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Snow Wetness Estimation from SSM/I Data Over Varied Terrain Using an Artificial Neural Network

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ABSTRACT

The Special Sensor Microwave/Imager (SSM/I) radiometer is becoming a useful tool for large-scale monitoring of snow wetness. To date, SSM/I snow wetness algorithms have been developed using statistical regression analysis for a specific region. However, the development of a general algorithm has been impeded by the lack of adequate ground-based snow wetness measurements and by the nonlinearity between SSM/I brightness temperatures (T_B's) and snow wetness over varied terrain. We used a previously defined linear relationship between snow wetness (% by volume) and air temperature (°C) to estimate the snow wetness data at ground-based weather stations over varied terrain. SSM/I T_B observations were then linked with the snow wetness estimates as an input/output relationship. An artificial neural network (ANN) was designed to learn the relationship. Results showed that the ANN method may overcome the limitations of the existing regression models in estimating snow wetness from SSM/I T_B's.

Key words: Artificial neural network, backpropagation, brightness temperature, passive microwave remote sensing, snow wetness.

INTRODUCTION

Knowledge of snow wetness, which is the liquid water content in a snowpack, is important in predicting the snowmelt runoff (Linlor *et al.* 1981) and assessing the snow strength (Brun 1989). Because snow wetness has a significant effect on the microwave emission at the snowpack surface, monitoring large-scale snow wetness is possible through satellite microwave radiometry (Chang *et al.* 1987, Rango 1993).

Recently, the Special Sensor Microwave/Imager (SSM/I) radiometers, on board the Defense Meteorological Satellite Program (DMSP) F8, F10, and F11 satellites, have been used to produce global hydrologic data (Ferraro et *al.* 1994). The SSM/I is a seven-channel, four-frequency, linearly polarized, passive microwave radiometric system (Hollinger 1989), which measures both vertically (V) and horizontally (H) linearly polarized brightness temperatures (T_B's), at 19.35, 37.0, and 85.5 GHz and only vertical polarization at 22.235 GHz. Unlike in situ methods, the SSM/I provides an indirect estimate of snow parameters by using parameter retrieval algorithms with T_B's as inputs. In order to develop the algorithm, SSM/I T_B data along with ground truth data are required.

To date, SSM/I snow wetness algorithms (e.g., Sun *et al.* 1995) have been developed using statistical regression analysis for a specific region (usually, a sparse-vegetated flat area). Since SSM/I T_B's increase and depolarize as the vegetation density over the snowpack increases (Hall *et al.* 1991), the existing algorithms often overestimate snow wetness in areas where evergreen forest cover dominates. Because of this, existing SSM/I snow wetness algorithms have limitations as general approaches for snow parameter retrieval over different geographical areas.

Nevertheless, the development of a general algorithm has been impeded by the lack of adequate ground-based snow wetness measurements and by the nonlinearity between SSM/I T_B observations and snow parameters over varied terrain. A study by Sun *et al.* (1995) indicated that snow wetness W_{SNOW} (% by volume) in the surface layer is significantly related to concurrent air temperature T_{AIR} (°C) by:

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$$W_{SNOW} = 1.0285 + 0.5708 \times T_{AIR} \qquad (1)$$

Since data of air temperature are generally available, Eq.(1) could be used to estimate the necessary ground-based snow wetness data at different SSM/I footprints to develop a general SSM/I snow wetness retrieval algorithm.

On the other hand, the use of artificial neural networks (ANNs) to retrieve snow parameters from passive microwave data (Tsang *et al.* 1992, Davis *et al.* 1993) has shown that ANNs have potential to learn the relationship between T_B patterns and snow parameters, whose complexity and nonlinearity make retrieval accuracy by existing regression methods impossible.

According to Simpson (1992), the backpropagation (backprop) ANN method has shown to be identical to the stochastic approximation technique for finding a relationship between inputs and outputs when the inputs and outputs are extremely noisy. In this study, we sampled the input/output relations between SSM/I T_B's and concurrent ground-based snow wetness estimates over a variety of geographical areas to train a backprop ANN.

STUDY SITE AND DATA

A study area bounded by latitude of 40°N to 45°N and longitude of 100°W to 115°W, which contained both plains and mountainous region in the western United States, was selected to represent a variety of vegetated terrain. Data of SSM/I T_B's and ground-based snow wetness from Oct. 1, 1989 to May 30, 1990, in the area were used for the study.

SSM/I T_B's from the DMSP-F8 satellite were obtained from the Naval Research Laboratory. Due to the failure of both SSM/I 85.5 GHz channels on DMSP-F8, only T_B's of the lower frequency channels, denoted as T19V, T19H, T22V, T37V, and T37H, were available.

Ground-based measurements of daily snow water equivalent (SWE), and maximum, minimum and average air temperature over mountainous terrain were obtained from the Soil Conservation Service (SCS) SNOwpack TELemetry (SNOTEL) system. Data of daily snow depth (SD), maximum and minimum air temperature, and air temperature at the observing time in the plains were derived from the National Oceanic and Atmospheric Administration (NOAA) cooperative weather observation network.

GROUND-BASED SNOW CLASSIFICATION

Daily snow conditions at each SNOTEL or NOAA weather station at either 06:00 or 18:00 (i.e., the DMSP-F8 local crossing time) were further classified as: (1) snow-free if SWE or SD was equal to zero, (2) dry snow if SWE or SD increased from the previous observation time and the concurrent air temperature was below 3.5°C, based on Eq.(1) by assuming the wetness of dry snow was below 3% by volume, (3) wet snow if SWE or SD was not equal to zero and the concurrent air temperature was greater than or equal to 3.5°C, or (4) refrozen snow if the concurrent air temperature was below freezing and the snow condition of the previous overpass was either wet or refrozen.

For the SNOTEL stations, the daily minimum and average air temperature were assumed to be the concurrent air temperature at 06:00 and 18:00, respectively. For NOAA weather stations, the concurrent air temperature at 06:00 or 18:00 was set to be the air temperature at observing time if the time was between 04:00 and 07:00 or between 16:00 and 19:00, respectively; otherwise, the concurrent air temperature at 06:00 was equal to the minimum air temperature and that at 18:00 was extrapolated. The extrapolation was done by assuming the maximum air temperature occurred at 14:00 and linearly decreased to the temperature at observing time if after 14:00 or the maximum air temperature of previous day decreased to the temperature at observing time if before 14:00.

INTEGRATION OF SSM/I AND SNOW DATA

Because the latitude/longitude coordinates of the SSM/I footprints change with each overpass, a neighborhood merging method was employed to integrate the SSM/I and in situ data into one database, by searching the ground weather stations, which fell within a 15-km search radius around a particular SSM/I latitude/longitude location (i.e., approximately the size of a 37.0 GHz footprint). Values of concurrent air temperature in each SSM/I footprint were averaged. Snow wetness at each footprint was then estimated using Eq.(1).

ANN-BASED SNOW CLASSIFICATION

Because of the temporal variability of air temperature, error could be introduced in the ground-based snow classification. This could result in different snow conditions being related to SSM/I footprints of similar T_B patterns. The SSM/I ANN snow classifier, developed by Sun (1996), was employed to reclassify the SSM/I T_B footprints. Only data of SSM/I footprints classified as wet snow condition by both ground-based and ANN-based classification methods were used for the input/output data pairs. Thus, a subset database of input/output data pairs was created.

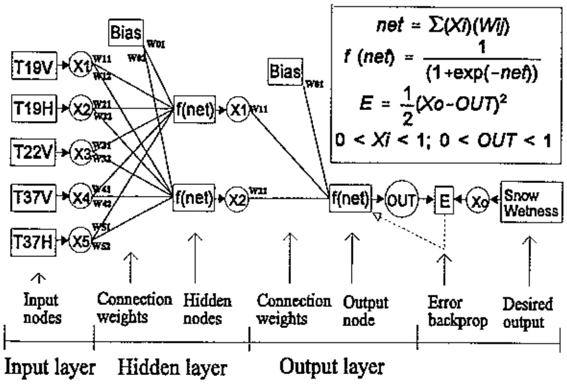

Figure 1. Example of a 5-2-1 backprop ANN.

ANN TOPOLOGY

A single-hidden-layer backprop ANN, as illustrated in Fig. 1, was created. It consisted of an input layer of five nodes representing the inputs of five T_B's, and an output layer of one node representing the desired snow wetness parameter.

Given the number of nodes in each layer from input to output as a sequence, the ANN topology was represented as 5-N-1, where N is the number of hidden nodes. For the hidden layer, the number of nodes was selected at 2, 5, 10, and 20. In addition, a bias node, functioning similar to a constant in a regression, was connected to the nodes in the hidden and output layers.

The error backpropagation training algorithm (Zurada 1992) was applied to train the ANN. This method allows forward feeding node outputs (i.e., Xi's in Fig. 1) through layers and backward propagating mapping errors (i.e., E in Fig. 1) to adjust connection weights between layers. The learning rate was set at 0.05, 0.10, and 0.20 for each ANN topology. The momentum method (Rumelhart et al. 1986) was applied to accelerate the learning process by adding the current weight adjustment with a proportion of the previous weight change. The momentum term was set at 0.90.

ANN TRAINING AND VALIDATION

As indicated by Masters (1993), the proportional representation of classes in the entire training data can have a profound influence on the ANN performance. Based on a prior study by Sun *et al.* (1996), the frequency distributions of data elements may also be important to the ANN training. Consequently, data elements in the subset database were divided into seven groups according to the frequency distributions of snow wetness (Table 1). Based on the smallest number of data elements in the groups, six data element were randomly selected from each snow wetness range to form the training data set. The rationale was to make the data sets as representative for the whole data and as balanced in size for each group as possible. From the remaining elements, a validation data set was also created.

Table 1. Data elements selected for ANN training and validation.

Range of snow wetness (% by volume)	*Number of data elements*		
	Entire data set	*Training Data set*	*Validation data set*
0-1	50	6	4
1-2	25	6	4
2-3	24	6	4
3-4	18	6	4
4-5	14	6	4
5-7	8	6	2
7-10	9	6	2
Total	148	42	24

The activation function, f(net) in Fig. 1, applied to the net input of nodes in the hidden and output layers was logistic, which maps the net output into the range between 0 and 1 (Zurada 1992). Accordingly, the inputs were scaled between 0 and 1 with respect to a T_B range from 200 to 270 K. The desired outputs of snow wetness were also scaled between 0 and 1 with respect to a range from 0 to 10 % by volume.

The training process started by randomly initializing all connection weights in the ANN to the range between -0.1 and 0.1. After each training epoch (i.e., the time for all the input/output pairs in the training data set to be processed by the ANN), a root-mean-squared (RMS) error was computed on the validation data to examine the performance of the ANN. The training epoch was repeated until a minimum RMS error was reached.

ANN TESTING

Data of SSM/I T_B's from the DMSP-F11 satellite in 1990 sampled at a footprint with concurrent snow wetness estimations during field work at Snowville, Utah (Sun *et al.* 1995) were used as the test data set to evaluate the performances of the resulting ANNs. Agreement between the ANN-estimated snow wetness and ground-based values, in terms of correlation coefficient (r), was measured for each ANN topology.

In addition, estimates of the best ANN (i.e., the

Table 2. Summary of the ANNs training and testing performances.

ANN		*Training results*		*Testing results*
Topology	*Learning rate*	*Total epochs*	*Minimum RMS*	*r*
5-2-1	0.05	1149	0.22398	0.539
5-2-1	0.10	558	0.22119	0.542
5-2-1	0.20	320	0.22250	0.533
5-5-1	0.05	1125	0.22519	0.536
5-5-1	0.10	581	0.22174	0.539
5-5-1	0.20	309	0.22241	0.528
5-10-1	0.05	1104	0.22536	0.525
5-10-1	0.10	597	0.22252	0.528
5-10-1	0.20	315	0.22237	0.516
5-20-1	0.05	997	0.22551	0.515
5-20-1	0.10	566	0.22280	0.509
5-20-1	0.20	337	0.22257	0.495

one with the largest r value) were compared to those estimated by the existing SSM/I algorithm (Sun *et al.* 1995):

$$W_{SNOW} = -4.75 + 339.53 \times (TD)^{-1} - 6159.53 \times (TD)^{-2} + 40112.00 \times (TD)^{-3} \quad (2)$$

where TD = T19V - T37H.

RESULTS AND DISCUSSION

Table 2 summarizes the training and testing performance of each ANN topology at different learning rates. For each ANN, there was no evidence to show that a lower or a higher learning rate ensures a better ANN performance (i.e., a smaller minimum RMS error). Overall, the best ANN (i.e., the 5-2-1 ANN trained at learning rate of 0.10) was derived from a number of training runs at different learning rates by trial and error.

In comparison, significant agreements were seen between Eq.(2)-estimated and ground-based snow wetness values (r = 0.940 in Fig. 2-A) as well as between Eq.(2)-estimated and ANN-estimated values (r = 0.848 in Fig. 2-B). Since Eq.(2) was developed for a sparse-vegetated terrain, using a regression method based on the same data as those in the test data set, it performed better. However, the ANN was learned from a completely different data set, including data from mountains and plains with different amounts of vegetation cover. The correlation (r = 0.848) shown in Fig. 2-B may imply that the backprop ANN approach has the potential to retrieve snow wetness from SSM/I T_B observations at different regions.

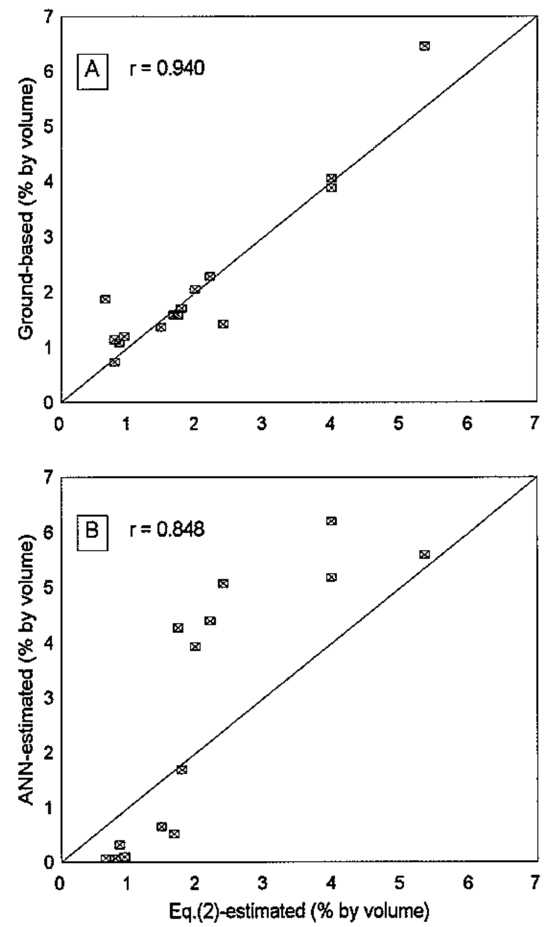

Figure 2. Comparison of (A) ground-based versus regression-model-estimated and (B) ANN-estimated versus regression-model-estimated snow wetness data from SSM/I T_B's in the test data set.

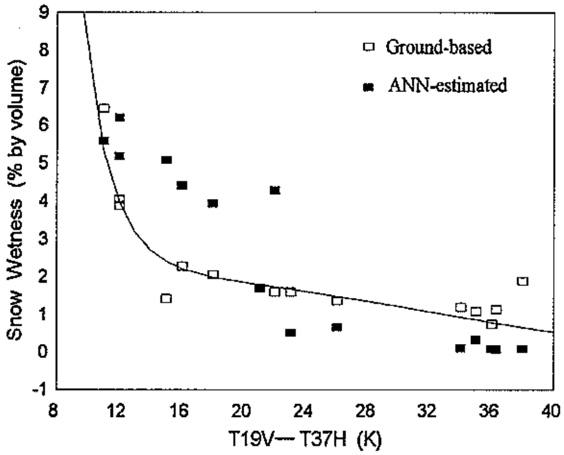

Figure 3. Comparison between ground-based and ANN-estimated snow wetness data (r = 0.702) from SSM/I T_B's in the test data set with respect to the regression line by Eq.(2).

Certain agreement (r = 0.702) was found between ground-based and ANN-estimated snow wetness data (Fig. 3). However, relatively higher estimates by the ANN with respect to the regression line were seen in the wetness range over 4% by volume. This could be due to the lack of representative data patterns over the range of 4% (see Table 1) for ANN training, resulting in a misinterpretation of the wetness in that range by the ANN.

The application of Eq.(2) to snow wetness estimation using the validation data set showed an overestimation in medium-vegetated SSM/I footprints (Fig. 4-A). One possible explanation is that the depolarization effect of vegetation cover resulted in a smaller T19V−T37H, which gave a higher estimate of snow wetness in Eq.(2), causing a weak overall correlation (r = 0.194). However, a better agreement (r = 0.546) was seen in the use of the ANN approach (Fig. 4-B). This finding confirms that a regression model can be developed for a specific region and should only be applied to areas with similar geographic features and vegetation cover (Sun *et al.* 1995).

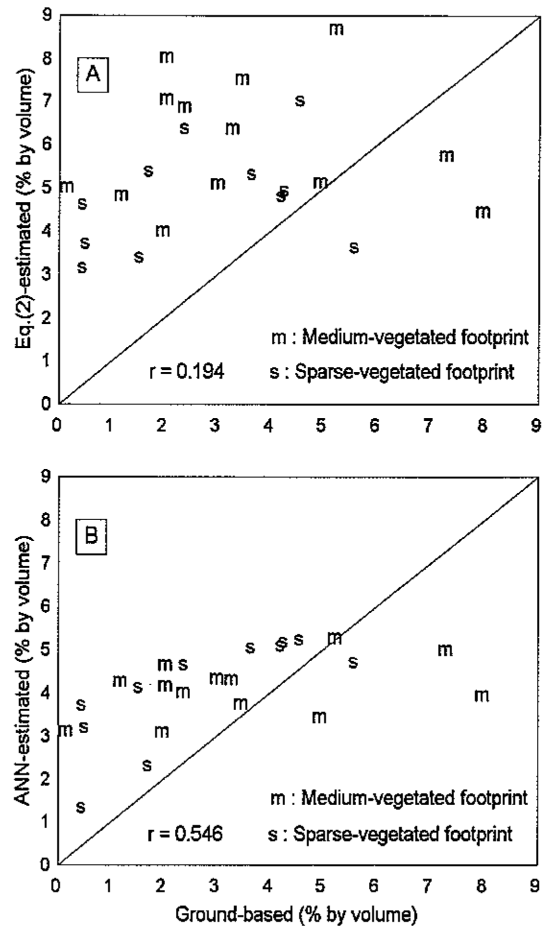

Figure 4. Comparison of (A) regression-model-estimated versus ground-based and (B) ANN-estimated versus ground-based snow wetness data from SSM/I T_B's in the validation data set.

CONCLUSIONS

This study has demonstrated a backprop ANN approach to find a mapping between SSM/I T_B observations and ground-based snow wetness data. Results showed that the ANN approximation may overcome the limitations of the existing regression models in estimatining snow wetness from SSM/I data over varied terrain with different amounts of vegetation cover.

Although the ANN has the capability to learn input/output relations from noisy samples, a sufficient number of representative data patterns should be available during training to improve the ANN performance. Further improvement is expected as more representative input/output relations between SSM/I observations and ground-based data over varied terrain are established.

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