Soil moisture estimates from TRMM Microwave Imager observations over the Southern United States

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Abstract

The lack of continuous soil moisture fields at large spatial scales, based on observations, has hampered hydrologists from understanding its role in weather and climate. The most readily available observations from which a surface wetness state could be derived is the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) observations at 10.65 GHz. This paper describes the first attempt to map daily soil moisture from space over an extended period of time. Methods to adjust for diurnal changes associated with this temporal variability and how to mosaic these orbits are presented. The algorithm for deriving soil moisture and temperature from TMI observations is based on a physical model of microwave emission from a layered soil–vegetation–atmosphere medium. An iterative, least-squares minimization method, which uses dual polarization observations at 10.65 GHz, is employed in the retrieval algorithm. Soil moisture estimates were compared with ground measurements over the U.S. Southern Great Plains (SGP) in Oklahoma and the Little River Watershed, Georgia. The soil moisture experiment in Oklahoma was conducted in July 1999 and Little River in June 2000. During both the experiments, the region was dry at the onset of the experiment, and experienced moderate rainfall during the course of the experiment. The regions experienced a quick dry-down before the end of the experiment. The estimated soil moisture compared well with the ground observations for these experiments (standard error of 2.5%). The TMI-estimated soil moisture during 6–22 July over Southern U.S. was analyzed and found to be consistent with the observed meteorological conditions.

Keywords: Soil moisture estimates; TRMM Microwave Imager; Southern United States

1. Introduction

There is a critical need in land surface hydrology to understand the feedback between the land surface and the atmosphere (Beljaars, Viterbo, Miller, & Betts, 1996; Koster & Suarez, 1996; National Aeronautics and Space Administration, 2000). The key state variables needed in this understanding are: soil moisture, soil temperature, vegetation and precipitation. Soil temperature, vegetation and precipitation are currently observed using satellite observations. Surface soil moisture is the only variable that is currently not observed over large areas and over an extended period of time using remote sensing. There are no validated large-scale or regional, long-term databases for this purpose. Presently, there are large discrepancies among the results of different land surface hydrology models forced with the same data (Robock, Vinnikov, & Schlosser, 1997). This gap in the center of the hydrologic cycle has resulted in a lack of knowledge ranging from the role of soil moisture in reinforcing or suppressing summertime convective precipitation, to its variability relative to other terms in the water budget.

Global soil moisture estimates at frequent temporal scales are required to understand the role of hydrologic land
surface processes in climate. Current climate models run at coarse resolutions (2.5–5 degree grid resolutions) (Boville & Gent, 1998). Aircraft-based extensive field campaigns can address small-scale studies, but it is virtually impossible to use airborne or ground monitoring systems for large-scale climatic studies. Spaceborne, low-frequency microwave radiometers can be used to measure surface soil moisture (Jackson, 1997). Previous microwave satellite missions lacked the ground observations needed to develop and validate soil moisture retrieval models. The Scanning Multi-frequency Microwave Radiometer (SMMR) with a frequency of 6.6 GHz offered the best opportunity for spaceborne soil moisture remote sensing (Owe, Van de Griend, & Chang, 1992). However, with a ground resolution of ~150 km, it was very difficult to design a validation experiment.

Recognizing the limitations of past, current and near-future microwave satellite systems, as well as the availability of adequate validation data, the research reported in this paper utilized Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) observations over the Southern portion of the U.S. The long-term goal is to develop a daily 4-year soil moisture Pathfinder data set using the TMI observations. This is the first time soil moisture estimates have been made from a spaceborne platform over large areas for an extended period of time. Earlier attempts have involved soil moisture mapping using airborne sensors over experimental areas (Jackson, Le Vine, Swift, Schmugge, & Schiebe, 1995; Jackson et al., 1999). TMI with a lowest frequency of 10.65 GHz, though not perfect for soil moisture, offers the opportunity to demonstrate the potential of future satellites (AMSR, AMSR-E, SMOS). The Advanced Microwave Scanning Radiometer on EOS Aqua launched in May 2002 (AMSR-E) and ADEOS-II (AMSR) launched in end of 2002, with a 6.9-GHz frequency channel, should provide more reliable estimates of soil moisture in regions of low vegetation. The Soil Moisture and Ocean Salinity Mission (SMOS) with an operating frequency of 1.4 GHz, scheduled for launch in 2007, is currently the best of the scheduled satellite missions for soil moisture remote sensing (Kerr et al., 2001). Soil moisture algorithms proposed for these satellite missions have not been rigorously tested outside the extensive soil moisture experimental regions. TMI provides a unique opportunity to test and develop these algorithms and to build a daily soil moisture data set for an extended period, over 4 years, for use in hydrologic research.

In this paper, an iterative model for estimating soil moisture from TMI observations is developed. The model is based on the forward soil moisture model described in Jackson (1993). TMI-based soil moisture estimates were made over the southern continental U.S. for July 1999 and June 2000. Several factors contributed to selecting and limiting the analyses to the Southern U.S. These included the observation domain of the TMI, the effects of vegetation on algorithm performance, temporal variability, and available resources for ground-based validation. The results obtained are validated against ground observations taken during the field experiments [Southern Great Plains 1999 (SGP99) and GA2000]. A meteorological validation based on precipitation events over Southern U.S. was also conducted for July 1999.

2. TRMM TMI

The Tropical Rainfall Measuring Mission (TRMM) is a joint mission between the National Aeronautics and Space Administration (NASA) of the United States and the National Space Development Agency (NASDA) of Japan. The objectives of TRMM are to measure rainfall and energy (i.e. latent heat of condensation) exchange of the tropical and subtropical regions of the world. The primary rainfall instruments on TRMM are the TRMM Microwave Imager (TMI), the precipitation radar (PR) and the Visible and Infrared Radiometer System (VIRS). The space segment of TRMM is a satellite in a 350-km circular orbit with a 35° inclination angle. The combination of satellite-borne passive and active sensors deployed on TRMM provides critical information regarding the three-dimensional distributions of precipitation and heating in the tropics (Kummerow et al., 2000; Simpson, 1988).

The TMI is a nine-channel passive microwave radiometer based upon the Special Sensor Microwave/Imager (SSM/I), which has been flying aboard the U.S. Defense Meteorological Satellite Program (DMSP) satellites since 1987. The TRMM has provided data since December of 1997. TRMM is in a sun asynchronous orbit providing 16 orbits per day. On a given day, there will be multiple orbits over the Southern U.S. at varying times of observation. One of the satellite instruments is the TRMM Microwave Imager (TMI). TMI is a dual-polarization passive microwave conical scanning radiometer operating at 10.65, 19.4, 21.3, 37.0 and 85.5 GHz. It has a spatial resolution of about 50 km at 10.65 GHz. TMI has a wide swath that can provide data between ±38° latitude.

Key differences between the TMI and SSM/I are the addition of a pair of 10.65-GHz channels with horizontal and vertical polarizations and a frequency change of the water vapor channel from 22.235 to 21.3 GHz. This change off the center of the water vapor line was made to avoid saturation in the tropical orbit of TRMM. The TMI also has an increased spatial resolution due to the lower orbit of the TRMM satellite with respect to the DMSP and due to a larger antenna, which is six times larger than the antenna on the DMSP satellite. The antenna beam views the earth surface with a “nadir” angle of 49°, which results in an incident angle of 52.8° at the earth’s surface. The TRMM orbit yields a swath width of 758.5 km. During each complete revolution (i.e., a scan period of about 1.9 s), the sub-satellite point advances a distance of
3. Soil moisture algorithm

The relationship between brightness temperature \( T_B \) and soil moisture, surface roughness and vegetation water content is nonlinear. The algorithm for deriving soil moisture and temperature from TMI observations is based on physical models of microwave emission from a layered soil–vegetation–atmosphere medium. Atmospheric effects were assumed to be minimal for this study, based on the work of Drusch, Wood, and Jackson (2001). A soil moisture retrieval algorithm similar to that as described in Jackson (1993) was developed.

The methodology uses the forward soil moisture model iteratively to minimize the error between the computed and observed brightness temperatures. The dielectric constant of the soil surface layer, which is based on soil texture, is computed using the dielectric mixing model of Wang and Schmugge (1980). The soil emissivity of the surface soil layer is computed using the Fresnel equation. Emissivity is equal to 1 minus the reflectivity. The effect of surface roughness \( s \) on soil reflectivity \( r \) can be characterized by (Choudhury, Schmugge, Chang, & Newton, 1979)

\[
r = r^* \exp(h \cos^2 \theta)
\]

where \( h \) is a roughness parameter \( = 4s^2k^2 \) proportional to the root mean square (RMS) height variations of the soil surface, and \( k = 2\pi / \lambda \) \( (\lambda \) is the wavelength).

At short microwave wavelengths (X-Band), the attenuation of the signal by vegetation increases. Vegetation cover behaves like a mask, which can be treated as an attenuating layer, and defines the local transmissivity (transmissivity of the region is a function of the optical depth \( O_\omega \) of vegetation cover). As a first-order approximation, this is a function of water content of the vegetation (VWC), and sensor response function (defined as the signal received by the sensor from a particular object, which in turn is a function of frequency and water content) for a particular plant canopy type (Jackson, Schmugge, & Wang, 1982). In this work, the pixel emissivity is corrected for vegetation using the approach proposed by Jackson and Schmugge (1991). In this approach, the vegetation is treated as an attenuating layer with transmissivity \( \gamma \) that depends on the vegetation optical depth \( \tau \) and the incidence angle \( \theta \). A semi-infinite soil layer of physical temperature \( T_s \), an air–soil reflectivity \( r \), and a layer of vegetation of physical temperature \( T_v = T_s \) was proposed.

\[
T_B = (1 - r)T_s \exp(-\tau) + T_v(1 - z)[1 - \exp(-\tau)] \\
[1 + r \exp(-\tau)]
\]

\[
\gamma^2 = \exp[-2\tau(\sec \theta)]
\]

where \( r \) is the reflectivity of the soil surface and \( z \) is the single scattering albedo of vegetation.

The optical depth of the canopy is determined using a first-order approximation of the vegetation parameter \( b \), which is a function of land use, and vegetation water content (VWC):

\[
\tau = bVWC
\]

Normalized Difference Vegetation Index (NDVI) was used as a surrogate for vegetation water content. A simple linear model was used to convert the observed NDVI to vegetation water content. Based on Eq. (4), conversion factor \( a \) and NDVI are substituted for the VWC and the product of \( a*b \) is optimized in the retrieval algorithm. The brightness temperature of the surface is computed by multiplying the surface emissivity \( c \) by the soil surface temperature \( T_s \).

It is impossible to separate the effects of surface roughness and vegetation (unless one of them is known a priori). A fixed value of 0.1 was used for surface roughness and the remainder was assumed to be automatically coupled with the vegetation effect. The effect of vegetation scattering was neglected in this approach, which enabled us to couple the surface roughness and vegetation effects. The following three variables are undefined based on the above relationships: soil moisture, soil surface temperature and the vegetation parameter \( a*b \).

A rainfall screening algorithm demonstrated in Ferraro (1997) and Ferraro, Smith, Berg, and Huffman (1998) was used to filter out pixels with precipitation. The radiative transfer algorithm was used only over clear pixels. Dual polarization observations at 10.65 GHz are used in the retrieval. An iterative, least-squares minimization method is employed in the retrieval algorithm. The algorithm is based on the multi-channel approach described in Njoku and Li (1999), Bindlish and Barros (2000), and Jackson and Hsu (2001). The method of soil moisture retrieval uses an iterative least-squares minimization algorithm based on the
forward model developed to estimate the measured brightness temperatures. Soil moisture is most sensitive to the lowest TMI frequency (10.65 GHz); thus, only the H and V polarization measurements at this frequency were used in the retrieval process.

The brightness temperatures at H and V polarizations provide two input or known variables, but are dependent on three unknown parameters as linked through Eq. (2) (soil moisture, soil temperature and the modified vegetation parameter). To overcome this, the polarization ratio \( \frac{T_{BH}}{T_{BV}} \) is used as third known variable in the retrieval algorithm. By using Eq. (2) and rearranging the equations we arrive at the following form

\[
\frac{T_{BH}}{T_{BV}} = \frac{(1 - r_H)e^{-\tau} + (1 - e^{-\tau})(1 + r_H e^{-\tau})}{(1 - r_V)e^{-\tau} + (1 - e^{-\tau})(1 + r_V e^{-\tau})}
\]

(5)

The polarization ratio \( \frac{T_{BH}}{T_{BV}} \) is independent of soil temperature and is dependent only on soil moisture and vegetation water content (Paloscia et al., 1992; Paloscia, Macelloni, Santi, & Koike, 2001), whereas the independent channel observations (H or V) are dependent on soil moisture, soil temperature and vegetation water content. Also, H polarization measurements have a higher sensitivity to soil moisture. Keeping these relationships in perspective, a least-squares minimization approach was adopted. The polarization ratio and the H and V band measurements (x) were optimized in the retrieval algorithm to obtain soil moisture, soil temperature and vegetation water content (y). An upper bound of 51% (maximum porosity) and a lower bound of 5% (wilting point) were used in our soil moisture computations.

A simple Newton–Raphson iteration is adopted to obtain convergence of these surface parameters. Assuming the forward model can be represented by \( Q(x) \), where x are the parameters soil moisture, soil temperature and vegetation water content. The solution for x is found iteratively. An initial guess for x is made based on the average value of the surface parameters. The sensitivity of each surface parameter (at iteration \( k \)) to the observation \( \frac{\partial Q}{\partial x} \) is computed by numerically perturbing the parameter by a small amount

\[
[J]_x = \left( \frac{\partial Q}{\partial x} \right)_x
\]

(6)

The next guess \( (k+1) \) iteration for the variables (x) is then computed as follows:

\[
x_{k+1} = x_k + (J^T_k J_k)^{-1} J^T_k [Q(x_k) - Q(x)]
\]

(7)

The estimates of x are iteratively refined by incrementing \( k \) in Eq. (6) until either the RMS difference between the measured and estimated values of \( T_B \) is sufficiently small or the change in x between iterations is suitably small. In practice, the model converges to a solution in three to five iterations. Based on this observation, a maximum number of iterations specified in the model was 10. It was observed that about 90–95% of the TMI pixels for a given day converged within 10 iterations.

This methodology requires multiple computations of the radiative transfer model (Jackson, 1993) for the purpose of computing the sensitivity matrix and for multiple iterations for every pixel. This methodology is significantly more ( \~{} 10–20 times) computationally intensive than the single-channel approach (Jackson et al., 1999; Jackson & Hsu, 2001).

4. Ancillary data

The algorithm in its current form requires several ancillary data sets for implementation: surface soil texture, land cover, and NDVI. The following summarizes the decisions and data sets selected for this process.

4.1. Surface soil texture

Soil properties do not change and, therefore, this data plane of ancillary data is constant. The multi-layer soil characteristics data set for the conterminous United States (CONUS-SOIL) developed at Penn State’s Earth System Science Center (ESSC) (http://www.essc.psu.edu/soil_info/) was adapted to this project.

4.2. Land cover

Land cover can also be assumed to be a nearly constant data plane. We are using the 1-km scale product from the University of Maryland (http://gief.umiacs.umd.edu/data/landcover/index.shtml). Land cover is used in the algorithm to mask out water and other categories.

4.3. Vegetation index

Vegetation index is used to estimate the vegetation water content. At the present time, we are using NDVI products provided by the NASA Data Active Archive Center (DAAC) (http://daac.gsfc.nasa.gov/data/dataset/AVHRR/01_Data_Products/02_Daily/index.html).

5. Temporal normalization

TMI coverage over the Southern U.S. is obtained on several orbits separated in time. To produce a synoptic product, it is necessary to normalize these data to a single point in time. We developed a technique to mosaic these orbits based on our experiences with aircraft mapping projects (Jackson et al., 1995, 1999). TRMM covers the entire study region (Southern U.S.) in six to eight orbits over a 4- to 6-h period. Surface soil temperature has a significant effect on the observations at 10.65 GHz. During the day-
time, changes in surface soil temperature have a far greater
effect than the changes in soil moistures over the 4- to 6-h
observation window. On a given day, the orbit with the
maximum number of footprints in the coverage area is
selected as the reference orbit. Typically, this reference orbit
occurs in the middle of the overpass window. All passes on
a day overlap this reference for some portion of the cover-
age. These overlap areas are used to normalize the different
passes. Fig. 1 is one example of a merged and normalized
data set. The TMI overpass window over the domain moves
forward in time on a daily basis (~ 0.5 h/day). Thus, it is
impossible to get a daily product with an exact repeat period
of 24 h.

6. Soil moisture results

Validation consisted of a series of increasingly more
comprehensive analyses. The initial effort included an
analysis of the TMI retrieval of soil moisture using the
SGP99 data set (Jackson & Hsu, 2001). Satellite data
collected by the TMI were compared to soil moisture
observations collected as part of the SGP99. Data collection
was conducted between July 8 and 20 during which there
was an excellent sequence of meteorological conditions for
validation.

Ground-based soil moisture measurements over a num-
ber of large area fields (~ 20–30 fields) were made during
these field campaigns. Watershed or large area averages of
field observed soil moisture during SGP99 were computed
for three study areas within the region; the Little Washita
watershed (LW), El Reno facility (ER), and an area called
the Central Facility (CF). TMI-estimated soil moisture based
on different orbits was compared to these soil moisture
observations (Fig. 2a–c). Over large areas, multiple orbits
of TMI observations were available. Results from all of the
orbits were used for the comparison with the ground
observations and then these orbital estimates were averaged
to obtain a daily soil moisture estimate.

The soil moisture conditions were dry (~ 10–15% soil
moisture) at the beginning of the SGP99 experiment (Fig.
2a–c). Most of the SGP99 area received significant precip-
itation on July 10–11, resulting in higher soil moisture
conditions. The El Reno area received about 8–10 cm, Little
Washita received between 2 and 4 cm, and the Central
Facility received about 4 cm of precipitation during this
period. After this meteorological event, there was standing
water in the El Reno area, and the soil at the sampling sites
was in a saturated condition. The conditions in Little Washita
and Central Facility were also wet (~ 30% soil moisture).
This increase in soil moisture is also seen in the TMI
estimates over the three sampling regions and the magni-
tudes of soil moisture are consistent with the observations for
the Little Washita watershed (~ 25% soil moisture) and
Central Facility (~ 30% soil moisture). The observed soil
moisture over the El Reno facility immediately after the rain
event was very high (~ 49%), as compared to the TMI
estimates (~ 38%). This error could be in part due to the
large foot print or due to the high vegetation present in the
area. The gravimetric-based soil moisture sampling was

Fig. 1. Normalized 10.65 H GHz TMI brightness temperature for July 8, 1999.
The TMI overpass on July 10th and 11th was around 12:30 pm local time. This offset between the sampling time and overpass time could also have resulted in drier conditions in the area. After this meteorological event, the entire region experienced a dry-down through the end of the experiment (July 20th). This dry-down is also captured by the TMI estimates of soil moisture. Both observations and TMI-estimated soil moisture returned to pre-experiment state at the end of the experiment (Little Washita—~ 5%; El Reno—~ 15%; and Central Facility—~ 10% soil moisture). Soil moisture estimates from multiple orbits were consistent with each other and with the observations.

To broaden the validation data set, we conducted a 1-week field experiment within the Little River Watershed located near Tifton, GA. The experiment was designed to provide spatially distributed surface soil moisture over a nominal TMI footprint area. It was timed for a morning sequence of TMI coverage between June 5th and 9th, 2000. Soil moisture conditions included a wide range of values.

The conditions during the Georgia experiment were comparatively drier over the duration of the experiment than those in SGP99 (Fig. 2d). Dry conditions (~ 7%...
Fig. 4. Daily TMI estimated soil moisture over southern United States for July 6–21, 1999.
soil moisture) prevailed at the onset of the experiment on June 5, 2000. The experimental region experienced light-to-moderate rainfall on the evening of June 5, which resulted in wetter soil moisture (~15% soil moisture) conditions throughout the watershed. This was followed by a dry-down for the remainder of the experiment. TMI-estimated soil moisture captured the wetting and the dry-down phases of the experiment, consistent with the ground observations.

The SGP99 and GA2000 field experiments provided data sets with a large dynamic range that were used for validation of the TMI-estimated soil moisture. Daily averages of TMI-estimated soil moisture over these large areas compared well with the observed soil moisture measurements (standard error of 2.5%) (Fig. 3). The soil moisture estimate over the El Reno facility immediately after the rain event (July 11th) did not compare well with the observations. Most of the soil moisture estimates fell along the 1:1 line. This provided the needed framework for validating TMI-estimated soil moisture over known conditions.

Unfortunately, it is not possible to validate satellite-based soil moisture estimates, at regional to continental scales using point-scale, ground-based observations (Crow, Drusch, & Wood, 2001). A climatological validation was conducted over the Southern U.S. for the SGP99 time period.

The soil moisture estimates from the point-based soil moisture estimation model were spatially interpolated to a uniform grid with a spatial resolution of 0.25°. These images were used to examine the temporal and spatial distribution of the soil moisture estimates. The following discussion provides a context for the series of soil moisture images shown in Fig. 4a–p. Day-to-day variations in soil moisture estimates are explained in the context of known meteorological conditions prevalent on that particular day.

6–7 July  The southern continental U.S. experienced dry soil moisture conditions on July 6, 1999. This provided a good base starting date for large-scale soil moisture analysis (Fig. 4a). Scattered thunderstorms associated with the low pressure over Northeast U.S. (Florida, Georgia, Alabama and North Carolina) were observed on July 7. These resulted in increased soil moisture conditions over these areas (Fig. 4b).

8–9 July  A cut-off low pressure slides across the western coast into Arizona. Due to the rainfall associated with the low pressure, parts of California, Arizona, Utah and Colorado experienced higher soil moisture conditions (Fig. 4c). Regions from Texas to Virginia experienced some rainfall associated with a dying cold front on July 9. This scattered precipitation resulted in higher soil moisture estimates over parts of Mississippi and Alabama (Fig. 4d).

10–11 July  Low pressure moves into Northern New England, with a cold front trailing west–southwest toward into West Texas resulting in showers along the front. During the following 2-day period, Northern Nevada, Northern Texas, Oklahoma and Tennessee received significant rainfall (~2.5 cm). The soil moisture estimates for Texas, Oklahoma, Tennessee and Georgia on July 10 are higher than July 8 estimates. On the contrary, estimates over California, Wyoming and Colorado also show a clear dry-down (Fig. 4e and f).

12–13 July  A series of weak low-pressure systems move along the front that is stalled in the southeastern U.S., triggering additional showers and thunderstorms. This results in high soil moisture conditions over Georgia, Florida and the Carolinas (Fig. 4g and h).

14–15 July  Another low associated with the front over the southeast moves northward along the Eastern Seaboard, triggering moderate rainfall. A frontal system is stalled over the New Mexico and into the Northern Great Lakes region, with low-pressure systems traveling along it and inducing pulses of rain. The dry-down over the middle Mississippi Valley continues, except for a few isolated showers (Fig. 4i and j).

16–17 July  The frontal system continues to result in rainfall over Kansas, Colorado and New Mexico regions. As a result, wet conditions are seen over New Mexico and Arizona regions (Fig. 4k and l). A weak low system also slides across the east coast over the Carolinas, resulting in some rainfall.

18–19 July  The low-pressure system over the eastern coast results in rainy conditions over the Carolinas and Tennessee regions. Wet conditions as a result of heavy rainfall are observed over New Mexico, Arizona, Tennessee and the Carolinas (Fig. 4m and n).

20–21 July  The frontal system moved through the Southern Great Plains, into the southeastern U.S., producing light to moderate rainfall over the region. The Southern Great Plains shows areas of increased soil moisture conditions (Fig. 4o–p). The entire area east of the Mississippi River experienced wet conditions.

7. Conclusions

This paper describes the development of a soil moisture pathfinder data set using TRMM (Tropical Rainfall Measuring Mission) Microwave Imager (TMI) observations. This is the first attempt to map at continental scales daily soil moisture from space over an extended period of time. Previously, such attempts have been either limited to small areas or over a limited period of time. The methodology used for soil moisture estimation uses data that can be easily observed over all areas. The methodology is dynamic and can be transported to any region.

The TMI-estimated soil moisture during the field experiments compared well with the observations. This provides a reasonable ground validation at catchment scale (or TMI pixel resolution). Large-scale validation of soil moisture was conducted using the meteorological observations over the
Southern U.S. Retrieved variables represent area averages over the 10.65-GHz footprints and also averages over the vertical sampling depth in the soil/vegetation medium. As the vegetation cover increases, the retrieval error increases. Uncertainties associated with land surface parameters (such as soil roughness, vegetation scattering and opacity coefficient, soil texture, etc.) propagate into the retrieval uncertainties for soil moisture and temperature. This methodology will be extended to the entire temporal domain of TMI data (December 1997–current). Further analysis and validation will be conducted for extended periods. It is anticipated that these estimates of soil moisture will provide a valuable data set for the hydrologic community.

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References


