Algorithm Theoretical Basis Document

Snow Algorithm

Marco Tedesco
City University of New York
New York, NY

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In this Algorithm Theoretical Basis Document (ATBD) we report the methodology that is currently planned for use in mapping snow storage with AMSR2 data. The basic techniques rely on the ATBD of the current AMSR-E operational product. The algorithm has been tested operationally on AMSR-E. We also include the description of plans for algorithm refinement, validation and error analysis.

The scope of this work is to develop, implement and refine an operational algorithm based on spaceborne passive microwave observations that map snow water equivalent, snow depth and snow extent on a daily, pentad and monthly period producing Level-3 products gridded in an equal area projection in azimuthal projection in the Northern and Southern Hemispheres. The knowledge of the water stored in snowpacks is crucial for studying the global water and energy balance, fresh water budgets and improving weather prediction capabilities. In many areas of the world where inhabitants indeed rely on snow stored in mountain snow packs as a source for drinkable water, for hydropower production, and for recreation and industrial purposes. The presence of snow on ground affects the Earth's energy budget through its high albedo and thermal insulating properties. Moreover, snow plays a key role in floods, and quantifying snow depth and/or SWE (snow water equivalent) provides critical information for flood forecast. For example, during summer 2011 melting of an above-average snow pack across the Northern Rocky Mountains and northern Great Plains, combined with above-average rainfall, caused the Missouri and Souris Rivers to swell beyond their banks, with estimated losses exceeding $2.0 billion structure (http://www.ncdc.noaa.gov/oa/reports/billionz.html). Supporting the continuity of a NASA SWE operational product based on spaceborne microwave measurements is essential for the ultimate development of a robust long-term data set, extending back more than 30 years. AMSR2 and AMSR-E measurements are, indeed, the latest in a lineage of passive microwave measurements dating back to 1979 and starting with the Nimbus-7 Scanning Multi-channel Microwave Radiometer (SMMR, November 1978 - August 1987) and Special Sensor Microwave Imager (SSM/I, July 1987 - today), these instruments potentially constitute a long time series of SWE maps at regional to global scales. It is therefore essential that the AMSR-E operational scheme be extended to the forthcoming AMSR2 data.

The baseline AMSR-E algorithm

In the original "baseline" SWE algorithm originally developed for SMMR and SSM/I data (Chang et al.1982, 1987, and Foster et al. 1997), and initially applied to AMSR-E data, SWE was computed from a linear regression between snow depth and the difference between the brightness temperatures at 19 and 37 GHz, or similar frequencies.

$$SD = Rc^{*} (TB_{19}-TB_{37}) \quad (1)$$

$$SWE=Rc'^{*}(TB_{19}-TB_{37}) \quad (2)$$

The retrieval coefficient (Rc) in the linear regression formula was set to 1.6 cm/K in the case of depth and Rc' was set to 4.8 mm/K for SWE, being static in both space and time. A fixed value of mean grain radius (0.3 mm) and a fixed snow density (0.3 g/cm^3) were assumed in the calibration. The algorithm was later modified to account for forest cover attenuation (Foster et al. 1997) by dividing the coefficient Rc by (1-ff), with ff representing the forest cover fraction (ranging between 0 and 1).

$$SD = Rc^* \, 1/\, 1\text{-}ff(TB_{19}\text{-}TB_{37}) \qquad (3)$$

The low computational cost of the linear regression-based algorithm makes it suitable for operational applications but it is obviously also the origin of several limitations. For example, the representation of physical snowpack processes is not accounted in the algorithm, nor the evolution of the key snow parameters, such as grain size, along the snow season.

Recently, a dynamic algorithm was introduced (e.g. Kelly 2009) where Rc is computed for every pixel and day from the polarization ratio of Tb measurements and will be discussed in detail in the following section.

The AMSR2 SWE operational algorithm

With respect to previous algorithms, the current AMSR-E SWE algorithm takes advantage of the low frequency channels available on the AMSR-E instrument with respect to the SSM/I and SMMR sensors. The data sets required for the retrieval algorithm are the following:

Table 1. Ancillary data sets required for the AMSR-E SWE operational algorithm. In the table, S stands for 'Static' where 'D' stands for 'Dynamic'.

Data set	***Source***	***Temporal Static/Dynamic***
Global forest fraction	Boston University IGBP data (*MOD12Q1IGBP*) (*Hansen et al., 2003*)	S
Global forest 'density'	UMD/VCF (based on *MOD09A1*)	S
Land, Ocean Coasts & Ice mask	derived from MODIS *MOD12Q1 IGBP* land cover data (collection V004).	S
Snow possibility/impossibility	Snow climatology data set (*Dewey and Heim, 1984*)	S
Snow density	Seasonal snow classification map *Liston and Sturm* (*1998*)	S

Snow depth retrieval is performed using AMSR-E/Aqua L2A Global Swath native resolution and spatially resampled brightness temperature (TB) measurements on the instantaneous field of view (IFOV) samples. Thresholds on Level 2A AMSR-E brightness temperatures are checked to minimize the presence of melting snow (Tb_{36H}<245K & Tb_{36V}<255K), where SWE retrieval is impossible. If dry snow is estimated to be present, then shallow or medium depth snow is retrieved. If Tb_{10V}-$Tb_{36V} > 0$ K or Tb_{10H}-$Tb_{36H} > 0$ K then medium to deep snow is assumed to be present. If Tb_{10V}-$Tb_{36V} <= 0$ K and Tb_{10H}-$Tb_{36H} <= 0$ K then snow presence is possible but it is likely to be shallow snow if: $Tb_{89V} <= 255$ K and $Tb_{89H} <= 265$ K & Tb_{23V}-$Tb_{89V} > 0$ K & Tb_{23H}-$Tb_{89H} > 0$ K & $T_{snow\_K} < 267$ K. If shallow snow is detected, snow depth is set to 5.0 cm. If medium or deep snow is present then snow depth is computed as follows:

$$SD = ff(SD_f) + (1\text{-}ff)*(SD_o) \tag{4}$$

where SD is the snow depth, SD_f is the snow depth from the forest component of the instantaneous field of view (IFOV) and SD_o is the snow depth from non-forested component of the IFOV. *ff* is the forest fraction (where 1.0 = 100% forest fraction and 0.0 = 0% forest fraction). The forest and non-forest components of the snow depth are computed as follows:

$$SD_f\,[cm] = polfact_{36} * (TB_{18V}\text{-}TB_{36V})/(1\text{-}fd*0.6) \tag{5}$$

$$SD_o\,[cm] = [polfact_{36}*(TB_{10V}\text{-}TB_{36V})] + [polfact_{18}*(TB_{10v}\text{-}TB_{18V})] \tag{6}$$

with polfact36 = $1/\log_{10}(pol_{36})$ and polfact18 = $1/\log_{10}(pol_{18})$, $pol_{36} = TB_{36V}$-TB_{36H}, $pol_{18} = TB_{18V}$-TB_{18H}, *fd* = forest density (g cm^{-3}) from UMD VCF data circular smoothed at 15km diameter and re-gridded to global 1 km. For practical purposes if $pol_{36} < 1.1$ then $pol_{36} = 1.1$ to ensure $\log(pol_{36}) > 0$. SWE is lastly estimated using the snow density data set as:

$$SWE\ [mm] = SD\ (cm) * density\ (g\ cm^{-3}) * 10.0 \tag{7}$$

To convert SD to SWE a density map in EASE-grid projection was produced by mapping the mean January through March density measurements from data sets of Brown and Braaten (1998) and Krenke (2004) to the Sturm et al. (1995) seasonal snow classification map. Within each Sturm et al (1995) seasonal snow class, the average *in* situ density was computed and this value is mapped to all pixels in that Sturm class. Hence, there is an average density for each of the 6 classes. Note the use of the difference between the 18 and 36 GHz channels to maximize spatial resolution in forested areas, and the use of 10V-36V (increased dynamic range) and 10V-18V for deep snow. Note also that *fd* is scaled (0.6) through optimization of validation data. Snow depth estimated from the L2A brightness temperatures is then accumulated within each 25 km x 25 km EASE-Grid projection. Then, average snow depth is calculated for each 25 km EASE-Grid cell. For each snow class, a static value of density is assigned which is then used to estimate SWE from SD following:

$$SWE\ (mm) = SD\ (cm) * density\ (g\ cm^{-3}) * 10.0 \tag{8}$$

Overview of Algorithm-Related Error Sources

There are several known algorithm-related error sources. Some are intrinsic to the problem of retrieving SWE at large spatial scales from passive microwave observations (e.g., the small sensitivity of TBs to snow depth with respect to other parameters such as grain size, for example) where other factors are related to the heterogeneity of the scene observed by the sensor (e.g., mixed pixel problem) and by the simplicity of the algorithm (which is suggested by the operational nature of the approach). Some of these error sources are the temporal and spatial evolution of grain size and density, obscuration by forest, inability to map the water equivalent of partially wet snow covers, presence of water bodies, effects of the atmospheric attenuation.

A significant source of uncertainty is linked to the dynamic nature of retrieval coefficients (e.g., Kelly et al. ,2003, Tedesco et al., 2010). These depend on snow grain size and density, which can change dramatically during the snow season, even on short-term scales (Tedesco et al., 2010). After snow deposition on Earth's surface, snow crystals metamorphose in response to vapor gradients within the snowpack (either kinetic or equi-temperature forms) and as a result of melting and refreezing cycles. Also snowpack bulk density usually increases during the snow season. Although empirical and physically-based models have been developed to predict the growth of the snow crystal (e.g. Navarre, 1974; Brun et al., 1992), it is not straightforward to select a general model that will account for regional to global scale conditions. The same can be said with regard to the snow density.

The presence of liquid water within the snowpack increases the absorption, reducing the penetration depth, making the SWE/snow depth retrieval impossible. To reduce the number of occurrences of erroneous retrievals in wet snow conditions, knowledge of surface or air temperature might not be enough: melting can occur also from the bottom of the snowpack from geothermal heat fluxes.

The presence of water bodies within the area under study can affect the retrieval of SWE because of the strong TB gradient between liquid and frozen water. Analysis of airborne passive microwave data acquired in the Northwest Territories, Canada in April 2005 showed the relationship between 37 GHz brightness temperature and lake cover fraction is reversed across the northern boreal forest compared to the open tundra (Derksen et al., 2006). Over forested sites, lower 37 GHz brightness temperatures were measured over lakes relative to land, while the 19 GHz data showed little sensitivity to lakes. Conversely, at tundra sites the 37 GHz brightness temperatures were higher over lakes than over terrestrial surfaces. This difference in response to lake ice at 37 GHz will have an effect on SWE retrievals because the increase in brightness temperature at 37 GHz across lake rich tundra areas will decrease the 37-19 GHz (or 37-10) difference, and therefore decrease SWE estimates with conventional algorithms.

Forest cover represents an important source of error, representing a major challenge to the refinement of a robust passive microwave SWE retrieval algorithm. Indeed, the presence of forest attenuates the radiation emitted by the underlying snowpack, affecting the retrieval accuracy of the algorithm. In general, the problem shows a high degree of complexity; both fractional volume and stem closure within a footprint are important modulators of the passive microwave emission. Crown closure, basal area and foliage biomass are all inversely related to visible reflectance (Franklin, 1986) and are also directly related to microwave emission.

Upwelling microwave radiation emitted from the Earth's surface passes through the atmosphere before being detected by the space-borne sensor, and thus it is subject to the effects of atmospheric absorption and (re-)emission. These effects have been neglected so far in the retrieval algorithm but recent studies show that they should be accounted to reduce retrieval errors further (e.g., Wang and Tedesco, 2007).

Tedesco and Narvekar (2010) show that the current SWE algorithm is suffering from the limitation of using a static mask for density (used to convert satellite-estimated snow depth into SWE), with optimal density values (e.g., derived from fitting operational density values with those obtained from an electromagnetic model) increasing along the snow season. In the same study, the authors also show that the current approach for accounting for grain size variability is not adequate. Moreover, error sources and limitations intrinsic to a linear regression-based algorithm include the fact that the retrieval is generally limited to a single parameter and there is a poor understanding of the physical processes involved, that the approach is not easily adaptable (as opposed to 'modular'), meaning that it is not possible to ingest additional information from other sources (e.g., either land models or other satellites/sensors or other AMSR-E or Terra/Aqua products) to improve the retrieval or to substitute some of the data sets or elements used in the retrieval.

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