Estimating Passive Microwave Brightness Temperature over Snow-covered Land in North America Using the GEOS-5 Catchment Land Surface Model and an Artificial Neural Network

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It is well established for atmospheric data assimilation systems that the assimilation of satellite radiance observations is preferable to the assimilation of geophysical retrievals. The former approach incorporates the radiative transfer model (RTM) into the assimilation system and thereby avoids inconsistencies in the use of ancillary data between the assimilation system and the (pre-processed) geophysical retrievals.

The GEOS-5 Catchment land surface model supports the use of a physically-based microwave RTM for warm-season processes (De Lannoy et al. 2013). However, the snow model components in the Catchment model, like those in other global land surface models, are too simplistic to support physically-based RTM modeling in the presence of snow. Specifically, global snow models lack reliable estimates of snow microphysical properties (such as grain size, ice layers, and depth hoar) which would be needed for physically-based forward modeling of the microwave brightness temperatures. We therefore constructed an empirical forward RTM for snow-covered land surfaces based on an Artificial Neural Network (ANN) and the GEOS-5 Catchment model.

The Catchment model state variables used as input to the ANN include the density and temperature of the snowpack at multiple depths, the temperature of the underlying soil, the overlying air, and the vegetative canopy, and the total amount of water equivalent within the snowpack. In addition, a cumulative temperature gradient index (TGI) is used as a proxy for snow grain size evolution in the presence of a vapor pressure gradient. Using the above inputs, the ANN is trained and (independently) validated using 10.7, 18.7, and 36.5 GHz microwave brightness temperatures at H- and V-polarization from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E). The independent validation is accomplished as follows: From the 9-year AMSR-E data record, each single year is withheld in turn from the ANN training, and skill metrics for the resulting ANN predictions are computed only against the AMSR-E data that have been withheld from the ANN training.
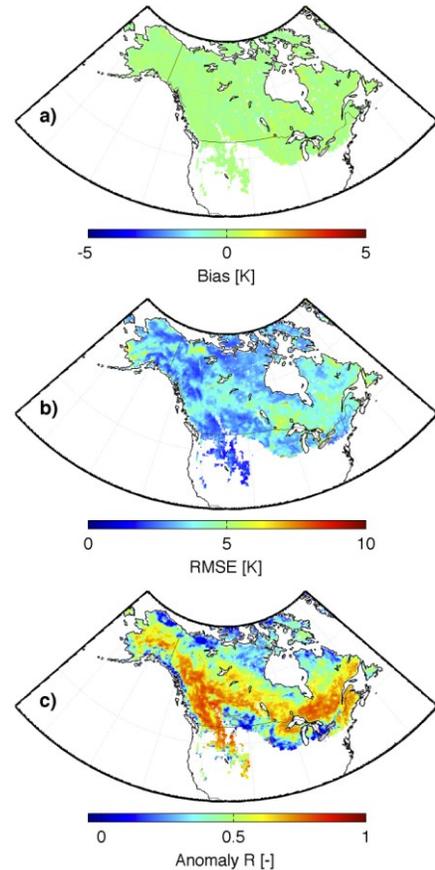
Figure 1: (a) Bias, (b) RMSE, and (c) anomaly R for ANN simulated 10 GHz V-polarized Tb from 1 September 2002 to 1 September 2011 vs. AMSR-E observations not used in training. Anomaly R values not statistically different from zero at the 95% significance level based on a Fisher Z transform are shown in gray. Such non-significant R values occur in only a few very small regions.

Figure 1 demonstrates the performance of the ANN predictions relative to AMSR-E measurements that were not used during training. The figure illustrates the overall ability of the ANN to predict Tbs for the 10 GHz V-polarized channel. The ANN predictions are essentially unbiased (relative to the AMSR-E measurements) across the 9-year period (Figure 1a). The RMSE is typically less than 5 K (Figure 1b). In addition, the ANN demonstrates skill in predicting interannual variability, with anomaly R values well above 0.5 over large parts of North America (Figure 1c). Relatively low skill can be seen in areas along the southern periphery, where the snowpack is relatively thin and ephemeral, as well as in areas north of the boreal forest, where sub-grid scale lake ice (which is not modeled in the land surface model) is common. In short, Figure 1 suggests considerable skill by the ANN at predicting interannual variability in 10 GHz V-polarized Tbs across North America with negligible bias and a reasonable RMSE. The RMSE is somewhat higher but still reasonable (less than 10 K) for the higher frequencies and for H-polarization Tb (see Figures 4-6 of Forman et al. 2013).
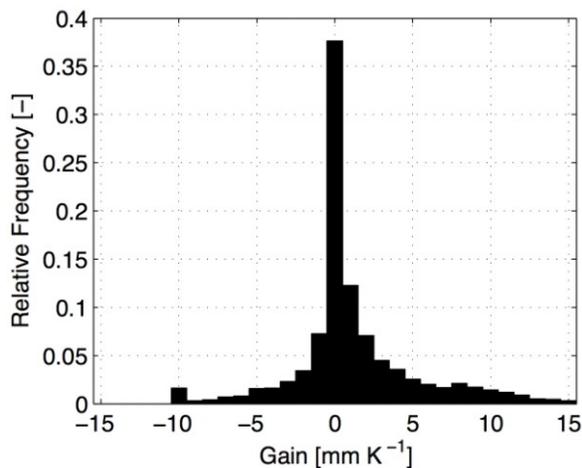
Figure 2: Histogram of the Kalman gain on 6 February 2003 for SWE versus ΔTb=(TbV(18 GHz)-TbV(36 GHz)).

We also assessed the potential for using the ANN as a forward observation operator in radiance-based snow assimilation. For this demonstration, the observations are considered to be in the form of spectral differences in V-polarization brightness temperatures, $\Delta Tb \equiv Tb_V(18\ GHz) - Tb_V(36\ GHz)$. Since ΔTb typically increases with increasing SWE, this spectral difference is commonly used to estimate SWE in retrieval algorithms. For the demonstration of the radiance-based assimilation considered here, observations of ΔTb imply that the resulting Kalman gain is proportional to error correlations between modeled SWE and ANN predictions of ΔTb. To obtain analysis increments, the Kalman gain would be multiplied with innovations in ΔTb (that is, the difference between actual AMSR-E observations of ΔTb and ANN predictions of ΔTb).

The Kalman gain computed for 6 February 2003 ranges from -10 mm K^{-1} to 15 mm K^{-1} as illustrated in Figure 2. A gain of 1 mm K^{-1} equates to an increase of 1 mm in the posterior (updated) modeled SWE for a 1 K innovation (that is, for a difference of 1 K between AMSR-E ΔTb measurements and ANN ΔTb predictions). Similarly, a negative Kalman gain in the presence of a positive-valued innovation would equate to a reduction in modeled SWE. Most importantly, the results suggest that there is a non-zero error correlation between the model SWE forecasts and the simulated ΔTb measurements across much of the North American domain. Overall, the results suggest that the ANN could serve as a computationally efficient observation operator for radiance-based snow data assimilation at the continental scale.

References:

De Lannoy, G. J. M, R. H. Reichle, and V. R. N. Pauwels, 2013: Global Calibration of the GEOS-5 L-band Microwave Radiative Transfer Model over Non-Frozen Land Using SMOS Observations. *J. Hydromet.*, (in press), doi:10.1175/JHM-D-12-092.1. (See separate Research Highlight.)

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