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A Semi-Empirical Inversion Model for Assessing Surface Soil Moisture using AMSR-E Brightness Temperatures

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Abstract: In 2004-2005, 2007 and 2009, three major drought disasters occurred in Guangdong Province of southern China, which caused serious economic losses. Hence, it has recently become an important research subject in China to monitor surface soil moisture (SSM) and the drought disaster quickly and accurately. SSM is an effective indicator for characterizing the degree of
drought. First, using the brightness temperatures ($T_b$) of the Advanced Microwave Scanning Radiometer on the EOS Aqua Satellite (AMSR-E), a modified surface roughness index was developed to map the land surface roughness. Then by combining microwave polarization difference indices (MPDI)-based vegetation cover classification and the modified surface roughness index, a simple semi-empirical model of SSM was derived from the passive microwave radiative transfer equation using AMSR-E C-band $T_b$ and observed surface soil temperature ($T_s$). The model was inverted to calculate SSM. The results show the ability to discriminate over a broad range of SSM (7%~73%) with an accuracy of 2.11% in bare ground and flat areas ($R^2 = 0.87$), 2.89% in sparse vegetation and flat surface areas ($R^2 = 0.85$), about 6%~9% in dense vegetation areas and rough surface areas ($0.80 \leq R^2 \leq 0.83$). The simulation results were also validated using in-situ SSM data ($R^2 = 0.87$, RMSE = 6.36%). Time series mapping of SSM from AMSR-E imageries further demonstrated that the presented method was effective to detect the initiation, duration and recovery of the drought events.

**Keywords**: surface soil moisture (SSM); Semi-Empirical model; brightness temperature ($T_b$); AMSR-E; passive microwave remote sensing; drought disaster; south China

1. Introduction

Surface soil moisture (SSM) is not only an important variable used to describe water and energy exchanges at the land surface and atmosphere interface (Wigneron et al., 2003); it is also an effective indicator for characterizing the degree of drought. In 2004, 2007 and 2009, three disastrous droughts occurred in Guangdong Province of southern China, causing serious economic losses (about 30 billion Yuan, http://www.chinadaily.com.cn/). Since the 1990s, the total economic losses caused by drought disasters have been equivalent to 1.1 percent of China's average annual
gross domestic product (about 324 billion Yuan, http://www.chinadaily.com.cn/). As a result there is a requirement for the timely estimation of regional SSM information on a large scale for drought disaster emergency management. Passive microwave remotely sensed data has great potential for providing estimates of SSM with good temporal coverage on a daily basis and on a regional scale (Wigneron et al., 2003). Here we develop an improved SSM retrieval model and demonstrate its utility to monitor the drought condition using passive microwave remote sensing data.

Passive microwave remote sensing data has been used to retrieve SSM for almost 35 years. Numerous studies indicated a strong relationship between the microwave brightness temperature ($T_b$) and SSM content (Eagleman and Lin, 1976; Schmugge et al., 1988; Wang et al., 1989; Wang et al., 1990; Jackson et al., 1995; Jackson et al., 1997; Schmugge, 1998; Jackson et al., 1999; Uitdewilligen et al., 2003). Ulaby et al. (1981) and Liebe (1989) recommended using absorption lines at 6.6GHz because of the high sensitivity to atmospheric water vapor at frequencies higher than 10.7 GHz. Building on this, Owe et al., (2008) used C band (6.6GHz) and L band (10.7 GHz) passive measurements to retrieve SSM from space. But microwave emissions are also strongly affected by land surface properties (such as soil physical properties, vegetation characters and surface soil temperature $T_s$), including C- and L-band emissions that were chosen because they are less sensitive to atmospheric and tenuous clouds emissions (Owe et al., 2001). So SSM retrieval algorithms from passive microwave data have to account for the effects of such land surface properties. Many studies have been conducted to develop a method for compensating for the errors caused by soil texture, soil roughness, soil temperature and land surface vegetation cover condition (Dobson et al., 1985; Hallikainen et al., 1985; Choudhury et al., 1982; Choudhury, 1987;
Jackson and Schmugge, 1989; Schmugge and Jackson, 1992; Chanzy and Wigneron, 2000; Uitdewilligen et al., 2003). Lacava et al. (2005) first eliminated the surface roughness and vegetation water content affects which impact the SSM retrieval accuracy from AMSR-E and then simulated the global SSM condition using soil wetness variation index (SWVI). Mallick et al. (2009) established a soil wetness index from surface soil temperature ($T_s$) and normalized difference vegetation index (NDVI) to retrieve SSM using AMSR-E $T_b$. The SSM retrieval accuracy reaches 0.027 m$^3$/m$^3$. Hong and Shin (2011) estimated the global SSM over land surface using a relation between the complex dielectric constant and SSM after retrieving the surface roughness and complex dielectric constant. SSM retrieval accuracy was about 0.06 m$^3$/m$^3$. Li et al. (2011) used two-parameter retrieval approach (TWRA) and three-parameter retrieval approach (THRA) to retrieve global SSM. Both methods firstly simulated the surface roughness, vegetation and $T_s$ condition and then retrieved SSM from AMSR-E $T_b$. The SSM retrieval accuracies were 0.089 and 0.037 m$^3$/m$^3$, respectively.

Former studies mainly focused on retrieving SSM information from simulated $T_s$, surface roughness and vegetation information (vegetation index, water content and optical depth). More recently, microwave polarization difference indices (MPDI) are proposed as a measure of differences in polarization signals and the soil dielectric properties (and therefore soil moisture). MPDI is also an effective indicator for characterizing the land surface vegetation cover condition (Paloscia et al. 1988; Wang et al. 2005). Based on land surface vegetation cover classification and land surface roughness classification, this paper presents a much simpler semi-empirical relation among SSM, AMSR-E $T_b$, MPDI and $T_s$. With simple land surface roughness and vegetation classification only, SSM information can be retrieved from the semi-empirical model integrating...
AMSR-E C-band $T_b$, MPDI, and $T_s$ data for each land classification type. This SSM retrieval model also achieves a much higher accuracy under dense vegetation cover and rough surface covered situations than most former studies, which find it difficult to retrieve SSM information accurately under dense vegetation or rough surface areas.

2. Study Data and Area

2.1. Study area

Guangdong Province (gray region in Fig. 1a), a coastal province, located in southern China, with a population of 86,420,000 people and area of 177,900 km$^2$, is chosen as the study area. Climate here is the typical subtropical monsoon maritime climate of southern Asia, with an average annual sunshine of 1688.9 hours, an average temperature of 22.8$^\circ$C (23.2$^\circ$C in urban region). Since 2004, three disastrous droughts have occurred in Guangdong Province of southern China, which caused serious economic losses. In 2004-2005, the drought spread in Guangdong’s 84 cities and counties, affecting more than 2 million residents (Fig. 1c). More than 689,000 hectares of farmlands were seriously affected. The economic losses from agriculture alone came to more than 1.4 billion Yuan (http://www.mwr.gov.cn/). In 2007, the amount of rainfall was about 60 % of normal year. Most cities even received less than 2,000 mm of rainfall. About 400,000 hectares of croplands were affected by drought, leading to total grain losses of 37.4 billion kg, causing 6.7 billion Yuan economic losses. In 2009, Guangdong Province had another unprecedented drought disaster. The average rainfall that year was 1,400 mm, 13 percent below normal years. This severe drought caused direct economic losses of 23.7 billion Yuan (http://www.chinadaily.com.cn). So, timely regional SSM information is useful for drought disaster monitoring, government decision-making and drought disaster prevention. To meet this
requirement to provide timely SSM information we have developed an improved SSM retrieval model using passive remote sensing data.

Insert Fig. 1 about here

2.2. Study data

The AMSR-E instrument on the NASA Earth Observing System (EOS) Aqua satellite is a modified version of the AMSR instrument launched on the Japanese Advanced Earth Observing Satellite-II (ADEOS-II) in 1999. AMSR-E is a successor in technology to the Scanning Multi-channel Microwave Radiometer (SMMR) and Special Sensor Microwave Imager (SSM/I) instruments. It can provide global passive microwave measurements of terrestrial, oceanic, and atmospheric variables for the investigations of global water and energy cycles. Each AMSR-E $T_b$ file contains images of six frequencies (6.9 GHz, 10.7 GHz, 18.7 GHz, 23.8 GHz, 36.5 GHz, and 89.0 GHz, Table 1). The instrument operated until October 4th, 2011, when AMSR-E reached its limit to maintain the rotation speed necessary for regular observations (40 rotations per minute), and the radiometer automatically halted its observations and rotations.

For this study we selected 4 days (October 28th & 31st, 2004 and December 7th & 8th, 2007) during the two drought disasters in 2004-2005 and 2007 to develop the SSM retrieval model, and used another 2 days (January 28th & 31st, 2009) during the 2009 drought disaster to validate the SSM retrieval model. AMSR-E $T_b$ data (version: AMSR-E/Aqua Daily EASE-Grid $T_b$) were downloaded from National Snow and Ice Data Center (NSIDC). Corresponding in-situ SSM and $T_s$ were acquired from 86 meteorological observation stations (Fig. 1b) of Guangdong Province
We also added the SSM mapping of another 5 days (April 1st, July 1st, December 31st, 2004 and April 1st & July 1st, 2005) in combination with October 31st 2004 to demonstrate the initiation, duration and recovery of the 2004-2005 severe drought disaster in Guangdong Province, southern China. A once-in-four-century heavy storm during June 18-25 caused an abrupt end to the 2004-2005 severe drought event.

3. Methods

3.1 Developing the SSM retrieval model

The upwelling radiation from the land surface as observed from above the canopy may be expressed in terms of the radioactive brightness temperature $T_{bp}$, and can be given as a simple radioactive transfer equation (Owe et al., 2001):

$$T_{bp} = T_s \ast (1 - r_sp) e^{-\tau_c} + T_c (1 - w_p) (1 - e^{-\tau_c}) + r_sp T_c (1 - w_p) (1 - e^{-\tau_c}) e^{-\tau_c} \quad (1)$$

where $p$ is the horizontal (H) or vertical (V) polarization mode; $T_s$ represents the soil thermometric temperatures; $r_sp$ is the smooth-surface reflectivity; $\tau_c$ is the optical depth of land surface vegetation; $e^{-\tau_c}$ is the transmissivity; $T_c$ is thermometric temperatures of the canopy; $w_p$ is the single scattering albedo. AMSR-E C channel is the low-frequency band, so this paper ignored the effects of single scattering albedo and atmosphere. Then, $T_{bp}$ can be simplified as expression 2. If the texture of land surface can be seen as homogeneous, $r_sp$ of the land surface can be seen as a constant, $A_l$.

$$T_{bp} = T_s \ast (1 - r_sp) e^{-2\tau_c} \quad (2)$$
According to Wang et al. (2006), $\tau_c$ can be simulated using an empirical function from MPDI and soil dielectric constant $\varepsilon$ near land surface. The relative error of simulated $\tau_c$ is smaller than 5% compared with the simulation results of Owe et al. (2001):

$$\tau_c = -0.223\ln\frac{MPDI}{\varepsilon^2} - 1.239^{0.12}MPDI - 0.001 + 0.00085e^2 - 0.0547e + 0.05411$$

What is more, according to Dobson et al. (1985), $\varepsilon$ can be expressed by body density of soil $\rho_s$, body density of solid materials $\rho_r$, SSM and the dielectric constant of pure water $\varepsilon_{fw}$.

$$\varepsilon = 1 + \frac{\rho_s}{\rho_r} (\varepsilon_{\eta})^t - 1 + SSM \varepsilon_{\eta} - SSM$$

where $t = 0.06$. If the soil texture of the study area is homogeneous, $\rho_s, \rho_r, \varepsilon$ and $\varepsilon_{fw}$ can be seen as constants, too. Thus, $\varepsilon$ can be simplified as:

$$\varepsilon = A_2 + A_3 SSM^{A_4} - SSM$$

where $A_2, A_3, A_4$ are constants.

On assumption that the land surface can be seen as a homogeneous texture, we can establish a relation (expression 6) between SSM, $T_s$, MPDI and AMSR-E $T_b$ from expression 2, 3 and 5.

$$\ln A_1 - 0.892\ln(A_2 + A_3 SSM^{A_4} - SSM) - 0.0017(A_2 + A_3 SSM^{A_4} - SSM)^2 + 0.1096(A_2 + A_3 SSM^{A_4} - SSM)$$

$$= \ln \frac{T_b - T_{bs}}{T_s} - 0.484\ln MPDI - 2.478^{0.12}MPDI - 0.001 + 0.10822$$

In summary, SSM can be easily retrieved using AMSR-E $T_b$, AMSR-E 6.9GHz MPDI and $T_s$ for homogeneous land surface. The next step is to classify the land surface into several types according to different land surface vegetation cover condition and degree of surface roughness. Then, we assume that each land surface type is a homogeneous texture. So, expression 6 can be used to derive SSM for each land type.

3.2. Match AMSR-E $T_b$ with in-situ data

The in-situ SSM and $T_s$ observed by 86 meteorological observation stations were point-based.
In order to obtain the point-based AMSR-E $T_b$ for each in-situ data, we averaged $T_b$ of imagery-pixels around the 86 meteorological observation stations to match with the in-situ SSM and $T_s$. Firstly, AMSR-E $T_b$ data was downloaded from ftp://n4ftl01u.ecs.nasa.gov. Then we extracted the latitude, longitude and $T_b$ information and displayed the point-based $T_b$ in ArcGIS software. About 2,223 pixels in total were extracted from each AMSR-E $T_b$ file within Guangdong Province (black dots in Fig. 2). Then we drew 86 circles (radius: 9,000 m) centralized at each meteorological observation station (triangle points in Fig. 2) and averaged the pixels’ $T_b$ values within the circles to match with the SSM and $T_s$ data from the meteorological observation stations.

3.3. Land surface vegetation cover classification method

Chen et al. (2011) has established an empirical classification rule for land surface vegetation cover classification in Guangdong Province using AMSR-E MPDI values. Three land surface vegetation cover types were produced according to different AMSR-E MPDI values. For dense vegetation cover land surfaces, AMSR-E 6.9GHz MPDI is smaller than 0.06; For sparse vegetation cover regions, MPDI is between 0.06 and 0.09; For bare soil areas, MPDI value is generally larger than 0.09. The land surface vegetation cover classification method proved to be effective in $T_s$ retrieval of Guangdong Province ($R^2 > 0.71$, $P < 0.05$).

3.4. Land surface roughness classification method

Surface roughness is another factor influencing SSM estimation. According to the empirical surface roughness model of Jin et al. (1998), the reflectivity of rough surface can be defined as:
\[ r_{sv} = [(1 - Q)r_{ov} + Qr_{oh}]e^{-h} \]  

\[ r_{sh} = [(1 - Q)r_{oh} + Qr_{ov}]e^{-h} \]

(7a)  

(7b)

where \( Q \) is a polarization mixing parameter, \( 0 < Q < 0.5 \); \( h \) is the vertical surface roughness parameter; \( r_{sv} \) and \( r_{sh} \) represent the vertical polarization and horizontal polarization reflectivity of rough surface respectively; \( r_{ov} \) and \( r_{oh} \) indicate the vertical polarization and horizontal polarization reflectivity of flat surface respectively.

Combining the radiative brightness temperature (expression 2) and the reflectivity of rough surface (expression 7), MPDI can be expressed as (Ma, 2007):

\[
\frac{1}{\text{MPDI}} = \frac{r_{sv} - r_{sh}}{(1 - 2Q)(r_{ov} - r_{oh})} = \frac{1}{(1 - 2Q)(r_{ov} - r_{oh})} 2e^{2\tau_c + h} \]

(8)

where \( r_{ov} + r_{oh} \) and \( (1 - 2Q)(r_{ov} - r_{oh}) \) are only influenced by SSM. Using MPDI from the AMSR-E 6.9GHz, 10.7GHz and 18.7GHz bands, Ma (2007) finally came to the following equation:

\[
\Gamma = \frac{1}{\text{MPDI}_{6.9}} - \frac{1}{\text{MPDI}_{10.7}} = \frac{e_{6.9}^{2\tau_c + h} - e_{10.7}^{2\tau_c + h}}{e_{18.7}^{2\tau_c + h} - e_{10.7}^{2\tau_c + h}} \]

(9)

However, \( \Gamma \) is not only influenced by surface roughness condition, but also by vegetation cover condition. Thus, \( \Gamma \) cannot be treated as a roughness index. This paper further assumes that \( \tau_c \) of different AMSR-E bands has a linear relationship with each other \( (e_{6.9}^{\tau_c} \approx m e_{10.7}^{\tau_c} \approx n e_{18.7}^{\tau_c} \), where \( m \) and \( n \) are constants). Then, expression 9 can be simplified as:

\[
\frac{1}{\text{MPDI}_{6.9}} - \frac{1}{\text{MPDI}_{10.7}} = \frac{e_{6.9}^{h} - e_{10.7}^{h}}{e_{18.7}^{h} - e_{10.7}^{h}} \]

(10)

Combing this result with the optical depth \( \tau_c \) simulated by Owe et al. (2001), we construct a modified roughness index \( \Gamma_{MPDI} \) (unit: cm).
\[
\Gamma_{\text{MPDI}} = -3.21111 \times \frac{1}{\text{MPDI}_{10.7}} - 1 \\frac{\text{MPDI}_{8.9}}{1} \times (\text{MPDI}_{6.9} - 0.33280) + 0.00178 \quad (11)
\]

We can see that \( \Gamma_{\text{MPDI}} \) is only influenced by surface roughness parameter \( h \). It is a more reasonable index for characterizing the land surface roughness degree than \( \Gamma \). In order to validate the accuracy of the improved surface roughness index \( \Gamma_{\text{MPDI}} \), three-day global land surface roughness mapping results (Fig.3) were produced from \( \Gamma_{\text{MPDI}} \) using AMSR-E/Aqua Daily Global Quarter-Degree Gridded \( T_b \) data on October 31\textsuperscript{st}, 2004, December 8\textsuperscript{th}, 2007 and January 31\textsuperscript{st}, 2009. 5535 samples were selected to compare with the global surface roughness results mapped by Hong (2010), who used a unique approach to estimate the small-scale roughness with the global AMSR-E \( T_b \) data on April 1\textsuperscript{st}, 2009. There was a strong linear relationship (Fig.4) between the surface roughness calculated by \( \Gamma_{\text{MPDI}} \) and the surface roughness simulated by Hong (2010). We further extracted the surface roughness condition of Guangdong Province (Fig.5) and used \( \Gamma_{\text{MPDI}} \) to classify Guangdong’s land surface roughness condition.

3.5. Data processing flow diagram

Land surface vegetation cover condition and land surface degree of roughness are two major factors influencing the SSM retrieval accuracy. Hence this paper classified the land surface of Guangdong Province into several types according to different land surface vegetation cover condition and degree of surface roughness. Further, we assumed each land surface type as a
homogeneous texture. Then, the algorithm containing SSM, $T_a$, MPDI and AMSR-E $T_b$ (expression 6) can be used to derive SSM for each land type. The processing flow and methods are shown in Fig. 6.

**Insert Fig. 6 about here**

4. Results and Discussion

4.1 Land surface classification

On the basis of the land surface roughness mapping results (Fig. 7a), this paper further classified the land surface roughness of Guangdong Province into four types (Fig. 7b) using the land surface roughness classification rule in Table 2. Results showed that the surface roughness was lower in south and center of Guangdong Province, where most regions were river delta plain areas. It was much higher in north, east and northwest of Guangdong Province, where most regions were distributed by mountainous and hilly areas (Fig. 7b).

Considering that SSM can be influenced strongly by dense vegetations, this paper developed an improved vegetation classification method (Table 3) on the basis of Chen’s empirical classification rule (Chen et al., 2011). Land surface vegetation cover classification results (Fig. 7c) showed that the land surface vegetation cover condition of Guangdong Province varied as latitude changed. Vegetation density at higher latitudes was much higher than vegetation density at lower latitudes (Fig. 7d). It was because that most regions at lower latitudes were close to sea and belonged to the built-up places, and most places at higher latitudes were mainly mountain areas or hilly grounds and were usually covered by dense broad-leaved forests, coniferous forests or
In combination with the land surface vegetation cover classification and land surface roughness classification results, 86 meteorological observation stations in Guangdong Province were classified into 5 types (Table 4 and Fig. 8). Then, each land surface type can be seen with a similar vegetation cover condition and surface roughness degree. In other words, each land type can be seen as a homogeneous land surface texture. Therefore, the SSM retrieval model (expression 6) can be used to retrieve the SSM information for each land type.

4.3. Surface soil moisture retrieval and validation

Using the land surface classification results of Guangdong Province and the SSM retrieval model (formula 6), this paper derived the SSM information for each land type separately from AMSR-E C-band $T_b$, MPDI and $T_s$. Levenberg-marquardt optimization algorithm (LMA) was used to solve the fitted coefficients (A1, A2, A3, A4) of SSM retrieval algorithm for each land type. As estimated by authors, the threshold value of A1 was between 0 and 1; the threshold value of A2
was larger than 10. Hence the original values of A1 and A2 were set as 0.5 and 11, respectively.

The number of the optimization loops was set to 10. There were always single solutions for A1, A2, A3, A4 (Table 5) for each land type.

**Insert Table 5 about here**

In-situ measurements of SSM on January 28th & 31st, 2009 were used to validate the simulation accuracy of SSM (Fig.9a) from the corresponding ANSR-E data (N=86*2). Results showed that the average errors between in-situ and model-derived SSM values of the five algorithms were between 2.11% and 8.52%, with RMSE between 0.94% and 6.69% (Table 6, Fig. 9b). The total average SSM error was 5.37% with average RMSE equaling to 6.36% ($R^2=0.87$). The accuracy of the SSM retrieval result was higher than former studies (Wigneron et al., 2003; Uitdewilligen et al., 2003; Cashion et al., 2005; Bindlsh et al. 2006; Loew et al., 2008; Panciera et al., 2009), of which the SSM retrieval accuracy was usually larger than 4%. Some former studies (Wigneron et al., 2003; Bindlish et al., 2006; Panciera et al., 2009) also found it difficult to retrieve SSM information accurately under dense vegetation or rough surface areas (SSM retrieval error in some studies even reached 32%). However, the SSM retrieval model developed in this paper achieved a much higher accuracy at 6.95% under dense vegetation cover (0.01<MPDI<0.06) and rough surface covered situations (roughness >0.3 cm). All the SSM retrieval errors were smaller than 20%. Results indicated that the semi-empirical SSM model can not only be applied to bare land areas and flat surface areas, but also to sparse vegetation covered areas, dense vegetation covered areas and rough surface areas.
The eight model-derived SSM maps and corresponding spatial-interpolated in-situ SSM maps from 86 meteorological observation stations on April 1st, July 1st, October 31st, & December 31st, 2004, April 1st & July 1st, 2005, December 8th, 2007 and January 31st, 2009 were presented in Fig.10. We can easily find that the initiation of the 2004-2005 drought disaster was on about July 1st, 2004, which should have lasted some days. The drought degree became more serious on October 31st, 2004. The most severe drought degree was about on December 31st, 2004. Then, it recovered a little on April 1st, 2005. There was nearly no drought condition in Guangdong on July 1st, 2005 because there was a synoptic process of heavy storm at once-in-four-century from June 18 to June 25, 2005 (http://news.gd.sina.com.cn/local/2005-12-31/2050082.html). The drought disaster lasted for almost one year. Time series of SSM mapping results during the 2004-2005 drought disaster indicated that the presented method was effective to detect the initiation, duration and recovery of a whole drought event.

5. Conclusions

Three severe droughts have occurred in Guangdong Province of southern China during the past 10 years with disastrous consequences for the people of Guangdong. It is of great
importance to establish an effective SSM retrieval model using passive microwave remote sensing for monitoring the drought disasters. A simple SSM retrieval methodology derived from the passive microwave radiance transfer equation is presented in this study and proves to be effective in retrieving SSM information using AMSR-E C-band $T_b$, MPDI and $T_s$.

Land surface vegetation cover condition and degree of roughness are two major factors influencing the SSM accuracy retrieval from AMSR-E $T_b$. This paper uses MPDI to characterize the vegetation cover condition of Guangdong Province, and develops a modified surface roughness index to map the surface roughness condition of Guangdong Province, which was validated at the global scale. Results show that land surface vegetation density of Guangdong is always higher at higher latitudes than at lower latitudes. Surface roughness is lower in south and central of Guangdong Province, while much rougher in north, east and southwest. Furthermore, this study classifies the land surface into five types according to different vegetation cover and surface roughness condition and then assumes each land surface type having a homogeneous land surface texture.

A simple semi-empirical SSM retrieval model is developed for each land surface type with much higher retrieval accuracy. Validation results from three different drought cases prove that it is an effective way to derive SSM information and monitor the degree of drought condition from AMSR-E $T_b$ data (average SSM error is 5.37%; $R^2=0.87$, RMSE=6.36%). All the SSM retrieval errors are smaller than 20%. What is more, the average SSM retrieval error is under 6.95% for dense vegetation cover (0.01<MPDI<0.06) and rough surface cover condition (roughness>0.3cm), which is also smaller than most former studies (Wigneron et al., 2003; Bindlish et al. 2006; Panciera et al., 2009). The semi-empirical SSM retrieval model can not only be applied to bare
ground and flat surface areas, but also to sparse vegetation covered areas, dense vegetation cover areas and rough surface areas. Time series of SSM retrievals from AMSR-E imageries indicate that the 2004-2005 drought event lasted more than one year from April 1\textsuperscript{st}, 2004 to July 1\textsuperscript{st}, 2005. Hence the method presented here was effective to detect the initiation, duration and recovery of drought disasters.

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Fig. 1 The location of study area: (a) Location of Guangdong Province in China (shadow area); (b) Eighty-six meteorological observation stations (black circle points) in Guangdong; (c) The scene of drought disaster in Lemin Town of Zhanjiang city of Guangdong Province on June 5th, 2005 during the severe drought of 2004-2005.
Fig. 2 The matching method of remote sensing pixel to ground observation of SSM: the $T_b$ values of circle-included pixels (dots) from AMSR-E data were averaged to match with the in-situ SSM data from the 86 meteorological observation stations (triangles) in Guangdong Province (circle radius: 9,000m).
Fig. 3 Mapping of global land surface roughness on (a) October 31\textsuperscript{st}, 2004, (b) December 8\textsuperscript{th}, 2007 and (c) January 31\textsuperscript{st}, 2009 using the modified surface roughness index $\Gamma_{MPDI}$ (unit: cm).
Fig. 4 Comparison between the surface roughness simulated using the modified roughness index ($\Gamma_{\text{MPDI}}$) in the study and the surface roughness calculated by Hong (2010), using AMSR-E/Aqua Daily Global Quarter-Degree Gridded $T_b$ data on October 31st, 2004, December 8th, 2007 and January 31st, 2009.
Fig. 5 Land surface roughness condition of Guangdong Province on October 31st, 2004 derived from the modified surface roughness index ($\Gamma_{MPDI}$).
Land surface vegetation cover classification  
Land surface roughness degree classification  
Land surface classification  
Retrieval of SSM for each land type using the algorithmic in expression 6  
Validation using in-situ SSM measurements  
Results and discussions  

Fig. 6 Data processing flow diagram for mapping SSM from AMSR-E $T_b$ data.
Fig. 7 (a) Land surface roughness classification results of Guangdong Province; (b) Elevation map of Guangdong Province in 2005; (c) MPDI-based Land surface vegetation cover classification results of Guangdong Province; (d) Vegetation coverage map of Guangdong Province in 2008.
Fig. 8 Vegetation cover- and roughness-based land surface types of the 86 meteorological observation stations in Guangdong Province. Different numbers represent different land surface types (1: type 1, 2: type 2, 3: type 3, 4: type 4, 5: type 5). The positions of the numbers indicate the positions of the 86 meteorological observation stations.
Fig. 9 Validation of SSM inversion: (a) Scatter diagram between in-situ and model-derived SSM on January 28th & 31st, 2009 (N=2*86); (b) Error boxplot between in-situ SSM and model-derived SSM for each land surface type. The maximum of the error bar represents the biggest error between in-situ and model-derived SSM; the minimum of the error bar represents the smallest error between in-situ and model-derived SSM; the center of the error bar represents the average error between in-situ and model-derived SSM.
Fig. 10 Mapping of the model-derived SSM and in-situ SSM in Guangdong Province including the initiation, duration and recovery for the disastrous drought event of 2004-2005 (a1-a12). The severe droughts of years 2007 and 2009 in Guangdong Province were spatially mapped in a13-a16.
Table 1 Spatial characteristic of AMSR-E brightness temperature products.

<table>
<thead>
<tr>
<th>Footprint Size</th>
<th>Mean spatial resolution</th>
<th>Channels (GHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>75km * 43km</td>
<td>56 km</td>
<td>△  △  △  △  △  △</td>
</tr>
<tr>
<td>51km * 29km</td>
<td>38 km</td>
<td>△  △  △  △  △  △</td>
</tr>
<tr>
<td>27km * 16km</td>
<td>21 km</td>
<td>△  △  △</td>
</tr>
<tr>
<td>14km * 8km</td>
<td>12 km</td>
<td>△</td>
</tr>
</tbody>
</table>

△ means including the corresponding AMSR-E channel.
Table 2 Land surface roughness classification rule.

<table>
<thead>
<tr>
<th>$\Gamma_{MPDI}$ value</th>
<th>Land surface roughness types</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 - 0.1</td>
<td>flat</td>
</tr>
<tr>
<td>0.1 - 0.2</td>
<td>less flat</td>
</tr>
<tr>
<td>0.2 – 0.3</td>
<td>less rough</td>
</tr>
<tr>
<td>&gt;0.30</td>
<td>rough</td>
</tr>
</tbody>
</table>
Table 3 Land surface vegetation cover classification rule.

<table>
<thead>
<tr>
<th>AMSR-E 6.9GHz MPDI value</th>
<th>Land surface vegetation cover types</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00-0.01</td>
<td>dense vegetation I</td>
</tr>
<tr>
<td>0.01-0.02</td>
<td>dense vegetation II</td>
</tr>
<tr>
<td>0.02-0.03</td>
<td>dense vegetation III</td>
</tr>
<tr>
<td>0.02-0.04</td>
<td>dense vegetation IV</td>
</tr>
<tr>
<td>0.04-0.06</td>
<td>dense vegetation V</td>
</tr>
<tr>
<td>0.06-0.09</td>
<td>sparse vegetation</td>
</tr>
<tr>
<td>&gt;0.09</td>
<td>bare soil area</td>
</tr>
<tr>
<td>Number</td>
<td>Land surface types</td>
</tr>
<tr>
<td>--------</td>
<td>----------------------------------------</td>
</tr>
<tr>
<td>1</td>
<td>bare ground &amp; flat</td>
</tr>
<tr>
<td>2</td>
<td>sparse vegetation &amp; flat</td>
</tr>
<tr>
<td>3</td>
<td>sparse vegetation &amp; rough</td>
</tr>
<tr>
<td>4</td>
<td>dense vegetation &amp; less flat</td>
</tr>
<tr>
<td>5</td>
<td>dense vegetation &amp; rough</td>
</tr>
</tbody>
</table>
Table 5 Regression coefficients of the SSM retrieval algorithm for each land surface type.

<table>
<thead>
<tr>
<th>Land surface type</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.2109</td>
<td>17.9657</td>
<td>0.0407</td>
<td>1.8675</td>
<td>0.87</td>
</tr>
<tr>
<td>2</td>
<td>0.1944</td>
<td>18.0755</td>
<td>0.0410</td>
<td>2.1593</td>
<td>0.85</td>
</tr>
<tr>
<td>3</td>
<td>0.1375</td>
<td>16.8792</td>
<td>2.3566</td>
<td>1.2871</td>
<td>0.83</td>
</tr>
<tr>
<td>4</td>
<td>0.1511</td>
<td>13.1687</td>
<td>0.0204</td>
<td>2.4673</td>
<td>0.80</td>
</tr>
<tr>
<td>5</td>
<td>0.0915</td>
<td>28.4136</td>
<td>1.4641</td>
<td>4.1881</td>
<td>0.81</td>
</tr>
</tbody>
</table>
Table 6 Errors between in-situ and model-derived SSM for each land surface type.

<table>
<thead>
<tr>
<th>Land surface type</th>
<th>Average errors between in-situ SSM and derived SSM (%)</th>
<th>RMSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.11</td>
<td>0.94</td>
</tr>
<tr>
<td>2</td>
<td>2.89</td>
<td>1.91</td>
</tr>
<tr>
<td>3</td>
<td>6.24</td>
<td>6.69</td>
</tr>
<tr>
<td>4</td>
<td>6.95</td>
<td>2.56</td>
</tr>
<tr>
<td>5</td>
<td>8.52</td>
<td>5.16</td>
</tr>
</tbody>
</table>
Research Highlights

1. The land surface was classified into five types based on different vegetation and roughness condition.
2. Improving a roughness index using three channels of AMSR-E $T_b$.
3. Developing a SSM model integrating $T_b$, MPDI and observed temperature data.
4. Inversed results discriminated over a broad range of SSM (7%~73%, RMSE: 6.36%).
5. The errors for dense vegetation and rough surfaces were smaller than former studies.
6. The method was effective to detect the initiation, duration and recovery of drought events.