Vegetation Effect on Soil Moisture Retrieval from Active Microwave Data

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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.

2. Data Acquisition and Study Area

The study area is located in Oklahoma, USA (37o53W, 36o15'N). One Radarsat-1 image acquired on July 13th, 1997 by ScanSAR Normal Mode at an incidence angle range of 20°-30° with a resolution of 25 m was used in this study. The soil moisture and other vegetation data (NDVI, vegetation optical depth, vegetation 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 Thin-Aperture Radarimeter) Land passive microwave radiometer at 850-m resolution.

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

4. Neural Network Classification Methodology

A subtractive clustering method is also used to estimate the soil moisture from a combination of input data. The subtractive clustering method assumes each data point is a potential cluster center and calculates a measure of the likeliness that each data point would define the cluster center, based on the density of surrounding data points.

The algorithm:
- Selects the data point with the highest potential to be the first cluster center.
- 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.
- 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.

5. Neural Network Optimization

6. Fuzzy Logic Method

A fuzzy logic method was also used to predict the soil moisture using the aterial input data and gave a low variation in soil moisture estimation accuracy.

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).

8. Preliminary Results and Discussion

- This study demonstrates a promising capability of neural network to retrieve soil moisture maps from active microwave data.
- The influence of various parameters (NDVI, vegetation optical depth, textual data) can be better understood by classifiers like neural network and fuzzy logic.
- The addition of optical depth and NDVI information to NN model have significant effect increases the accuracy by ~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 high.
- The neural network model shows high 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 aterial 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.

9. Future Approaches

- 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.

Regression analysis of basic backscattering and soil moisture estimate

Accuracy assessment was carried out using confusion matrices generated from the comparison between real soil moisture values (truth data) and predicted soil moisture values (estimated data). To avoid that the network forces the classification of all the pixels, we have introduced a threshold (values 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 the project. The threshold value has been varied from 0.4 to 0.7.

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

Confusion Matrices (Threshold = 0.5)

Confusion Matrices (Threshold = 0.6)

Effect of the selected threshold on the overall classification

Effect of optical depth on classification accuracy

Effect of NDVI on classification accuracy

Data (25 x 25 m resolution)

Calibration and Geocoding

Simulation

Methodology applied in soil moisture estimation

SAR Data Characteristic:
- Beam Mode: (B)  W2 S5 S6
- Projection: UTM Zone 14S
- Earth Ellipsoid: Clarke 1866

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