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AN EMPIRICAL MODEL TO ESTIMATE SOIL MOISTURE OVER VEGETATED AREAS

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1. INTRODUCTION.

An empirical model to estimate soil moisture over vegetated areas was developed. Soil moisture exhibits spatial and temporal variability. It has been noted that the temporal variability for a given area exhibits long- and short-term variations that can be expressed by an empirical model. The major components of the empirical model are the long-and short-term variability. The long-term variability is mostly associated to long-term climatology patterns and modeled by an artificial neural network. The neural network was trained by using the following variables: monthly soil moisture (*in-situ* observations), monthly accumulated rainfall (NEXRAD), monthly vegetation index (MODIS), monthly land surface temperature (MODIS), soil texture, elevation, and slope. The short-term memory model is a stochastic transfer function that estimates the soil moisture response in hourly basis for every grid (1 km). Estimation of soil moisture response requires using the cumulative rainfall during the last week (NEXRAD), the hourly rainfall (NEXRAD), the hourly temperature estimated from MODIS and the initial level of soil moisture estimated from the long term-variability model.

The empirical model was applied to Puerto Rico climate conditions, and it is expected that the model can be implemented to a similar tropical region. The proposed method can be used to create the initial conditions of soil moisture for running atmospheric and hydrological models such as: the regional atmospheric modeling system (RAMS), the mesoscale model (MM5), the MIKE SHE and VFLOW hydrological models. Cross-validation techniques show that the proposed algorithm is a potential tool to estimate soil moisture over densely vegetated areas.

1.1 Background

Soil moisture is a fundamental component of the surface water and energy budget. The soil moisture regulates the partition of latent and sensible heat fluxes at the surface, affecting the boundary layer. Therefore, incorrect soil-moisture initial conditions may generate misleading modeling results. For instance Balsamo, et al., (2004) reported that erroneous estimation of total soil moisture affected the quality of the forecast for several days when using a numerical weather prediction scheme. It is well known that soil moisture plays an important role in detection and attribution of global climate changes (Huang et al., 1996).

Njoku and Entekhabi (1996) used a space borne microwave remote sensing techniques to estimate soil moisture at a spatial resolution of 10-20 km. They pointed out that applications under different conditions need to be investigated. Wetzel and Woodward (1987) studied the statistical relationships between soil moisture and infrared surface temperature observations taken from the visible Infrared Spin Scan Radiometer (VISSR) at the Geostationary Operational Environmental Satellites (GOES). They used linear regression to relate soil moisture to surface temperature, wind speed, vegetation cover, and low-level temperature advection. Recently, soil moisture has been retrieved from a passive microwave radiometer known as the Advanced Microwave Scanning Radiometer (AMSR-E). The AMSR-E is an instrument that measures brightness temperature at six frequencies: 6.925, 10.65, 18.7, 23.8, 36.5 and 80.0 GHz with vertical and horizontal polarizations at each frequency for a total of twelve channels. It has been shown that the C and X band channels at 6.9 and 10.7 GHz are strongly related to land surface soil moisture and are used to generate the global land data products (Njoku, and Li, 1999; and Njoku et al., 2003). Daily products are available from the National Snow and Ice Data Center (NSIDC) since June 2002. Soil moisture estimation from AMSR-E is still in the process of validation; however, reasonable estimation for soil moisture over the moderately vegetated areas is available. The AMSR-E data is likely to be contaminated with radio-frequency interference (RFI). It has been detected interference with C band, especially over the United States, Japan and the Middle East, and the X band exhibited some interference on England, Italy and Japan (Njoku et al. 2005). The AMSR-E sensor has the limitation that the brightness temperature does not provide any information about the dielectric constant when the area is densely vegetated. Issues associated to

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RFI have diminished the utility of C-band measurements in determining soil moisture over large areas of the globe; however, McCabe et al. (2005) have reported a successful application of the AMSR-E (X band) to retrieve soil moisture over some parts of United States.

Satalino et al. (2002) study the feasibility of retrieving soil moisture content over smooth bare-soil fields using European Remote Sensing synthetic aperture radar (ERS-SAR) data. The retrieval approach consists on inverting the integral equation method by using an ANN. The overall root mean square error in the retrieved volumetric soil moisture content was 6%. They reported that the major source of soil moisture estimation is the roughness conditions, which influence the relationship between soil moisture coefficient and the radar backscattering coefficient. Jiang and Cotton (2004) implemented an artificial neural network (ANN) algorithm for soil moisture estimation. They used daily precipitation, vegetation index, cloud-mask infrared skin temperature and soil moisture profile. They found a high correlation between ANN estimates and the actual observations. They claim that ANN based algorithm is capable of estimating soil moisture from remote sensed IR data with high spatial and temporal resolution. They reported that the application of ANN exhibits some difficulties during the training process due to the need of high quality training data. In this work we are using a self-organized ANN for identifying spatial similarities among grids and a feedforward ANN for estimating the soil moisture at different depths. Guill, et al. (2006) recently implemented the support vector machines (SVM) to predict the soil moisture at Washita River experimental watershed. They compare the SVM with the ANN algorithm and concluded that SVM autoperforms the ANN in the sense that it provides smaller prediction errors. They also pointed out that the ANN is not stable since every time it is run it provides different results. In this study we are using ANN and successful results were obtained. The instability problem was solved by running the algorithm *n* times and the central tendency of results was computed as the final result of the ANN, and this procedure always provides the same result. An empirical and satisfactory result for the variable *n* was equal or grater than 5. In the future we plan to implement the SVM to test whether or not this algorithm improves the ANN performances.

This paper is organized as follows: the second section presents the *in-situ* and remote sensing data used to build the soil moisture models. The third section presents the proposed methodology. This section describes a neural network model to represents the long-term soil moisture response; describes the short-term memory model to express the hourly soil moisture response. The third section also describes the algorithm to estimate the parameters of the transfer function mode, and illustrates the use of a self-organized neural network to identify similarities among grids to select the appropriate transfer function. The fourth section presents preliminary results, and the last section introduces some conclusions.

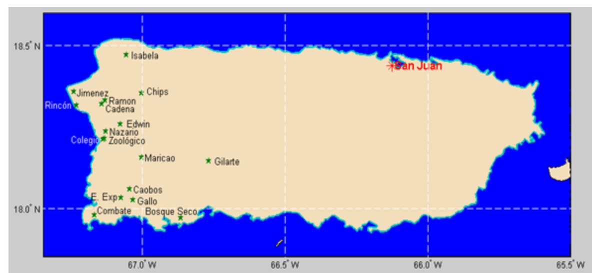

Figure 1. Location of soil moisture stations.

2. DATA.

Essentially two types of data were used in this research: the in-situ measurements and remote sensing observations.

2.1 In-situ measurements.

In-situ soil moisture observations were obtained from a local soil moisture network. Figure 1 shows the location of the soil moisture stations used in this study. The soil moisture network included 17 stations, twelve of which were owned and operated by the University of Puerto Rico-Mayagüez (UPRM) research project and to the remaining five were owned and operated by the Natural Resources Conservation Services (NRCS). The UPRM stations collected soil moisture, air temperature and rainfall on an hourly basis. The NRCS stations collected the following parameters: soil moisture, soil temperature, rainfall, solar radiation, wind speed, wind direction, and other physical parameters. Preliminary experimentation revealed that the most important parameters controlling the soil moisture response were soil texture, and precipitation, and therefore this study focused on these factors. An experimental field campaign was conducted to collect undisturbed soil samples in the neighborhood of stations to measure volumetric water content and calibrate the soil moisture sensors.

2.2. Remote Sensing data.

Land surface temperature and vegetation index were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. The MODIS instruments are on board of the Terra and Aqua satellites and scan the entire Earth's surface every 1 to 2 days. The MODIS information was obtained at the NASA Goddard Distributed Active Archive Center (DAAC). Weekly land surface temperature was provided at 1 km of spatial resolution. Monthly surface temperatures were developed for the difference between the maximum and the minimum surface temperatures. In the remaining part of this paper this variable is called the difference surface temperature. The monthly normalized difference vegetation index (NDVI) was also extracted from MODIS. Total monthly rainfall data were obtained from the Next Generation Weather Radar (NEXRAD), Rainfall data were obtained by using the multisensor precipitation estimation (MPE) algorithm, which was developed by the Hydrologic Research Laboratory (Breidenbach and Bradberry, 2001). The XRMG is a MPE product that uses radar precipitation and rain gauge measurements to derive the best estimators of rainfall for specific area and time. The XRMG rainfall data was obtained throughout the National Weather Service in about 4 Km spatial resolution and was interpolated to 1 km.

2.3. Soil texture and topography data

A soil texture map at 1 km resolution was developed based on irregular distribution of 118 soil samples provided by the USDA/NRCS. The map of percent silt was obtained by subtracting the percentages of sand and clay from 100, i.e., it is assumed that the percent soil organic matter is negligible, which may in fact not be the case at some locations and represents a potential source of error in the methodology.

Puerto Rico (PR) digital elevation model (DEM) at 30 m resolution was obtained from the United States Geological Survey (USGS). This map was interpolated to 1 km spatial resolution to obtain all the variables in the same spatial resolution. A map of average surface slope at 1 km was also developed based on the 30 m DEM for PR. All the pixel elevations within a 1 km distance were pairwise selected, the angles between points were computed, and the average slope for every pixel determined.

3. METHODOLOGY

One of the purposes of this work is to develop a soil moisture estimation model for tropical areas such as Puerto Rico, which has complex topography, vegetation, and persistent cloud cover. The soil moisture exhibit long- and short-term variability and it will be modeled by a long- and short-term memory models, respectively.

Figure 2 shows the scheme of the soil moisture model algorithm in which the long- and short-term models are integrated. This figure also shows the major source of information to derive the soil moisture estimates.

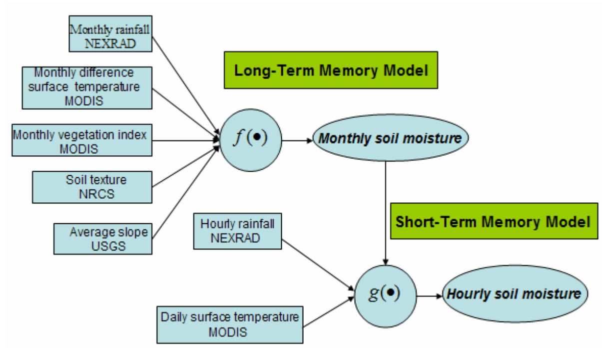

Figure 2. Soil moisture algorithm.

3.1. Long term memory model

The formulation of the model is based on analysis of soil moisture observations. Historical data show that the long-term response of the soil moisture is mostly related to soil texture, rainfall, vegetation and surface temperature. These variables were used to train a neural network to model the soil moisture long-term response. Figure 3 shows an example of the long-term response and Figure 4 shows the short-term response of the soil moisture.

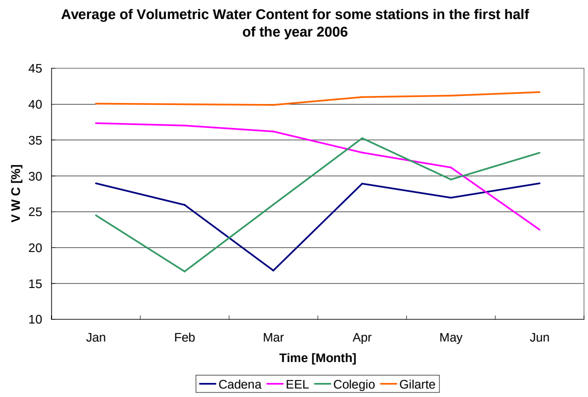

Figure 3. Monthly soil moisture response.

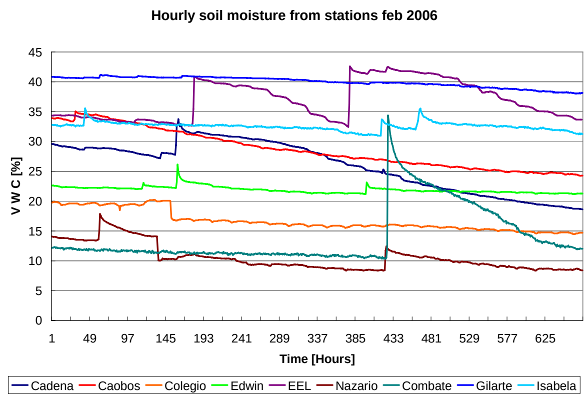

Figure 4. Hourly soil moisture response.

A feedforward artificial neural network (ANN) was used to estimate soil moisture long-term response. An ANN was selected because the dynamic water content of soil is a nonlinear process and the ANN has been proven to be and efficient approach when the variables of a system are related in a highly nonlinearly way. The ANN algorithm is a general nonlinear modeling approach that is based on various characteristics of the brain functionality (Hagan et al., 1996). An ANN determines an empirical relationship between the inputs and outputs of a given system. Therefore, it is important that the user has a good understanding of the science behind the underlying system to provide the appropriate inputs, and consequently to support the identified relationship. Thus, a key issue to obtain a successful ANN application is to select the appropriate training variables and to identify a suitable ANN structure. The structure of the ANN consists of determining the number of layers, the number of neurons in the hidden layers, and selecting the best activation function for each layer. An efficient procedure to identify the appropriate structure of a neural network is provided by Ramirez-Beltran and Montes (2002).

The training patterns of the neural networks are formed by the input and output vectors of monthly data that can be expressed as follows:

$$P_{m,j} = \begin{bmatrix} c_j & s_j & r_{m,j} & v_{m,j} & d_{m,j} \end{bmatrix} \qquad (1)$$

$$\text{and} \quad Q_{m,j} = \begin{bmatrix} h_{m,j} \end{bmatrix} \qquad (2)$$

where P is the input vector and Q is the output vector. The output vector is also known as the target; the variable h is the monthly average of soil moisture measured at 20 cm depth, *s,* and *c* are the percentage of sand and clay at the given location, respectively; the variable r is the accumulative rainfall during a month, v is the monthly vegetation index; d is the difference of monthly surface temperatures, (max. – min.). The subscripts m and j have been omitted to simplify notation and represent the m^{th} month and the j^{th} location respectively.

In order to derive a stable and robust estimation an ensemble procedure was used. Five members of the ensemble were generated with the best initial points that were obtained by a random search that minimizes the difference between the output of the neural network and the observed soil moisture.

The final estimates from the long-term memory model will be soil moisture on a monthly basis, at 1 km spatial resolution and will be used as the initial conditions for the hourly soil moisture model.

3.2. Short-term memory model.

The short-term memory model represents the soil moisture response in an hourly basis. Experimental results were used to develop an empirical model of soil moisture. It was observed that if the precipitation during consecutives days is not present and the soil is relatively dry a significant rainfall event will produce a relatively large increase in the soil moisture. On the other hand if several rainfall events occurred frequently during the previous few days then the soil moisture response is relatively small due to the soil moisture already being near to the field capacity or possibly the saturation point. Therefore, the soil moisture response can be represented by two impulse response functions. The first impulse response function models the contribution of air temperature. Essentially the air temperature controls the memory of the soil moisture response and introduces the diurnal seasonal behavior into the soil moisture response. The second impulse response function models the intervention event caused by the presence of the rainfall events. This impulse response function controls the soil moisture response according to instantaneous and accumulative rainfall events. Therefore, the proposed stochastic transfer function to model the soil moisture is:

$$h_{t,j} = \left(\frac{\omega_{0,1} - \omega_{0,2}B}{1-\delta_{0,1}B}\right)T_{t,j} + \left(\frac{\omega_{1,1} - \omega_{1,2}B}{1-\delta_{1,1}B}\right)r_{t,j} + a_{t,j} \quad (3)$$

where $h_{t,j}$ is the soil moisture at hour *t* and at the j^{th} location, $r_{t,j}$ is the instantaneous rainfall at time *t* and at the j^{th} location, $T_{t,j}$ is the air temperature at time *t* and at the j^{th} location, the ω's and δ's are the parameters of the impulse response functions for a given location. The variable $a_{t,j}$ is a sequence of errors with zero mean and constant variance.

3.3. Parameter estimation.

A transfer function model was fitted for a single station and the remaining equations will be derived later, since this is an ongoing research project. It should be noted that the coefficients of the impulse response function characterize the terrain properties for a given location. Thus, it is assumed that ω's, and δ's, are coefficients that exhibit inherent terrain characteristics of a specific location, and consequently the spatial variability will be expressed by the coefficients of the impulse response function. Thus, evaluating the transfer function in another location that exhibits similar terrain characteristics will estimate the response of the soil-moisture dynamics. It should be noted that the self-organized neural network identifies those spatial terrain similarities.

The estimation of the transfer-function parameters is not a trivial task; it requires a well planned procedure. The proposed estimation procedure includes three main steps:

1. The first step consists of applying the periodgram and the autocorrelation function to determine whether or not the soil moisture is a stationary process. Typically, the soil moisture is a nonstationary process due to significant changes of the mean that have occurred over the time, due to rainfall long-term impact over the soil moisture response. The process becomes stationary after the trend is removed. This is accomplished by taking the first, $(1-B)h_t$, or the second, $(1-B)^2 h_t$, difference to the process or by removing a parametric function.

2. The second step consists of performing a random search to determine the initial point for the stochastic transfer function. The uniform probability distribution was used to generate 100 points over specific range and the mean square error (MSE) was used to identify a suitable initial point, i.e., the one that exhibits a small MSE. The empirical selected range that provides satisfactory results is given by two vectors:

$$L = [-2 \quad -2 \quad -0.9 \quad -2 \quad -2 \quad -0.9]$$
$$U = [2 \quad 2 \quad 0.9 \quad 2 \quad 2 \quad 0.9]$$

where *L* and *U* represent the minimum and maximum value, respectively, that can be assigned to the parameters, organized as in the following vector:

$$par = [\omega_{0,1} \quad \omega_{0,2} \quad \delta_{0,1} \quad \omega_{1,1} \quad \omega_{1,2} \quad \delta_{1,1}]$$

3. The third step consists of using the sequential quadratic programming (SQP) algorithm to estimate the parameters of the impulse response functions, (Reklaitis et al. 1983). This task was successfully accomplished by using the Matlab software (MathWorks, 2000).

It should be noted that the decay function of the soil moisture response can be controlled by the δ coefficient; the subscripts are eliminated to simplify the description. If δ is close to zero the rainfall effect on soil moisture will disappear very fast; on the other hand if the δ coefficient is close to one the rainfall effect on soil moisture will last several time intervals. If δ is larger than one, the process becomes unstable and the estimates of soil moisture increase without control (Brockwell and Davis 2002). Therefore, the values of delta must be limited to the following range: $-1 < \delta < 1$. Table 1 shows the optimal parameter estimation for each station.

3.4 Soil moisture estimation.

Once the parameters of the transfer function models have been estimated, they will be applied with radar and satellite data for a larger region. A self-organized neural network (SONN) is used to identify a grid point that exhibits the similar terrain properties to a place where a soil-moisture station is located, and the identified station is called the *similar station*. The variables used to identify the similar station were: the percentage of clay, the percentage of sand, elevation, vegetation index and the accumulated rainfall of the corresponding month. Once the SONN identifies the similar station the corresponding TF model is evaluated using radar rainfall and satellite surface temperature data. The soil moisture estimated from the long-term memory model is added to the estimated from the transfer function to obtain the final soil moisture for each grid. The final estimates from the stochastic transfer function are soil moisture in hourly basis at 1 km horizontal resolution.

4. PRELIMINARY RESULTS

The proposed algorithm is under development, i.e., only preliminary results are presented here. The long-term memory model was applied to the climatic condition of Puerto Rico. The neural network was trained with 2005 and validated with 2006 data. Since the available number of stations is small the leave 4 stations out was used to validate the neural network model.

Figures 5 to 9 shows an example of the input data to train the artificial neural network. Figure 5 shows the percentage of clay, Figure 6 shows the percentage of sand, Figure 7 shows the rainfall form the NEXRAD data for March of 2006, Figure 8 shows the MODIS vegetation index for March 2006. Figure 9 shows the MODIS difference of surface temperature for March 2006. Figure 10 shows the Puerto Rico soil moisture estimates for March 2006, and these estimates are used as the initial level for the transfer function model. Figure 11 shows the comparison of the observed and estimated values for March 2006.

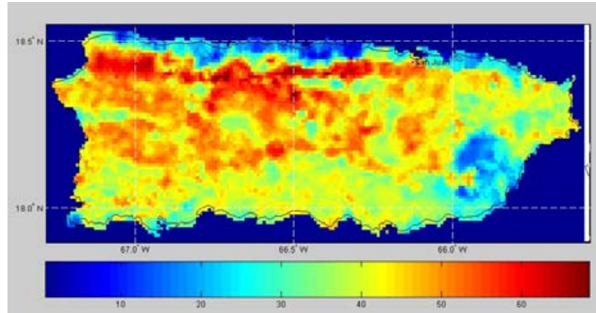

Figure 5 Percentage of clay.

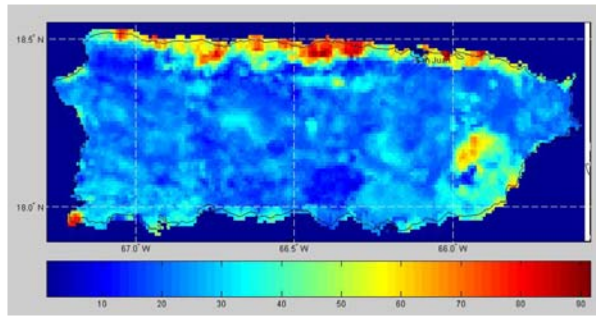

Figure 6. Percentage of sand.

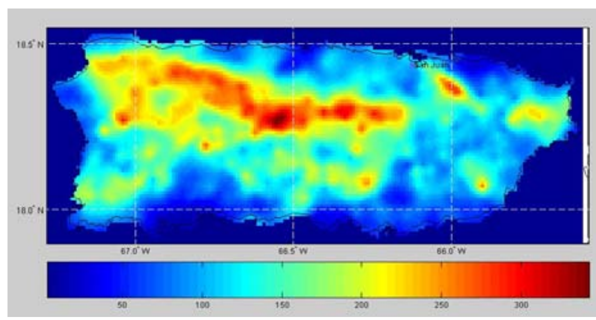

Figure 7. NEXRAD rainfall for March 2006

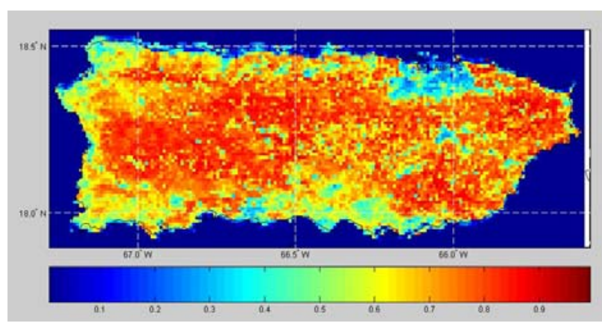

Figure 8. MODIS vegetation index for March 2006.

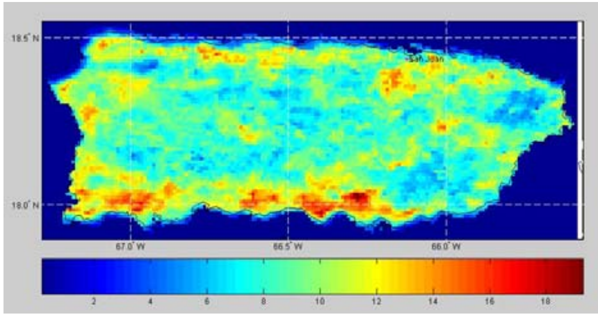

Figure 9. MODIS difference of surface temperature March 2006.

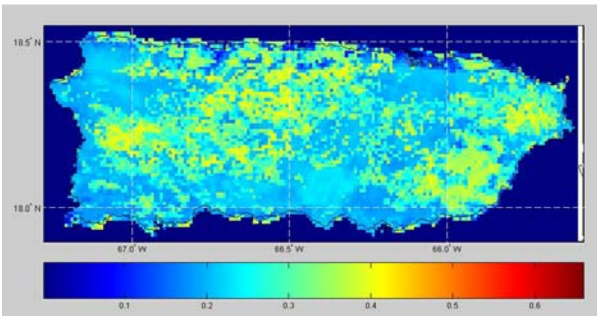

Figure 10. Estimates of soil moisture for March 2006.

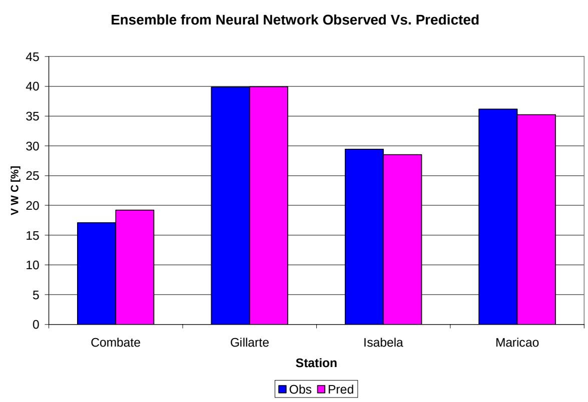

Figure 11. Comparison between the observed and estimated soil moisture for March 2006.

For purposes of showing feasibility of the proposed methodology a TF model has been developed for the Colegio station. Table 1 shows the parameter estimation results for the fitted TF model. The TF model parameters depend on the soil type, vegetation, topography and the atmospheric conditions of a given area. Thus, the value of the δ parameter of equation (7) controls the length of the soil moisture, the $\omega_{0,i}$ coefficients control the soil moisture response due to air temperature values, and $\omega_{1,i}$ coefficients control the instantaneous soil moisture response to the current rainfall. Figure 12 shows the observed and estimated soil moisture from the transfer function at Colegio station during March 2006. Hourly rainfall data was used to evaluate the TF model. Approximately the first half of the soil moisture station data were used to build the model and the remaining observations were used to perform model validation. This figure exhibits the performance of the transfer function model during the model fitting and validation process. Model validation results at 20 cm depth are presented in Table 2. The first column shows the name of the soil moisture station. The second column shows the mean absolute error (MAE) of the percentage of volumetric water content. The third column shows the mean square error (MSE) of the percentage volumetric water content.

Table 1. Soil moisture parameter estimation results for Colegio station.

Parameter	$\omega_{0,1}$	$\omega_{0,2}$	$\delta_{0,1}$
Estimation	0.021544	0.068314	0.72695
Parameter	$\omega_{1,1}$	$\omega_{1,2}$	$\delta_{0,2}$
Estimation	1.1883	0.72792	0.9

Table 2. Accuracy of soil moisture estimation at 20 cm depth.

Station Name	MAE (% v w c)	MSE
Colegio	*0.84677*	*2.2106*

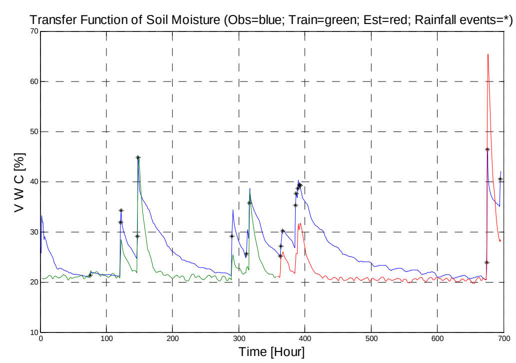

Figure 12. Validation of soil moisture TF model

Similarities of terrain characteristics for Puerto Rico were derived by using a self organized neural network. The neural network used soil texture, monthly rainfall, vegetation index, and elevation to identify the regions with similar properties. Figure 13 shows the results of the self-organize neural network. The similar regions will be used to evaluate the corresponding TF model to obtain the final soil moisture estimates.

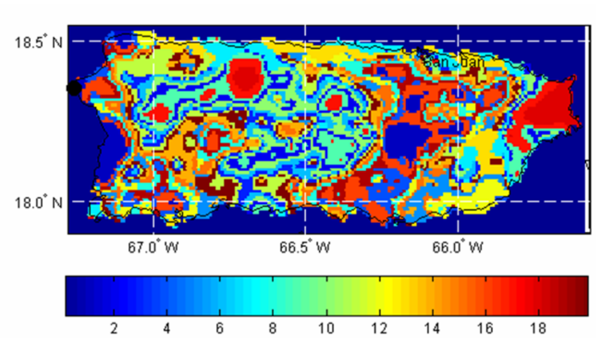

Figure 13. Areas with similar terrain properties.

5. CONCLUSIONS.

A new method for estimating soil moisture over densely vegetated areas is proposed. The estimation algorithm will include a short- and a long-term memory models.

Soil moisture behavior show that the critical variables to estimate soil moisture are: rainfall, soil texture, vegetations index and surface temperature. .

The proposed stochastic TF model has the advantage of estimating soil moisture based on rainfall, and surface temperature; assuming that the initials conditions of soil moisture over the selected area are similar to a known location. The TF model will be initialized with soil moisture information obtained from a known location that exhibits similar characteristics of the given grid. Similarities are identified by using a self-organized neural network with the following discriminate variables: accumulative precipitation of the current month, soil texture, vegetation index and elevation. Once similarities of spatial variability are found the TF model is evaluated using rainfall from radar and surface temperature from satellite.

7. ACKNOWLEDDGEMENTS

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