Vegetation Effect on Soil Moisture Retrieval from Active Microwave Data

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3. Soil Moisture, SAR, Optical Depth and NDVI Data (July 12, 1997)

Class Selection

Routout combinations for those cit

National Oceanic and Atmospheric Administration Cooperative Remote Sensing Science and Technology Center

1. Soil Moisture and Microwave Data

- · The brightness temperature and backscatter coefficient from microwave remote sensing data is related to soil moisture based on dielectric properties of soil and water.
- · The relationship between backscatter coefficient and soil moisture becomes non-linear and complex by the presence of vegetation cover present on ground surface.
- · The vegetation cover is the function of normalized vegetation difference index and vegetation optical depth
- · The microwave energy backscattered from vegetated terrain is highly dependent on the dielectric constant of the soil and vegetation, which is in turn directly affected by water content.
- · Radar energy is able to operate independently of cloud cover, smoke and solar illumination which hardly limit the use of optical sensors such as SPOT and LANDSAT.

Regression Analysis of SAR Backscattering and Soil Moisture Range of Backscattering values (DN) vs Soil Moisture Classe Vertical line shows + one

4. Neural Network Classification Methodology



SAR Image

Std Deviation

Mean

Thematic Man

Homogenity Optical Depth

number of nodes in each layer.

Neural Network

NOAA CREST

2. Data Acquisition and Study Area





The study area is located in Oklahoma, USA (97d35'W, 36d15'N). One Radarsat-1 image acquired on July 12th, 1997 by ScanSAR Narrow Mode at an incidence angle range of 20°-39° with a resolution of 25 m was used in this study. The soil moisture and other vegetation data (NDVI, vegetation water content, vegetation b parameter, etc) were collected during SGP97 mission have been used in this research. The SGP97 experiment was a large, interdisciplinary experiment carried out in 1997 with the objective to test formerly established soil-moisture retrieval algorithms for the ESTAR Instrument (Electronically Scanned Thinned Array Radiometer) L-band passive microwave radiometer at 800-meter resolution.

7. Threshold Limit and Confusion Matrix

Accuracy assessment was carried out using confusion matrices generated from the comparison between real values (truth data) and predicted values (estimated data).

To avoid that the network forces the classification of all the pixels, we have introduced a threshold (value between 0 and 1) to decide if a class will be assigned to the input pixel or if this pixel will be considered as unclassified. Thus, a pixel is considered unclassified if all output values are lower than this threshold; otherwise the pixel is assigned the class corresponding to the neuron with the highest value. In this project, the threshold value has been varied from 0.4 to 0.7.

The two following matrices show that the increase of threshold limit from 0.5 to 0.6 leads to more Nil pixels in the final soil moisture map. However, it makes more sure that the classified pixels have been correctly classified.



Effect of the selected threshold on the

overall classification

Nil Pixels

o.ss Threshold Limit

Soil Moisture Classes

Class 1 : < 10 %

Class 2: 11-10 %

Nil Pixel

- Correct Pixels

Class 3: 21 % <

a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points.

The algorithm:

Confusion Matrix (Threshold = 0.5)

36

187 20 242

Class 2

Class 3

Nil Pixel

Class 1

Class 2

Class 3

Nil Pixel

Class 1 Class 2 Class 3 Total Pixel

Class 1 Class 2 Class 3 Total Pixel

173

29 116

37

240

125

nold = 0.6)

47

165

50

213

149

- o Selects the data point with the highest potential to be the first cluster center.
- o Removes all data points in the vicinity of the first cluster center (as determined by radii), in order to determine the next data cluster and its center location.
- o Iterates on this process until all of the data is within radii of a cluster center

The variable radii is a vector of entries between 0 and 1 that specifies a cluster center's range of influence in each of the data dimensions, assuming the data falls within a unit hyperbox. Small radii values generally result in finding a few large clusters. The Good values for radii is estimated as 0.55 based on various run of model for a set of input data.

8. Preliminary Results and Discussion

- This study demonstrates a promising capability of neural network to retrieve soil moisture maps
 - The influence of various parameters (NDVI, Vegetation optical depth, textural data) can be better understood by classifiers like neural network and fuzzy logic
 - The additions of optical depth and NDVI information to NN model have significant effect (increase the accuracy by ~6-10%) on the final soil moisture accuracy.
 - The areas with lower NDVI values showed better classification accuracy due to less contribution of vegetation to the backscatter.
 - High optical depth and NDVI values generate more confusion in the NN prediction.
- > The correlation between SAR backscattering and soil moisture is better with higher soil moisture content, which validates the study carried out by Wang et al. (2004) stipulating that the dominance of soil moisture on backscattering is higher at wet soil than dry soil.
- Adding the vegetation data is important to improve the accuracy at dry soil condition, where the dominance of vegetation water content is higher.
- The neural network model shows higher potential to estimate soil moisture. However, high variation in soil moisture estimation accuracy has been observed at different runs of NN model.
- The fuzzy logic model was also used to predict the soil moisture using the similar input data and gave a low variation in soil moisture estimation accuracy.
- The prediction made by neural network is higher than fuzzy logic in several runs of the model, but we found that the prediction made by fuzzy logic is more stable in nature.
- These results gave us a thought to couple these two techniques to come out with better and reliable method such as "neuro-fuzzy" to improve the soil moisture estimation accuracy





- Development of soil moisture retrieval algorithm using a combination of parametric and non-parametric tools such as maximum likelihood, neural networks, fuzzy logic etc...
- Assess the effect of normalized difference vegetation index (NDVI) and vegetation optical depth on the retrieval of soil moisture from microwave data.
- Production of qualitative and quantitative soil moisture maps with different levels of accuracy.

NDVI Output (supervised 5. Neural Network Optimization A best neural network is described as a combination of better accuracy, training stability and processing time. Those three parameters depend on the network size and the network complexity, which are the function of the number of network layers and the

To optimize the internal configuration of the neural network, the same network was run 25 times for each architectural configuration. The results showed that, by using two hidden layers with an equal number of nodes, the standard deviation of the 25 runs is very low. Further, the increase of the number of hidden nodes increases the training and the classification time without any improvement of the overall accuracy. The results indicate that better classification accuracy was reached when the number of hidden nodes is the same in each hidden laver.

When using a single layer, the number of nodes should be greater than the number of input data to get reliable results. Further, the variance of overall accuracy in 25 runs becomes more stable when the number of hidden nodes is less than 22.

