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The effects of variation in snow properties on passive microwave snow mass estimation

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ABSTRACT

Estimating snow mass at continental scales is difficult, but important for understanding land-atmosphere interactions, biogeochemical cycles and the hydrology of the Northern latitudes. Remote sensing provides the only consistent global observations, but with unknown errors. We test the theoretical performance of the Chang algorithm for estimating snow mass from passive microwave measurements using the Helsinki University of Technology (HUT) snow microwave emission model. The algorithm's dependence upon assumptions of fixed and uniform snow density and grainsize is determined, and measurements of these properties made at the Cold Land Processes Experiment (CLPX) Colorado field site in 2002–2003 used to quantify the retrieval errors caused by differences between the algorithm assumptions and measurements. Deviation from the Chang algorithm snow density and grainsize assumptions gives rise to an error of a factor of between two and three in calculating snow mass. The possibility that the algorithm performs more accurately over large areas than at points is tested by simulating emission from a 25 km diameter area of snow with a distribution of properties derived from the snow pit measurements, using the Chang algorithm to calculate mean snow-mass from the simulated emission. The snow mass estimation from a site exhibiting the heterogeneity of the CLPX Colorado site proves only marginally different than that from a similarly-simulated homogeneous site. The estimation accuracy predictions are tested using the CLPX field measurements of snow mass, and simultaneous SSM/I and AMSR-E measurements.

1. Introduction

Remote sensing is the only feasible way to monitor the global distribution of snow mass, which is important for water resource management, environmental risk assessment and to determine the sensitivity of climate to change (Randall & Wood, 2007). Comparisons between global models, reanalysis data and satellite observations have revealed differences in distribution and magnitude of snow water equivalent (Clifford, 2010), but errors in the observations must be quantified in order to assess the accuracy of the models. Chang et al. (1987) used a simple model of soil/snow microwave emission to devise a means for estimating snow water equivalent (SWE) in mm from passive microwave measurements, by multiplying the difference between the horizontally-polarised 19 GHz and 37 GHz emission by a factor of 4.77, assuming snow density of 300 kg m^{-3}. This technique, which we refer to here as the Chang algorithm, was recommended for snow no deeper than a metre, approximately equivalent to a snow water equivalent of 300 mm, due to increasing non-linearity in the relationship around this depth. The Chang algorithm has, with minor variations, been operationally used since 1987 to estimate snow mass globally from satellite observations from instruments such as SSM/I and AMSR-E.

There have been a few comparisons between snow mass measured by the Chang algorithm and by ground-based observation, showing both substantial over- and underestimation. Armstrong and Brodzik (2000) found a substantial underestimation around 20–40% in SWE when applying the Chang algorithm to snow in the former Soviet Union in the Winter 1988–89 season, for SWE between 10 mm and 100 mm. Pardé et al. (2007) found the Chang algorithm to overestimate snow mass with an RMSE of 40 mm over Winter in 2002–2003 in Central Canada, for a range of SWE between about 20 mm and 150 mm. They improved this to an RMSE of 12 mm by incorporating a simultaneous retrieval of snow grain size into an inversion of the Helsinki University of Technology (HUT) model (Pulliainen et al., 1999). Butt (2009) demonstrated that a retrieval applying the Chang algorithm to SSM/I observations of snow in the UK with a mean depth of 90 mm (so a SWE approximately 30 mm), with depths up to 500 mm, underestimated snow depth by a mean of 51%. He also demonstrated an approach to resolving this by a simultaneous retrieval of snow grain size, improving performance to a mean 11% overestimate. This seems to indicate a considerable range of performance of the Chang algorithm, apparently dependent upon the physical characteristics of the snow local to each study. We aim here to explore more generally the relationship between the physical characteristics of snow and the efficacy of the Chang

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algorithm, to simulate the retrieval to identify the flawed assumptions, and validate the approach by estimating snow mass from remotely-sensed data in an area with an extensive set of physical measurements.

By modelling the emission of microwave radiation by a snowpack and the underlying ground, we firstly test the dependence of the microwave emission of a snowpack/ground combination upon the physical characteristics of the snow, using the HUT snow microwave emission model, and use this to estimate how the Chang algorithm performance would be affected by variation in snow properties. To evaluate the effects of this variation on snow mass estimation, we also need to know how much variability in these properties is typically found in snow. We study this by using the planimetrically extensive measurements made at snow pits in the CLPX Colorado site in 2002–3 (Cline et al., 2003). We examine how accurately the Chang algorithm would retrieve snow mass from snow with these characteristics by simulating emission with the HUT emission model driven by measured snow properties. Finally, we compare our predictions of the accuracy of the Chang algorithm over the CLPX area to the application of the algorithm to SSM/I and AMSR-E measurements.

2. Methods

2.1. The sensitivity of the Chang algorithm to snow grain diameter and density

Most SWE retrievals make use of an empirical retrieval first derived by Chang et al. (1987), consisting of a linear fit to brightness temperatures at 18 GHz and 37 GHz, Eq. (1):

$$\mathrm{SWE(mm)} = 4.77(\mathrm{TB}_{18\mathrm{H}} - \mathrm{TB}_{37\mathrm{H}}) \tag{1}$$

where $\mathrm{TB}_{18\mathrm{H}}$ refers to the microwave brightness temperature measured at 18 GHz at horizontal polarization, and $\mathrm{TB}_{37\mathrm{H}}$ refers to the microwave brightness temperature measured at 37 GHz at horizontal polarization. The gradient of the linear fit, in this equation 4.77, depends on the density and grain diameter of the snowpack. While it is clear that a density of 300 kg m^{-3} was used to determine the gradient, the grain diameter used is uncertain. Chang et al. (1987) refer to a figure which shows brightness temperature curves as a function of SWE for two different grain radii, 0.3 mm and 0.5 mm, and describe the algorithm as a linear fit from the data shown in the figure, but it is not clear which grain radius, or whether a combination of both, were used. Many authors (e.g. Butt, 2009; Foster et al., 1997; Kelly et al., 2003) have assumed this algorithm relates to a grain radius of 0.3 mm.

To test the effect of variation in grain diameter, we use the HUT emission model (Pulliainen et al., 1999) which is based on the same Mie scattering model used in Chang et al. (1987). This model is used to simulate emission at a range of snow water equivalents and grain diameters and at 19 and 37 GHz, 53° from vertical. The Chang algorithm is then applied to estimate snow mass from this emission, indicating the effect of snow grain diameter on the algorithm's performance. To investigate the effects of variation in snow density, we use a fixed grain diameter and range of snow water equivalents and densities, and apply the Chang algorithm to the emission to retrieve snow water equivalent. For the purposes here, some parameters have a negligible effect (Pardé et al., 2007), and are kept constant, e.g. soil moisture is assumed 0.1 m^3 m^{-3}, soil temperature 272.15 K, snow temperature 263.5 K, and snow liquid water content and salinity are set to zero.

2.2. The dependence of snow variability on planimetric scale

A semi-variance analysis is used to examine the characteristic length scale of variability of measured snow properties, to test for evidence that certain spatial scales are more suitable than others for averaging snow properties and estimating snow mass. It is possible that the increased variability of snow properties over large areas mean that the remote sensing relationships with areal snow mass are different, possibly better, than the relationships found at an individual field site. We attempt to identify whether the range of snow properties measured has a strong dependence upon spatial scale by geostatistical analysis of snow properties. The semivariance $\gamma(d)$ for distance d of a set of spatially distributed measurements of $z(\underline{x})$ is given by comparing all pairs of measurements of z separated by d, of which there are $n(d)$, using Eq. (2). The resultant plot has historically been referred to as a semivariogram, but more recently by Bachmaier and Backes (2008) as a variogram.

$$\gamma(d) = \frac{1}{2n(d)} \sum_{i=1}^{i=n(d)} \left(z\left(\underline{x_i} + d\right) - z\left(\underline{x_i}\right)\right)^2 \tag{2}$$

The NASA Cold Land Processes Experiment (CLPX) experiment produced a large number of measurements of snow properties, mass, and other variables in Colorado over 2002–2003 (Cline et al., 2002a; Cline et al., 2002b; Elder et al., 2009). Fig. 1 shows a map of the area of the experiment, and the locations of the main field sites. There were four Intensive Observation Periods (IOPs) during the snow seasons, over the periods February 2002, March 2002, February 2003 and March 2003. Anisotropic distance semivariograms were calculated from the measurements of mean snow grain diameter in the top 5 cm snow layer, snow water equivalent, snow depth, and mean snow density throughout the pack, using the North Park Meso-cell Study Area (MSA) measurements made during IOP3 over 20–23 Feb 2003. We used all the measurements from the ISA Snow Pits set, including the Gamma pits, but measurements within the three densely sampled areas labelled NISP, NMSP, NPSP were excluded from this analysis, since when analysed separately they showed nugget (minimum) semivariance consistently around double that of the rest of the measurements, suggesting a different measurement technique with a higher measurement error.

2.3. Measured snow properties as a function of snow mass

The snow pit measurements made during all four Intensive Observation Periods over the entire area of the CLPX experiment in Colorado were used to calculate the mean snow grain diameter and density within a number of SWE classes. These classes were designed to each encompass snow with a range of SWE with similar properties. Each snow pit measurement set included the minor and major axis diameters of medium size grains, and the mean of these measurements down through the snow layers is used here as representative of the site grain diameter. The depth-integrated mean snow density at each site was used to calculate the mean density within each SWE class.

2.4. The effects of measured snow properties on snow mass retrieval via the Chang algorithm

To assess the effects of measured values of density and grain diameter on the accuracy of the Chang algorithm, microwave emission at 19 and 37 GHz at 53° from the vertical was simulated using the HUT model, driven by the mean snowpit measurements of SWE, density and grain diameter within the SWE classes described in Section 2.3. For each SWE class, we applied the Chang algorithm to the modelled emission, and compared the SWE estimated by the algorithm to the SWE driving the emission model. To distinguish between the effects of grain diameter and density, they were separately changed within the forward model from the Chang algorithm assumptions to the measured class mean values. This demonstrates, for any given SWE, how accurately the Chang algorithm would estimate snow mass, depending on whether its assumptions of grain diameter and snow