A new modeling framework for estimating snow water equivalent using artificial neural networks, passive microwave data and geostatistics

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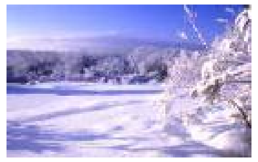
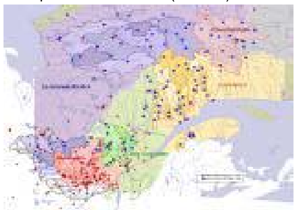
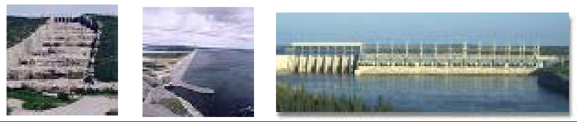
1. Context

Hydro-Quebec is the biggest producer of electricity in North America (97% hydraulic). Hydro-Quebec operates more than 500 dams, 75 reservoirs and 52 hydroelectric power generating stations located in over 90 basins in the province of Quebec (Canada).





A reliable estimation of snow cover and snow water equivalent (SWE) is needed as SWE is a dominant source of water supply in Canada and is a key state variable of our hydrologic models, which forecast water inflows into the reservoirs during spring.

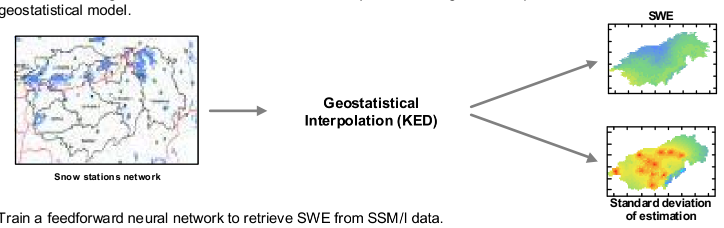


2. Modeling framework

Many inversion algorithms that retrieve SWE by using passive microwave brightness temperature data or indices have been proposed during the last 20 years. These algorithms are multivariate linear regression models (Tait, 1998; Chang *et al.*, 1987, Hallikainen and Jolma, 1992). Including physiographic and atmospheric data as predictors gave meaningful algorithms (Singh and Gan, 2000). Very few studies have used neural network models for SWE retrieval from SSM/I data (Tedesco et al., 2004).

Our goal is to use a neural network model to retrieve SWE by using passive microwave brightness temperature raw data (SSM/I channels in vertical and horizontal polarization) and gradients as predictor variables. The modeling framework involves the following steps:

1. Mapping ground-based SWE observations by geostatistical interpolation such as kriging with an external drift (KED). This map is used as the target of the neural network model and is provided along with a map of the standard deviation of estimation of the geostatistical model.



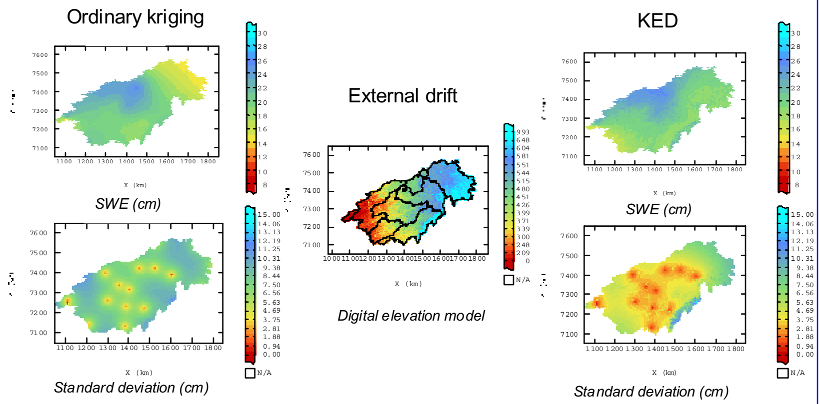
2. Train a feedforward neural network to retrieve SWE from SSM/I data.

3. Mapping SWE observations: Kriging with an external drift (KED)

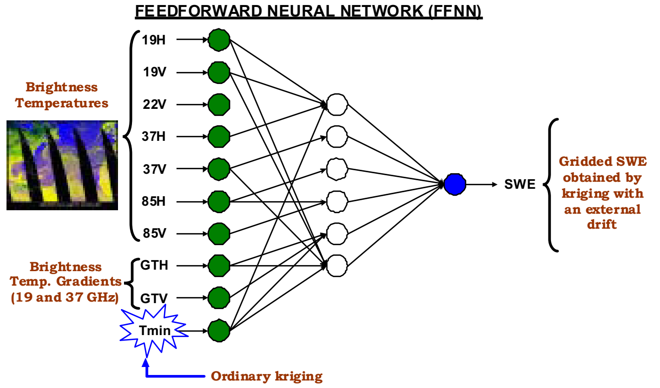
Context
• Scattered single point data giving measurements of snow depth and density. SWE observations, typically sparse both spatially and temporally, are derived from snow depth and density.
• Elevation data derived from a Digital Elevation Model (DEM) giving information about the variation of SWE away from the single point data.

Problem
How to combine single point data and elevation information properly to provide reliable interpolated values at each pixel over a river basin?

Results
The application of universal kriging with elevation used as an external drift resulted in a better estimation precision than ordinary kriging. KED method (Wackernagel, 2003) helps depict a more natural looking SWE distribution over a river basin (Tapsoba et al., 2005). SWE estimation accuracy is showed here by the smaller standard deviation values around measurement sites and at unsampled areas.



4. Neural network model and training



FFNN TRAINING

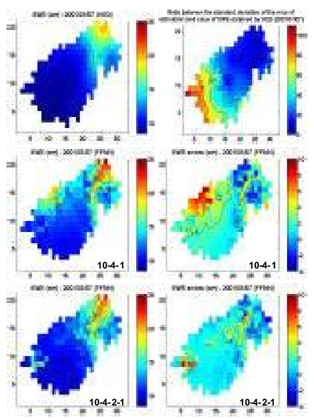
- Study area: La Grande river basin (Northern Quebec, Canada)
- 15 images for SSM/I and SWE from 1993 to 2002. Microwave data are provided by the seven SSM/I sensors on the U.S. DMSP F-11 and F-13 satellites in descending mode
- Input and output data are scaled in the range [0,1]
- Ratio between the standard deviation of the error of estimation and value of SWE obtained by KED is 20%
- Pixels input and output data clustering: SOM, 2D Kohonen layer (15×15) with an hexagonal topology
- 25 km mask when sampling each representative clusters
- Levenberg-Marquardt training algorithm for the FFNN that is trained 30 times i.e. we are 99% confident that the best-of-30 random starts will result in one of the best 14.2% values of sum-of-squared errors (Iyer and Rhinehart, 1999)
- Matlab Neural Network Toolbox Version 4.0.6 (R14SP3)

Best FFNN models

Network architecture	10-4-1	10-4-2-1
Training set (pixels)	404	
Validation set (pixels)	157	
Test set (pixels)	127	
Extra set (pixels)[1]	1608	
Generalization error (estimation based on the extra set)		
Bias (cm)	0.19	**0.12**
Bias (%)	1.04	**0.67**
RMSE (cm)	2.65	**2.63**
RMSE (%)	14.80	**14.72**
MAE (cm)	1.99	**1.96**
MAE (%)	11.11	**10.96**
Correlation coefficient	0.83	**0.84**
Nash coefficient	0.67	**0.68**

[1] The extra set gathers all the pixels not in the training, validation and test sets

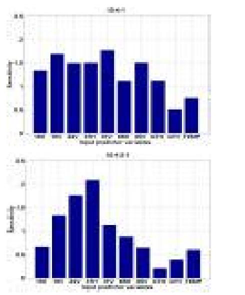
A major advantage of this training methodology is the possibility of analyzing graphically the training performance of the FFNN. As a matter of fact, only a few pixels of an image are selected by the sampling procedure to constitute the training, validation and test sets for the FFNN training.



2001/01/07 (based on 234 pixels of the extra set for this image)		
Network architecture	10-4-1	10-4-2-1
Bias (cm)	2.25	**1.28**
Bias (%)	21.69	**12.29**
RMSE (cm)	3.00	**1.82**
RMSE (%)	28.87	**17.47**
MAE (cm)	2.44	**1.43**
MAE (%)	23.43	**13.74**
Correlation coefficient	0.61	**0.82**
Nash coefficient	0.15	**0.48**

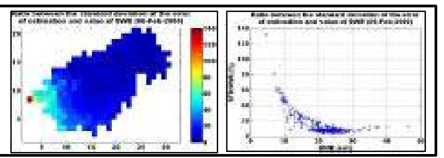
Sensitivity Analysis

Sensitivity is estimated by dividing the standard deviation of the output by the standard deviation of an input which is varied between its mean +/- *n* times standard deviation (*n* between 1 and 3) while the remaining input values are set to their respective means

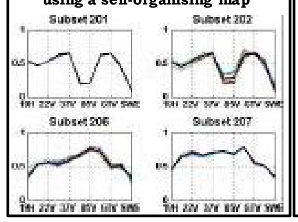


NEURAL NETWORK TRAINING METHODOLOGY

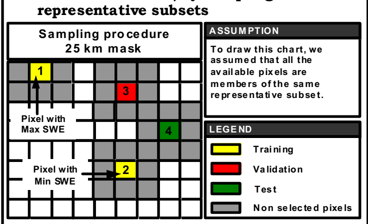
1. Select the best pixels according to the ratio between the standard deviation of the error of estimation and the interpolated values of SWE obtained by KED



2. Divide the best pixels set into representative subsets by using a self-organising map



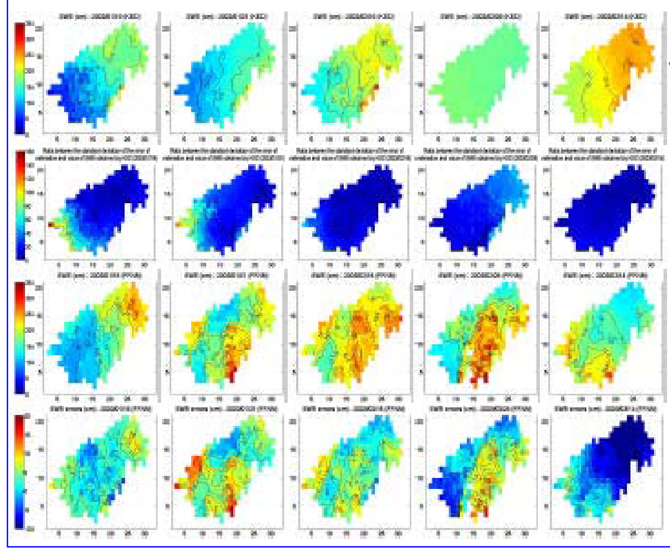
3. Create 3 data sets (training, validation and test data sets) by sampling each representative subsets

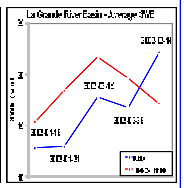


5. Application

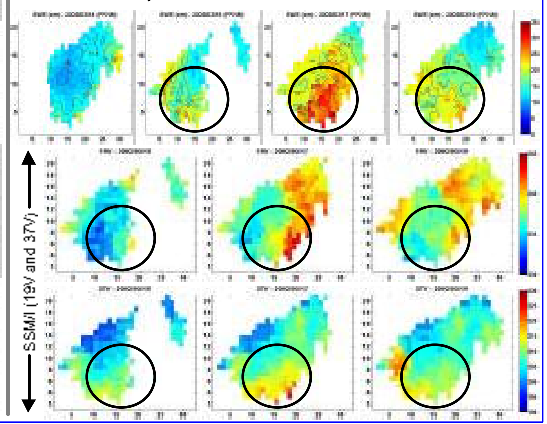
The 10-4-2-1 FFNN has been used for SWE mapping in 2003. The SSM/I grid for each channel is an average over a few days before and/or after the date of interest. The opposite table gives some statistics when considering the KED mapping of SWE observations as the ground truth. For winter 2003, the FFNN has overestimated the average SWE over La Grande River basin except in March. The FFNN average SWE seems consistent when compared to the average SWE estimated by KED.

Date	2003-01-18	2003-01-31	2003-02-15	2003-02-28	2003-03-14
Bias (cm)	2.56	5.47	3.94	2.76	-5.01
Bias (%)	20.02	42.17	22.18	16.43	-22.61
RMSE (cm)	3.75	6.74	4.97	5.81	7.22
RMSE (%)	29.34	51.97	28.01	34.55	32.58
MAE (cm)	3.12	5.69	4.17	4.84	5.96
MAE (%)	24.39	43.88	23.47	28.79	26.88
Correlation coefficient	0.83	0.39	0.44	-0.44	-0.69
Nash coefficient	0.54	0.04	-0.06	-0.06	-0.39





SSM/I data exhibit some variability on a daily basis. As an example, we have provided FFNN SWE maps for March, 14, 16, 17 and 19 using the SSM/I data for each of these days.



6. Discussion and Conclusion

This new modeling framework for SWE mapping combines artificial neural networks, passive microwave data (SSM/I) and geostatistics (KED). The neural network training methodology is very attractive and efficient. It facilitates the training performance evaluation. SWE mapping by using a FFNN was performed in 2003 and the results, although showing some overestimation, were consistent with the ground truth provided by KED mapping of SWE observations over the La Grande River basin.

Future studies will involve:
- taking into account additional variables as external drifts in KED method to improve the accuracy of the SWE ground-based map
- using brightness temperature difference indices and gradients as input predictor variables of the FFNN instead of brightness temperature raw data that do not provide sufficient accuracy on a pixel scale
- providing an uncertainty map along with the FFNN SWE map.

7. References

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