Analysis of simulated and spaceborne passive microwave brightness temperatures using in situ measurements of snow and vegetation properties

A. Langlois, A. Royer, and K. Goïta

Abstract. Variations in snow cover and vegetation in the Province of Quebec, Canada, were characterized for a transect spanning from 50°N to 60°N during the International Polar Year field campaign of February 2008. The main objective of this study was to compare measured (AMSR-E) and modeled (MEMLS) brightness temperature ($T_b$) and to analyze differences in the in situ measurement of snow water equivalent (SWE) and vegetation. Sampling involved detailed snow measurements on the ground in four different ecological environments. Measured and modeled SWE were compared using a thermodynamic multilayered snow model (SNOWPACK) driven with North American Regional Reanalysis (NARR) data. The root mean square error (RMSE) of modeled data compared with measurements was 63 mm (30%). The simulated SWE was generally underestimated throughout the transect but stayed within the large standard deviation observed for measured SWE. In situ snow measurements were used as input to a microwave emission model (MEMLS) to simulate $T_b$. An innovative approach using calibrated near-infrared reflectance photographs was used to characterize the effective snow grain-size parameter needed for the radiative transfer model. Although some results provided $T_b$ predictions similar to AMSR-E data for certain areas, large differences remained for the majority of sampling sites. The derived RMSE of 16 K and 32 K, respectively, for 18.7 and 36.5 GHz (vertical polarization) throughout the transect cannot be explained solely in terms of grain-size variations introduced into the simulations. Local variability in snow structure and thickness produced large variability (up to 60 K within one AMSR-E pixel) compared with AMSR-E $T_b$ throughout the transect (15 K for 18.7 GHz and 35 K for 36.5 GHz).

Résumé. La variation latitudinale des propriétés nivales et de végétation est analysée le long d’un transect dans le nord du Québec, Canada durant une campagne de mesure associée à l’Année Polaire Internationale (Février 2008). L’objectif principal de l’article est de comparer les températures de brilliance ($T_b$) mesurées (AMSR-E) et modélisées (MEMLS) et d’analyser les différences à l’aide de mesures de propriétés de neige (équivalent en eau de la neige, EEN, en particulier) et de végétation. L’échantillonnage a eu lieu le long d’un transect latitudinal (50–60°N) et des mesures détaillées de neige et de végétation ont eu lieu dans quatre différents environnements écologiques. Des valeurs mesurées et modélisées d’EEN sont comparées le long du transect en utilisant un modèle thermodynamique de neige (SNOWPACK) dirigé avec des données de réanalyses météorologiques (NARR). L’erreur quadratique moyenne par rapport aux valeurs mesurées se situe à 63 mm (30%). L’EEN simulé est généralement sous-estimé le long du transect, mais reste à l’intérieur du large écart-type issu des mesures (i.e. grande variabilité spatiale). Les mesures de neige in situ sont utilisées comme intrants à MEMLS en utilisant une approche innovatrice pour la caractérisation des grains de neige à l’aide de la photographie infrarouge. Même si certaines simulations de $T_b$ se situent près des valeurs satellites, de larges différences sont observées pour la plupart des sites. L’erreur est de 16 K et 32 K respectivement pour les fréquences 19V et 37V le long du transect, et ne peut être entièrement expliquée par les variations sur la taille de grain. La variabilité spatiale de la structure du manteau neigeux génère une grande variabilité du $T_b$ modélisé (jusqu’à 60 K à l’intérieur d’un pixel AMSR-E) lorsqu’on la compare aux valeurs satellites (15 K pour 19 GHz et 35 K pour 37 GHz).

Introduction

Snow cover represents a very important element of the cryosphere, and extensive studies have examined the impact of recent climate variability on its spatial and temporal distribution (e.g., Brown, 2000; Slater et al., 2007). Snow can cover as much as 62% of Eurasia and 35% of North America (Singh and Singh, 2001) and is an important freshwater reservoir around the world (Barnett et al., 2005). Snow cover spans numerous ecological regions, such as


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boreal forest, taiga, and tundra and affects various aspects of the cryosphere surface energy balance (e.g., Betts and Ball, 1997; Derksen, 2008). The climatological and geophysical processes governing snow cover thickness and water equivalent are highly variable (e.g., Essery and Pomeroy, 2004), and their impact has not yet been properly assessed.

The attempts of scientists to monitor changes in snow properties have met with limited success. Microwave remote sensing from space has proven useful for estimating snow mass balance and snow water equivalent (SWE) in particular. Numerous studies have examined the relationship between SWE and passive microwave brightness temperature $T_b$ (e.g., Chang et al., 1982; Kunzi et al., 1982; Walker and Goodison, 1993; Tait, 1998; Pulliainen and Hallikainen, 2001; Walker and Silis, 2002; Kelly et al., 2003; Durand and Margulis, 2007; Derksen, 2008). Although recent improved snow models can provide reasonable SWE predictions (Armstrong and Brun, 2008), uncertainty still surrounds the role of vegetation in seasonal interception (e.g., Hedstrom and Pomeroy, 1998) and its impact on passive microwave emission (e.g., Kurvonen and Hallikainen, 1997; De Roo et al., 2007).

Several field campaigns have been conducted to quantify the effect of vegetation on SWE retrieval for various ecological environments. Most projects have focused on boreal forests (e.g., Kruopis et al., 1999; Foster et al., 2005; Goits et al., 2003; Derksen et al., 2005; Pulliainen, 2006) and have combined spaceborne and airborne passive microwave measurements to improve SWE predictions. However, a lack of knowledge remains regarding satellite-scale applications such as the Advanced Microwave Scanning Radiometer (AMSR-E; 12.5 km resolution), in which the signal includes contributions from various surface features such as changing forest fraction, density, and type, the presence of lakes, and changing terrain. Large-scale studies including ecological region transitions (i.e., boreal to taiga, taiga to tundra) are thus required, and the potential combination of modeled and measured brightness temperatures for the improvement of regional SWE algorithms should be explored. The modeling approach is interesting because it simulates brightness temperatures from measured and (or) modeled snow information, thus isolating the snow signature from the aforementioned other spatial contributions. This approach should provide information about the amplitude of the contributions of these surface features to satellite measurements.

To improve SWE predictions and the understanding of satellite passive microwave spatial signatures using emission models, we addressed four specific objectives: (i) quantify SWE and vegetation variations at the AMSR-E scale for boreal, taiga, and tundra environments; (ii) compare SWE ground measurements and snow model predictions driven by meteorological reanalysis data; (iii) simulate $T_b$ from the microwave emission model of layered snowpacks (MEMLS) using in situ snow measurements including snow grain information derived from digital infrared photography; and (iv) compare variations of modeled and measured $T_b$ regionally.

**Data and methods**

**International Polar Year (IPY) field campaign measurements**

The primary goal of this study within the Canadian International Polar Year (IPY) project “Variability and change in the Canadian cryosphere” was to improve the retrieval of SWE from passive microwave brightness temperature measurements using measured ground vegetation and physical snow properties over subarctic and arctic areas, in view of the impact of these parameters on microwave emission. The intensive field campaign over 10 days in February 2008 included four sites and high-resolution sampling at fixed locations over a 2000 km transect in northern Quebec (hereafter referred to as “the transect”) (Figure 1; Table 1). The transect spanned a transition in vegetation ranging from dense boreal forest in the south to open tundra in the north. At the first three sites, located at Sept-Îles (SI), Schefferville, (SC), and Kuujjuaq (KU), Quebec, in situ sampling was conducted at 1 km intervals over an 8 km × 16 km grid, close to AMSR-E spatial resolution. At the fourth site, located north of Puvirnituq (POV), depth measurements were acquired with global positioning system (GPS) equipped automated probes (MagnaProbes produced by SnowHydro) along the sampling transect. Nearly 20 km were sampled in this manner, with measurements made every 3–5 m. Direct measurements of SWE were made with an ESC-30 snow corer at regular intervals along the snow depth transects.

In situ snow and vegetation information was gathered by large-scale sampling approximately every 40 km along the transect. A helicopter was used to transport personnel for this purpose.

**Snow measurements**

Snow pits were dug at each station along the transect and the high-resolution sampling grids (SI, SC, and KU) such that direct solar illumination of the snow wall from the south was avoided. Layered SWE profiles were obtained by extracting snow samples at 3 cm intervals from the surface to the snow–soil interface with a 200 cm$^2$ density cutter and weighing the samples using a Pesola light series scale to obtain density. Additional SWE measurements were made using a snow core at each site. Photographs of snow grains were acquired for each layer sampled to attribute a snow “class” as proposed by Colbeck et al. (1990). The following three main observed snow classes were considered: hoar layer grains (large grains, class 1), noncohesive spheres (medium grains, class 2), and cohesive spheres – crust (small grains, class 3). Temperature profiles were also measured at 3 cm intervals using a Traceable 2000 digital temperature probe.
Snow grain size, a critical parameter strongly affecting microwave snow emission (e.g., Mätzler, 1987), was measured using a near-infrared (NIR) photographic approach recently proposed by Matzl and Schneebeli (2006) and improved by Langlois et al. (2010). NIR-converted digital cameras (830 nm) were used throughout the field campaign. All measurements were made under diffuse light conditions using a transparent blanket, avoiding direct solar illumination. The snow profile image was normalized using a reference panel image taken simultaneously to eliminate the illumination variation within the snow pit. The derived normalized digital counts were then converted to calibrated reflectance using Spectralon reference targets. Complete details on the calibration and retrieval of reflectance data can be found in Langlois et al. (2010). The infrared reflectance $R$, spectrally integrated within the spectral limit of the filter ($\lambda_1$, $\lambda_2$), was converted to snow grain optical diameter ($d_{opt}$) using the spectrally integrated model of Kokhanovsky and Zege (2004):

$$\lambda_2 \int_{\lambda_1} s(\lambda) \exp\left(-k_o b \sqrt{\gamma_2 d_{opt}}\right) d\lambda \approx \beta(b) \exp\left[\alpha(b) \sqrt{d_{opt}}\right]$$

where $s(\lambda)$ is the spectral response on the NIR filter, $k_o$ is a coefficient for the reflected light distribution function, $\gamma_2$ is the spectral ice absorption coefficient, the constant $b$ represents the shape factor and accounts for various types of grains for which values are discussed in Picard et al. (2009), and $\alpha$ and $\beta$ are fitted coefficients. Based on the discussion in Langlois et al. (20010), fixed values of 3.7, 4.0, and 4.3 were assigned to $b$ in Equation (1) to obtain $\alpha$ and $\beta$ fitted coefficients. The optical diameter was then calculated from the measured NIR reflectance ($R$) using a fitted

**Table 1.** Sites where detailed sampling of snow and vegetation properties occurred within grids SI, SC, KU, and POV.

<table>
<thead>
<tr>
<th>Site–line</th>
<th>Dominant land cover</th>
<th>No. of sampling sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sept-Îles (SI)</td>
<td>Dense boreal forest</td>
<td>57</td>
</tr>
<tr>
<td>Sept-Îles to Schefferville</td>
<td>Boreal forest to taiga transition</td>
<td>10</td>
</tr>
<tr>
<td>Schefferville (SC)</td>
<td>Taiga</td>
<td>38</td>
</tr>
<tr>
<td>Schefferville to Kuujjuaq</td>
<td>Taiga to tundra transition</td>
<td>7</td>
</tr>
<tr>
<td>Kuujjuaq (KU)</td>
<td>Open taiga and tundra</td>
<td>31</td>
</tr>
<tr>
<td>Kuujjuaq to Kangirsuk</td>
<td>Open tundra</td>
<td>8</td>
</tr>
<tr>
<td>Puvirnituq (POV)</td>
<td>Open tundra</td>
<td>7062$^a$</td>
</tr>
</tbody>
</table>

*Note: The sampling occurred every 40 km along the helicopter transect. $^a$Only SWE measurements were taken.*
function defined by

\[ d_{opt} \approx \frac{1}{|\xi(b)|} \ln \left( \frac{b}{R} \right) \]  

(2)

It should be noted that \( \xi \) is a function of the shape factor \( b \). A calibration factor \( \varphi \) was introduced to estimate an effective grain “size” input for the microwave radiative transfer model. A detailed vertical profile of the grain-size optical diameter was derived from Equation (2) using the calibrated photographs of each snow pit. Since snow grain type varies with depth (from smaller cohesive spheres on the top to hoar grains at depth), the resulting vertical profile of the optical grain diameter (from different \( b \) values) was adjusted vertically.

Vegetation measurement and land cover database

Tree diameter at breast height (DBH), height \((h)\), density, and type were measured at each sampling site along the transect and on the sampling grids. DBH is the outside bark diameter at breast height (defined as 4.5 ft or 1.37 m) above the forest floor on the uphill side of the tree. This measurement is used widely for multiple calculations such as growth and stem volume and was done on each tree located within the 10 m diameter sampling zone of each site. In addition, the height of four trees was measured in each of four directions (north, south, east, and west) from the centre of the sampling zone. The dry biomass was calculated for each tree using the equations proposed by Ter-Mikaelian and Korzukhin (1997) for different types of vegetation (DBH and \( h \) dependent). The stem volume (SV, in \( m^3 \cdot ha^{-1} \)) was then calculated from biomass using dry biomass measurements and the basal volume and mass specific to each species and cumulated over the sampling zone. Small shrubs were not considered in the calculations because their contribution to the total SV of the parcel was negligible. The equations used were adjusted according to latitude and region (dominant species).

The land cover information used was obtained from the land cover mapping of the North and Central America Global Land Cover 2000 study (Latifovic et al., 2004). This product was prepared by the Canada Centre for Remote Sensing (CCRS), Natural Resources Canada (NRCan), and the US Geological Survey (USGS) Earth Resources Observation and Science (EROS) Data Center (EDC) using a new mapping approach for transforming satellite observations acquired by the SPOT4/VEGETATION (VGT) sensor into land cover information. A database with 28 different classes of vegetation was generated from this methodology. We resampled the initial 1 km resolution to obtain the equivalent EASE-Grid microwave satellite resolution for comparison with AMSR-E brightness temperature data. Due to the nature of the study region, only seven of the classes for which total coverage (in percent) is given were used: (1) temperate or subpolar needleleaf evergreen forest – closed canopy; (2) temperate or subpolar needleleaf evergreen forest – open canopy; (3) temperate or subpolar needleleaf mixed forest – closed canopy; (4) temperate or subpolar mixed broadleaf or needleleaf forest – closed canopy; (5) temperate or subpolar mixed broadleaf or needleleaf forest – open canopy; (6) temperate or subpolar needleleaf evergreen shrubland – open canopy; and (7) subpolar needleleaf evergreen forest open canopy – lichen understory. Each class was weighted according to its characteristics to obtain a forest cover fraction \((F)\) for each satellite footprint, from closed boreal forest to open tundra. The latitudinal dependency of vegetation properties on both forest fraction (Figure 2a) and stem volume (Figure 2b) is clearly visible. The forest fraction on the EASE-Grid scale was close to unity in the Sept-Îles area and decreased as \( \text{53}^\circ \text{N} \) was approached, remaining under 30% until \( \text{58}^\circ \text{N} \), where it reached zero (open tundra). Stem volume displayed a similar latitudinal gradient, from a mean value of 370 \( m^3 \cdot m^{-2} \) around Sept-Îles to an average of 50 \( m^3 \cdot m^{-2} \) over the taiga and zero in the tundra. Detailed gridded sampling (1 km intervals, within a

![Figure 2](image_url). Latitudinal evolution of (a) forest fraction \((F)\) and (b) total vegetation volume (SV) \((m^3 \cdot m^{-2})\).
Meteorological data (NARR)

Meteorological data are needed for determining satellite atmospheric corrections (cloud cover and air temperature) and to drive snow models. North American Regional Reanalysis (NARR) data from the National Centers for Environmental Prediction (NCEP) Environmental Modeling Center (EMC) (Mesinger et al., 2006) were used in the present study. The NARR horizontal resolution is 0.3° (approximately 32 km) and the temporal resolution is eight times per day (every 3 h). Langlois et al. (2009) demonstrated that in most cases the thermodynamic multilayered snow model SNOWPACK driven by NARR data did provide fair SWE predictions for different ecological regions throughout the province of Quebec. NARR meteorological data were thus used starting from the beginning of the winter (fall 2007) to simulate the accumulation of the snowpack for each sampling site along the transect. Since NARR precipitation data were significantly underestimated in Sept-Îles (Langlois et al., 2009), simulations were not performed.

Snow model (SNOWPACK)

The SNOWPACK model solves the partial differential equations governing snow mass and energy fluxes using a Lagrangian finite element implementation (Bartelt and Lehning, 2002; Lehning et al., 2002). Thermophysical processes of interest in SWE studies such as phase change, water vapour transport (i.e., metamorphism), and loss (runoff, evaporation, and sublimation) are included. The details of the internal models are provided elsewhere (Lehning et al., 2002; Bartelt and Lehning, 2002). Model settings are specified to the extent made possible by input data availability. Two main types of output data can be visualized through user-friendly software (SN-GUI), namely scalar and vector data (Spreitzerhofer et al., 2004). Scalar data are related to individual layers of the snowpack such as SWE, whereas vector data are attributed to layered parameters, such as the simulated vertical profiles of snow density. The number of layers varies according to the predicted snow depth, and the transition between solid and liquid precipitation occurs at +1.2 °C. SNOWPACK requires air temperature (°C or K), wind speed (m s⁻¹), incoming long-wave radiation (W m⁻²), incoming solar radiation (W m⁻²), and precipitation (mm). These parameters are available through NARR, given the possibility of simulating SWE in near real time.

Snow passive microwave emission model (MEMLS)

The microwave emission model of layered snowpacks (MEMLS) can be used in the frequency range between 5 and 100 GHz (Mätzler and Wiesmann, 1999; Wiesmann and Mätzler, 1999). The model is based on radiative transfer theory, which allows the scattering coefficient to be predicted from physical snow parameters and the absorption coefficient from dielectric properties of ice. Snow cover is considered as a series of horizontal layers (L), each characterized by thickness, reflectivity (rL), emissivity (eL), transmissivity (tL), and temperature (TL). The model automatically computes these parameters using snow information as input. To obtain accurate characterizations of rL, eL, and tL, a six-flux three-dimensional (3D) approach is used within each layer. The horizontal fluxes represent radiation that is trapped in the snow cover and cannot exit at incidence angles θ greater than the critical angle θc. The vertical fluxes represent the radiation that escapes the snow cover at θ < θc. Further details on the radiation transfer theory used in MEMLS can be found in Mätzler and Wiesmann (1999) and Wiesmann and Mätzler (1999).

The primary input profile data are density (ρs), snow temperature (Tb), liquid water content (WL), correlation length (lC), vertical extent (zL), physical ground temperature (Tg), and snow–ground interface reflectivity (r0). From these primary parameters, the dielectric properties (for dry and wet snow) and the absorption (γL) and scattering (gL) coefficients can be derived. All input data were measured throughout the field campaign. Snow correlation length (lC) was derived from the optical diameter extracted from NIR reflectance photographs using the equation lC = 2(1 − v)dcrop/3, where v is the ratio between snow and ice density (Mätzler, 2002). In this study, different model runs were investigated using measured snow parameters and evolving soil reflectivity values within the limits of the sensitivity of the model to ground dielectric properties (Wegmüller and Mätzler, 1999) and for different values of the calibration factor φ (Equation (2)) for the effective grain size input. Each simulation was compared with AMSR-E brightness temperatures.

AMSR-E brightness temperatures

Brightness temperatures (Tb) were extracted from the Advanced Microwave Scanning Radiometer onboard the Aqua satellite (AMSR-E) at 18.7 and 36.5 GHz and both horizontal (H) and vertical (V) polarizations (Cavalieri et al., 2004), and thus the channels used in this study are designated 19V, 19H, 37V, and 37H. The instantaneous fields of view (IFOV) for these channels are 27 km × 16 km and 14 km × 18 km, respectively, for the 19 and 37 GHz data. These data were resampled to generate datasets with spatial resolutions of 12.5 km × 12.5 km on the EASE-Grid. The total radiometric precision ranges from 0.66 at 100 K to 0.68 at 250 K. Brightness temperatures were extracted from each pixel over the sampling sites of the transect and for each grid (one pixel per grid) throughout the IPY project (Figure 1).
Previous work on SWE retrieval using satellite passive microwave data has shown that the impact of atmospheric absorption–emission can be large (e.g., Aschbacher, 1989; Pulliainen and Hallikainen, 2001) and can contribute 25%–50% of the estimate of SWE (Wang and Tedesco, 2007). In the present work, atmospheric corrections were made based on passive microwave sky measurements reported by Mätzler (1992), who obtained optical thickness values for arctic regions, which we adjusted according to the cloud cover fraction extracted from NARR data. To estimate the contribution of atmospheric temperature to the satellite data, the transmissivity ($\tau_{\text{atm}}$) of the atmosphere can be derived from the following equation:

$$\tau_{\text{atm}} = e^{-\text{OT} \sec \theta}$$  \hspace{1cm} (3)

where $\text{OT}$ is the optical thickness, and $\theta$ is the incidence angle (e.g., Mätzler, 1987). Therefore, considering initial ground brightness temperatures ($T_b$), the corresponding satellite brightness temperatures ($T_{b,\text{SAT}}$) correspond to

$$T_{b,\text{SAT}} = (T_b \tau_{\text{atm}}) + (1 - e)(\tau_{\text{atm}} T_{\text{sat}}) + (1 - \tau_{\text{atm}}) T_{\text{air}}$$  \hspace{1cm} (4)

where $(1 - \tau_{\text{atm}}) T_{\text{air}}$ is the sky brightness temperature derived from the surface air temperature $T_{\text{air}}$, and $e$ is the emissivity of the snow. Since $e$ is very high, the downward $T_{\text{sat}}$ portion reflected to the satellite and through the atmosphere was neglected. Thus, the corrected brightness temperature from satellite measurements can be derived from Equation (4) such that

$$T_{b,\text{corr, atm}} \approx T_{b,\text{SAT}} - (1 - \tau_{\text{atm}}) T_{\text{air}}$$  \hspace{1cm} (5)

where $T_{b,\text{corr, atm}}$ is the brightness temperature corrected for atmospheric effects, and the optical thickness values (Equation (3)) were obtained from Mätzler (1992) using linear regression.

The measured satellite brightness temperature also needs to be corrected for vegetation effects to extract the snow effective brightness temperature ($T_{b,\text{snow}}$). Several studies have examined the effect of forest (both fraction and volume) on passive microwave brightness temperatures (e.g., Mätzler, 1994; Kurvonen and Hallikainen, 1997; Kruopis et al., 1999; Goïa et al., 2003; Pardé et al., 2004; Derksen, 2008). It has been shown that the forest attenuates the signal from the surface as a function of its density or fraction and biomass–stem volume (e.g., Pulliainen et al., 2006). The transmissivity can be expressed as a function of forest parameters such that

$$\tau_{\text{veg}}(f, SV) = a + [1 - a] \exp(-b SV)$$  \hspace{1cm} (6)

where $f$ is the frequency, and $SV$ is the stem volume (from field measurements). Parameters $a$ and $b$ are constants fitted by nonlinear regression. In a simplified form (Pulliainen et al., 1999), the vegetation brightness temperatures can be expressed as

$$T_{b,\text{veg}} = FT_{b,\text{surf}} + (1 - F)T_{b,\text{snow}}$$  \hspace{1cm} (7)

where $T_{b,\text{surf}}$ is the brightness temperatures coming from the surface through the vegetation canopy, and $F$ is the forest cover fraction. Equation (7) can be rewritten as follows:

$$T_{b,\text{corr}} = T_{b,\text{snow}} + F(\tau_{\text{veg}} T_{\text{veg}} + (1 - F) T_{b,\text{snow}})$$  \hspace{1cm} (8)

The final corrected (atmosphere and vegetation) brightness temperature ($T_{b,\text{corr}}$) corresponding to the snow signal is obtained from the combination of Equations (5) and (8), assuming the vegetation temperature to be equal to the air temperature (extracted from NARR data at AMSR-E ascending pass at approximately 1330 local time). Although the assumption of $T_{\text{air}} = T_{\text{veg}}$ is not entirely true, the resulting bias to $T_{b,\text{corr}}$ is negligible because only small differences were observed in cold weather, producing a bias of 0.48 K·°C$^{-1}$ at 19 GHz and 0.75 K·°C$^{-1}$ at 37 GHz:

$$T_{b,\text{corr}} = T_{b,\text{snow}} - F(1 - \tau_{\text{veg}}) T_{\text{air}}$$  \hspace{1cm} (9)

Over open areas (without forest), $F = 0$, for which case

$T_{b,\text{corr}} = T_{b,\text{snow}} = T_{b,\text{corr, atm}}$.

Results and discussion

Snow water equivalent (SWE) variations

Snow water equivalent (SWE) was measured at each sampling station and compared with SNOWPACK simulations run using the NARR meteorological data for the same sites. Figure 3 displays the evolution of measured and modeled SWE as a function of latitude. Due to missing precipitation data, no model run was conducted for Sept-Îles (SI). It is apparent that the SNOWPACK model generally underestimated SWE in boreal environments (south of 54°N), where vegetation is dense, whereas over-estimation occurred in tundra environments (north of 58°N). The average difference between predicted and measured values was rather small in the intermediate latitudes (between 54°N and 58°N), where the vegetation is dominated by taiga.

The overall correlation between measurements and modeled results was 0.88, with an RMSE of 63.9 mm (30%) and an average SNOWPACK underestimation (bias) of −17 mm. In addition to inherent SNOWPACK errors, a number of factors could alter the accuracy of modeled SWE, including errors in NARR meteorological data such as precipitation (Langlois et al., 2009), errors from forest interception (Rutter et al., 2009) that are not taken into account, and blowing-snow effects (Pomeroy et al., 1997). Even if the reanalysis surface parameter output field could include uncertainties (Luo et al., 2007; Tsuang et al., 2008), such a database appears to be the best available gridded meteorological dataset over northern regions. Although NARR provides much improved representation...
of precipitation when compared to other reanalysis products (Bukovsky and Karoly, 2007). Mesinger et al. (2006) identified some of the known weaknesses, such as precipitation inaccuracies over Canada. However, NARR data are preferred because of their improved temporal and spatial resolution and their availability (Uppala et al., 2005). It is expected that the assimilation of passive microwave brightness temperatures into a snow model could improve these simulations, as discussed recently by Durand et al. (2008) and Dong et al. (2007), who showed that snow stratigraphy can dominate modeled passive microwave $T_b$, and that the corresponding snowpack information is required. Coupling with a multilayered snow model having greater vertical fidelity also provided more accurate $T_b$ simulations (Durand et al., 2008).

Also interesting in Figure 3 is the strong local variability compared to the regional trend variation shown by the transect sampling. For the IPY observation period (end of February 2008), the relative standard deviations (standard deviations over the mean) of SWE measurements were 28%, 30%, 55%, and 73%, respectively, for Sept-Iles, Schefferville, Kuujjuaq, and Puvirnituq. Furthermore, the difference between lake and land snow conditions is illustrated in Figure 3, with significantly lower SWE values over lakes (i.e., increasing regional variability, given the large number of lakes across northern Canada). Over tundra near the Puvirnituq transect, SWE values ranged between 0 and 387 mm (averaging 102 mm), with a standard deviation of ±74 mm, illustrating the significance of local spatial variability (presence of lakes, windy areas, wind-protected areas, microtopography effects, etc.). This aspect of strong local variability is a key issue for validating low-resolution satellite data as discussed below.

To strengthen our argument that the modeling approach can help existing SWE algorithms, we compared our measured SWE values with values obtained using the existing operational satellite product at the grid cells in Sept-Iles, Schefferville, Kuujjuaq, and Puvirnituq where the forest fractions were 83%, 28%, 5%, and 0%, respectively; the satellite-derived SWE (from the AMSR-E/Aqua 5 day L3 global snow water equivalent EASE-Grid (Kelly et al., 2004)) values were 18, 72, 82, and 50 mm, respectively. Based on Figure 3, it is clear that the algorithm yielded lower SWE values than the mean in situ measurements (even taking into account the standard deviation) and the model results from SNOWPACK. It is noted with interest that the difference between AMSR-E SWE values and field measurements decreased with decreasing vegetation cover and volume. The AMSR-E product applies a correction for the vegetation fraction but does not consider vegetation stem volume, which plays a significant role in radiative transfer, as shown in Figure 4. The errors associated with the algorithm assumptions are discussed below.

**AMSR-E brightness temperature variations**

As described in the Data and methods section, NARR cloud fraction data were employed for atmospheric corrections of the satellite data using nearest concordant NARR reanalysis time with AMSR-E ascending passes over each station where snow and vegetation were sampled. The vegetation data (fraction and volume) were also used to
obtain brightness temperatures corrected for atmosphere and vegetation. The results are plotted against the total vegetation volume (in cubic metres per pixel) in Figure 4. It is clear that the effect of vegetation on brightness temperatures was considerable for the southern part of the transect (south of 51° N) over closed boreal forest (total volume > 2 Mm³/pixel). Such dense vegetation decreased the initial noncorrected brightness temperatures by 7, 14, 17, and 24 K for 19V, 19H, 37V, and 37H, respectively, for the Sept-Îles area (50° N, total volume > 5 Mm³/pixel). The differences measured between corrected and raw values near the end of the transect (north of 58° N) were due primarily to atmospheric effects, considering the virtual absence of vegetation. The atmosphere contributed up to 6.7 and 11.8 K at 19 and 37 GHz, respectively, based on the cloud cover fraction. These impacts on SWE may be significant in view of the characteristics (or limitations) of the algorithm used.

Dry snow emissivity depends on several snow properties, including frequency, snow grain size, snow depth, density, and subsurface conditions (roughness, relative humidity) (Grody, 2008; Mätzler, 2006). Complex interactions among these properties depend primarily on snow stratification and compaction (metamorphism, wind, and temperature). The brightness temperature is the result of two compensating factors: (i) the scattering effect of small-sized grains, which decreases $T_b$; and (ii) scattering losses due to increases in ice crystal size and density resulting from metamorphic processes. An increase in the single-scattering albedo can result from metamorphic processes that increase the imaginary part of the grain dielectric constant, thereby increasing $T_b$ (Rosenfeld and Grody, 2000). This behaviour depends on the seasonal evolution of the snowpack structure and is frequency dependent. At a lower frequency (19 GHz), the scattering effect is small and the penetration depth is typically greater than the snow depth, so emissivity is mainly dependent on subsurface conditions (i.e., dielectric properties of the soil). At a higher frequency (37 GHz), the emissivity is very sensitive to variations in both particle size–structure and snow depth. Thus, the correlation between brightness temperature and snow depth (i.e., SWE) becomes insignificant as snow depth increases and the snowpack ages.

**Figure 4.** Raw and corrected AMSR-E brightness temperatures (K) at 19 and 37 GHz vertical and horizontal polarization (V-Pol. and H-Pol.) with respect to total vegetation volume (Mm³ per pixel).
We therefore investigated the association between the atmosphere–vegetation corrected AMSR-E brightness temperature differences or $\Delta T_b$ (37V–19V) and snow depth. **Figure 5** clearly shows the expected decrease in $\Delta T_b$ due to increasing volume scattering as snow depth increased up to a thickness of approximately 80 cm. Beyond this thickness, the relationship between $\Delta T_b$ and snow depth shows no particular trend, indicating saturation. This $T_b$ behaviour for low to medium snow depths is the main basis for existing operational AMSR-E snow depth – SWE algorithms using passive microwave remote sensing (Chang et al., 1982; Kelly et al., 2004; Armstrong et al., 2005). The decrease in $\Delta T_b$ observed in the present study (from $-25$ K to $-40$ K for 0–80 cm, or approximately 5 cm·K$^{-1}$) is larger than that used with current AMSR-E SWE products discussed earlier. The difference probably comes from the assumptions made in the operational product (snow density and grain size set as constants). Our work shows that the grain size vertical profile can affect $T_b$ simulated by MEMLS. The densities measured at our sites ranged from 100 to 500 kg·m$^{-3}$.

Furthermore, large uncertainties associated with the retrieved values arise from spatial heterogeneities (terrain and forest cover, type, and density), which can induce thickness errors of 10–40 cm (or up to 120 mm SWE) at local scales of estimation (Kelly et al., 2005). We suggest that a modeling approach combined with more accurate snow density and grain size information as well as better characterization of the vegetation could reduce some of this uncertainty.

**Simulated versus measured $T_b$**

We conducted different MEMLS runs to be compared with AMSR-E brightness temperatures corrected for atmospheric conditions and vegetation. Runs utilize the soil reflectivity derived from Wegmüller and Mätzler (1999) and the correction factor $\varphi$ (Equation (2)) for the characterization of the effective snow grain size. **Figure 6** compares two runs of simulated $T_b$ with $\varphi = 1.0$ and $\varphi = 1.5$ along the transect. The snow depth measured at each sampling site is also given.

Without applying any correction (i.e., $\varphi = 1.0$) to the optical diameter calculations in the program, a general overestimation of simulated brightness temperatures by MEMLS is observed along the transect for all frequencies and polarizations, in comparison with satellite $T_b$. This overestimation is variable without any particular latitudinal trend, with an average overestimation value varying between $+12.4$ K and $+33.2$ K, depending on frequency and polarization. The RMSE is 16 K and 32 K, respectively, for 19V and 37V throughout the transect (Table 2). In addition, **Figure 6** shows the greater variability of the simulated $T_b$ values compared with AMSR-E $T_b$. Several factors can explain the observed differences, mainly the sensitivity of the snow parameters affecting the snow emissivity in the model, combined with the scale effect when comparing a snow pit against a 12.5 km × 12.5 km average $T_b$. These aspects are discussed below. We analyzed the sensitivity of the simulated $T_b$ to the snow grain correlation length, keeping all other measured parameters constant. For the observed snowpack, larger correlation

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**Figure 5.** Relationship between spectral brightness temperature gradient ($\Delta T_b = 37V–19V$) with respect to snow depth (cm). No trend is shown beyond 80 cm snow depth (vertical line), indicating saturation.
lengths correspond to decreases in $T_b$ values due to an increasing volume scattering effect, the attenuation being larger for 37 GHz than for 19 GHz. By iteration on MEMLS, we found that applying a correction factor of $\varphi = 1.5$ to the optical diameter for each snow profile improved results slightly for some sites, based on comparison with satellite data (Figure 6). However, the overall RMSE is not significantly different (Table 2). Soil reflectivity, even over a very wide range, had only a small effect on predicted brightness temperatures (changes of 4–5 K).

As shown in Figure 6, snow depth decreased significantly between 50°N and 60°N. Looking at the differences between simulated and measured brightness temperatures, we investigated the relationship between these differences with respect to snow depth. We found that the difference between predicted and measured brightness temperature increased with an increase in snow depth – SWE at 19 GHz in both polarizations. The correlation coefficients between the difference ($T_b$-MEMLS – $T_b$-AMSR-E) and snow depth were 0.56 and 0.68 for 19V and 19H, respectively, and were not significant for 37 GHz. These differences between simulated and satellite $T_b$ must be analyzed in a spatial context.

We therefore investigated the spatial variability of brightness temperature by averaging all the brightness temperatures simulated at each site within each grid (SI, SC, and KU) (Table 1). The standard deviation of $T_b$ is clearly very

### Table 2. Mean difference between simulated (MEMLS) and measured (AMSR-E) brightness temperature $T_b$ for all sampling sites.

<table>
<thead>
<tr>
<th></th>
<th>19 GHz V</th>
<th>19 GHz H</th>
<th>37 GHz V</th>
<th>37 GHz H</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\varphi = 1.0$</td>
<td>$\varphi = 1.5$</td>
<td>$\varphi = 1.0$</td>
<td>$\varphi = 1.5$</td>
</tr>
<tr>
<td>RMSE (K)</td>
<td>16.0</td>
<td>16.8</td>
<td>25.6</td>
<td>22.9</td>
</tr>
<tr>
<td>$R$</td>
<td>0.37</td>
<td>0.26</td>
<td>0.39</td>
<td>0.24</td>
</tr>
<tr>
<td>$p$</td>
<td>0.05</td>
<td>0.13</td>
<td>0.04</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Note: Statistical results (root mean square error, RMSE; correlation coefficient, $R$) are given for two MEMLS runs as a function of the grain-size calibration factor $\varphi$ (see Equation (2)).
Table 3. Comparison between spatially integrated $T_b$ (AMSR-E) and mean simulated $T_b$ (MEMLS) from high-resolution sampling grids.

<table>
<thead>
<tr>
<th>Grid site</th>
<th>AMSR-E $T_b$ (K)</th>
<th>MEMLS $T_b$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\varphi = 1.0$</td>
<td>$\varphi = 1.5$</td>
</tr>
<tr>
<td>Channel 19V</td>
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<td></td>
</tr>
<tr>
<td>SI</td>
<td>223.6</td>
<td>258.3</td>
</tr>
<tr>
<td>SC</td>
<td>240.0</td>
<td>241.3</td>
</tr>
<tr>
<td>KU</td>
<td>240.8</td>
<td>248.8</td>
</tr>
<tr>
<td>Channel 19H</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>203.1</td>
<td>242.0</td>
</tr>
<tr>
<td>SC</td>
<td>217.6</td>
<td>231.0</td>
</tr>
<tr>
<td>KU</td>
<td>214.0</td>
<td>233.5</td>
</tr>
<tr>
<td>Channel 37V</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>215.4</td>
<td>237.6</td>
</tr>
<tr>
<td>SC</td>
<td>203.3</td>
<td>205.8</td>
</tr>
<tr>
<td>KU</td>
<td>207.4</td>
<td>229.0</td>
</tr>
<tr>
<td>Channel 37H</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI</td>
<td>193.3</td>
<td>225.5</td>
</tr>
<tr>
<td>SC</td>
<td>186.4</td>
<td>200.0</td>
</tr>
<tr>
<td>KU</td>
<td>186.8</td>
<td>216.6</td>
</tr>
</tbody>
</table>

Note: SD, standard deviation.

The observed variabilities are summarized in Table 3. This suggests that the mean brightness temperature obtained from AMSR-E can be very different from the average simulated brightness temperature at approximately similar scales. The snowpack stratigraphy results from various local meteorological forcing and terrain factors that interact and evolve differently over the winter. Snow structure at two given sites may thus be quite different despite their proximity. Since the effects of grain size, snow depth, density, and temperature on the microwave emission are not linear, the observed snowpack variability translated into very large variability in $T_b$. This could explain the large difference observed between mean satellite $T_b$ and the $T_b$ average within a pixel. Thus, as numerous studies have shown, it is difficult to compare simulated $T_b$ obtained using point measurements with observed $T_b$ integrated over the entire satellite footprint.

Conclusions

We characterized the variation of snow and vegetation properties in the northern portion of the Province of Quebec, Canada, as a function of latitude and the impact of these variations on satellite and modeled passive microwave brightness temperature data. Detailed ground-based snow measurements were conducted during an intensive field campaign (end of February 2008) within the framework of the Canadian International Polar Year (IPY) project. The effect of vegetation on microwave signatures was investigated, and a comparison was conducted with a vegetation-independent microwave emission model. The evolution of measured snow water equivalent (SWE) and SWE modeled using a thermodynamic multilayered snow model (SNOWPACK) driven with North American Regional Reanalysis (NARR) meteorological data showed an overall root mean square error (RMSE) of 63 mm (30%), with SNOWPACK generally underestimating SWE throughout the latitudinal range of the sampled transect. This error can be explained by uncertainties in meteorological input data and landscape influences.

Regarding landscape influences, we examined forest fraction and type in adjacent pixels near our sampling grids (i.e., Sept-Îles, Schefferville, Kuujjuaq, and Puvirnituq) and found that little variation exists (needleleaf dominant throughout the transect). We analyzed the variation in vegetation fraction from the initial 1 km product and averaged the information on $3 \times 3, 5 \times 5, and 7 \times 7$ pixels up to the EASE-Grid projection information used in this paper. Little variation was observed, suggesting that the satellite-scale average is quite representative of the area. However, other landscape features such as lake fraction and topography can affect measured brightness temperatures, and further investigation is required. Moreover, over a detailed sampling grid within the satellite scale (12.5 km × 12.5 km), we determined that the local variability of the SWE can be great, particularly over the open tundra.

We analyzed the Advanced Microwave Scanning Radiometer (AMSR-E) brightness temperature variation throughout the transect. The atmospheric and vegetation correction applied to the measured data allowed us to compare the latitudinal trend of the snow signal. In a dense boreal environment, the contribution of vegetation to brightness temperature $T_b$ reached more than 20 K, depending on the frequency–polarization combination. The AMSR-E brightness temperatures exhibited a relatively low variability over the transect (maximum deviation of 15 K and 35 K, respectively, for the 19V and 37V channels) compared with the local variability (maximum standard deviation of 38 K and 55 K, respectively, for the 19V and 37V channels), even when the pixels included numerous lakes.

The relationship between the corrected AMSR-E spectral gradient $\Delta T_b$ (37V–19V) and latitudinal variation of snow depth showed the expected decreasing trend with a saturation effect at around 80 cm, at which the emission from the soil–snow interface was completely masked. In situ snow measurements were used as input to a microwave emission model (MEMLS) to simulate the brightness temperature. We used an innovative approach to characterize the snow grain correlation length using calibrated near-infrared reflectance photographs. Results provided predictions similar to those of AMSR-E data in certain areas, but large differences remained in the majority of cases. The derived RMSE of 16 K and 32 K for 19V and 37V, respectively, throughout the transect cannot be explained by changing snow grain correlation length using a scaling factor ($\varphi$, see...
Equation (2)). This highlighted the issue of spatial variability, in view of the very large range of simulated brightness temperatures within one AMSR-E pixel over our high-resolution sampling areas. We demonstrated that the variability due to local variations in snow structure and thickness generates large variability in brightness temperature. The spatial variability in thickness decreased with an increase in latitude and therefore decreased with a decrease in the forest fraction, which plays a major role in causing significant SWE variations with catchment and interception mechanisms. This statement is in agreement with the modeled results from MEMLS, for which the values closest to the AMSR-E results are also found farther north, where the spatial variability is smaller (Figure 6). The standard deviation of SWE was found to be 30% in Sept-Iles, whereas a decrease to around 18% was found in Kuujjuuaq. Furthermore, site location and accessibility played a crucial role. The reality of the terrain was such that some areas were inaccessible (especially in Sept-Îles), and their contributions to the AMSR-E $T_b$ are therefore unknown. Future work will focus on improving SWE modeling using measured airborne brightness temperatures, since this study has clearly shown that validation of microwave-retrieval algorithms must be investigated at appropriate scales.

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