AMSR2 Global soil moisture retrievalS using the NormaliZed Polarization Difference (NPD) algorithm and Single Channel Algorithm (SCA)

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This Algorithm Basis Theoretical Document (ATBD) describes the AMSR2 Land Product. This product consists of two algorithms in the output data fields. The soil moisture estimates from the USDA’s Single Channel Algorithm (SCA); and JPL’s Normalized Polarization Difference (NPD) algorithm are combined in the output files. The output data fields in both groups are geolocated on the 25-km global EASEv1 Grid projection.

1. Single Channel Algorithm (SCA)

SCA approach uses horizontally polarized (h-pol) brightness temperature observations from the lowest frequency channel due to its highest sensitivity to soil moisture observations. The AMSR-E SCA algorithm uses h-pol X-band observations due to widespread RFI observed in C-band observations. The AMSR-E SCA approach is based on the simplified radiative transfer model developed under the assumption of minimal atmospheric contribution, equal canopy and soil temperature (Jackson 1993). The SCA is applied to the individual AMSR-E footprint brightness temperature observations (L2) to produce a swath based time-order product.

In the SCA approach, brightness temperatures are converted to emissivity using a surrogate for the effective physical temperature () of the emitting layer. The derived emissivity () is corrected for vegetation and surface roughness to obtain the smooth soil emissivity (). The Fresnel equation is then used to determine the dielectric constant of the soil-water mixture (). Finally, a dielectric mixing model is used to obtain the soil moisture (). Additional details on these steps follow.

At the X-band frequency used by AMSR-E, the brightness temperature of the land surface is proportional to its emissivity (, where) multiplied by its physical temperature (*T*). It is typically assumed that the temperatures of the soil and the vegetation are the same.

Based upon the above, the complete radiative transfer model can be simplified yielding the following expression for the observed :

, Equation 1

where the second term in the above equation represents the contributions of the cosmic background and down-welling radiation from the atmosphere as reflected by the soil surface. This term is very small and is dropped for computational. Equation 1 can be re-arranged to derive emissivity:

 Equation 2

The effective physical temperature of the emitting medium is estimated using vertically polarized Ka-band observations following the approach offered by De Jeu and Owe (2003).

The emissivity retrieved above is that of the soil as modified by any overlying vegetation and surface roughness. In the presence of vegetation, the observed emissivity is a composite of the soil and vegetation. To retrieve soil water content, it is necessary to isolate the soil surface emissivity (). The correction for the presence of vegetation is done based on Jackson and Schmugge (1991)

 Equation 3

Both the single scattering albedo () and the one-way transmissivity of the canopy () are dependent upon the vegetation structure, polarization and frequency. The transmissivity is a function of the optical depth () of the vegetation canopy:

 Equation 4

where is the system incidence angle.

The single scattering albedo tends to be very small, and is ignored in the AMSR-E SCA algorithm in order to reduce dimensionality for computational purpose. Substituting Equation 4 into Equation 3 and re-arranging yields

 Equation 5

The vegetation optical depth is also dependent upon the vegetation water content (). In studies reported inJackson and Schmugge (1991), it was found that the following functional relationship between the optical depth and vegetation water content could be applied:

 , Equation 6

The vegetation water content can be estimated using several ancillary data sources. The baseline approach utilizes a set of land cover-based equations to estimate from values of the Normalized Difference Vegetation Index (), an index derived from visible-near infrared reflectance data.

The emissivity that results from the vegetation correction is that of the soil surface, including any effects of surface roughness. These effects must be removed in order to determine the smooth surface soil emissivity (), which is required for the Fresnel equation inversion. One approach to removing this effect is a model described in Choudhury et al. (1979) that yields the bare smooth soil emissivity:

 Equation 7

The term is often dropped to avoid overcorrecting for roughness. The parameter is dependent on the polarization, frequency, and geometric properties of the soil surface.

Emissivity is related to the dielectric properties () of the soil and the viewing or incidence angle. For ease of computational inversion, it is assumed that the real component () of the dielectric constant provides a good approximation of the complex dielectric constant; however, this assumption can be modified if additional evidence is found to support the use of this more complex formulation. The Fresnel equations link the dielectric constant to emissivity. For horizontal polarization:

 Equation 8

The dielectric constant of soil is a composite of the values of its components – air, soil, and water, which have greatly different values. A dielectric mixing model is used to relate the estimated dielectric constant to the amount of soil moisture. The AMSR-E SCA uses Wang and Schmugge (1980) dielectric mixing model to estimate soil moisture.

1. Normalized PolarizaTIon Difference (NPD) Algorithm

The Normalized Polarization Difference (NPD) algorithm was developed by NASA JPL for the AMSR-E mission. The algorithm was implemented for the AMSR2 mission to maintain data continuity. NASA’s initial implementation was done using C-band observations. However, due to RFI issues the NASA AMSR-E C-band data, especially over the U.S., the product is derived using X-band brightness temperature data.

The foundation of this algorithm is the use of the Microwave Polarization Difference Index ():

 Equation 9

The is used since it can be approximated in a form that is independent of surface temperature and has separable soil moisture and vegetation dependencies. Assuming soil and canopy temperatures are the same and , we obtain:

, Equation 10

where

 Equation 11

A key concept introduced here is the parameter , which is a vegetation/roughness surface characteristic representing combined height and information. is a frequency-dependent coefficient. The applicability of this lumped parameter representation is discussed in Njoku and Chan (2006).

Combining Equations 9 and 10, and assuming that the atmospheric effects are negligible yields:

,Equation 12

where:

 Equation 13*a*

 Equation 13*b*

 and are both functions of , and represents the of bare, smooth soil.

It was shown in Njoku and Chan (2006) that Equation 12 can be further approximated as:

,Equation 14

where is a coefficient that is approximately independent of soil moisture. Values for the coefficients , and were obtained for AMSR-E by as described below.

The parameters and have similar impact on (see Fig. 1 in Njoku and Chan 2006) and consequently there is some redundancy in varying both of these parameters to establish best fits. Therefore, (incorporated in the term) was selected to represent the spatial variability, while was treated as a fixed global factor. was determined for each frequency by calibrating Equation 14 to the AMSR-E computed values over two desert regions with smooth topography (Niger and Saudi Arabia, see Njoku and Chan (2006) for the specific coordinates of each box). The radiative transfer runs were carried out assuming bare, smooth, dry land surface conditions with and . As computed, the values estimated over these calibration sites would represent minimum roughness conditions ( and ). The lower Saudi Arabia value was selected as a global parameter.Spatial variations in surface roughness were then accounted for by allowing to vary globally.

The coefficients and were determined using a similar approach. Simulations performed to estimate these parameters were done using the Dobson dielectric model (Dobson et al. 1985) for dry () to moderate () soil moisture conditions assuming uniform (sandy loam) soils. It should be noted that the soil type selected for the simulation runs will to a certain degree restrict and predetermine the range of the final soil moisture estimates. Sandy loam soils are characterized by relatively low clay content; generally, the higher the clay content the greater the water holding capacity of the soil.

Calibration of was performed over a region of naturally varying vegetation and roughness that had uniform dry soil moisture (portions of Chad, Sudan, and the Central African Republic). AMSR-E observations for a dry month (March 2004) over this domain were used to estimate .

The NASA AMSR-E soil moisture retrieval algorithm is derived from Equations 14. Njoku and Chan (2006) examined the sensitivity of the function , which characterizes the soil moisture response. The function shows good sensitivity over the full soil moisture range, although the sensitivity decreases at higher moisture values (see Fig. 4 of Njoku and Chan 2006).

To implement the retrieval, Equation 14 can be inverted and written in the form:

, Equation 15

The NPD retrieval algorithm uses only the 10.7 GHz frequency. Once is determined using the observed and the roughness/vegetation correction factor (), Equation 13 can be used with the Fresnel equations, a global soil texture database, and a dielectric model to determine soil moisture. Alternatively, a linear approximation to the relationship between and soil moisture can be used and Equation 15 written as:

, Equation 16

where and are coefficients that are determined empirically. Equation 16 can also be expressed in time-differenced relative change form, where soil moisture is expressed as a departure from a minimum or “dry” condition at each location (grid point or pixel). Using this formulation the coefficient drops out:

, Equation 17

Similarly, we can write the exponential factor as:

 Equation 18

The optimum time window for computing for use in these equations depends on the specific location.

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