3.7 DISAGGREGATION OF MICROWAVE REMOTE SENSING DATA FOR ESTIMATING NEAR-SURFACE SOIL MOISTURE USING A NEURAL NETWORK

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1. INTRODUCTION

1.1 Statement of problem

Estimation of soil moisture using microwave remote sensors holds great promise for many applications, including numerical weather prediction and agriculture. However, a scale disparity exists between the resolutions of future satellite-borne microwave remote sensor data (30-60 km) and the much finer scales at which soil moisture estimates are desired (~ 1 km). Hydrology models may be useful for bridging this gap, as the factors controlling soil moisture variability (precipitation, soil and vegetation properties, topography) are known with reasonable accuracy at fine spatial scales and can be used in models to estimate the spatial distribution of soil moisture at high resolutions. Therefore, in order to facilitate the assimilation of remote sensing data, it is important to explore ways to disaggregate low-resolution passive microwave remote sensing data to the higher resolution of a hydrologic model.

1.2 Scientific Objective and Approach

The objective of this study is to test the performance of a Neural Network-based model, called DisaggNet, developed to address the feasibility of disaggregating low-resolution satellite microwave remote sensing data to estimate soil moisture, and to quantify estimation errors as a function of input data resolution. Ideally, the purpose of a disaggregation scheme is to produce the 'correct' high-resolution (sub-pixel) pattern of soil moisture from lower-resolution remotely-sensed observations. However, there are several practical issues to address in developing such a scheme. First, the 'correct' sub-pixel soil moisture pattern within a satellite footprint is rarely, if ever, known within acceptable error bounds. Thus, the data for developing statistical models or more complex models such as neural networks, both of which rely on some type of data fitting, do not exist, and may never exist, for areas larger than field scale. When satellite data become available operationally on a global scale, it may be possible to develop a disaggregation scheme using a combination of remotely-sensed data and land surface hydrology/radiative transfer model output. Currently, however, high-resolution data from aircraft platforms are available for limited areas and times during intensive field experiments. While these could theoretically be used to develop a disaggregation scheme, the results would likely not be transferable to other geographical areas or even to different hydrometeorological conditions in the same region. Furthermore, the amount of data needed to adequately train a neural network exceeds the amount obtained in a typical field campaign.

Because of this paucity of remotely-sensed observations, we believe that the most tenable approach is to train a neural network using solely model output, and then test its performance using the remotely-sensed data. In this scenario, model-simulated data serves as a proxy for satellite-borne microwave remote sensor data. This approach requires the following assumptions:

1. The surface hydrology/radiative transfer model accurately simulates the spatial patterns of soil moisture and brightness temperature within a satellite footprint, although the footprint mean may be biased with respect to the ground truth.
2. The low-resolution brightness temperature observations are unbiased and have a known noise variance with respect to the ground truth.

In other words, the neural network is designed to reconstruct the model (high-resolution) soil moisture pattern within a satellite footprint while preserving the mean remotely-sensed brightness temperature (T_B) or microwave emissivity (ε), which may differ significantly from the model mean over the footprint. To the extent that the emissivity-soil moisture relationship is linear, the neural network will also preserve the footprint-mean soil moisture.

In this paper we present a description of the disaggregation methodology and results related to training and testing of the scheme using solely model data. In future research we will apply the scheme to aircraft remote sensing data as a more relevant application of the method.

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2. DESCRIPTION OF MODELS AND DATA

2.1 Models

SHEELS

The land surface flux-hydrology model used in this study is SHEELS (Simulator for Hydrology and Energy Exchange at the Land Surface), the physics of which are based on the Biosphere-Atmosphere Transfer Scheme (BATS) of Dickinson et al. (1993). Variables such as surface energy fluxes and temperatures are modeled similarly to an earlier version of the model (Smith et al. 1993). Sub-surface processes in SHEELS differ significantly from BATS (Crosson et al., in press). In SHEELS, the number and depth of soil layers is user-defined, permitting higher vertical resolution near the surface where temperature and moisture gradients are large. The soil water dynamics algorithms in SHEELS include Darcy flow to model vertical sub-surface fluxes and a kinematic wave approach to simulate overland flow. Together, these modules estimate the three-dimensional soil water fluxes.

Forward radiative transfer model

The forward radiative transfer model (RTM) coupled with SHEELS is based on the coherent wave model of Njoku and Kong (1977) and is used to estimate L-band microwave brightness temperature. The effects of surface roughness and vegetation are corrected for using accepted techniques. Required RTM inputs of surface temperature and soil moisture and temperature profiles are provided through the coupling with SHEELS. The remaining input variables (surface roughness, vegetation water content and soil density profiles) are based on measurements.

Disaggregation Neural Network (DisaggNet)

We have approached the problem of disaggregation using a linear Artificial Neural Network (ANN). The ANN chosen is the simplest imaginable ANN, consisting of a single neuron. All of the inputs are weighted and then summed. The input to output mapping function is linear. Inputs and outputs of DisaggNet are described in section 2.3.

2.2 Model domain and data

We have applied the disaggregation scheme using data collected across the Little Washita River Basin (LWRB) in central Oklahoma (Figure 1) during the Southern Great Plains 1997 Hydrology Experiment (SGP '97) conducted during June and July, 1997 (Jackson, 1999). Aircraft remote sensing data were collected on near-daily basis by the Electronically Steered Thinned Array Radiometer (ESTAR) for a region of approximately 40 x 280 km region encompassing the LWRB. We restricted our simulations to the approximate 600 km^2 area of the LWRB because it contains the highest concentration of meteorological and soil moisture measurements in the SGP '97 experimental domain. The time period for which we have applied the disaggregation scheme is from 18 June (DOY 169) through 20 July (DOY 201).

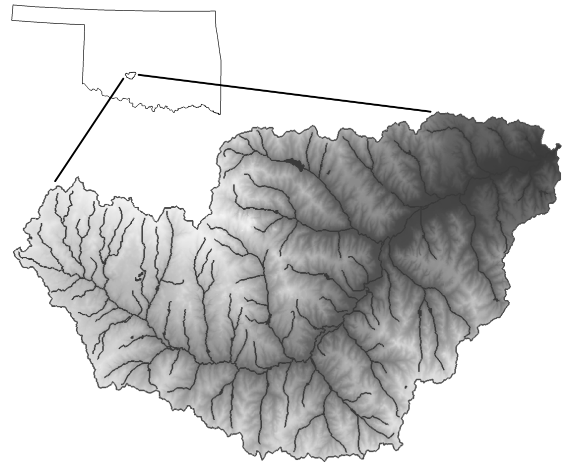

Fig. 1. Digital Elevation Model and stream network for the Little Washita River Basin, OK.

A model grid of 800 m was used in model simulations. Land surface properties were specified on that grid in SHEELS by the following data sets:

- Elevation, slope: USDA/ARS 30 m DEM
- Hydrography: USGS DLG's
- Vegetation parameters: SGP '97 30 m Land Cover
- Soil properties: CONUS 1 km multi-layer soil characteristics
- Meteorological and soil moisture and temperature data: Oklahoma Mesonet, USDA/ARS Micronet, SGP '97 soil profile stations
- Precipitation: USDA/ARS Micronet raingage data

Original data were aggregated using the mean or mode, whichever was more appropriate. The CONUS soil properties were resampled to the model grid; surface soil texture classes are shown in Figure 2. Meteorological data, with the exception of rainfall, were averaged across all sites and applied uniformly across the LWRB. Micronet raingage point measurements were converted to 800 m gridded data by constructing Thiessen polygons around each gage location.

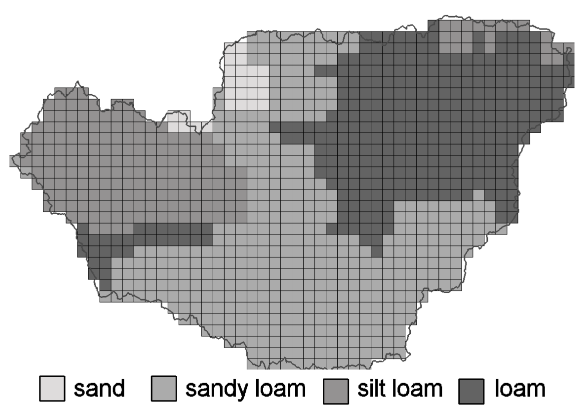

Fig. 2. Surface soil texture classes for the LWRB, OK.

Figure 3 shows the temporal behavior of basin-mean near-surface (0-5 cm) fractional water content estimated at hourly time steps by SHEELS. This quantity is the proportion of saturation and is defined as volumetric water content divided by soil porosity. From the beginning of the period until day 191, there was a general drying trend, interrupted by four minor rain events. On days 191-192 a substantial basin-wide rain event occurred, with a basin mean rainfall of 46.7 mm. This resulted in the wettest observed conditions, with much of the watershed, especially the western end, briefly reaching saturation.

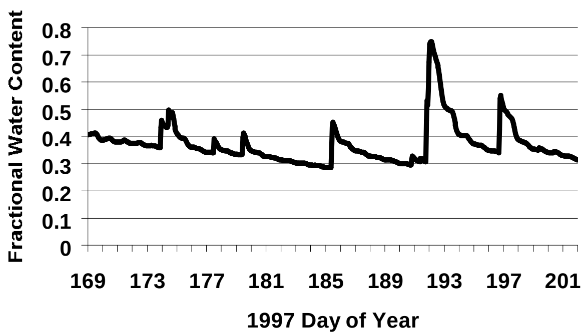

Fig. 3. Basin-mean fractional soil water content estimated by SHEELS for the 0-5 cm layer.

3. DISAGGNET TRAINING USING MODEL OUTPUT

As discussed in section 1, our approach was to train DisaggNet using soil moisture and emissivity output from the coupled SHEELS/RTM model. In so doing, the DisaggNet learns a 'mapping' from low (sensor) resolution ε to high (model) resolution soil moisture that is conservative in ε at the footprint scale and seeks to replicate the model patterns of soil moisture. We use ε instead of T_B to eliminate the diurnal cycle caused by surface temperature variations. The accuracy of this relationship depends on how well SHEELS/RTM characterizes these sub-pixel scale patterns, i.e. the validity of our first assumption. Once DisaggNet is trained, this mapping can be applied to actual remotely-sensed observations. Because the mapping preserves the pixel-scale means, any large-scale errors in the model estimates will be 'corrected' via application of DisaggNet, based on our second assumption that the remotely-sensed measurements are unbiased with respect to ground truth.

Model outputs used to train and validate DisaggNet were generated by running SHEELS/RTM at an hourly time step over the LWRB for the 33-day study period beginning at 0:00 UTC on day 169. Initial soil moisture conditions were specified using the ESTAR estimates from that morning. The model produces, among other variables, soil moisture, T_B and skin temperature at each model time step on the 800 m model grid. L-band emissivity was calculated by dividing T_B by skin temperature. Emissivity was then aggregated by averaging over 2x2, 4x4, 8x8, 16x16 and 32x32 grid cells. An independent Normal random deviate with zero mean and a standard deviation of 0.02 was added to each aggregated emissivity value to more realistically represent actual remotely-sensed microwave observations. The emissivity standard error of 0.02 corresponds to a standard error in T_B of 6 Kelvins for a skin temperature of 300 K, or approximately 2% in volumetric water content.

DisaggNet was trained to predict high-resolution SHEELS upper zone (0-5 cm) fractional soil moisture using approximately one-half of the study period (350 consecutive hours from days 179-193) over all pixels simultaneously. Training was performed separately for each emissivity aggregation (2x2 pixels, 4x4, etc.) Once trained, DisaggNet generalizes to estimate outputs for times outside of the training period. DisaggNet is trained with the following inputs:

- Remotely sensed (low-resolution) emissivity with noise
- Antecedent precipitation for the following time periods, in hours prior to current time: 0-1, 1-3, 3-6, 6-12, 12-24, 24-48, 48-96 and 96-192
- Clay content
- Sand content
- Vegetation water content
- Upstream contributing area (surface area draining into a grid cell)

4. VALIDATION OF DISAGGNET SOIL MOISTURE ESTIMATES

At each model time step, the trained DisaggNet generates estimates of fractional soil water content at each grid cell using the inputs listed above. Two points in time were selected to demonstrate the performance of DisaggNet. These times fall within the period used to train DisaggNet, so this is not an independent test, but were selected because they are close to the driest and wettest times in the study period. Output from DisaggNet for two input resolutions (2x2, or 1.6 km, and 16x16, or 12.8 km) is compared with SHEELS soil moisture estimates for these two times in figures 4-5. As shown in fig. 4 for dry soil conditions at 1400 UTC on day 184, the SHEELS soil moisture pattern is captured by DisaggNet using either 1.6 km or 12.8 km input. This is not unexpected as the input emissivities are derived from the SHEELS soil moisture via the RTM. The sources of differences between soil moisture estimated by DisaggNet and by SHEELS are (1) aggregation of emissivity, (2) random noise added to the emissivity, and (3) inherent error associated with the Neural Network. In this case the 1.6 km inputs produce an overall soil moisture estimate that is slightly biased toward higher values with respect to SHEELS, while the 12.8 km inputs produce virtually unbiased estimates, but with greater noise.

Fig. 4. DisaggNet soil moisture estimates for the dry soil case for 1.6 km (top) and 12.8 km (middle) aggregated emissivity input, compared to SHEELS 0-5 cm soil moisture (bottom). Light shading corresponds to low soil moisture, dark to high soil moisture.

The wet case corresponds to 1400 UTC on day 192 and is shown in fig. 5. The anomalously dry area just northeast of the center is due to missing rainfall observations from the gage in that area. This 'feature' is well-estimated in the DisaggNet output using 1.6 km emissivity, but is not captured quite as well in the 12.8 km case.

Fig. 5. Same as fig. 4 except for the wet soil case, with a different gray scale.

A quantitative evaluation of the agreement between soil moisture estimated by DisaggNet and by SHEELS is shown in figure 6 in the form of root-mean-square differences (RMSD) across the LWRB at each model time step (hour). Outside of the very wet periods, RMS differences for both cases tend to be between 0.03 and 0.07 (3-7% fractional water content, or 1.5-3.5% volumetric water content). However, during and immediately following rain periods, errors become quite large – typically greater than 0.10 and occasionally above 0.15. Surprisingly, RMS differences in fractional water content are slightly higher for the 1.6 km case than for the 12.8 km case, with mean values of .053 and .048, respectively. We believe that this is related to way the random noise was added to the input emissivity, but this is an area of ongoing investigation.

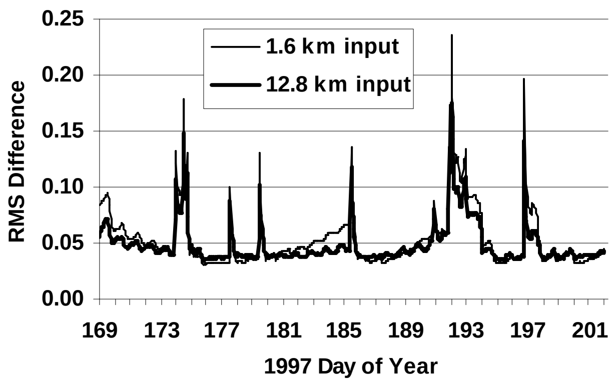

Fig. 6. Root-mean-square difference time series between fractional water content estimated by SHEELS and by DisaggNet using inputs aggregated to 1.6 km and 12.8 km grid cells. The time period used for training was from day 179-193.

The spatial distribution of DisaggNet-SHEELS root-mean-square differences in fractional water content, averaged over the 33-day study period, is shown in figure 7 for the 12.8 km case. RMS differences are slightly higher in the western part of the basin, where rainfall was greater, but are less than 0.1 for almost the entire basin. The two points that are shown as having very high RMS differences are, in fact, classified as water bodies in SHEELS, where the soil is treated as always saturated. This condition is not well handled by DisaggNet due to its linear mapping functions.

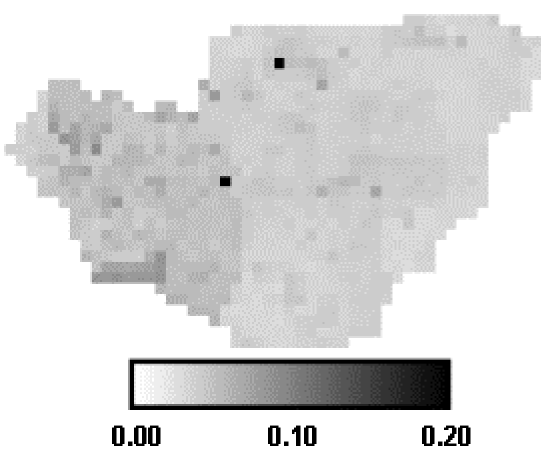

Fig. 7. Root-mean-square differences averaged over the 33-day study period, between fractional water content estimated by SHEELS and by DisaggNet using inputs aggregated to 12.8 km grid cells.

5. SUMMARY AND CONCLUSIONS

A neural-network based scheme called DisaggNet has been developed for disaggregating low-resolution satellite microwave remote sensing data to higher resolutions compatible with hydrologic data requirements. DisaggNet has been trained using output from a coupled hydrologic/radiative transfer model using input data from the SGP '97 field experiment. Results are shown here with a focus on the driest and wettest days during the study period.

In this procedure, microwave emissivity was simulated by the coupled model and used as input to train the disaggregation scheme. Emissivity data were degraded to various resolutions by simple averaging from the model resolution of 800 m, and random Gaussian noise was added. Results are shown here for the cases using 1.6 km data (2x2 pixel averaging) and 12.8 km data (16x16 averaging). Overall, the 12.8 km inputs produced slightly lower RMS differences with model-simulated soil moisture, a result that can not be explained at this time. RMS differences are quite low during dry periods, but much larger under very wet conditions. We believe that this is due to an overestimation of soil moisture in the presence of heavy rainfall, which results from the linear nature of the rainfall-soil moisture relationship inherent in DisaggNet. For the same reason, wetlands or water bodies that are constantly saturated are also not well-simulated by the disaggregation scheme.

6. ACKNOWLEDGMENTS

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