Characterization of Errors in a Coupled Snow Hydrology–Microwave Emission Model

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ABSTRACT

Traditional approaches to the direct estimation of snow properties from passive microwave remote sensing have been plagued by limitations such as the tendency of estimates to saturate for moderately deep snowpacks and the effects of mixed land cover within remotely sensed pixels. An alternative approach is to assimilate satellite microwave emission observations directly, which requires embedding an accurate microwave emissions model into a hydrologic prediction scheme, as well as quantitative information of model and observation errors. In this study a coupled snow hydrology [Variable Infiltration Capacity (VIC)] and microwave emission [Dense Media Radiative Transfer (DMRT)] model are evaluated using multiscale brightness temperature ($T_B$) measurements from the Cold Land Processes Experiment (CLPX). The ability of VIC to reproduce snowpack properties is shown with the use of snow pit measurements, while $T_B$ model predictions are evaluated through comparison with Ground-Based Microwave Radiometer (GBMR), aircraft [Polarimetric Scanning Radiometer (PSR)], and satellite [Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E)] $T_B$ measurements. Limitations of the model at the point scale were not as evident when comparing areal estimates. The coupled model was able to reproduce the $T_B$ spatial patterns observed by PSR in two of three sites. However, this was mostly due to the presence of relatively dense forest cover. An interesting result occurs when examining the spatial scaling behavior of the higher-resolution errors; the satellite-scale error is well approximated by the mode of the (spatial) histogram of errors at the smaller scale. In addition, $T_B$ prediction errors were almost invariant when aggregated to the satellite scale, while forest-cover fractions greater than 30% had a significant effect on $T_B$ predictions.

1. Introduction

The importance of snow to the hydrologic cycle, through its effects on water storage and the land surface energy balance, has long been recognized. Seasonal snow can cover from 7% to 40% of the Northern Hemisphere annually (Hall 1988) and has a significant impact on large-scale atmospheric circulations (Barnett et al. 1989). Furthermore, spring snowmelt controls runoff generation over much of this area, making snow an important aspect of water resources management in mountainous mid- and north-latitude basins. Nonetheless, predicting the evolution of snow cover and snow water storage is complicated by a number of factors, among them the inability of ground measurements to capture the spatial and temporal variability of snow properties over large areas. For this reason, large-scale observation strategies now rely mostly on remote sensing (Schmugge et al. 2002).

Microwave emissions of snowpacks strongly depend on snow properties such as depth, grain size, density, temperature gradient, and liquid water content, as well as the underlying soil properties. These dependencies...
provide the basis for attempts to relate passive microwave brightness temperatures to snow depth and water equivalent, snow cover, and freeze–thaw state (Rango et al. 1979; Chang et al. 1987). Microwave sensors also have the ability to penetrate clouds, do not depend on solar illumination, and can provide data at both horizontal and vertical polarizations for a range of frequencies. Passive microwave satellite observations have been available since the late 1970s and have been used extensively for snow depth and cover extent estimation (Tait 1998; Grody and Basist 1996; Josberger and Mognard 2002).

Nonetheless, retrievals of snow parameters from passive microwave satellite observations are hindered by several factors. Hardware configurations on current operational satellites produce relatively coarse spatial resolutions (dependent on frequency, 27 km × 17 km for 18.7 GHz, and 14 km × 11 km for 36.5 GHz), which are then resampled to 25 km × 25 km (Lobl 2001). Problems arise due to the mixed pixel problem, especially when pixels have a combination of forest (which has a much higher emissivity than snow) and open land cover. Problems also occur in areas of complex topography (Brown et al. 2003). Furthermore, dry snow radiation extinction in the microwave frequencies is dominated by scattering, which is stronger for larger snow crystals and shorter wavelengths. The variability of snow grain size with time and depth can have a large impact on the snowpack brightness temperatures (Foster et al. 2005). Additionally, differences in the dielectric properties between liquid and frozen water lead to decreased volume scattering and amplified absorption, as the liquid water content of the snowpack increases. This means that meaningful derivation of snow parameters from passive microwave satellite observations for wet snowpacks is difficult.

Land surface hydrology models produce potentially usable information about snow parameters by representation of the physical processes that control snowpack accumulation and ablation. These models are forced by surface meteorological and (downward) surface radiation data and represent the effects of topography, soils, and vegetation on snow accumulation and ablation processes. Nevertheless, this information contains errors because of uncertainties in the forcings and model parameters and the nonlinearity and scaling effects of the processes modeled (Pomeroy et al. 1998; Blöschl 1999). Data assimilation offers the potential to merge information on snow variables from satellite observations and hydrologic model predictions and account for the uncertainties in both (McLaughlin 1995). One option would be to directly assimilate the satellite-derived snow water equivalent (SWE; see, e.g., Pulliainen 2006). However, for many of the reasons noted above, SWE data products often have large errors, and their error characteristics are difficult to parameterize (Andreadis and Lettenmaier 2006). A more attractive option is to assimilate microwave radiances, and then to use the latter to derive SWE (Durand and Margulis 2006). For this approach to succeed, an accurate electromagnetic model is required to predict microwave brightness temperatures from modeled snow parameters. Although many studies have examined the performance of various snow microwave emission models (e.g., Pulliainen et al. 1999; Tedesco and Kim 2006), no studies were found that examined the performance of a coupled snow hydrology–microwave emission model, similar to a model that would be used in a data assimilation system. The Cold Land Processes Experiment (CLPX), which collected a variety of snow-related measurements at multiple spatial scales, offers an ideal opportunity to evaluate such a coupled model, and to characterize and quantify the errors in brightness temperature model predictions as well as the spatial scaling behavior of these errors.

In the next sections we present the CLPX data that were used in this study and the methodology of evaluating the coupled model. Then we describe the snow hydrology and microwave emissions models, and we follow with results of tests of the model over a range of spatial scales and model prediction errors. Finally, we discuss some of the implications of the results to radiation-based assimilation of snow microwave emissions.

2. Methodology

a. CLPX data

CLPX was a multisensor and multiscale field experiment aimed at obtaining a variety of snow-related measurements at scales ranging from point to regional spatial scales, and using ground, aircraft, and spaceborne sensors. The study, which was conducted over the winters of 2002 and 2003, included a set of nested sites in Colorado and Wyoming. The regions of interest in this study include the mesocell study areas (MSA) with a spatial resolution of 25 km × 25 km (Fraser, Rabbit Ears, and North Park), the intensive study areas (ISA) that were areas of 1 km², three in each MSA, and the Local Scale Observation Site (LSOS), a 100 m × 100 m area at the Fraser ISA. Within the LSOS, measurements of snow depth, density, temperature, and stratigraphy were taken at six snow pits. Radiometric measurements of the LSOS snow cover were taken by a Ground-Based Microwave Radiometer (GBMR-7) at 18.7, 23.8, 36.5, and 89 GHz and varying incidence angles (30 to 70 degrees) during selected days in Janu-
ary and December 2002 and February and March 2003 (Graf et al. 2003). Aircraft multiband polarimetric brightness temperature imagery was obtained over the three MSAs, using a Polariometric Scanning Radiometer (PSR/A) in February 2002 and February and March 2003 (Stankov and Gasiewski 2004). We also used satellite brightness temperatures from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) at 6.9, 10.7, 18.7, 23.8, 36.5, and 89.0 GHz with a spatial resolution of 25 km × 25 km. These data covered the period 1 February 2003 through 31 May 2003 (Brodzik 2003).

b. Experimental design

The snow hydrology model is the Variable Infiltration Capacity (VIC) model, while the microwave emissions model is based on the Dense Media Radiative Transfer (DMRT) theory (Tsang et al. 1985), both of which represent the snowpack as a single layer and are described below. We performed winter 2002 and 2003 simulations over the CLPX LSOS (essentially point scale), and the three MSAs at spatial resolutions of 1/16th (~6 km), 1/8th (~12 km), and 1/4th degree (~25 km). Multiscale simulations were chosen to be roughly equivalent to the CLPX experimental design and allow examination of the spatial scaling behavior of model brightness temperature prediction errors. The value of quantifying model errors in the prediction of brightness temperatures will become apparent. Therefore, we simulated brightness temperatures after imposing errors in VIC simulated snow grain size (diameter), depth, and density, and evaluated the sensitivity of estimation errors.

c. Dense Media Radiative Transfer model

The electromagnetic model used in this study is based on the DMRT with the quasi-crystalline approximation (QCA) (Tsang et al. 1985, 2000a). In densely packed media, such as snow, the assumption of independent scattering becomes invalid and needs to be taken into account (Ishimaru and Kuga 1982; Tsang et al. 1992). In classical theory, scattering intensity is the sum of the scattering intensities of each particle in the medium (Chandrasekhar 1960). Scattering from correlated particles is represented in the QCA by means of a pair distribution function that describes the relative position of particles in the medium (these are assumed to be nonpenetrable spheres). The effective propagation constant and the coherent exciting field can be computed using the QCA, and the solution from the Lorentz–Lorenz law and the Ewald–Oseen extinction theorem (Tsang and Kong 1992). This allows for the absorption coefficient to be calculated, as well as the incoherent bistatic scattering coefficients using the distorted Born approximation. The scattering coefficient is calculated by integrating the bistatic coefficients over 4π solid angles. The phase matrix is calculated as the bistatic scattering cross section per unit volume. The sum of the absorption and scattering coefficients is the extinction coefficient (so that energy is conserved) and is used in the radiative transfer equations to include multiple scattering effects for the incoherent wave.

The particle position distribution functions, which measure the probability of finding a particle at a certain distance r given a particle at r = 0, are calculated using the Percus–Yevick approximation (Baxter 1970). In natural media interparticle forces lead to the adhesion of particles and formation of aggregates that collectively scatter radiation (Tsang et al. 2000a,b). This is represented in DMRT with a sticky particle model, which allows for particles to stick together and form clusters. These aggregate effects require the use of higher-order multipoles beyond the electric dipole scattering in the earlier DMRT model (Tsang et al. 2000a). Frequency dependence of QCA-sticky particle scattering is weaker than independent scattering using the same physical grain size (Tsang et al. 2001). Physical interpretation of the weaker frequency dependence of QCA/DMRT can be attributed to the effect that at low frequencies, sticky particles scatter equivalent to a particle with a larger effective size, while at higher frequencies the clustering effect becomes weaker and scattering follows usual dense media theory. The degree of particle clustering is modeled through the stickiness parameter τ, taken as 0.2 here. The stickiness parameter controls the scattering dependence on frequency, with τ = 0.5 being almost identical to independent scattering, and usually has a range of 0.1–0.2. Other distinguishing features of the model are that the phase matrix exhibits more forward scattering than the Rayleigh phase matrix and that the scattering saturates at high snow density. Recently, considerable simplifications were made in the equations of the QCA/DMRT/Sticky model (Tsang et al. 2007). Numerical simulations with this model have shown good agreement with simulations from NMM3D, a detailed model that solves the Maxwell equations in three dimensions, for particle densities up to 25% (Chen et al. 2003).

To represent the effects of land surface heterogeneity on microwave emissions, we enhanced DMRT with canopy, bare soil, and atmospheric emission models. The scene brightness temperature is then given by $T_B = f [f T_{B,\text{tot}} + s T_{B,\text{snow}} + (1 - f - s) T_{B,\text{soil}} + T_{\text{atm,up}} + (1 - e_p) (T_{\text{atm,down}} + 2.7 t)]$, where $f$ is the forest-cover fraction, $s$ is the snow cover fraction, $t$ is the atmo-
spheric transitivity, $e_g$ is the emissivity of the ground scene, $T_{\text{atm,up/down}}$ is the upwelling (downwelling) atmospheric brightness temperature, $T_{B,\text{vegetation}}$ is the brightness temperature from the vegetated part of the scene pixel, $T_{B,\text{snow}}$ is the emission from the snow-covered area, and $T_{B,\text{bare}}$ is the brightness temperature from the bare soil portion of the pixel. The snowpack microwave emission is calculated as a function of snow depth, fractional volume, temperature, grain size, and ground temperature, as described above. The microwave emission model of soils is based on Liou and England (1996), with dielectric constants calculated from Dobson et al. (1985) and Wang and Schmugge (1980). The vegetation $T_{B}$ is modeled using the zero-order approximation, as a function of vegetation single-scattering albedo and optical depth, assuming exponential attenuation. Single-scattering albedos are estimated following de Griess and Wigneron (2004), while vegetation optical depths are calculated using the approach of Kirdiashev (1979) and Wegmüller et al. (1995), as a function of canopy water content and temperature (provided by the hydrology model). Atmospheric upwelling/downwelling brightness temperatures are estimated using the Millimeter wave Propagation Model (Liebe 1989) and assuming a clear (noncloudy) standard U.S. atmospheric profile.

3. Variable Infiltration Capacity model

1) MODEL DESCRIPTION

VIC is a macroscale hydrology model that essentially solves the energy and water balance over a gridded domain (Liang et al. 1994). It is distinguished from other land surface models by the parameterization of subgrid variability of soil moisture, precipitation, topography, and vegetation. Each grid cell can have multiple soil layers and can be partially covered by different vegetation types in a mosaic-type representation, while topography is represented by a maximum of five elevation bands. Moisture and energy fluxes are computed separately for each vegetation class and elevation band within each grid cell and then area-weighted and summed over the grid cell.

Snow accumulation and ablation processes are simulated using a two-layer energy and mass balance approach (Cherkauer and Lettenmaier 2003). The surface layer represents the energy balance at the snow–air interface, while the lower layer simulates deeper snowpacks and acts as a reservoir for the excess snow mass from the surface layer (Wigmosta et al. 1994). Energy exchange between the layers through conduction and diffusion is ignored. Snowfall can be intercepted by an overstory canopy and then released to the ground snowpack through meltwater drip, mass release, or throughfall. The model accounts for melting/refreezing water within each layer, with water percolation simulated based on a preset liquid water holding capacity for each layer. In addition, VIC can also simulate frozen soils as well as heat conduction between the pack and the soil layer (Cherkauer and Lettenmaier 1999).

Because snow density and depth strongly affect microwave emissivity, the snow densification algorithm was modified. Originally, VIC used a constant density of $50 \text{ kg m}^{-3}$ for newly fallen snow, and accounted for densification by compacting the snowpack with the weight of new snowfall. We replaced these assumptions with the algorithm by Hedstrom and Pomeroy (1998) that calculates the density of fresh snow as a function of air temperature. We also modified the snow densification algorithm by calculating a compaction rate according to Jordan (1991),

$$\frac{\Delta \rho_s}{\Delta t} = (C_m + C_s)\rho_s z,$$

where $\rho_s$ is the snow density, $C_s$ are the compaction rates, and $z$ is the snowpack depth. This parameterization accounts for settling due to snow metamorphism $C_m = c_1 e^{-c_2(z-T)}$, where $c_1$ and $c_2$ are coefficients that depend on snow density and liquid water content (increasing densification for melting snow), and $T$ is the snowpack temperature. Compaction from the weight of new snowfall and an effective internal snowpack compaction $C_s = \frac{1}{2} (g \rho_s W_{\text{snowfall}} + f W)$, where $g$ is the gravity acceleration, $\rho_s$ is the density of water, $\eta$ is a viscosity coefficient, $W_{\text{snowfall}}$ is the snowfall mass, $W$ is the water equivalent of the snowpack, and $f$ a coefficient that accounts for internal compaction (here taken as 0.6, after calibration to LSOS snow pit measurements). In addition, the SNThERM (Jordan 1991) snow crystal growth algorithm was added to the model, with the modification that the temperature difference rather than temperature gradient is used, and the value of an adjustable scaling factor,

$$\frac{\Delta d}{\Delta t} = \frac{G}{d} D_{os} C_T |T_s - T_g|,$$

was implemented, where $d$ is the snow grain diameter, $D_{os}$ is the effective diffusion coefficient for snow, $C_T$ is the variation of equilibrium vapor density with temperature, $G$ is an adjustable scaling factor (here taken as $7 \times 10^{-7} \text{ m}^2 \text{ kg}^{-1}$), and $T_s$, $T_g$ are the snow surface and ground temperatures. In the case where liquid water content within the snowpack exceeds a threshold ($0.01\%$) grain growth rates increase and are modeled using the Jordan (1991) algorithm:
\[ \frac{\Delta d}{d} = \frac{G}{d} (\theta_l + 0.05), \tag{3} \]

where \( \theta_l \) is the liquid water content (set to a maximum of 0.09 if it exceeds that value), and \( G \) is \( 4 \times 10^{-12} \text{ m}^4 \text{ kg}^{-1} \). The grain size estimated by the model is a depth-weighted average of the grain size of newly fallen snow (taken as 0.2 mm) and the grain size of the existing snowpack after applying the growth models in Eqs. (2) and (3).

2) LSOS SNOW PIT VALIDATION

Within the LSOS site detailed ground measurements of snow depth, density, temperature, grain size, and soil temperature were taken on selected dates between November 2002 and March 2003. The snow pit data that we used for evaluation of the VIC algorithms were taken at four locations within the clearing northeast of the GBMR-7 instrument (see http://nsidc.org/data/docs/daac/nsidc0165_clpx_gbmr/index.html). We simulated the snowpack using VIC run for a point (no vegetation cover, one elevation band) and forced the model with hourly meteorological measurements from the nearby towers. These included precipitation, air temperature, relative humidity, and incoming short-wave radiation. The simulation period extended from 30 September 2002 to 28 March 2003. The initial conditions were no snow on the ground. Figure 1 shows simulated SWE (1a), snow density (1b), and snow grain size (1c) along with measurement depth averages. The simulated SWE and snow density (and therefore snow depth) match snow pit measurements quite well throughout the winter season. Measured snow grain sizes were characterized by the minimum, mean, and maximum sizes of representative small, medium, and large crystals. It is difficult to compare the simulated snowpack average with such measurements; this difficulty arises because of the inherent inability of an essentially single-layer model to capture the significant vertical variability in snow grain size. Here, we compare simulated grain diameters to the median size of all snow grain categories along with the 25th and 75th percentile sizes of the snowpack grain size distribution. VIC is able to match the grain size distributions reasonably well, although it does not capture the large increase of grain size during midwinter. This occurs mostly because of the snowpack representation as a single layer and the resulting smaller temperature gradient. Nevertheless, it can be argued that VIC does provide a reasonable and plausible estimate of the average snow grain size, given that the VIC estimate is always within the 25th–75th percentile range and close to the median values during the time of GBMR-7 measurements (February 2003).

Evaluation of a grain growth algorithm would be different for different applications (e.g., only the surface grain size would matter for albedo modeling). We discuss the effects of using an average snow grain size for the entire snowpack in the context of microwave remote sensing in the following sections.

3) SPATIAL MODEL IMPLEMENTATION

Simulations were performed over the three 625-km² MSAs at three different spatial resolutions and hourly time steps, from 30 September 2001 to 31 March 2003. Minimum requirements for VIC forcing data include daily precipitation and minimum and maximum air temperature and wind speed, which were disaggregated to hourly values using algorithms described in Maurer et al. (2002). The model can internally estimate other meteorological forcing variables such as downward solar radiation and relative humidity at the hourly time step. Precipitation and air temperature data were obtained by spatial interpolation of National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer data using the synergraphic mapping system.
algorithm (SYMAP) (Widmann and Bretherton 2000) and were gridded to the desired spatial resolution. VIC also requires information about topography, as well as land cover. Topographic information was derived from a Shuttle Radar Topography Mission (SRTM30) digital elevation model (DEM), by using bilinear interpolation to the specified spatial resolutions. Fractional vegetation cover grids at 1/16th, 1/8th, and 1/4th degree were derived from the 1-km Advanced Very High Resolution Radiometer (AVHRR) global land-cover dataset using the University of Maryland classification (DeFries and Townshend 1994). Model calibration did not have a significant impact on snow-related simulations (using a snow roughness length of 0.1 m); therefore we used the Land Data Assimilation System (LDAS) calibration model parameters (Maurer et al. 2002).

3. Results

a. Comparison with point measurements

Brightness temperature measurements were taken with the GBMR-7 at the point scale within the LSOS. Two measurement approaches were followed: 1) single direction angular scans (i.e., measurements at varying incidence angles) designated “fraser10” and 2) constant incidence angle scans (55°) in which the sensor changed position (azimuth angle between 140° and 210°) designated as “fraser07.” The measurement scans from fraser10 were minimally affected by contributions from tree emissions, with the exception of higher incidence angles (Tedesco et al. 2006) because the sensor was situated to look directly toward the open area of the LSOS. On the other hand, the influence of tree emissions on the measurements from fraser07 (sensor position changing horizontally) is not clear, therefore, we used only “fraser10” measurements since our focus at the point scale was on snow emissivity.

The DMRT model was used to simulate brightness temperature (at a 55° incidence angle) on the dates when GBMR-7 measurements were available. The LSOS VIC simulations discussed above [section 2d(2)] provided the snow parameters required by DMRT. It should be noted that the only information used to predict $T_B$ is the LSOS meteorological data (snow pit measurements, which would not generally be available, were not used); that is, the snow microphysical characteristics were all predicted by the VIC model, rather than observations. Figure 2 shows scatterplots of observed versus simulated $T_B$ for 18.7 and 36.5 GHz at both horizontal and vertical polarizations. The model
overestimates $T_B$ for the 18.7-GHz horizontal channel with a root-mean-squared error (RMSE) of 11.3 K, while predictions for the 18.7 vertical polarization channel appear more accurate with an RMSE of 4.1 K (respective biases are 9.9 and 1.3 K). However, the correlation between model estimates and measurements shows a different picture, with correlations quite low (0.32 and 0.16 respectively). For the 36.5-GHz frequency, model predictions have a comparable error for both polarizations, 14.0- and 15.2-K RMSE (biases of 3.0 and $-8.1$ K) for the horizontal and vertical polarization, respectively. The model underestimates $T_B$ for two days (19 and 20 February) as shown by Figs. 2c and 2d (cluster of points on the left of the plots), whereas model predictions for the rest of the measurement dates are reasonably good, at least for the vertical polarization. The correlation for 36.5 GHz is much higher than the lower frequency, 0.77 and 0.84, respectively.

From Fig. 1 it is evident that VIC simulates snow depth and density quite accurately for the LSOS and that the largest uncertainty is in the snow grain size predictions. The discrepancy between the correlation and the actual errors illustrates two major problems in the coupled modeling of microwave emission from snow. Both these problems relate to the assumption of a homogeneous snowpack by the models. The relationship between the effective snow properties that control the microwave emission at different wavelengths is not well known, while the snowpack stratigraphy, which can affect scattering and absorption (Colbeck 1991), is not captured by single-layer models. For example, DMRT underpredicts 36.5-GHz $T_B$ during 19 and 20 February leading to a relatively larger error. This can be attributed to a larger snow grain diameter than the optical particle size at that frequency. A grain size smaller by 0.1 mm reduces the error for those measurement dates from 12.8 and 23.0 K to 4.7 and 5.3 K for the horizontal and vertical polarization, respectively. Microwave penetration depth depends on frequency and snow properties, primarily crystal size and water content (Mätzler et al. 1984; Bingham and Drinkwater 2000). As frequency increases and wavelengths decrease, microwave scattering becomes a function of snow properties averaged over the upper portion of, rather than the entire, snowpack.

Figure 3 shows the simulated versus observed $T_B$ differences for 18.7- and 36.5-GHz frequencies, and horizontal and vertical polarizations for both frequencies. The coupled model captures the $T_B$ frequency differences quite well for both polarizations, with overall RMSEs of 12.8 K for the horizontal and the 13.6 K for the vertical polarization (correlations of 0.87 and 0.90, respectively). On the other hand, the difference between polarizations (for the same frequency) is consistently underestimated by DMRT, with errors on the order of 9.1 and 11.5 K for the 18.7- and 36.5-GHz frequencies, respectively (correlations of 0.33 and 0.13). This discrepancy can be again related to the snowpack homogeneity assumption by the models and the different penetration depth at each frequency. Snowpack structure is known to affect the snow microwave emission signature (Colbeck 1991), especially the formation of characteristic layers such as depth hoar. Moreover, reflectivities at the interfaces between the internal snowpack layers can decrease the microwave emissivity especially for the horizontal polarization (Wiesmann and Mätzler 1999).

The “fraser10” scans include measurements at varying incidence angles (from 30° to 70°). The angular behavior of the simulated brightness temperatures appears to agree fairly well with observations (not shown). Theoretically brightness temperatures, in general, tend to decrease with increasing incidence angles, with VIC/DMRT following that behavior. However, an exception occurs for the higher angles when measured $T_B$ increases while model-predicted $T_B$ decreases. This can be explained by either the effects of soil heterogeneity for the lower frequencies (since the GBMR footprint changes with incidence angle), or by contributions from trees at incidence angles higher than $-60\degree$ (Tedesco et al. 2006). Table 1 shows that the RMSEs between model-predicted and observed $T_B$ are almost constant with varying incidence angle, suggesting that the coupled VIC/DMRT is able to capture $T_B$ variability with varying incidence angle, even though it does not necessarily match the observed $T_B$ closely. This is also corroborated by the correlation coefficients be-

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**Figure 3.** Scatterplots of GBMR-7 observed vs VIC/DMRT simulated brightness temperature differences between 18.7 and 36.5 GHz, and horizontal and vertical polarizations for both frequencies (18–26 Feb 2003).
Table 1. RMSE and bias (K) between simulated and observed $T_B$ (18–26 Feb 2003) at varying incidence angles (30° to 60°).

<table>
<thead>
<tr>
<th>Incidence angle</th>
<th>Frequency</th>
<th>30°</th>
<th>40°</th>
<th>50°</th>
<th>60°</th>
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<tr>
<td>18.7 H</td>
<td>13.31</td>
<td>13.49</td>
<td>13.11</td>
<td>13.11</td>
<td>9.60</td>
</tr>
<tr>
<td>18.7 V</td>
<td>4.02</td>
<td>3.53</td>
<td>3.44</td>
<td>5.71</td>
<td>3.72</td>
</tr>
<tr>
<td>36.5 H</td>
<td>12.36</td>
<td>11.23</td>
<td>12.50</td>
<td>12.26</td>
<td>13.39</td>
</tr>
<tr>
<td>36.5 V</td>
<td>12.95</td>
<td>11.83</td>
<td>12.88</td>
<td>13.89</td>
<td>3.30</td>
</tr>
</tbody>
</table>

tween model and observed $T_B$ at different incidence angles (averaged over time), 0.48 and 0.58 for the 18.7-GHz horizontal and vertical polarizations, respectively, and 0.90 and 0.82 for the 36.5-GHz horizontal and vertical polarizations, respectively.

b. Comparison with aircraft measurements

Brightness temperature measurements taken from PSR/A have footprint sizes ranging from 215 to 749 m for 18.7 GHz, and 65 to 229 m for the higher frequencies. The data were georegistered and resampled to 1-km spatial resolution to match the spatial resolution of the land-cover dataset used in this study. Considering the spatial resolutions of macroscale hydrologic simulations, we chose to use 1/16th degree as the highest spatial resolution to compare to aircraft measurements and resampled (spatial averaging) the latter accordingly. Figure 4 shows spatial maps of PSR/A observed versus model-predicted $T_B$ over the three MSAs at 18.7 and 37.0 GHz (vertical polarization) for 23 February 2003. The model predictions show close agreement with the aircraft measurements for Fraser and Rabbit Ears for both frequency channels. The agreement between the model and observations is very good throughout the measurement dates for these MSAs, with RMSEs and correlation coefficients shown in Table 2. The coupled model performs much better than the point comparisons. This can be partly explained by the relatively dense forest cover at the Fraser and Rabbit Ears sites, as well as the effects of areal averaging on the model errors. Forest canopy can mask the scattering signal of the underlying snowpack (Chang et al. 1996), reducing the snow microwave emission model prediction errors that were evident in the point simulations. Figure 5 shows the forest-cover fraction map (smoothed) for Fraser and the observed 1-km $T_B$ from PSR/A at 18.7 GHz (vertical). The two maps are consistent, with higher $T_B$ corresponding to denser forest and sparser canopies having lower $T_B$. Results are similar for Rabbit Ears (not shown). Additionally, we performed two sensitivity experiments: 1) artificially removing forest cover and 2) removing 50% of snow depth (without changing forest cover) and simulating $T_B$. The spatial patterns from the nominal simulation were very similar to the second sensitivity experiment rather than the first, suggesting that the presence of forest largely controls the microwave emission.

On the other hand, prediction errors are larger over the North Park MSA (Fig. 4 and Table 2), especially for the higher-frequency channels. VIC underestimates snow depth over most of the MSA leading to overestimation of $T_B$ at both 18.7 and 37.0 GHz. Snow depth measurements at the three ISAs within North Park indicate a daily (spatial) mean depth of 17.2, 24.7, 26.4, and 29.3 cm between 22 and 25 February 2003, while VIC simulates average snow depths of ~5 cm over the entire MSA. Although this is a comparison of areal estimates to point measurements, it is apparent that qualitatively VIC underestimates snow depth. This could perhaps be due to precipitation errors or wind redistribution of snow that is not modeled by VIC (as it was implemented here). For a similar comparison over Fraser, the mean depth from VIC is 123.2 cm, and 127.5 cm on 23 and 25 February 2003, while measurements had average snow depths of 91.2 and 88.6 cm on the same days. The better performance of VIC in snow depth estimation in Fraser is also reflected by the better $T_B$ predictions, whereas in North Park the model-predicted $T_B$ are larger and mostly affected by the model soil properties, due to the very thin snowpack.

c. Comparison with satellite measurements

An important question in a microwave radiance assimilation system is whether the relatively coarse spatial resolution satellite observation (25 km × 25 km) can be successfully inverted to the higher spatial resolution model predictions. A key aspect involves the spatial scaling behavior of the model errors, from the typically high, macroscale model resolution to the satellite footprint scale. This behavior is examined in Fig. 6, which shows spatial histograms of $T_B$ model prediction errors (VIC/DMRT versus PSR/A) and the corresponding model prediction error with the AMSR-E observation. The left column shows the model errors for 18.7 GHz (vertical), while the 37.0-GHz (vertical) errors are shown in the middle column for Fraser (top row), Rabbit Ears (middle row), and North Park (bottom row). The spatial distribution of errors for Fraser and Rabbit Ears (relatively dense forest cover) appears to be lognormal, with the error at the satellite scale (AMSR-E observation minus averaged 1/16th degree model predictions) well approximated by the mode of the spatial distribution of the higher-resolution errors. This result is similar for the other dates of PSR/A observations (average RMSE of 0.31 and 1.10 K, 18.7 and
37.0 GHz, respectively, for Fraser and 0.17 and 0.15 K, 18.7 and 37.0 GHz, respectively, for Rabbit Ears). Some insight can be obtained by examining the spatial histograms of the 1-km airborne \( T_B \) measurements, shown in the right column of Fig. 6. The AMSR-E observation can also be approximated by the mode of the 1-km spatial distribution of \( T_B \), similar to the results reported by Tedesco et al. (2005). The spatial distribution of model errors exhibit similar behavior to the actual \( T_B \) distributions. The shape of the latter (lognor-

**Table 2. Brightness temperature RMSE (K) and correlation coefficients between VIC/DMRT model predictions and aircraft measurements from PSR/A, over the three CLPX MSAs (22–25 Feb 2003).**

<table>
<thead>
<tr>
<th>MSA</th>
<th>18.7 (vertical)</th>
<th>18.7 (horizontal)</th>
<th>37.0 (vertical)</th>
<th>37.0 (horizontal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraser</td>
<td>3.42 (0.93)</td>
<td>5.62 (0.91)</td>
<td>8.61 (0.91)</td>
<td>11.25 (0.90)</td>
</tr>
<tr>
<td>Rabbit Ears</td>
<td>3.84 (0.96)</td>
<td>5.97 (0.70)</td>
<td>7.47 (0.96)</td>
<td>10.21 (0.94)</td>
</tr>
<tr>
<td>North Park</td>
<td>10.71 (0.40)</td>
<td>16.30 (0.41)</td>
<td>28.28 (0.50)</td>
<td>23.81 (0.47)</td>
</tr>
</tbody>
</table>
mal) is mostly governed by the forest cover of the MSAs, with the higher $T_B$ tail corresponding to higher forest densities.

The error spatial histograms are different for North Park, where the shape of the distributions for both 18.7 and 37.0 GHz is less distinct (Fig. 6). At North Park, the 1-km spatial histogram of PSR/A $T_B$ observations is better approximated by a bimodal distribution. One
difference between North Park and the other two MSAs is partial snow cover, which probably leads to the two distinct histogram peaks. The snow-covered areas contribute to the lower peak, and the snow-free areas are responsible for the higher \( T_B \) values. In addition, the satellite-scale model error, as well as the AMSR-E observation, is not consistent with the behavior seen for Fraser and Rabbit Ears; that is, it cannot be approximated well by the mode of the \( T_B \) spatial distribution for most measurement dates.

Another aspect of a microwave radiance data assimilation system that would include a coupled model such as VIC/DMRT involves the different spatial resolution of the simulations, and how the aggregation to the satellite footprint size affects the hydrologic/radiative transfer model scale. To address this issue, we conducted VIC and DMRT simulations at 1/16th, 1/8th, and 1/4th degree spatial resolutions and compared with the AMSR-E observations (25 km × 25 km) over the three MSAs. Although data were also available for March–May 2003, we chose to use February to ensure dry snow conditions. Figure 7 shows time series of AMSR-E observations (both ascending and descending orbits) and VIC/DMRT simulations aggregated from the three model spatial scales for 18.7 (vertical polarization) GHz over Fraser (top) and 36.5 (vertical polarization) GHz over Rabbit Ears (bottom). Results were similar for the other frequency channels and MSAs (Table 3). The model is able to follow the variability of the observations very closely throughout, with larger errors for the higher frequency. The most important feature, however, is that the model resolution has a minimal effect on the aggregated model \( T_B \) prediction. This result indicates, at least for the scales examined here, that the coarser-scale satellite observation can be estimated linearly from the nested model pixels, a finding that is consistent with results from soil moisture studies (Drusch et al. 1999). This would allow the innovations (observed minus predicted measurement) at the satellite scale to be spatially disaggregated consistently using the finer-scale meteorological and other information that drive the models. One additional issue involved with spatial upscaling/downscaling of passive microwave brightness temperatures are the effects of topographic relief, which can be corrected for by calculating the increase in upwelling \( T_B \) (Mätzler and Standley 2000).

It appears that at least for fully snow-covered areas, data assimilation can act as a spatial downscaling technique for the coarse satellite \( T_B \) observation (Reichle et al. 2001). The spatial distribution and the approximation of the satellite-scale error with the mode of that distribution can be built in the observation operator leading to a consistent update of the spatially nested model states. In the case of partially snow-covered areas, ancillary information, such as snow cover extent, seems to be required in order to model the shape of the

![Figure 7. Time series of AMSR-E observations and VIC/DMRT simulations during February 2003 aggregated from 1/16, 1/8, and 1/4 degree for (top) 18.7 GHz (vertical) and (bottom) 36.5 GHz (vertical).](image)

**Table 3.** Brightness temperature RMSE (K) between VIC/DMRT predictions aggregated from different spatial resolutions, and AMSR-E observations over the three MSAs.

<table>
<thead>
<tr>
<th>Frequency channel (GHz)</th>
<th>Fraser</th>
<th>Rabbit Ears</th>
<th>North Park</th>
</tr>
</thead>
<tbody>
<tr>
<td>18.7 (vertical) 1/16 km</td>
<td>3.42</td>
<td>3.84</td>
<td>10.71</td>
</tr>
<tr>
<td>18.7 (horizontal) 1/16 km</td>
<td>5.62</td>
<td>3.84</td>
<td>16.30</td>
</tr>
<tr>
<td>37.0 (vertical) 1/16 km</td>
<td>8.61</td>
<td>7.47</td>
<td>28.28</td>
</tr>
<tr>
<td>37.0 (horizontal) 1/16 km</td>
<td>11.25</td>
<td>10.21</td>
<td>23.81</td>
</tr>
</tbody>
</table>
error spatial distributions and to resolve the satellite subgrid variability.

d. Model error sensitivity to imposed parameter errors

In most data assimilation applications (Margulis et al. 2002; Natvik and Evensen 2003), model errors are estimated by imposing errors on model parameters that result in the largest sensitivity. This approach assures that model errors are consistent with model physics. Taking advantage of the data availability at CLPX, we can statistically characterize the errors in model parameters (e.g., snow density) that result in $T_B$ model prediction errors equivalent to the estimation errors from the coupled VIC/DMRT model. This can be achieved by perturbing model parameters including snow grain size, depth, density, and temperature and evaluating the $T_B$ model prediction error sensitivity to those imposed errors. We can then quantify the uncertainty in model parameters that results in $T_B$ model prediction errors that are statistically similar to the errors observed at the CLPX. That uncertainty can be used to specify appropriate errors in a data assimilation application.

Here we focus on model error sensitivity to errors in snow grain size, since the microwave signal from a snowpack is most affected by variations in grain size (Josberger et al. 1996). Figures 8a and 8b show $T_B$ model prediction errors at the point scale (observed minus simulated) as a function of grain size error, where the latter is defined as the difference from the nominal VIC grain size. Zero error in snow grain size does not necessarily correspond to zero error in $T_B$, but the motivation behind this analysis is to examine how the uncertainty in the simulated snow grain size affects the estimates of $T_B$ relative to the measurements at different spatial scales. From the error sensitivity at 18.7 GHz shown in Fig. 8a, we see that an increase in grain size by 0.1 mm reduces the error by $\sim 50\%$ for the vertical polarization. On the other hand, to achieve the same result for the horizontal polarization, a grain size increase of more than 0.3 mm is required. This indicates that the lower-frequency, horizontal polarization error may well be attributable to limitations in the model structure (e.g., failure to account for profiles of microphysical parameters in the snowpack) rather than errors in grain size. In the case of 36.5 GHz (Fig. 8b), the slope of both sensitivity lines are higher than for 18.7 GHz, which reveals the larger effect of grain size variation to the $T_B$ signal for higher frequencies. The errors correspond to $\sim 0.1$ and $\sim 0.2$ mm in grain size error for vertical and horizontal polarization, respectively.

As spatial scale and surface heterogeneity increase we expect the effect of uncertainty in snow properties on $T_B$ estimation to be reduced. Figures 8c and 8d show model error sensitivity as a function of grain size error at 1/16 degree spatial resolution, with resampled PSR/A measurements used as observations. For this
analysis, we only used the snow-covered pixels of the MSAs to avoid $T_B$ overestimation problems in the partially snow-covered areas of North Park. The $T_B$ error sensitivity at 18.7 GHz at this scale is quite similar to the one shown in Fig. 8a. However, the error magnitude is smaller as grain size error varies. A correction in grain size of 0.3 mm (slightly higher than the one shown at the point scale) corresponds to reduction of the mean error for both polarizations. The impact of surface heterogeneity is mostly evident though at the higher frequency (Fig. 8d). Although the magnitude of the error sensitivity is smaller than at the point scale, the steeper slope indicates that as frequency increases the effects of forest cover become stronger.

Model error sensitivity appears to be different at the satellite scale. Figures 8e and 8f show $T_B$ model error with difference from the nominal snow grain size, using AMSR-E observations and model predictions at 1/4 degree spatial resolution. The error sensitivity magnitude is larger on average than for a higher resolution at 18.7 GHz, which is counterintuitive. On the other hand, the 36.5-GHz channels show a smaller sensitivity, which might have to do with how soil properties, such as surface roughness, moisture, and temperature, affect the microwave signal at different scales (6 and 25 km). Because the model underestimates $T_B$ compared to AMSR-E, the model error decreases as snow grain size increases. At smaller grain sizes, there is a slight discontinuity in the slope of the vertical polarization curves. The results shown are averaged over the three MSAs. As snow grain size decreases at small snow depths, the soil contamination into the snow $T_B$ signal is more evident (this is particularly an issue for North Park, which has a very thin snowpack); this is perhaps obscured to a degree as grain size increases giving a smoother curve for the vertical polarizations. Table 4 shows the sensitivity coefficients of the $T_B$ model prediction errors at the different spatial scales and is essentially complementary to Fig. 8. Although these results are limited by the short time span, small region, and dependency model, they provide insights into the spatial scaling of model errors, as well as their statistical characterization, which is of importance in a data assimilation system.

e. Model error sensitivity to forest cover

The effects of vegetation on the microwave emission of snow-covered pixels were evident from the comparisons with the aircraft and satellite observations (see sections 3c and 3d), a result found in other studies as well (e.g., Kurvonen and Hallikainen 1997). Therefore, we attempt to quantify those effects. Figure 9 shows the $T_B$ estimation error for all frequency channels as a function of forest-cover fractions. The figure shows some large overestimation errors for nonexistent forest that correspond to the North Park MSA and the problem of thin snowpack and partially snow-covered ground discussed above. Excluding those points, the errors are very similar for both frequencies and polarizations at densely forested areas (more than \(\sim70\%\)). As forest-covered area fractions increase, the 37-GHz errors become smaller up to about forest-cover fractions of 40%. Model errors become almost constant on average (about 2 K for the vertical and 4 K for the horizontal polarization). The 18.7-GHz errors appear to be consistent up to \(\sim40\%\) forest cover, which might also have to do with the underlying soil properties. At forest-cover fractions less than 30% $T_B$ prediction errors become larger and the model overestimates $T_B$ at most points.

Given the effects of forest cover on microwave $T_B$ signal, we can evaluate the model error sensitivity resulting from imposing errors on model parameters for different forest-cover fractions. We followed a similar approach in section 3d, and Fig. 10 shows the average $T_B$ model prediction errors with different grain size errors, for 1/16 degree pixels with forest-cover fractions of 25%, 50%, and 75%. Two frequencies (18.7- and 37.0-GHz vertical polarization) are shown, but results are similar for the other channels as well. Error sensitivity is, as expected, smaller for the lower frequency with a range of \(\sim5\) K, while the higher-frequency errors have a range of \(\sim50\) K for a range of 0.6 mm in snow grain size. This underlines the importance of an accurate grain size estimate at higher frequencies. When snow grain size is relatively small, error sensitivity is fairly constant as grain size increases, especially as forest cover becomes denser. For such areas poor knowledge in grain size does not have a significant impact on $T_B$ model prediction error at 18.7 GHz. On the other hand, for higher frequencies the impact of errors in grain size is much larger, especially for sparsely forested areas. As grain size becomes larger, a small grain size error leads to a relatively larger error in $T_B$ estimation; this effect is more pronounced for smaller for-

<table>
<thead>
<tr>
<th>Scale</th>
<th>Frequency channel (GHz)</th>
<th>18.7</th>
<th>18.7</th>
<th>36.5</th>
<th>36.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(horizontal)</td>
<td>(vertical)</td>
<td>(horizontal)</td>
<td>(vertical)</td>
<td></td>
</tr>
<tr>
<td>Point</td>
<td>-1.82</td>
<td>-1.81</td>
<td>-11.90</td>
<td>-12.19</td>
<td></td>
</tr>
<tr>
<td>Aircraft</td>
<td>-0.46</td>
<td>-0.44</td>
<td>-4.36</td>
<td>-4.21</td>
<td></td>
</tr>
<tr>
<td>Satellite</td>
<td>4.44</td>
<td>0.76</td>
<td>3.81</td>
<td>1.03</td>
<td></td>
</tr>
</tbody>
</table>

TABLE 4. Sensitivity coefficients of brightness temperature model prediction error (K) relative to a 0.1-mm change in snow grain size at different spatial scales.

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est densities. Combining these results with Fig. 8 (errors in forested areas between $-10$ and $10$ K and $-20$ and $10$ K for nonforested areas), we can see that a grain size error of $0.2$ and $0.3$ mm corresponds to those $T_B$ prediction errors, for forested and nonforested areas respectively.

4. Conclusions

We evaluated a coupled snow hydrology and microwave emission model (VIC/DMRT), using observations from the CLPX multiscale and multisensor dataset. The coupled model uses only meteorological data as forcings and is able to predict brightness temperatures at both small and large scales. Comparisons with a ground-based radiometer illustrated the problems in $T_B$ prediction related to the model being unable to capture the effects of the snowpack vertical variability on passive microwave emissions. It is hypothesized that multiple-layer formulations for both VIC and DMRT might lead to improved $T_B$ estimates, by accounting for the dependence of penetration depth on frequency, and reflection between layer boundaries.

Limitations of the model that were shown at the point scale were not as evident when comparing areal estimates. The presence of relatively dense forest cover, as well as the effects of spatial aggregation, reduces the errors at both lower and higher frequencies at the larger spatial scales. A more interesting result occurs when examining the spatial scaling behavior of the
higher-resolution errors; the satellite-scale error is well approximated by the mode of the (spatial) histogram of errors at the 6-km scale. The error distribution was shown to follow a lognormal shape for forested, fully snow-covered areas, while a bimodal distribution appeared more suited for partially snow-covered areas. Furthermore, the importance of ancillary information, such as land cover, was shown. This information will be crucial in modeling the $T_B$ error structure. With better modeling of the $T_B$ model prediction errors, data assimilation can potentially act as a spatial downscaling technique via updating of the higher-resolution model estimates with the coarser satellite observations. Sensitivity analyses, such as those found in sections 3d and 3e, can be used to quantify the errors in both the model-predicted measurements and observations, and characterize the uncertainty in a data assimilation system (e.g., an ensemble-based approach).

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