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How well do indicator variograms capture the spatial connectivity of soil moisture?

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Abstract:

Indicators are binary transforms of a variable and are 1 or 0, depending on whether the variable is above or below a threshold. Indicator variograms can be used for a similar range of geostatistical estimation techniques as standard variograms. However, they are more flexible as they allow different ranges for small and large values of a hydrological variable. Indicator geostatistics are also sometimes used to represent the connectivity of high values in spatial fields. Examples of connectivity are connected high values of hydraulic conductivity in aquifers, leading to preferential flow, and connected band-shaped saturation zones in catchments. However, to the authors' knowledge the ability of the indicator approach to capture connectivity has never been shown conclusively. Here we analyse indicator variograms of soil moisture in a small south-east Australian catchment and examine how well they can represent connectivity. The indicator variograms are derived from 13 soil moisture patterns, each consisting of 500–2000 point TDR (time domain reflectometry) measurements. Winter patterns are topographically organized with long, thin, highly connected lines of high soil moisture in the drainage lines. In summer the patterns are more random and there is no connectivity of high soil moisture values. The ranges of the 50^{th} and 90^{th} percentile indicator semivariograms are approximately 110 and 75 m, respectively, during winter, and 100 and 50 m, respectively, during summer. These ranges indicate that, compared with standard semivariograms, the indicator semivariograms provide additional information about the spatial pattern. However, since the ranges are similar in winter and in summer, the indicator semivariograms were not able to distinguish between connected and unconnected patterns. It is suggested that new statistical measures are needed for capturing connectivity explicitly. © 1998 John Wiley & Sons, Ltd.

KEY WORDS indicator variogram; soil moisture; connectivity; continuity; spatial pattern; range; correlation length

INTRODUCTION

Soil moisture is highly variable in both time and space. This variability has a significant impact on many hydrological processes. For example, the spatial distribution of soil moisture determines rainfall–runoff response in many catchments (Dunne *et al.*, 1975). Soil moisture also has an important influence on processes such as erosion (Moore *et al.*, 1988), solute transport, land — atmosphere interactions (Entekhabi *et al.*, 1996) and various geomorphic (Beven and Kirkby, 1993) and pedogenic processes (Jenny, 1980). The

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spatial distribution of soil moisture can be measured either by remote sensing techniques or by multiple point field measurements. Remotely sensed soil moisture data have the advantage of great spatial detail, but the signal is difficult to interpret and reliable estimates of remotely sensed soil moisture are not generally available at present (Jackson and Le Vine, 1996). Multiple point field measurements of soil moisture are easier to interpret. These field measurements typically come from small research catchments. There is a need to transpose these field measurements to other small catchments and to larger catchments. There is also a need to interpolate between the point measurements to obtain estimates of the spatial distribution of soil moisture. Both tasks require spatial estimation procedures. For these, geostatistical techniques are often used.

A central concept in geostatistics is the semivariogram. The semivariogram describes the variance between two points in a spatial field as a function of their separation. The main features of the semivariogram are the sill, the range (or correlation length) and the nugget. If a stable sill exists, the spatial field is stationary and the sill can be thought of as the variance between two points separated by a large distance. The range is the maximum distance over which spatial correlation exists. It is the distance (separation or lag) at which the semivariogram reaches the sill. The correlation length is the average distance of spatial correlation and it is closely related to the range. The numerical value of the correlation length is about one-third of the range, depending on the shape of the semivariogram. The nugget is the variance between two points separated by a very small distance. It is the value at which the semivariogram intersects the y-axis. The semivariogram is a measure of the spatial continuity of the field. Semivariograms of smooth, or highly continuous, spatial fields have a large range, while semivariograms of discontinuous, or rough, spatial fields have a short range.

Geostatistical techniques can be divided into linear and non-linear categories (Journel, 1986; ASCE, 1990). In linear geostatistics, the intrinsic hypothesis is an important assumption which states that the spatial variance between any two points of a random field (i.e. the variogram) exists and depends only on the separation of those points. Based on this assumption, linear kriging algorithms (e.g. ordinary kriging) provide the *best linear unbiased estimate* of the value of a random field at any point, using the semivariogram and the sample data (Journel and Huijbregts, 1978; Isaaks and Srivastava, 1989).

To obtain more detailed information about a spatial field further assumptions are required (Journel, 1983). For example, to obtain confidence intervals for kriged values, or the exceedance probability for a given threshold, assumptions about the probability density function of the kriging errors are required (ASCE, 1990). Furthermore, unless the spatial field is multi-Gaussian, estimates from linear kriging algorithms are not the best possible estimates of the expected value of the spatial field, just the best *linear* unbiased estimates (ASCE, 1990). A random field is multi-Gaussian if all linear combinations of the random variable are normally distributed (Deutsch and Journel, 1992). This is equivalent to assuming that there is no spatial structure beyond that captured by the semivariogram, i.e. the random field varies in a way that produces the maximum disorder consistent with the semivariogram (Journel and Deutsch, 1993). Because multi-Gaussianity enables a much wider range of inferences to be made, it is often assumed in geostatistics (Journel, 1986). However, it is important to recognize that natural spatial fields often show features that are not multi-Gaussian and hence are not captured by the semivariogram (Journel, 1986). Incorrectly assuming multi-Gaussianity can lead to significant errors in an analysis (Gómez-Hernández and Wen, 1997).

There are at least two ways in which hydrological spatial fields can deviate from a multi-Gaussian random field: (a) different semivariograms at different thresholds of the variable; and (b) spatial connectivity.

(a) *Different variograms at different thresholds*. There are many hydrological processes where heuristic considerations suggest that different values of the variable (low and high) possess different variograms. In rainfall fields, for example, high rainfall intensities may be a result of small-scale convective processes and hence exhibit short ranges, while lower rainfall intensities may be related to large-scale synoptic processes and hence exhibit large ranges. Similarly, in aquifers, low and high values of hydraulic conductivity may be a consequence of different depositional processes and hence exhibit different semivariograms (Anderson, 1997). Another example is the spatial distribution of soil moisture. In saturated source areas the spatial variability tends to be controlled by soil properties (porosity) while in other areas with lower soil moisture the spatial variability is due to lateral flow processes (Western *et al.*, 1998a). Because of this, high soil moisture values may exhibit different variograms to low soil moisture values.

One way of capturing different variograms for high and low values is to use indicator techniques (Journel, 1983, 1993). Indicator semivariograms are similar to traditional semivariograms, except that they are calculated on indicator values rather than the actual value of the variable of interest. Indicator values indicate whether the value of the variable is above (indicator value = 1) or below (indicator value = 0) a particular threshold. The threshold is usually given as the percentile of the univariate distribution of the variable. Since indicator semivariograms can be calculated for a number of different thresholds, they allow for a different spatial structure (i.e. semivariogram) at each threshold. For a multi-Gaussian random field, the range of the indicator semivariogram changes with the threshold in a unique way. The range is at a maximum for the 50% threshold and decreases symmetrically as the threshold approaches its extreme values of either 0% or 100% (Deutsch and Journel, 1992; Gómez-Hernández and Wen, 1997). Because of this, a property of multi-Gaussian random fields is that extreme values do not cluster in space. Indicator variograms for natural hydrological fields may deviate from those prescribed by multi-Gaussianity. Therefore, indicator variograms are more flexible and contain more information than traditional semivariograms if the field is not multi-Gaussian. Unfortunately, for estimating reliable indicator variograms, a substantial amount of data is needed. Because of this, very few indicator semivariograms have been derived from actual data in the literature. However, a few studies derived indicator variograms from synthetic spatial fields of hydraulic conductivity in aquifers that show realistic geological features. Scheibe (1993) found that the ranges for the 90th percentile (high hydraulic conductivity) were generally larger than those for the 10th percentile (low hydraulic conductivity). While the actual values depended on the geological structure assumed, the ranges for the 90th percentile were of the order of three times those for the 10th percentile. In a similar analysis, Blöschl (1996) found ranges at the 82nd percentile that were three times those at the 50th percentile and five times those at the 10th percentile. The latter aquifer consisted of two sinusoidal high conductivity flow paths representing buried stream channels in a lower conductivity medium.

For obtaining estimates of the spatial distribution of hydrological variables, a number of non-linear geostatistical techniques have been proposed that are based on indicator variograms. These techniques include indicator kriging, sequential indicator simulation (SIS) and the simulated annealing method (Deutsch and Journel, 1992). All of these techniques are able to generate spatial fields that are not multi-Gaussian with different ranges for different thresholds. Their main application is in the simulation of aquifer heterogeneities (Kolterman and Gorelick, 1996). They also allow the estimation of the exceedance probability for a given threshold and hence the estimation of confidence intervals.

(b) *Spatial connectivity*. Another way in which spatial hydrological fields can differ from multi-Gaussian fields is the connectivity of high (or low) values of a variable. Often, in aquifers, high saturated hydraulic conductivity values are connected and, as a consequence, form preferential flow paths (Blöschl, 1996; Sánchez-Vila *et al.*, 1996). These are important hydrologically because they can lead to an early break-through of contaminants (Desbarats and Srivastava, 1991; Blöschl, 1996; Gómez-Hernández and Wen, 1997). We refer to these interconnected features as connectivity. They are characterized by bands or long thin lines of high saturated hydraulic conductivity media. These bands are not necessarily straight lines nor are they necessarily oriented in any particular direction, but their effect is to create hydraulically efficient pathways that carry a disproportionately high percentage of the flow through an aquifer. Their most important feature is not their size but the degree to which they are interconnected.

Another example of connectivity is the existence of wet bands along drainage lines in catchments, when soil moisture is topographically controlled. These areas are very important hydrologically because they are often the source areas for surface runoff (Dunne *et al.*, 1975), thus they control rainfall–runoff response in general and flood behaviour in particular. Grayson *et al.* (1995) and Blöschl (1996) simulated the rainfall–runoff response from a catchment with two different antecedent soil moisture patterns using a physically based hydrological model. One was a pattern based on the topographic wetness index. This pattern had highly connected wet zones in the drainage lines. The second was a random field which did not have any connectivity. Both antecedent soil moisture fields were identical in terms of their univariate probability density function and their semivariogram. Simulated peak flow and runoff volumes were markedly different for the connected and the random patterns. The differences were also dependent on the depth and intensity of the rainfall event. It is important to emphasize here that continuity and connectivity are two completely different properties. Continuity relates to the smoothness of a spatial pattern while connectivity relates to interconnected paths through the spatial pattern. It should also be noted that connectivity is different from statistical anisotropy. Statistical anisotropy refers to different ranges in different directions. However, as the interconnected features of a pattern exhibiting connectivity are not necessarily oriented in the same direction, anisotropy and connectivity are different properties of a spatial pattern.

It is clear that connectivity is a structural feature not present in multi-Gaussian random fields. Because of this, it is not possible to capture connectivity by traditional semivariograms (Grayson *et al.*, 1995; Blöschl, 1996; Sánchez-Vila *et al.*, 1996; Gómez-Hernández and Wen, 1997). However, it has been suggested by a number of authors that the indicator approach can capture connectivity (e.g. Journel and Alabert, 1989; Rubin and Journel, 1991; Kolterman and Gorelick, 1996; Anderson, 1997; Gómez-Hernández and Wen, 1997). For example, Anderson (1997, p. 39) states, "The most promising approach for simulating geological heterogeneity may be the use of indicator geostatistics with conditional stochastic simulations . . . It can quantify the important property of connectivity of units and thereby capture preferential flow paths." One of the arguments that is sometimes suggested in support of this conjecture is that the indicator approach allows for much greater spatial correlation of extreme values than the multi-Gaussian approach (Journel and Alabert, 1989; Rubin and Journel, 1991). However, to our knowledge the ability of the indicator approach to capture connectivity has never been shown conclusively.

There have been a number of studies in the context of groundwater transport addressing this question. Specifically, these studies examined whether indicator variograms can capture connectivity any better than traditional variograms. The approach used in these studies is to use geostatistical simulations based on traditional geostatistics and on indicator geostatistics to generate spatial fields. The relative merits of the approaches are then assessed either by comparison of the simulated and real patterns or of the hydrological behaviour of the fields using hydrological modelling techniques. Journel and Alabert (1989) conducted an indicator analysis of 1600 permeability measurements taken on a vertical 60 cm $\times$ 60 cm slab of sandstone, and then used a sequential indicator simulation (SIS) to reconstruct the field from 16 data points. Compared with an approach based on traditional semivariograms, the indicator approach was better at reproducing certain connectivity measures, but was not able to reproduce the connectivity fully. On the other hand, Guardino and Srivastava (1993) found that approaches based on indicator variograms were not able to reproduce curvilinear connected features. Blöschl (1996) generated a synthetic aquifer containing highly connected preferential flow paths. This field was then subsampled and SIS and sequential Gaussian simulation (SGS) were used to simulate the original field (Deutsch and Journel, 1992). Solute transport simulations were then run for both the original field and the reconstructed fields. The performance of the SIS and SGS approaches was assessed in terms of how close the simulated breakthrough curves were to those of the 'true' synthetic aquifer. The results depended on the average spacing of the sample points. When the sample spacing was one-third of the correlation length (one-ninth of the range) of the original field, both SIS and SGS were able to capture partially the connectivity and the indicator approach had a slightly superior performance. When the sample spacing was similar to the correlation length, neither SIS nor SGS were able to capture a significant component of the connectivity. Finally, in a similar study, Gómez-Hernández and Wen (1997) showed that random fields based on three different indicator-based models led to mean breakthrough times that were up to an order of magnitude shorter than those simulated for a multi-Gaussian field. These studies suggest some, but by no means, universal success in capturing connectivity using indicator approaches. Specifically, it appears that conditioning of the simulated patterns on the real data is important for capturing connectivity. If there is no, or little, conditioning (i.e. a large spacing of the samples) the connectivity tends not to be captured by the indicator variograms.

An alternative to hydrological simulations is to examine visually whether connectivity is present in the spatial patterns and to analyse, in a second step, the characteristics of the indicator variograms for different thresholds. The idea then is to relate these characteristics to the presence of connectivity. This is the approach taken in this paper.

The aim of this paper is twofold. First, we examine the characteristics of indicator variograms of spatial soil moisture patterns. Specifically, we examine the ranges for different percentile thresholds. An important feature of this analysis is that we are using real spatial patterns. Other authors have used synthetically generated patterns because large data sets are required to derive meaningful indicator semivariograms. This study uses an extensive data set of soil moisture patterns based on a large number of data points. Secondly, we examine whether the indicator variograms can distinguish between those soil moisture patterns that exhibit connectivity and those that do not. Specifically, we relate the differences in the ranges for different thresholds to the presence or absence of connectivity in the soil moisture patterns for the various sampling occasions.

STUDY SITE AND DATA

Detailed soil moisture patterns from the 10·5 ha Tarrawarra catchment in south-eastern Australia (Figure 1) are analysed here. Western and Grayson (1998) describe the catchment and data collection methods in detail. Tarrawarra has a temperate climate. Rainfall is spread relatively evenly through the year, while potential evapotranspiration peaks in summer. Average soil moisture levels are generally high during winter (April to October) and low during summer (November to March). The Tarrawarra catchment is used for cattle grazing and has pasture vegetation. The soils have a 20–35 cm deep A horizon, which is the hydrologically active zone from the perspective of lateral subsurface flow. The topography is undulating, with maximum

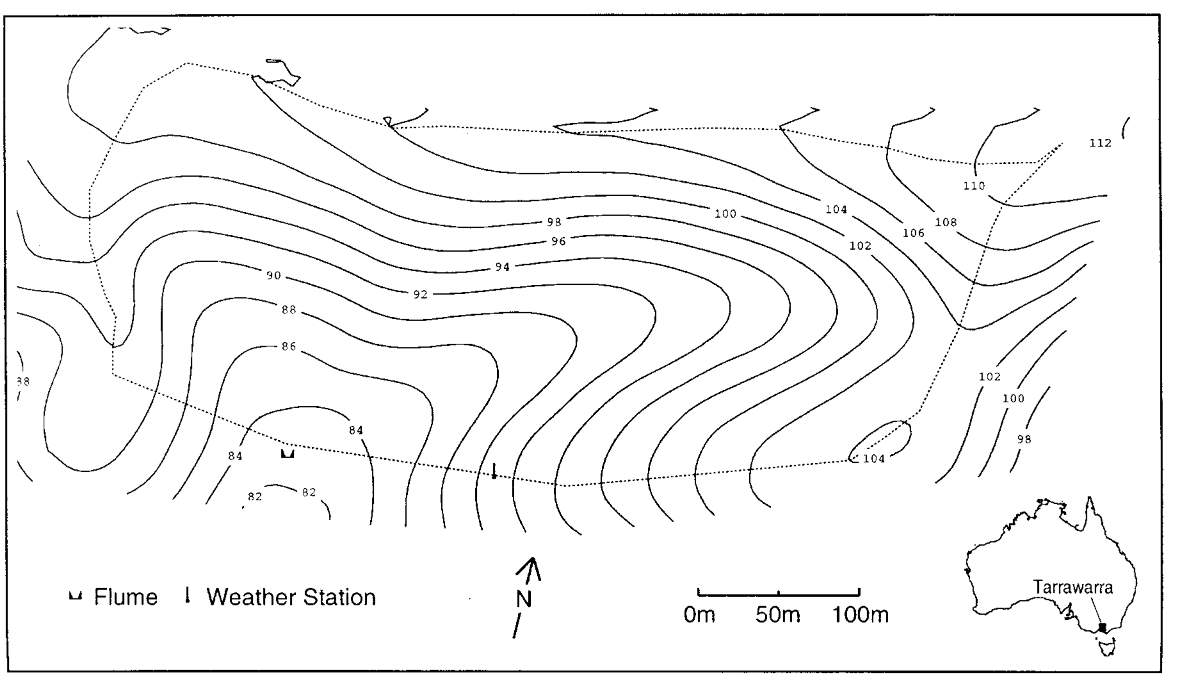

Figure 1. The Tarrawarra catchment, south-eastern Australia. The catchment boundary is shown as a dashed line. Topographic contours (2 m contour interval) are shown with elevations in m

Table I. Summary of the 13 soil moisture patterns from Tarrawarra

Date	Antedent rainfall (10 days, mm)	Sample size	Mean (%V/V)	Variance $(\%V/V)^2$	Coefficient of variation	Percentiles		
						50th (%V/V)	75th (%V/V)	90th (%V/V)
27 Sept 95	15·6	502	37·7	24·1	0·13	38·1	39·6	44·6
14 Feb 96	58·4	498	26·2	10·6	0·12	26·6	28·4	29·8
23 Feb 96	0	518	20·8	5·31	0·11	20·8	22·1	23·7
28 Mar 96	7·0	501	23·9	7·06	0·11	24·0	25·8	26·9
13 Apr 96	65·2	507	35·2	12·3	0·10	35·8	37·5	38·6
22 Apr 96	70·8	513	40·5	14·6	0·09	39·5	43·0	46·0
2 May 96	5·6	2056	41·4	19·4	0·11	40·4	45·0	46·8
3 Jul 96	20·0	505	45·0	14·0	0·08	45·6	47·0	48·6
2 Sept 96	22·2	515	48·5	13·9	0·08	48·2	50·4	53·8
20 Sept 96	39·6	512	47·3	15·2	0·08	47·4	48·9	52·3
25 Oct 96	14·6	490	35·0	19·2	0·13	34·9	37·4	39·3
10 Nov 96	28·2	1008	29·3	10·8	0·11	29·5	31·3	33·4
29 Nov 96	12·0	514	23·9	6·28	0·11	24·2	25·5	26·6

slopes of 14%. There are two distinct drainage lines which join at the runoff measuring flume (Figure 1). These drainage lines become saturated during wet periods.

Thirteen spatial patterns of soil moisture have been collected in this catchment over a period of a year. Each pattern consists of approximately 500 point measurements on a 10 m by 20 m grid, or up to 2000 point measurements with greater spatial detail. Average soil moisture in the top 30 cm of the soil profile was measured at each point using time domain reflectometry (TDR). The TDR probes were inserted using a hydraulic insertion system mounted on an all-terrain vehicle. Differences between gravimetric and TDR soil moisture measurements collected in the field have a variance of 6·6 $(\%V/V)^2$. An analysis of the magnitude of different error sources indicates that during normal operating conditions approximately half of this variance is due to errors in the gravimetric measurements and half to errors in the TDR measurements. Estimates of nugget variance support this conclusion (Western *et al*., 1998b). The all-terrain vehicle is fitted with a position-fixing system that has a resolution of $\pm 0{\cdot}2$ m. Table I provides the dates, antecedent rainfall, number of sample points, mean, variance, coefficient of variation, and 50th, 75th and 90th percentiles for each of the data sets used in the analysis. Very detailed information on soil properties and climate data have also been collected which can assist in interpreting the soil moisture patterns (Western and Grayson, 1998).

METHODS OF ANALYSIS

The analysis of the soil moisture patterns consists of four steps. First, indicator values at each measurement site were calculated and indicator maps were plotted. Indicator values were calculated by thresholding the data at the p^{th} percentile and assigning an indicator value of zero to sites with a soil moisture less than or equal to the p^{th} percentile, and a value of one to sites with a soil moisture greater than the p^{th} percentile. The indicator map is then referred to as the p^{th} percentile indicator map. Indicator maps were calculated for thresholds equal to the 50th, 75th and 90th percentiles. Table I provides these percentiles for each soil moisture pattern.

The second analysis step consisted of calculating indicator semivariograms for each indicator map. Indicator semivariograms were calculated in the same way as standard semivariograms (see, e.g., Isaaks and Srivastava, 1989), except that the indicator values were substituted for the actual soil moisture values. For one of the occasions (10 November 1996), indicator semivariogram maps were calculated to examine the statistical anisotropy of the data set. Since the anisotropy did not change between the percentile thresholds, the rest of the analysis was based on omnidirectional indicator semivariograms. These were calculated using all data pairs separated by lags up to 305 m. This is about half of the maximum separation distance in the catchment. Pairs were grouped into lag 'bins' and Equation (1) was used to calculate the indicator semivariance for that bin. The mean lag of all the pairs in a particular bin was used as the representative lag for that bin. The sample semivariance, $\gamma_s(h)$, is the value of the semivariogram at a given lag, h

$$\gamma_s(h) = \frac{1}{2N(h)} \sum_{(i,j)} (I_i - I_j)^2 \tag{1}$$

where, N is the number of pairs, I_i and I_j are the indicator values at points i and j, respectively, and the summation is conducted over all i, j pairs in the lag bin. For indicator semivariograms the range is the main feature that contains information about the structure of the spatial field, while the sill is simply a function of the percentile at which the data are thresholded. Therefore, the indicator semivariograms were normalized by the sill such that $\gamma_n(h) = \gamma_s(h)/\sigma_p^2$, where $\sigma_p^2 = (1 - p/100)p/100$ is the variance of the indicator values at the p^{th} percentile. The sill of the normalized indicator variograms is equal to 1. The range of the normalized indicator variograms is equal to the range of the original indicator variograms. The differences in range for the different thresholds are of most interest.

The third analysis step involved calculating ranges for each sample indicator semivariogram. Three approaches were used to calculate the ranges. The first approach was to fit an exponential semivariogram model to the sample semivariogram and to use the range parameter from the fitted semivariograms as estimates of the range

$$\gamma_e(h) = \frac{\sigma_0^2}{\sigma_p^2} + \left(1 - \frac{\sigma_0^2}{\sigma_p^2}\right)(1 - \mathrm{e}^{-h/\lambda}) \tag{2}$$

In Equation (2), λ is the correlation length, and the practical range is 3λ. σ_0^2/σ_p^2 is the normalized nugget. The second approach was similar but used a spherical variogram model

$$\gamma_{sp}(h) = \frac{\sigma_0^2}{\sigma_p^2} + \left(1 - \frac{\sigma_0^2}{\sigma_p^2}\right)\left[1{\cdot}5\frac{h}{a} - 0{\cdot}5\left(\frac{h}{a}\right)^3\right] \quad h < a \tag{3a}$$

$$\gamma_{sp}(h) = 1 \quad h \geqslant a \tag{3b}$$

In Equation (3), a is the range. The third approach consisted of estimating the range directly from the sample indicator semivariograms by visual inspection.

The last analysis step was to compare the estimated ranges for the different thresholds. For a multi-Gaussian random field, the ratio of the ranges at two percentile thresholds is uniquely defined by the percentile values and the shape of the (traditional) semivariogram. Western *et al.* (1998b) showed that the (traditional) semivariograms of the Tarrawarra soil moisture data set are approximately exponential with a nugget. For this type of variogram, the ratio of the ranges at the 90$^{\text{th}}$ and the 50$^{\text{th}}$ percentiles is about 0·8 if the field is multi-Gaussian (Deutsch and Journel, 1992, equation V.20, p. 139). Estimated values of the ratio different from 0·8 indicate that the field is not multi-Gaussian. If the indicator approach is able to capture connectivity one would expect significantly different ratios for connected and not connected soil moisture patterns.

To assist in the interpretation of the soil moisture results in terms of topographic controls, a similar analysis has been performed for the topographic wetness index of Beven and Kirkby (1979) at Tarrawarra. The topographic wetness index is calculated as $\ln(a/\tan\beta)$, where a is the specific upslope area and β is the surface slope. In a first step, indicator maps have been derived. Figure 2 shows the 50$^{\text{th}}$, 75$^{\text{th}}$ and 90$^{\text{th}}$ percentile indicator maps of the wetness index. The wetness index is large in the drainage lines and small on the hillslopes. It is evident from Figure 2 (bottom panel) that the high values of wetness index are connected in long thin bands in the drainage lines. This pattern shows a high degree of connectivity. In a

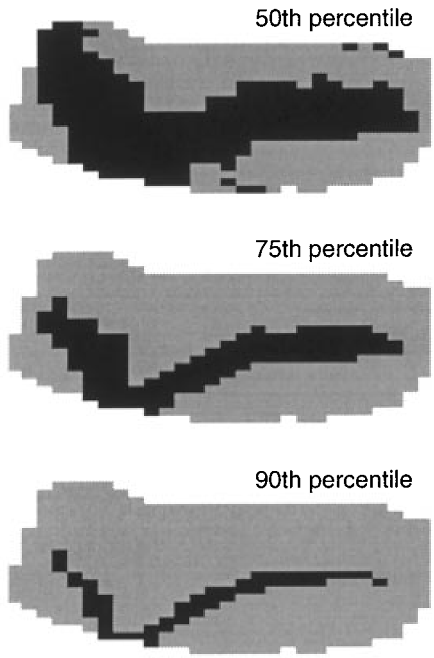

Figure 2. Indicator maps the topographic wetness index in the Tarrawarra catchment. Top 50th, middle 75th and bottom 90th percentile. The raster grid is 20 m by 10 m. Black cells have wetness index values greater than the threshold and grey cells have wetness index values less than or equal to the threshold

second step, indicator semivariograms were derived from these indicator plots. Figure 3 shows 50th, 75th and 90th percentile indicator semivariograms for the wetness index. Here, the range for the 90th percentile indicator semivariogram is about two-thirds of the range of the 50th percentile indicator semivariogram. This is significantly lower than the theoretical value of 0·8 which indicates that the wetness index spatial field is not multi-Gaussian. The field is less spatially continuous (the bands are narrower) at high wetness index values than at the median wetness index value and the difference is larger than would be expected for a multi-Gaussian field. Because of this, there is more spatial structure in the wetness index field than can be captured using a traditional semivariogram. If the soil moisture field is topographically organized, similar indicator plots and similar indicator semivariograms can be expected for the soil moisture field.

RESULTS

Indicator maps

Here the spatial pattern of soil moisture is examined using indicator maps. Figures 4–6 show 50th, 75th and 90th percentile indicator maps, respectively, for soil moisture in the Tarrawarra catchment on 12 different occasions. When comparing the 50th and 90th percentile indicator maps, the most striking difference is the low proportion of high moisture (black) cells in the 90th percentile map. Obviously this is due to the higher moisture threshold, which is exceeded only by 10% of the cells. The 90th percentile map shows the core or the wettest part of the wet areas in the 50th percentile map. Two other comparisons are more hydrologically interesting.

The first is a comparison of the characteristics of the soil moisture patterns during different seasons. This can be illustrated using the 75th percentiles in Figure 5. In the patterns from 14 and 23 February, and 28 March 1996 there are black patches spread across the catchment in a relatively random manner. While there is some tendency for high moisture measurements to group together, the high moisture patches are not

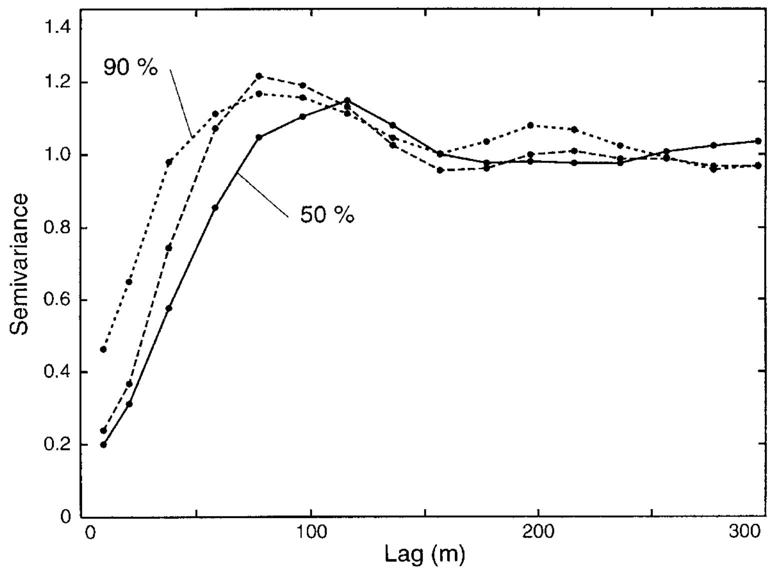

Figure 3. Indicator semivariograms of the topographic wetness index in the Tarrawarra catchment. 50th percentile solid line, 75th percentile dashed line, 90th percentile dotted line.

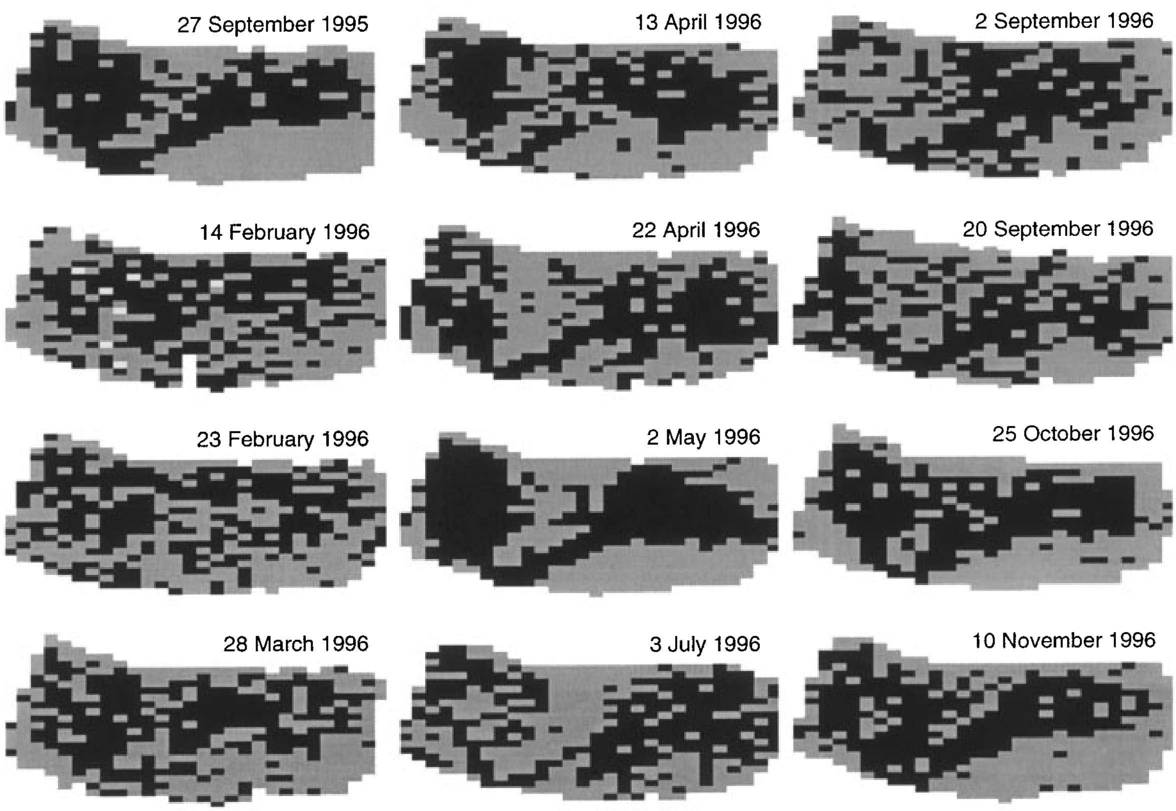

Figure 4. Fiftieth percentile indicator maps of soil moisture in the Tarrawarra catchment on 12 occasions. Note that the raster cell size is 20 m by 10 m and each cell represents one point measurement of average volumetric soil moisture in the top 30 cm of the soil profile. Black cells have soil moisture values greater than the threshold and grey cells have soil moisture values less than or equal to the threshold

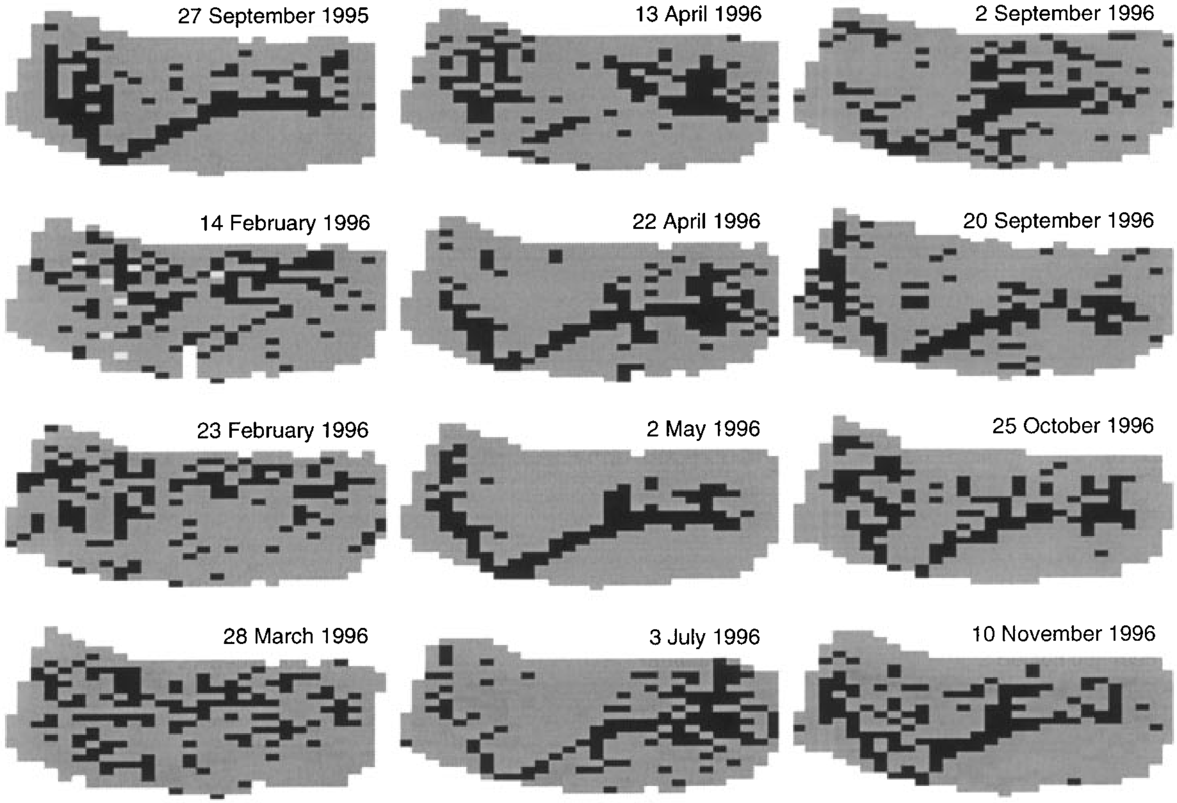

Figure 5. Seventy-fifth percentile indicator maps of soil moisture in the Tarrawarra catchment on 12 occasions. Note that the raster cell size is 20 m by 10 m and each cell represents one point measurement of average volumetric soil moisture in the top 30 cm of the soil profile. Black cells have soil moisture values greater than the threshold and grey cells have soil moisture values less than or equal to the threshold

connected in any systematic fashion; i.e. the patterns show some continuity but no connectivity. These random patterns occur during summer when the catchment is dry. In the patterns from 27 September 1995, and 22 April, 2 May and 3 July 1996 the pattern no longer has a random appearance. The wet measurements are grouped together and form long connected wet strips; i.e. the patterns show both continuity and connectivity. The connected wet strips are located within the drainage lines (see Figure 1). These cases show topographically organized soil moisture patterns. Connectivity is also present but is slightly less obvious in the patterns from 2 September and 20 September 1996. This is because the catchment is extremely wet during this period (mean soil moisture is 48·5 and 47·3%V/V, respectively) (see Table I) and the saturated areas have expanded out of the drainage lines and are very extensive. Figures 4 and 6 show similar seasonal changes in the 50^{th} and 90^{th} percentile indicator patterns.

The connectivity is important here because the saturated source areas, which produce the majority of runoff in this landscape, are hydraulically connected to the catchment outlet. If the wet areas were not connected to the outlet, overland flow produced in the source areas would have to flow across relatively dry areas and would have the opportunity to infiltrate before it reached the catchment outlet.

The second important comparison is between different indicator patterns for each occasion. On 23 February 1996, the indicator pattern is random for all three indicator thresholds. There is continuity but no connectivity at all three thresholds. On 22 April 1996, the soil moisture is topographically organized and there is connectivity as well as continuity at all three thresholds. These occasions are typical of other dry and wet patterns, respectively. In general there is continuity in all the patterns at all thresholds, but there is

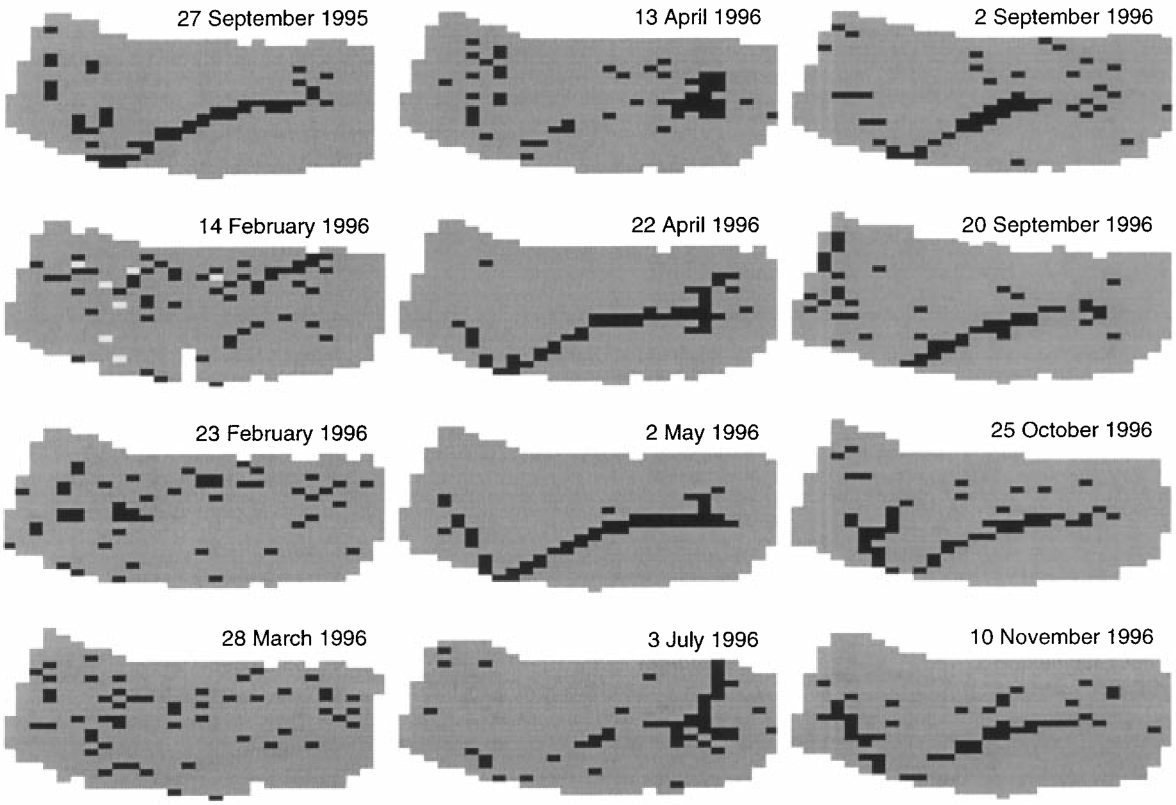

Figure 6. Ninetieth percentile indicator maps of soil moisture in the Tarrawarra catchment on 12 occasions. Note that the raster cell size is 20 m by 10 m and each cell represents one point measurement of average volumetric soil moisture in the top 30 cm of the soil profile. Black cells have soil moisture values greater than the threshold and grey cells have soil moisture values less than or equal to the threshold

connectivity only during wet periods. When there is connectivity present, it is present at all three soil moisture thresholds.

Indicator semivariograms

The indicator maps discussed above provide a qualitative appreciation of the soil moisture patterns. The spatial structure of the different indicator patterns can be considered more quantitatively using indicator semivariograms. As a first step, indicator semivariogram maps were calculated to examine the statistical anisotropy of soil moisture (Figure 7). In the indicator semivariogram maps, light and dark values correspond to small and large values of the semivariogram, respectively. The value at the centre of the map is zero as this corresponds to a zero lag. Figure 7 indicates that the soil moisture patterns are indeed anisotropic. The ranges are largest in the direction of the main gully. Clearly, this is related to the shape of the catchment and the consistently high values of soil moisture in the main gully on 10 November 1996 (Figures 4–6). However, the anisotropy for the three thresholds (Figure 7) is quite similar. This is typical of the other occasions. Since the focus in this paper is on the differences between thresholds and these are small in terms of the anisotropy, only omnidirectional indicator semivariograms are considered in the further analysis.

Omnidirectional indicator semivariograms are shown in Figure 8 for the 50^{th}, 75^{th} and 90^{th} percentiles (solid, dashed and dotted lines, respectively). The graphs can be compared in a number of ways. The first is a comparison of the distinguishing features of the indicator semivariograms for summer (14 and 23 February and 28 March 1996; dry) and winter (27 September 1995, and 22 April, 2 May and 3 July 1996; wet) soil

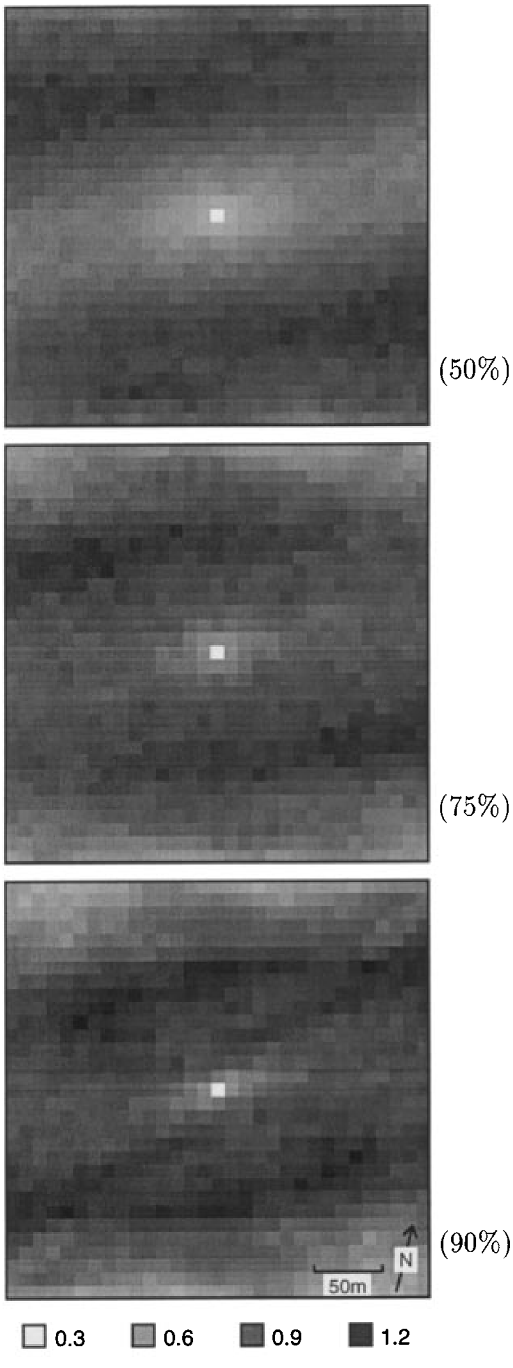

Figure 7. Indicator semivariogram maps of soil moisture in the Tarrawarra catchment on 10 November 1996. Top 50th, middle 75th, and bottom 90th percentile indicator threshold. The grid size is 10 m which is the grid size of the measurements. Light and dark values correspond to small and large values of the semivariogram, respectively. The value of zero at the centre of the map corresponds to a zero lag

Table II. Summary of the ranges estimated for the 50th, 75th and 90th percentile indicator sevivariograms. The ranges were obtained by three different methods: fitting exponential and spherical semivariograms and visual estimation of the range. Units are m

Date	Exponential model (practical range = 3λ)			Spherical model (range a)			Visual estimation (range)		
	50th	75th	90th	50th	75th	90th	50th	75th	90th
27 Sept 95	105	90	90	105	80	80	115	95	75
14 Feb 96	90	75	75	75	60	60	75	65	55
23 Feb 96	105	60	45	105	60	45	55	45	35
28 Mar 96	105	75	45	105	60	45	75	55	45
13 Apr 96	120	90	60	120	90	90	115	95	75
22 Apr 96	120	90	60	120	75	75	95	75	75
2 May 96	120	90	75	105	75	60	115	95	75
3 Jul 96	135	105	75	120	90	75	95	85	75
2 Sept 96	135	105	75	135	90	75	105	95	75
20 Sept 96	120	90	75	105	75	75	85	75	75
25 Oct 96	120	90	75	105	75	75	115	85	75
10 Nov 96	120	75	75	105	75	75	135	95	75
29 Nov 96	120	90	60	105	90	60	95	75	55

moisture patterns. During summer the normalized nugget is larger than during winter. This is related to the measurement error and the variance of the soil moisture pattern. When the ratio of the measurement error to the variance of the soil moisture is high, the normalized nugget is high. In summer the variance of the soil moisture is low while during the winter the variance of the soil moisture is high. Since the measurement error is relatively constant, there is a high normalized nugget in summer and a low normalized nugget in winter.

Another feature distinguishing the indicator semivariograms for the summer (dry) and winter (wet) soil moisture patterns is the periodicity that appears in the indicator semivariograms, particularly for the 90th percentile, during wet periods. This is related to the organization of the soil moisture pattern, specifically the wet drainage lines. This organization introduces a periodic component into the soil moisture pattern which appears as periodicity in the semivariogram. However, this is likely to be an artefact of having a single catchment and is probably not a characteristic of the landscape as a whole. We would expect it to disappear if multiple catchments were studied. Neither the nugget nor the periodicity are features of the indicator semivariograms that would be useful for distinguishing between the connected and unconnected (i.e. the wet and the dry) patterns in a general way.

The most important general feature of the indicator semivariogram is the range. Table II provides ranges for each soil moisture pattern. Typical ranges during summer for the 50th, 75th and 90th percentile are 100, 75 and 50 m, respectively. During winter, typical ranges for the 50th, 75th and 90th percentile are 110, 90 and 75 m, respectively. In all cases the range for the 90th percentile indicator semivariogram is shorter than that for the 50th percentile. This consistency indicates that the differences in range for different thresholds are a property of the real soil moisture patterns rather than a property of the sample only. If we compare, visually, the presence or absence of connectivity in the patterns (Figure 6) with the differences in the ranges for different thresholds (Figure 8) no clear relationship is apparent. The connected and the unconnected cases have similar differences in the ranges for the 50th and 90th percentiles.

Figure 9 examines the seasonal pattern of the contrast between the ranges for the 50th and 90th percentiles in more detail. The ratio of the range for the 90th percentile indicator semivariogram and the range for the 50th percentile indicator semivariogram is plotted as a time-series. The different methods for estimating the range (shown as dashed, dotted and solid lines in Figure 9) give different seasonal patterns of the ratios but none of the seasonal patterns are very clear. The ratios in Figure 9 tend to be significantly lower than 0·8, which means that none of the soil moisture patterns are multi-Gaussian. Figure 9 also highlights the

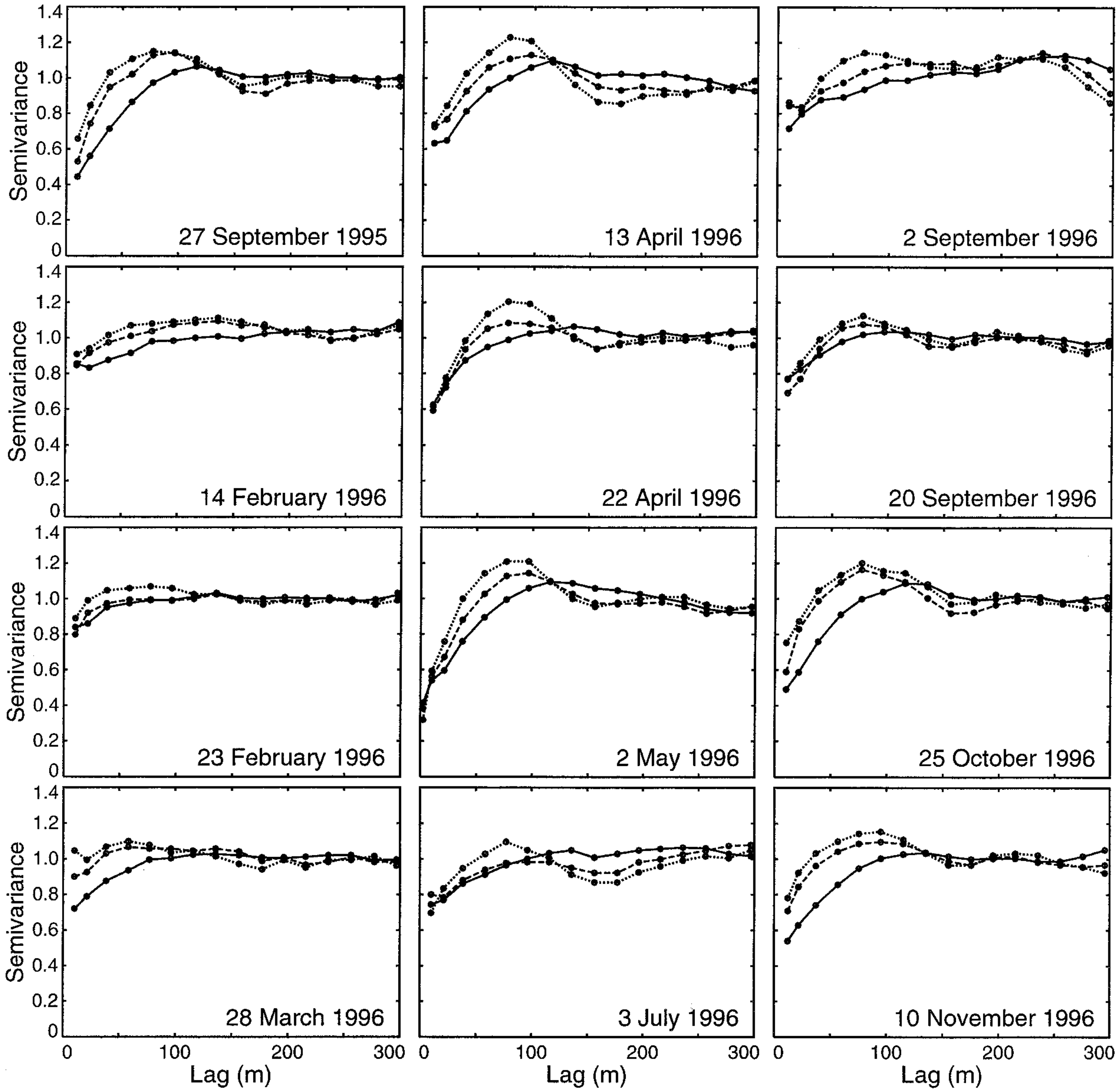

Figure 8. Indicator semivariograms of average soil moisture in the top 30 cm of the soil profile in the Tarrawarra catchment for 12 occasions. 50th percentile solid line, 75th percentile dashed line, 90th percentile dotted line

relationship between the ratio of ranges and the connectivity of patterns. Open circles represent wet winter patterns that exhibit connectivity, while the filled circles represent dry summer patterns that do not exhibit connectivity. It is clear from Figure 9 that the ratio of ranges for different thresholds is not related in a significant way to the presence of connectivity as assessed by visual inspection. In other words, the difference in connectivity between the wet and the dry soil moisture patterns is not captured by indicator geostatistics, even though connectivity is clearly present in the wet patterns and clearly absent in the dry patterns.

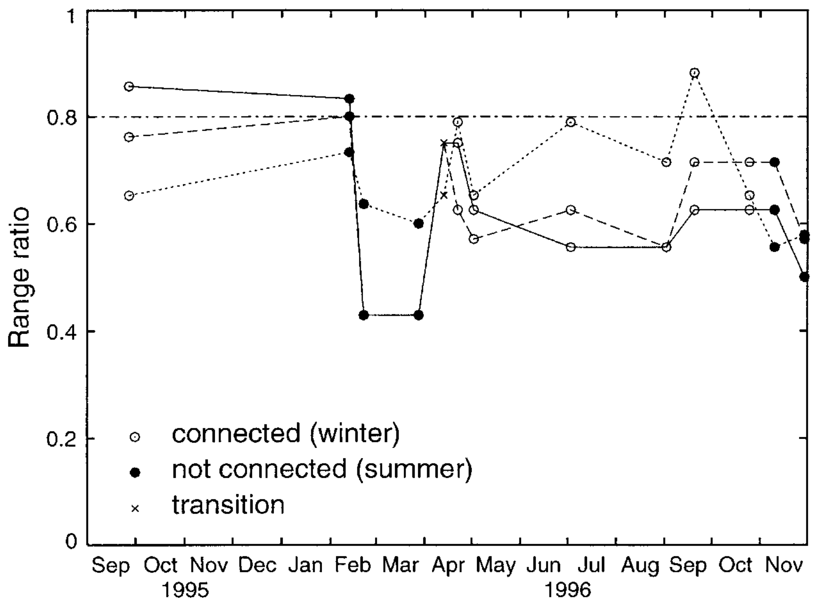

Figure 9. Ratios of the range of the 90th percentile indicator semivariogram to the 50th percentile indicator semivariogram for the Tarrawarra catchment. Ranges were obtained from fitted exponential (solid line) and spherical (dashed line) semivariogram models, and by visual estimation (dotted line)

DISCUSSION

Indicator semivariograms for soil moisture patterns at Tarrawarra exhibit ranges at the 90th percentile threshold that are typically about two-thirds of the ranges at the 50th percentile threshold. This is significantly less than would be expected for a multi-Gaussian field.

In interpreting these results it is important first to assess the accuracy of the estimates. Depending on the fitting method, estimated range ratios for the 90th and 50th percentiles varied from about 0·6 to 0·8 on some occasions, while they varied from about 0·5 to 0·7 on other occasions. This indicates that the indicator semivariograms are not very well defined. They are less well defined than standard semivariograms for the soil moisture patterns (Western *et al.*, 1998b) where the uncertainty is of the order of 5% rather than 30% as it is here. This is because thresholding the data, when deriving the indicator plots, reduces the information content of the data (Deutsch and Journel, 1992). The indicator semivariograms here are typically based on 500 points. It is clear that large data sets are required for accurate estimation of the indicator semivariogram parameters. The shorter range for the 90th percentile consistently occurs for all patterns, which strongly suggests that this is a property of the real soil moisture patterns rather than a property of the sample only. This difference in range is providing different information to the traditional semivariogram. Therefore, the loss of information owing to thresholding in a single indicator semivariogram is compensated for by the increased flexibility of the indicator approach (Journel, 1983; Deutsch and Journel, 1992).

From a hydrological perspective, the much smaller ranges at the 90th percentile than at the 50th percentile can be explained in terms of the lateral redistribution processes for the wet patterns. In the wet state, water is moving laterally down the hillslopes and being collected by the (linear) drainage lines. The majority of the hillslopes are arranged on either side of the drainage lines. The soil moisture generally decreases with distance up the hillslope from the drainage line because of the decreasing contributing area. Because the drainage lines are long compared with the hillslopes and because of the relationship between hillslope position and soil moisture, the indicator pattern remains connected and gets much wider but only slightly longer as the soil moisture threshold decreases. Since larger patches (at a given percentile threshold) in the indicator plot relate to longer ranges, the range increases as the threshold decreases. This interpretation is supported by the indicator plots and the indicator semivariograms of the wetness index (Figures 2 and 3). Both the indicator plots and the indicator semivariograms of the wetness index are similar to those of soil moisture for the wet (winter) conditions. The wetness index can be thought of as a limiting case of a spatial pattern that is strongly controlled by topography. Indeed, Figure 2 very clearly illustrates the increasing width of the indicator pattern as the threshold decreases from the bottom to the top panel. This change in width translates into a change in the range of the indicator semivariograms of the wetness index from about 60 m at the 90th percentile to about 100 m at the 50th percentile (Figure 3). In other words, the large differences in range for the wet soil moisture patterns can be interpreted in terms of the strong topographic control.

For the dry case, there is no topographic control but the ranges at the 90th percentile are still significantly smaller than those at the 50th percentile. There is no clear explanation for this result. It is possibly related to soil variations, particularly zones of different soil types, to a slight influence of aspect and slope on evapotranspiration (owing to different radiation inputs) or to some small patches of local lateral redistribution.

It is interesting to note that the change in range with changing threshold for the soil moisture patterns is opposite to the characteristics found for the conductivity in aquifers. In the aquifer case, often, the ranges for the highest percentiles are significantly larger than those for the lower percentiles (Scheibe, 1993; Blöschl; 1996; Gómez-Hernández and Wen, 1997). This is not a contradiction, as the processes giving rise to the spatial patterns are vastly different in the soil moisture and the aquifer cases.

While there is a large difference in range for different thresholds, this difference was present for both connected and unconnected patterns. There was no clear dependence of the difference in range on the presence or absence of connectivity. Therefore it must be concluded that the indicator semivariograms did not capture the connectivity. This is opposite to what some authors have suggested in the literature. To shed more light on this question we need to consider two things. First, what does the indicator semivariogram capture and how is this related to connectivity, and secondly, what are the features of our patterns that change with threshold?

Standard semivariograms are a measure of spatial continuity in general. Indicator semivariograms are a measure of spatial continuity at a specific threshold. Multiple indicator semivariograms capture spatial continuity at multiple thresholds and can thus be used to capture differences in continuity at different thresholds, an important feature of many natural spatial patterns. Depending on the nature of the spatial patterns, connectivity may or may not be associated with differences in continuity at different thresholds. However, because continuity and connectivity are two distinct properties of a spatial pattern, there are many possible combinations of connectivity and continuity at different thresholds.

Consider first the case of a multi-Gaussian random field such as would be simulated by the turning bands methods (Mantoglou and Wilson, 1981). This type of field has no connectivity (rounded shapes on a map) and the continuity (i.e. the range) is equal for all thresholds. The second case is the summer (dry) patterns analysed in this study. These patterns have no connectivity and different continuity at the 50th, 75th and 90th percentiles. In an indicator plot, smaller continuity at the 90th percentile translates into a larger number of smaller patches at the 90th percentile as compared with a multi-Gaussian field. These patches tend to be isolated and not connected with each other. The third case is the winter (wet) patterns. These patterns have connectivity at all percentile thresholds and different continuity at the 50th, 75th and 90th percentiles. The presence of connectivity at all thresholds is related to the significant topographically routed lateral flow along both subsurface and surface flow paths during the wet conditions in winter. Because there are lateral redistribution processes operating everywhere and because these processes, along with the convergence of catchments in general, have an inherent tendency to create connectivity, there is connectivity at all thresholds. A fourth possible case is an aquifer with high conductivity flow paths which has connectivity at the high percentile thresholds only and different continuity at the different percentiles. The processes leading to connectivity can include fluvial sedimentary processes, fracturing and faulting (Sánchez-Vila *et al.*, 1996; Anderson, 1997). These are not processes that operate at all points in the field at the same time and therefore it would not be expected that they would lead to connectivity at all thresholds. The same processes may give rise to differences in continuity at the different percentiles. In other words, this is an example where differences in connectivity are likely to be associated with differences in continuity at different thresholds.

It is clear that for some spatial hydrological patterns, connectivity may be associated with differences in continuity at different thresholds. However, this depends on the nature of the spatial process and there does not appear to be a universal correspondence.

CONCLUSIONS

Indicator semivariograms of soil moisture patterns at Tarrawarra have been examined. Indicator semivariogram maps indicate that there is substantial anisotropy with the larger ranges in the direction of the main gully. However, this anisotropy is present for all indicator thresholds. Omnidirectional indicator semivariograms have been analysed in terms of their ranges. Typical ranges during summer for the 50^{th}, 75^{th} and 90^{th} percentile are 100, 75 and 50 m, respectively. Typical ranges during winter for the 50^{th}, 75^{th} and 90^{th} percentile are 110, 90 and 75 m, respectively. In all cases the range for the 90^{th} percentile indicator semivariogram is shorter than that for the 50^{th} percentile. This consistency indicates that the differences in range for different thresholds are a property of the real soil moisture patterns rather than a property of the sample only. The ranges are similar to those of the indicator semivariograms for the topographic wetness index of Beven and Kirkby (1979). For the wetness index, the ranges for the 50^{th}, 75^{th} and 90^{th} percentile are about 100, 80 and 60 m, respectively. Since, for the soil moisture patterns, the ratio of the ranges at the 90^{th} percentile and the ranges at the 50^{th} percentile is always smaller than its theoretical value of 0·8 for a multi-Gaussian field, none of the soil moisture patterns are multi-Gaussian. Because of this, the indicator semivariograms provide additional information about the spatial pattern, compared with standard semivariograms. Using this information may be an improvement over assuming multi-Gaussianity, especially in the summer (dry) case, where no connectivity is present. For example, sequential indicator simulation (Deutsch and Journel, 1992), instead of multi-Gaussian simulation methods such as the turning bands method, could be used to simulate the spatial pattern of soil moisture for input into a physically based rainfall–runoff model.

This study also examined how well indicator semivariograms can capture the spatial connectivity of soil moisture. The winter (wet) patterns exhibited a large degree of connectivity, while the summer (dry) patterns did not exhibit any connectivity. However, the indicator semivariograms for the winter and the summer patterns are similar in terms of their range. Specifically, the ratio of the ranges at the 90^{th} and 50^{th} percentiles is on the order of 0·6 to 0·7 for both the winter and the summer patterns. This ratio is the key property that can capture spatial structure beyond that of a traditional semivariogram. Since there is no clear dependence of the ratio of the ranges on the presence (winter patterns) or absence (summer patterns) of connectivity, it must be concluded that the indicator semivariograms did not capture the connectivity. Multiple indicator semivariograms capture spatial continuity at multiple thresholds and can thus be used to capture differences in continuity at different thresholds. Depending on the nature of the spatial patterns, connectivity may or may not be associated with differences in continuity at different thresholds.

There are a number of possible approaches to consider connectivity more explicitly. These may be more appropriate for generating spatial patterns of soil moisture for the wet (winter) case than indicator-based approaches. One approach is to consider topograph explicitly, either as a covariate or by using coordinate systems defined by topographic contours and flow lines. Another possible approach is to use explicit connectivity measures (see Allard, 1994). Work along these lines will be reported in the near future.

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