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RESEARCH ARTICLE

The Monitoring Analysis for the Drought in China by Using an Improved MPI Method

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Abstract

MPI (microwave polarization index) method can use different frequencies at vertical polarization to retrieve soil moisture from TMI (tropical microwave imager) data, which is mainly suitable for bare soil. This paper makes an improvement for MPI method which makes it suitable for surface covered by vegetation. The MPI by using single frequency at different polarizations is used to discriminate the bare soil and vegetation which overcomes the difficulty in previous algorithms by using optical remote sensing data, and then the revision is made according to the different land surface types. The validation by using ground measurement data indicates that revision for different land surface types can improve the retrieval accuracy. The average error is about 24.5% by using the ground truth data obtained from ground observation stations, and the retrieval error is about 13.7% after making a revision by using ground measurement data from local observation stations for different surface types. The improved MPI method and precipitation are used to analyze the drought in Southwest China, and the analysis indicates the soil moisture retrieved by improved MPI method can be used to monitor the drought.

Key words: drought, soil moisture, climate change, microwave remote sensing

INTRODUCTION

The surface soil moisture is an important bridge between land surface and atmosphere, which directly influences the exchange of energy. The soil moisture is also an important parameter to monitor drought in agriculture. It is very difficult to obtain the soil moisture by ground measurement in both time and space at large spatial scales, but microwave remote sensing from satellite can overcome these problems (Owe *et al*. 2001). The microwave radiometry has been proved to be one of the best methods to retrieve soil moisture during the last 25 yr. Microwave observations are sensitive to soil moisture through the effects of the moisture on the dielectric constant, and hence the emissivity of the soil (Wang and Schmugge 1980; Njoku *et al*. 2003). Wang (1985) and Njoku and Patel (1986) investigated the potential of the 6.6 and 10.65 GHz channels of the scanning multichannel microwave radiometer (SMMR) for soil moisture monitoring. These studies were followed by others (Choudhury and Golus 1988; Owe *et al*. 1988;

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Jackson and O'Neill 1990; Jackson and Schmugge 1991; Owe *et al*. 1992; Jackson 1993, 1997; Kerr and Njoku 1993; Griend and Owe 1994; Jackson and Hsu 2001; Bindlish 2002). Vegetation and surface roughness reduce the sensitivity of microwave observations of soil moisture and many studies indicated that vegetation and roughness effects become more pronounced at higher frequencies (Jackson *et al*. 1982; Wigneron *et al*. 2004). Although the method is relative mature for retrieving soil moisture in bare soil, the accuracy is not stable when soil is covered by vegetation, especially for thick forest. Many retrieval algorithms utilized optical remote sensing data (for example, MODIS data) as the priori knowledge of vegetation. The optical remote sensing is influenced by cloud and rainfall, which can not keep the synchronism with microwave remote sensing data (Mao *et al*. 2008).

It is more than 20 yr about study on the influence of vegetation for the observation of microwave remote sensing. Ulaby and Dobson (1983) used airborne microwave radiometer (1.4 and 5 GHz) to monitor the bare land, wheat and corn, and the analysis indicated that the vegetation is the main influence factor for monitoring soil moisture by using microwave remote sensing. Paloscia and Pampaloni (1984) used thermal radiation and microwave radiometer (Ka-band, 36 GHz) to study water stress of vegetation by defining microwave polarization index, and analysis showed that there is an exponential relationship between microwave polarization index and the index of water stress. Paloscia and Pampaloni (1985) used microwave radiometer (X and Ka-band) to monitor vegetation, and the analysis showed that the microwave polarization index is very sensitive for vegetation types, especially for water content in vegetation. Choudhury and Tucker (1987a, b) made a correlation analysis between microwave polarization index in 37 GHz and the normalized difference vegetation index (NDVI) of AVHRR, which showed that there is an exponent relationship between them, and microwave polarization index can be used to monitor the global vegetation. Paloscia and Pampaloni (1988) used microwave polarization index (10 and 36 GHz) to monitor the change of vegetation, which indicated that the polarization index becomes increasingly large with the vegetation growing. The theoretical model and experimental analysis showed that microwave index can be used to monitor crop biomass and water condition of vegetation (Paloscia and Pampaloni 1992). Many other people have done some similar work (Calvet *et al*. 1994; Felde 1998; Owe *et al*. 2001; Jeu and Owe 2003). Microwave polarization index has great potential in soil moisture and biological inversion (Mao *et al*. 2008). Passive microwave remote sensing can also be used to retrieve the ground temperature (Mao *et al*. 2007a, b), water content in vegetation, and other surface parameters.

In most soil moisture retrieval algorithms, the optical data (NDVI and leaf area index (LAI)) is usually made as a supplementary data which is used to describe the state of vegetation (Njoku *et al*. 2003). In fact, microwave polarization index can better reflect the distribution, biomass, and other related information of vegetation because of the penetration ability of microwave. This paper will make a derivation for microwave polarization index, and use the microwave polarization index to discriminate the vegetation for bare soil to make an improvement for MPI method for retrieving soil moisture, which will be used to monitor the drought in China.

RESULTS

Validation with ground truth data is also important for retrieval method in many applications. It is very difficult to obtain the *in situ* ground truth measurement of soil moisture matching the pixel scale (24 km×24 km at nadir) of AMSR-E data at the satellite pass for the validation of algorithm. Generally speaking, soil moisture varies from point to point on the ground, and ground measurement is generally point measurement. It is a problem to obtain the measured soil moisture matching the pixel of AMSR-E data. On the other hand, precisely locating the pixel of the measured ground in AMSR-E data is also a problem. Since there exist many difficulties in obtaining ground truth data, validation with the use of ground truth data is quite difficult. However, soil moisture experiments (2002-2005) were made (http://nsidc.org/data/amsr_validation/) by overcoming many of these difficulties and managing to get some data set to evaluate the AMSR-E soil moisture retrieval system. In order to improve the monitoring accuracy for soil moisture which is used for agriculture, the Min-

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istry of Agriculture in China built 200 ground observation stations to obtain the soil moisture and other parameters which were located the places covered with most of crops in China (Fig. 1). Most of these observation sites are large and flat in common which can present the local region.

In this study, we selected the measurement data in SMEX02 and some data obtained by observation stations in China to make some analysis for retrieval results. A program was made to read out the brightness temperature data from AMSR-E L2A data (2002/06/25-2002/07/13, 2009/05/01-2009/11/01) by setting the range (latitude and longitude) according to the range of experiment field. We retrieved soil moisture for these pixels. As shown from experiment data, there was some rainfall in some days and the weather is not very good. The retrieval result was not very well during rainfall day, and the main reason was that 18.7 GHz frequency was sensitivity for rain, so the data from clear days were selected. Some experiment sites were not matched with the single pixels very well because of the satellite scanning characteristics, so we just selected the best approximation in range and the average value of the experiment sites to make some analysis. The comparison results were like Fig. 2. The retrieval error of soil moisture is underestimated about 24.5% by our method. The main reason is that the influence of atmosphere for 18.7 GHz is more than for 10.7 GHz. On the other hand, the vegetation is also an important influence factor for accuracy because the influence is different for different vegetations, so we make some revisions according to the ground measurement data obtained from ground observation stations which showed in Fig. 1. After we make a revision by using ground measurement data from local observation stations for different surface types, the retrieval error is about 13.7%.

DISCUSSION

It experiences a long time drought in the southwest of China including Yunnan Province, Guangxi Zhuang Autonomous Region, Sichuan Province, and Chongqing City. The agricultural drought is the severest for Yunnan Province in the passed 100 yr. In order to provide an application example, we utilize the improved MPI algorithm to retrieve soil moisture from AMSR-E data in China. Fig. 3 is the part of soil moisture retrieval results from 2009-9-1 to 2010-4-1. The AMSR-E data is downloaded from the National Snow and Ice Data Center, China. Four or five AMSR-E images can cover the whole of China which are obtained on the same day. The soil moisture in Yunnan Province was relative low at all the time which was labeled by red circle in Fig. 3. The drought is not only determined by soil moisture, but also determined by the effective precipitation. The China National Meteorological Administration provides monthly precipitation totals (mm) about 700 observation sites in China. The distribution map is like Fig. 4 after making linear interpolation, which indicates that there is little effective precipitation in the southwest of China from September, 2009 to April, 2010. The soil moisture is relative low and effective precipitation is little for so long time, so the drought is very serious. Due to the cumulative effect, the retrieval re-

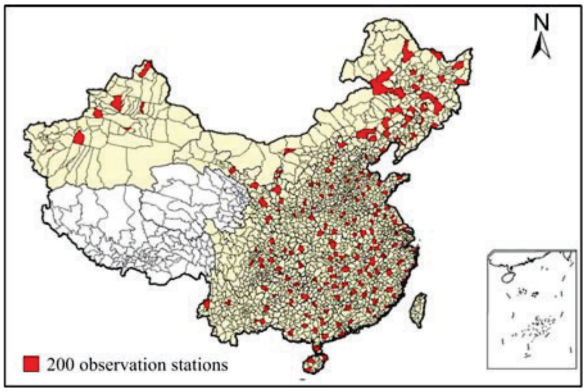

Fig. 1 The distribution of ground soil moisture observation stations in China.

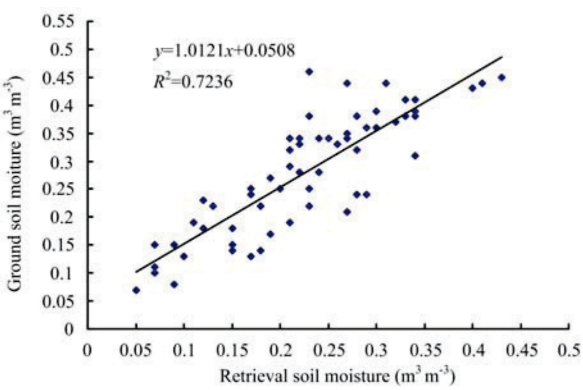

Fig. 2 Comparison between measured ground soil moisture and retrieval soil moisture.

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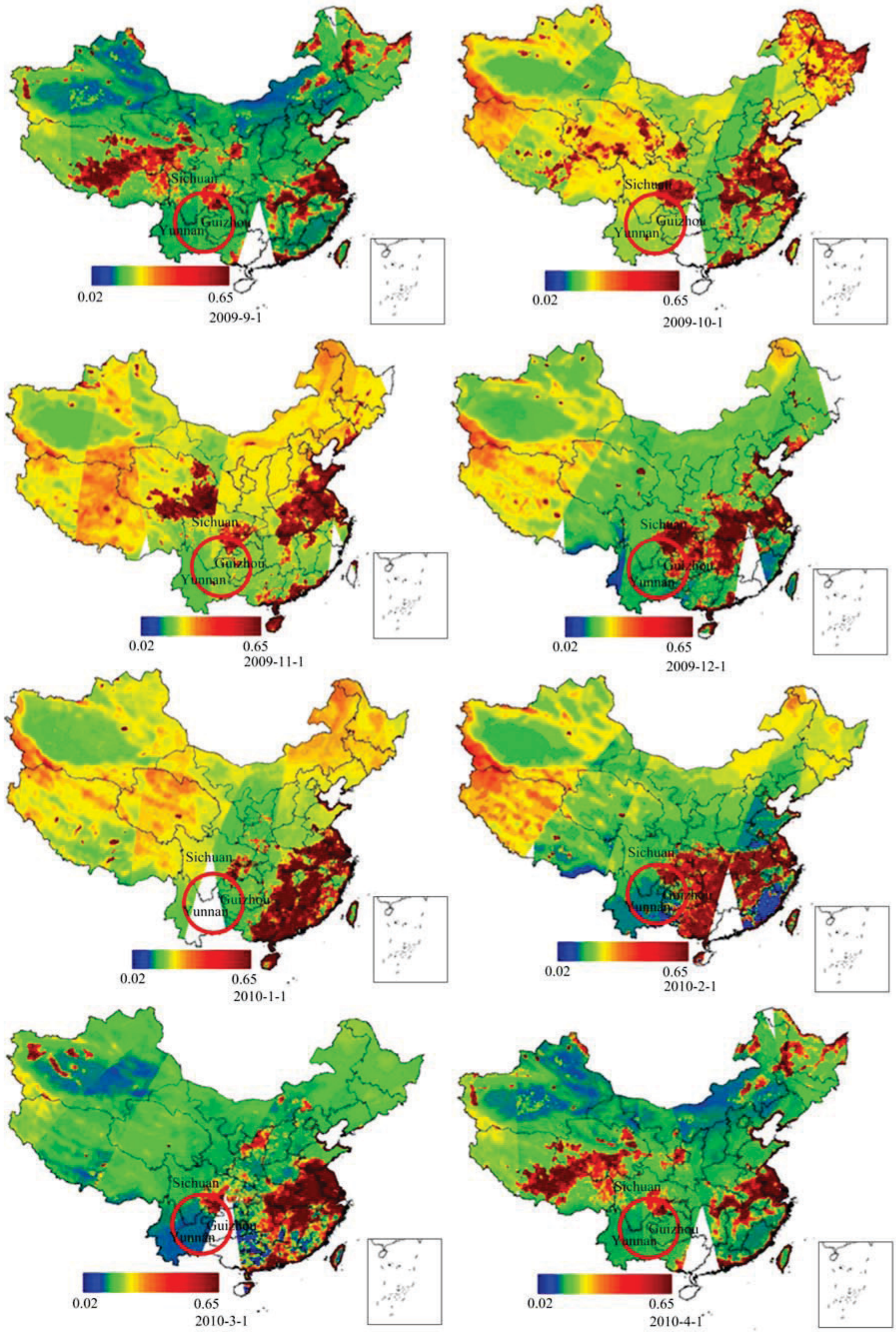

Fig. 3 The distribution of soil moisture from September 1, 2009 to April 1, 2010.

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sults were consistent with the distribution of the national drought which is reported by the National Meteorological Services of China. The census data showed that there were 67 000 km^2 field can not be cultivated due to the influence of drought. 5 297 000 km^2 crops have been damaged, and 1 471 990 km^2 cultivated field can not be sowed due to be lack of water. As shown from Figs. 3 and 4, the distribution of soil moisture was very reasonable. The highest value of soil moisture was at the verge of Changjiang River watershed, Zhujiang River valley, and around of some large lakes. An interesting thing can be found in Fig. 4, which was labeled by the blue diamond. The effective precipitation was little, but no serious drought has been reported

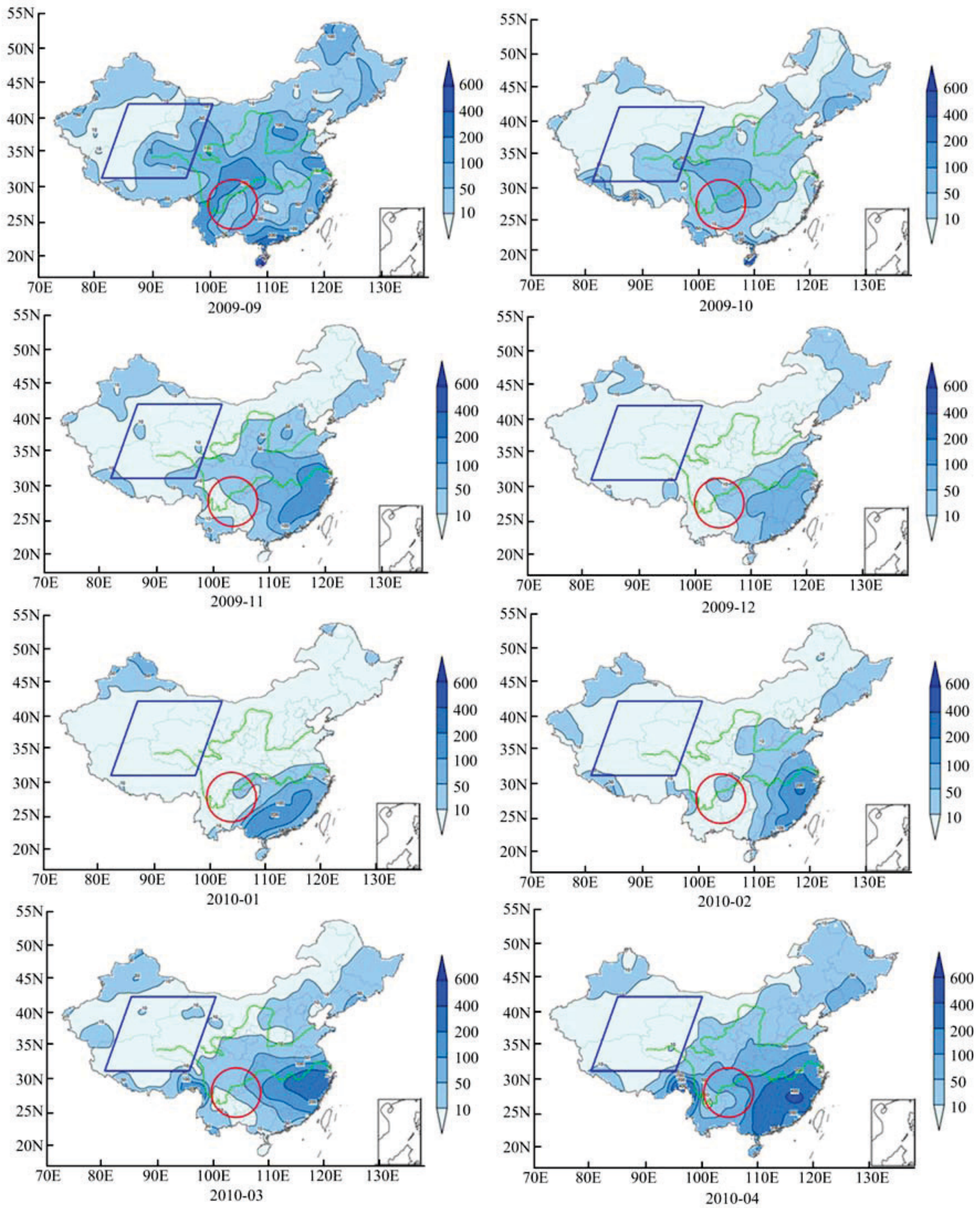

Fig. 4 Monthly precipitation totals (mm) from September 2009 to April 2010.

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because there is little crop in these regions. For monitoring of agricultural meteorological drought, there are another two factors. One is irrigation system which can water the crop when there is no effective precipitation, and the other is the growth stage of crops in different regions which determine water requirement of crops.

CONCLUSION

On the basis of derivation for microwave polarization index, the analysis between AMSR-E MPI and the MODIS LAI/NDVI showed that there was an exponent relationship between MPI and LAI/NDVI, and the relationship became better with decreasing of frequency and the squared correlation coefficients were about 0.77 and 0.85, respectively. So, the MPI can be used to discriminate the vegetation from bare soil, which can be used to improve retrieval accuracy when the surface is covered by vegetation. The soil moisture was retrieved by using the improved MPI method, and the analysis results indicated that our method was very good in clear days, and the average error about 24.5% by using the ground truth data obtained from ground observation stations. After making a revision by using ground measurement data from local observation stations for different surface types, the retrieval error was about 13.7%.

The application analysis for retrieving soil moisture from AMSR-E data in China confirmed the algorithm practical. The southwest of China experienced a long drought, which has no effective precipitation in most parts of Yunnan Province from September, 2009 to April, 2010. The drought is the largest in Yunnan Province in the passed 100 yr. The retrieval result indicated that the soil moisture in Yunnan Province was relative low all the time, and the effective precipitation was also little in southwest of China. The time was more than half a year, so the drought was very serious. According to the cumulative effect, the retrieval results were consistent with the distribution of the national drought which was reported by the National Meteorological Services of China. For the monitoring of agricultural meteorological drought, although soil moisture and effective precipitation are very important, the irrigation system and the growth stage of crops are also another two important factors. How to build a perfect monitoring system of drought should be made further research.

MATERIALS AND METHODS

The advanced microwave scanning radiometer (AMSR-E) and the moderate resolution imaging spectroradiometer (MODIS) are two earth observing system (EOS) sensor instruments in Aqua satellite. AMSR-E is a passivemicrowave radiometer, which observes atmospheric, land, oceanic, and cryospheric parameters, including precipitation, sea surface temperature, ice concentration, snow water equivalent, surface wetness, wind speed, atmospheric cloud water, and water vapor content. The AMSR-E level 2A product (AE_L2A) contains brightness temperatures (TBs) at 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz, which are resampled to be spatially consistent, and it is available at a variety of resolutions that correspond to the footprint sizes of the observations (56, 38, 24, 21, 12, and 5.4 km, respectively) (http://nsidc.org/data/ae_l2a.html). MODIS has 36 bands which are designed for retrievals of SST, LST, and atmospheric properties. The resolution of MODIS is from 250 to 1 000 m. The two instruments can make up for each other. The MODIS has high resolution but it is influenced great by cloud. The LAI/NDVI can be used to describe the growth statement of vegetation. In this study, the MODIS LAI/NDVI product is made as the large scale ground measurement to match the large scale of passive microwave AMSR-E data at the satellite pass.

The derivation of microwave polarization index is based on radiative transfer equation. Vegetation is usually assumed as a parallel of medium when the microwave radiation is transferred in the vegetation. The transmittance for microwaves is very high and approximates to 1 even when the atmospheric water vapour content is about 5 g cm^{-2} (Mao *et al.* 2008), so the influence of the atmosphere can be omitted. According to the Rayleigh-Jeans approximation to the Planck function, the eq. (1) is used to describe the process after simplification (Paloscia and Pampaloni 1984; Mao *et al.* 2008).

$$T_{bp}(\tau,\mu)=(1-\omega)(1-e^{-\tau/\mu})T_c+\varepsilon_p T_s e^{-\tau/\mu} \tag{1}$$

Where P stand for horizontal (H) or vertical (V) polarization, u=cos$a$, e_p is emissivity, t (equivalent optical depth) and w (the single scattering albedo) are two importand parametens that characterize the absorbing and scattering properties of vegetation, T_S is land surface temperature, T_c is average temperature of vegetation, T_{bp} (t, u) is brightness temperature of radiation emitted by canopy at an angle a. As the microwave radiation has polarization, and the vegetation can de-polarize, the microwave polarization can be used to depict the condition of vegetation if the vegetation-soil is made as a system. The microwave polarization index usually is defined as follows (Paloscia

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and Pampaloni 1984; Mao *et al.* 2008):

$$MPI(\tau,\mu)=\frac{T_{bv}\text{-}T_{bh}}{1/2(T_{bv}+T_{bh})} \tag{2}$$

Submitting (2) into (1), we can get

$$MPI(\tau,\mu)=\frac{(\varepsilon_v T_{bsv}\text{-}\varepsilon_h T_{bsh})e^{-\tau/\mu}}{(1\text{-}w)(1\text{-}e^{-\tau/\mu})T_c+1/2(\varepsilon_v T_{bsv}+\varepsilon_h T_{bsh})e^{-\tau/\mu}} \tag{3}$$

For bare soil, the τ=0 and we can have (Paloscia and Pampaloni 1988):

$$MPI(0,\mu)=\frac{(\varepsilon_V\text{-}\varepsilon_h)}{1/2(\varepsilon_V+\varepsilon h)} \tag{4}$$

After assuming T_C=T_S, ε_s=1/2(ε_v+ε_h) and some other condition (like albedo), the eq. (3) can be written as follows:

$$MPI(\tau,\mu)\approx MPI\,(0,\mu)e^{-\tau/\mu} \tag{5}$$

There is exponent relationship between microwave polarization index in bare soil (eq. (4)) and vegetation (eq. (5)). The MPI is mainly used to describe the characteristics of vegetation through the difference between different polarizations at same frequency. The more analysis for MPI can be referred to Meesters *et al.* (2005). In eq. (5), the microwave polarization index is mainly determined by equivalent optical depth (*t*) of vegetation, which is influenced by water content in vegetation. In fact, there is a more complex relationship than eq. (5). The emissivity in eq. (4) is determined by dielectric constant, which is sensitive to soil moisture (Wang and Schmugge 1980; Njoku *et al.* 2003). There is a positive relationship between the water content in vegetation and soil moisture, so the microwave polarization index can also reflect the change of soil moisture when the ground is covered by vegetation (Mao *et al.* 2008).

The NDVI and LAI are two important indexes to describe the status of vegetation. In order to analyze how to use MPI to discriminate the vegetation from bare soil, a program has been made to read simultaneously the data from AMSR-E brightness temperature and MODIS LAI/NDVI by using the longitude/latitude as control condition. The eq. (2) was used to compute MPI, and the eq. (6) was used to compute the LAI/NDVI obtained from MODIS product matching an AMSR-E pixel. The average value of MODIS LAI/NDVI pixels was made as ground surface data of AMSR-E pixel:

$$LAI\,(NDVI)_{AMSRE}=\frac{\sum_{i=1}^{N} LAI_i\,(NDVI_i)_{MODIS}}{N} \tag{6}$$

10 396 data sets were collected from the north-west of China and part of Russia. Fig. 5 is the relationship between LAI and MPI, which showed that the change range of MPI becomes larger with the decreasing of frequency. Fig. 6 is the relationship between MPI and NDVI, which has some differences with Fig. 5, but the general trend is similar. The relationship between MPI and LAI/NDVI can be referred to Tables 1 and 2, which showed that the relationship becomes better with decreasing of frequency. Compared Fig. 5 with Fig. 6, the correlation between NDVI and MPI was better than LAI and MPI. There was a common characteristic between them that the microwave polarization index is very small when the value of NDVI and LAI was great (a lot of vegetation), and the microwave polarization index was very large when the value of NDVI and LAI was small (especially for bare soil), which showed that the microwave polarization index can be used to distinguish bare soil from vegetation. In many applications, NDVI is usually used to depict the condition of vegetation (Njoku *et al.* 2003). Here, according to the largescale (24 km×24 km) characteristics of passive microwave pixel, the pixel can be considered with very little or no vegetation when NDVI 0.1; the pixel is considered as mixed pixel when 0.1<NDVI<0.6; the pixel is covered with dense vegetation when 0.6 NDVI. Therefore, MPI can also be used to depict the condition of vegetation counterparts from NDVI. For 6.9 GHz, and the value of range is as:

(1) When NDVI 0.1, MPI 0.04, for the large scale of the passive microwave, the pixel can be considered for the bare land or very little vegetation, and the impact of vegetation may not be considered for soil moisture retrieval.

(2) When 0.1<NDVI<0.6, 0.02<MPI<0.04, under these conditions, the pixel should be considered as mixed-pixel. During the soil moisture retrieval process, the vegetation should be considered.

(3) When 0.6 NDVI, MPI<0.02, the pixel is completely covered by vegetation, and the impact of vegetation must be eliminated in the soil moisture retrieval process. In order to improve the retrieval accuracy, a revision is needed by the use of ground-based measurements data (Mao *et al.* 2008).

As shown from Figs. 5 and 6, the threshold of MPI for different frequencies is needed to be adjusted appropriately according to the reality of ground (vegetation type and mixed-pixel).

Mao *et al.* (2006, 2008) made some analysis by using advanced integral equation model (AIEM), which is one of the best models to simulate the emission characteristics of a rough surface and has been demonstrated to have a wider application range for surface roughness than the conventional models such as the small perturbation model, the physical model and the geometrical optical model (Fung 1994). The improvements were mainly done by overcoming some weak assumptions in the original IEM model development (Chen *et al.* 2000; Wu *et al.* 2001; Chen *et al.* 2003). Many comparisons of the AIEM with a three dimensional (3-D) Monte Carlo model simulated data (Chen *et al.* 2003; Shi *et al.* 2005) showed a significant improvement in more accurate calculation of surface emission signals over a wide range of surface dielectric, roughness, and frequencies. A large simulation database is built by utilizing the simulation data of AIEM under a wide range of conditions. The simulation analysis indicated that the linear relationship between the emissivity and soil moisture can be obtained under given

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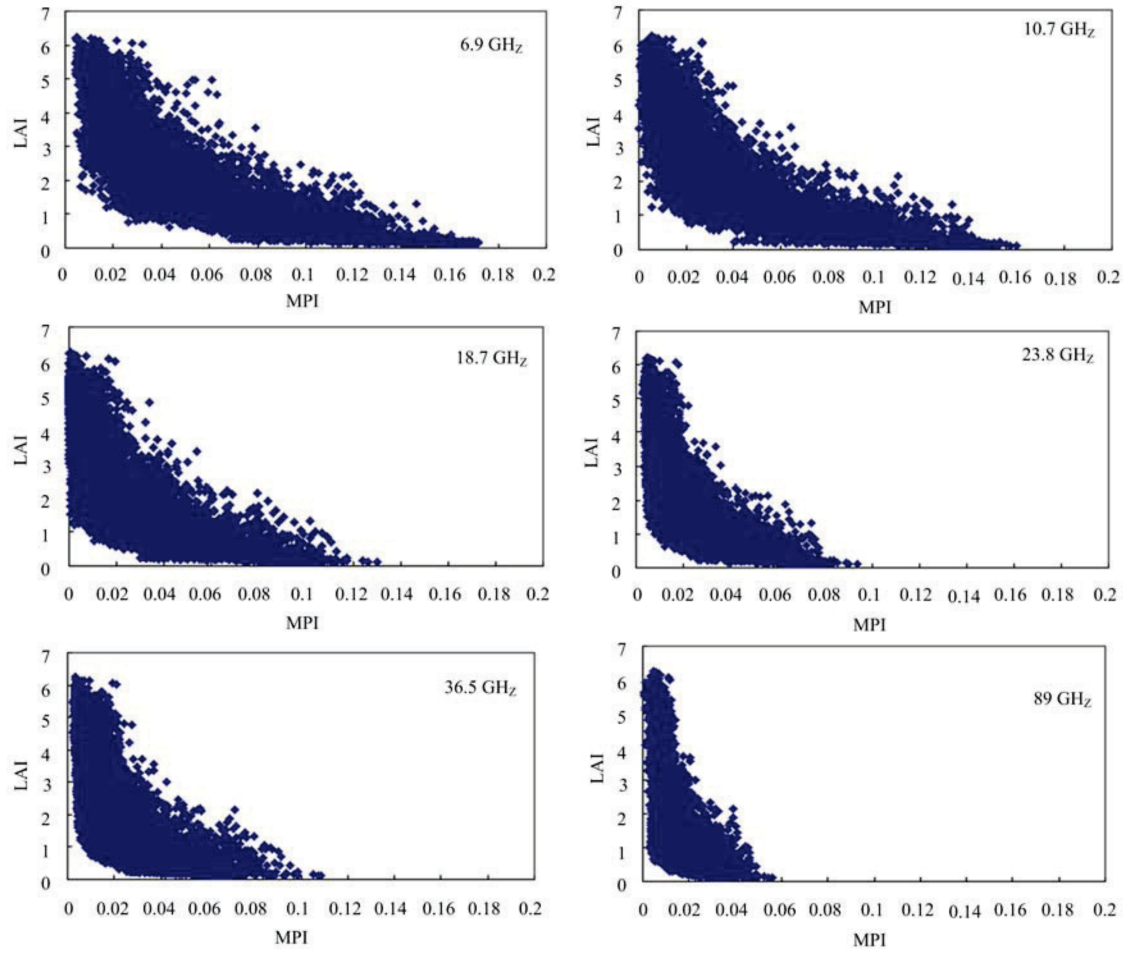

Fig. 5 The relationship between MPI and LAI.

conditions. A better relationship can be built between soil moisture and the normalized difference at the emissivity of different frequency which can partly eliminate the influence of roughness and atmosphere. The normalized emissivity difference between 18.7 and 10.7 GHz (V) can eliminate the most part influence of roughness. The squared correlation coefficient was about 0.98, which indicated that the polarization different index methods is very good. The derivation eq. (7) indicated that the normalized emissivity equal to the normalized brightness temperature which avoid the key parameter land surface temperature. The derivation can be referred to Mao *et al.* (2008).

$$NDE_{i\text{-}j}=\frac{\varepsilon_i-\varepsilon_j}{\varepsilon_i+\varepsilon_j}=\frac{\frac{T_i}{T_s}-\frac{T_j}{T_s}}{\frac{T_i}{T_s}+\frac{T_j}{T_s}}=\frac{T_i-T_j}{T_i+T_j} \quad (7)$$

Where, $NDE_{i\text{-}j}$ is the polarization different index, ε_i is emissivity, T_i is brightness temperature at sensor, T_S is land surface temperature. The land surface temperature (T_S) is very difficult to obtain because the emissivity is changed with the change of soil moisture (Mao *et al.* 2007). Mao *et al.* (2006, 2008) proposed a method by using microwave polarization difference index by using different frequency at vertical (*V*) polarization to retrieve soil moisture from passive microwave data. The soil moisture retrieval is like eq. (8):

$$SM=0.033+10.99\times NDE_{18.7\,\text{GHz-}10.7\,\text{GHz}}+563.8\times NDE^2_{18.7\,\text{GHz-}10.7\,\text{GHz}} \quad (8)$$

Where, SM is soil moisture, $\text{NDE}_{18.7\,\text{GHz-}10.7\,\text{GHz}}$ is microwave polarization difference index at 18.7 and 10.7 GHz (*V*). The most meaning of this method was that the normalized difference of brightness temperature avoids the key parameter land surface temperature which is used to compute emissivity. This method was mainly suitable for bare soil, and almost every pixel was mixed for large scale passive microwave data in land, so we need to use the ground measurement data to improve retrieval accuracy, especially for the surface covered by vegetation. The best method was that we make a revision for different surface types. The MODIS data product is often used to judge the sur-

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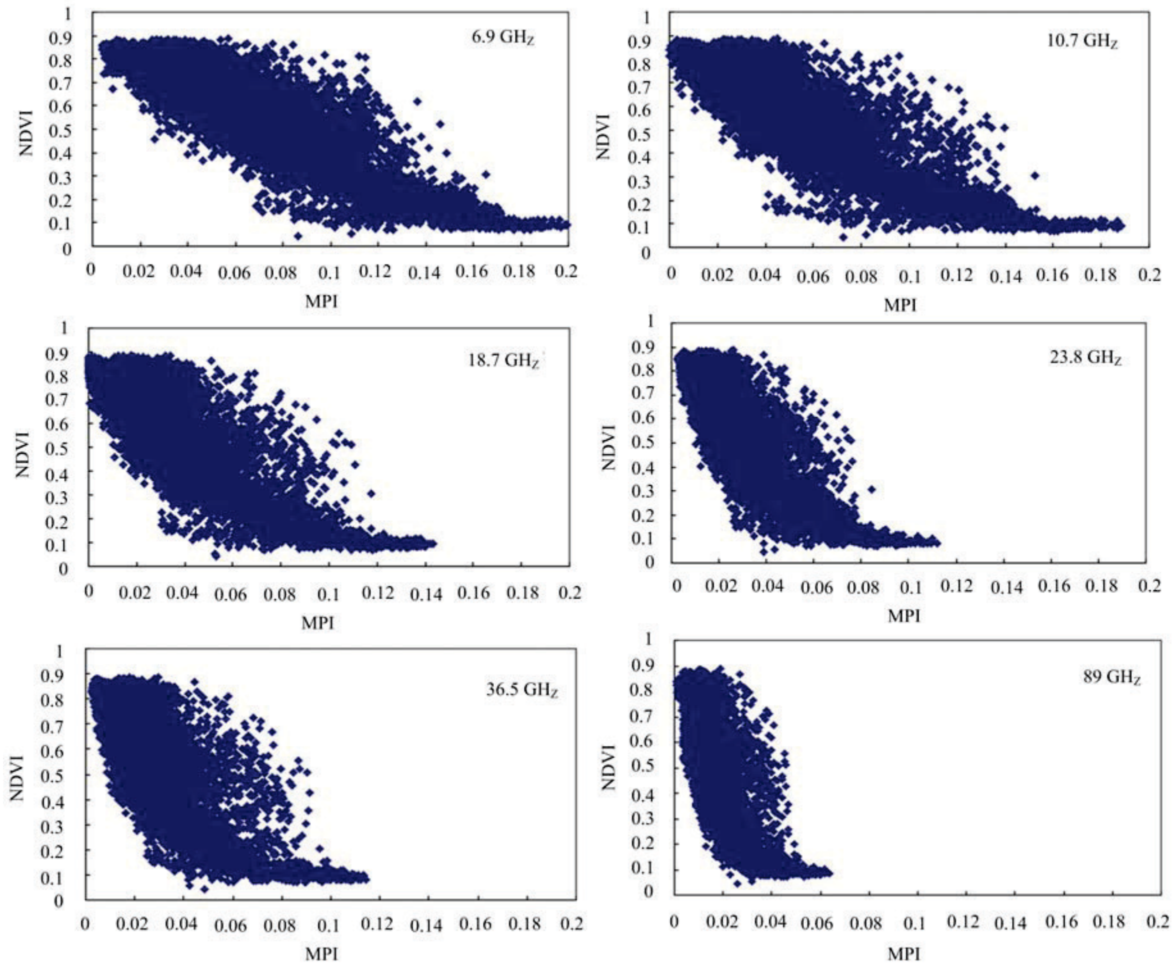

Fig. 6 The relationship between NDVI and MPI.

Table 1 The relationship between LAI and MPI

Frequency (GHz)	Eq.	R^2
6.9	LAI=5.61261 $e^{-\frac{MPI}{0.03533}}$+0.30348	0.767
10.7	LAI=4.94514 $e^{-\frac{MPI}{0.02772}}$+0.33631	0.724
18.7	LAI=4.22754 $e^{-\frac{MPI}{0.01777}}$+0.41986	0.689
23.8	LAI=5.74679 $e^{-\frac{MPI}{0.01226}}$+0.39931	0.665
36.5	LAI=5.37457 $e^{-\frac{MPI}{0.01187}}$+0.48411	0.591
89	LAI=6.2589 $e^{-\frac{MPI}{0.00751}}$+0.33862	0.484

Table 2 The relationship between NDVI and MPI

Frequency (GHz)	Eq.	R^2
6.9	NDVI=7.696 $e^{-\frac{MPI}{1.47227}}$ -6.78207	0.845
10.7	NDVI=1.71175 $e^{-\frac{MPI}{0.2348}}$ -0.81402	0.825
18.7	NDVI=1.21772 $e^{-\frac{MPI}{0.11091}}$ -0.3495	0.796
23.8	NDVI=1.1829 $e^{-\frac{MPI}{0.06709}}$ -0.24856	0.799
36.5	NDVI=1.04562 $e^{-\frac{MPI}{0.05607}}$ -0.11741	0.705
89	NDVI=1.1471 $e^{-\frac{MPI}{0.03043}}$ -0.15852	0.655

face type, but the MODIS is influenced by cloud and more than 50% is unavailable in an MODIS image data, so it can not keep with synchronism. However, the resolution of MODIS data is about 1 km×1 km and the resolution of AMSR-E is about 24 km×24 km, so the matching is anther problem. In order to improve retrieval accuracy and make the method more practical, we use the MPI judge the surface type and make a revision by using ground measurement data. The frame routine of soil moisture retrieval can be described as Fig. 7.

The detailed scheme was as follows:

1) Reading the AMSR-E data, and getting some information of different frequency from head file, and transferring the value of DN into brightness temperature.

2) Computing the microwave polarization index which has been discussed above. The V and H polarization of 6.9 GHz are used to judge the surface type.

3) The V polarization of 10.7 and 18.7 GHz were used to computer the NDE (eq. (9)), and the eq. (8) was used to compute soil moisture (Mao *et al*. 2006, 2008):

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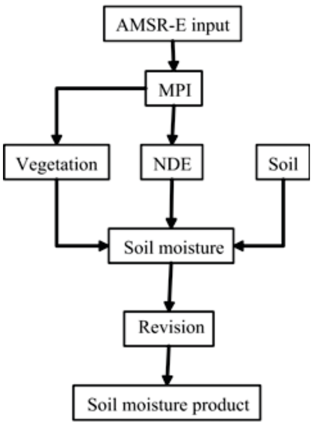

Fig. 7 The scheme map of soil moisture retrieval from AMSR-E.

$$NDE_{18.7\,\text{GHz}-10.7\,\text{GHz}}=\frac{T_{18.7V}-T_{10.7V}}{T_{18.7V}+T_{10.7V}} \tag{9}$$

4) The ground measurement data were used to revise the retrieval result. If there is rainfall in the pixel, the retrieval result will be labeled as invalid.

5) Making geometric correction and outputting the soil moisture product.

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