A White Paper for the Global Soil Moisture Data Products of NOAA NESDIS

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1. Introduction

Soil moisture is a critical hydrological variable that plays an important role in the exchange of water and energy between the atmosphere and land surface, controls the partitioning of rainfall among evaporation, infiltration and runoff, and impacts vegetation photosynthetic rate and soil microbiologic respiratory activities. Observing large regional or global scale soil moisture is thus required for global water, energy, and carbon cycle science and many other societal applications [Entekhabi et al, 1999]. For NOAA, global soil moisture data are critical input for operational weather, seasonal-to-interannual climatological and hydrological prediction models.

Conventional ground measurements of soil moisture might be accurate for individual locations but it is not practical to produce global maps through this method. Satellite remote sensing becomes a viable approach for observing the surface soil moisture regionally or globally in recent years. In the past several decades, microwave remote sensing soil moisture has been explored by many scientists and engineers. Several soil moisture-capable satellite sensors have been launched. Among them are the Advanced Microwave Scanning Radiometer (AMSR-E) on-board NASA's Aqua satellite [Njoku et al, 2003], the WindSat on-board Navel Research Lab's CORIOLIS satellite [Jackson et al, 2008], the Microwave Imager (TMI) on-board NASA's Tropical Rainfall Measuring Mission (TRMM) satellite [Gao et al, 2006], the scatterometers on-board the European Remote Sensing Satellites ERS-1/ERS-2 (ESCAT) and the MetOp satellites (ASCAT) [Wagner et al, 2003]. For research purposes, several soil moisture products have been generated from these satellite sensors. Among them the NASA baseline global soil moisture data product from AMSR-E has been constantly freely available since June 2002 while others are available for certain regions at some time periods.

However, application of NASA's AMSR-E soil moisture data product has met several difficulties. The soil moisture spatial and temporal dynamics are believed to be too small [Choi et al, 2008; Zhan et al, 2006] although they may be preprocessed before assimilating into numerical weather prediction models [Reichle & Koster, 2004].

As an effort of the Joint Center for Satellite Data Assimilation (JCSDA) of NOAA, NASA and DoD Air Force Weather Agency (AFWA) and with collaboration from scientists at USDA Agricultural Research Service (ARS), scientists at NOAA-NESDIS Center for Satellite Applications and Research (StAR) are creating an alternative global soil moisture data product from the same AMSR-E observations but using an alternative soil moisture retrieval algorithm - the Single-Channel Retrieval (SCR) algorithm [Jackson, 1993]. This white paper describes the retrieval algorithm, ancillary data requirements, data product quality evaluation, data format, data access method. Since the generation of this product is work in progress, frequent updates or reprocesses may be carried out without public notice.

2. Algorithm Description

The Single Channel Retrieval (SCR) method is mainly based upon an algorithm developed by Jackson (1993). In this approach, brightness temperature from a single AMSR-E channel (10.7 GHz H) is converted to emissivity that is further corrected for vegetation and surface roughness effect. The Fresnel equation is then used to determine the dielectric constant and a dielectric mixing model is used to obtain the soil moisture.

2.1. Relationship between brightness temperature and emissivity

The major input for this algorithm is the brightness temperature, $T_{b,}$ from AMSR-E sensor, which includes contributions from the land surface, the atmosphere, and reflected sky radiation. Considering the later two are negligible at the frequency we are using, the relationship between land surface imissivity, e, and T_b for pure soil can be expressed as

$$T_b = eT_s, \tag{1}$$

where, T_s is the soil effective temperature. If T_s is estimated independently, emissivity can then be determined.

In the case where there is vegetation above the soil, the above forward microwave emission model can be expressed as

$$T_{Bp} = T_s e_{r,p} \exp(-\tau_p / \cos\theta) + T_c(1-\omega_p)$$
$$[1-\exp(-\tau_p / \cos\theta)][1+R_{r,p}\exp(-\tau_p / \cos\theta)], \tag{2}$$

where, the subscript p refers to polarization (H or V) and subscript r stands for rough surface, T_s is the soil effective temperature, T_c is the vegetation temperature, τ_p is the nadir vegetation opacity, ω_p is the vegetation single scattering albedo, and $R_{r,p}$ is the soil reflectivity. The rough surface soil reflectivity is related to the soil emissivity by $e_{r,p} = (1 - R_{r,p})$, and ω_p, $R_{r,p}$ and $e_{r,p}$ are values at an assumed radiometer incident angle of $\theta=40°$. $R_{r,p}$ is related to smooth surface soil reflectivity R_s through the soil roughness parameter h so that $R_s = R_r \exp(h \cos^2\theta)$ without notification for polarization. While Eq. (2) and these parameterizations of τ and R_s represent simplifications of the actual microwave emission process, they are widely utilized for low-frequency (L-band) microwave emission and retrieval modeling of the land surface – especially within lightly to moderately vegetated regions.

In SCR algorithm, with the assumptions of $T_c = T_s$ and $\omega_p = 0,$ Eq. (2) can be simplified as

$$T_B = T_S[1 - R_r \exp(\frac{-2\tau}{\cos\theta})]. \tag{3}$$

Note that SCR algorithm only uses the H-pol T_b observations, polarization indications in Eq. (3) has been dropped.

The vegetation optical depth, τ, is dependent upon vegetation water content (*W*). A simple linear relationship is employed to calculate τ from *W*:

$$\tau = bW, \tag{4}$$

where, *b* is an empirical parameter associated with different land cover types. Vegetation water content, *W*, is estimated using MODIS Normalized Difference Vegetation Index (NDVI).

2.2. Relationship between emissivity and dielectric constant

The Fresnel reflection equations are used to predict the surface microwave emissivity as a function of dielectric constant (ε_r) and the viewing angle (θ) based on the polarization of the sensor (Ulaby., 1986). Since the imaginary part of the complex dielectric constant is relatively small and thus is often ignored, the Fresnel equation can be simplified by including only the real part of the complex dielectric constant (only H-pol is presented):

$$e_H = 1 - \left| \frac{\cos\theta - \sqrt{\varepsilon_r - \sin^2\theta}}{\cos\theta + \sqrt{\varepsilon_r - \sin^2\theta}} \right|^2 . \quad (5)$$

By inverting above equation, the real part of the dielectric constant of the soil can be solved given the estimated emissivity.

2.2. Relationship between dielectric constant and volumetric soil water content

Both components of wet soil, soil and water, contribute to its dielectric constant. The fundamental principle of this algorithm is the large contrast in dielectric properties of water and soil. Water has a relative complex dielectric constant of about 80 for the real part as compared to about 3.5 for dry soil. Thus, the real part of relative dielectric constant for wet soil can be around 40. This large dielectric constant difference between wet and dry soil correspondingly impacts the soil emissivity that can be related to the brightness temperature measured by the satellite sensor as showing in above section. Since the dielectric constant is a volume property, the volumetric fraction of each component must be considered.

In the SCR algorithm, the Dobson's semi-empirical soil dielectric mixing model is used to retrieve the volumetric soil moisture (Dobson *et al*., 1985). This model requires soil textural composition as input, such as proportions of clay and sand, and porosity. Their evaluation results show that this model yields an excellent fit to the measured data at frequencies above 4 GHz.

3. Ancillary Data

The ancillary data for the SCR algorithm include land cover map, MODIS NDVI, clay map and sand map.

3.1. Land Cover Map

The land cover map used in this algorithm is the 8-km land cover map produced by University of Maryland Geography Department.

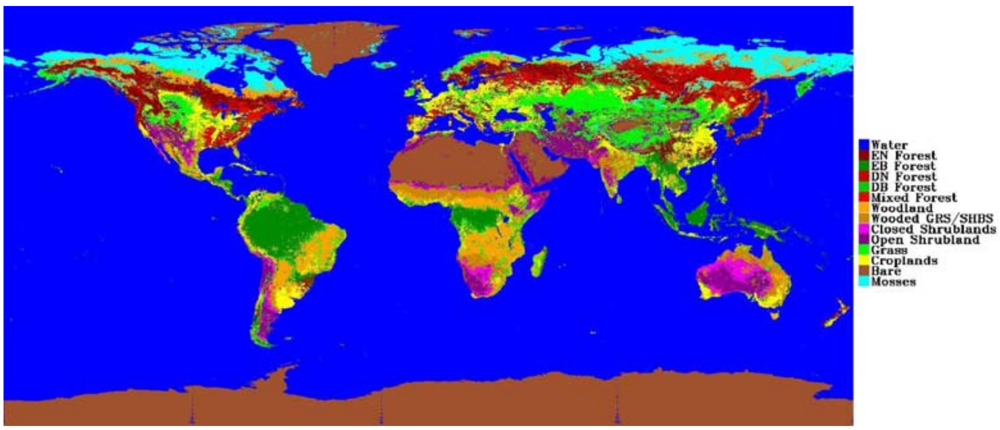

Figure 1. Land Cover Map

The codes for the land covers are as follows:

0	water
1	Evergreen Needleleaf Forests
2	Evergreen Broadleaf Forests
3	Deciduous Needleleaf Forests
4	Deciduous Broadleaf Forests
5	Mixed Forests
6	Woodlands
7	Wooded Grasslands/Shrubs
8	Closed Bushlands or Shrublands
9	Open Shrublands
10	Grasses
11	Croplands
12	Bare
13	Mosses and Lichens

3.2. MODIS NDVI

MODIS NDVI maps are used to derive the vegetation water content maps, which is further converted to vegetation optical thickness maps using a constant *b* value of 0.35 (see Eq. (4)). The MODIS NDVI data set (MOD13Q1) has spatial resolution of 250 meters and temporal resolution of 16 days. In the case where the MODIS NDVI data are not available, a AVHRR climatology data is used. Considering the nonlinearity of scale impact of vegetation water content (VWC) on soil moisture retrieval, a non-linear aggregation method [Zhan et al, 2008] for scaling 250m NDVI data to AMSR-E footprint scale VWC is tested and applied.

3.3. Clay Map

The clay map used in the SCR algorithm is produced by Reynolds *et al*. (2000). This data sets are a result of a study to estimate global soil water-holding capacities by linking the Food and Agriculture Organization (FAO) soil map of the world with global pedon databases and continuous Pedo Transfer Functions (PTF). It has a 5-min spatial resolution, which is equivalent to a 9 km x 9 km cell size at equator.

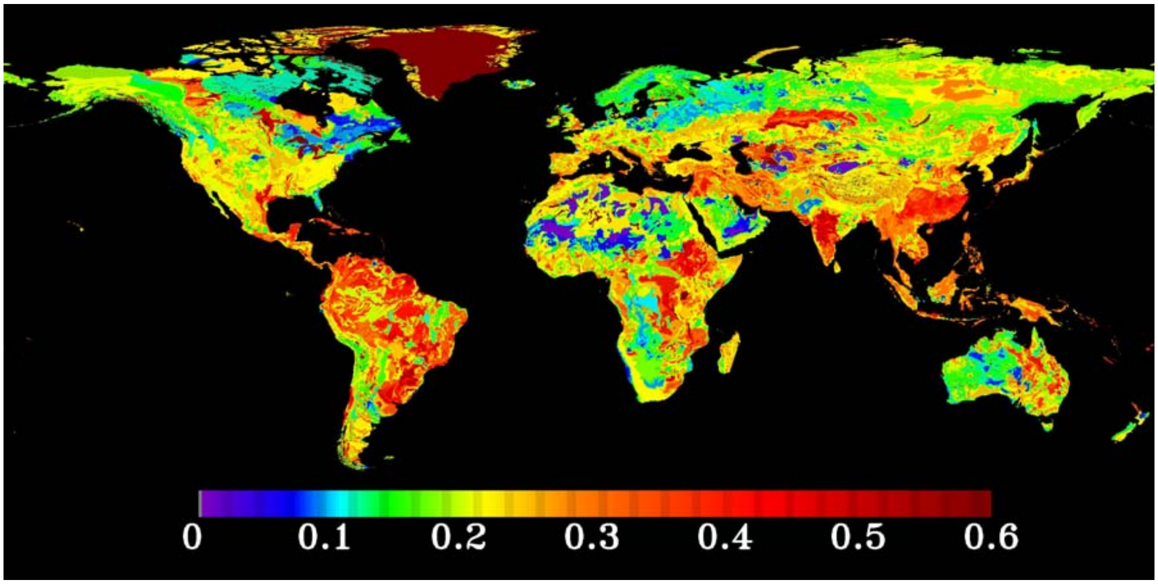

Figure 2. Clay map.

3.4. Sand Map

The sand map used in the SCR algorithm is also produced by Reynolds *et al*. (2000).

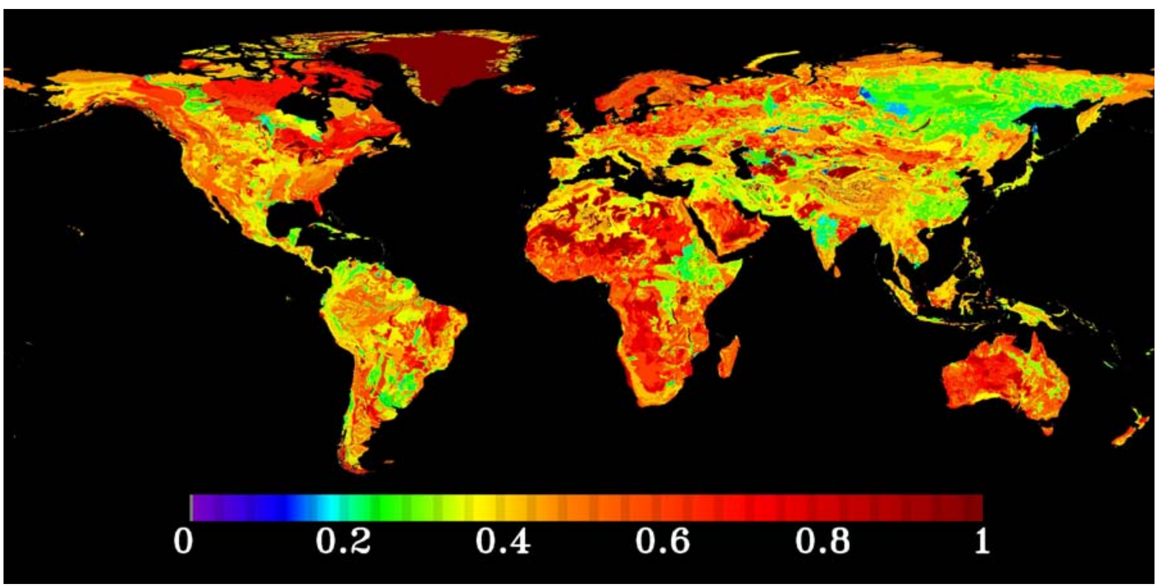

Figure 3. Sand map.

4. Validation Efforts

As a part of the validation efforts, soil moisture ground observations from three watersheds are used and they are Little River, GA, Little Washita, OK, and Walnut Gulch, AZ. The Little River Watershed has flat terrain with row crops and annual rainfall of 1200 mm. The Little Washita Watershed is a sub-humid area with annual rainfall of 750 mm and its topography is gently rolling and the dominant land cover type is grass rangeland. The Walnut Gulch Watershed is a semiarid area covered mainly by rangeland with annual rainfall of roughly 320 mm. The NASA L3 soil moisture data set is also used as a reference.

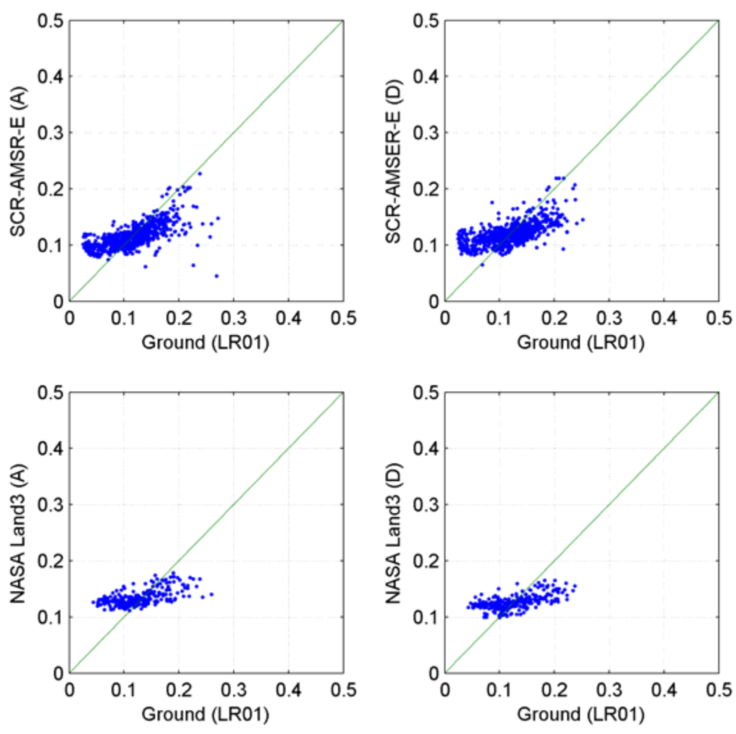

Figure 4. Comparison between the soil moisture values from the field measurements and the retrieval results (Little River, GA).

The validation results show that the retrieval results from the SCR algorithm have larger variation range than the NASA L3 product. The one-to-one line between the ground measurements and the retrieval results both from SCR and NASA L3 product in Figure 4, for instance, shows that, for the time period used for comparison, the NASA L3 soil moisture value does not have much change while the results from the SCR algorithm shows greater variation and better agreement with the ground measurements. There's no significant different between the results from ascending orbit and descending orbit.

Table 1 summarizes the preliminary validation results. Overall, the retrieval results from the SCR algorithm show better agreement with the field data than the NASA L3 soil moisture product does.

Table 1. Comparison results summary.

Watershed	RMSE	Bias	R
Little River, GA	0.038 / 0.040	0.002 / 0.002	0.648 / 0.538
Little Washita, OK	0.053 / 0.062	-0.024 / 0.002	0.587 / 0.228
Walnut Gulch, AZ	0.034 / 0.033	0.014 / 0.056	0.701 / 0.596

5. Data Access

Please see the contact information below for acquiring the data set.

6. Data Format

Table 2 provides an overview of the NOAA soil moisture data set.

Table 2. An overview of NOAA AMSR-E soil moisture product

Category	Description
Data format	Binary
Spatial coverage	Global (720 lines x 1440 samples)
Spatial resolution	0.25 degree (~25 km on the equator)
Temporal coverage	June 19, 2002 –
Temporal resolution	Daily

Projection	Lat/Long	
File name convention	NOAA-AME-SoilMoisture_yyyymmdd_f.dat	
File size	4 bytes/grid ~4MB/file 2 files/day	
Parameters	Soil moisture:	First byte (unsigned integer; scale factor: 100)
	QA:	Second byte
	Time:	Third byte: Hour Forth byte: Minute

Quality Assessment (QA):

Bit number	Description
1	Forest, woodland or moss
2	Cold desert (Fill value)
3	Snow cover or precipitation (Fill value)
4	Invalid soil texture data (Fill value)
5	Dense vegetation (Fill value)
6	Invalid brightness temperature data (Fill value)
7	Partial water (Fill value)
8	Not used

7. Contacts

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