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Accuracy evaluation of the CCI remote sensing soil moisture for revealing drought in Northeast China

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Abstract. The validation research is the basis of application of remote sensing data. This study using soil surface measured data for 10 cm in Northeast China in 1992-2013 to verify the European space agency soil moisture data set (ESA CCI SM). In this study, two methods evaluating CCI data for revealing drought was used: common Pearson coefficient method and drought judgement method for coincidence degree of drought. This verification study is located in the main grain producing areas of Northeast China, which is dominated by rain-fed agriculture. After the result analysis, CCI remote sensing soil moisture is feasible for assessment research on agricultural drought. Through the evaluation of this study, this remote sensing soil water can be used as an effective indicator of agricultural drought in the main grain-producing region of Northeast China.

1. Introduction

The climate drought has a significant impact on food production. Drought affects crop growth to a certain extent, especially in large areas of rain-fed agriculture. Therefore, drought monitoring on large scale and timely manual intervention should be carried out during the critical period of crop growth in the food production base to ensure food production and food security. Because of the complexity of the drought, the traditional monitoring method is difficult to fully grasp the drought information completely. Satellite remote sensing technology overcame the scarcity of traditional monitoring sites, low level of automation and data processing technology, etc. This technology can get continuous surface information quickly and efficiently, and it has obvious advantage in space representation and sampling period. Remote sensing technology also can obtain the information of surface soil, vegetation, surface temperature and meteorological aspects, and monitor drought from different angles. Soil moisture, as a direct and timely indicator of drought monitoring, is the essence of agricultural drought. With the development of microwave remote sensing technology, the accuracy of remote sensing soil moisture has improved further. A variety of global remote sensing soil moisture data have been produced, and a series of study about remote sensing data accuracy have been carried out [1-2]. Among them, the research on the relationship between soil surface and deep water content is the theoretical basis for remote sensing of soil moisture to characterize the soil moisture change in deep roots and to carry out practical application.

According to the root depth study of various crops, 0~50cm is generally regarded as the depth of the root layer of crops [3]. Spring corn is main rain-fed crop in northeast China, followed by soybean. The root of spring corn distributes in less than 40 cm soil layer at seedling stage, will grow to 160 cm at flowering period, and right along grow to 180 cm at ripening period. However, the main root system that absorbed water in the whole reproductive stage always distribute in the soil layer of 0~40 cm deep [4]. The main root system of soybean is within 0~20cm underground depth [5]. Within a certain depth of soil, soil water content has good continuity and removable property, and is a typical regional variable. When there is little water content in the shallow layer, the deep soil water will supply shallow layer water content, so there is a certain correlation between the soil moisture content in the adjacent areas. Biswas and Dasgupta [6] firstly proposed a linear expression for estimating deep water based on surface soil moisture, which was widely used as an empirical formula for the relationship between soil moisture in different layers. Combined different land use and hydrological and meteorological conditions, Mahmood and Hubbard [7] revealed a certain correlation between surface and deep soil water in Nebraska area of the United States. Ragab [8] estimated deep soil moisture using remote sensing surface soil water based on the relationship between the soil water of surface layer and each layer within 50cm. In the study about the relationship between different depth data of 31 soil moisture observation sites of different land use types in China, results show that the surface soil moisture and soil moisture in 0~100 cm soil deep has good correlation, and this correlation has a certain reduce with the increase of depth [3]. Estimating deep soil water content by surface remote sensing of soil water directly may lead to error. For remote sensing data analysis, the analysis of relative dynamic change is more important than the absolute value change [1]. The long time series of remote sensing of soil water can reflect the change of soil water in the deep roots to some extent. With the studies on relationship between soil moisture at different soil depth, remote sensing soil water has gradually become an effective means for large-scale agricultural drought monitoring research.

The key to the application of remote sensing soil moisture in agricultural drought assessment is the correlation between remote sensing soil water and measured soil moisture during the process of soil water reduction, that is, the accuracy of revealing drought. Because of the inconsistency between measuring methods and measuring depth, it is a great challenge to evaluate the remote sensing data by using the field measured data. The scarcity of measuring site in China adds the difficulty in evaluation.

First of all, the measured soil water is expressed by field capacity in China which is different from the international remote sensing data. The conversion between these two kinds expression is related to regional soil texture (density, porosity, etc.) information. Secondly, remote sensing data is the average moisture in a certain thickness of soil surface, but the measured data by using sensor probe in China represent the moisture of current certain depth soil. Thirdly, remote sensing data is the instantaneous data at a certain time, which is not consistent with the continuous monitoring data of the actual measurement. Fourthly, remote sensing data in each grid reflects different meteorological conditions, land cover, soil types, and the soil moisture conditions, terrain conditions. The sparse monitoring site data cannot represent a grid within the scope of the overall situation [9]. In order to assess the expressing ability of CCI, this study introduced four quantitative evaluation indexes to reflect the judgment accuracy of the drought. This method can directly analyse the times of drought events by CCI and measured data instead of the absolute value comparison. This research has important theoretical and application value on remote sensing evaluation of drought.

As one of the three black earth regions in the world, Northeast China is an important commodity grain production base and a large granary for ensuring national food security. In the context of global climate change, Northeast China, as one of the most sensitive regions to global warming, will continue to show a trend of warming and drying, especially in summer. The rain and heat resource allocation in Northeast China is accordance with crop growth cycle. Therefore, rain-fed agriculture is the main planting pattern in there. In Northeast China, with the backwardness of agricultural infrastructure, crops growth is dependent on natural precipitation. In recent years, agricultural drought occurred frequently, which have greatly affected the agricultural production. Due to wide distribution of farmland, flat terrain, and small differences between soil types, the underlying surface condition is relatively simple. Northeast China has favorable conditions to carry out agricultural drought remote sensing evaluation. In this study, accuracy evaluation of CCI remote sensing soil moisture for revealing agricultural drought was carried out in Northeast China.

2. Data and pre-treatment

In this study, the accuracy of CCI remote sensing soil moisture revealing drought was evaluated in 39 counties and 6 municipal districts in the west of Northeast China where is urgently needed for agricultural drought monitoring for frequent drought disasters in recent years. In there, spring corn is the main crop, and its planting proportion increase continuously. There are 8 monitoring sites called Keshan, Fuyu, Helen, Tailai, Anda, Qianguo, Harbin and Changling. The distribution of the study area and monitoring site is shown in Figure 1.

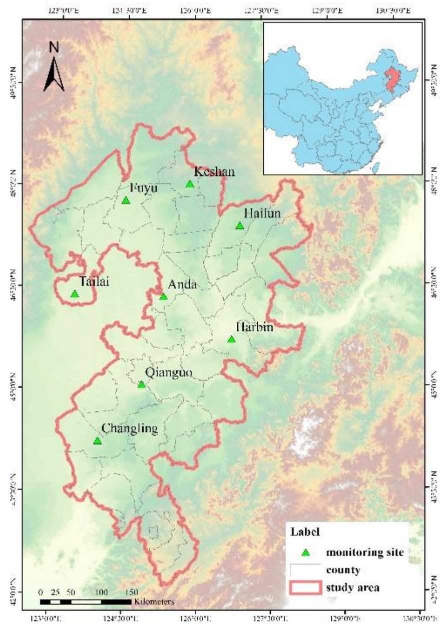

Figure 1. Study area and monitoring site distribution map.

2.1. *CCI remote sensing data*

CCI remote sensing soil moisture data is a set of global soil moisture data products based on active and passive microwave sensors including SMMR, SSM/I, TMI, AMSR-E, Windsat, AMSR2, ERS-1/2 etc.. This combination of C-band scatterometer and multi-frequency radiometer data makes the product highly suitable for soil moisture inversion and long-term technical inheritance. As a set of soil moisture data products with a long time series, CCI data has been widely concerned since its release and has been verified and applied in many regions of the world [10-12].These studies indicated that CCI data are in good agreement with measured data from sites in many regions of the world, and can accurately represent soil moisture and its spatial and temporal changes. In this study, daily CCI data covers 1979-2013 in the latest version (v02.2) was used, and its spatial resolution is 0.25.

The original CCI data is in NetCDF format. After downloading, the data is stored in ASCII format with one scene per day. Due to the scarce site in study area and the offset of remote sensing data itself, the average of several remote sensing grid data nearby the site was be compared with the site monitoring data in this study. Considering the cumulative effect of soil water content, CCI soil moisture is treated to the average for 10 days.

2.2. *Measured data*

This study chooses relative soil moisture every ten days in 10 centimeters (most shallow) issued by the China meteorological data network, to evaluate soil moisture data of CCI. It is from 1992 2013 with 8 stations of measurement. The measured data were converted into the same volume water content as the remote sensing soil water firstly.

3. Evaluation methods

3.1. Pearson coefficient method

Pearson correlation coefficient is a common correlation analysis method, which can be used to describe linear correlation between two different random variables. In the correlation analysis, the correlation between the two variables can be intuitively shown by coefficient value and scatter diagram.

Pearson correlation coefficient analyses the correlation between the two, and the formula is as following:

$$\rho_{XY} = \frac{Cov\left(X, Y\right)}{\sqrt{Var(X)Var(Y)}} \tag{1}$$

where, Var represents the variance of variables, and Cov represents the covariance of variables. The domain value of the correlation coefficient is [-1, 1], where 1 indicates the complete positive correlation between X and Y, -1 indicates the complete negative correlation, 0 indicates the independence, and the greater the absolute value indicates the stronger the correlation. The correlation coefficient is also usually represented by the symbol R [13].

3.2. Drought judgement method

The purpose of this research is to assess the accuracy of CCI remote sensing data in revealing agricultural drought. This study introduced four quantitative evaluation indexes: Hit ratio, False alarm rate, Equitable Threat Score and deviation coefficient Bias to reflect the judgment accuracy of the drought. Among them, Equitable Threat Score (ETS) is used to test the coincidence degree between remote sensing soil moisture data and measured data [14].The higher the ETS value, the higher the Hit rate, the lower the False alarm rate, indicating the closer between the remote sensing data and the truth. Deviation coefficient Bias, namely, the ratio of number of drought judged by remote sensing soil moisture and by the measured soil moisture data. When the Bias value is greater than 1, this value represents the drought event number remote sensing overestimated. When the Bias value is less than 1, this value represent the drought event number remote sensing underestimated. The comprehensive result of ETS and Bias can evaluate the accuracy of remote sensing soil moisture revealing drought.

These four indexes are calculated by a, b, c and d. The drought event number detected both by the remote sensing data and measured data is a. The drought event number detected only by the remote sensing data is b. The drought event number detected only by the measured data is c. The drought event number neither detected by the remote sensing data nor detected by the measured data is d.

The calculation formula of hit ratio H is:

$$H = \frac{a}{a + b} \tag{2}$$

where, the value range of H is 0~ 1, 1 is the best.

The calculation formula of false alarm rate F is:

$$F = \frac{b}{b + d} \tag{3}$$

where, F value range 0~ 1, 0 is the best.

The calculation formula of Equitable Threat Score is:

$$ETS = \frac{a - a_{ref}}{a - a_{ref} + b + c} \tag{4}$$

where, ETS value range -1/3~1, 1 is the best. The a_{ref} is calculated as:

$$a_{ref} = \frac{(a + b)(a + c)}{(a + b + c + d)} \tag{5}$$

The calculation formula of deviation coefficient Bias is:

$$Bias = \frac{a + b}{a + c} \tag{6}$$

where, the value range of Bias is 0~ infinity, and 1 is the best [15].

4. Results analysis

For correlation analysis, both remote sensing and measured data were selected from May to September covering 1992 to 2013.

4.1. Pearson correlation analysis of CCI and measured data

The following Table 1 shows the Pearson correlation of 8 monitoring sites and remote sensing data. Pearson correlation coefficients in Keshan, Tailai, Harbin and Changling exceeded 0.5. Pearson correlation coefficients in Fuyu exceeded 0.4. The Pearson correlation between remote sensing and measured data of Hailun, Anda and Qianguo site was poor. Considering the remote sensing feature and the different mechanism, Pearson correlation of absolute value comparison cannot fully express the application performance of remote sensing data in agricultural drought. Therefore, this study proposed another new assess method to evaluate the accuracy of the CCI remote sensing soil moisture for revealing drought.

Table 1. Pearson correlation coefficient between monitoring site data and remote sensing data.

County	ρ_{xy}
Fuyu	0.428
Keshan	0.517
Hailun	0.268
Tailai	0.581
Anda	0.379
Harbin	0.531
Changling	0.476
Qianguo	0.364

4.2. Analysis of drought coincidence degree between CCI and measured data

Hit ratio H, false alarm rate F, Equitable Threat Score (ETS) and deviation coefficient Bias may express drought coincidence degree between CCI and measured data quantitatively. The comparison of 8 sites in the study area was calculated as shown in the Table 2. The H value of Keshan, Fuyu, Tailai, Anda, Qianguo, Harbin and Changling are all more than 0.4, which indicates that the CCI has a high hit rate in judging drought events. Among of these, H of Keshan is more than 0.6. The false alarm rate of all 8 sites was lower than 0.18. It indicates that the false alarm rate of CCI on agricultural drought events is low. The deviation coefficient Bias of all 8 stations remained between 1 and 1.16, indicating that remote sensing data had few overestimations of drought events. The comprehensive ETS value of seven sites is more than 0.1.Based on literature summary and analysis [14], these seven

Equitable Threat Scores indicate that CCI data in most areas can revealing most drought events. The drought expressing ability of the CCI was poor in Hailun city, which was consistent with Pearson result. The reason why the CCI data in Hailun city has more error in revealing drought remains to be further analyzed. Generally, it is concluded that CCI remote sensing soil moisture can revealing drought event in this study area. This method remedied the defect of Pearson absolute value comparison in terms of performance expression.

Table 2. The drought coincidence degree between CCI remote sensing data and measured data.

County	H	F	ETS	BIAS
Fuyu	0.51	0.22	0.17	1.1
Keshan	0.62	0.19	0.26	1.16
Hailun	0.36	0.28	0.04	1.01
Tailai	0.58	0.18	0.25	1
Anda	0.54	0.2	0.2	1.05
Harbin	0.47	0.23	0.13	1.07
Changling	0.43	0.24	0.1	1
Qianguo	0.46	0.23	0.13	1.05

5. Conclusion and discussion

Assessment of remote sensing data based on site measured data is challenging. The scarce monitoring sites in Northeast China are one reason of poor management for agricultural drought. Considering the characteristics of large area, simple land use, flat and open topography, the Northeast China is a favorable area to apply remote sensing data. Based on this, absolute and relative method is proposed in this study to evaluate the accuracy of CCI remote sensing data in revealing drought. Pearson correlation coefficient assessed the accuracy of CCI in absolute value. Four quantitative indexes evaluate the remote sensing data by drought events in relative mode. In Pearson absolute comparison, the correlation coefficient of CCI and monitoring data exceed 0.5 only in three sites. However, the accuracy of CCI reveals drought event in seven sites. The drought events judgment by CCI data only has a small of overestimate. Drought judgment method is more suitable for the evaluation of remote sensing data applying in agricultural drought. Based on the above analysis, CCI data is feasible for research on agricultural drought assessment. The method put forward in this study has important value in remote sensing application assessment.

To evaluate the remote sensing data by site monitoring data, two points should be considered. Firstly, the correlation of soil water between surface and deep soil; Secondly, the representativeness of the measured site. For agricultural drought, its essence is the lack of soil moisture in root region. When the relationship between surface and deep soil moisture has obvious positive correlation, the surface water reduce can indirectly reflect the deep water situation and agricultural drought. The objective of this study is to evaluate the accuracy of remote sensing soil moisture in revealing agricultural drought. Drought judgment method proposed in this study is more suitable remote sensing application research. And this method may obtain better evaluation results when applied to the dense area of the site. CCI remote sensing soil moisture data has long time series, which has advantage in frequency analysis. Due to the slow update frequency of data, it is difficult to carry out real-time drought assessment analysis, which is an obstacle in CCI data application. The fusion study of different remote sensing data with different time series characteristics is a hot topic in the application research of remote sensing data in the future.

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