Improvement of the AMSR-E Algorithm for Soil Moisture Estimation by Introducing a Fractional Vegetation Coverage Dataset Derived from MODIS Data

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Abstract

Soil moisture is an important component of the hydrology of land surfaces. Accurate monitoring of soil moisture is essential in understanding energy and water cycles and ecological system processes. Microwave remote sensing using satellites is an effective method for collecting global information on land surface hydrology. In this study, the soil moisture algorithm of Koike et al. was revised by focusing on the vegetation component, with the goal of improving the accuracy of the soil moisture product of the Advanced Microwave Scanning Radiometer for the Earth Observing System mounted on the satellite Aqua.

The water content of vegetation affects the sensitivity of the microwave remote sensing of soil moisture. In the Koike algorithm, a semi-empirical vegetation model with the assumption of uniform vegetation coverage was used to evaluate the vegetation effects on the retrieval of soil moisture data. However, satellite microwave radiometer observations have large footprints of several tens of kilometers. There are few land surface regions in the world that are uniformly covered with vegetation at this scale. The results of ground-based experiments demonstrated that non-uniformities in the vegetation coverage have very large effects on horizontally polarized waves. We therefore created a global fractional vegetation coverage dataset from the data gathered by the Moderate Resolution Imaging Spectroradiometer, and attempted to incorporate this into the algorithm. In addition, model parameters in the semi-empirical vegetation model were replaced on the basis of a ground-based experiment.

The results were verified by the comparison of estimated and measured data for three locations with differing vegetation coverage conditions. Compared with results estimated by the Japan Aerospace Exploration Agency standard product version 5 (created by the algorithm before the current revision), the results estimated by the revised algorithm showed a significant improvement in accuracy and reduction in the number of erroneous estimations.

Keywords: AMSR-E, soil moisture, fractional vegetation coverage, MODIS

1. Introduction

Land surface hydrological quantities have a significant impact on the seasonal changes and interannual variations of the climate through interactions with the atmosphere. In particular, variation of the soil moisture content affects the heat balance of the land surface. Information on the soil moisture conditions over a large region is important for understanding, modeling, and forecasting climate changes. When viewed from a short-term perspective, soil moisture has a strong effect on land surface evapotranspiration and plays an important role in the process of re-distributing precipitation that reaches the land surface into runoff and evapotranspiration. Therefore, from the perspective of disaster prevention and water resources management, frequent observations of soil moisture are required. Furthermore, soil moisture is the water source for vegetation, and monitoring soil moisture is important in understanding ecological processes.

Microwave remote sensing using satellites is an effective method for collecting global information on land surface hydrological quantities. The method has two advantages: being able to periodically perform observations over a large region regardless of whether it is night or day without the microwaves being affected by the atmosphere, and the sensitivity of these instruments to land surface hydrological quantities due to liquid water having an extremely high dielectric constant in the microwave band compared with soil.

The Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) was developed in 2002 by the National Space Development Agency of Japan (NASDA),
now the Japan Aerospace Exploration Agency (JAXA). AMSR-E was launched on the Aqua satellite of the U.S. National Aeronautics and Space Administration (NASA). Aqua is still operational and the AMSR-E is also operating normally except for the 89GHz-A system, which was shut-down in November 2004. As shown in Table 1, the AMSR-E has a swath width of approximately 1450 km and is able to observe the entire planet in approximately 2 days.

Research related to algorithm development for soil moisture began with experimental research using aircraft-based and ground-based microwave radiometers. Because vegetation also contains moisture, soil moisture can only be estimated from satellite observation data by correctly accounting for the effects of vegetation. Although the radiative transfer is complicated owing to vegetation having widely varying properties such as shapes, sizes, and spatial distributions, in the long wavelengths from the 1-GHz band to the 6-GHz band, radiation and absorption are dominant, and a good correlation between optical thickness \( \tau \) and vegetation water content \( W_v \) has been demonstrated by observation and theory. The relationship between \( \tau \) and \( W_v \) can be expressed as a linear equation. It is used in many soil moisture algorithms under an assumption of uniform vegetation coverage. However, for satellite observations, the microwave radiometer footprint is several tens of kilometers. There are few land surface regions in the world that are uniformly covered with vegetation at this scale. The problem of the surface containing a mixture of different radiative characteristics within a footprint has been investigated using algorithms that make use of other physical quantities. The algorithm for estimating sea surface wind speed considers the fractional coverage of foam on the sea surface in the calculation of emissivity because the emissivity changes if foam occurs. Furthermore, there are also instances of the opposite situation of calculating fractional coverage from satellite data. The algorithm for estimating sea ice concentrations estimates the area ratio of the footprints of mixed sea ice and sea surface on the basis of differences of radiative characteristics between them. Non-uniformities in the surface cannot simply be ignored.

Regarding land regions, Chang et al. (1996) pointed out that the signal from snow-covered surfaces was reduced by forest cover when inferring the snow water equivalent using a microwave radiometer. Chang and Kelly (2002) created fractional forest coverage data from a global albedo dataset and introduced this into the snow depth retrieval algorithm. Similarly for soil, because the radiative characteristics differ between vegetation and soil surface in the same way as for snow cover, it is important to consider the coverage conditions.

In this study, the soil moisture algorithm of Koike et al. (2004), which is employed as the JAXA standard algorithm, was revised to increase the accuracy. Although a fractional vegetation coverage dataset was introduced into the algorithm for the JAXA standard products version 2 as ancillary data, it was not fully investigated. It was ascribed as a cause of the poor accuracy of soil moisture estimates in vegetation regions. In addition, the low quality of the dataset potentially resulted in poor estimations of soil moisture even for less vegetated surfaces such as those in semi-arid regions. In this study, a
new fractional vegetation coverage dataset was created from the normalized difference vegetation index (NDVI), which has been provided as a standard product using the Moderate Resolution Imaging Spectroradiometer (MODIS), and used in the algorithm. Parameters of the vegetation model were also replaced at the same time as the dataset update to improve the accuracy of the radiative transfer model for the vegetation, which is used to evaluate the vegetation effect.

2. Radiative Transfer Model of the Soil Surface–Vegetation Layer

2.1 Radiative Transfer Model

The low-frequency range microwave radiative transfer used in soil moisture calculations is only slightly affected by the atmosphere. If the effects are ignored, the microwave brightness temperature $T_{Bsp}$ of a land surface uniformly covered by vegetation as observed by satellites can be expressed as follows.

$$T_{Bsp} = T_s \cdot e^{-c} + (1-\omega_s)(1-e^{-c})T_c + (1-\omega_s)(1-e^{-c}) T_r \cdot \Gamma(\theta, p) \cdot e^{-c}$$

(1)

where the subscript $p$ represents the polarization of the waves; the subscript $c$ refers to a component related to the vegetation; $T_{Bsp}$ is the microwave brightness temperature of the soil surface; $\tau_s$ and $\omega_s$ are the optical thickness and single scattering albedo of the vegetation layer, respectively; $T_c$ is the physical temperature of the vegetation; $\Gamma$ is the Fresnel power reflectivity; and $\theta$ is the incidence angle, which is fixed at 55 degrees for the AMSR-E. The first term on the right hand side of Eq. (1) represents the radiation from the ground surface dissipated by the vegetation layer, and the second and third terms represent the upward radiation from the vegetation layer itself and the reflection of the downward radiation, respectively.

In the case of sufficiently moist soil, the microwave brightness temperature $T_{Bsp}$ can be approximated by the product of the soil surface emissivity with the soil physical temperature. Under the conditions of thermal equilibrium, the emissivity is derived from the reflectivity. For a smooth surface, the reflectivity is equal to the Fresnel power reflectivity found from the incidence angle and soil mixture dielectric constant, where the soil mixture dielectric constant is found by substituting the soil moisture into Dobson’s model. In addition, the emission is also affected by the roughness of the soil surface, and $T_{Bsp}$ is given by the following equation.

$$T_{Bsp} = [1 - \{1 - Q \cdot \Gamma(\theta, p) + Q \cdot \Gamma(\theta, q) \cdot e^{-k_0 \cdot \omega_s} \}] \cdot T_s$$

(2)

where $T_s$ is the soil physical temperature, $Q$ is the polarization-mixing ratio, $h$ is the roughness height, and $q$ is the opposite polarization from $p$. $Q$ and $h$ are constants that depend on the surface roughness of the soil. In this study, we define $H = e^{-k_0 \cdot \omega_s}$. Values of $Q$ and $H$ for each band of 10 GHz and 36 GHz, which are used in the Koike algorithm as described in section 4.1, are determined by comparing the brightness temperature data observed by the AMSR-E with the in-situ data. Because roughness has the effect of weakening the signal from the soil in the same way as vegetation does, analysis of the roughness requires the use of data obtained under the condition of there being no vegetation effects.

Analysis of roughness was performed on data covering Mongolia for the period of early spring when there is no vegetation. The in-situ data used was the 2003 and 2004 datasets published by the Coordinated Enhanced Observing Period (CEOP) (http : //www.ceop.net). The CEOP reference site in Mongolia consists of 16 stations within a region spanning 120 km north-south and 160 km east-west centered on latitude 46.283°N and longitude 107.298°E. Automatic weather stations (AWS) were installed at four of these stations. Because this region is covered with frozen soil in winter and with grasslands in summer, the analysis periods were selected by referring to the AWS data within the period each year after the frozen soil thaws until the first precipitation event. The values of $Q$ and $H$ that minimized the differences between the values observed from satellite and values estimated from in-situ data over all of the soil moisture measurement sites were $H = 0.873$ and $Q = 0.189$ at 10 GHz, and $H = 0.680$ and $Q = 0.344$ at 36 GHz. Here, the polarization index (PI) and the index of soil moisture (ISW) (described in section 4.1) were used for this analysis.

In relation to the vegetation, the optical thickness $\tau_s$ and single scattering albedo $\omega_s$ in the radiative transfer model are strictly determined using characteristics such as the water content, shape, size, orientation, number density, and distribution of voids of each of the components that make up the vegetation itself, such as leaves, stems, and branches. Jackson and Schmugge (1991) demonstrated that $\tau_s$ is highly correlated with the overall water content $W_s$ (kg/m²) of vegetation, and proposed the following linear equation based on experimental research results of existing ground-based observations and aircraft observations.

$$\tau_s = b \cdot W_s$$

(3)

where $b$ is a vegetation parameter and depends on the type of vegetation. Regarding $\omega_s$, there is very little quantitative information. This is because, in addition to the small amount of scattering in the lower frequency range, the scattering depends mainly on the geometrical characteristics of each of the components that make up the vegetation. Representing such features would require a complicated radiative transfer
mium temperature divided by the surface temperature. The validity of this equation is discussed in section 3. The vegetation observation experiments were carried out for three months from September in 2003 with the Ground-Based Microwave Radiometer (GBMR) at the Field Production Science Center (UT-FPSC) of the Graduate School of Agricultural and Life Sciences at the University of Tokyo (Nishi-Tokyo City, Tokyo) and involved buckwheat (Fagopyrum esculentum Moench). Values of $b$ and $\omega_0$ were determined for each frequency and polarization. In the vegetation observation experiments, only the 10 and 18 GHz bands of the GBMR were available; therefore, the values of $b$ and $\omega_0$ for the 36 GHz band used in our soil moisture algorithm were determined subjectively on the basis of experimental results. The values of $b$ and $\omega_0$ used in this study are given in Table 2.

The radiative transfer model described above is valid for the case where the interior of the footprint is uniformly covered with vegetation. In actual satellite measurements, there are few regions of the world where a land surface with uniform vegetation coverage exists. In cases where the footprint contains a mixture of bare and vegetation conditions, the microwave brightness temperature $T_{bp}$ measured by the satellite can be expressed by the following linear equation obtained from Eqs. (1) and (2).

$$T_{bp} = (1-f_v) \cdot T_{bp} + f_v \cdot T_{bvp}$$

where $f_v$ is the fractional vegetation coverage. The validity of this equation is discussed in section 3.

### 2.2 Introduction of the Extinction and Emission Model for the Soil Layer

In the soil radiative transfer model given by Eq. (2), although only the property of the soil surface is considered, it has been noted that radiative transfer within the soil layer is important in dry soil. Using the GBMR, Fujii et al. (2000) observed that the apparent emissivity (the value of the microwave brightness temperature divided by the surface temperature) increased when the soil moisture increased for dry conditions of volumetric soil moisture of 0.1 m$^3$/m$^3$ or less. In general, emissivity is considered to decrease as the soil moisture increases. This result was the complete opposite. Our explanation of this behavior was that the radiative transfer process increases in the soil layer owing to an increasing penetration depth when the soil dries. In other words, as the soil dries, the emissivity decreases owing to extinction in the soil layer. Furthermore, the apparent emissivity can be considered to decrease owing to the soil temperature in the deeper regions being lower than the surface temperature.

To incorporate this aspect of the soil radiative transfer processes into the algorithm, the four-stream fast model, which is used to determine precipitation particles in the atmosphere, was applied to the soil layer. A new radiative transfer model for the soil system that combines this with the conventional soil surface model was developed. In this model, the soil layer is treated as a system composed of an absorbing and radiating medium with a dielectric constant derived from the soil moisture, which is embedded with a scattering material composed of many orb-shaped soil particles, and not having an upper boundary. This is combined with a soil surface model on top of the soil layer that has no thickness and exhibits only the effects of refraction and reflection. When the soil is dry, the extinction process has a strong effect in the soil layer. As the soil moisture increases, the effect of the soil layer disappears and the effect of radiation for the soil surface becomes dominant. This algorithm works well in dry regions because it incorporates this radiative transfer within the soil layer. In the current study, the model of radiative transfer within the soil layer is used without alteration.

### 3. Evaluation of the Effect of Non-uniform Vegetation Coverage

#### 3.1 Ground-based Observation Experiments

To evaluate the effects of non-uniform vegetation coverage, observations of vegetation were performed using the GBMR. The GBMR has a small footprint of several meters, and has the advantage of being able to perform detailed observations of the measurement target.

The vegetation observation experiments were carried out in December 2003 at the UT-FPSC and involved crimson clover (Trifolium incarnatum L.). The crimson clover is native to the study site and germinated after land leveling in September. It grew to a plant height of 10 to 15 cm during the experiment. Three footprints with different coverage conditions were configured (A, B, and C), and observations of the vegetation physical temperature, soil physical temperature, and soil moisture were performed simultaneously using the GBMR. Vegetation water content was obtained from the difference between the total and dry weights of biomass. Here, the total weight was measured by complete sampling after the observations were complete, and the dry weight was measured after

![Table 2: Vegetation parameters](https://example.com/table2)

<table>
<thead>
<tr>
<th>Frequency</th>
<th>V</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.65 GHz</td>
<td>V</td>
<td>H</td>
</tr>
<tr>
<td>36.5 GHz</td>
<td>V</td>
<td>H</td>
</tr>
<tr>
<td>$b$</td>
<td>1.93</td>
<td>1.25</td>
</tr>
<tr>
<td>$\omega_0$</td>
<td>0.061</td>
<td>0.063</td>
</tr>
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</table>
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drying for 3 days in an oven at 80°C. Vegetation water contents were 0.342, 0.374, and 0.054 kg/m$^2$ for footprints A, B, and C, respectively. Fractional vegetation coverage was estimated from photographs taken from the position of the microwave radiometer antenna. The fractional vegetation coverage for footprints A, B, and C was 96%, 60%, and 20%, respectively. For footprint B, the measurements were performed twice (fractional vegetation coverage of 47% and 53%) during November, and this data was also included in the analysis. However, as complete mowing was not performed, the estimation of the vegetation water content was alternatively performed using the modified soil adjusted vegetation index (MSAVI) based on spectral data measured using a FieldSpec Pro from ASD Inc. The MSAVI—leaf area index (LAI) coefficient and the LAI—$W_v$ coefficient were determined from the measurement data taken during complete mowing. These were used to estimate the vegetation water content. The estimated vegetation water contents during the two November observations were 0.210 and 0.307 kg/m$^2$. The soil in each footprint was kept very moist with moisture ratios ranging from 0.3 to 0.4 m$^3$/kg$^3$.

Figure 1 shows the results of comparing the estimated and observed values of brightness temperature at 10 GHz in footprints B and C. Two types of estimation results are shown: the results when the fractional vegetation coverage was taken into consideration using Eq. (4) ($f_v$-model) and the results calculated using Eq. (1), assuming that vegetation with the same water content was distributed uniformly throughout the footprint (layer-model). The roughness parameters $Q$ and $H$ in the radiative transfer model were based on observation data for each footprint taken after complete mowing. Furthermore, the vegetation parameters $b$ and $d_v$ for this experiment were determined from the measurement data for footprint A, which had the most uniform cover.

Two results are suggested by Fig.1. First, the model estimates that consider the fractional vegetation coverage using Eq. (4) are a good match to the observed values, regardless of the vegetation water content. This shows that the linear model of Eq. (4) is suitable for taking the vegetation coverage conditions into consideration. The mean absolute error was 2.3 K. Second, results calculated by assuming a uniform surface using Eq. (1) exhibited a significant deterioration in accuracy for horizontal polarization. In particular, the difference between the calculated and observed values increased as the vegetation water content increased and reached 20 to 30 K. This is because there was little radiation from the soil surface and the contrast between bare ground and vegetation was large. Because polarization differences are used in the algorithm for estimating the soil moisture as described in section 4.1, the accuracy of the radiative transfer model for horizontal polarization affects the soil moisture estimation accuracy. That is, it is important for the algorithm to consider the vegetation coverage.

3.2 Creation of the Global Fractional Vegetation Coverage Dataset

Although it is easy to obtain the fractional vegetation coverage with ground-based observations of a small area, the satellite algorithm requires fractional vegetation coverage data for the entire planet. Here, the NDVI data published as part of the MODIS vegetation indices (16-Day L3 Global 1 km V5) by the Land Processes Distributed Active Archive Center was used to create a global fractional vegetation coverage dataset. MODIS data are available from two satellites, Terra and Aqua, and the 16-day composite 1-km resolution MODIS vegetation indices are provided as MOD13A2.
for Terra and MYD13A2 for Aqua. The quality flag was checked before data processing to ensure quality, and NDVI data that excluded cloudy regions, snow and ice regions, and water surface regions was used. The fractional vegetation coverage was calculated from NDVI data using the model developed by Carlson and Ripley (1997)\(^20\). They performed simulations using a radiative transfer model for the vegetation-soil-atmosphere, which showed that the NDVI changes up to total surface coverage by vegetation depend mainly on the fractional vegetation coverage. They then proposed the following fractional vegetation coverage model.

\[
f_c = \left( \frac{\text{NDVI} - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right)^2
\]

where \(\text{NDVI}_{\text{max}}\) and \(\text{NDVI}_{\text{min}}\) are the NDVI when the fractional vegetation coverage reaches 100\% and the NDVI for bare ground, respectively. In this study, \(\text{NDVI}_{\text{max}}\) was taken to be 0.7 and \(\text{NDVI}_{\text{min}}\) was taken to be 0.2 by referring to the variation in NDVI for wheat fields in the grain belt of the state of Victoria in Australia.

Here, two types of processing were carried out to create in advance the fractional vegetation coverage dataset from the NDVI using Eq. (5). The first processing was the spatial averaging. To match the AMSR-E footprint size, spatial averaging was performed using a \(33 \times 33\) pixel circular boxcar filter at 0.05° grid points. The area of this filter is approximately 797 km\(^2\). The AMSR-E footprint is elliptical and its size is different in each frequency band. However, these factors are not considered for the dataset in the interests of computational cost in this study. The second processing was temporal averaging. The MOD13A2 and MYD13A2 both have compositing periods of 16 days, but the periods start on different days. One starts in the middle of the compositing period of the other. The temporal averaging was performed every 8 days using the two products to reduce temporal discontinuities. The global fractional vegetation coverage dataset was created for the period from June 2002, when Aqua measurements began, to May 2008.

4. Inverse Analysis Method

4.1 Inclusion of the PI and ISW

A radiative transfer model can be used to determine the radiative brightness temperature when all parameters are known. An inverse analysis method is required for the estimation of soil moisture from the observed brightness temperatures. Here, we used a method for simultaneously retrieving the soil moisture and vegetation water content from the PI\(^2\) and ISW\(^2\) in the same way as the Koike algorithm does\(^3\). The PI and ISW are respectively the polarization and frequency differences divided by the average value of brightness temperature as defined by Eqs. (6) and (7).

\[
\begin{align*}
\text{PI} &= \frac{T_{\text{BV}} - T_{\text{BH}}}{\frac{1}{2}(T_{\text{BV}} + T_{\text{BH}})} \\
\text{ISW} &= \frac{T_{\text{BH}} - T_{\text{BI}}}{\frac{1}{2}(T_{\text{BH}} + T_{\text{BI}})}
\end{align*}
\]

where \(T_{\text{BV}}\) and \(T_{\text{BH}}\) are the microwave radiative brightness temperatures of the vertical and horizontal polarizations, respectively. The subscripts \(i\) and \(j\) in Eq. (7) indicate high and low frequencies, respectively. There are four unknowns in the radiative transfer model described by Eqs. (1) to (4) and its related assumptions. They are soil moisture, vegetation water content, soil physical temperature, and vegetation physical temperature. The PI and ISW mainly depend on soil moisture and vegetation water content rather than physical temperatures. Effects of the physical temperatures become small by dividing by the average brightness temperature. Characteristics of the PI and ISW are as below.

**PI**

The microwave brightness temperature of a ground surface generally has a larger value for the vertical polarization than for the horizontal polarization. As the soil moisture increases, the difference between the brightness temperatures of the two polarizations increases significantly, and the PI increases. If there is a layer of vegetation on the soil, the difference in brightness temperature between the polarizations is reduced by the extinction process within the vegetation layer. The degree to which this occurs depends on the optical thickness \(\tau\) of the vegetation layer. Because \(\tau\) from Eq. (3) is proportional to the vegetation water content \(W_v\), a small value for the PI indicates the vegetation water content is high.

In this study, the PI is defined by the horizontal and vertical polarizations of the 10 GHz band. Low frequency bands for which vegetation exhibits good transparency are useful for performing measurements of soil. However, the 6 GHz band, which is the lowest frequency band of the AMSR-E, cannot be used in many regions owing to problems with radio-frequency interference.

**ISW**

The dielectric constant of water exhibits significant frequency dependence. As a result, the emissivity of a ground surface is high in the high frequency range and low in the low frequency range. Using these characteristics, the soil moisture content can be effectively represented by the ISW described using the difference in brightness temperature between the high and low frequency ranges as expressed by Eq. (7). The ISW increases as the amount of soil moisture increases. Although the relationship with vegetation water
content is not monotonous, there is a trend of the ISW decreasing as the vegetation water content increases. In this study, the ISW is defined using 36 GHz horizontally polarized waves and 10 GHz horizontally polarized waves. Because the usefulness of this index increases as the difference in frequency increases, it is preferable to use two frequencies that are widely separated. However, the contribution of the atmosphere is great at higher frequency. To account for the atmospheric effect roughly, the PI and ISW were used for the analysis of roughness parameters as mentioned in section 2.1. Roughness parameters $Q$ and $H$ were selected to minimize the difference between the PI and ISW values observed by the AMSR-E from satellite and values simulated from in-situ data measured at the surface.

### 4.2 Lookup Tables

It is possible to obtain the soil moisture and vegetation water content corresponding to the PI and ISW calculated from microwave brightness temperatures. The mechanism for correlating these two indices with the soil moisture and vegetation water content is called a lookup table. This is used as an inverse analysis table when retrieving the soil moisture and vegetation water content from the microwave brightness temperatures. The lookup tables are created in advance for each fractional vegetation coverage from the results of radiative transfer value simulations using Eq. (4). The simulation conditions in this study are as follows.

- Soil moisture: range of 0.000–0.600 m$^3$/m$^3$, step size of 0.001 m$^3$/m$^3$;
- Vegetation water content: range of 0.000–1.800 kg/m$^3$, step size of 0.001 kg/m$^3$;
- Fractional vegetation coverage: range of 1–100%, step size of 1%;
- Soil and vegetation physical temperature: 293 K (fixed).

### 4.3 Overview of Data Processing

Figure 2 shows an overview of the data processing in this study. First, the fractional vegetation coverage, $f_v$, of each footprint is retrieved using the $f_v$ dataset and information for the observation date, latitude, and longitude. The appropriate lookup table is then selected. Second, the PI and ISW are calculated from the 10 and 36 GHz brightness temperature data passed by the quality check. Finally, the soil moisture and vegetation water content are retrieved using the lookup table. The ancillary data for the algorithm only consist of the fractional vegetation coverage information calculated from the MODIS data and do not require further information.

### 5. Verification of the Algorithm

The algorithm described here was applied to three locations with differing vegetation conditions and the results were compared with in-situ data. The analysis period was the year 2003. The selected verification sites were (a) Tibet Gaize (32.30°N, 84.05°E, China), (b) Balranald Bolto (34.658°S, 143.549°E, Australia), and (c) Little River (31.50°N, 83.55°W, USA). Sites (a) and (b) were CEOP reference stations. Although site (c) was not a CEOP reference station, it was a Soil Climate Analysis Network (SCAN) (http://www.wcc.nrcs.usda.gov/scan/) observation site. SCAN data are

![Flowchart of the AMSR-E soil moisture algorithm.](image)
published by the United States Department of Agriculture (USDA) and the Natural Resources Conservation Service (NRCS). The measurement depths of the soil moisture data used in the comparisons were 3, 0 to 7, and 5 cm for sites (a), (b), and (c), respectively. Figure 3 shows the variations in the enhanced vegetation index (EVI) for 2003 at each site. The EVI values are included in the Terra/Aqua MODIS standard products as described in section 3.2. The EVI value of each product was spatially averaged over 33 × 33 pixels centered at a site to check the vegetation condition over the AMSR-E footprint. The EVI values are plotted at the starting date of compositing period with filled symbols for Aqua and blank symbols for Terra in Fig. 3. The EVI is an index with improved sensitivity for high biomass regions. It is a better indicator of vegetation than the NDVI used for the fractional vegetation coverage dataset in this study. Site (a) is a region with sparse vegetation and it had the lowest EVI values throughout the year. Site (b) is located near the wheat belt in Australia and it had high EVI values in September and October during the winter wheat growing season. Site (c) has a temperate climate and much precipitation and was the site with the most vegetation. The EVI was high throughout the year, reaching approximately 0.5 in summer.

Figure 4 shows the soil moisture at each site. The AMSR-E estimates are from the nearest footprint when the center position of the footprint was within 5 km of the target site. The solid lines in Fig. 4 show in-situ data. Daily precipitation is shown as bar graphs in the upper part of each graph. Missing data for precipitation are indicated by gray triangles. The numbers of estimated values are shown in this figure for both ascending and descending orbits. The AMSR-E observation time of each orbit is almost constant each day because Aqua is a polar orbiting satellite. The ascending (node is PM 1:30 ± 15 in local sun time) and descending (node is AM 1:30 ± 15 in local sun time) observations are day time and night time observations, respectively.

The estimated values follow the changes in the observations well for all sites. In the case of Tibet Gaize, the radiative transfer for vegetation that is focused on in this study is not important because this site has almost no vegetation and the radiative transfer for soil is dominant in the AMSR-E observation. However, there were a large number of estimated values for this site. While there were 214 estimated values for the descending orbit and 200 for the ascending orbit in this study, there were respectively 22 and 79 in the JAXA standard product version 5 during same period at this site. In the previous version of the algorithm, the vegetation dataset had many erroneous values that resulted in poor estimation of the soil moisture content. By introducing a new dataset, the estimation was improved. In the cases of the two other sites having vegetation, for both Balranald Bolto, which has a relatively small amount of vegetation, and for Little River, which has a relatively large amount of vegetation, the estimated values are also a good match to the observation values. From this, we can surmise that both the fractional vegetation coverage dataset and the radiative transfer model of the vegetation appropriately evaluate the effects of vegetation on the soil moisture estimation.

However, many instances of over-estimation can be seen during precipitation events. When there is ongoing precipitation, it is easy for errors to occur in estimating soil moisture from satellite observation data. However, this is opposite to the precipitation effect on the soil moisture algorithm that is ignored in this study. The estimated soil moisture content will be too low because precipitation particles reduce the signal of polarization and frequency difference. It is difficult to directly compare the two owing to uncertainties under precipitation conditions and surface drying just after precipitation. There are two major uncertainties. One is non-uniformities of the soil moisture distribution within a footprint. This is unavoidable in a validation using point measurement data. The other is the vertical profile of soil moisture at near the surface layer. When only soil in the skin surface becomes wet with precipitation, the satellite observation detects a signal of wet soil that the soil moisture sensor cannot measure. Water droplets adhering to the vegetation are another uncertainty.

To eliminate errors due to such uncertainties, comparisons were made between monthly averages of the estimated values
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Fig. 4 Comparison of the estimated volumetric soil moisture content with in-situ data at three sites: (a) Tibet Gaize in China (32.30°N, 84.05°E), (b) Balranald Bolto in Australia (34.65°S, 143.54°E), and (c) Little River, GA in the U.S.A. (31.50°N, 83.55°W). The period is for one year from January 1, 2003.

and in-situ values. Figure 5 shows scatter diagrams of the monthly averages, with ascending and descending orbit data indicated, for the period of 60 months from 2003 to 2007. Figure 5 (a) shows the results for the JAXA standard product version 5 (the previous version of the algorithm). Figure 5 (b) shows the results for the algorithm after introducing the fractional vegetation coverage data from MODIS as performed in this study. Although the satellite estimation values are the data for the footprint that is the closest to the in-situ observation point, the in-situ values were determined for the monthly averages by sampling the data for the time closest to the satellite observation time within one hour. These results clearly demonstrate that the accuracy was improved by the revision.

Table 3 gives each of the statistical quantities. Although a bias of approximately 0.03 m³/m³ remains, both the bias and RMSE were improved by the revision. Regarding the bias, it is possible that the measurements were even lower than the surrounding soil moisture owing to the characteristics of the soil moisture sensor used in the measurements and the characteristics of the observation sites. There were 11 soil moisture observation sites within the Little River watershed (watershed area of 334 km²) [10]. When their data were compared with soil moisture data from observation sites near SCAN sites, the observation values of the SCAN sites were typically found to be slightly lower. The results obtained using the algorithm as revised in this study are largely validated for the site.
Figure 5 Scatter diagram of monthly averaged soil moisture estimated from the AMSR-E data (y-axis) versus in-situ data at Little River, GA in the U.S.A.; (a) the results from the JAXA standard product version 5 and (b) the results from this study. The period is from January 2003 to December 2007. (1:1 line is shown as a dashed line.)

6. Conclusions

In this study, a fractional vegetation coverage dataset was created corresponding to the footprint scale of the microwave radiometer from the MODIS standard product, and this was introduced into the Koike algorithm. Vegetation parameters in the radiative transfer model were also replaced on the basis of results from ground-based experiments. The soil moisture contents estimated from the AMSR-E observation data were compared with in-situ data at three locations with differing vegetation coverage conditions. Although the algorithm has a trend that the estimated value is larger than the in-situ data under a precipitation condition, the estimated values follow the changes in the in-situ data well for all sites. In addition, we confirmed that poor estimations by the algorithm improved for the Tibet Gaize site located in a less-vegetated region. Quantitative verification using SCAN site data at Little River also showed improved accuracy compared with the JAXA standard product version 5.

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References


Table 3 Algorithm validation statistics at Little River. (The monthly averaged volumetric soil moisture (m^3/m^3) from January 2003 to December 2007 was used.)

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Improvement of the AMSR-E Algorithm for Soil Moisture Estimation by Introducing a Fractional Vegetation Coverage Dataset Derived from MODIS Data


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