Microwave Soil Moisture Remote Sensing

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ABSTRACT

Everyone has observed the darkening, or decrease in reflectance, of soil when it becomes wet. This distinct threshold between wet and dry surfaces suggests the concept that remote-sensing of soil moisture is possible. Microwave remote sensing offers most potential for truly quantitative soil moisture measurements, and has the distinct advantage of being able to penetrate cloud cover, some vegetation, and soil to quantify soil moisture below the surface. Both passive and active microwave remote sensing of soil moisture are based on the large changes in the soil dielectric constant with changing soil moisture. Water has a dielectric constant of 80 at the lower microwave frequencies that results from the alignment of the permanent electric dipole of the water molecule. This is much higher than the dielectric constant of 3 to 5 for dry soils. These properties produce a large range of soil emissivities (from about 0.95 for dry soils to 0.6 or less for wet soils) with changes of corresponding magnitude in the soil's reflectivity. However, the microwave emission of land surfaces is also dependent on surface roughness, vegetative cover, soil heterogeneity, incidence angle, surface cover heterogeneity, atmospheric effects, and mixed scenes, which can obscure the soil moisture signal. A 21-cm wavelength, L-band passive microwave sensor is considered to be the best soil moisture sensor because it has little contamination by vegetation and roughness, it has no man-made contamination sources, and it penetrates the soil to a depth of several centimeters. The drawbacks are that it requires a very large antenna to get reasonable spatial resolution. Several airborne L-band radiometers (PBMR and ESTAR) have been used to successfully quantify soil moisture in a variety of field experiments (FIFE, HAPEX, MACHYDRO, MONSOON90, WASHITA 92-94, SGP97, etc.), and there are currently efforts underway to deploy a L-band radiometer is space (i.e. HydroStar). An overview of the theory and limitations of microwave soil moisture remote sensing, a review of past microwave remote sensing experiments, and a look towards the future application of this promising technology are presented.

The quality of microwave soil moisture observations is limited by roughness and vegetation induced noise, the depth of observation is limited to the top few centimeters of soil, and the frequency of observations will be limited to every few days. However, nearly-continuous spatial-temporal distribution of near-surface soil moisture is central to the regulation of land-atmosphere water, energy, and carbon interaction. The development of land hydrology parameterizations that emphasize soil moisture, and innovative microwave remote sensing for measuring soil moisture, together promise a mechanism for the synthesis of continuous four-dimensional fields of this vital hydrologic variable using data assimilation methods. Schemes for the four-dimensional data assimilation (4DDA) of remotely-sensed microwave soil moisture were developed by Houser *et al.* [1998] that could ultimately be applied at the regional scale. The assimilation of remotely-sensed soil moisture leads to an improved characterization of near-surface soil moisture space-time dynamics and attendant processes, and contributes to an improved understanding of surface soil moisture scaling behavior and its impact on surface flux parameterization. A brief overview of this research is given below.

MONSOON '90 SOIL MOISTURE DATA ASSIMILATION

Surface soil moisture derived from the passive microwave L-Band observations of NASA's Push Broom Microwave Radiometer (PBMR) [Schmugge *et al.*, 1994] was assimilated into the TOPLATS [Famiglietti and Wood, 1994] land surface model using several approaches.

Direct insertion, the simplest form of data assimilation, assumes that observations are perfect and model calculations contain no information. Model state variables are simply replaced with observed data at the time of the observation in an updating scheme, and no spatial propagation of the observations are made. Updating was found to improve model predictions in the areas where soil moisture was observed, but it created undesirable discontinuities in model predictions, preserved local observation error patterns, and was unable to extend information from the observation region to other areas.

A second very simple assimilation technique, which we term 'statistical correction', was developed to address some of the weaknesses of updating. This technique involves adjusting the mean and standard deviation of the entire model domain to match the mean and standard deviation of the observation image. It is only applicable to areas that have large numbers of observations (such as remotely sensed data), and is computationally efficient. In the time domain it performs similarly to updating, but is also able to spread observation information horizontally and it does not preserve local observation errors within the model fields.

Newtonian nudging was implemented to address deficiencies on the above-described simple data assimilation methods and to extend information vertically into the root and transmission zones. Newtonian nudging adds an increment to the model's prognostic equation that nudges the model toward an observation or set of observations in a predefined space-time window using the equation:

$$\frac{\partial \alpha}{\partial t} = F(\alpha, X, t) + GW(\alpha_o - \alpha) \qquad (1)$$

where α is the state variable being predicted by the model; α_o is the observation of α; F is the forcing on α, which depends on previous values of α, other model fluxes X, and time t; G is the nudging coefficient, which accounts for the observational quality; and W is the four dimensional weighting function. These weights are determined using a set of three simple, predefined (horizontal, vertical, and temporal) functions which assign a weight to an observation that decreases as that observation's temporal and spatial distance increases from the model point being corrected.

The Newtonian nudging methodology, was found to result in spatial patterns that are very similar to those derived from the statistical correction methodology, but it gave the added benefit of vertical assimilation and more gradual temporal change.

Statistical Interpolation is implemented using the following equation:

$$f_A(r_i) = f_B(r_i) + \sum_{k=1}^{K} W_{ik}[f_O(r_k) - f_B(r_k)] \qquad (2)$$

where K is the number of observation points, W_{ik} is the weight function, $f(r)$ is the analysis variable (soil moisture), r is the three-dimensional spatial coordinates, $f_Z(r_i)$ is the analyzed value of f at the analysis gridpoint r_i, $f_B(r_i)$ is the background, or first guess value of f at r_i, and $f_O(r_k)$ and $f_B(r_k)$ are the observed and background values, respectively, and the observation station r_k. The weights are determined by least squares minimization of the above equation. With the assumptions of no correlation between background and observation error and isotropic, time invariant error correlation, the weight can be found by solving K equations for K unknowns, thus

$$\sum W_{il}[\rho_B(r_l-r_k)+\epsilon^2_{O}\rho_O(r_l-r_k)]=\rho_B(r_l-r_k) \qquad (3)$$

where ρ_O is the observation error correlation matrix, and ρ_B is the background error correlation matrix. Solving for K (~35,000 per PBMR image) unknowns with K equations for each grid in the model domain (~90,000) poses a excessive computational demand. Therefore, the problem was scaled down using a random selection of observations including the closest observation which contains the most information, or by computing 'super observations' which are simple averages of observation groups. The random approach approximates the fully-posed problem giving undesirable banding patterns outside the observation area, and the super observation approach yields smoother, more realistic spatial patterns.

Figure 1 shows the temporal surface soil moisture improvements, and Figure 2 gives examples of typical spatial patterns for each of the assimilation techniques described.

Important new contributions are made here, the most significant being the assimilation of soil moisture data into a spatially distributed hydrological model, enhancing prediction ability.

4. REFERENCES

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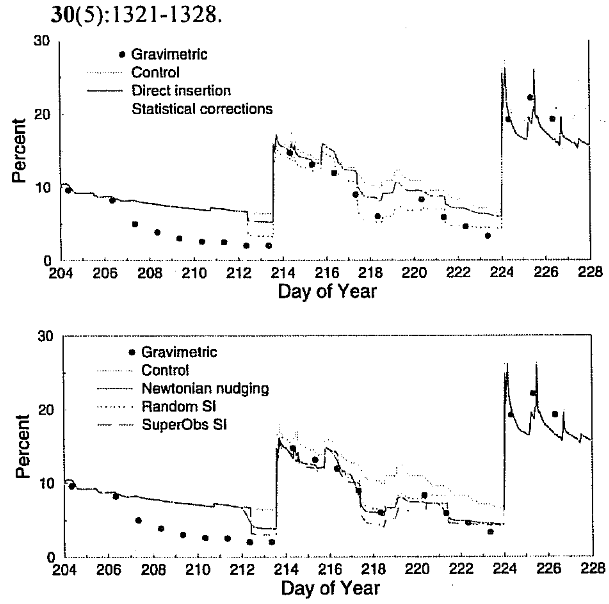

Figure 1: Temporal areal average surface soil moisture patterns produced by various assimilation techniques.

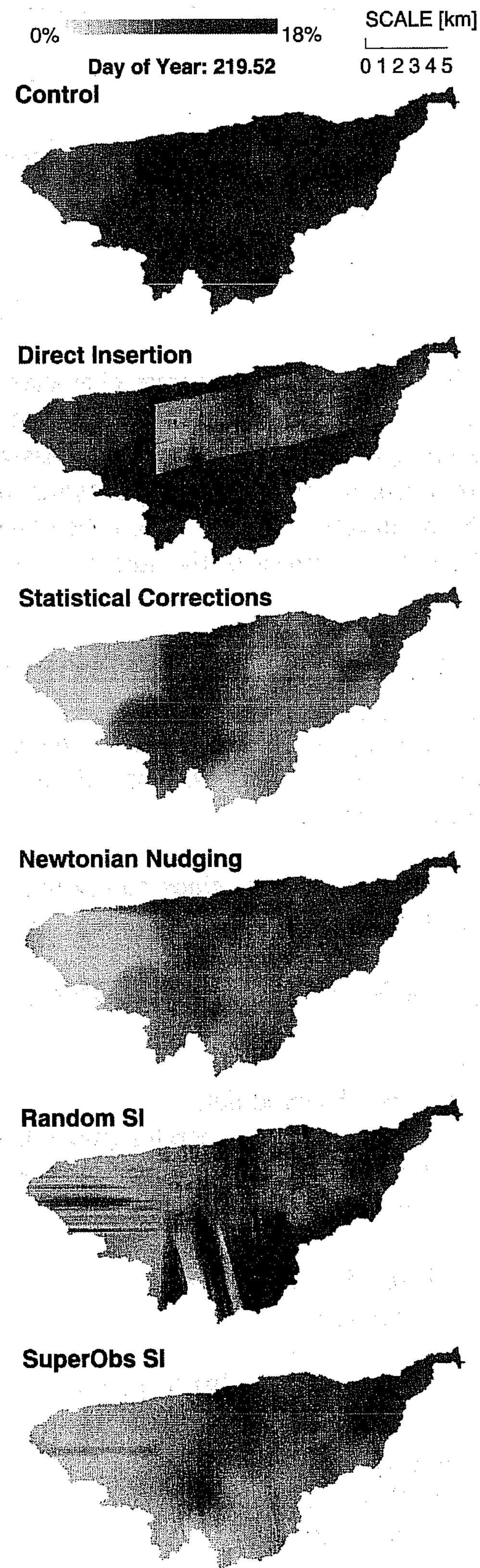

Figure 2: Typical spatial patterns (day of year=219) produced by a) no assimilation, b) direct insertion, c) statistical corrections, d) nudging, and e) random observation and f) super observation statistical interpolation.