International Conference "Water, Environment, Energy and Society" (WEES–2009)
New Delhi, 12–16 January 2009

Effective Soil Hydraulic Parameter Estimation at Different Spatial Scales

Binayak P. Mohanty[1], Narendra N. Das and Raghavendra B. Jana
Department of Biological and Agricultural Engineering
Texas A&M University, College Station, TX 77840, USA
E-mail: [1]bmohanty@tamu.edu

Amor V.M. Ines
International Research Institute for Climate and Society
Columbia University, Palisades, NY 10964, USA

ABSTRACT: A review of multiple approaches to the problem of soil hydraulic parameter estimation at different spatial scales is presented. Methods reviewed include traditional bottom-up approaches, as well as newer top-down approaches such as use of genetic algorithms, Monte Carlo simulations, and data assimilation; and multiscale methods such as artificial neural networks.

INTRODUCTION

Soil hydraulic properties (hydraulic conductivity, water retention) are by far the most important land surface parameters to govern the partitioning of soil moisture between infiltration and evaporation fluxes at a range of spatial scales. However, an obstacle to their practical application at the field, catchment, watershed, or regional scale is the difficulty of quantifying the "effective" soil hydraulic functions *theta(h)* and *K(h)*, where *theta* is the soil water content, h is the pressure head and K is unsaturated hydraulic conductivity. Proper evaluation of the water balance near the land-atmosphere boundary depends strongly on appropriate characterization of soil hydraulic parameters under field conditions and at the appropriate process scale. In recent years a multi-facet approach has been adopted to tackle this problem including: (1) a *bottom-up* approach, where larger-scale effective parameters are calculated by aggregating point-scale *insitu* hydraulic property measurements, (2) a *top-down* approach, where effective soil hydraulic parameters are estimated by inverse modeling using remotely sensed soil moisture measurements, and (3) an *artificial neural network* approach, where effective soil hydraulic parameters were estimated by exploiting the correlations with soil texture, topographic attributes, and vegetation characteristics at multiple spatial resolutions. Numerical and experimental results using these various effective soil hydraulic parameter estimation approaches including some comparisons between the approaches are presented.

BOTTOM-UP APPROACH

Traditional Soil Physics

For meso-/regional-scale Soil-Vegetation-Atmosphere Transfer (SVAT) schemes in hydro-climatic models pixel dimensions may range from several hundred square meters to several square kilometers (Figure 1).

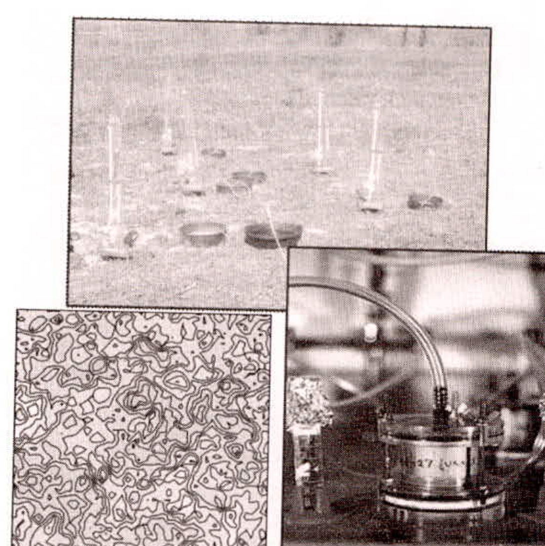


Fig. 1: Hydraulic property measurement across the pixel: Bottom-up approach

Pixel-scale soil hydraulic parameters and their accuracy are critical for the success of hydro-climatic and soil hydrologic models. Thus for a typical soil textural combination in a real field condition (Figure 2), what will be the effective/average hydraulic properties for the entire field (pixel), if soil hydraulic properties can be estimated for each individual texture?

Numerical simulations of unsaturated flow typically use closed-form functions to represent water-retention characteristics and unsaturated hydraulic conductivities. Gardner's exponential model of hydraulic conductivity, Brooks and Corey and van Genuchten soil water retention functions represent some of the most widely used models.

Gardner-Russo Model,

$$K = K_s e^{-\alpha\psi} \qquad \dots (1)$$

Brooks-Corey Model,

$$K(\psi) = K_s(\alpha\psi)^{-\beta} \qquad \alpha\psi > 1 \qquad \dots (2)$$

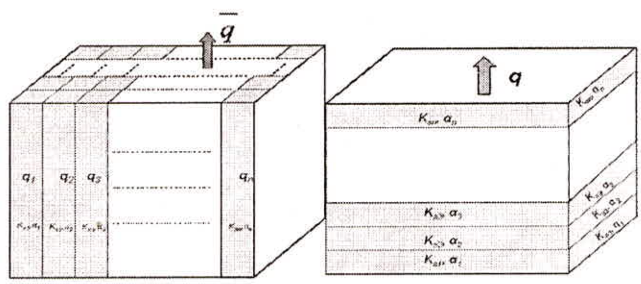
$$K(\psi) = K_s \qquad \alpha\psi \pounds 1 \qquad \dots (3)$$

Van Genuchten Model,

$$K(\psi) = K_s\left\{1-(\alpha\psi)^{mn}\left[1+(\alpha\psi)^n\right]^{-m}\right\}^2 \Big/ \left[1+(\alpha\psi)^n\right]^{ml} \qquad \dots (4)$$

where ψ is the pressure head, K_s is the saturated hydraulic conductivity, α and l are related to pore-size distributions, m and n are empirical parameters, l is a parameter which accounts for the dependence of the tortuosity and the correlation factors on the water content estimated to be about 0.5 as an average for many soils.

When these models are used in large heterogeneous scale processes, major questions remain about how to average hydraulic properties over a heterogeneous soil volume and what averages of hydraulic property shape parameters to use for these models. The purpose of this approach is to provide some guidance for upscaling hydraulic properties of both horizontally and vertically heterogeneous field. Some specific objectives of our ongoing studies include: (1) addressing the impact of averaging methods of shape parameters, parameter correlation, correlation length on ensemble flow behavior in heterogeneous soils; (2) developing effective parameters that will predict ensemble behavior of the heterogeneous soils; and (3) investigating the effectiveness of the "effective parameters" in terms of the degree of correlation between parameters for the steady state and transient evaporation and infiltration in unsaturated soil (Mohanty and Zhu, 2007; Zhu and Mohanty 2002a, b, c; 2003–2004, 2006; Zhu *et al.*, 2004, 2006). We investigate the effective parameters under various flow scenarios and field conditions, such as the dryness of the fields, the presence of plant roots. We also study the importance of parameter statistics, especially the skewness of the hydraulic parameters which was usually not considered in previous studies, on the effective parameters.



Schematic view of hydraulic parameter heterogeneity, (Left) horizontal (areal) heterogeneity; (Right) vertical heterogeneity

Fig. 2: Horizontal vs. vertical heterogeneities

For vertically heterogeneous soils, effective coefficient for the upscaled α^* field is consistently greater than 1, indicating that the arithmetic mean is too small. The effective coefficient for the K_s field is consistently smaller than 1, meaning that the arithmetic mean is too large. In other words, the heterogeneous medium does not discharge as much moisture flux as the equivalent homogeneous medium of arithmetic mean values for the hydraulic parameters. For horizontally heterogeneous soils, effective coefficient for the α^* field is generally smaller than 1, meaning that the arithmetic mean is too small. For the situation of evaporation, the effective coefficients are dictated more by the α^* heterogeneity, while for the scenario of infiltration they are mainly controlled by the K_s variability. For the case of vertical heterogeneity, α^* heterogeneity dominates the effective coefficients.

TOP-DOWN APPROACH

Pixel-based effective soil hydraulic parameters are paramount for large-scale hydro-climate modeling. As remotely sensed soil moisture data become widely available in the future, the prospect of quantifying such effective parameters would be more a reality (Figure 3). Currently, soil moisture data from Remote Sensing (RS) are limited to the near-surface soil layers. Under minimal vegetation cover, the maximum penetration depth of a microwave L-band sensor is about 5 cm. Many studies have been done to retrieve soil moisture profiles using these near-surface data. Less efforts have been made towards quantifying the effective soil hydraulic parameters, which are prerequisites of a soil moisture retrieval procedure. This practice is common because they are assumed to be initially known. Under such spatial scale, due to model uncertainties caused by spatial and process aggregation, it is but worthy to derive these parameters using the observed hydrological data.

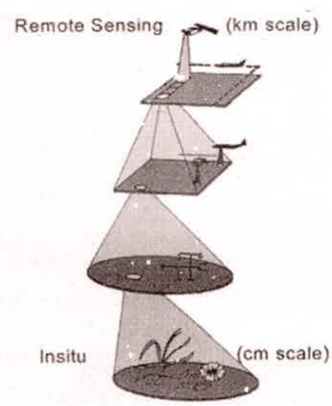


Fig. 3: Hydraulic property estimation across the pixel: Top-down approach

The main objective of this approach (Ines and Mohanty, 2008a, b, c) is to develop a method that can be possibly used to quantify these effective soil hydraulic parameters. This is the first stage of this study thus we chose to conduct field scale numerical studies to explore better the proposed approach by accounting several possible scenarios that can be encountered in the field. The research questions that we aim to address are: (1) can we quantify the effective soil hydraulic parameters in the soil profile using near-surface soil moisture data?; and (2) how robust are they, can they describe the processes occurring at the sub-surface layers of the soil? Figure 4 below shows the schematic of the research problem. The near-surface soil moisture data (Figure 5) is used to derive $\theta(h)$ and $K(h)$ assuming the constitutive functions of Mualem-Van Genuchten. The vertical soil water movement in the unsaturated zone is defined by the Richards' equation.

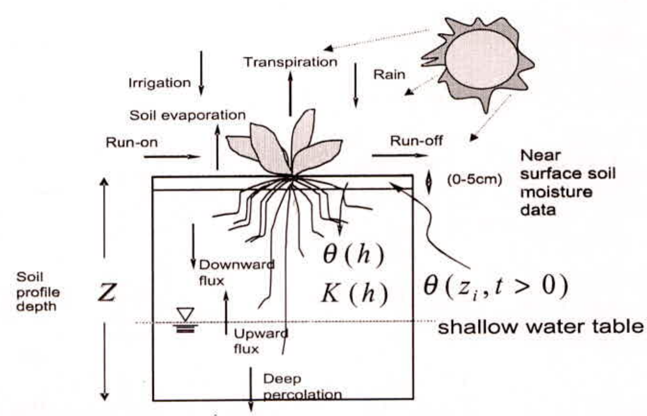


Fig. 4: Schematic of top-down research problem

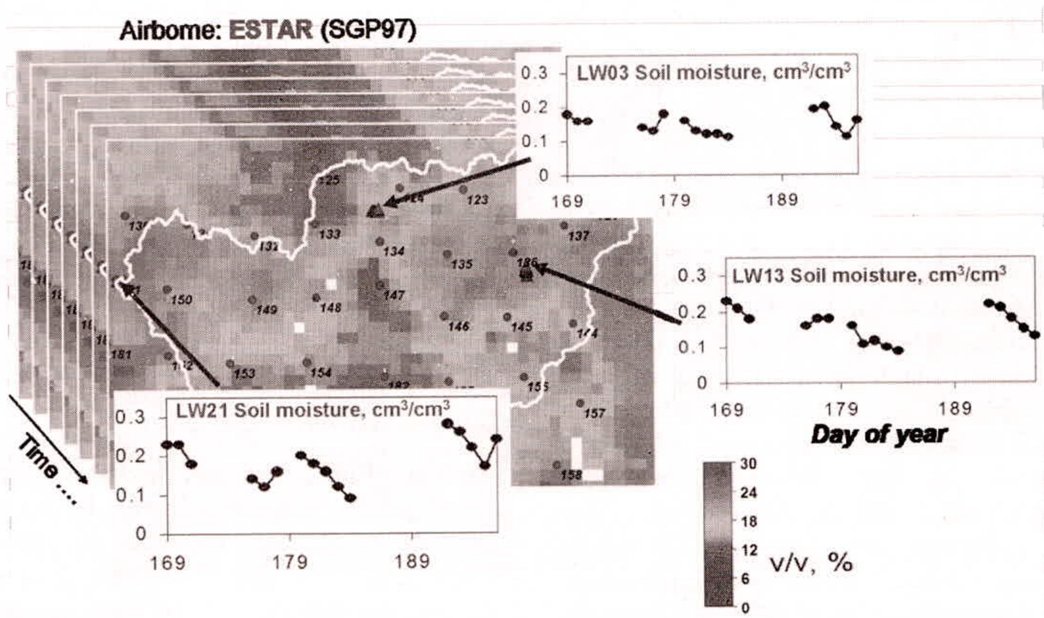


Fig. 5: Remote sensing soil moisture data

Sample results from this approach are shown in Figure 6 below.

Soil hydraulic parameters

	Statistics	α	n	θ_{res}	θ_{sat}	K_{sat}
LW03	Mean	0.022	1.601	0.101	0.373	46.0
	Std. Dev.	0.006	0.012	0.005	0.005	6.1
LW13	Mean	0.023	1.570	0.062	0.391	30.3
	Std. Dev.	0.006	0.043	0.001	0.020	15.3
LW21	Mean	0.026	1.577	0.118	0.379	30.7
	Std. Dev.	0.006	0.027	0.008	0.010	14.9

(Sandy Loam): cross-validation SGP97 site 133

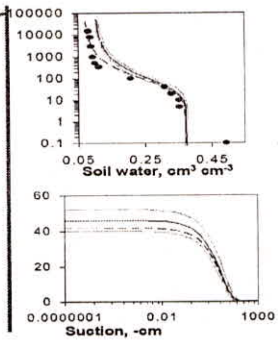


Fig. 6: Sample results

Noisy Monte Carlo Genetic Algorithm

In another study (Ines and Mohanty, 2008d), we used the concept of the noisy Genetic Algorithm (NMCGA) to develop a more generic method to estimate the effective soil hydraulic parameters (and their uncertainties) at the satellite RS footprint scale. The main assumption of our domain-dependent parameter estimation concept is based on the idea that the effective forms of the soil hydraulic functions (at the RS footprint) can be inferred by the derived effective soil hydraulic parameters from large scale RS soil moisture data inversion. A flow chart representation of the assimilation process is shown in Figure 7.

In the synthetic case studies under pure (one soil texture) and mixed-pixel (multiple soil textures) conditions, NMCGA performed well in estimating the effective soil hydraulic parameters even with pixel complexities contributed by various soil types and land management practices (rainfed/irrigated). With the airborne and satellite remote sensing cases, NMCGA also performed well for estimating effective soil hydraulic properties so that when applied in forward stochastic simulation modeling it can mimic large-scale soil moisture dynamics. The results also suggest a possible scaling down of the effective soil water retention curve θ(h) at the larger satellite remote sensing pixel compared to air-borne remote sensing pixel. Hypothetical behavior of the effective soil hydraulic properties at different scales is shown in Figure 8.

MCMC Algorithm for Upscaled SVAT Modeling

In yet another study (Das *et al.*, 2008a), a Markov chain Monte Carlo (MCMC) based algorithm was developed to derive upscaled land surface parameters for a Soil-Vegetation-Atmosphere-Transfer (SVAT) model using time series data of satellite-measured atmospheric forcings (e.g., precipitation), and land surface states (e.g., soil moisture and vegetation). This study focuses especially on the evaluation of soil moisture measurements of the Aqua satellite based

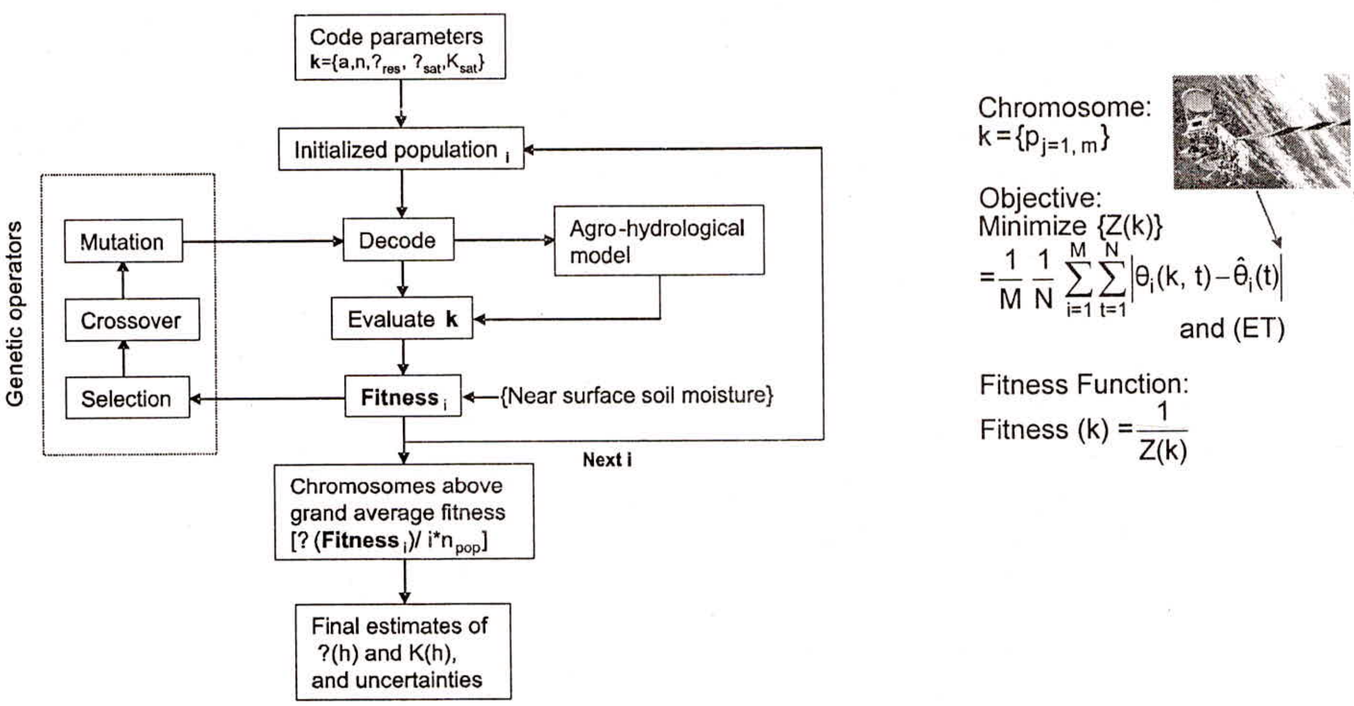


Fig. 7: Implementation of the near-surface soil moisture assimilation

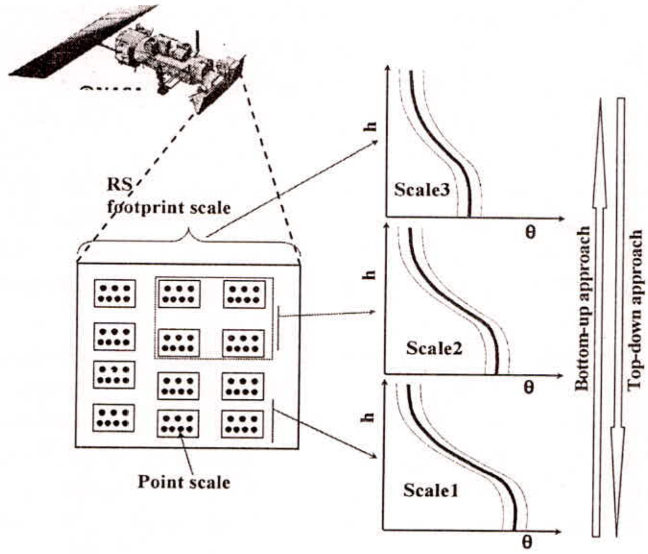


Fig. 8: Hypothetical behavior of effective properties at varying scales

Advanced Microwave Scanning Radiometer (AMSR-E) instrument using the new MCMC-based scaling algorithm. Soil moisture evolution was modeled at a spatial scale comparable to the AMSR-E soil moisture product, with the hypothesis that the characterization of soil microwave emissions and their variations with space and time on soil surface within the AMSR-E footprint can be represented by an ensemble of upscaled soil hydraulic parameters. We demonstrated the features of the MCMC-based parameter upscaling algorithm (from field to satellite footprint scale) within a SVAT model framework to evaluate the satellite-based brightness temperature/soil moisture measurements for different hydro-climatic regions, and identified the temporal effects of vegetation (leaf area index) and other environmental factors on AMSR-E based remotely sensed soil moisture data. The SVAT modeling applied for different hydro-climatic regions revealed the limitation of AMSR-E measurements in high-vegetation regions. The study also suggests that inclusion of soil moisture evolution from the proposed upscaled SVAT model with AMSR-E measurements in data assimilation routine will improve the quality of soil moisture assessment in a footprint scale. The technique also has the potential to derive upscaled parameters of other geophysical properties used in remote sensing of land surface states. The developed MCMC algorithm with SVAT model can be very useful for land-atmosphere interaction studies and further understanding of the physical controls responsible for soil moisture dynamics at different scales. A schematic of this parameter estimation process is shown in Figure 9.

Multiscale Data Assimilation Algorithm

A new study (Das *et al.*, 2008b) focuses on downscaling of soil moisture from coarse remote sensing footprints to finer scales. The approach implements a multiscale ensemble Kalman filter (EnKF) that assimilates remotely sensed soil moisture footprint, attributes of fine scale geophysical parameters/variables (i.e., soil texture, vegetation, topography, and precipitation) and coarse/fine scale simulation into a spatial characterization of soil moisture at the finer scales. To downscale the remotely sensed soil moisture to another spatial scale, the multiscale EnKF uses a bridging model. The bridging model infers the pixel-specific

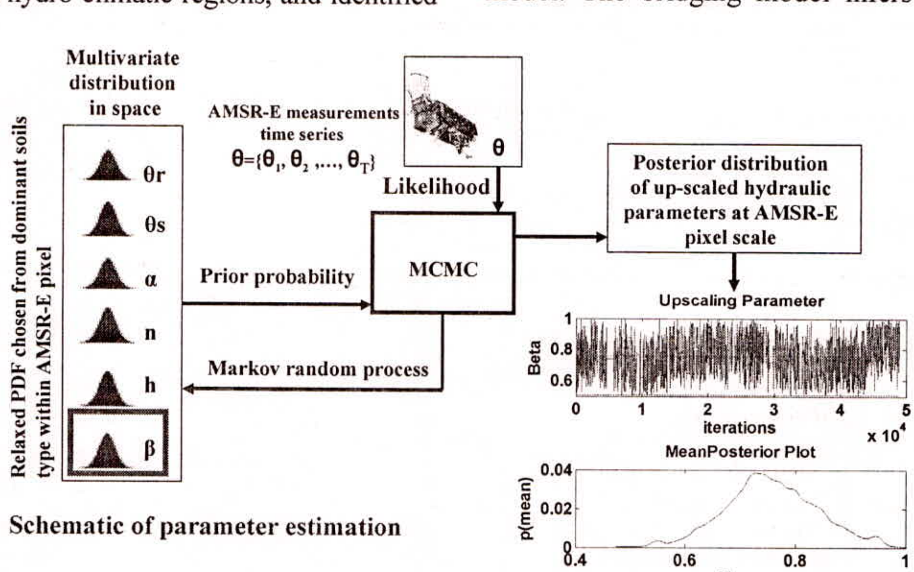


Fig. 9: Up/Down scaling of soil hydraulic properties using AMSR-E soil moisture measurements

scaling coefficient from the compatible geophysical parameters/variables that influence the soil moisture evolution process at that particular spatial scale. A schematic of the multiscale data assimilation algorithm is presented in Figure 10. Data from diverse hydro-climatic regions from the semiarid Arizona region, the agricultural landscape of Iowa, and the grassland/ rangeland of Oklahoma are used in the study to implement the multiscale downscaling algorithm. Results demonstrate that the bridging model helps to characterize the evolution of soil moisture within the remotely sensed footprint. Validation at the finest scale also shows reasonable agreement between the measured field data and the simulated downscaled soil moisture evolution.

NEURAL NETWORK APPROACH

Direct measurements of soil hydraulic properties are time-consuming and costly to characterize large regions. Indirect estimation techniques using Pedotransfer Functions (PTFs) provide an effective alternative to direct measurements. This approach examines the effect of including topographic and vegetation attributes, besides pedologic attributes, on the prediction of soil hydraulic properties using PTFs. With the increasing availability of remote sensing products from air- and space-borne sensors at different spatial scales, topographic and vegetation attributes are easily available from Digital Elevation Models (DEMs) and Normalized Difference Vegetation Index (NDVI).

Pedo-Topo-Vegetation-Transfer Functions

Soil hydraulic properties across the Southern Great Plains of the USA were estimated using this approach in one study. Hierarchical Pedo-Topo-Vegetation-Transfer Function (PTVTF) models were developed based on multiple combinations of soil physical properties, the vegetation, and topographic features (Sharma *et al.*, 2006). Eighteen models combining bootstrapping technique with artificial neural networks were developed in a hierarchical manner to predict the soil water contents at eight different soil water potentials (at 5, 10, 333, 500, 1000, 3000, 8000, and 15000 cm) and the van Genuchten hydraulic parameters. The performance of the neural network models was evaluated using the Spearman correlation coefficient between the observed and the predicted values and Root Mean Square Error (RMSE). Although variability exists within bootstrapped replications, improvements (of different levels of statistical significance) were achieved with certain input combinations of basic soil properties, topography and vegetation information compared with using only the basic soil properties as inputs. Topography (DEM) and vegetation (NDVI) attributes at finer scales were useful to capture the variations within the soil mapping units for the SGP97 region dominated by perennial grass cover. Sample predictions of van Genuchten parameters are provided in Figure 11.

Multiscale Artificial Neural Networks

Limited availability of (detailed) soil hydraulic data for large-scale hydro-climatic models (with grids ranging from several kilometers to several hundred kilometers) is a major challenge. To address this need, Pedotransfer Functions (PTFs) have been used to estimate the required soil hydraulic parameters from other available or easily measurable soil properties. While most previous studies derive and adopt these parameters at matching spatial scales (1:1) of input and output data, we have developed a methodology to derive soil water retention functions at the point or local scale using the PTFs trained with coarser scale input data (Jana *et al.*, 2007). This study was a novel application of an Artificial Neural Network (ANN)-based PTF scheme across two spatial support scales within the Rio Grande basin in New Mexico. The ANN (Figure 12) was trained using soil texture and bulk density data from the SSURGO database (scale 1:24,000) and then used for predicting soil water contents at different pressure heads with point-scale data (1:1) inputs. Figure 13 provides a graphic representation of the multiscale ANN methodology.

The resulting outputs were corrected for bias before constructing the soil water characteristic curve using the van Genuchten equation. A hierarchical approach with training data derived from multiple clustered sub-watersheds (with varying spatial extent) was used to study the effect of the increase in spatial extent. The results show good agreement between the soil water retention curves constructed from the ANN-based PTFs and field observations at the local scale near Las Cruces, NM. The robustness of the multiscale PTF methodology was further tested with a separate data set from the Little Washita watershed region in Oklahoma. Overall, ANN coupled with bias correction was found to be a suitable approach for deriving soil hydraulic parameters at a finer scale from soil physical properties at coarser scales and across different spatial extents. The approach could potentially be used for downscaling soil hydraulic properties.

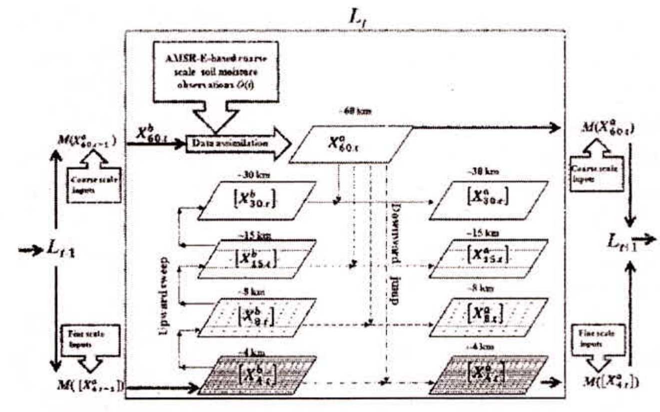


Fig. 10: Schematic of multiscale data assimilation

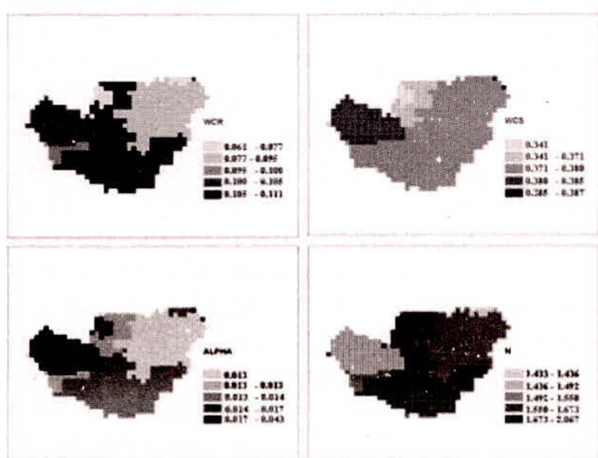


Fig. 11: Predictions of van Genuchten hydraulic parameters based on neural network model

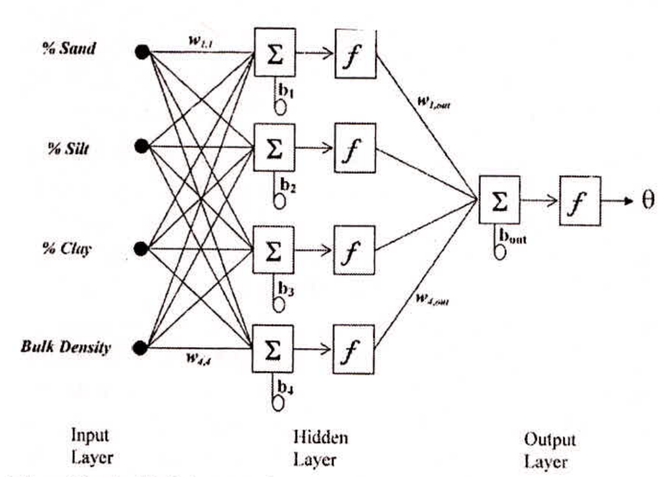


Fig. 12: Artificial neural network model: *w* represents the layer weights, *b* the bias, *f* is the transfer function, and θ is the output

Bayesian Neural Networks with Remote Sensing Data

In another study (Jana *et al.*, 2008; Jana and Mohanty, 2008), Bayesian Neural Networks (BNNs) were applied across spatial scales to estimate soil water retention with data from the Rio Grande Basin in New Mexico (Figure 14). BNNs inherently provide uncertainty estimates for their outputs due to their utilization of Markov chain Monte Carlo (MCMC) methods. The objective in this study was to obtain soil hydraulic parameters at a finer scale using pedo-transfer functions developed from inputs to a neural network trained at a much coarser (sub-watershed) scale. BNN application is across scales as the network was trained at a remote-sensing-pixel-scale and asked to predict soil water content values at a point-scale.

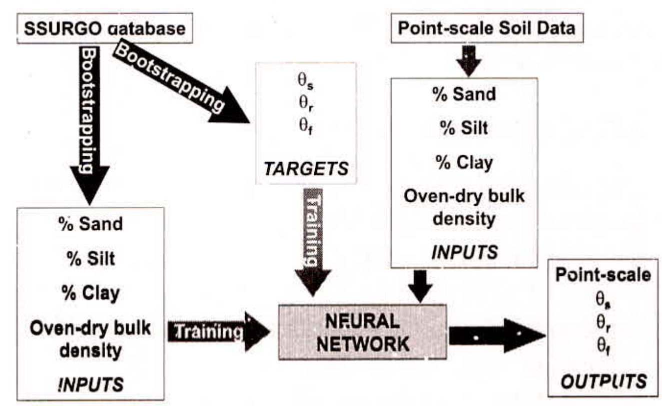


Fig. 13: Multiscale ANN methodology

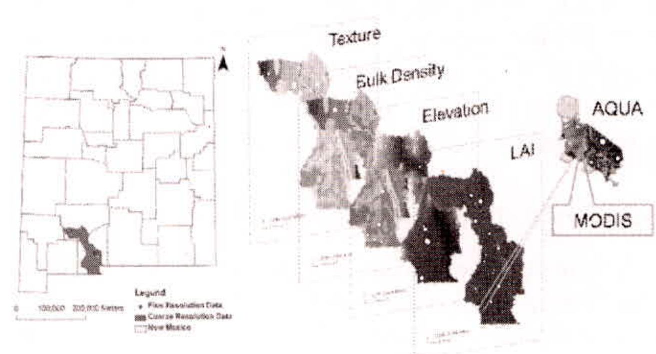


Fig. 14: Bayesian neural network study area and data

Improvement in prediction capability is seen by using Bayesian statistical techniques in the ANN training process to obtain better weights. Bayesian neural networks update the weight vector with information from the data. This makes the predictions better. Use of additional information such as remotely sensed topographic and vegetation data slightly enhances the prediction accuracy of the BNN methodology.

Bias can exist between data sets due to difference in measurement techniques, instrument or human errors, and averaging methods, or due to the scale disjoint

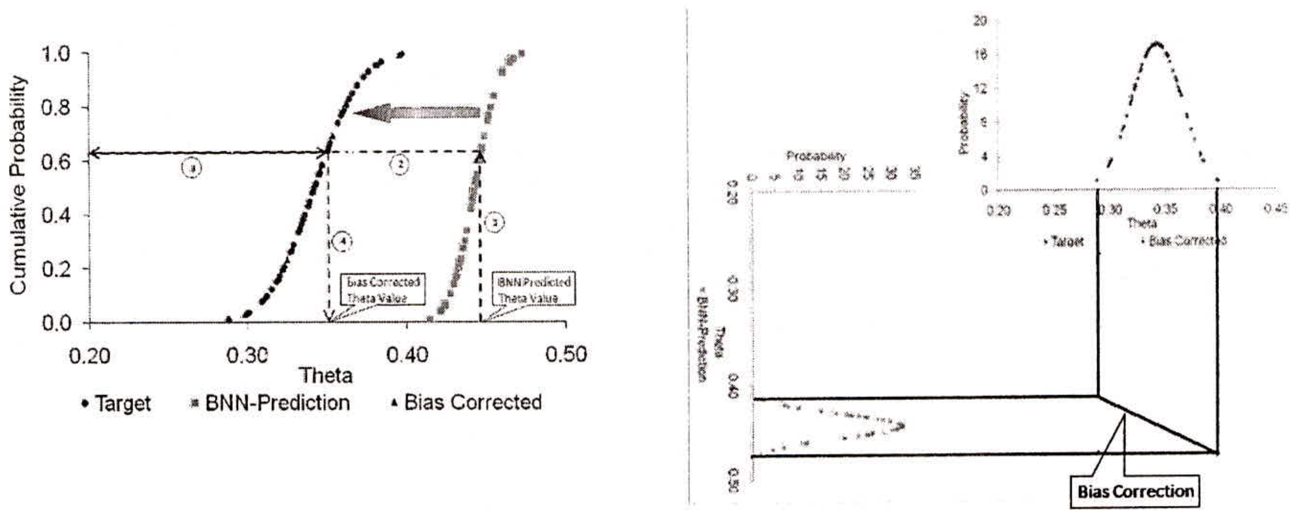


Fig. 15: Non-linear bias correction

between the training and simulation datasets used in the BNN (Schaap and Leij, 1998; Jana *et al.,* 2007, 2008]. Since the training of the neural network is by coarse-scale (1:250,000, or 1 km resolution) data, the BNN model developed is a coarse-scale model. Although point-scale (1:1) inputs are fed to this model, the predictions obtained for the soil water contents are technically still at the coarser scale. This gives rise to a bias between the BNN predicted values and the measured values at the point scale. Different governing hydrologic processes dictate the soil water contents at different spatial scales. However, the BNN is not based on the physical processes underlying the hydrology. Hence, a suitable bias correction technique needs to be applied to the predicted water content values. It is known that most processes in the vadose zone are non-linear in nature. Parametric scaling is a non-linear process too. Hence, it makes sense to apply non-linear bias correction schemes in our methodology. A simplistic representation of the non-linear bias correction technique by CDF-matching is shown in Figure 15.

Overall, the Bayesian neural network, coupled with a non-linear bias correction scheme, appears to work well for estimation of soil hydraulic properties at a fine scale from data at coarser scales.

REFERENCES

Das, N.N., Mohanty, B.P. and Njoku, E.G. (2008a). "An MCMC algorithm for upscaled SVAT modeling to evaluate satellite-based soil moisture measurements", *Water Resources Research,* 44, W05416, doi:10.1029/2007WR006472.

Das, N.N., Mohanty, B.P. and Efendiev, Y. (2008b). "A new Multiscale Data Assimilation Algorithm to Downscale Satellite-Based Surface Soil Moisture Data", *Water Resources Research,* Submitted.

Ines, A.V.M. and Mohanty, B.P. (2008a). "Near-surface soil moisture assimilation for quantifying effective soil hydraulic properties under different hydro-climatic conditions", Vadose Zone J., 7: 39–52.

Ines, A.V.M. and Mohanty, B.P. (2008b). "Near-surface soil moisture assimilation to quantify effective soil hydraulic properties using genetic algorithm. 1. Conceptual modeling", *Water Resources Research,* In Press.

Ines, A.V.M. and Mohanty, B.P. (2008c). "Near-surface soil moisture assimilation to quantify effective soil hydraulic properties using genetic algorithm. 2. With air-borne remote sensing during SGP97 and SMEX02", *Water Resources Research, Under Revision.*

Ines, A.V.M. and Mohanty, B.P. (2008d). "Parameter conditioning with a noisy Monte Carlo genetic algorithm to estimate effective soil hydraulic properties from space", *Water Resources Research,* In Press.

Jana, R.B., Mohanty, B.P. and Springer, E.P. (2007). "Multi-Scale Pedo-Transfer Functions for Soil Water Retention", *Vadose Zone J.,* 6: 868–878.

Jana, R.B., Mohanty, B.P. and Springer, E.P. (2008). "Multi-Scale Bayesian Neural Networks for Soil Water Content Estimation", *Water Resources Research,* doi: 10.1029/2008WR006879, In Press.

Jana, R.B. and Mohanty, B.P. (2008). "Use of Remotely Sensed Data for Fine Scale Soil Water Content Estimation", *Remote Sensing of Environment,* Submitted.

Mohanty, B.P. and Zhu, J. (2007). "Effective hydraulic parameters in horizontally and vertically heterogeneous soils for steady state land-atmosphere interaction", *J. Hydrometeorol.,* 8(4), 715–729.

Schaap, M.G. and Leij, F.J. (1998). "Database-related accuracy and uncertainty of pedotransfer functions", *Soil Science*, 163, 765–779.

Sharma, S. K., Mohanty, B.P. and Zhu, J. (2006). Including Topography and Vegetation Attributes for developing Pedo Transfer Functions in Southern Great Plains of USA, Soil Sci. Soc. Am. J., 70: 1430–1440.

Zhu, J. and Mohanty, B.P. (2002a). "Spatial Averaging of van Genuchten Hydraulic Parameters for Steady State Flow in Heterogeneous Soils", *Vadose Zone J.*, 1, 261–272.

Zhu, J. and Mohanty, B.P. (2002b). "Upscaling of Hydraulic Properties for Steady State Evaporation and Infiltration", *Water Resour*. Res., 38(9).

Zhu, J. and Mohanty, B.P. (2002c). "Effective Hydraulic Parameters for Steady State Flows in Heterogeneous Soils", *Water Resour.* Res., 39(8).

Zhu, J. and Mohanty, B.P. (2003). Upscaling of Hydraulic Properties of Heterogeneous Soils, In Methods of Scaling in Soil Physics, CRC Press, 97–117.

Zhu, J. and Mohanty, B.P. (2004). "Soil hydraulic parameter upscaling for steady-state flow with root water uptake", *Vadose Zone J,* 3, 1464–1470.

Zhu, J. and Mohanty, B.P. (2006). "Effective scaling factor for transient infiltration in heterogeneous soils", *J. Hydrol.*, 319, 96–108.

Zhu, J., Mohanty, B.P., Warrick, A.W. and Genuchten, M. Th. van (2004). "Correspondence and Upscaling of Hydraulic Functions for Heterogeneous Soils", *Vadose Zone J.*, 3, 527–533.

Zhu, J., Mohanty, B.P. and Das, N.N. (2006), "On the effective averaging schemes of hydraulic properties at the landscape scale", *Vadose Zone J*, 5, 308–316.