that a random variable falls within a certain interval in the sample space, and is the integral of the probability density function. The formula is defined as the sum of the probability of all values less than or less than a:

$$F(a)=P(\mathrm{x} \le a) \tag{1}$$

where x is he random variable, F(a) is the cumulative probability.

In this study, the long-time serial CCI remote sensing soil moisture data is used as the benchmark data; real-time SMOS data need to be fused to the long time series of CCI data through the cumulative distribution function matching method. This method can make fusion remote sensing data has a long time sequence features and reflects nearly real-time conditions. After the CDF match, SMOS soil water and CCI soil water have a similar distribution curve. The fused SMOS soil water can be written as following:

$$cdf_c(x') = cdf_s(x) \tag{2}$$

where cdfc is the CDF of CCI soil water, cdfs is the CDF of SMOS soil water, x is the soil water of SMOS product, x' is the fused soil water of SMOS.

After establishing the relationship of the cumulative distribution curve of these two soil water data by some kind of algorithm, a set of real-time updated and long-term remote sensing soil water data can be synthesized.

3.2. Construction of Lagrange continuous fusion algorithm

In order to obtain the fused remote sensing data, this study analysed the cumulative probability distribution of SMOS and CCI data firstly. Then the method of fusion will established a relationship of two cumulative probability curve to complete the fusion of two kinds of data. The calculation error of fusion in the process of establishing the relationship between two curves is very important, which determines the data guarantee for the later application of remote sensing data. In this study, Lagrange continuous fusion algorithm has been proposed to establish the relationship between SMOS and CCI cumulative probability distribution curves. Through the verification, this algorithm reduced the calculation error. Based on the CDF fusion principle, this study put forward this new Lagrange equidistant interpolation continuous fusion method to fuse the CCI and SMOS remote sensing data. In this method, Lagrange equidistant interpolation algorithm is the key.

Functions are used to represent some internal relations or laws in practical problems. Many functions need to be understood through experiments and observations. As a physical variable in the process of practice in the different places, a polynomial can be obtained by Lagrange interpolation method using a number of observations, which can make the corresponding observations at various points. This polynomial is called Lagrange interpolation polynomial. Lagrange interpolation formula is as following:

$$L(x) = \sum_{j=0}^{k} y_j \ell_j(x) \tag{3}$$

where, lj(x) is Lagrange's basic polynomial (also called interpolation basis function), and its formula is as following:

$$\ell_j(x) = \prod_{i=0, i\neq j}^{k} \frac{x - x_i}{x_j - x_i} = \frac{(x - x_0)}{(x_j - x_0)} \cdots \frac{(x - x_{j-1})}{(x_j - x_{j-1})} \frac{(x - x_{j+1})}{(x_j - x_{j+1})} \cdots \frac{(x - x_k)}{(x_j - x_k)} \tag{4}$$

Through Lagrange interpolation, each SMOS data has a corresponding CCI value, and the CCI value obtained by this method interpolation has a small deviation on the cumulative probability curve. As shown in figure 1, the red is the original SMOS cumulative distribution curve, through this Lagrange interpolation continuous fusion method, merged SMOS (labelled as SMOS’ in figure 1) in blue can be obtained. The cumulative distribution curve of blue merged SMOS and green CCI cumulative distribution curve was almost completely overlapped. There is still a closely conformability especially in the low value region revealing the drought characterization.

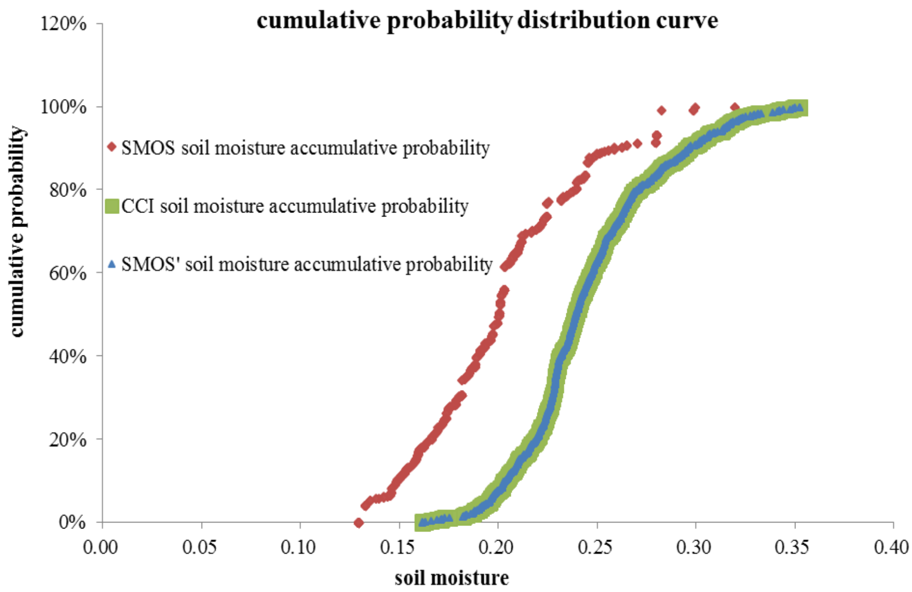


Figure 1. Schematic diagram of Lagrange continuous fusion between SMOS and CCI soil moisture.

4. Results analysis

4.1. Cumulative probability distribution of fusion data

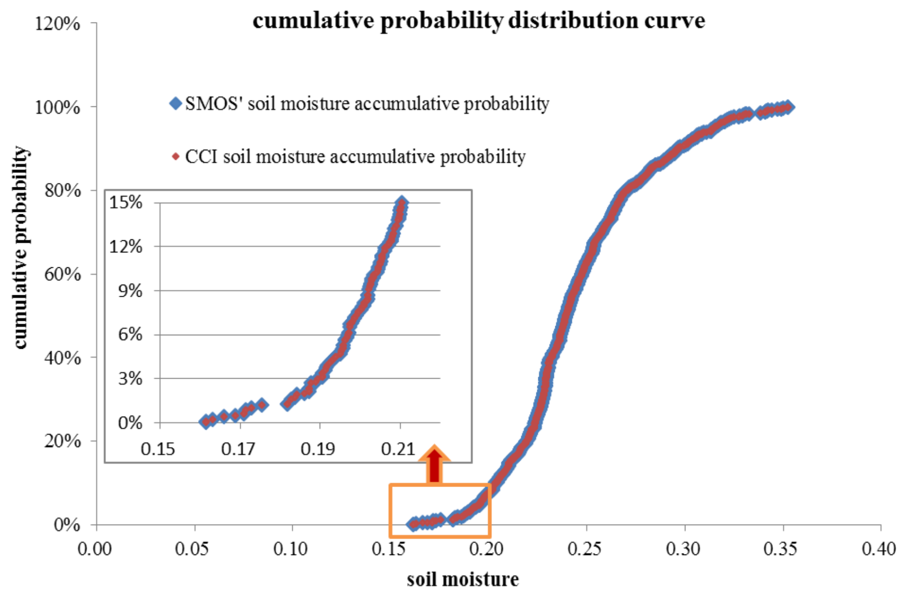


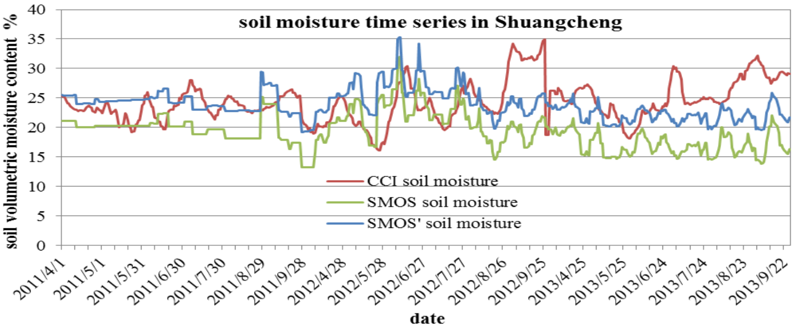
Figure 2. Cumulative probability distribution of CCI and fusion SMOS by Lagrange continuous fusion method in Shuangcheng.

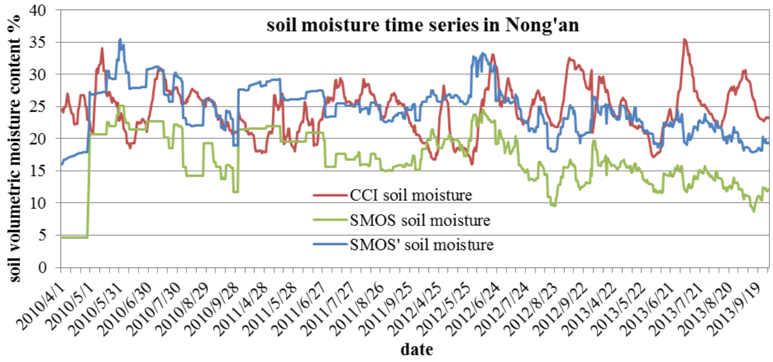
Taking the fusion calculation of SMOS and CCI grids in the farmland area of Shuangcheng as an example, the accumulation probability distribution curve relationship between SMOS and CCI data after the integration of the Lagrange interpolation was established respectively as shown in figure 2. Through fusion, the cumulative probability distribution curve of fused SMOS (labelled as SMOS' in figure 2) and CCI overlap almost completely. There is still a closely conformability especially in the low value region revealing the drought characterization. The fusion effect in other counties is consistent with that of Shuangcheng fusion effect. The new fusion method using the Lagrange interpolation algorithm for remote sensing soil moisture data comes from different sources can improve the fusion accuracy and improve the application of remote sensing data. This study produced a remote sensing soil moisture data product with long time sequence and real-time updated feature by using this new method in the study area.

4.2. Analysis of Fusion data time series

The comparison of time series of remote sensing soil moisture before and after fusion can directly show the change of scope of remote sensing data by fusion algorithm. The time series comparisons between SMOS and CCI before and after the fusion of some counties in the study area are presented in figure 3.

Through the fusion, SMOS (labelled as SMOS' in figure 3) is closer to CCI data distribution, and retains the relative change pattern of original data. In figure 3, the value of the SMOS data time series before fusion is generally less than the CCI data value, and the individual date SMOS value is higher than the CCI value. After the fusion, the soil water content of SMOS data increased as a whole, and significantly in the months with low soil water content. The fused SMOS data preserves the changing characteristics of the original data time series, and the data value range is adjusted to a certain extent, which makes the data more similar to CCI data range. As shown in figure 3, the SMOS data range in Shuangcheng changed from 13% - 30% before the match to 19 - 35%. SMOS data range in Nongan changed from 5% - 25% before the match to 16 - 35%. SMOS data in Fuyu changed from 10 - 29% before match to 16-27%. SMOS data in Lishu changed from 6 - 23% before match to 15 - 28 percent. The soil moisture data were improved as a whole, and the change of individual time points was not obvious.





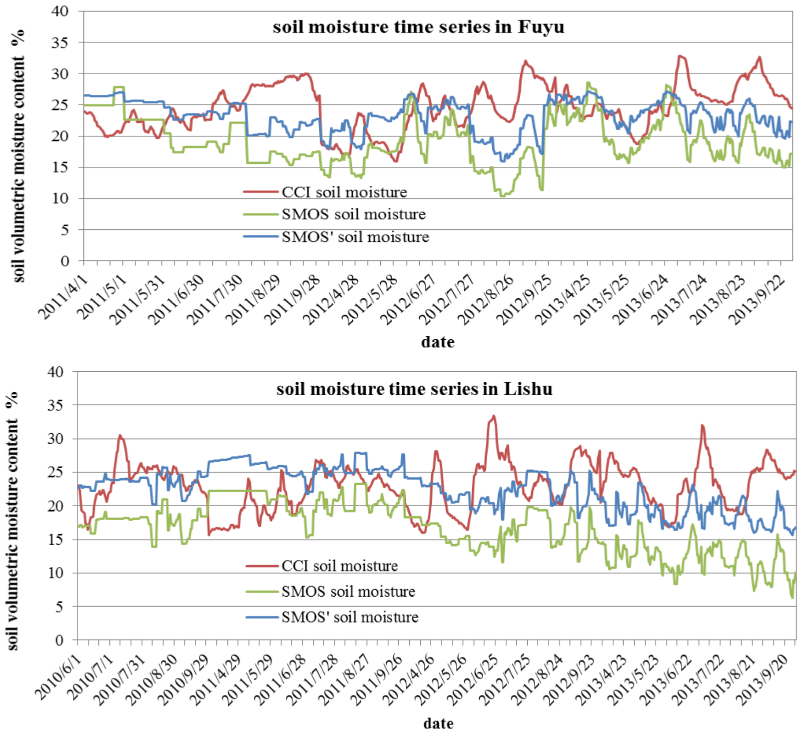


Figure 3. Soil moisture time series of fusion SMOS.

5. Discussion

The point of application of remote sensing soil water data in agricultural drought is mainly reflected in the validity and accuracy of remote sensing data when the soil water is low (impending or emerging drought). Remote sensing data fusion is the important means to improve the performance of application of remote sensing data, the fusion precision of remote sensing data has significant effects play a practical application. Research on fusion algorithm is the key problems of the application of remote sensing.

Based on the fusion principle of CDF, this study constructed a continuous fusion algorithm and conducted an analysis of soil water data fusion of SMOS and CCI remote sensing at county level in Songnen plain. This Lagrange continuous fusion algorithm proposed in this paper improved the fusion precision of multi-source remote sensing data. Through time series analysis of data before and after the fusion, SMOS data range is closer to CCI data range after the fusion, and the relative change mode of original data is retained. By applying the fusion algorithm, a set of CCI-SMOS remote sensing soil water fusion data product in county level was generated in Songnen plain area. The system deviation of fused remote sensing soil water is reduced, at the same time, the fusion data have the advantage of long time sequence and near real-time features. The results of this study can provide data support for further real-time evaluation and frequency analysis of large-scale agricultural drought in the region scale.

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