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Research article

An empirical approach towards improved spatial estimates of soil moisture for vegetation analysis

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Abstract

Landscape-level spatial estimates of soil water content are critical to understanding ecological processes and predicting watershed response to environmental change. Because soil moisture influences are highly variable at the landscape scale, most meteorological datasets are not detailed enough to depict spatial trends in the water balance at these extents. We propose a tactical approach to gather high-resolution field data for use in soil moisture models. Using these data, we (1) describe general soil moisture trends for a 6400 ha watershed in the Oregon Western Cascades, USA (2) use this description to identify environmental variables to stratify across in collecting data for a statistical explanatory model of soil moisture spatial pattern at the onset of seasonal drought, and (3) examine the spatial scale of variability in soil moisture measurements compared to the scale of variability in potential explanatory factors. The results indicate that soil moisture dynamics and controls are different for different soil depths across this mountainous watershed. Soil moisture variability exhibits complex spatial patterns that can be partially estimated (up to 50 percent of the variation accounted) with easily measurable climatic and terrain variables. The analysis incorporates both macroscale (climate) and mesoscale (topographic drainage and radiation) influences on the water balance. Without additional data on the distribution of edaphic and biotic factors, we are not able to model the variability of soil moisture at the microscale. The regression approach can be used to extrapolate field measurements across similar topographic areas to examine spatial patterns in forest vegetation and moisture-controlled ecological processes.

Introduction

Improved spatial estimates of soil water content are needed for a variety of ecological applications (Stephenson 1990). Soil moisture levels influence such fundamental ecological processes as photosynthesis, respiration, and nutrient uptake (Band et al. 1993). Moisture acts as a primary constraint on forest productivity (Vertessy et al. 1996), affects species composition (Stephenson 1998), and plays a major role in determining forest flammability and fire regime (Clark 1990; Miller and Urban 1999). It influences erosion (Moore et al. 1988), pedogenesis (Jenny 1980), geomorphology (Beven and Kirkby 1993), and infiltration-runoff partitioning in response to precipitation events (Grayson et al. 1997). For these reasons, spatial characterization of soil water are critical to understanding current ecological conditions and predicting future conditions under scenarios of climate change (Pastor and Post 1988).

Soil moisture is highly variable in time and space, particularly at the catchment scale (Crave and Gascuel-Odoux 1997). *In time*, seasonal climatic patterns influence rates of precipitation, evaporation and soil water uptake by vegetation (D'Odorico et al. 2000; Mackay and Band 1997). Grayson et al. (1997) describe two distinct states in soil moisture patterns for seasonal watersheds in Australia: one for the wet season when nonlocal controls (terrain) dominate and the other for the dry season when local controls (soils, vegetation, radiation) are more important. Yeakley et al. (1998) also describe two distinct states in soil moisture, though they credit a different seasonal mix of local and nonlocal controls. For a hillslope gradient in the southern Appalachian Mountains of western North Carolina, drainage (terrain) was a particularly important moisture control for upper soil layers and for deeper soils during periods of drought. Storage properties (soils) were important to moisture content in lower horizons during watershed recharge. An important conclusion of the Yeakley work that we test in our analysis is that shallow and deep soils can have very different hydrologic controls.

For a given point in time, the *spatial* distribution of soil water is determined by the balance between water supply and demand (Stephenson 1990; Stephenson 1998). Demand is influenced by relative radiation load and temperature. In the northern hemisphere, south-facing slopes receive more insolation than north-facing slope. This relationship is modified by latitude, which determines the solar angle; local slope, which affects the incident angle; and landscape context, which can create topographic shading (Dubayah and Rich 1995). Cloud cover also can reduce solar radiation (Nikolav and Zeller 1992). Temperature differences are traditionally estimated using lapse rates, simple regression equations that describe how air cools as it moves uphill (Barry 1992). The relationship between temperature and elevation is similarly confounded by primary (e.g., hillslope angle and aspect) and secondary (e.g., cold air drainage and evaporative cooling) topoclimatic effects (Lookingbill and Urban 2003).

Water supply is determined by inputs and storage. Inputs consist of precipitation and drainage, both of which are functions of elevation at the landscape level. As air rises in altitude, it cools adiabatically, resulting in a decreased capacity for vapor storage and the condensation of water (Barry 1992). At higher elevations, this precipitation falls in the form of snow during the winter months, and snowmelt can act as an additional input when temperatures rise in the summer (Running et al. 1987). Drainage moves water from upslope to downslope positions. In terms of inputs, therefore, precipitation generally increases with increasing elevation, while hillslope drainage can result in local decreases with increasing elevation. In terms of storage, volumetric water-holding capacity varies with soil texture and depth (Brady and Weil 1999). In general, soils with high clay content have higher moisture content than sandy soils in similar environments, though determining the amount of plant available water is complicated by texture-specific, soil-water release curves. For a given soil type, the greater the soil depth, the greater the potential for storing water. Several studies have found that soil storage properties can be at least as important as topographic variables in dictating soil water distributions (Helvey et al. 1972; Boyer et al. 1990).

These underlying influences to the soil water balance vary at different characteristic spatial scales. For example, Neilson (1991) describes how temperature and precipitation influence soil moisture at regional scales, while topographic drainage and soil water storage are important at more local scales. Urban et al. (2000) depict different environmental factors governing soil moisture at different characteristic spatial scales: climate (macroscale), topography (meso- and microscales), and soil depth and texture (microscale). As for the common physical surrogates for the water balance, elevation typically varies along large-scale hillslope gradients in mountain watersheds. Drainage indices, such as the topographic convergence index (TCI; Beven and Kirkby 1979) and the terrain relative moisture index (TRMI; Parker 1982), are designed to capture local topography. In this analysis, we investigate patterns of soil moisture at multiple scales in a montane ecosystem and try to discern how these patterns can be reproduced by a composite of physical factors.

Several shortcomings hamper the use of existing climate datasets in a modeling effort of this type. Available data are usually sparsely (and often irregularly) sampled, necessitating some form of interpolation to smooth across gaps. Common smoothing techniques are not appropriate when it is desirable to represent the variability between point measurements, which are typically collected at the regional scale (Cramer et al. 1999). It is important to represent moisture variability at the landscape scale and finer, because these are the scales at which the supply and demand components, and consequently the entire water balance, vary. These are also the scales that are most relevant to ecosystem management (Christensen et al. 1996). Although a few techniques do exist for modeling unmeasured variance in environmental factors (e.g., Richardson's (1981) weather generator algorithm), the data required to run these analyses have been notoriously difficult to gather (Cramer et al. 1999).

In this study, we examine the summer soil moisture regime of the H.J. Andrews Forest, an experimental watershed in the Oregon Western Cascades. The goal is not to exhaustively characterize the complex temporal dynamics of this highly seasonal system, but instead to develop an estimate of spatial differences in soil moisture during the peak of the growing season. The need for such information grew out of our landscape-scale vegetation studies of these forests. We begin with a cursory examination of the general spatial and temporal trends in soil moisture during the period of summer drought. We next develop a statistical model for combining potential explanatory variables and map the spatially implicit model back onto the landscape to give a spatial representation of soil moisture that can be tested with future samples. We then examine the spatial scale of variability in soil moisture measurements and compare this scale with the scales at which potential moisture influences vary in the study area. Finally, we test our ability to reproduce the characteristic spatial scaling of soil moisture with our statistical explanatory model.

Figure 1. Locator map for the H.J. Andrews Experimental Forest LTER. The study site is located on the west side of the Cascade Mountains approximately 80 km east of Eugene, Oregon, USA.

Methods

Study area

The study site is located on the west slope of the Cascade Mountains approximately 80 km east of Eugene, Oregon, USA (Figure 1). The 6400 ha Lookout Creek watershed was established as an experimental forest in 1948, and in 1980 was incorporated into the Long Term Ecological Research (LTER) network as the H.J. Andrews (HJA) Experimental Forest (McKee 1998). Elevation ranges from 410 m to 1630 m in the HJA, which maintains roughly 40 percent of its total area in old-growth forest (*i.e.*, 400-500 years old).

As an LTER site, the HJA maintains an extensive database of meteorological data. Climate is characteristic of the Pacific Northwest, with dry summers and wet winters. Annual precipitation ranges from 2200 mm at the watershed base to 3400 mm at upper elevations, with less than 300 mm normally falling during the growing season (Grier and Logan 1977). Soils are mostly deep, well-drained Inceptisols. Rooting occurs almost entirely in the upper 200 cm of soil. Textures range from gravelly, silty clay loam to very gravelly, clay loam. Lower elevation soils are older than upper elevation soils, dating back to the Oligocene-lower Miocene Epoch. Upper elevation soils are comprised of younger andesite lava flows and High Cascade rocks.

Topographic position is an important control on vegetation in this region (Zobel et al. 1976). *Pseudotsuga menziesii* (Douglas fir), *Tsuga heterophylla* (western hemlock), and *Thuja plicata* (western redcedar) are the dominant species at lower elevations. *Abies amabilis* (Pacific silver fir), *Abies procera* (noble fir), and *Tsuga mertensiana* (mountain hemlock) dominate upper elevations (Franklin and Dyrness 1988). Ohmann and Spies (1998) suggest that elevation and associated macroclimate are the major correlates with regional patterns of forest community composition throughout Oregon.

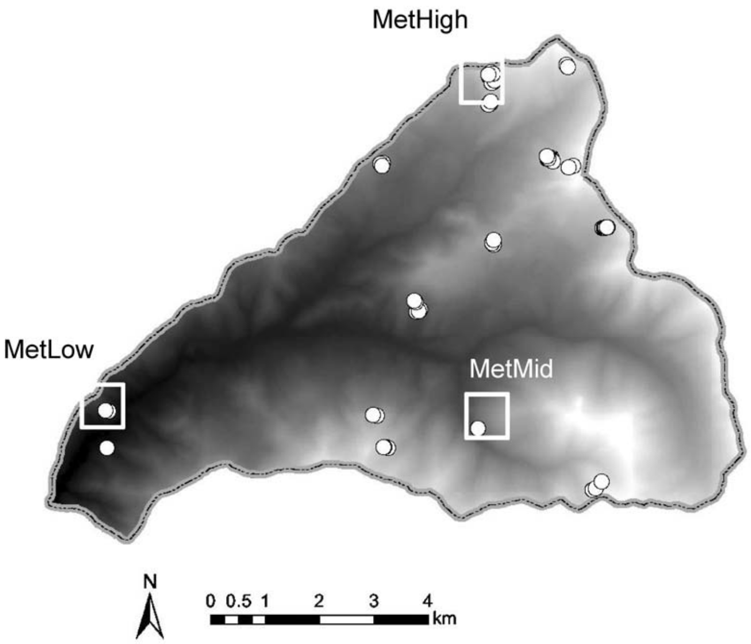

Figure 2. Map of sample locations. Boxes identify small watersheds containing permanent dataloggers and from which samples for regression analyses were collected. Points represent 60 (20x20 m) plots used for semivariance analyses. Underlying image is a digital elevation model in which higher elevation areas are lighter in color.

Table 1. Environmental statistics for permanent meteorological stations established in 1999. A surface soil (0-20 cm) and a deep soil (80-100 cm) sensor were located at each location.

	Site Average	Upper Slope TDR Location	Mid Slope TDR Location	Down Slope TDR Location
Elevation (m)				
MetHigh	1288	1299	1287	1278
MetMid	887	899	887	876
MetLow	642	652	643	632
Aspect (º)				
MetHigh	227	220	234	228
MetMid	236	231	241	235
MetLow	225	220	240	214
Slope (º)				
MetHigh	28	26	28	29
MetMid	34	36	29	36
MetLow	29	22	30	35

Exploratory studies

In an initial effort to better understand the general dynamics of the watershed, we installed a network of three permanent datalogger stations in 1999. The three stations were located at low, mid and high elevation sites within the HJA (Figure 2; Table 1). Two sampling stations were located in the *T. heterophylla* vegetation zone. The third was located in the *A. amabilis* zone. All sites were installed on southwest-facing slopes to maintain consistency in exposure while sampling across hillslope gradients. By selecting southwest aspects we focused on areas of highest insolation in this analysis.

Time domain reflectometry (TDR) units were run from each datalogger to three locations at different hillslope positions (Table 1). At each location, we took continuous measurements at two depths (0-20 cm and 80-100 cm). TDR determines soil moisture content by measuring the travel velocity of electromagnetic waves as they pass through the soil (Herkelrath et al. 1991). The velocity of the waves is strongly correlated with the soil water content. The probes were oriented along hillslope gradients of approximately 20 m in relief. Over the summer 1999, measurements were taken every 60 seconds from these units and hourly statistics (average, maximum and minimum) were stored in dataloggers (CR10X, Campbell Scientific Incorporated).

From this exploratory study, we hoped to capture the temporal pattern of soil moisture drawdown during the dry summer growing season. This information would be used to guide the timing of future synoptic sampling. We also hoped to identify primary physical constraints on the watershed moisture regime. Additional sampling would stratify across these variables. The data from these stations were meant to represent the amount of baseline data typically available for montane study sites. In fact, these three stations probably overestimate the amount of available data for most watersheds.

To help identify potentially important variables to stratify across in later sampling, we also collected two small synoptic samples of gravimetric moisture during summer 1999. These samples covered a much larger spatial area than the three TDR stations. Soil samples were collected from 30 (1 × 1 m) plots spread across the entire HJA, once on July 22 and once on August 12, six days after the largest rainstorm of the summer season. Samples from the top 0-20 cm of soil were weighed wet, oven dried, then weighed again to provide gravimetric moisture estimates.

Empirical model

On July 4 2001, we collected one-time synoptic moisture measurements to build a simple regression model that would capture important components of the water balance in a statistical relationship. Measurements were taken using handheld reflectometers (Hydrosense, Campbell Scientific Incorporated). These sensors combine important features of the permanent TDR sampling station and the gravimetric approach that allowed us to increase our sampling coverage substantially. Their portability allowed us to collect measurements of soil moisture on a volumetric basis over a large area, as compared to the more permanent stations where sensors were restricted to within a relatively short radius of the central dataloggers. Further, measurements are provided instantaneously in the field by the reflectometers, as compared to the gravimetric approach in which samples need to be brought back to the lab for weighing, drying and reweighing.

The sample design met two objectives: (1) it stratified across variables deemed as potentially important to the water balance in the exploratory analyses and (2) it covered a range of spatial scales. At each of the permanent datalogger stations we extended the spatial network of data points up and down the hillslopes and to different slope-aspect combinations within the local watersheds. Sample locations were aligned along short transects (no more than 110 m) with a separation interval of 5-10 m. Each sample represented the average of three measurements taken within 1 m^2. A total of 79 locations were sampled: 19 at low elevation, 31 at mid elevation and 29 at high elevation (Figure 2). An additional nine locations were added to the analysis from the permanent datalogger stations at the center of each of the three sampling areas. Surface soil measurements integrated over the top 0-20 cm of soil. For a small subset of the locations, we dug pits 80 cm deep in order to sample moisture at 80-100 cm in depth. The time required to create suitable pits in rocky soil constrained our sampling considerably, and the interpretation of the deep soil model should be tempered by this limited sample size. From these data, we developed a set of regressions to describe deep ($N = 16$) and shallow ($N = 88$) soil water trends.

Forward stepwise regression analysis (Sokal and Rohlf 1995) was used to select the most important variables to explain the observed trends in moisture. Each of the variables chosen as a candidate for the models was selected because of its potential influence on soil moisture (Table 2). Additionally, we considered only variables that could be derived easily from commonly available geographic information systems (GIS) data. This restriction allowed us to map the results back into geographic space. Unfortunately, it precluded the use of field measurements such as canopy cover and soil properties in the model. Soil spatial information is generally the least known of the land surface attributes (Band and Moore 1995), and reliable, landscape-scale soils estimates were not available for our study area at the high resolution needed to capture the variability in this attribute. Variables considered for the model include elevation, slope, distance from stream, relative slope position, and a topographic convergence index calculated according to the formula:

Table 2. Potential predictor variables for empirical moisture models.

Variable	Definition	Comment
Temperature and Precipitation Proxy		
Elev	elevation (m)	relationship commonly represented via lapse rates (Running et al. 1987, Daly et al. 1994)
Drainage Proxies		
Slope	hillslope angle (°)	steep slopes drain quicker than shallow slopes
Dstrm	distance to stream (m)	water drains towards stream channels
RSP	relative slope position	high values: ridges; low values: valleys
TCI	topographic convergence index (ln (a/tanβ))	high values: convergent; low values: well drained (Beven and Kirkby 1979; Moore et al. 1991)
Evaporative Demand Proxies		
TAsp	transformed aspect (-1 * cos(α − 45))	varies from − 1 for NE facing slopes to 1 for SW facing slopes (Beers et al. 1966, Urban et al. 2000)
TASL	slope-corrected transformed aspect (-1 * cos(α − 45) * sin(s))	values increased for steep SW facing slopes and decreased for steep NE facing slopes
HS	hillshade (ϕ[cos(S) sin(s) cos(α-A) + sin(S) cos(s)])	corrects for local topographic features; solar azimuth set to 225 degrees and solar inclination set to 45 degrees (ESRI 1994)
PRR	potential relative radiation ΣΣ (monthly, hourly HS)	integrates solar azimuth and inclination over the course of the day and entire summer (Pierce et al. in review)

$$TCI = \ln(a/\tan\beta) \tag{1}$$

where a = upslope contributing area in m^2 and β = local slope angle (Beven and Kirkby 1979).

We also examined a wide variety of radiation proxies ranging from simple transformed aspect (Beers et al. 1966) to a potential relative radiation (PRR) index developed from a digital elevation model (DEM). Pierce et al. (*in review*) describe the radiation proxies in detail. The PRR index, developed specifically for use in community-level vegetation analysis, is a measure of how topography translates to spatial differences in relative radiation.

$$\text{PRR} = \sum\sum(\text{monthly, hourly hillshade (HS)}) \tag{2}$$

$$\text{HS} = \phi[\cos(S)\sin(s)\cos(\alpha - A) + \sin(S)\cos(s)] \tag{3}$$

where ϕ is an eight-bit integer ranging from 0 (total shade) to 255 (no shade), S is the solar inclination, s is the local slope, A is the solar azimuth and α is the azimuth of the slope facet. PRR both accounts for hillshading effects and integrates over time to account for the fact that solar position changes over the course of the day and year. For this analysis, we integrated PRR over only the summer growing season (June through September).

Spatial scale of variability

In July 2002, we collected 540 field measurements of volumetric soil moisture to test whether our surface soil moisture model was able to reproduce the spatial scaling attributes of actual soil water data (Figure 2). The synoptic measurements were spread across the landscape in 60 (20 × 20 m) plots, covering a range of separation distances from 10's to 1,000's of m. Three (2 × 2 m) quadrats were located randomly within each 20 × 20 m plot and three randomly located measurements were taken within each quadrat. We assessed the characteristic scaling of this dataset through semivariance analysis (Legendre and Fortin 1989) with 250 m lag distance intervals and 5 km set as the largest lag distance (i.e., one-half the smallest dimension of the study area).

Semivariograms are a central tool in geostatistics and are an effective means of describing soil moisture spatial scaling (Western et al. 1998). The features of note in a variogram are the sill (value at which semivariance asymptotes), range (the lag distance at which the sill is reached), and nugget (the Y-intercept, reflecting variation finer-scaled than the minimum lag distance). We normalized the semivariance by simple variance for each of the variograms in order to compare trends in variance across variables (Urban et al. 2000).

We compared the characteristic scaling of measured soil moisture with that of factors highlighted as potentially important to the water regime in the earlier analyses. These included: (1) Elevation as an indicator of temperature and precipitation variability; (2) TCI, Slope, and Dstrm as topographic measures of drainage and relative slope position; and (3) PRR, HS, and TAspect as measures of radiation (see Table 2 for definitions of each of the variables). We also examined potentially fine-scale variables that were not included in the regression analyses because they were not available as digital coverages for the entire watershed. Specifically, we investigated the characteristic scaling of: (1) soil depth as a measure of water storage and (2) canopy cover as a modifier of radiation and transpiration. Thus we analyzed the scaling of both supply terms (precipitation, drainage and storage) and demand terms (temperature, radiation and transpiration) of the water balance equation.

Data on these terrain, biotic, and edaphic factors were obtained for the same 60 landscape-wide plots for which we had moisture data. We sampled the terrain-based variables using a 10-m resolution DEM of the HJA. Canopy measurements were taken using a concave spherical densiometer with readings averaged from the four cardinal directions at each 2×2 m plot. Soil depth was sampled using a 1-m tile probe and the average of three measurements was recorded for each 2×2 m plot.

Results

Comparison among permanent TDR sites

Moisture levels were consistently greater for the TDR probes at the high elevation site than the two lower elevation sites (Table 3; Figure 3). The deep soil, in particular, was much wetter at the upper elevation site.

Precipitation throughfall was minimal but increased with elevation, reaching its maximum at the high elevation site (Table 3; Figure 3). All three of the sites experienced an average of less than 3.5 mm of throughfall/day over the three-month period of study, typical for this dry summer system. Figure 3 illustrates the strong recharge effect of storm events at the low and mid elevation sites. Recharge was not as great at the high elevation site, which had higher pre-storm moisture levels due, at least in part, to greater levels of storage in winter snowpack.

Comparison within permanent TDR sites

The average moisture level recorded by the deep soil probes increased from upslope to downslope position within all three sites. The three downslope probes had moisture levels 160 to 260 percent greater than the upslope probes (Table 3). Differences were less consistent for the surface soil measurements. For eight of the nine locations, the temporal variability at the surface soil sensor was greater than the variability at its corresponding deep soil sensor. Temporal variability also was greater at downslope positions than upslope positions (Table 3). There were a few occasions where the rank order of the wettest to driest probes changed as the soils became desiccated (Figure 3), supporting the findings of Grayson et al. (1997) and Yeakely et al. (1998) that moisture controls may shift seasonally. As a consequence, we had to decide whether to conduct our handheld synoptic sampling at the beginning or end of the summer dry season. We chose near the onset of drought (i.e., the beginning of July) because this was a period of high variability among the nine locations for both the shallow and deep soil moisture measurements. We also suspected that terrain influences, which can be more readily incorporated in landscape-scale models, might be overwhelmed by more difficult to model fine-scale influences (e.g., soil variability) under conditions of increasing drought.

The permanent TDR data emphasized the importance of stratifying across elevation and hillslope position. These associations were examined further through gravimetric sampling.

Gravimetric sampling

A general increase in moisture with elevation was observed in the gravimetric samples (Figure 4). Moisture levels were higher for the August 12 sample than for the July 22 sample because of the August 5-6 rain event. The storm acted to homogenize moisture across the landscape, as the amount of variation explained by elevation decreased from the pre- (r^2 = 0.60, F-statistic = 30.1, $P < 0.001$) to the post-storm sample dates (r^2 = 0.31, F-statistic = 8.8, P = 0.008). After accounting for elevation differences, radiation was highlighted as a potential explanatory variable (e.g., partial r^2 for PRR = 0.15, P = 0.001 for the July 22 data). We, therefore, made certain to stratify across hillslope position (highlighted in the permanent TDR data analysis), aspect (highlighted in

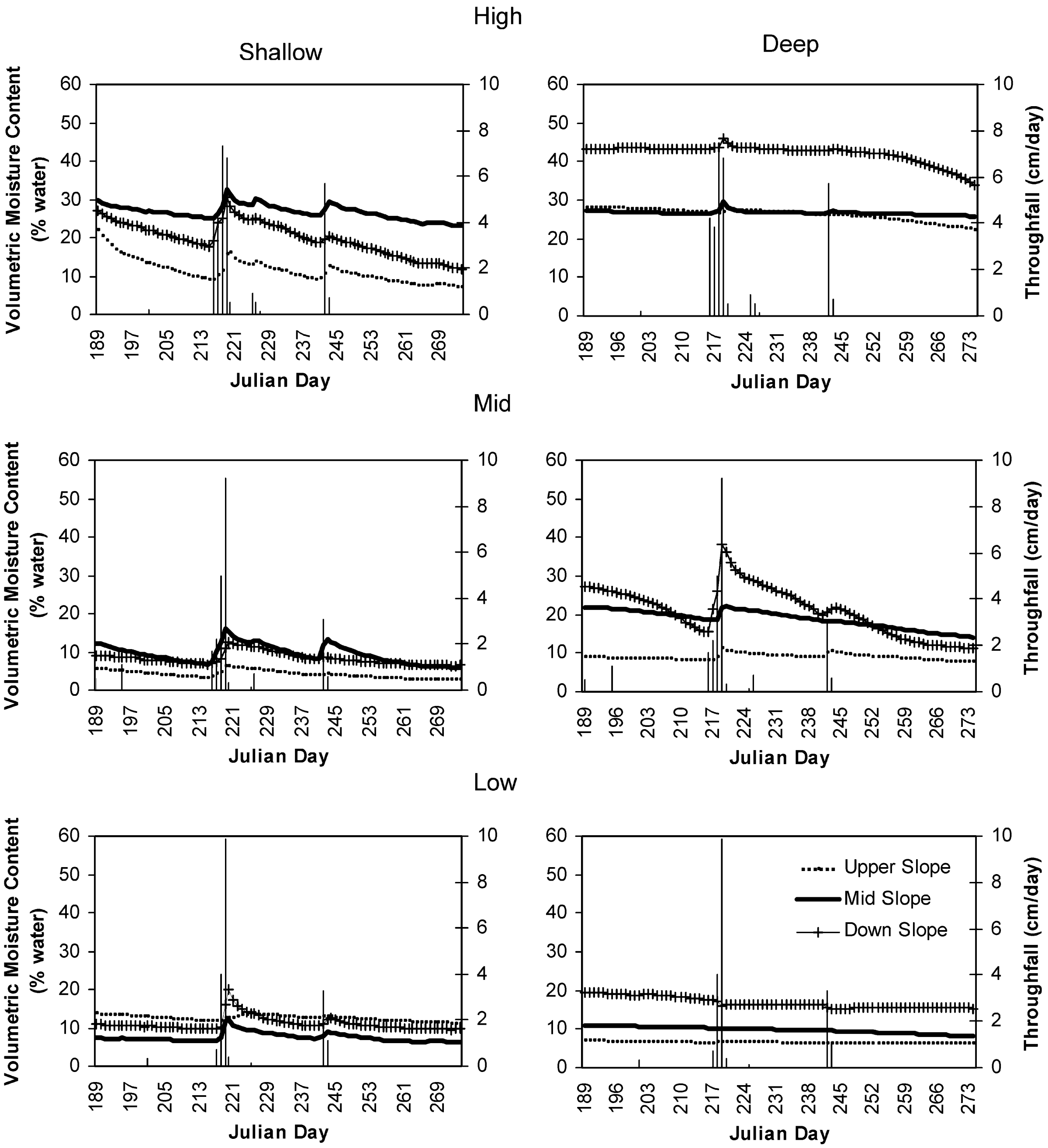

Figure 3. Soil moisture levels for the permanent TDR sites for the summer 1999. Julian day 189 = July 7; Julian day 273 = September 29. Sensors were placed along a hillslope gradient (upper slope, mid slope and down slope) at each site (high, mid and low elevation). Surface soil measurements are from the top 20 cm of soil; deep soil measurements are from 80-100 cm. Droplines represent throughfall during precipitation events.

the gravimetric analysis), and elevation (highlighted in both exploratory studies) in sampling for our empirical model.

Gravimetric samples taken at the permanent TDR sensors allowed for a comparison between the different measurement techniques. Relative moisture levels were highly correlated for the two methods (Figure

Table 3. Summary of permanent meteorological station data for July-September 1999.

	Temperature (°C)		Soil Moisture (volumetric % water)						Throughfall (cm/day)
	Air	Soil	Upper Slope		Mid Slope		Down Slope		
	1.37m	− 30cm	0-20cm	80-100cm	0-20cm	80-100cm	0-20cm	80-100cm	
Mean									
MetHigh	15.2	11.0	11.2	26.2	26.7	26.7	19.9	42.2	0.35
MetMid	15.9	12.7	4.0	8.9	9.5	18.8	8.3	21.0	0.28
MetLow	17.6	15.3	12.4	6.4	7.5	9.8	11.0	16.8	0.23
Minimum									
MetHigh	1.3	8.0	7.0	22.3	22.9	25.9	11.7	34.4	0
MetMid	1.2	10.1	2.4	7.7	5.8	14.2	6.2	11.3	0
MetLow	1.2	12.7	10.7	6.1	6.1	8.1	9.2	15.2	0
Maximum									
MetHigh	27.4	14.1	21.2	28.2	33.9	32.0	35.5	49.1	7.3
MetMid	29.9	15.5	6.8	12.3	20.6	22.6	12.8	43.7	9.2
MetLow	32.7	17.9	13.8	7.0	13.6	11.0	22.2	19.5	9.9
Standard Deviation									
MetHigh	5.3	1.3	2.8	1.5	1.9	0.5	4.2	2.1	1.4
MetMid	5.3	1.1	1.0	0.7	2.4	2.3	1.6	6.3	1.2
MetLow	5.9	1.0	0.7	0.2	1.2	0.8	1.8	1.4	1.2

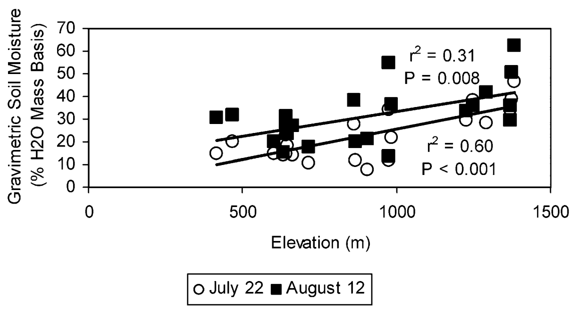

Figure 4. Gravimetric moisture as a function of elevation for August 12 and July 22, 1999 samples. The August sampling was preceded by a two-day rain event the previous week and has higher values, on average.

5a). The permanent TDR readings also were highly correlated with the handheld volumetric measurements used for the empirical model (Figure 5b).

Empirical model

According to the regression analyses of the volumetric samples, factors important to deep soil and surface soil moisture patterns are similar but have some important differences (Table 4). Elevation and slope accounted for a significant amount of the variation within the deep soil moisture measurements (R^2 = 0.40, F-statistic = 4.3, P = 0.04, N = 16). The model for surface soils was slightly more complicated. Local hillslope/drainage factors (distance from stream) and elevation also were important, but radiation differences were more significant than they were for deep soils. Sites with a high solar exposure had significantly drier surface soils than more shaded sites. Nearly 50 percent of the variance in surface soil moisture was explained by these three factors (R^2 = 0.48, F-statistic = 25.5, $P < 0.001$). Distance from stream was significantly positively correlated with elevation (r = 0.43, t = 4.4, df = 86, $P < 0.001$). None of the other explanatory factors were significantly cross-correlated; nor were interaction effects significant in the regressions. In considering potential nonlinear relationships, adding a quadratic distance from stream term improved the surface soil moisture model significantly (F-statistic for adding quadratic term = 10.5, P = 0.002).

The residuals from the surface soil model were normally distributed (Figure 6b) and not significantly correlated with elevation, although there was a cluster of points from one transect between 850 m and 900 m with measured soil moisture values more than one standard deviation below the modeled values (Figure 6c). The clustering is likely indicative of the autocorrelation in the data rather than a persistent elevation trend, as model residuals were autocorrelated up to a distance of approximately 50 m (Figure 6d). This distance represents approximately one-half the average transect length. Removing the 850-900 m transect from the analysis improved the regression model fit (R^2 = 0.58, F-statistic = 35.4, $P < 0.001$),

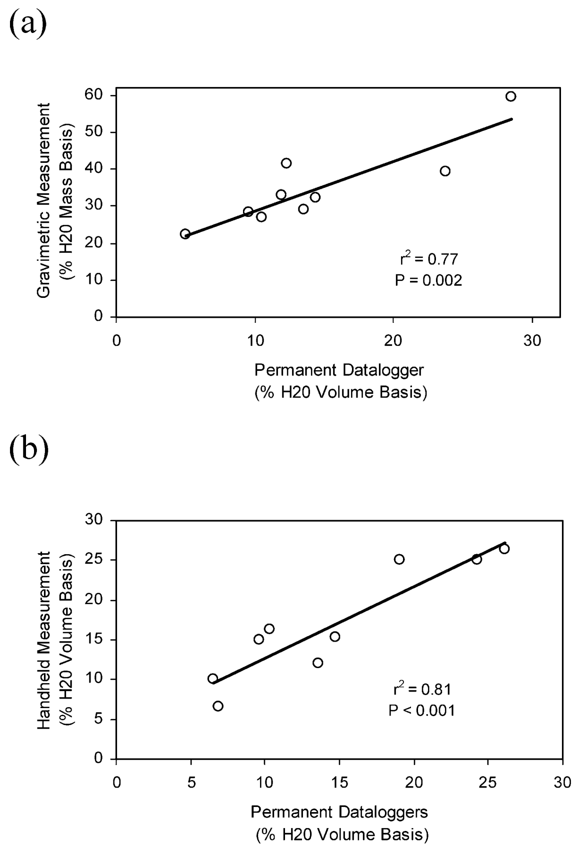

Figure 5. Comparison of different soil moisture measurement techniques. (a) Surface soil gravimetric samples compared to surface soil moisture measurements recorded by permanent TDR stations for the same locations and the same time on August 12, 1999. (b) Handheld reflectometer samples compared to measurements recorded by permanent TDR stations for the same locations and the same time on July 4, 2001.

but the resulting model may be less representative of the diversity of the landscape.

The regression models can be used in a GIS framework to make predictive maps of soil moisture differences for the study area. Figure 7 provides an example of the surface soil moisture model projected across the HJA watershed for the onset of the seasonal drought period.

Variograms

The landscape-wide soil moisture samples exhibited variability at multiple scales. Fine-scale variability was indicated by the relatively large nugget variance (i.e., Y-intercept on variogram in Figure 8). The average variance within the 2 × 2 m sample quadrats (5.5) and within the 20 × 20 m sample plots (9.6) also was fairly high relative to the total variance for all 540 measurements (16.8). The empirical variogram (points in Figure 8) did not fit a classic variogram model of increasing variance to an asymptotic sill, and is presented with a lowess-smoothed curve in Figure 8. The variance did reach a peak at 1500-2000 m, but decreased for separation distances from 2000-4000 m. A second increase in variance was observed at larger distance lags. This complex pattern of variability confirmed that any explanatory model of soil moisture spatial trends would need to account for influences at multiple scales.

The environmental variables that we had determined to be important in our earlier analyses differed considerably in their characteristic ranges. Elevation exhibited a monotonic increase in variance with lag distance, indicative of a simple gradient (Figure 8). Other DEM-based variables were finer-scaled than elevation. PRR and other measures of radiation reached their maximum values at a range of 1000-2000 m. This distance roughly matches the average hillslope length for the major watersheds contained within the HJA. Like the moisture measurements, these variables did not conform to a classic variogram model, but instead exhibited a decrease in variance at larger lag distances. Though this decrease is undoubtedly a sampling effect (e.g., a complete sampling of the PRR grid for the HJA results in no such decrease), it may be important in explaining the similar trend observed for the moisture measurements. TCI and other measures of hillslope position/drainage also were highly related to hillslope length. They reached asymptotic sills at around 1500 m. That this distance corresponds with the peak observed for the soil moisture measurements provides corroborating support that these small watershed-scale topographic variables can be used effectively to describe some of the spatial patterning in soil moisture. The monotonic elevation gradient likely acts as an underlying forcing variable for soil water.

The fine-scale variability in soil moisture indicated by the large nugget (0.43) is unlikely a consequence of topography. None of the terrain-based variables had exceptionally large nugget variances (largest is for TCI = 0.23). It is important to note that although the smooth curve fit through the PRR data in Figure 8 does suggest a sizable nugget variance, the variance in the smallest distance class for PRR and the other radiation proxies was very small. Canopy cover (0.62) and soil depth (0.65), in comparison, had large nugget variances indicating variation at lag distances

Table 4. Partial regression statistics for empirical moisture models. N = 88 for surface soil moisture model. N = 16 for deep soil moisture model.

Response Variable	Site Characteristic	r^2	Slope	F-Statistic	Pr(F)
Surface Soil Moisture (0-20cm)					
	Dstrm	0.19	–	30.4	< 0.0001
	Elev	0.21	+	33.7	< 0.0001
	PRR	0.08	–	12.2	0.0001
Deep Soil Moisture (80-100cm)					
	Slope	0.21	+	4.4	0.055
	Elev	0.19	+	4.1	0.062

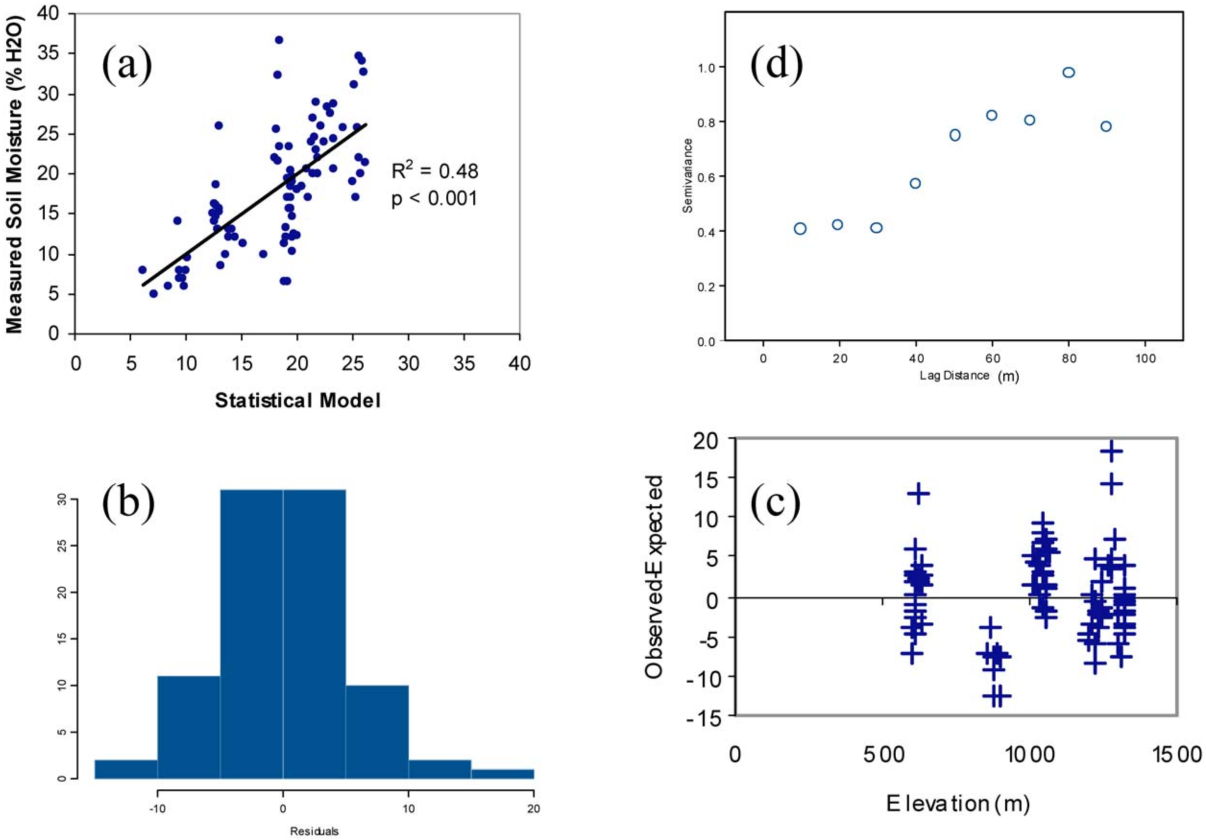

Figure 6. Comparison of surface soil moisture estimates from the regression model and field data used to construct the model (N = 88). (a) The model combines the influences of elevation, distance from stream, and potential relative radiation into a single factor. The residuals are (b) normally distributed, (c) not significantly associated with elevation, although one transect at mid elevation was consistently drier than predicted, and d) autocorrelated up to 50 m.

finer than were captured in the analysis (Figure 8). These biotic and edaphic factors were highly variable across all spatial scales.

To pursue the large nugget variance in soil moisture, we examined the variation in the 88 surface soil moisture measurements collected for the empirical modeling, which were gathered at a much finer resolution (Figure 9). The variation in these measurements increased over the first 100 m in lag distance, indicating some consistency in measurements taken over 10’s of m. In other words, moisture measurements taken at lag distances of 250 m (the closest distance bin in Figure 8) had substantially more variability than measurements taken 10 m apart.

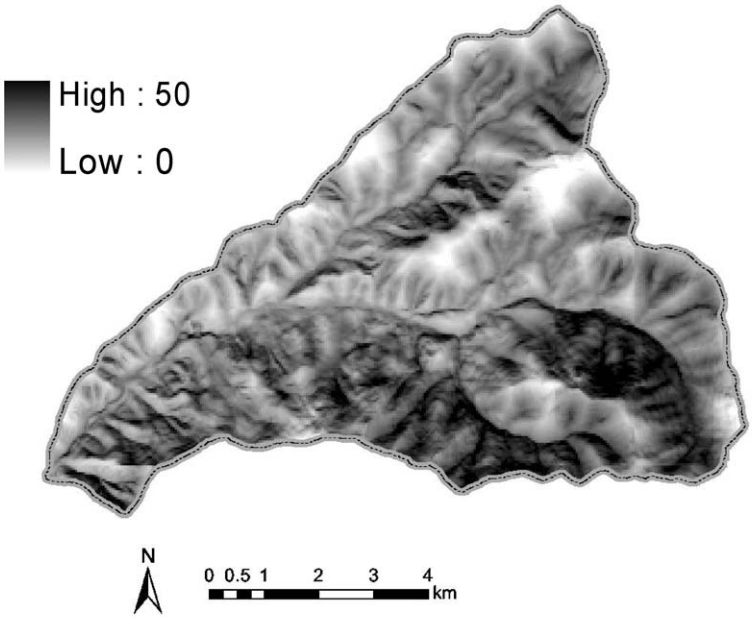

Figure 7. Statistical model of surface soil moisture mapped back onto the landscape. Darker areas are predicted to be wetter than lighter areas. These estimates of relative moisture differences were derived from measurements taken on July 4, 2001.

The complex spatial scaling of soil moisture in the variogram analysis supports the contention that soil water content is a function of multiple physical and biological influences (Figure 8). We were able to reproduce the approximate shape, sill and nugget variance in Figure 8a through our regression modeling using easily measurable environmental variables (Figure 10).

Discussion

Our soil moisture regression models were able to combine multiple physical factors with different characteristic spatial scaling into a single coherent equation that explains up to 50 percent of the variance in moisture field measurements. The models provide a snapshot of how components of the water balance can influence additively the soil moisture regime at a critical time in the growing season (i.e., the onset of summer drought). They include meso- and macro-scale factors at two depths (0-20 cm and 80-100 cm) relevant to forest vegetation.

Influence of topography on surface soil moisture

A major challenge in describing ecological patterns is that they are sensitive to the scale of observation (Levin 1992). Chen et al. (1999) argue that microclimate has distinct spatial scales corresponding to distinct components of landscape structure. These relationships rarely have been examined across a continuum of spatial scales, because of difficulties in sampling simultaneously at fine grain across large spatial extents. More typical is for the relationships to be simplified using general rules such as the increase in precipitation and decrease in evapotranspiration associated with increases in elevation. Technology developments over recent years, however, have greatly increased the feasibility of multi-scale studies. Here, we have shown that while soil moisture does vary positively with elevation at the landscape scale, it varies negatively with distance from stream at more local scales. Because distance from stream is positively correlated with elevation (at the hillslope level), the sign of the elevation-soil moisture relationship changes when examined at the meso-scale. Within a hillslope, water flows downhill resulting in wetter soils at lower elevations.

Even this two-factor description is oversimplified, as indicated by the potential significance of an additional quadratic distance from stream term in the surface soil moisture model. This factor, which was positively associated with soil moisture, reflects the field observation that at locations very close to streams soil moisture measurements may decrease

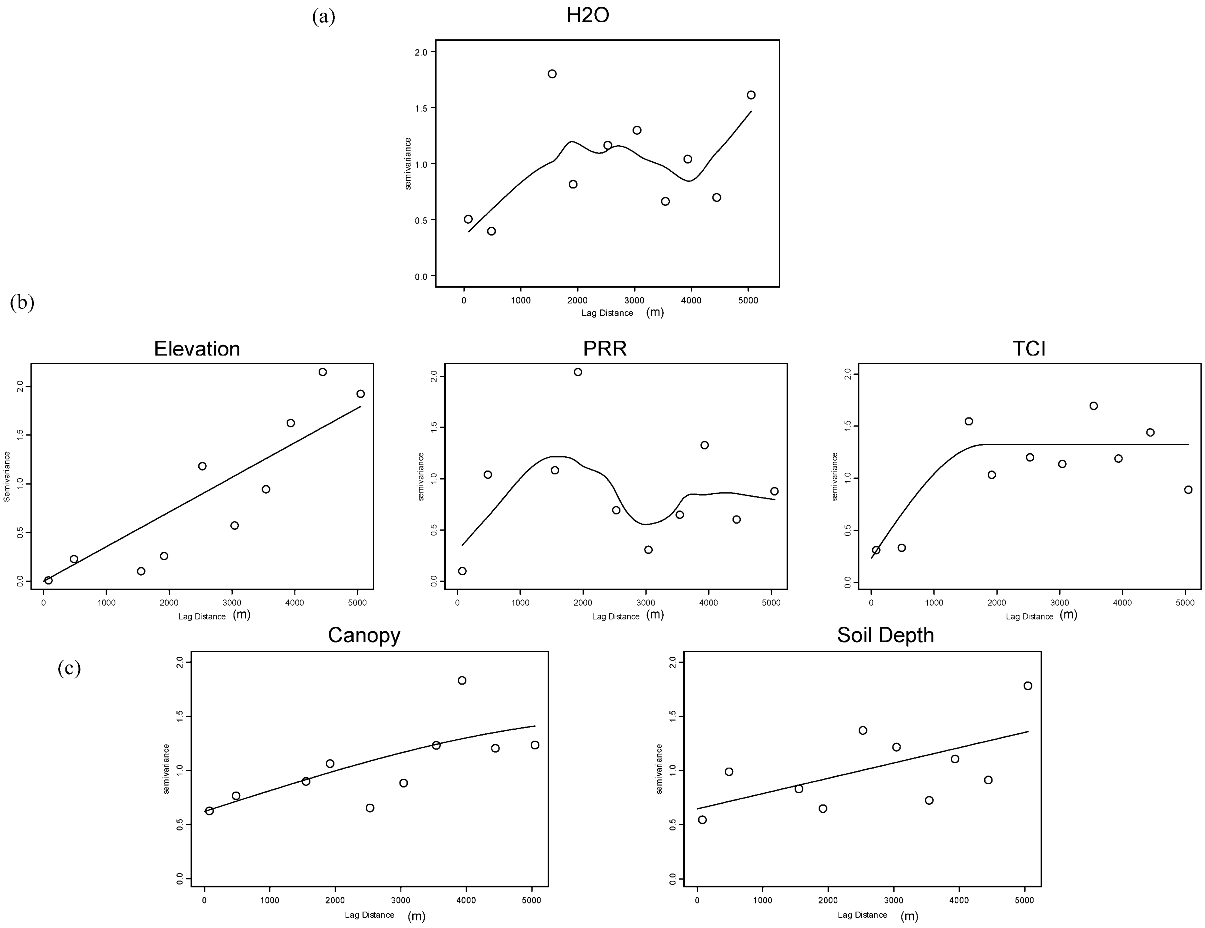

Figure 8. Spatial scaling of soil moisture and factors important to the water budget as depicted by variograms. Data were obtained from 60 (20x20 m) plots sampled across the HJA landscape (nine measurements taken per plot). All semivariance values have been relativized by total variance for that variable in order to facilitate comparisons across variables. Lag distance was set to 250 m and only bins with at least 50 sample pairs were graphed. (a) Measured volumetric soil moisture. (b) Terrain-based explanatory variables elevation, summer PRR, and TCI. Values were derived from a 10-m DEM. These three variables are representative of the types of curves calculated for terrain variables. (c) Canopy and soil depth. Values were measured in the field.

rapidly. In our sample site, this relationship is likely a function of the change in soil type to rocky cobbles along many of the stream channels.

Differences in radiation also were important to surface soil moisture levels. The 1500 m range of soil moisture variability indicated by the variogram analysis (Figure 8) may be a reflection of topographically induced patterns in soil moisture associated with shaded north-facing slopes compared to hot, dry south-facing slopes. This distance corresponds with the average hillslope length in the basin. The importance of topographic exposure also is reflected by the radiation term in the regression equation. These findings are consistent with others that have shown that topographic variability is an important control of spatial differences in July air temperatures for the HJA (Smith 2002; Lookingbill and Urban 2003). Temperature, in turn, can be a significant control on soil moisture.

Microscale variability difficult to represent

Although we were able to capture the influences of both macroscale (climate) and mesoscale (topographic drainage and radiation) factors on summer soil moisture in the HJA, we did not have the data to add microscale factors (e.g., soil variability) to the regression models. The high nugget variance in the landscape-level soil moisture variogram (Figure 8a) indicates that much of the variability in soil moisture

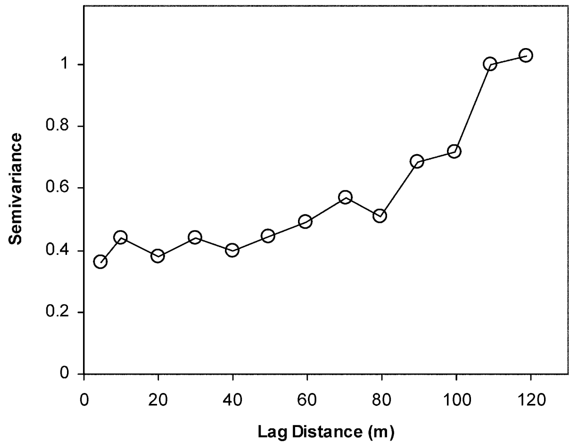

Figure 9. Variogram of fine-scale trend in moisture content from samples collected as part of regression analysis ($N = 88$). Samples were taken along short transects (up to 110 m in length) at intervals of 5-10 m.

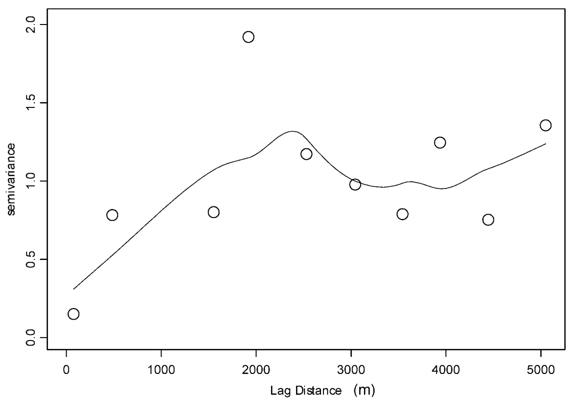

Figure 10. Variogram of fitted values derived from regression model of surface soil moisture for the 60 plots used to construct Figure 8. The model captures many of the same scaling relationships depicted for field measurements of soil water content (Figure 8a) by using elevation (increasing trend), radiation (decrease in variance after ~ 2000 m), and distance from stream (sill at ~2000 m).

occurred below the sampling grain averaged across by the 20 × 20 m plots. The finer-scale variogram of soil moisture confirmed a large amount of variation at small lag distances (Figure 9), and the average within plot variance (9.6) was more than one-half the total variance for all samples (16.8). Grayson et al. (1997) also found a high level of local control during the dry season in their seasonal watersheds. In the HJA, Post and Jones (2001) found the greatest exertion of fine-scale influences on the hydrologic regime at the end of the summer drought period, so it is likely that the importance of fine-scale factors would only increase at later sample dates.

Much of the local variability in soil moisture is likely due to edaphic and biotic variation rather than fine-scale topographic differences. Improved slope, aspect, and elevation readings (e.g., as from a higher resolution LIDAR-derived DEM), therefore, should not alter greatly our results. These attributes had relatively low nugget variances for the 20 × 20 m plots used in the semivariance analyses, suggesting that the 10-m resolution DEM used in deriving their values for the regression analysis captured most of the relevant variation in these terms. Soil depth and canopy cover, in contrast, exhibited substantial fine-grain variability in our semivariance analyses.

Quality information on the fine-scale variability of soils is rarely available for even the best-studied systems (Band and Moore 1995). Yet, numerous studies have illustrated that soil properties can be at least as important as terrain-based variables in determining soil moisture content (e.g., Helvey et al. 1972; Boyer et al. 1990; Yeakley et al. 1998). Even if we had the field data to add edaphic variables to the regression models, we do not currently have the necessary coverages to extrapolate this type of model to the entire landscape. The HJA is aggressively working to develop a spatial mapping of soil properties that would allow edaphic factors to be incorporated in future work. For now, we caution that because much of the fine-grained variability in soil moisture may be due to variability in soil properties, failure to include these properties in our models compromises their explanatory and predictive capabilities for fine-grained applications.

Deep soil water patterns

Our empirical model results corroborate Yeakley et al.'s (1998) conclusion that deep soil water distributions may be very different from surface soil moisture patterns. This finding has important implications for the analysis of ecological processes. For example, the surface soil moisture model that includes radiation as an explanatory factor is probably not the best model for predicting rates of growth for trees whose roots can integrate over a much deeper area than the top 20 cm of soil. A weighted model combining the deep and shallow estimates may be more suitable for this application. For understory species and seedlings, however, the 20 cm model would be the appropriate choice.

Again, we emphasize that any interpretation of the deep soil regression must bear in mind the logistical difficulties of sampling deeper soil layers and the resultant small sample size. We have presented primarily the surface soil moisture results as an example of our approach and offered the deep soil moisture results where applicable as a crude comparison with the shallow soil model only. For example, there were insufficient deep soil measurements to conduct a semivariance scaling analysis and, thus, this test was not included in our study.

Value and limitations of approach

The lack of high-resolution field data has been a major limitation to soil moisture modeling. The few field measurements available for most sites are typically from locations that are not representative of the landscape as a whole (e.g., watershed base or few prominent peaks; Phillips et al. 1992; Daly et al. 1994). Collecting additional data has been logistically and economically prohibitive. Permanent TDR stations, such as those employed in the first phase of this study, are costly and are limited in coverage to small areas surrounding central dataloggers. Targeted synoptic sampling using handheld reflectometers can help fill this important data need.

In response to the shortage of field data, digital terrain-based indices have become increasingly popular in describing soil moisture (Beven and Kirkby 1979; Parker 1982; Iverson et al. 1997). The value of field data is not diminished by the expanse of this new approach, however, but rather GIS and field sampling should be viewed as complementary activities. As shown here, field data can be a valuable tool in calibrating relationships for GIS derived variables. Conversely, GIS can be useful in helping to identify the best sites to locate field samples. For example, the GIS map derived from the surface soil moisture regression model (Figure 7) identifies geographic locations within the HJA that could be targeted to capture a representative range of moisture values in future sampling efforts.

It is important to emphasize that the results presented in this analysis are applicable to only a very narrow range of conditions. As with any statistical model, our model should not be extrapolated beyond the range of conditions specified by the input data. These include the topographic and climatic conditions of the study area, the timing of the sampling at the beginning of summer soil moisture drawdown, and the stand structure of old-growth forest. We were interested in developing a simple moisture model for exactly these conditions as part of an effort to explain landscape-scale patterns in vegetation. We present this analysis as an example for others who may be interested in developing models of their own for other specific applications. The empirical approach provides an alternative to more commonly used moisture proxies that rely solely on geographic abstractions of the landscape (e.g., TCI: Beven and Kirkby 1979). If the objective was to develop a more comprehensive spatio-temporal description of the HJA's moisture regime, the data and patterns described in this paper would be of great value as a calibration tool and/or reality check of the subsequent model (Lookingbill et al. in review).

Conclusions

A thorough examination of the major components of the water balance can provide a basis for varied studies of ecological processes in montane systems. We are interested particularly in better understanding the relationship between the distribution of forest vegetation communities and the physical environment. Soil moisture is without question a dominant factor in shaping these distributions. Using a tactical approach to gather high-resolution field data over large spatial extent, we have shown that (1) factors important to the summer water balance vary at different characteristic spatial scales; (2) soil moisture itself exhibits variation at multiple spatial scales; and (3) the complex spatial patterns inherent in soil moisture measurements can be reproduced through a regression equation of more easily measured environmental variables. Specifically, the interaction of multiple physical and biological influences (including microscale biotic and edaphic factors, mesoscale variability in topography, and an underlying elevation forcing) combine to shape the complex water dynamics of the HJA during this important period of seasonal drought. Further, we found evidence supporting the claims that soil moisture dynamics and controls are different for different depths of the soil profile. The regression modeling allowed us to extrapolate field measurements of volumetric moisture across similar topographic areas, although we caution that great care should be taken to apply the models only within the restricted domain for which they were built. This type of improved spatial mapping of soil water variability should be beneficial to the study of a wide range of moisture-controlled ecological processes.

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