

SCALING OF SOIL MOISTURE: A Hydrologic Perspective

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■ **Abstract** Soil moisture is spatially and temporally highly variable, and it influences a range of environmental processes in a nonlinear manner. This leads to scale effects that need to be understood for improved prediction of moisture dependent processes. We provide some introductory material on soil moisture, and then review results from the literature relevant to a variety of scaling techniques applicable to soil moisture. This review concentrates on spatial scaling with brief reference to results on temporal scaling. Scaling techniques are divided into behavioral techniques and process-based techniques. We discuss the statistical distribution of soil moisture, spatial correlation of soil moisture at scales from tens of meters to thousands of kilometers and related interpolation and regularization techniques, and the use of auxiliary variables such as terrain indices. Issues related to spatially distributed deterministic modeling of soil moisture are also briefly reviewed.

INTRODUCTION

Soil moisture is a small proportion (only 0.15%) of the liquid freshwater on Earth (Dingman 1994), but it is an influential store of water in the hydrologic cycle. It modulates interactions between the land surface and the atmosphere, thereby influencing climate and weather (Entekhabi 1995), and is important in determining the rainfall-runoff response of catchments, especially where saturation excess runoff processes are important (Dunne et al. 1975). Soil moisture also influences a variety of processes related to plant growth [and hence ecological patterns (Rodríguez-Iturbe 2000) and agricultural production], as well as a range of soil processes (Brady 1990, White 1997).

Soil moisture is variable in space and time and many moisture dependent processes are nonlinear. This leads to scale effects that need to be understood if we are to make accurate predictions of the behavior of hydrologic systems, where it is generally necessary to aggregate in space and/or time. Similarly, many other spatial and temporal fields (e.g., soil, vegetation, topography, meteorology) that influence soil moisture and other hydrologic responses are variable. The consequence of this is that scale effects are complex, making hydrologic simulation and prediction very challenging. This review concentrates on the scale characteristics and the scaling of soil moisture in the root zone, focusing on catchment-scale spatial patterns with some reference to temporal patterns.

For both measurements and models, scale can be thought of as consisting of a triplet of characteristics: support, spacing, and extent (Blöschl & Sivapalan 1995). Figure 1 illustrates each component of the scale triplet. Support is the area (or time) over which a measurement averages the underlying variations, or over which a model assumes homogenous conditions. As support increases, variability decreases due to the effects of averaging, and small-scale features disappear. Spacing is the separation between points at which measurements are made or between computational points in a model. As the spacing increases, the amount of detail resolved decreases, leading to an apparent increase in the spatial size of features. Interestingly, the variability apparent in the data is unaffected (Western & Blöschl 1999). Extent refers to the total coverage of the measurements or model. As extent increases, larger scale features are included in the data, and both the variability and the average size of the features tend to increase.

The effect of changing each component of the scale triplet individually by a factor of three is illustrated in Figure 2. Figure 2a shows a background of large-scale variation (essentially a hill) with a set of smaller-scale features (the letters of the word scale) superimposed. Figure 2b shows the loss of small-scale features resulting from increasing the support by passing a three-by-three pixel averaging window over the data. Figure 2c shows the loss of detail in the small-scale features when a higher spacing is used. Figure 2d shows the loss of large-scale features when the extent is limited. Clearly, scale has an effect on the characteristics of the information obtained from a data set (or model).

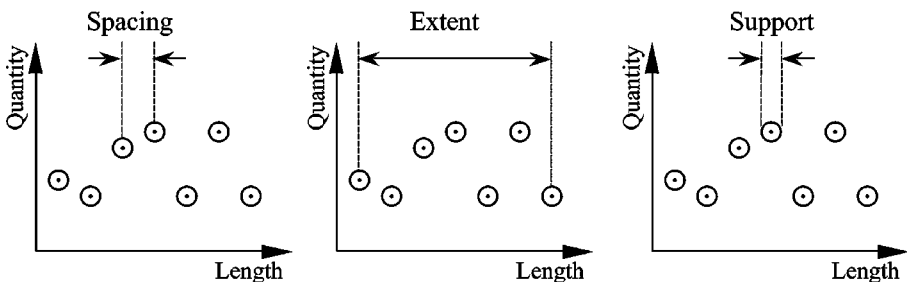


Figure 1 The scale triplet (after Blöschl & Sivapalan 1995).

We often need to use information from one scale at another scale. This is the scaling problem (Beven 1995), and it is challenging because practical problems typically involve using information from one scale to make predictions at a scale that has a greater information requirement; i.e., taking sparse data and estimating intervening values (converting Figure 2*c* to 2*a*), taking areal averages and disaggregating them (converting Figure 2*b* to 2*a*), or taking results at small extents and extrapolating to larger areas (converting Figure 2*d* to 2*a*). Also, scaling often involves changing more than one component of the scale triplet at a time (e.g., often both support and spacing change together). The essence of successful scaling is to distill the key patterns from information at one scale and to use these to make good predictions at another scale. Such efforts often rely on a suite of relevant supplementary information ranging from digital elevation models to meteorological time series data.

It is important to note at this point that there are several uses of the term scaling in soil science and hydrology. We have chosen the broad definition outlined above and have opted to confine most of our discussion to soil moisture; however, a brief overview of related concepts is in order. In soil science, scaling is sometimes limited to concepts of similar media in the context of scaling soil hydraulic properties and flow and transport equations (Kutílek & Nielsen 1994, Sposito 1998a). The essential aim has been to either describe soil heterogeneity or the integrated effect of soil heterogeneity on flow or transport processes. The concept of geometrically similar media was first introduced by Miller & Miller (1955a,b) to relate soil hydraulic properties to the pore structure. Using capillary theory, this assumption leads to the soil water pressure head functions and hydraulic conductivity functions being related to a microscopic length scale that can be used to characterize heterogeneity. Further research has led to approaches for scaling static soil hydraulic behavior (Warrick 1990). Attempts are also being made to scale the dynamic unsaturated flow equations directly (Haverkamp et al. 1998, Sposito 1998b); however, limitations related to the dependence on the type of boundary condition used in the analyses exist at present. Stochastic approaches are also being used to understand the effects of heterogeneity on flow and transport in porous media (Jury et al. 1987, Russo 1998) and to derive effective hydraulic properties for analysis of flow and transport processes in heterogeneous soils at field scales (Yeh 1998). Research into the characteristics and representation of soil heterogeneity can contribute to the broader understanding of the effect of scale on the hydrologic cycle to the extent that soil heterogeneity is one of several scale-dependent influences on hydrologic fluxes and states. In summary, these approaches relate soil hydraulic properties to media properties, whereas in this review the focus is on inferring the spatial distribution of soil moisture from a few point data and on inferring the temporal dynamics of soil moisture from a few snapshots.

In hydrology, the term scaling is sometimes used to refer to techniques based on fractal approaches or scaling invariance (Gupta & Waymire 1998, Rinaldo & Rodríguez-Iturbe 1998, Rodríguez-Iturbe & Rinaldo 1997). These have been used to analyze properties of stream networks and topography. However, in this paper we use the term scaling exclusively to denote a transfer of information from one scale to another as discussed above.

The literature contains a number of examples of important scale effects associated with soil moisture variation. Merz & Plate (1997) studied the effect of spatially variable patterns of soil moisture and soil infiltration characteristics on the event rainfall-runoff response at Weiherbach in southwest Germany using a process-based distributed rainfall-runoff model. Three types of spatial patterns were considered: uniform, structured, and random. The structured patterns were characterized by relatively wet gullies and dry hilltops and/or by lower infiltration capacity in the gullies. Substantial differences in both peak discharge and event runoff volume were found between each of the three types of patterns, with initial soil moisture being more important than the infiltration properties. The differences were dependent on the rainfall characteristics, with medium-sized events influenced most by the spatial variability. Similar studies have been conducted by Grayson et al. (1995) and Western et al. (2001).

Variability in the land surface can also have a significant impact on atmospheric processes. Weaver & Avissar (2001) studied the impact of variations in the surface latent and sensible heat fluxes on mesoscale atmospheric circulation over Oklahoma and Kansas, using the Colorado State University Regional Atmospheric Modeling System. At the land surface boundary, they applied a 2-km grid pattern of land surface sensible and latent heat flux over a 252-km square area, derived from surface measurements. The spatial variations were primarily due to vegetation patterns and moisture availability, and they had characteristic scales of 20–100 km. The simulations suggested that strong mesoscale atmospheric circulations developed under a range of synoptic conditions as a result of surface heterogeneity. They led to moisture being transported higher into the atmosphere and would be expected to lead to increased cloud formation and precipitation. The atmospheric simulations were also compared with satellite cloud images, which could not be simulated realistically when ignoring the spatial variability of surface latent and sensible heat fluxes.

While the studies described above are model based and the conclusions, therefore, depend on the validity of the model assumptions, significant efforts have been made to test the models using appropriate spatial data. The studies indicate significant scale effects associated with variability in soil moisture, or, in the second case, evapotranspiration, which is partially moisture controlled. The effects on fluxes are of practical significance in both cases, but the characteristic scales of importance are very different, illustrating the problem-specific nature of scaling issues.

The rest of this paper is structured as follows. First, the key physical processes controlling soil moisture are briefly discussed. Second, measurement of soil moisture by ground-based and remote sensing techniques is discussed, and the key scale characteristics of different measurements are identified. In the final section, scaling techniques applicable to soil moisture are presented, including a brief discussion of temporal scaling and then concentrating on spatial controls on soil moisture, scaling based on behavioral analysis, and scaling based on process analysis.

There are several published reviews that also provide useful information of relevance to soil moisture scaling. They include reviews on scaling in hydrology

in general (Blöschl & Sivapalan 1995, Dunne et al. 1975, Koltermann & Gorelick 1996), on land-atmosphere interactions (Entekhabi 1995, Giorgi & Avissar 1997, Pielke 2001), and on soil moisture modeling (Mahmood 1996). Sposito (1998a) presents a collection of papers on scaling in hydrology and soil science.

SOIL MOISTURE PROCESSES

In this section we briefly describe the parts of the hydrologic cycle that directly affect soil moisture, as well as some elementary soil physics. More detailed treatments can be found in text books (Dingman 1994, Hillel 1998, Kutílek & Nielsen 1994). Soil is a complex porous media containing mineral particles, water and air, together with small amounts of organic matter, and the soil biota. Soil water is a reservoir in the hydrologic cycle that influences runoff, evapotranspiration, and drainage to groundwater systems and to streams. There are two standard quantitative definitions of soil moisture: gravimetric, θ_g , and volumetric, θ_v . θ_g is defined as the mass of water divided by the mass of dry soil, and θ_v is defined as the volume of water divided by the volume of soil. It is possible to convert between the two using the dry soil bulk density, ρ_b : $\theta_v = \rho_b \theta_g$. Soil moisture is an integral quantity that represents the average conditions in a finite volume of soil. For proper interpretation, it is important to know the volume, and particularly the depth range, that a soil moisture value represents.

From a theoretical perspective, the range in soil moisture is bounded by zero and the soil porosity, η . η is the volume of soil pores divided by the volume of soil. In the field the practical lower limit on soil moisture is positive due to the inability of plants to extract water below a particular level, commonly called the wilting point. The bounded nature of soil moisture has important implications for its statistical characteristics in space and time, as is explored in more detail later.

Figure 3a illustrates a standard one-dimensional conceptualization of the soil profile and the fluxes that influence the soil moisture stored in the profile. Generally, the exchanges between the atmosphere and the soil dominate changes in soil moisture. The soil moisture store is primarily replenished by infiltration and depleted by soil evaporation and plant transpiration. The relative importance of evaporation and transpiration depends on the vegetation cover, with transpiration dominating in well-vegetated landscapes. Fluxes between the soil and groundwater (or deeper parts of the regolith) can be important in some contexts. Drainage from the soil profile is the primary source of recharge for many groundwater systems, and capillary rise from shallow groundwater tables can be an important source of water replenishing the soil water store during drier periods.

Included in Figure 3a is a series of soil moisture profiles measured for a clay-loam soil in Victoria, Australia. Both the amount of soil moisture and its dynamics change with depth. In the upper 50 cm, soil moisture is strongly influenced by the fluxes between the active root zone and the atmosphere; the moisture here is more variable than the moisture at depth. Surface soil moisture also responds

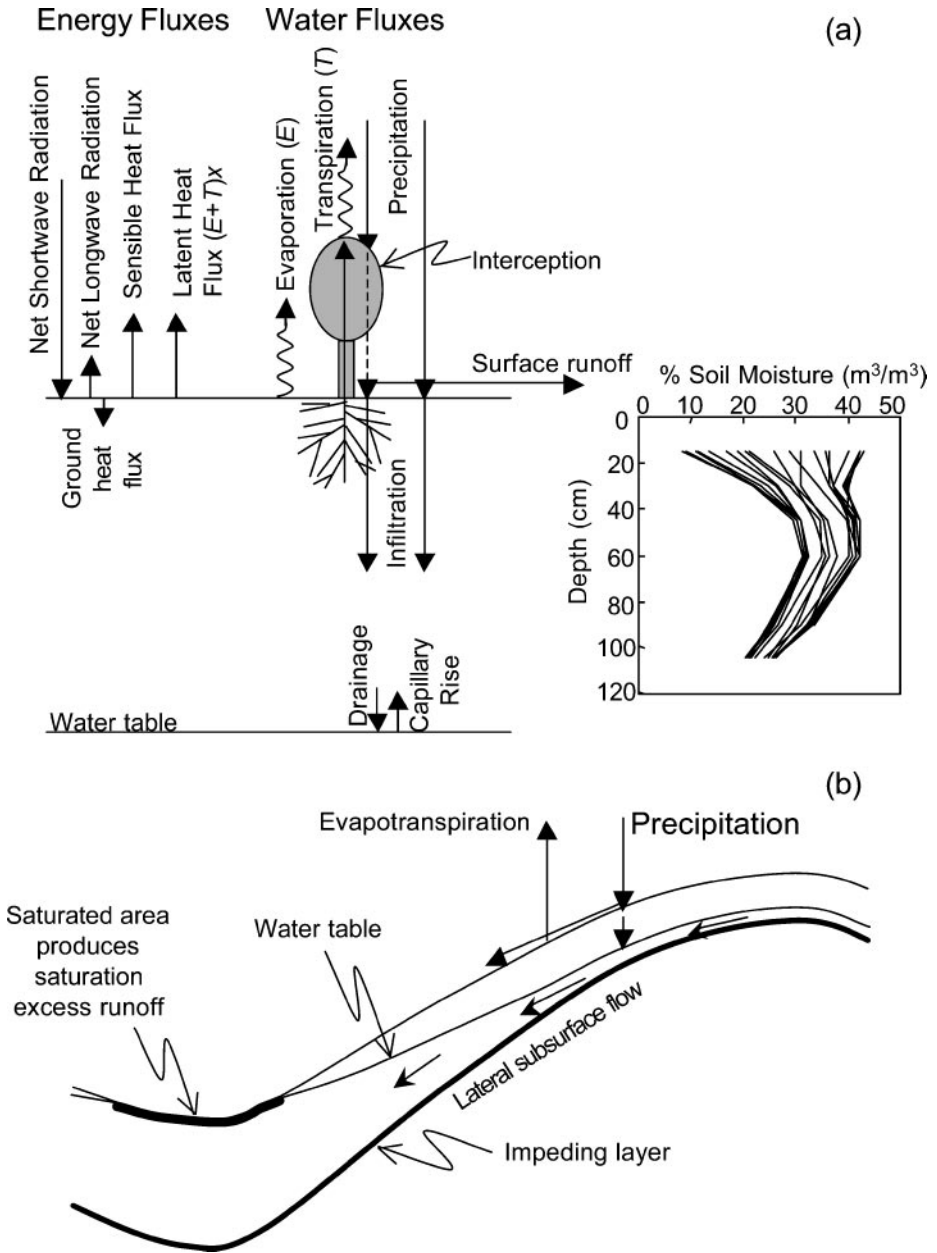


Figure 3 (a) One-dimensional conceptualization of fluxes affecting soil moisture. This is applicable where lateral flows are insignificant. Also shown are the surface energy fluxes. The soil moisture-depth profiles are from the Tarrawarra catchment, Australia. (b) A two-dimensional conceptualization of fluxes affecting soil moisture.

more quickly and so has both short and long timescale variability, whereas the moisture at depth is less responsive to short term variations in the fluxes across the soil-atmosphere interface.

Figure 3*b* illustrates a standard conceptualization of a hillslope. The key difference between Figure 3*a* and 3*b* is that lateral flows now act to redistribute soil water and influence runoff processes. For significant lateral drainage to occur the following conditions are necessary.

- Topographic relief (surface slopes greater than a few percent).
- An impeding layer in the soil profile limiting vertical drainage [or anisotropy between vertical and horizontal hydraulic conductivities (Zavlasky & Sinai 1981)].
- Sufficiently high moisture contents for periods long enough for flow to occur over significant distances.

In higher parts of the landscape lateral drainage can deplete the soil moisture store. This lateral drainage collects in convergent parts of the hillslope (the hollows) and replenishes the soil moisture store in those areas, often leading to soil saturation and generation of saturation excess runoff. It is important to emphasize that the existence of lateral flow depends on the above conditions, which only occur in some landscapes and at some times.

Figure 4 shows the changes in hydraulic conductivity and soil water tension (or soil suction) with soil moisture content for a typical loam soil. There is a rapid decline in hydraulic conductivity or increase in resistance to flow as the soil dries. Also, as smaller and smaller pores are emptied of water, the tension increases due to capillary effects. The combined effect of these influences results in hydraulic gradients dominated by gravity and relatively conductive soils at high moisture contents. Provided a soil is free to drain, wet soils drain to the point where gravity can no longer remove water from the soil pores. The soil moisture at this point is the field capacity, θ_f . At lower moisture contents, the hydraulic gradients are dominated by soil water tension and the resistance to flow increases rapidly. Because of the

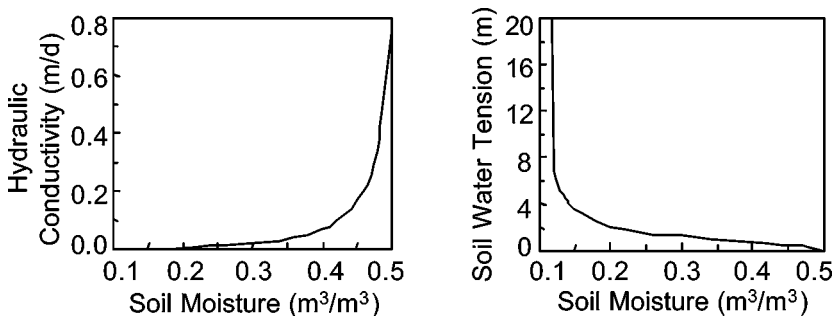


Figure 4 Typical hydraulic conductivity and water retention curves.

rapidly decreasing flow velocities as soil dries, the spatial scale at which soil water flow processes operate is very much smaller for dry soils than for wet soils. The changes in soil water tension also affect evapotranspiration by increasing the energy required to extract water from the soil as soil moisture decreases. This leads to a marked reduction in evapotranspiration under dry conditions. Eventually the tension becomes so large that plants can no longer extract water from the soil and they wilt. This soil moisture content is referred to as the wilting point, θ_w . The plant-available water (paw) is the soil water storage capacity that is readily available to plants. $Paw = (\theta_f - \theta_w)D$, where D is the depth of soil exploited by the plant roots.

It is important to realize that typical soil hydraulic conductivity curves, such as that shown in Figure 4a, often neglect the effects of plant roots and other soil biota in creating macropores that can transmit water rapidly through the soil profile, effectively bypassing the soil matrix under certain conditions (Beven & Germann 1982). Soil cracks can also be important in conveying water rapidly in both the vertical and horizontal directions (Western & Grayson 2000).

The change in evapotranspiration with moisture content has important implications for both the moisture and energy fluxes involved in the interaction between the atmosphere and the land surface. The surface energy balance components are shown in Figure 3a in addition to the moisture fluxes. The energy and moisture fluxes are intimately linked together via the evapotranspiration process. When soil moisture is evapotranspired a phase change from liquid water to water vapor occurs. The moisture flux, E , and latent heat flux, λ , are linked by the latent heat of vaporization of water x such that $\lambda = xE$. Soil moisture availability, in conjunction with atmospheric conditions, controls the evapotranspiration and the partitioning of incoming solar energy into latent and sensible heat fluxes. Because of the effects on atmospheric heating and the atmospheric moisture content, land-surface interaction and the role of soil moisture in this interaction have become an area of great interest to atmospheric modelers. Improving our understanding in this area has motivated, and will continue to motivate, a series of major interdisciplinary studies, many of which are coordinated under GEWEX (Global Water and Energy Cycle Experiment—see <http://www.gewex.com/>). Scaling of soil moisture is especially important for these studies because much of our understanding of soil moisture and related processes is based on point and small catchment studies, but atmospheric modeling requires land-surface predictions over large 5–500-km grid sizes and global extents.

MEASUREMENT OF SOIL MOISTURE

Soil moisture is a difficult quantity to measure in a comprehensive manner. There are essentially two groups of approaches to moisture measurement; remote sensing and ground-based measurements. The data collected using each of these approaches have quite different scale characteristics.

Remote Sensing Measurement

Most remote sensing of soil moisture has concentrated on using microwave wavelengths (Dobson & Ulaby 1998, Engman 2000, Jackson et al. 1996). Both active [e.g., synthetic aperture radar (SAR), where a signal is sent from the sensor and the returned signal measured] and passive (e.g., microwave radiometers that measure the naturally emitted microwave radiation) have been used. These instruments respond to soil moisture in the top few mm to few cm of the soil profile, depending on the exact wavelength used, so long as the vegetation canopy is not too dense (Du et al. 2000). Compared with instruments using visible and infrared wavelengths, microwave instruments have the advantage of “seeing through” cloudy conditions (Engman 2000). From a user’s perspective, the most fundamental difference between these instruments is their spatial and temporal resolution. As implemented at the present time on satellites (or spaceborne), SAR provides data with pixel sizes of roughly 10 m, although some aggregation is required to overcome the problem of noise due to speckle. This increases the effective pixel size at which sensible interpretations of soil moisture can be made to roughly 100 m (A.W. Western, T. Sadek, R.B. Grayson, H.N. Turrall, in review). Spaceborne SAR imagery has a typical repeat time of about two weeks. In contrast to SAR, spaceborne microwave radiometer instruments have spatial resolutions of tens of km, that is three orders of magnitude coarser than SAR, but coverage is repeated daily. Airborne microwave radiometers including ESTAR (electronically scanned thinned array radiometer) and PBMR (push broom microwave radiometer) have been used quite extensively to map soil moisture at pixel sizes of hundreds of m during large-scale field experiments such as FIFE, MONSOON90, Washita 92 (Jackson et al. 1996), and SGP97 (Jackson et al. 1999).

Several important practical issues for operational measurement of soil moisture exist. These are primarily related to the fact that the microwave signal responds to the dielectric constant (largely determined by soil moisture), soil surface roughness, and the vegetation canopy (Dobson & Ulaby 1998, Jackson et al. 1996). This means that several pieces of information are required to extract an estimate of soil moisture from the signal. Either this extra information can be preexisting mapping or it can be remotely sensed; however, because the vegetation and soil roughness are dynamic characteristics, at least some generally need to be remotely sensed.

Another important limitation of microwave remote sensing is that the instruments respond only to near surface soil moisture, not to the soil water stores of most interest to hydrologists, which are the root zone and the whole profile. One approach to overcome this limitation is to assimilate a series of surface soil moisture measurements into a soil moisture model, thereby estimating the moisture profile (Entekhabi et al. 1994, Walker et al. 2001), although the accuracy will be highly dependent on the validity of the models.

Another option is to use thermal remote sensing to measure land surface temperature and to infer evapotranspiration rates via a surface energy balance model (e.g., Bastiaanssen et al. 1998). Because the evapotranspiration response depends to some extent on root zone moisture availability, this can provide semiquantitative

information on soil moisture availability; however, this approach can only be applied during cloud-free conditions, and it is unlikely to provide the same degree of quantification of absolute soil moisture content as microwave techniques.

Ground-Based Measurement

Ground-based soil moisture measurements will provide more precise soil moisture data than remote sensing in the foreseeable future, provided appropriate calibration of instruments is performed. It also allows measurement of soil moisture over depths of more interest to hydrologists than does remote sensing. Standard techniques include thermogravimetric determination, neutron scattering, and measurement of dielectric properties of the soil. One example of the latter method is time domain reflectometry (TDR). Modern sensor and logging technology allow routine monitoring at points, and the Global Positioning System allows accurate location of roving instruments such as the University of Melbourne's Terrain Data Acquisition System (TDAS) (Tyndale-Biscoe et al. 1998, Western & Grayson 1998). Highly detailed temporal and spatial soil moisture data sets such as those from Tarrawarra (Western & Grayson 1998) and MARVEX (Woods et al. 2001) can be collected with these systems, but logistical considerations mean it is only possible to study small areas (generally $<1 \text{ km}^2$).

All of the common ground-based soil moisture measurement techniques have very small supports, typically from 1 cm to 10 cm. This is three to six orders of magnitude smaller than remote sensing measurements, and it enables collection of more highly detailed spatial information than does remote sensing. However, spacing between permanently installed moisture sensors varies widely, from meters up to hundreds of km, depending on experimental objectives. This means that, unlike remotely sensed soil moisture patterns, moisture contents are measured in a very small proportion of a study area. Another key difference between ground-based techniques and remote sensing is that ground-based sensors can be logged providing detailed temporal patterns at a point, whereas remote sensing typically provides spatial patterns at points in time.

There is a substantial amount of spatial variability in soil moisture. Given the small support and large spacing of ground-based techniques, interpretation of the data is challenging. Two possibilities exist. The first is to make a large number of measurements with sufficiently high spatial resolution to define the spatial variability or the spatial pattern (Western & Grayson 1998). The second is to relate the point scale measurements to areal soil moisture, a promising possibility that has been studied by Grayson & Western (1998), Kachanoski & de Jong (1988), and Vachaud et al. (1985). To be practical, such an approach requires that a predictable time-stable relationship exist between point soil moisture and the spatial mean.

Remote sensing and ground-based measurement methods are in many ways complementary. Remote sensing provides excellent spatial coverage over large areas, but the shallow measurement depth, confounding influence of vegetation (and surface roughness for SAR), indirect nature of the method, and relatively

infrequent repeat cycles make use of the data problematic. On the other hand, ground-based methods can be applied over any depth, accurately calibrated, and logged at any time scale, but are essentially point measurements, making spatial interpretation difficult. It is obvious that future work should focus on combining these two data sources to exploit their complementary features.

SCALING OF SOIL MOISTURE

In any problem it is important to be clear on the objectives of the scaling exercise. Where spatially or temporally variable quantities are important, there is a range of characteristics that can characterize the variation. One possible classification is given below, approximately in order of increasing detail. Some example applications of each piece of information are then given in the context of spatial soil moisture. It should be noted that all but the first of these is scale dependent. How far we need to progress down this list for any given problem will depend on our objectives.

- Central tendency (i.e., mean, median, etc.)
- Spread (i.e., variance, interquartile range, etc.)
- Extremes (i.e., percentage above or below a threshold, a high or low percentile)
- Probability density function (pdf)
- Spatial (or temporal) relationships [correlation functions or variograms and cross-correlations or covariograms with, say, terrain, connectivity (see below)]
- The actual pattern

The most fundamental problem in hydrology is to understand the water balance. Making measurements of the fluxes in and out of a soil profile is possible with varying degrees of accuracy. To close the water balance, the change in the amount of soil water and hence the mean soil moisture at the start and end of a period is required. If this change in soil moisture is to be measured to some specified accuracy, knowledge of the variance is also required to calculate the required number of sampling points. In the absence of spatial correlation between measurements, this can be done using standard statistical approaches based on Student's *t* distribution.

An important runoff process in many landscapes is saturation excess runoff, which is runoff generated from areas of saturated soil. To predict this runoff we need to know about the wet extreme of the soil moisture distribution; specifically we want to know about the percentage of area with soil moisture above a threshold value close to porosity. It is likely that one would also need to know the mean moisture and possibly the variance if one needed to predict (rather than measure) this area. Evapotranspiration processes depend on soil moisture in a nonlinear manner, and this can lead to important scale effects in atmospheric models (Giorgi & Avissar 1997, Pielke 2001). One way in which the variability of soil moisture could be

accounted for in this situation is to integrate the evapotranspiration processes over the area using the probability density function of the soil moisture as input in the manner suggested by Beven (1995). This would provide the mean flux and the spatial variability in the flux, both of which may be important for atmospheric processes.

There are a variety of reasons for which one may wish to know about spatial relationships relevant to soil moisture that are discussed in more detail below. One example is for predicting the change in subgrid variance due to changing the grid size in a model that parameterizes the effects of subgrid variability in soil moisture using the variance. If the correlation function is known, the technique of regularization (discussed later) can then be employed to predict this change in variance.

The most complete description of the variation in soil moisture in space is to know the actual spatial pattern. If the actual pattern is known, then all the preceding characteristics can be estimated from the data. It is rare to know the actual pattern of soil moisture from readily interpretable measurements. Actual patterns of soil moisture can provide initial conditions for, or spatial data for testing of, distributed hydrologic models, although most often such patterns are estimated through some scaling analysis. Recently, actual patterns have been used to test distributed models and they have been found to be extremely valuable in assessing model performance (Grayson & Blöschl 2000) particularly for soil moisture (Western & Grayson 2000).

TEMPORAL SCALING

Here we discuss briefly the temporal scale characteristics of soil moisture before concentrating on the spatial scaling of soil moisture. Figure 5 shows time series of 0–30 cm and 30–60 cm volumetric soil moisture recorded at one point in the

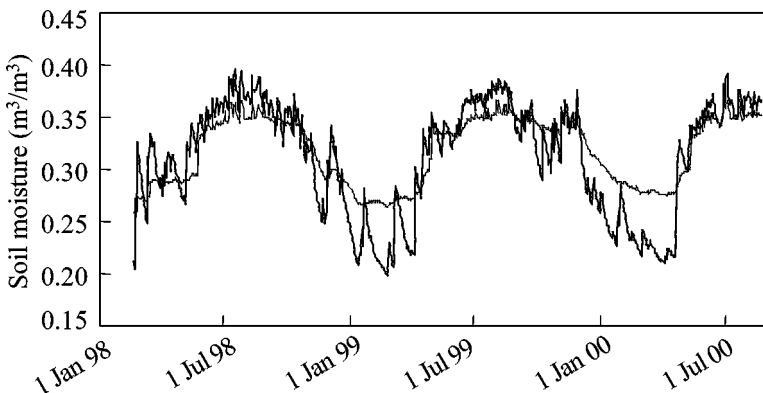


Figure 5 Volumetric soil moisture variation at a mid-slope location at Satellite Station in the Mahurangi River catchment, New Zealand. The rapidly varying moisture is for the top 30 cm layer, and the slowly varying moisture is for the 30–60 cm layer.

Mahurangi River Catchment, New Zealand (Woods et al. 2001). The largest scale feature of the time series is the seasonal variation in soil moisture. This occurs in response to seasonal changes in the balance between potential evapotranspiration (PET) and precipitation, as a consequence of seasonal changes in PET, in this case. Superimposed on this seasonal cycle is a series of wetting and drying events with time scales related to storm duration and inter-storm period, respectively. The rate of depletion during drying periods is mainly related to the rate of evapotranspiration plus drainage divided by the rooting depth. The contrast in the rates of change for increasing and decreasing soil moisture are primarily related to the different flux magnitudes for precipitation and evapotranspiration processes.

Grayson et al. (1997) discuss the presence of preferred states in the temporal distribution of soil moisture. Where PET dominates over precipitation, soil moisture tends to be consistently low. Similarly, where precipitation dominates over PET, soil moisture tends to be consistently high. This behavior is a consequence of the bounded nature of soil moisture. In many landscapes there is a seasonal shift between these two states. In landscapes where there is significant lateral movement of water, this temporal behavior corresponds with a change in controls on the spatial soil moisture pattern from being dominated by local vertical fluxes (Figure 3a) during the dry state to being dominated by lateral fluxes (Figure 3b) during the wet state.

Several theoretical studies of soil moisture at a point have been conducted using statistical dynamic models. Initially, these examined the average behavior (Eagleson 1978a,b), and later, temporal dynamics was incorporated (Milly 1994, 2001; Porporato et al. 2001; Rodríguez-Iturbe 1991a,b; Rodríguez-Iturbe et al. 1999). Slightly different assumptions have been made by the various authors, but similar patterns of behavior have emerged from the analyses, including bimodal temporal pdfs of soil moisture under some circumstances (D'Odorico et al. 2000, Milly 2001), which can be interpreted as preferred states. These arise due to the interaction between the random rainfall and the bounding of the soil moisture in the model. All of these models currently ignore seasonality in the forcing by rainfall and evapotranspiration, whereas the key feature leading to the preferred states discussed by Grayson et al. (1997) was the seasonal change in the balance between PET and precipitation rates. If these models incorporated seasonality in the forcing, we would expect that this would reinforce the bimodal behavior predicted by the models. The stochastic approach is clarifying the key characteristics of the temporal dynamics of soil moisture within the hydrologic cycle and is also providing insights into interactions between atmosphere and land surface (e.g., D'Odorico et al. 2000, Rodríguez-Iturbe 1991a) and also between the soil water hydrology and ecological (largely vegetation) patterns (Eagleson 1982a,b; Laio et al. 2001a,b; Rodríguez-Iturbe et al. 2001).

Temporal correlation scales have been analyzed by Entin et al. (2000), Vinnikov & Robock (1996), and Vinnikov & Yeserkepova (1991) who divided the timescales into short (event) and long components and found typical correlation scales of about two months for the long component. Entin et al. (2000) found that temporal scales were slightly less for the top 10-cm layer compared to the top 1-m layer

and that timescales increased with latitude. Timescales also increased in winter. These latitudinal and seasonal effects were attributed to changes in PET. These studies lend support to the hypothesis that the temporal correlation scale of soil moisture is linked to the ratio paw/PET (Delworth & Manabe 1988). The correlation timescales for soil moisture are much longer than for precipitation due to the “memory” of the soil moisture store, which smoothes out the relatively rapid variations in precipitation. Also, recycling of precipitation at continental scales allows the possibility of feedback between the soil moisture store and atmosphere, and such recycling is thought to prolong soil moisture and precipitation anomalies (Entekhabi 1995).

SPATIAL SCALING

In this section we first discuss the controls on spatial soil moisture patterns and then examine techniques for the spatial scaling of soil moisture. The scaling techniques are divided into behavioral techniques and process-based techniques. Behavioral techniques aim to quantify the apparent behavior of soil moisture patterns as a function of scale and to use this quantification to predict the effects of changing scale. These techniques rely on data and statistical analysis, which may be combined with a conceptual understanding of process controls on soil moisture in some cases. In contrast, process-based techniques aim for a deeper understanding of the physical processes causing the spatial patterns of soil moisture. They use this process understanding, usually within a deterministic reductionist framework of distributed water balance modeling, to predict the effects of changing scale.

Spatial Control of Soil Moisture

Figure 6 illustrates a number of spatial soil moisture patterns in which the effects of different spatial controls on soil moisture are evident. At small scales, soil moisture responds to variations in vegetation (Qui et al. 2001), soil properties (Famiglietti et al. 1998), topographically driven variations in lateral flow (e.g., Dunne & Black 1970a,b), radiation (e.g., Western et al. 1999a), and precipitation. Figures 6a and 6b illustrate soil moisture patterns at Tarrawarra (Western & Grayson 1998) where terrain plays an important role in lateral flow during wet conditions (Figure 6a) but not during dry conditions (Figure 6b), and radiation is also important. The soil moisture state has an important influence in determining the controls on spatial soil moisture patterns here (Grayson et al. 1997). This contrast in dominant processes can be used to advantage when calibrating different process parameters in models (Albertson & Kiely 2001). The primary effect of vegetation is on evapotranspiration from the soil profile; however, canopy storage affects precipitation reaching the soil surface, particularly in forests (Vertessy et al. 2001). Vegetation can also influence infiltration properties at the plant scale (Seyfried & Wilcox 1995). Soil properties can affect infiltration during intense rainfall events, they determine the saturated moisture content and,

in conjunction with the vegetation, the wilting point. They also influence drainage (both vertical and lateral). Figure 6c shows a soil moisture pattern on sandy soils at Point Nepean, Australia, where consistently high soil moisture is associated with areas of finer soils in the center and on the east side of the sampling area.

As the spatial scale increases, different sources of variation become apparent. Variation in vegetation shifts from the plant to the patch to the community scale. Some vegetation communities are associated with changes in moisture availability, for example riparian vegetation. Soil properties vary as different soil types and geologies are encountered. Figures 6d and 6e show soil texture and a soil moisture pattern respectively, measured on June 18, 1997, using ESTAR during SGP97 (Jackson et al. 1999). The correlation between soil texture and surface soil moisture is clearly evident. Variations in rainfall can occur at spatial scales as small as hundreds of meters due to the passage of storm cells (Goodrich et al. 1995); however, the long-term effect on soil moisture variability may be at a larger space scale as the soil store integrates precipitation over time and thus smoothes some of the spatial and temporal variation in instantaneous rainfall rates. Certainly at spatial scales of kms, examples of soil moisture variability due to spatial variability in event rainfall depth can be found. Figure 6f shows the effect of rainfall pattern on soil moisture on June 30, 1997 during the SGP97 field experiment (Jackson et al. 1999).

At still larger scales, climatic variations in precipitation lead to substantial changes in general soil moisture conditions between climate regions. Variation in humidity, temperature and radiation also affect soil moisture through the evapotranspiration process. Figures 6g and 6h show the pattern of maximum vegetation greenness (a measure of vigor of vegetation growth) across Australia during 1996 and 2000, mapped using data from AVHRR (advanced very high resolution radiometer). Climatic impacts are clear, with inland Australia generally having low amounts of vegetation due to low precipitation and soil moisture. The interannual variation in vegetation is also clear. This is a response to variation in precipitation and moisture availability between 1996 and 2000. 1996 was a dry year in central Australia and wet in the Southeast and Southwest, whereas 2000 was a wet year with significant rainfall over large areas of inland Australia, but drier in the Southeast and Southwest.

All of the factors affecting the distribution of soil moisture mentioned above are correlated in space to some degree. For example, rainfall is likely to be more similar for two points 1 m apart than for two points 1 km apart. These spatial correlations introduce spatial correlations into the soil moisture pattern. In addition lateral redistribution of soil water enhances spatial variation and correlation.

Behavioral Scaling Techniques

In this section we review results relating to the statistical distribution of spatial soil moisture, spatial correlation of soil moisture, and relationships between soil moisture and surrogate variables. The joint use of the latter two for spatial interpolation is discussed at the end of the section. All of these characterize different

aspects of the statistical behavior of soil moisture, although sensible selection of surrogate variables enables consideration of the physical processes controlling the spatial pattern of soil moisture.

As discussed, the volumetric soil moisture probability density function (pdf) is bounded between wilting point and porosity. Theoretically, this pdf cannot be normal, although normality may be an adequate practical assumption. Bounded pdfs typically become skewed and less variable as the mean approaches a boundary, and a greater proportion of the population is affected by that boundary. If a lower boundary is approached, positive skew (long upper tail) is typical since the lower tail is affected by the boundary first. Likewise, negative skew results as the mean approaches an upper boundary.

A number of studies have examined the pdf of soil moisture (e.g., Bell et al. 1980, Charpentier & Groffman 1992, Famiglietti et al. 1999, Loague 1992, Mohanty et al. 2000b, Nyberg 1996). Typically some form of testing of the null hypothesis that soil moisture has a normal spatial pdf is conducted and/or histograms are presented. The results of the hypothesis testing are equivocal, and there is a tendency for larger samples to fail the test due to increased statistical power. Studies with a larger number of sample occasions (Bell et al. 1980, Charpentier & Groffman 1992, Famiglietti et al. 1999) have tended to find that 50–80% of soil moisture patterns can be approximated by a normal distribution. A number of authors have reported decreasing coefficient of variation with increasing wetness, which is primarily due to the changing mean. Systematic increases in variance with wetness are reported by Bell et al. (1980), and systematic decreases are reported by Famiglietti et al. (1999). Famiglietti et al. (1999) report a systematic change in skewness from positive to negative as moisture increases from low to high values.

We are currently analyzing the pdf characteristics of data sets from a sample of approximately 15 experimental catchments from around the world. These catchments range from semiarid to humid. Taken separately, the patterns of changes in variance with moisture content are inconsistent due to climate and soil differences; however, taken together, these data sets clearly demonstrate a pattern of variance that increases from near zero at wilting point to a peak at moderate moisture levels and then decreases to near zero as the mean moisture approaches saturation. At low moistures, positive skew is evident; however, the negative skew expected at high mean values for a bounded distribution is not evident in the data.

One use of the spatial soil moisture pdfs is in representing subgrid variability in modeling. Beven (1995) outlined a general framework for representing variability with pdfs. Many conceptual catchment models use algorithms that can be interpreted as utilizing pdfs of soil moisture (or a related variable such as profile soil water storage) in some of their flux calculations (Beven 1995). Other catchment models have been developed by taking explicit consideration of the statistical distribution of soil water. The most notable of these are Topmodel (Beven & Kirkby 1979) and the Xinanjiang, or VIC, model (Wood et al. 1992, Zhao 1992). Both these models have seen wide application, and many current models are based on the core concepts and distribution functions that they incorporate. All of the above

models are capable of representing catchment scale runoff; however, the shapes of the underlying distribution functions have not been widely tested, and there is a marked difference in shape between the Topmodel and VIC distribution functions, for example. Western et al. (1999a) tested the ability of a variety of different terrain indices (see below for a more detailed discussion of terrain indices), including the wetness index underlying Topmodel, to predict the shape of the soil moisture pdf at Tarrawarra; they found all indices to be poor representations. Kalma et al. (1995) tested the assumed soil water storage capacity pdf in VIC and found it to be a good representation of the available data, but Western et al. (1999b) found the pdf of saturation deficit derived from the storage capacity pdf to be a poor representation of the soil moisture data at Tarrawarra.

These studies suggest that while a range of pdfs can be used successfully in catchment models to predict catchment runoff, a detailed comparison of these pdfs by spatial soil moisture data shows that some of them are more realistic than others. The normal distribution appears to be the best two-parameter distribution for spatial soil moisture. Departures from normality are most likely as mean moisture approaches low or high values and the soil moisture is affected by the wilting point or porosity, respectively. The normal distribution provides a better representation of typical soil moisture pdfs than those based on terrain indices.

Although the statistical distribution of soil moisture in space discussed above is important for a range of applications in hydrology and related earth sciences, often one is also interested in the spatial arrangement of soil moisture. This is not captured by the pdf. One way of representing the spatial arrangement is by spatial correlations. The main idea is that locations that are close in space also have similar soil moisture values, which are reflected in good correlations. More technically speaking, soil moisture is assumed to be a spatial random variable (or, equivalently, a random field) with a given pdf and a given spatial correlation structure. The observed (and possibly simulated) spatial field of soil moisture is then one (out of many possible) realizations of that random variable. The important thing here is that, instead of attempting to quantify the actual spatial pattern of soil moisture (where every location is associated with one soil moisture value), one quantifies the spatial statistical structure. This statistical structure is usually represented as the variogram, which is a plot of the variance of soil moisture differences between two points as a function of the distance (or lag) between these two points. As two locations that are close together usually have rather similar soil moisture values, the variogram value (or gamma value) is small for small lags and increases as lag increases. The shape of the variogram can be conveniently described by three parameters: the sill, correlation length (or range), and nugget. The sill is the level at which the variogram flattens out. If a sill exists, the soil moisture variability is stationary and the sill can be thought of as the spatial variance of two distantly separated points. The correlation length (or range) is a measure of the spatial continuity of soil moisture. The nugget relates to the variance between pairs of points separated by very small distances, and can be due either to sampling error, to short scale variability, or both.

There are two main applications of spatial soil moisture statistics; descriptive and predictive. In the first, one calculates the variogram from field data to coalesce the field information into one single curve, which is easier to interpret than a large set of data points. This is a behavioral (or phenomenological) approach that aims to represent the overall effect of the spatial soil moisture processes in terms of spatial continuity. From knowledge of the spatial continuity (i.e., the spatial correlation length), one then infers what the important processes dominating the hydrologic response in a certain environment may be. Western et al. (1998, 1999a) and Grayson et al. (1997) have shown that this is indeed possible, as they were able to capture the switch over from mainly vertical soil moisture redistribution (associated with long correlation lengths and differences in radiation between hillslopes) to lateral soil moisture redistribution (associated with short correlation lengths and water movement down a hillslope) in a small humid catchment in Southeast Australia, and there are a number of other studies that have also linked spatial soil moisture statistics with process (Fitzjohn et al. 1998, Nyberg 1996).

In a predictive mode, one can use the spatial correlation structure for solving a number of spatial estimation problems. These are, among others, calculating spatial fields of soil moisture from a few point observations [i.e., interpolation based on geostatistical techniques such as kriging, (e.g., Bárdossy & Lehmann 1998)]; correcting for measurement error of field measurements (based on similar geostatistical techniques); simulating spatial fields of soil moisture without data [based on stochastic simulation techniques such as the turning bands method (Mantoglou & Wilson 1981) and sequential Gaussian simulations (Deutsch & Journel 1997)]; and estimating the change in variance one would expect when aggregating (or changing the support of) data or a model (based on regularization). Additionally, most of these techniques can be used in conjunction with covariates (or auxiliary variables) that are related to soil moisture and are sometimes used to improve the spatial soil moisture estimates (see below). As two of the methods are particularly relevant to soil moisture scaling, we discuss them here in more detail.

Spatial interpolation, based on geostatistical concepts, consists of two phases. In the first phase (termed structural analysis) a variogram is estimated from the observed data. This is done by plotting the sample variogram and fitting a smooth function, known as the theoretical variogram, which is assumed to be the variogram of the population. There are a number of functions that can be used for the theoretical variogram, but it is common to use an exponential function or a power law function. In the second phase, a spatial pattern is estimated from both the data and the characteristics of the variogram, based on best linear unbiased estimation (BLUE). BLUE implies a linear combination of all of the measurements with a different weight for each measurement calculated such that the mean of the data and the mean of the interpolated pattern are identical (unbiased), and the variance of the estimation error is minimized (best). There is a wide range of geostatistical estimation methods that differ in the assumptions about the way the random function varies spatially and in the way they are constrained by other information, resulting in different levels of complexity of the interpolation method. One

of the simpler and widely used methods is ordinary kriging (Journel & Huijbregts 1978).

Regularization, in contrast, is concerned with estimating changes in variance and correlation properties as one or more of the three components of the scale triplet—spacing, extent, and support—vary. These changes can be calculated directly from the variogram and checked against data analyses. For example, Western & Blöschl (1999) analyzed the scaling effects using the Tarrawarra data set (Western & Grayson 1998) and found that the apparent correlation lengths always increase with increasing spacing, extent or support. The apparent variance increases with increasing extent, decreases with increasing support, and does not change with spacing. Their data also suggested that regularization techniques produce acceptable predictions of the effects of scale changes for both spatially organized (e.g., wet drainage lines) as well as spatially random soil moisture patterns. Diagrams such as those in Figure 7 can be used to estimate the biases that are introduced by the grid resolution of a spatially distributed model and to correct for them. For example, Western & Blöschl (1999) showed, for typical parameter combinations, that if a model of 150-m grid size predicts saturation of say 0.2% of the land surface, the true percentage of saturation may be as large as 8%, and the bias increases with the grid size.

In order to apply both descriptive and predictive techniques of spatial soil moisture statistics, one needs to know the actual shape of the soil moisture variogram.

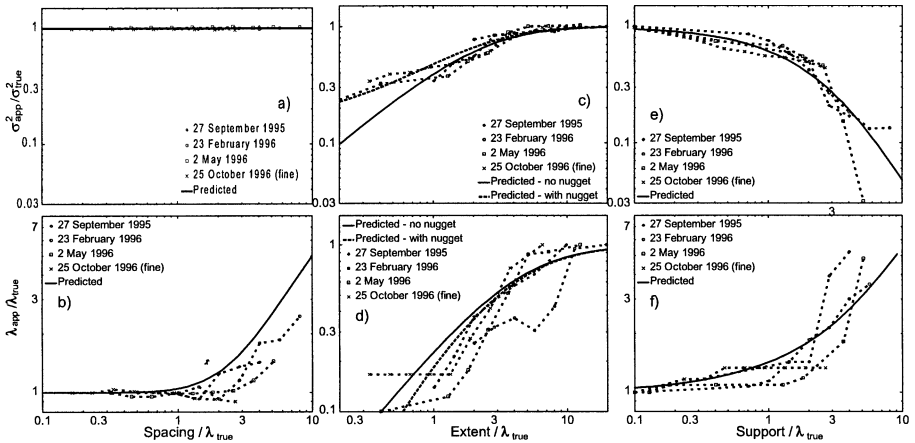


Figure 7 Effect of scale on apparent variance and the apparent correlation length as a function of spacing, extent, and support. Dotted lines with markers show the results of a resampling analysis, and the solid lines show the regularization results as derived from the variogram. All scales have been normalized by the true correlation length, λ_{true} , and the apparent variances have been normalized by the true variances, σ_{true}^2 . After Western & Blöschl (1999).

Soil moisture correlation scales have been analyzed in numerous small catchments, and a small number of studies have considered larger scales (Western et al. 1998). Figure 8 provides some example sample variograms from small catchments in Australia and New Zealand. When considering spatial correlation, a fundamental question is whether the variability is stationary. Most small catchment studies conclude that the variability is approximately stationary. Western et al. (1998) provide a summary of six small catchment studies that have analyzed the correlation length of soil moisture. Values of the correlation length, λ , vary between 1 m and 600 m, and there is a tendency for λ to increase with extent and spacing, as would be expected given the effects of these scale characteristics on λ (Western & Blöschl 1999). Most of these and more recent small catchment studies (e.g., Mohanty et al. 2000a) suggest that λ lies in the range of 20 to 300 m.

Analyses of larger scale (extent) data sets produce very different results. Rodríguez-Iturbe et al. (1995), Hu et al. (1997), and Peters-Lidard (2001) analyzed the remotely sensed ESTAR soil moisture data set collected during Washita '92 (Jackson et al. 1995) and supplemented this with some ground-based measurements. They presented their results in terms of changes in variance with increasing levels of aggregation. They found that soil moisture was nonstationary at the scales studied (30 m to 10 km) and that the changes in variability with aggregation scale were linear in the log domain and could therefore be represented using a fractal approach.

Studies at even larger scales (50–1000s km) (Meshcherskaya et al. 1982 cited in Vinnikov & Robock 1996, Entin et al. 2000) from agricultural sites in the Former Soviet Union, Mongolia, China, and the USA have found that soil moisture variation could be represented as a stationary field with a correlation length of about 400–800 km. Vinnikov & Robock (1996) and Entin et al. (2000) noted the existence of a smaller scale (<50 km) component to the spatial variability that was unresolved by their data.

Part of the differences in correlation lengths in small-scale and large-scale studies may be explained by sampling effects, as illustrated in Figure 7, but there may

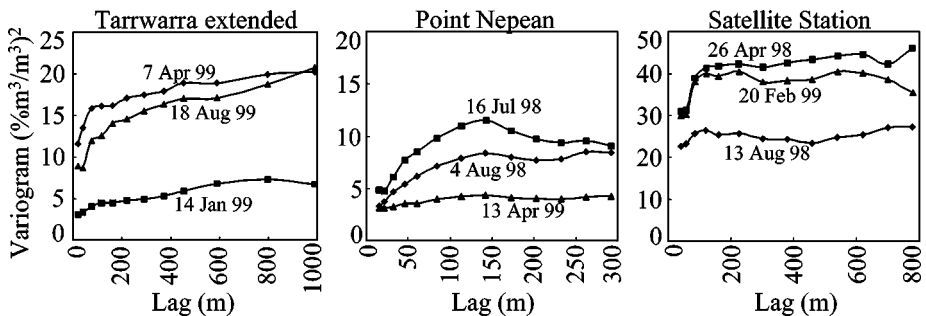


Figure 8 Example soil moisture variograms from Tarrwarra (~470 points) and Point Nepean (~580 points), Australia, and Satellite Station (~370 points), New Zealand, for the wettest, driest, and an intermediate sampling occasion. Note the different axes scales used.

also be important process controls causing such differences. Generally the spatial soil moisture field has been found to be stationary at small catchment scales (<1 km) and at large (100s + km) scales. It should be noted that this is not inconsistent because there is a large difference (three orders of magnitude) in the correlation lengths, so the large-scale variability component basically has no effect at the small catchment scale. Seasonal changes occur in the correlation length at both small and large scales that are associated with changes in the processes controlling the soil moisture pattern. Robock et al. (1998) and Entin et al. (2000) have proposed that spatial soil moisture correlation is controlled by catchment processes with short correlation lengths at smaller scales and by atmospheric processes with large (100s km) correlation lengths at regional scales. In their conceptualization, a wide separation in the scales of variability exists that needs to be confirmed with data from intervening scales. It would be expected that soil characteristics and vegetation may play a significant role over these intervening scales; however, this has not been fully analyzed to date. The one data set analyzed for small and intermediate scales suggests nonstationary behavior. This data set was remotely sensed rather than ground measured, and at small scales it is inconsistent with the rest of the literature in that Rodríguez-Iturbe et al. (1995) suggest that variances change at lags of 30–200 m. Clarification of the behavior of soil moisture at these intermediate scales will require further studies.

As well as being correlated to soil moisture at nearby locations, soil moisture can be correlated to other characteristics of the landscape. Such relationships can be used to assist in spatial scaling of soil moisture by providing more spatially complete patterns that can be combined with sparse spatial moisture measurements and by providing a basis for disaggregating data from large supports. Terrain data is often used to calculate patterns of surrogate variables (such as the wetness and radiation indices described below) that are used to estimate the spatial pattern of soil moisture. Terrain data is widely available from mapping agencies, terrain analysis techniques are well developed, and many are implemented within common geographic information systems and related software (Moore et al. 1991, Wilson & Gallant 2000). Indeed, terrain data is the most readily available source of spatially distributed data used in hydrological modeling. As a result, its use may be overly prominent, compared to topography's role in hydrologic processes (Grayson & Western 2001).

Nevertheless, there are two key processes that affect soil moisture and are influenced by terrain. Lateral redistribution of moisture by shallow subsurface flow can be a dominant process controlling soil moisture patterns at the hillslope scale (see Figure 3*b*). In this case, indices reflecting upslope area, slope, or convergence should be related to the soil moisture. The most commonly used terrain index is the topographic wetness index of Beven & Kirkby 1979 (see also O'Loughlin 1981, 1986). The standard topographic wetness index assumes:

- steady-state lateral flow;
- spatially uniform recharge;
- hydraulic gradient equal in magnitude and direction to the surface slope; and

- a spatially uniform (in plan) exponential saturated hydraulic conductivity-depth profile.

With these assumptions the wetness index, w_i , can be derived as $w_i = \ln\{a/\tan(\beta)\}$, where a is the specific contributing area and β is the surface slope. Beven and Kirkby's index forms the basis of Topmodel. Various authors have relaxed different assumptions underlying the topographic wetness index [Barling et al. (1994)—steady-state assumption; Woods et al. (1997)—uniform recharge; Ambroise et al. (1996) and Duan & Miller (1997)—exponential conductivity profile; Quinn et al. (1991)—hydraulic gradient assumption]. Willgoose & Perera (2001) have combined wetness index concepts with landscape slope-area relationships to produce lumped models that parameterize the spatial variability in moisture.

Similarly, if evapotranspiration is important, slope and aspect may be related to soil moisture due to their effect on the distribution of solar radiation across the landscape. This can be represented using the potential solar radiation index (Moore et al. 1991, Western et al. 1999a) or alternatively, a radiation-weighted index developed by Vertessy et al. (1990), which solves a spatially distributed steady-state water balance.

The predictive ability of terrain indices has been examined in a number of small catchment studies. The standard approach to analysis has been to correlate some measure of soil water with the values of terrain indices at corresponding spatial locations. It is rare to find that more than 50% of the variation in soil moisture (or depth to saturation) is explained by the best performing terrain indices. Among studies that have considered soil moisture, the best R^2 value quoted in the literature is 81% for a site near Beer-Sheba in Israel two weeks after 250 mm of rainfall (Zavlasky & Sinai 1981). In this case curvature was used as the index, and it is likely that the lateral redistribution occurred as unsaturated flow. At Wagga Wagga in N.S.W, Australia, a combination of the steady-state wetness index and aspect explained 31–41% of the variance (Moore et al. 1988). In Kansas, Ladson & Moore (1992) found that less than 10% of the variance was explained. At the Gårdsjön catchment in Sweden, Nyberg (1996) found that the wetness index could explain 34–42% of the soil moisture variance. Western et al. (1999a) analyzed detailed spatial patterns of soil moisture from the Tarrawarra catchment and found R^2 values of 0–50% for either the specific upslope area or the steady-state wetness index. When one of these was combined with a radiation index, the best R^2 was 61%. There was a substantial reduction in R^2 as the catchment dried and the soil moisture came to be controlled by local vertical fluxes. Figure 9 shows the wetness index pattern at Tarrawarra, the soil moisture pattern on October 25, 1996, an error map for predictions based on a combination of the wetness index and a radiation index, and a scatter plot of soil moisture against wetness index. The randomness of the error map indicates that these terrain indices do a good job of predicting the general pattern of soil moisture on this occasion at Tarrawarra. Famiglietti et al. (1998) measured soil moisture in the top 5 cm on an along slope

transect in Texas and found R^2 of up to 73% with clay content and 69% with relative elevation. These two parameters were highly cross-correlated and the fact that the high R^2 values occurred during dry conditions indicates that the clay content was probably the dominant control on the moisture.

A key lesson from the various studies on soil moisture and terrain indices is that the indices can explain a significant proportion of variance under favorable conditions, but this explanatory power drops off rapidly as catchments dry and terrain becomes less important. Also there is always a significant amount of unexplained variance, which is likely to be related to variation in soils and vegetation.

All of these indices can be used in assisting with the spatial interpolation of soil moisture. More specifically, they can be used to estimate a spatial pattern (or a spatial distribution) from average catchment soil moisture (i.e., downscaling) and to estimate a spatial pattern from point measurements. In the latter case, similar geostatistical methods can be used as discussed above, but they are extended to accommodate the index as an auxiliary variable. One popular approach is external drift kriging (Ahmed & de Marsily 1987) where the existence of a linear relationship between the additional information and soil moisture is postulated and the auxiliary variable is assumed to be error free. Due to these assumptions, the interpolated patterns look very similar to the pattern of the auxiliary variable, i.e., a lot of spatial structure is imposed. Another variant is co-kriging, where the covariance (or the cross-variogram) between the auxiliary variable and soil moisture is exploited. Both the auxiliary and the original variables may be subject to measurement error. This method imposes less structure than external drift kriging and hence the interpolated patterns tend to be smoother. However, in co-kriging the appropriate choice of the variograms (of the auxiliary data and the original data) and the cross-variogram is not straightforward and needs to meet certain criteria for the method to work (e.g., Deutsch & Journel 1997, Journel & Huijbregts 1978). Both external drift kriging and co-kriging require the additional information to be numerical, such as a wetness index, rather than categorical, such as land use or soil type. Methods such as Bayes Markov Kriging (Zhu & Journel 1993), or the simpler Bayes Markov updating (e.g., Bárdossy & Lehmann 1998) can be used to incorporate this type of categorical information and so enable a wide range of auxiliary information to be utilized for interpolating and downscaling soil moisture.

Process-Based Scaling Techniques

The terrain indices discussed above are a simple attempt to model process controls on patterns of soil moisture and, under appropriate circumstances, can be useful in scaling of moisture patterns. But these approaches are limited in practice by their restrictive assumptions. Dynamic, spatially explicit, hydrological models relax many of these restrictive assumptions and can be used to address scaling issues, including soil moisture. The notion is that if we can represent key hydrological processes and their interactions in a model, then we can use these models to

investigate scale effects by running them at different scales or aggregating model output, and potentially provide a basis for scaling up or down. If we are to interpret the modeled scale effects physically, the models must be a true representation of the processes, otherwise we are simply representing the scaling behavior of the model. This may be useful for setting parameters in the models when applied to different scales [e.g., Topmodel—(Bruneau et al. 1995)], but it does not represent the manifestation of the basic processes at different scales.

To model the spatial behavior of soil moisture, we need a distributed model. Here we solve equations describing the water balance for an array of elements, each of which can have its own input information (to allow for spatial variability in, say, precipitation) and parameters of the algorithms in the water balance (to allow for differences in vegetation, soils, topography, etc.) (e.g., Abbott & Refsgaard 1996). All models are greatly simplified representations of reality and are developed for particular applications, focusing on the key processes that dominate the response at the scale of interest, while other processes may be either ignored or represented simply. By focusing on particular ranges of time and space scales, the modeling task becomes tractable, but it also imposes limits to the scales over which output from the models can be applied (and interpreted). For example, models of hillslope hydrology need to represent the controls on lateral redistribution of water and variations in moisture content, but the models do not need to be able to represent atmospheric feedbacks (atmospheric influences are simple inputs to these models). Alternatively atmospheric general circulation models (GCMs) treat lateral redistribution very crudely and concentrate on vertical fluxes of water and energy so that they feed back the appropriate information to the atmospheric components of the models.

There are also considerations regarding the basic equations that are used to describe the water balance. For example, it is common to use simplifications of the Richards Equation to represent saturated and unsaturated soil water movement. This equation was derived by consideration of small-scale water movement processes as might be observed in a laboratory soil column. Even at that scale there is some debate about its efficacy, but as the scale of application increases, the physical validity decreases. The functional behavior of the model may still be acceptable if the parameters are chosen to represent the appropriate scale of response, but this makes the parameters scale dependent. Similarly overland flow processes (that dramatically affect, and are affected by, soil moisture patterns) are conceptualized in a way that makes their parameters scale dependent (Grayson & Blöschl 2000). These problems of scale dependency in model formulation and parameterization limit the interpretations of scaling behavior of natural systems, using distributed models.

Applications of distributed models need distributed parameter values and input information on the patterns of climate, terrain, soils, and vegetation. Climate information is generally good at larger scales but can be problematic at catchment scales where rain gauge distribution is often poor and there may be strong spatial

precipitation gradients (due, for example, to elevation or type of storm activity). We generally have quite good data on topography or at least can relatively easily obtain such information from additional surveys. Patterns of vegetation type can be obtained over a range of scales from remote sensing, but key features of the vegetation that affect soil moisture such as rooting behavior and evapotranspiration parameters are less certain. The most problematic information for distributed hydrologic modeling is soils data. There is often information on soil type (and some index to soil texture) but little on the soil hydrological properties that control soil moisture. Pedo-transfer functions are relationships derived between mapped soil properties (generally percent sand, silt, clay, organic matter, etc.) and soil hydraulic properties (e.g., Rawls et al. 1982, Romano & Santini 1997, Elsenbeer 2001). These are widely used to convert maps of soil type into patterns of soil hydraulic properties for use in distributed models across virtually all scales of models from hillslope to GCM. However, these patterns of soil hydraulic properties can dominate the resulting patterns of soil moisture and mislead interpretations of model output, including scale effects, if the imposed patterns are not correct (e.g., Christiaens & Feyen 2001, Houser et al. 2000, Vertessy et al. 2000).

Despite all of these limitations, carefully developed models supported by detailed data sets and applied over an appropriate range of scales, are capable of reproducing bulk soil moisture response, as well as observed patterns (Figure 10) (Western & Grayson 2000). This implies that they may be useful for investigating the scaling of hydrological behavior, albeit over a limited range of scales. They can also be useful in establishing and/or testing some of the relationships needed in models used at larger scales to represent the effects of the process scale variability—e.g., to develop the shape of functions that relate saturated area to average catchment wetness, or to parameterize the effects of spatial variability on evapotranspiration over heterogeneous areas.

Although there has been some success at modeling soil moisture patterns at small scales, in the studies conducted so far at continental or global scales (e.g., Entin et al. 1999, Robock et al. 1998, Srinivasan et al. 2000), model performance has been quite poor with particular problems in high latitudes and failure to capture observed interannual variability. With corrections for biases, some models in the Global Soil Wetness project were able to represent seasonal cycles, but these biases were different in different areas. The problems with soil moisture simulation at large scales are not only in the algorithms that define moisture behavior in a soil column or a landscape, but also in (a) the accuracy of the forcing (atmospheric) information (especially where the land-surface model is coupled to an atmospheric model) and (b) the difficulty in obtaining measurements at the right scale for comparisons with modeled response (remote sensing fails to capture root zone soil moisture and ground measurements can be highly uncertain at the model grid scales due to small measurement supports). Future studies, particularly in the context of climate impact analyses, are likely to shed more light on the potential of large-scale soil moisture simulations.

SUMMARY

Spatial and temporal variability of soil moisture is ubiquitous. Because many soil moisture-dependent processes are nonlinear, this variability leads to significant scale effects. There are a variety of scaling techniques that can be used to estimate the effect of changing the scale (spacing, support, or extent) of data or a model. These have been reviewed above, and progress is being made in understanding their applicability and reliability.

Many of the techniques rely on statistical methods. Fundamental to understanding and applying statistical methods is knowledge of the underlying statistical distribution and statistical relationships between different data. The number of studies that have examined statistical characteristics is still fairly small, and they are often for agricultural land uses; nevertheless, some general patterns have emerged. Results from small catchment studies suggest that the normal distribution is a reasonable approximation of the soil moisture pdf, but departures from normality do occur and they are probably more likely under very wet or very dry conditions. Some progress is also being made on understanding the links between the pdf characteristics (parameters) and the wetness state. Soil moisture is correlated in space and time due to a variety of processes. An understanding of correlation scales for small catchments and also regionally is emerging, but there is a gap in understanding for intermediate scales due to a lack of data. It appears that it is often possible to assume stationarity at both these scales. The spatial pattern of soil moisture is also related to environmental characteristics such as terrain, soils, and vegetation. Studies of the correlation between terrain indices and soil moisture suggest that useful statistical relationships explaining up to 50% (occasionally more) of the variance can be developed under favorable conditions, but that quite often these relationships are weak.

Process-based scaling techniques also exist and rely on distributed hydrological models. Such models are applicable to specific spatial scale ranges, and they are very data intensive. At small scales, models have been used to successfully simulate spatial patterns of soil moisture, but at large scales there has been limited success.

A major constraint on furthering our understanding of soil moisture scaling is data availability. At small scales (< 1 km), ground-based measurements are possible and advances in measurement technology mean that more and more detailed data sets are being collected. At larger scales, surface soil moisture can be measured using remote sensing, but we need proven methods for interpreting soil moisture at greater depth because this is much more significant hydrologically. While remote sensing technology is advancing, this is still a major challenge. Exploiting the complementary advantages of ground-based and remotely sensed methods should be a focus of future work.

It is likely that future applications of soil moisture scaling will tend to be concentrated in the area of parameterizing the effects of variability on moisture-dependent environmental processes. This will require developing new algorithms that can integrate the emerging knowledge of moisture variability with our understanding of

dominant processes at different scales. It will also require that we generalize our understanding of moisture variability and scaling from existing and future case studies.

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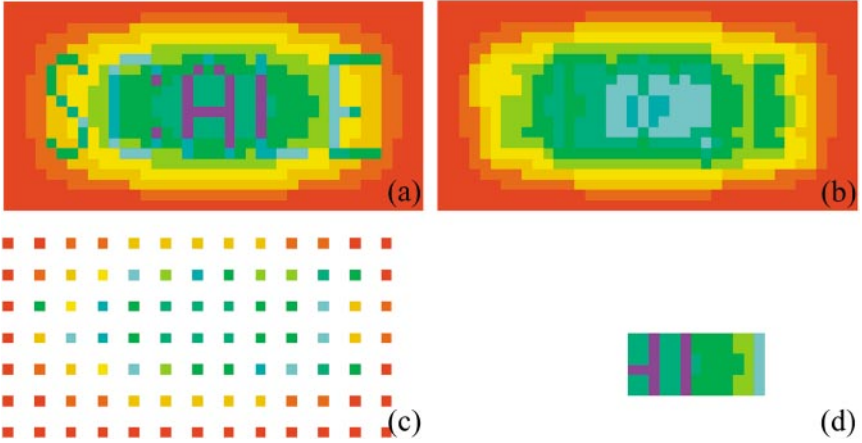


Figure 2 The effect of changing each component of the scale triplet by a factor of three. (a) Original data. (b) The effect of increasing support. (c) The effect of increasing spacing. (d) The effect of decreasing extent.

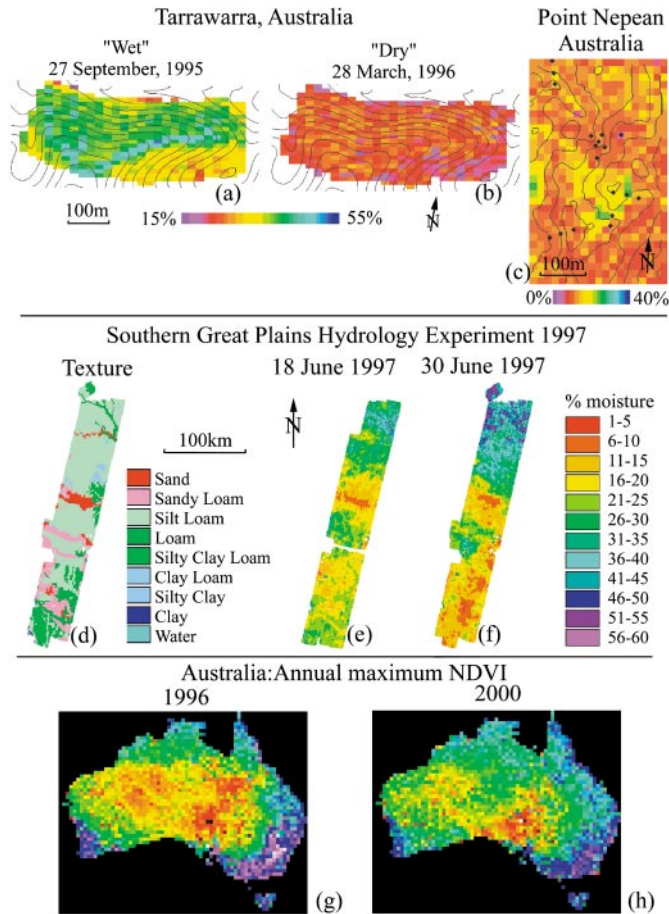


Figure 6 A number of spatial soil moisture patterns that illustrate different sources of variability at different scales. (a) A “wet” soil moisture pattern from Tarrawarra showing topographic control of soil moisture. (b) A “dry” soil moisture pattern from Tarrawarra showing local control of soil moisture (no lateral drainage). (c) A soil moisture pattern from Point Nepean, Australia, showing soil texture control on soil moisture. The soil moisture values in a–c are volumetric moisture in the top 30 cm measured using TDR. (d) The pattern of soil texture in the Southern Great Plains (SGP97) Hydrology Experiment study area. (e) A soil moisture pattern controlled by soil texture measured during SGP97. (f) A soil moisture pattern showing the influence of rainfall variations collected during SGP97 (Jackson et al. 1999). The soil moisture values in e and f are volumetric moisture in the top 5 cm (approximately) measured using ESTAR. (g) The pattern of maximum NDVI over Australia during 1996. (h) The pattern of maximum NDVI over Australia during 2000. Red represents low NDVI and blue/pink represent high NDVI. Figures f and g are Commonwealth of Australia, copyright reproduced by permission from the Environmental Resources Information Network website, Environment Australia Online, Department of the Environment and Heritage, Australia (2001).

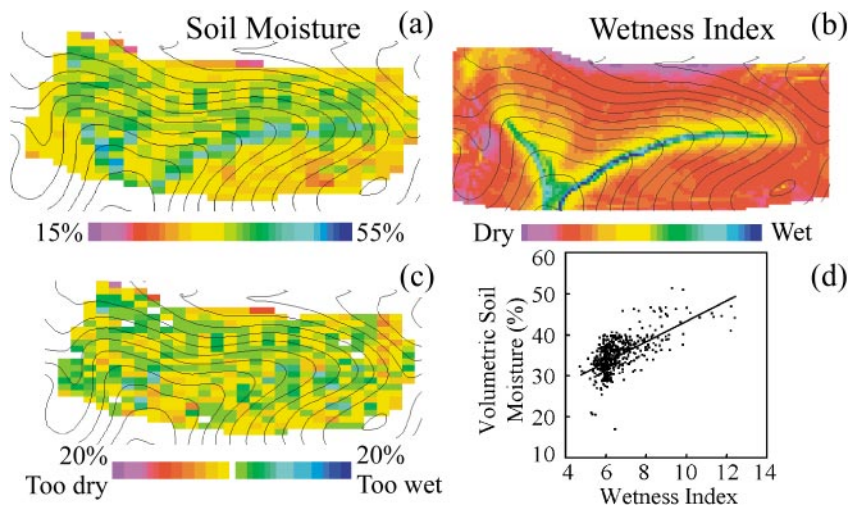


Figure 9 (a) Soil moisture measured in the top 30 cm using TDR on October 25, 1996, at Tarrawarra. (b) The wetness index pattern at Tarrawarra, Australia. (c) Residuals from a regression of soil moisture against wetness index and radiation index. (d) The relationship between the soil moisture and the wetness index.

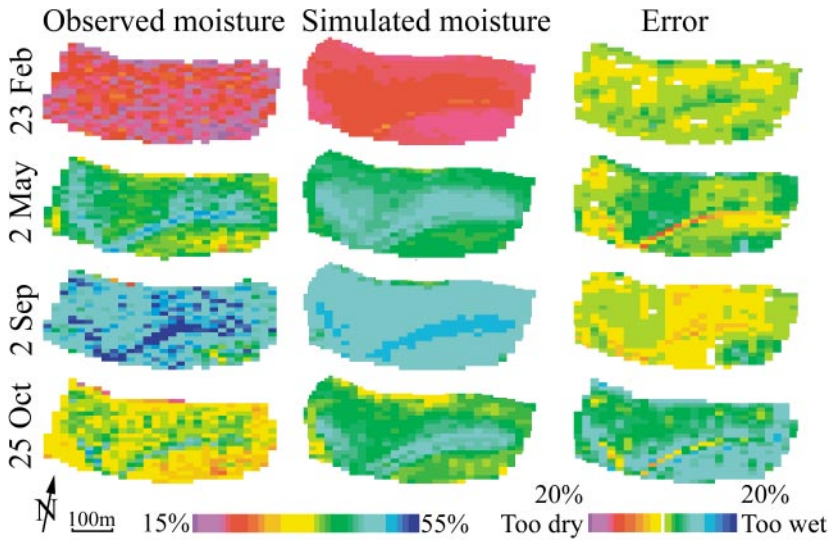


Figure 10 Observed, simulated, and error patterns from Tarrawarra for four occasions during 1996.