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An Improved Algorithm for Discriminating Soil Freezing and Thawing Using AMSR-E and AMSR2 Soil Moisture Products

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Received: 4 September 2018; Accepted: 25 October 2018; Published: 27 October 2018

Abstract: Discriminating between surface soil freeze/thaw states with the use of passive microwave brightness temperature has been an effective approach so far. However, soil moisture has a direct impact on the brightness temperature of passive microwave remote sensing, which may result in uncertainties in the widely used dual-index algorithm (DIA). In this study, an improved algorithm is proposed to identify the surface soil freeze/thaw states based on the original DIA in association with the AMSR-E and AMSR2 soil moisture products to avoid the impact of soil moisture on the brightness temperature derived from passive microwave remotely-sensed soil moisture products. The local variance of soil moisture (LVSM) with a 25-day interval was introduced into this algorithm as an effective indicator for selecting a threshold to update and modify the original DIA to identify surface soil freeze/thaw states. The improved algorithm was validated against in-situ observations of the Soil Moisture/Temperature Monitoring Network (SMTMN). The results suggest that the temporal and spatial variation characteristics of LVSM can significantly discriminate between surface soil freeze/thaw states. The overall discrimination accuracy of the improved algorithm was approximately 89% over a remote area near the town of Naqu on the East-Central Tibetan Plateau, which demonstrated an obvious improvement compared with the accuracy of 82% derived with the original DIA. More importantly, the correct classification rate for the modified pixels was over 96%.

Keywords: soil freeze/thaw states; AMSR-E and AMSR2; soil moisture; dual-index algorithm

1. Introduction

Seasonal change of surface soil freeze/thaw states is one of the most crucial characteristics of the land surface in higher latitudes, which is closely related to hydrological and ecological processes as well as climatic changes [1–4]. It has a far-reaching impact not only on surface runoff and plant growth but also on energy exchange and water balance [5,6]. With global climate change, the corresponding changes in soil freezing and thawing will have a significant influence on the regional environment and ecosystems [7–9].

Traditionally, the spatiotemporal behavior of soil freezing and thawing has been monitored via a limited number of station records, which cannot satisfy the need for conducting comprehensive studies. Satellite remote sensing, especially the development of microwave remote sensing technology provides a valid measure for ground surface observations over large areas [10]. Earth observation with remote sensing on the frozen ground is also one of the critical objectives of the scientific plan of the Earth Observing System (EOS). The potential of remote sensing in the study of surface soil freeze/thaw states has been a major area of interest.

Passive microwave remote sensing is not influenced by atmospheric conditions and cloud cover [11]. Passive microwaves can obtain information within a certain depth. Moreover, the microwave is very sensitive to the variability of the soil moisture content; fewer microwaves are emitted when soil moisture becomes higher and vice versa. Consequently, surface soil freeze/thaw states could be detected by the characteristics of the microwave emissivity, which contains significant information regarding the dielectric differences between frozen and thawed soils [12–15]. Objects with different temperatures, compositions, and structures emit different microwave radiation energies [11]. The dielectric properties of water and ice differ significantly, which makes it possible to monitor surface freezing and thawing processes using microwave technology [16]. Brightness temperature data, obtained by passive microwave radiometer, has been successfully applied in some cases to discriminate surface soil freeze/thaw states [5,17,18]. With the new generation of passive microwave radiometers on board the EOS satellite, passive microwave remote sensing of freezing soils has become an interesting topic for many researchers [19,20]. Additionally, high revisit frequency of passive microwave remote-sensing satellites and their ability to provide data with multiple scales has satisfied the high demand of the long-term ground surface freeze/thaw data series for the study of the relationship between the cryosphere and climate change.

Zuemdorfer et al. (1989) found that the negative spectral gradient of the brightness temperature is a good indication of frozen soils. England (1990) revealed that brightness temperature is particularly sensitive to the liquid water content in the soil surface and the scattering effect of frozen soils. Frozen soils have considerably different physical characteristics compared with thawed soils, such as low physical temperature, high emissivity, and low brightness temperature [21]. As the ground-based radiometer measurement suggests [22], the emissivity and the brightness temperature of soils vary in dry and wet states. However, wet soils will have higher emissivity and higher brightness temperatures in the frozen state. Therefore, it can be deduced that changes in radio-brightness are heavily dependent on the soil moisture. However, variations of soil moisture content might result in uncertainty when using the brightness temperature for the discrimination of surface soil freeze/thaw states [23]. For this reason, we attempted to improve the previous discrimination algorithm by taking the soil moisture effect into account.

Several microwave radiometry satellites, i.e., SSM/I (Special Sensor Microwave/Imagery, 1987), AMSR-E (Advanced Microwave Scanning Radiometer-EOS, 2002) and AMSR2 (The second Advance Microwave Scanning Radiometer, 2012), have been launched after the SMMR (Scanning Multichannel Microwave Radiometer) in 1978. Having a long-term microwave data series, accumulated approximately over 40 years, these microwave radiometry satellites provide a unique chance for the study of the temporal and spatial variations of freeze/thaw cycles under the background of global climate changes. Many theories and research experiments are available for monitoring and discriminating ground surface freeze/thaw states by using passive microwave data. Among the few algorithms proposed, the dual-index algorithm (DIA) has been widely used with a 37 GHz vertically polarized brightness temperature (Tb37v) and negative spectral gradient (SG) between 37 GHz and 19 GHz [2,5,6,21,24]. The 37 GHz vertically polarized brightness temperature was selected because of its comparative sensitivity to the near-surface temperature. However, limited soil moisture information can be obtained from Tb37v and SG indices, and the spectral gradient of shallow frozen soils could be positive due to weak scattering which might introduce bias into the results [24,25]. The decision tree algorithm proposed by Jin et al. (2009) by using three indices (the scattering index, the 37 GHz vertically polarized brightness temperature and the 19 GHz polarization difference) to describe the uncertainty in the discrimination of ground surface freeze/thaw states [26]. In this algorithm, the influence of soil moisture variations has not been considered, leading to the development of a discriminant function algorithm [27,28], seasonal threshold methods [15,29,30], a standard deviation method [20], and a polarization ratio-based algorithm [31–33] to address the issue. However, to our knowledge, only a few studies have investigated the impact of soil moisture on surface soil freeze/thaw states.

In recent decades, a variety of microwave soil moisture products have been made available in several parts of the world [34–37]. Release and application of the above-mentioned soil moisture products have made it possible to take full account of the spatial and temporal variations of soil moisture content in the discrimination of freeze/thaw states of the ground surface.

In the present study, an improved algorithm based on the DIA was proposed to include the influence of soil moisture variations when using microwave data products for the discrimination of surface soil freeze/thaw states. The improved algorithm was verified against the measurements acquired from the Soil Moisture/Temperature Monitoring Network (SMTMN), and, finally, was applied to the whole territory of China for demonstrating its feasibility.

2. Materials and Methods

2.1. Methodology

As the most widely used algorithm that only requires two parameters (Tb37v and SG) for the discrimination of the frozen and thawed ground surfaces [3,21], the DIA was selected as the fundamental approach in this study. We attempted to improve the discrimination performance of the DIA by taking the effect of soil moisture into account. For this purpose, we analyzed the temporal variations of soil moisture derived from AMSR-E and AMSR2 products to enhance the performance of the DIA. Algorithms used for extracting characteristics of soil moisture from ground-based measurements or satellite products were referenced from Gonzalez and Woods, (1992), Ajafernandez et al. (2006), and Wang (2008) [38–40]. Figure 1 illustrated the framework of the improved algorithm. The implementation of the proposed approach will be presented with a case study in the following sections.

Figure 1. The overall framework of the improved algorithm proposed in this study.

2.2. Materials

2.2.1. Ground-Based Measurements

In the present study, we selected a remote area near the town of Naqu on the East-Central Tibetan Plateau as an experiment site. Here, there is a multi-scale and densely settled ground-based Soil Moisture/Temperature Monitoring Network (SMTMN) which helped us to develop and validate the improved algorithm. As the highest plateau in the world, covered by seasonal frozen or permafrost

with an area of about $2.5 \times 10^6 \text{ km}^2$ above an average elevation of 4000 m a. s. l., the Tibetan Plateau has been the focus of numerous studies related to monitoring soil freeze/thaw states using remote sensing [26–28].

Ground-based observation data sets of soil moisture and temperature were obtained by ECH2O EC-TM electromagnetic sensors. Temporal coverage of the SMTMN was from 1st August 2010 to 31st July 2014. The soil moisture data of the SMTMN were calibrated with measured di-electricity according to the soil texture and soil organic carbon content; the temperature data used are observed in-situ and processed with quality control. The SMTMN covers a total number of 56 stations distributed over 4470 to 4950 m a.s.l., and provided data for three spatial scales (1.0° , 0.3° , 0.1° gridded) at four soil depths (0–5, 10, 20, and 40 cm) [41,42]. The experimental area is characterized by low biomass, high soil moisture variations, and typical seasonal freeze/thaw cycles in high elevations.

The 1.0° gridded ground-based measurements of soil temperature and moisture content from 1st August 2010 to 31st July 2011 and from 1st August 2012 to 31st July 2014 at a depth of 0–5 cm were selected to ensure the data availability and synchronicity of the experiment. The selected depth (5 cm) is approximately equivalent to the depth of microwave observations. As shown in Figure 2, the stations were divided into 20 blocks to match the corresponding AMSR-E and AMSR2 pixels. Only one station from several distributed stations in each of the blocks was selected to match the gridded microwave products, then the values of all the stations in the given pixel were averaged and substituted for the value of the selected station. In total, 12 retained stations were chosen for the purpose, as illustrated in Figure 2.

Figure 2. The geographic location of the study area with an overview of the Soil Moisture/Temperature Monitoring Network with 1.0° gridded blocks.

2.2.2. Datasets of Microwave Satellite Products

The National Aeronautics and Space Administration (NASA) AMSR-E daily level-3 land surface soil moisture products in the Equal-Area Scalable Earth Grid (EASE-Grid) format with a 0.25° spatial resolution (NASA National Snow and Ice Data Center Distributed Active Archive Center, http://nsidc.org/data/AE_Land3/versions/2), and the Japan Aerospace Exploration Agency (JAXA) AMSR2 daily level-3 land surface soil moisture products in the Equidistant-Cylindrical Rectangular (EQR) format with a 0.25° spatial resolution (Global Change Observation Mission, <http://gcom-w1.jaxa.jp>) were utilized in this study [43]. The temporal coverage of the AMSR-E products is from June 2002 to

October 2011, while the AMSR2 is from May 2012 to present. As a follow-up passive microwave sensor, the AMSR2 can be used as a continuous dataset with AMSR-E [44]. The gridded products include daily measurements of brightness temperatures, sea surface temperature, wind speed, as well as land surface soil moisture and quality control variables. The passive microwave remote-sensing products used as original data in the soil freeze and thaw discrimination are the 18.7 GHz and 36.5 GHz vertically polarized brightness temperature and surface soil moisture products. The detailed specifications of the data used in this study are listed in Table 1.

Table 1. The detailed specifications of the AMSR-E and AMSR2 products.

Data Type	Data	Spatial Resolution	Temporal Resolution	Time Range	Application
AMSR-E	SM ¹	0.25°	Daily	From 1 August 2010, to 31 July 2011 (P1)	Basic data for soil moisture characteristic parameters extraction
	Tb19v ²	0.25°	Daily		Original data for freeze and thaw discrimination
	Tb37v ³	0.25°	Daily		Original data for freeze and thaw discrimination
AMSR2	SM	0.25°	Daily	From 1 August 2012, to 31 July 2013 (P2) and from 1 August 2013, to 31 July 2014 (P3)	Basic data for soil moisture characteristic parameters extraction
	Tb19v	0.25°	Daily		Original data for freeze and thaw discrimination
	Tb37v	0.25°	Daily		Original data for freeze and thaw discrimination

¹ SM represents soil moisture. ² Tb19v represents the 18.7 GHz vertically polarized brightness temperature. ³ Tb37v represents the 36.5 GHz vertically polarized brightness temperature.

The AMSR-E soil moisture product was retrieved by using C-band (6.9 GHz) and X-band (10.7 GHz) brightness temperatures following the algorithm by Njoku et al. [43]. The local solar times of ascending and descending orbits of Aqua across the equator are about 1:30 p.m. and 1:30 a.m. The retrieval accuracy of the AMSR-E soil moisture product is less than the Root Mean Square Error (RMSE) of 0.06 m³·m^{−3}. Because vegetation also contains moisture, attenuation from vegetation increases the retrieval error in soil moisture [45]. The study area is mainly covered with sparse vegetation of alpine shrubs, alpine meadows, and alpine grasslands [46]. Fortunately, sparse vegetation cover in the cold elevations of the plateau guarantees the accuracy of the AMSR-E soil moisture product for this region. AMSR2 soil moisture product was estimated by using X-band (10.7 GHz) and Ka-band (36.5 GHz) brightness temperatures as employed by Fujii et al. [47] by introducing the vegetation fractional area into the soil moisture retrieved algorithm to consider the effects of vegetation cover. This algorithm showed the basis for the AMSR2 soil moisture algorithm. Zeng et al. [48] proved that the JAXA AMSR2 product could capture the soil moisture temporal dynamics better than the NASA AMSR-E product by evaluating the two kinds of soil moisture products over the Tibetan Plateau.

2.3. DIA

The original and improved versions of the DIA proposed by Zuerndorfer, et al. (1990) involved two parameters for the description of frozen ground surfaces. The core algorithm can be summarized in Equations (1) and (2).

$$Tb_{37v} \leq P_{37} \quad (1)$$

$$\frac{\partial}{\partial f} Tb(f) \leq P_{SG} \quad (2)$$

where Tb_{37v} represents vertical polarization brightness temperatures at 37 GHz (K), and $\frac{\partial}{\partial f} Tb(f)$ the negative spectral gradient between 19 GHz and 37 GHz ($K \cdot GHz^{-1}$). P_{37} and P_{SG} stand for the thresholds of two indicators of Tb_{37v} and $\frac{\partial}{\partial f} Tb(f)$, respectively. Usually, the value of P_{SG} is set to zero. When the condition for Equations (1) and (2) is satisfied simultaneously, the ground surface can be identified as freezing, otherwise, it's thawing.

Overall, more than 4000 measurements over 12 blocks were used in this study. Figure 3 illustrated the time series of Tb_{37v} and ground-based measurements of soil temperature and moisture at stations L9 and L27 for 1 August 2010 to 31 July 2011. The ground-based measurements of soil temperature and moisture were illustrated in the same figure to help better characterize the surface soil freeze/thaw states. Generally, in order to simplify the analysis, the ground surface can be treated as frozen when the soil temperature at 5 cm reaches below $0^\circ C$. As can be seen in Figure 3, the freezing period in the study area typically started from late October and ended in early April of the following year. Tb_{37v} and SG shared many similarities in the two stations on frozen and thawed ground surfaces. However, the hydrothermal conditions differed over specific periods of time. Both indicators manifested a significant spatial and temporal variability, which fluctuated with the phase transition between liquid water and ice. Additionally, some Tv_{37v} and SG anomalies were detected at the L27 station over the transition periods between freezing and thawing with a sharp drop in the soil moisture, implying a relationship between soil moisture and brightness temperature.

Figure 3. Time series of Tb_{37v} and ground-based measurements of soil temperature and moisture at Station L9 (a) and Station L27 (b) over the study periods.

To determine the threshold of Tb_{37v} , the correlation between the ground-based measurements of the soil temperature at depth of 5 cm and Tb_{37v} derived from the satellite observations over the study periods was calculated, and the results are shown in Figure 4.

As exhibited in Figure 4, only a moderate correlation was found between the soil temperature at 5 cm depth and a Tb_{37v} index with $R_{P1} = 0.64$ and $R_{P2, P3} = 0.65$. The threshold of Tb_{37v} (P_{37}) for two time periods (time series of AMSR-E and AMSR2 products) can be estimated around a soil temperature of 257.60 K ranging from 250.00 K to 265.20 K and 258.69 K ranging from 251.24 K to 266.14 K.

This moderate correlation can be attributed to the following reasons. First of all, the influence of snow cover on the freeze/thaw states of the underlying soil was not included in the analysis of the passive microwave data. Secondly, the temporal variability of Tb37v is one of the characteristics of AMSR-E and AMSR2 brightness temperature data products, which have different characteristics compared with the observed values [43]. Consequently, this becomes one of the inherent disadvantages of the DIA, which results in uncertainties in surface soil freeze/thaw state discriminations. This shortcoming is the main point of focus in this study that must be overcome.

Figure 4. The linear relationship between soil temperature and Tb37v over the periods of P1 (a) and P2, P3 (b).

2.4. Soil Moisture Characteristics

Soil moisture significantly affects seasonal patterns of surface soil freeze/thaw states [49–51]. The seasonal variations of the mean daily soil moisture values, measured at 5 cm soil depth in 12 stations over the area, were used to characterize the spatial and temporal variations of this parameter. The results were plotted with different colors in Figure 5 to illustrate the observed fluctuations of this parameter, where the solid blue line, solid red line, and blue filled area represent the variations of the averaged soil moisture, averaged soil temperature, and variance of soil moisture in 12 stations, respectively, over the study periods. As shown, there was an evident temporal and spatial variability of soil moisture over the experiment site. This variability implied that the limited in-situ observations could result in a considerable error in the quality assessment of soil moisture products. Furthermore, dramatic seasonal variations of soil moisture in summer (between $0.1 \text{ m}^3 \cdot \text{m}^{-3}$ to $0.6 \text{ m}^3 \cdot \text{m}^{-3}$) and slight variations in winter (between 0 to $0.2 \text{ m}^3 \cdot \text{m}^{-3}$) gave a clear indication of the significant differences between soil moisture content in the frozen and thawed soils.

Figure 5. The seasonal variations of mean daily soil moisture measured at 5 cm in 12 stations over the study area.

2.5. Soil Moisture Characteristic Parameter Extraction

The temporal and spatial heterogeneity of soil moisture marks the complexity of its influence on climate change and hydrology. A simple statistical indicator [38] of the local variation of the soil moisture was adopted to evaluate the seasonal fluctuations of the data series in this study. Local variance, as the measure of the fluctuation of datasets within a specific period, is the most widely used digital processing technique, especially in graphics and image processing [40,52]. Unlike a local variance parameter in image interpretation in two dimensions, the local variance of soil moisture (LVSM) should be assessed from both spatial and temporal aspects. The local variance of soil moisture, therefore, can be represented by Equations (3) and (4).

$$LVSM_{(k,i,j)} = \frac{1}{\lambda} \sum_{p=k}^{k+\lambda} (\eta_{(p,i,j)} - \mu_{\lambda})^2 \quad (3)$$

$$\mu_{\lambda} = \frac{1}{\lambda} \sum_{p=k}^{k+\lambda} \eta_{(p,i,j)} \quad (4)$$

where, $LVSM_{(k,i,j)}$ is the local variance of soil moisture ($\text{m}^3 \cdot \text{m}^{-3}$) at (i, j) at time k ; η is the pixel value of soil moisture at pixel (i, j) at time p ; λ is a fixed partial time span (days) of the time series used to calculate local variance; and, μ_{λ} is the average value of soil moisture over the time span. We assigned different values (e.g., 5, 10, 15, ..., 45 and 50) to λ to calculate LVSM. The value explaining the largest variations in seasonal LVSM was selected as an appropriate λ . Finally, λ was found to be 25 in this study.

It should be noted that the fixed partial time span of the time series λ , similar to a sliding window, was used to calculate the local variance from the beginning to the end of the time series. In this process, the sliding window has two positions (before or after the unresolved pixel, except for the first and the last day) relative to an unresolved pixel. The local variances of each pixel, if available, were calculated at two positions, and then the minimum value was selected as the local variance of this pixel. $LVSM^a_{(k,i,j)}$ and $LVSM^b_{(k,i,j)}$ represented the local variances of the two positions at (k, i, j) , respectively. This approach can be represented by Equation (5).

$$LVSM_{(k,i,j)} = \begin{cases} LVSM^b_{(k,i,j)} & , \quad \lambda < k \leq L - \lambda \\ \min(LVSM^a_{(k,i,j)}, LVSM^b_{(k,i,j)}) & , \quad k \leq \lambda \\ LVSM^a_{(k,i,j)} & , \quad k > L - \lambda \end{cases} \quad (5)$$

where, L is the total length of the time series.

2.6. Improvement of the DIA by Using LVSM

Integrating LVSM with the DIA to further improve the performance of the DIA is a key issue in this study. The LVSM based on the passive microwave soil moisture products were derived by the approach described above, and the result was plotted in Figure 6 together with time series of the AMSR-E and ASMR2 soil moisture products and in-situ temperature products at station L9 (a) and L27 (b). The result exhibited different temporal variation characteristics under different passive microwave soil moisture products between AMSR-E and AMSR2. Even so, it can be noted that most of the LVSM values were comparatively higher in summer and reasonably lower and with fewer fluctuations in winter over the entirety of the three year period of the study. Compared with soil temperature variations, LVSM values fluctuated dramatically in thawed soils but remained constant at a low level in frozen ground surfaces.

The scatter plot of LVSM along with the corresponding cluster data of Tb37v and SG were displayed in Figure 7. In this figure, darker cluster data points indicate higher LVSM values.

According to the soil temperature, the cluster data points were divided into two regions, namely, the frozen ground (A_1) and the thawed ground (A_2). As indicated, a large proportion of high LVSM values are scattered in region A_2 , while most of the data with low LVSM values were concentrated in region A_1 . This finding, which was inconsistent with the hypothesis that the LVSM values always stay at a low level in the frozen ground surfaces and was the main issue with the original DIA in discriminating freeze/thaw cycles.

Figure 6. Seasonal variations of local variance of soil moisture (LVSM), AMSR-E, and AMSR2 soil moisture products and soil temperature products at station L9 (a) and L27 (b).

Figure 7. The scatter plot of LVSM along with corresponding cluster data of Tb37v and spectral gradient (SG) over the periods of P1 (a) and P2, P3 (b).

Several tactics are possible to improve the original DIA by taking LVSM into account. For example, one could adjust the threshold of Tb37v and SG by statistical analysis of the relationship between LVSM and the two indices of the original DIA, or modify the results of the original DIA through LVSM directly. Lastly, with regard to the characteristics of LVSM, the second approach was selected,

which involved integrating the LVSM as a correction index with the original DIA to reduce uncertainty. The procedure to improve the original DIA by taking LVSM into account can be summarized as follows: (1) Constructing the temporal and spatial sequence of ground-based soil temperature over the 12 stations; (2) Extracting LVSM values at the soil temperature of 0 °C and organizing them as an array; (3) Assigning the maximum value of this array as a new threshold to update the results of the DIA. Through this procedure, the new threshold was determined as 0.168.

3. Results

3.1. Performance Comparisons of the Improved Algorithm with Original DIA over the Experiment Site

Daily surface soil freeze/thaw states from 1st August 2010 to 31st July 2011 over the experiment site were discriminated with the improved algorithm based on passive microwave soil moisture products (AMSR-E and AMSR2 products) as described in Section 2. Correspondingly, initial days (date and day of the year (DOY)) of soil freeze and thaw at each station over the study periods can be obtained through classification of the discriminated surface soil freeze/thaw states' images. The soil temperature slightly fluctuated around 0 °C over the experiment period. Thus, the first day of the period, when the ground surface remained frozen or thawed for longer than three days, was defined as the initial day. The starting dates and DOY of soil freeze and thaw at 12 stations are shown in Table 2. The initial days obtained for soil freezing and thawing by the improved and original DIA had a considerable difference.

Table 2. Initial days of soil freezing and thawing at 12 stations.

Study Period	Sta. ¹	Initial Days (Date/DOY) of Soil Freezing			Initial Days (Date/DOY) of Soil Thawing		
		Improved Algorithm	DIA	SMTMN obs. ²	Improved Algorithm	DIA	SMTMN obs.
P1	L1	03 Nov/307	12 Oct/285	02 Nov/306	29 Mar/088	29 Mar/088	01 Apr/091
	L9	03 Nov/307	12 Oct/285	03 Nov/307	29 Mar/088	29 Mar/088	01 Apr/091
	L11	01 Nov/305	12 Oct/285	03 Nov/307	29 Mar/088	29 Mar/088	19 Mar/078
	L14	03 Nov/307	12 Oct/285	04 Nov/308	24 Mar/083	24 Mar/083	19 Mar/078
	L19	28 Oct/301	05 Oct/278	04 Nov/308	02 Apr/092	16 May/136	31 Mar/090
	L23	12 Sep/255	25 Aug/237	05 Nov/309	02 Apr/092	17 Jun/168	16 Mar/075
	L26	10 Sep/253	10 Sep/253	04 Nov/308	18 Apr/108	04 May/124	18 Apr/108
	L27	28 Oct/301	12 Oct/285	29 Oct/302	24 Mar/083	24 Mar/083	12 Apr/102
	L30	28 Oct/301	12 Oct/285	04 Nov/308	02 Apr/092	04 May/124	25 Mar/084
	L32	04 Nov/308	12 Oct/285	04 Nov/308	24 Mar/083	24 Mar/083	19 Mar/078
	L35	28 Oct/301	12 Oct/285	04 Nov/308	29 Mar/088	29 Mar/088	27 Mar/086
	L37	10 Sep/253	08 Sep/251	04 Nov/308	09 May/129	17 Jun/168	17 Mar/076
P2	L1	02 Nov/307	26 Oct/300	01 Nov/306	19 Apr/109	19 Apr/109	09 Apr/099
	L9	02 Nov/307	16 Sep/260	30 Oct/304	19 Apr/109	19 Apr/109	29 Mar/088
	L11	26 Oct/300	08 Oct/282	02 Nov/307	19 Apr/109	19 Apr/109	15 Mar/074
	L14	02 Nov/307	10 Oct/284	06 Nov/311	03 Apr/093	03 Apr/093	15 Mar/074
	L19	28 Oct/302	12 Oct/286	07 Nov/312	05 Apr/095	07 May/127	22 Mar/081
	L23	24 Oct/298	21 Aug/234	30 Oct/304	12 Apr/102	25 May/145	10 Apr/100
	L26	24 Oct/298	10 Oct/284	03 Nov/308	19 Apr/109	19 Apr/109	10 Apr/100
	L27	02 Nov/307	12 Oct/286	29 Oct/303	03 Apr/093	03 Apr/093	13 Apr/103
	L30	28 Oct/302	10 Oct/284	30 Oct/304	03 Apr/093	03 Apr/093	14 Mar/073
	L32	25 Oct/299	19 Oct/293	30 Oct/304	22 Mar/081	19 Apr/109	15 Mar/074
	L35	25 Oct/299	08 Oct/282	09 Nov/314	19 Apr/109	5 May/125	29 Mar/088
	L37	22 Oct/296	21 Aug/234	30 Oct/304	20 Apr/110	28 May/148	14 Mar/073
P3	L1	26 Oct/299	04 Oct/277	31 Oct/304	03 May/123	24 May/083	06 Apr/096
	L9	02 Nov/306	20 Oct/293	30 Oct/303	30 Mar/089	30 Mar/089	31 Mar/090
	L11	20 Oct/293	06 Oct/279	31 Oct/302	03 May/123	03 May/123	26 Mar/085
	L14	22 Oct/295	22 Oct/295	31 Oct/302	23 Mar/082	23 Mar/082	27 Mar/086
	L19	22 Oct/295	22 Oct/295	03 Nov/307	10 Feb/041	10 Feb/041	28 Mar/087
	L23	22 Oct/295	15 Oct/288	08 Nov/312	25 Mar/084	25 Mar/084	06 Apr/096
	L26	20 Oct/293	15 Oct/288	05 Nov/309	23 Mar/082	23 Mar/082	06 Apr/096

Table 2. Cont.

Study Period	Sta. ¹	Initial Days (Date/DOY) of Soil Freezing			Initial Days (Date/DOY) of Soil Thawing		
		Improved Algorithm	DIA	SMTMN obs. ²	Improved Algorithm	DIA	SMTMN obs.
P3	L27	20 Oct/293	15 Oct/288	08 Nov/312	23 Mar/082	23 Mar/082	06 Apr/096
	L30	22 Oct/293	22 Oct/295	31 Oct/304	10 Feb/041	10 Feb/041	28 Mar/087
	L32	20 Oct/293	20 Oct/293	08 Nov/312	26 Feb/057	26 Feb/057	26 Mar/085
	L35	20 Oct/293	06 Oct/279	04 Nov/308	03 May/123	03 May/123	29 Mar/088
	L37	20 Oct/293	04 Oct/277	31 Oct/304	08 Apr/098	03 May/123	17 Mar/076

¹ Sta. is an abbreviation for “Station”. ² obs. is an abbreviation for “observation”. Feb, Mar, Apr, Jun, Aug, Sep, Oct, and Nov are abbreviations for February, March, April, June, August, September, October, November, respectively.

A total number of 3240 pixels with frozen soils (from 20th September to 5th November) and thawing (from 5th April to 20th May) with the duration of approximately 90 days in each year at each station were selected to validate the improved algorithm. The validated results at the 12 stations over the period from 1st August 2010 to 31st July 2011 and 1st August 2012 to 31st July 2014 were listed in Table 3. The accuracy obtained for the improved algorithm in the range of 71.1% to 98.9% was generally higher than that of the original DIA ranging from 63.3% to 96.7%. In total, the application of the improved algorithm resulted in 356 incorrectly discriminated pixels with an average discrimination accuracy of 89.0%. Using the original approach produced 588 incorrectly discriminated pixels with an average accuracy of 81.9%. A frequency histogram of the observed soil temperatures over the incorrectly discriminated pixels is presented in Figure 8.

Table 3. Validation of the discrimination results by in situ observations at 12 stations over the period of 1st August 2010 to 31st July 2011 and 1st August 2012 to 31st July 2014.

Study Period	Sta.	DIA			Improved Algorithm		
		Validation	Incorrect Discrimination	Accuracy (%)	Validation	Incorrect Discrimination	Accuracy (%)
P1	L1	90	15	83.3	90	8	91.1
	L9	90	9	90.0	90	4	95.6
	L11	90	8	91.1	90	3	96.7
	L14	90	7	94.4	90	2	97.8
	L19	90	20	77.8	90	4	95.6
	L23	90	27	70.0	90	12	86.7
	L26	90	24	73.3	90	15	83.3
	L27	90	22	75.6	90	14	84.4
	L30	90	14	84.4	90	4	95.6
	L32	90	3	96.7	90	1	98.9
	L35	90	4	95.6	90	1	98.9
P2, P3	L37	90	30	66.7	90	26	71.1
	Total	1080	183	83.1	1080	94	91.3
	L1	180	42	76.7	180	29	83.9
	L9	180	23	87.2	180	15	91.7
	L11	180	28	84.5	180	16	91.1
	L14	180	12	93.3	180	11	93.9
	L19	180	28	84.5	180	14	92.2
	L23	180	41	77.3	180	25	86.2
	L26	180	43	76.1	180	28	84.5
	L27	180	34	81.1	180	30	83.3
	L30	180	26	85.6	180	21	88.4
P1, P2 and P3	L32	180	24	86.7	180	19	89.5
	L35	180	38	78.9	180	23	87.2
	L37	180	66	63.3	180	31	82.8
	Total	2160	405	81.3	2160	262	87.9
	Total	3240	588	81.9	3240	356	89.0

Figure 8. Frequency histogram of the observed soil temperatures for the incorrectly discriminated pixels.

3.2. Performance of the Improved Algorithm as Compared with the DIA over the Whole Territory of China

The areal extent of the frozen soils over China was derived by the improved and the original DIA, respectively, and the results are shown in Figure 9. The original DIA overestimated the areal extent of the frozen soils with 1% to 60% seasonal deviations. As only the incorrectly discriminated frozen soils can be corrected by the improved algorithm, the areal extent of the frozen soil over the period from late October to early April of the following year differed between the two algorithms.

Figure 9. The areal proportions of the frozen soil over the study periods derived from the improved and original DIA, respectively.

The number of the frozen days over 1st August 2010 to 31st July 2011 and 1st August 2012 to 31st July 2014 (365 days a year) in China were calculated with the improved algorithm, and the results are exhibited in Figure 10a–c. The number of days for the frozen soils varied from 0 to 360 days over this period. The longest freezing period, ranging from 300 to 360 days, was found in the West and Northwest part of the Qinghai Tibetan Plateau where permafrost is widely distributed, and the shortest period (less than 30 days) was found in some parts of Central China and most parts of Southern China. The geocryological regionalization and classification map (2000) [53] provided by the National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China is shown in Figure 10d.

The low brightness temperatures found near the rivers and lakes of the temperate and humid regions of China were caused by the higher soil moisture levels and the corresponding lower emissivity. Higher moisture contents can result in less accuracy when employing the brightness temperature for the discrimination of surface soil freeze/thaw states, which was the case for the areas close to the Beijing–Hangzhou Grand Canal and the Yangtze River Basin with an extensive duration of the frozen days.

Figure 10. The numbers of days for the frozen soil in China over the study periods of P1 (a), P2 (b) and P3 (c), and the geocryological regionalization and classification of China (d) downloaded from <http://www.geodata.cn>.

4. Discussion

In this study, most of the initial days of soil freezing obtained from the improved algorithm differed slightly by about 1 to 10 days when compared with the observed values of SMTMN in the time period of P1, as shown in Table 2. Nevertheless, the initial days obtained for soil thawing by the improved algorithm differed by about 1 to 20 days from the SMTMN. Even so, the results obtained by the improved algorithm were closer to those observed by SMTMN than that by the original algorithm, especially at station L26. In the time periods of P2 and P3, see Table 2, the initial days of soil freezing and thawing obtained from two algorithms had similar characteristics with the period of P1. Overall, the results of initial days of soil freezing held better reliability than that of soil thawing. The relatively poor performance of both algorithms in the determination of initial days of surface soil freeze/thaw states was attributed to the temporal and spatial differences of passive microwave data products and SMTMN observations.

The higher accuracy of the improved algorithm demonstrated its superiority in distinguishing ground surface freeze/thaw cycles, see Table 3. Approximately 250 pixels were modified by the improved algorithm during the verification stage (with 241 pixels correctly modified), which resulted in a correct classification rate for the modified pixels of higher than 96.4%. It was shown that the classification performance of surface soil freeze/thaw states discrimination algorithm significantly improved by integrating with LVSM.

The incorrectly discriminated pixels were mainly distributed in the soil temperatures between -1°C to 1°C , which suggest that incorrect discriminations mainly occurred over the period of phase

transition between liquid water and ice, see Figure 8. Additionally, incorrect discriminations were found to occur much more frequently in the thawed soils compared to in the frozen soils. This might be due to the following reasons: (1) An observation depth of 18.7 GHz and 36.5 GHz passive microwave sensor was not exactly the same as the in-situ soil moisture measurement depth, which brought errors in discrimination of freeze/thaw states of the ground surface; (2) soil moisture increased with depth when the ground surface thawed, which resulted in a higher instability of soil emissivity; (3) most of the incorrect discriminations for the frozen ground surfaces were corrected by soil moisture information.

The distribution map of the number of days for the frozen soil over China, see Figure 10a–c, were in good agreement with the geocryological regionalization and classification map of China, see Figure 10d. Besides, the distribution map of the numbers of days for the frozen soil revealed much more detailed information compared with the map of the geocryological regionalization and classification of China.

5. Conclusions

An improved algorithm was proposed to identify the surface soil freeze/thaw states based on the original DIA in association with the AMSR-E and AMSR2 soil moisture products. By doing so, obviating the impact of soil moisture on the brightness temperature derived from passive microwave remote sensing was attempted. The local variance of soil moisture (LVSM) was introduced into the improved algorithm as an effective indicator for selecting a threshold to update and modify the original algorithm to better identify freeze/thaw states. The improved algorithm was validated with the in-situ observations from the Soil Moisture/Temperature Monitoring Network (SMTMN).

Based on our findings, the LVSM had evident seasonal variations which in fact represented soil freeze/thaw states. Our results showed a major improvement in the discrimination accuracy of the proposed algorithm compared with the original one. Additionally, the correct classification rate for the modified pixels was over 96%. Integrating a surface soil freeze/thaw states discrimination algorithm with the AMSR-E and AMSR2 soil moisture product improved the classification performance reasonably and effectively. Overall, the methodology adopted and the results obtained in this study will have great implications for simulations of hydrological processes, and studies on cryosphere and global changes in cold regions.

Author Contributions: The first two authors (H.G. and W.Z.) contributed equally to this paper. H.G. and W.Z. conceived and designed the experiment; H.G. performed the experiments; H.C. processed and analyzed the data. H.G. wrote the paper manuscript. W.Z. revised the manuscript to improve the quality of the work. All authors have read the final manuscript.

Funding: This research was funded by the National Key R&D Program of China grant number [No. 2016YFA0602302 and No. 2016YFB0502502].

Acknowledgments: The soil moisture and soil temperature datasets utilized in the present study was generously provided by Data Assimilation and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences. We would also wish to thank all the graduate students of Wanchang Zhang's group for their helpful comments in our weekly seminars.

Conflicts of Interest: The authors declare no conflict of interest.

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