POTENTIALS AND LIMITATIONS OF RADASAT SAR IN ESTIMATING SNOW WATER EQUIVALENT (SWE) IN THE GREAT LAKES REGION OF THE UNITED STATES

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Abstract- This study is part of a research to evaluate the feasibility of satellite borne active microwave to estimate snow water equivalent in Great Lakes area of the United States.
The study area covers approximately 120 000 square kilometers (300 X 400 km) between the states of Minnesota and Wisconsin. A variety of land covers such as deciduous broadleaf forests, grassland, cropland, and dry land is present in the area. One winter and one summer RADARSAT SAR image were acquired for this project. The backscattering ratio between winter and summer images was used in order to reduce the effect of radiometric distortions due to topography and to minimize the effect of soil roughness. The basic hypothesis of this research is that the snow cover characteristics influence the underlying soil temperature which in turn has an effect on the SAR backscattering since the dielectric properties of the soil are highly related to the soil temperature. The backscattering ratio of the winter and summer images along with land cover are used in an Artificial Neural Network (ANN) algorithm to estimate snow water equivalent (SWE). To take the land cover effect into account, Normalized Difference Vegetation Index (NDVI) was added to the ANN as an input. The preliminary results have shown that the addition of vegetation-related information to the neural network model has a positive effect on the SWE retrieval accuracy. The ground truth data are obtained from NOHRSC (National Operational Hydrologic Remote Sensing Center) SNODAS (Snow Data Assimilation System) products. SNODAS data are produced using snow gauge measurements along with Gamma radiation measurements run in a physical model. Comparing the estimated results to the SWE obtained from SNODAS, it is shown that in high latitudes there is a better potential to retrieve SWE than in low latitudes.

Introduction

Synthetic Aperture Radar (SAR) particularly C-band SAR has shown the potential for monitoring snow and ice for more than two decades. The high spatial resolution and the independence of the sensors from sun illumination and cloud cover make SAR an ideal tool for snow studies. Launched in 1995, Radarsat-1 offers spatial resolutions between 10m to 100m and a swath up to 500km. To estimate SWE using C-band SAR, Bernier and others (1998) introduced their approach based on the fact that snow cover characteristics influences the underlying soil. The snow influence on soil temperature affects the dielectric properties of the soil which has a major role on the backscattered signal. To recover the SWE from SAR data an algorithm made of two equations were used. The first equation defines a linear relationship between the snow thermal resistance and the backscattering ratio between a winter image and a reference (snow-free) image in DB. The snow-free image helps to eliminate the radiometric distortion due to topography as well as minimize the effect of soil roughness on the signal. The second equation is a linear relationship between thermal resistance and the SWE. To estimate SWE from thermal resistance the mean density of the snowpack has to be derived. This approach has been applied for cold winter condition and dry snow, Bernier (1999). The critical variables influencing the algorithm are variety of land cover specifically forest density, Snowpack properties (depth>2m), and severe topography. In this research project we are going to investigate the potentials and limitations of Radarsat C-band SAR in estimating Snow Water Equivalent (SWE) in Great Lakes area of United States.

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Data Acquisition and Processing

Radarsat Images

Radarsat ScanSAR images were obtained for Feb 06, 2003 (winter image) and May 01,2002 (snow-free image). ScanSAR images (500km by 500km) have the nominal spatial resolution of 100m . The ScanSAR products currently offered by us do not come in a map-projected format. However, images have the georeferencing information contained in the CEOS format. This information is derived from the satellite orbit (ephemeris) and is typically accurate to 100-200 meters, depending on beam mode and the topography. To reduce geometric distortions caused by radar sensor viewing geometry satellite movement, earth curvature and rotation, both Radarsat images were registered to a Landsat image of the study area. More than 15 Ground Control Points and a second order model and nearest neighbor resampling mode were used to register the Radarsat images. The images were projected to a UTM projection and subseted for the in common area of coverage.

The other steps for processing Radarsat SAR images involved: converting the DN values to power values, averaging the power values for a 1km spatial resolution, and deriving the DB values of backscattering for each pixel. In the last step the DB backscattering values of winter and reference image were subtracted.

Normalized Difference Vegetation Index (NDVI)

NDVI is used to represent the variety of land cover in the study area. The NDVI data obtained from the NOAA/NASA Pathfinder AVHRR is distributed at Goddard Space Flight Center (GSFC). The spatial resolution is 8km by 8km obtained within a 10 day period that has the fewest cloud. To match the with Radarsat images, NDVI image was resampled and projected to UTM. Figure 1 shows the NDVI image of the study area. The lakes and water bodies are filtered out of the image.

Ground Truth Data

NOAA National Weather Service's National Operational Hydrologic Remote Sensing Center (NOHRSC) started producing SNOw Data Assimilation System (SNODAS), beginning 1 October 2003. SNODAS includes and procedures to assimilate airborne gamma radiation and ground-based observations of

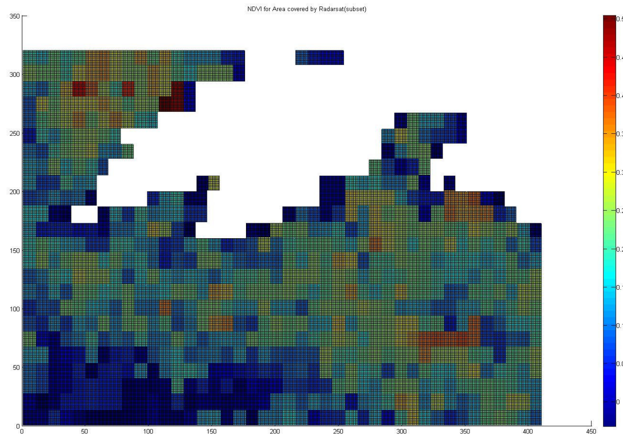

Figure 1. NDVI for the study area

snow covered area and snow water equivalent, downscaled output from Numerical Weather Prediction (NWP) models combined in a physically based, spatially-distributed energy- and mass-balance model. The output product has 1km spatial and daily temporal resolution. The SWE SNODAS was georeferenced and projected to UTM system to match Radarsat and NDVI images.

Model- Artificial Neural Networks

An adaptive network is a network structure that consists of a number of nodes (neurons) connected through directional links. Each node represents a process unit, and the links specify casual relationship between the connected nodes. Nodes are adaptive meaning that the outputs of these nodes depend on modifiable parameters pertaining to these nodes. The learning rule specifies how these parameters should be updated to minimize error which is discrepancy between the networks actual output and desired one. In our study we used a feed forward backpropagation model. The network has two hidden layers with ten nodes at each layer (2 10 10 1). The input consists of backscattering ratio vector and NDVI vector. The output is SWE. To train the network data were divided into three sets (training, validation, and test). The model testing is the process by which the input vectors from input/output data sets on which the network is not trained, are presented to the trained model, to see how well the ANN model predicts the corresponding data set output values. The other type of validation which is also referred as checking data set is used to control the potential for the model over fitting the data. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for checking data suddenly increases.

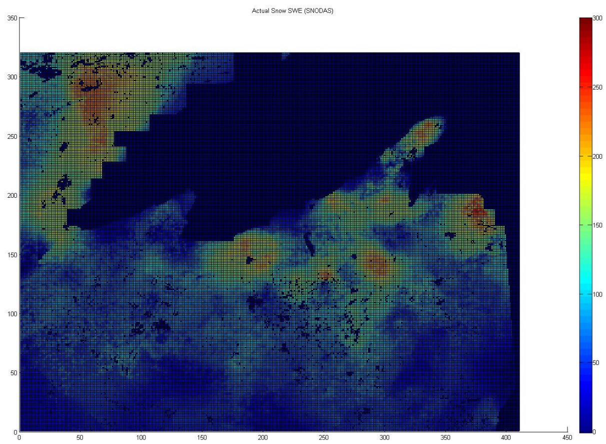

Figure 2. Actual Snow Water Equivalent (SWE), Min=0 Max=300mm

Figure 3. Estimated Snow Water Equivalent (SWE), Min=0 Max=300

Discussion

The actual image of the snow water equivalent provided from SNODAS data set shows high amounts of SWE in high latitudes and especially closer to the lake. On the other hand in low latitudes the SWE is reduced to zero. The estimated SWE by the ANN model (Figure 3) shows a good correlation with the actual SWE. However, the model tends to underestimate the SWE. There are various reasons for this underestimation. First of all is backscattering ratio and SWE. The correlation between backscattering ratio and SWE is due to the changes in dielectric properties of the underlying soil. This can be influenced by the variety in land cover and ground temperature. Second, ANN models limitations. ANN model performance is based on minimizing the error between output and the target values. Input Data with very steep changes or noise increases the error and therefore limits the predicting accuracy. The other source of error can be data it self. Since most of the data set consists of low SWE pixels it forces the training weights in ANN to minimum error for those pixels. This makes the ANN incapable of predicting high values of SWE. To overcome these limitations, the following methods can be applied in further research: 1- Classifying the area in different categories based on land cover or NDVI. Pick the same number of pixels from each category and train the model by inputs and output corresponding to the selected pixels. 2- Train the model for each of the categories separately and measure the error for different classes of land cover.

Conclusion

Our findings reveal that the ANN algorithm developed with C-Band SAR and NDVI input data underestimates SWE. This can be attributed to ANN modeling limitation –based on minimizing the error between output and the target values; varying landcover which affect correlation between backscattering and SWE and inherent data input errors. However, although largely underestimated the use of C-Band SAR overlapped with NDVI in developing ANN models is a step in the right direction. An investigation of the effect of SAR bands Ku-bands is worthwhile.

References

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