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Influence of Grid Cell Size and Flow Routing Algorithm on Soil-Landform Modeling

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수치고도모델의 격자크기와 유수흐름 알고리듬의 선택이 토양경관 모델링에 미치는 영향

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Abstract : Terrain parameters calculated from digital elevation models (DEM) have become increasingly important in current spatially distributed models of earth surface processes. This paper investigated how the ability of upslope area for predicting the spatial distribution of soil properties varies depending on the selection of spatial resolutions of DEM and algorithms. Four soil attributes from eight soil-terrain data sets collected from different environments were used. Five different methods of calculating upslope area were first compared for their dependency on different grid sizes of DEM. Multiple flow algorithms produced the highest correlation coefficients for most soil attributes and the lowest variations amongst different DEM resolutions and soil attributes. The high correlation coefficient remained unchanged at resolutions from 15 m to 50 m. Considering decreasing topographical details with increasing grid size, we suggest that the size of 15-30 m may be most suitable for soil-landscape analysis purposes in our study areas.
Key Words : digital elevation model, scale, soil-landform modeling, terrain analysis, upslope area

요약 : 수치고도모형으로부터 산출된 지형변수는 지표면 프로세스와 관련된 공간모델의 개발에 있어 중요한 요소이다. 이 논문에서는 사면유역지수(upslope contributing area)가 토양성질의 공간적 분포를 예측하는 능력이, 사용한 알고리듬과 격자크기에 따라 어떻게 변하는지를 연구하였다. 상이한 환경조건을 지니는 여덟 군데의 연구지역에서 토양-경관 자료를 획득하여 이중 4개의 토양성질을 분석에 포함시켰다. 다섯 가지의 알고리듬을 통해 사면유역지수를 산출하여 이 지수들이 수치고도모형의 해상도에 얼마나 민감한지를 분석하였다. 다방향유수흐름 알고리듬(multiple flow algorithm)을 통해 계산된 지형변수가 대부분의 토양변수와 높은 상관관계를 보임과 동시에 격자크기의 변화에 낮은 민감도를 보였다. 지형변수와 토양변수 사이의 높은 상관관계는 15-50 m의 해상도에서 유사한 예측능력을 보였다. 격자크기를 증가시켰을때 발생하는 미세지형정보의 손실을 감안한다면, 15-30 m 정도의 공간적 스케일이 토양경관 모델링에 적합할 것으로 판단된다.
주요어 : 수치고도모형, 스케일, 토양경관 모델링, 지형면 분석, 사면유역지수

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1. Introduction

As modeling approaches become more spatially oriented, the identification of the spatial distribution of energy and material flows over complex landscapes is essential. Digital elevation models (DEM) have been widely used to meet these goals in modeling geomorphological, hydrological, and pedological processes (Moore *et al.*, 1993a; Wilson and Gallant, 2000). Many previous researchers, however, have already shown that the source of DEM, its grid resolutions, and the different algorithms for calculating specific landform variables have a strong influence on the spatial distribution of individual terrain parameters and modeling results (e.g. Zhang and Montgomery, 1994; Desmet and Govers, 1996; Wilson *et al.*, 2000; Thompson *et al.*, 2001). Among many issues related to the use of DEM in environmental research, we focus on two issues: grid resolution and algorithms for calculating upslope area. Specifically, we are interested in the application of raster DEM to predict the spatial distribution of soil attributes over the landscape.

The appropriate size of the horizontal resolution (grid size) has been a central issue for the application of DEM. Notwithstanding the rapid development in field surveying techniques, construction of reliable DEM at a fine resolution is still one of the most difficult tasks, especially for scientists working in regions with poor access and heavily vegetated areas. Consequently, the choice of the optimum grid size for a given purpose is one of the most frequently asked questions before a field investigation is launched. Several recent studies have already explored this issue in relation to various modeling attempts, notably terrain-based hydrological process modeling (Hutchinson and Dowling, 1991; Jenson, 1991; Panuska *et al.*, 1991; Quinn *et al.*, 1991, 1995; Wolock and Price, 1994; Garbrecht and Martz, 1994; Zhang and Montgomery, 1994; Thieken *et al.*, 1999).

Despite the difference of selected DEM in terms of both data source and quality, the general conclusions in the research so far are similar: the coarser grid resolution tends to smoothen landforms and consequently key geomorphological and hydrological features are lost. It is thus a common belief that more detailed depiction of surface topography yields more accurate modeling results. Quinn *et al.* (1995) compared different grid sizes to validate a terrain-based hydrological model (TOPMODEL) prediction and suggested that a grid size of 10 m or less is necessary. Mitasova *et al.* (1996) also proposed that a grid resolution of 5 m or less may be required to predict erosion and depositional processes in agricultural landscapes. In contrast to these reports, others argued that DEM with very fine resolutions (e.g. with 2 or 5 m grid size) only slightly improve model performance, despite the more realistic presentation of surface topography (Beven, 1995; Thieken *et al.*, 1999; Wilson and Gallant, 2000). An appropriate grid resolution depends entirely on the purpose of modeling and the quality of DEM, but the selected grid size should match the terrain-dependent natural geomorphological and hydrological processes (Hutchinson and Gallant, 2000). Zhang and Montgomery (1994) conclude that a 10 m grid size may be a rational compromise between increasing resolution of grid size and the data volume needed for geomorphological and hydrological process modeling.

Another widely discussed technical issue in terrain analyses is the choice of algorithms for calculating an ‘upslope area’. Upslope area (A) is defined as the area above a given length of contour that contributes flow across the contour (Speight, 1974; Moore *et al.*, 1993a). The upslope area plays an important role in terrain analyses since it is used to estimate the water-mass flow potentials at a specific location (Moore *et al.*, 1993a). Reflecting its importance, many different algorithms for calculating the upslope area are reported in current literature (O'Callaghan and Mark, 1984; Bauer *et al.*, 1985; Fairfield and Leymarie, 1991; Freeman, 1991; Quinn *et al.*, 1991; 1995; Costa-Cabral and Burges, 1994; Tarboton, 1997; Wilson *et al.*, 2000). There has been much theoretical discussion on the suitability of different algorithms, based on either statistical comparison of calculated parameters or visual assessment of flow representation (e.g. Quinn *et al.*, 1991; Tarboton, 1997). However, only few researchers have investigated the advantages and disadvantages of each individual algorithm using empirical data. Furthermore, the few available empirical assessments are mostly limited to hydrological responses in a specific modeling framework (Wolock and McCabe, 1995; Wilson *et al.*, 2000). Such a framework considers a catchment as a whole without taking into account the flow routing processes on an individual hillslope or in a landscape. Desmet and Govers (1996) presented a notable exception by comparing different algorithms to predict the spatial occurrence of gully positions in Belgium.

In this study, we contend that the spatial distribution of selected soil properties (e.g. soil moisture, soil pH, clay content) may provide an opportunity for investigating the suitability of different grid resolutions and algorithms. Attempts to predict the distribution of soil attributes using terrain analysis have a long history in pedological communities. Since Ruhe and his colleagues (e.g. Ruhe and Walker, 1968) first attempted to establish a functional correlation between certain soil properties and selected topographical parameters on loess-covered hillslopes in Iowa, many similar studies have followed. This approach has become the backbone for modern soil-landscape analysis (McBratney *et al.*, 2000; Park and Vlek, 2002a). In a soil-landscape analyses framework, the upslope area and its derivates (e.g. specific catchment area, wetness index, stream power index) are the most widely used terrain parameters (see Park and Vlek, 2002b for a summary). Previous investigations have proved that there is a strong correlation between soil variability and upslope area calculated from DEM, because the landform configuration frequently governs the movement of materials and water on the landscape (Burt and Butcher, 1985; Moore *et al.*, 1993a; Gessler *et al.*, 1995; Western and Blöschl, 1999; Park and Vlek, 2002b).

The objective of this paper is to examine the influence of different grid resolutions and methods for calculating the upslope area on the environmental correlation between the landform and the spatial distribution of soil attributes under the framework of soil-landscape analyses. The investigation of relationships between selected soil attributes and terrain parameters may also provide a clear insight for other terrain-based modeling approaches, since the spatial distribution of soils provides a direct means to identify causal relationships between terrain parameters calculated from DEM and actual processes occurring at the hillslope and catchment level. Previous soil-landscape studies have shown that individual soil attributes respond differently to given pedological and hydrological processes at the same slope (Park and Vlek, 2002b). We therefore selected soil attributes showing a clear linear relationship between the distribution of soil attributes (soil pH, soil moisture, clay content, and soil organic matter) and possible flow processes modeled by the upslope area. Due to the complexity involved in the spatial distribution of soils in different environmental settings and also the varying quality of DEM, we need a large number of soil attributes in order to generalize the issues raised. We were in the fortunate situation of having eight soil-terrain data sets from all over the world encompassing coastal and inland systems, which include 19 different soil attributes.

2. Comparison of flow routing algorithms

We selected five different algorithms for calculating upslope area using grid-based DEM. Although several contour-based algorithms are available (Gallant and Wilson, 2000), our research considers only grid-based methods. Algorithms in current literature may be grouped into three categories: single flow algorithms, multiple flow algorithms, and flow tubing methods. The main difference between these groups is how to disperse the flow potential from the center cell to neighboring cells. The following is only a brief summary of the different methods, and many excellent descriptions are already available in Quinn *et al*. (1991), Costa-Cabral and Burges, (1994), Desmet and Govers (1996), Tarboton (1997), Conrad (1998), and Gallant and Wilson (2000).

1) Deterministic single-flow direction method (D8)

This method, first developed by O'Callaghan and Mark (1984), assigns flow from each cell to one of its eight neighbors. This algorithm allows flow in only one direction (one cell), which is determined by the steepest gradient among the eight possible flow directions. This algorithm was first developed to identify drainage systems, but has widely been used to calculate upslope area due to its simplicity. The upslope area is estimated by multiplying the pixel area with the number of pixels draining through each pixel. The known problem of this method is the inability to model flow divergence. Since the flow can accumulate into a cell from several upslope cells but flows out only into a single cell, this method can model flow convergence in valleys but not in ridge areas (Gallant and Wilson, 2000). This method produces many parallel flow lines on slopes having the same aspect, which is a 'visually' unrealistic flow pattern. Moreover, the single flow algorithm is highly sensitive to small topographical changes, especially at finer resolutions.

2) Randomized single-flow direction method (Rho8)

In this method, the flow path of D8 along the steepest gradient was replaced by a stochastic flow path decision in order to avoid the parallel flow paths problem of the D8 method (Fairfield and Leymarie, 1991). This method replaces the fixed distance factor in the calculation of the slope gradient of the D8 by a uniformly distributed random variable ranging from 0 to 1. While this algorithm is considered to produce a more realistic distribution of flow paths, the main limitation of single flow algorithm, i.e. the lack of flow dispersion, remains. Furthermore, due to the random values in the determination of the downslope flow direction, the result is not reproducible.

3) Multiple-flow direction method (MFD)

Unlike the two previous methods, the multiple flow direction method (MFD) distributes the flow from one cell to multiple neighboring cells at lower elevation (Freeman, 1991; Quinn *et al*., 1991). This method was developed to overcome the lack of flow dispersion in the D8 and Rho8 algorithms by dividing the amount of flow from one cell to adjacent downslope cells. The fraction of flow is calculated either in proportion to slope gradient (Freeman, 1991) or by a combination of slope gradient and contour length (Quinn *et al.*, 1991). The method proposed by Freeman (1991) and Quinn *et al.* (1991) shows virtually similar results (Desmet and Govers, 1995), and Freeman's (1991) method is selected for this study. These methods generate smoother and more realistic flow accumulation patterns at low-lying slope areas, but the main disadvantage is that the flow variance is high (Costa-Cabral and Burges, 1994; Tarboton, 1997). Desmet and Govers (1995) compared six upslope area algorithms to predict the occurrence of ephemeral gullies in a piece of agricultural land in Belgium, and recommended that multiple-flow algorithms may be more suitable for upland areas to reduce the parallel flow lines and sharp boundaries between major flow lines and surrounding area. On the other hand, single-flow algorithms may be more suitable for valley positions, because they minimize the over-dispersion of flow patterns. Similar recommendation was also made by Quinn *et al.* (1995).

4) Braunschweiger relief model (BRM)

This method also allows flow dispersion from one cell to neighboring low elevation cells (Bauer *et al.*, 1985). Unlike MFD, the flow direction is limited to maximum three neighboring cells in order to avoid excessive dispersion of flow. The calculation of the proportion of the flow to the neighboring cells is determined iteratively by categorizing slope direction. In each iteration, an upslope polygon is constructed until the source raster cell is reached, and the direction of the flow route is calculated by the aspect and slope gradient of the four neighboring raster points (cited from Conrad, 1998).

5) D Infinite (Dinf)

This method was developed to avoid excessive flow divergence of multiple algorithms (Tarboton, 1997). The main difference between single and multiple flow algorithms is the fact that the flow is dispatched along a 'stream tube' from one central cell to one neighboring downslope cell. The method was originally developed by Lea (1992) and DEMON (Costa-Cabral and Burges, 1994). From a central cell in a 3 by 3 fixed window, eight triangular facets are first formed. Each of these facets has a downslope vector drawn outwards from the center cell. The slope and flow direction associated with the grid cell is taken as the magnitude and direction of the steepest downslope vector from all eight facets. The flow from each cell either drains fully to one downslope cell if the steepest downslope vector falls along a cardinal, or two adjacent neighboring cells if the vector falls between two cells. The upslope area for each cell is thus calculated as the sum of its own area and the area of upslope neighbors that have some fraction draining to it.

3. Data sets and methods

1) Study areas and soil attributes

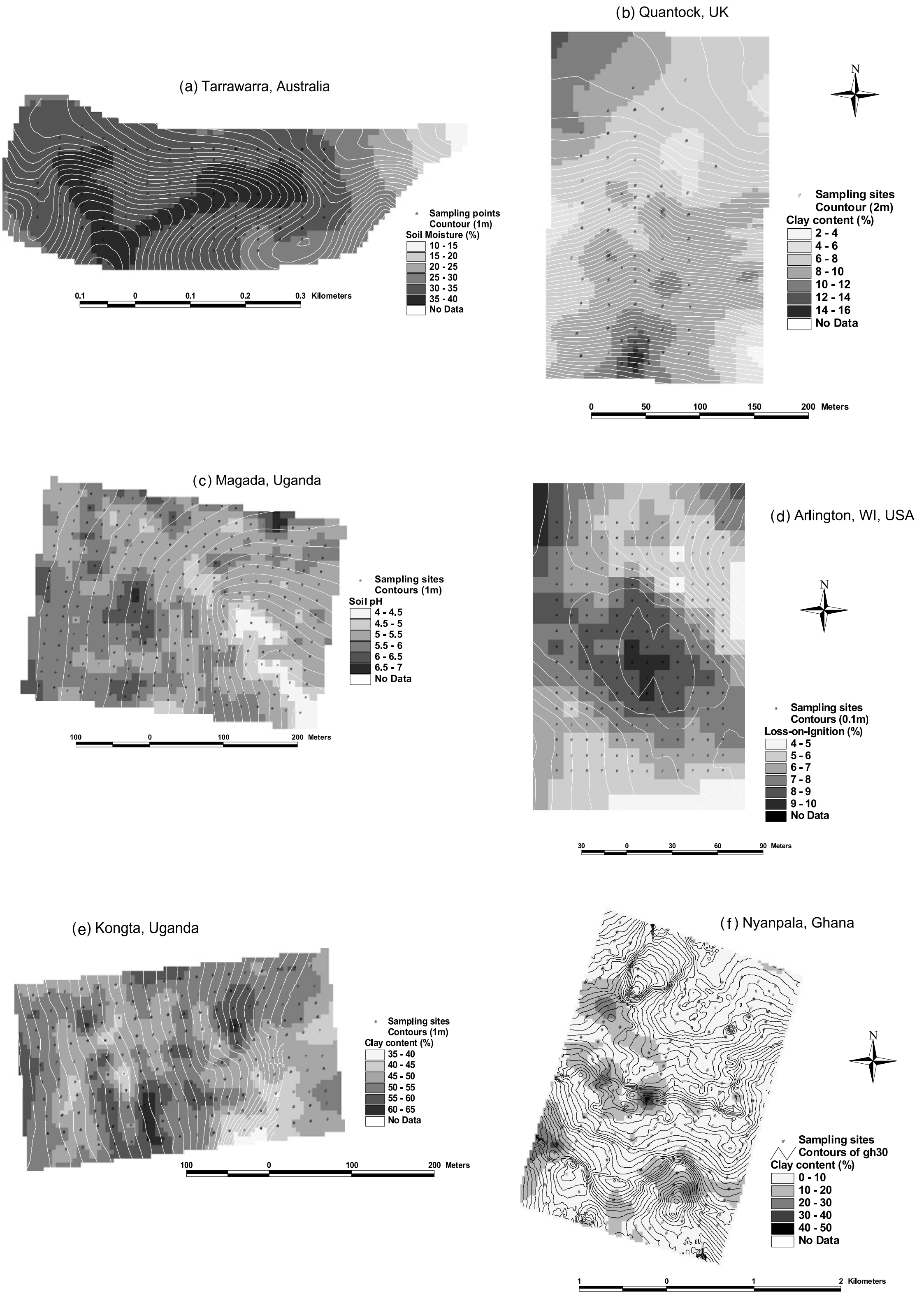
Eight soil and terrain information collected from seven different countries were used for this study. The data sets have large variations, both in general environmental conditions and terrain characteristics. Table 1 summarizes geographical location, environmental conditions, and soil-terrain data. Figure 1 gives the general geometry and also the distribution of a selected representative soil attribute from each data set. The size of the study areas varies from 0.03 to 12

Table 1. Comparison of environmental factors at eight research sites

Site	Tarrawarra, AU	Arlington, US	Bicknoller, UK	Kongta, Uganda	Magada, Uganda	Nyanpala, Ghana	Khiva, Uzbekistan	Sindu, South Korea
Location	37° 39´S, 145° 26´E	43° 39´N, 89° 38´W	51° 09´N, 3° 15´W	1° 16´N, 34° 45´E	0° 32´N, 33° 28´E	0° 55´S, 9° 28´E	41° 3´N, 60° 3´E	36° 51´N, 126° 12´E
Country	Australia	Wisconsin, US	United Kingdom	Uganda	Uganda	Ghana	Uzbekistan	South Korea
Area	ca. 0.27 km^2	ca. 0.033 km^2	ca. 0.10 km^2	ca. 0.13 km^2	ca. 0.24 km^2	ca. 8.4 km^2	ca. 12 km^2	ca 0.05 km^2
Climate †	Moist Continental Climate (Cf)	Boreal forest Climate (Df)	Moist Continental Climate (Cf)	Moist tropical climates (Am)	Tropical Moist climates (Af)	Moist tropical climates (Am)	Dry Tropical Climate (BW)	Humid Subtropical Climate (Cwa)
Bedrock	Lower Devonian siltstone	Calcareous loess over glacial tills	Devonian fine to medium grained sandstone	base-rich volcanic ash and agglomerates	Lake sediment from B.C. gneisses	Sandstone and shale	Stratified fluvial and eorian sediments	Stratified aeolian sediments
Soil types	n.a.	Orthic/Gleyic Luvisols	Humic/Gleyic Podzols	Calcic Vertisols	Plinthic/Xanthic Ferralsols	Lixisols and Luvisols	Gleyic and Takyric Solonchaks	Psamments
Land use	Crop rotation	Maize monoculture	Sheep grazing	Small-holder farming	Small holder farming	Small-holder farming	Cotton, wheat, maize	Conserved as Natural Monuments
Soil properties measured	Average soil moisture	Soil pH; Loss-on-ignition; Soil moisture	Soil pH; Loss-on-ignition; Clay content	Soil pH; Soil organic matter; Clay content	Soil pH; Soil organic matter; Clay content	Soil pH; Organic carbon; Clay content	Soil pH; Soil organic matter; Clay content	Soil Moisture; Soil pH; Soil organic matter
Mean elevation (STD)	99.03 (8.37) m	269.36 (0.32) m	198.5 (42.6) m	1897.2 (8.50) m	1167.75 (6.51) m	169.66 (11.38) m	92.1 (1.21) m	4.2 (2.3) m
Elevation difference	79.51-116.85 m	268.9-270.3 m	100.5-247.1 m	1873.6-1912.9 m	1151.6-1176.4 m	147.02-196.02 m	87.9-97.5 m	0.7-17.1 m
Mean slope angle (STD) ǂ	5.33° (4.71)	0.47° (0.38)	17.82° (10.99)	5.19° (3.13)	2.15° (1.24)	1.34° (0.96)	0.24° (0.25)	-
Range of slope angle (°)	0.11-46.56	0.004-1.85	0.44-41.01	0.07-74.26	0.07-8.96°	0.00-17.25	0.00-3.15	-
No. of point measurements	1,156	320	150	378	416	1,812	305	1,384
Accuracy of measurement	±1m (horizontal) ±0.1m (vertical)	±0.5 m (horizontal) ±0.1m (vertical)	±0.04m (horizontal) ±0.05m (vertical)	n.a.	n.a.	n.a	n.a.	±0.02 m (horizontal) ±0.02 m (vertical)
Further reading	Western and Grayson (1998)	Park and Burt (2002)	Park and Vlek (2002a), Park and Burt (2002)					Kim *et al.* (2008)

† Köppen's climatic zone (Strahler and Strahler, 1984)

ǂ based on a 10 m grid digital elevation model, STD: standard deviation


(a) Tarrawarra, Australia
Sampling points
Countour (1m)
Soil Moisture (%)
10 - 15
15 - 20
20 - 25
25 - 30
30 - 35
35 - 40
No Data
0.1 0 0.1 0.2 0.3 Kilometers
(b) Quantock, UK
N
Sampling sites
Countour (2m)
Clay content (%)
2 - 4
4 - 6
6 - 8
8 - 10
10 - 12
12 - 14
14 - 16
No Data
0 50 100 150 200 Meters
(c) Magada, Uganda
Sampling sites
Contours (1m)
Soil pH
4 - 4.5
4.5 - 5
5 - 5.5
5.5 - 6
6 - 6.5
6.5 - 7
No Data
100 0 100 200 Meters
(d) Arlington, WI, USA
N
Sampling sites
Contours (0.1m)
Loss-on-Ignition (%)
4 - 5
5 - 6
6 - 7
7 - 8
8 - 9
9 - 10
No Data
30 0 30 60 90 Meters
(e) Kongta, Uganda
Sampling sites
Contours (1m)
Clay content (%)
35 - 40
40 - 45
45 - 50
50 - 55
55 - 60
60 - 65
No Data
100 0 100 200 Meters
(f) Nyanpala, Ghana
N
Sampling sites
Contours of gh30
Clay content (%)
0 - 10
10 - 20
20 - 30
30 - 40
40 - 50
No Data
1 0 1 2 Kilometers

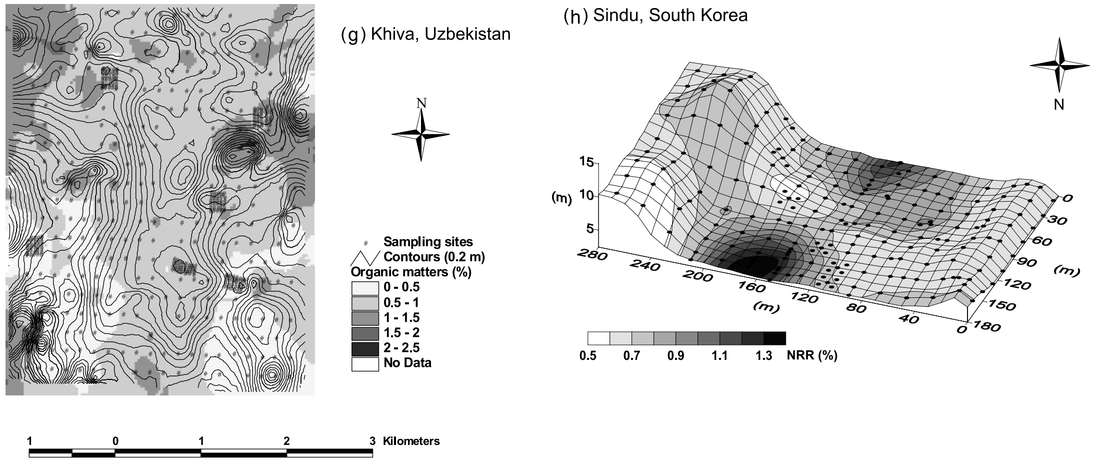


Figure 1. Study areas, soil sampling sites and the distribution of a representative soil attribute

See Table 1 for detailed information on environmental conditions and soil sampling. (a) Tarrawarra catchment, Australia, and distribution of soil moisture; (b) Quantock, UK, and clay content distribution; (c) Magada hillsope, Uganda, and soil pH distribution; (d) Arlington research station, Wisconsin, USA, and distribution of loss-on-ignition; (e) Kongta, Uganda, and clay content distribution; (f) Nayangpala, Ghana, and clay content distribution; (g) Khiva farm, Uzbekistan, and distribution of organic matter; (h) Sindu coastal dunefield, South Korea, and distribution of soil moisture.

km^2. The first five study areas (Tarrawarra, Arlington, Bicknoller, Kongta, and Magada) are single hillslopes or microcatchments, but the Nyankpala and Khiva areas show more complex landscapes covering larger areas (8.4 and 12 km^2 respectively). In addition to these inland environmental settings, we included a coastal dune landscape located at western Korea (Figure 1H).

These soil and terrain data sets were collected with different research objectives in mind and contain a great deal of additional soil and topographical information. Four soil attributes, i.e. soil moisture, soil pH, clay content, and soil organic matter, were selected for this study. In a previous attempt to compare the spatial distribution of 32 soil attributes, Park and Vlek (2002b) showed that soil moisture, soil pH, and clay content in topsoil generally have a clear linear relationship with waterflow potential governed by hillslope geometry. The spatial distribution of these soil attributes is strongly influenced by lateral hydrological and slope processes with relatively simple vertical depth functions, and quickly reaches equilibrium with current slope processes. We consider that these soil attributes are most indicative of the relationship between the spatial distribution of soils and the water flow potential modeled by the upslope area. Even though much more complex pedological processes are involved in the spatial distribution of soil organic matter (Park and Burt, 2002), we included soil organic matter content, considering its general importance in soil and land management. Table 2 shows the descriptive statistics and analytical methods used to measure each soil attribute.

2) Terrain analyses

For all study areas except Khiva and Sindu, a Differential Geographical Positioning System

(DGPS) was used to generate point measurements. The point measurements in Khiva were produced by an aerial photo analysis by the State Land Committee, Uzbekistan, while a total station was used for topographical survey at Sindu. The numbers of point measurements are given in Table 1. The information on the vertical and horizontal accuracy is only available for the Arlington, Tarrawarra, Bicknoller, and Sindu terrain data sets. The quality of the DEM may influence the correlation between soil attributes and individual terrain parameters (Hutchinson and Gallant, 2000), but we assume that the quality is sufficient for our objectives. Thompson *et al.* (2001) recently reported that soil-landscape analysis is relatively insensitive to the absolute accuracy of elevation measurement.

Semivariogram analyses were conducted prior to a kriging interpolation of each data set (Table 3). One of Gaussian, power, and linear functions were used to interpolate the point measurement. Modeling of the semivariogram was performed using S-PLUS™ 6.0 software and interpolation was performed with Surfer™ 7.0 program. Ten different grid sizes of DEM (1, 2.5, 5, 7.5, 10, 15, 20, 30, 40, and 50 m) were generated for each study area to investigate the grid resolution effect. The five different upslope area algorithms, reviewed in section 2, were calculated by DiGem 2.0, a terrain analysis program (see Conrad, 1998). The upslope area values at individual soil measurement coordinates were derived from

Table 2. Summary of soil attributes examined

Data set	Attributes	Method	N	mean	STD*	min	max
Tarrawarra	Soil moisture	Average of 13 TDS reading	125	33.97	2.02	27.60	38.00
Quantock	Soil pH	1:2.5 in 0.01M $CaCl_2$	64	2.77	0.49	2.19	4.62
	Clay content	Laser granulometery	64	8.71	1.83	5.43	15.37
	Organic matter	Loss-on-ignition	64	9.30	4.71	4.88	39.94
Magada	Soil pH	1:2.5 in water	277	5.42	0.49	4.00	7.20
	Clay content	hydrometery	277	20.74	5.97	1.60	34.90
	Organic carbon	Anderson and Ingram (1993)	277	3.01	0.86	1.20	7.50
Arlington	Soil pH	1:2.5 in 0.01M $CaCl_2$	204	6.71	0.17	6.25	7.09
	Soil moisture	hydrometery	204	20.82	1.84	17.00	26.56
	Organic matter	Loss-on-ignition	204	6.96	1.18	4.85	9.35
Kongta	Soil pH	1:2.5 in water	153	5.73	0.39	5.00	7.00
	Clay content	hydrometery	153	50.95	5.43	38.00	64.30
	Organic carbon	Anderson and Ingram (1993)	153	5.09	1.16	2.70	9.70
Nyankpala	Soil pH	1:2.5 in water	202	4.86	0.51	3.55	7.34
	Clay content	hydrometery	202	7.31	6.15	0.44	47.20
	Organic carbon	Anderson and Ingram (1993)	202	0.49	0.28	0.04	1.35
Khiva	Soil pH	1:2.5 in water	440	7.21	0.29	6.37	7.99
	Clay content	hydrometery	440	24.94	15.33	0.40	72.20
	Organic carbon	Anderson and Ingram (1993)	440	0.67	0.31	0.04	1.97
Sindu	Soil moisture	Gravimetric method	193	7.13	6.09	2.51	30.94
	Soil pH	1:2.5 in water	193	6.98	0.74	5.66	8.98
	Organic matter	Loss-on-ignition	193	1.24	0.28	0.70	2.20

* STD: standard deviation

Table 3. Variogram models for the DEM used

Site	Anisotropy	Model	Nugget	Sill	Range	Slope
Tarrawarra, AU	-	Gaussian	0.002	39.00	126.26	-
Bicknoller, UK	135°	Power	0.000	-	2.03	0.049
Kongta, UG	90°	Power	0.348	-	1.601	0.001
Magada, UG	115°	Gaussian	0.061	19.23	153.90	-
Arlington, US	45°	Gaussian	0.002	0.133	59.69	-
Nyanpala, Ghana	-	Power	0.339	-	1.404	0.003
Khiva, Uzbekistan	45°	Linear	0.541	-	-	0.00028
Sindu, South Korea	75°	Linear	0.385	-	-	0.027

different algorithms and grid resolutions, using ArcView 3.2.

Prior to the calculation of upslope area, the 'sinks' in the DEM were removed. Artificial sinks in DEM are common, and they often cause serious problems in calculating upslope areas (Gallant and Wilson, 2000). We observed some natural depressions in the glaciated landscape in the Arlington and in the fluvial deposits in the Khiva, but no further attempt was made to distinguish real depressions from artificial sinks. In order to estimate the flow routing processes, it is important to include clear drainage boundaries for each catchment (Moore *et al.*, 1993b). The Kongta, Magada, and Nayanpala data sets lack clear drainage boundaries since the study areas are nested within a much larger slope section. We expect that this may cause some error in the correlation between soil properties and the calculated upslope area.

3) Statistical comparison

Some of the soil parameters examined show positive skewness, and were transformed into a logarithmic scale before correlation analyses (Table 2). In addition, all calculated upslope area values were transformed into a logarithmic scale with base 10 prior to further statistical analyses. Pearson's r was primarily used to estimate the association between calculated upslope area and soil attributes, based on the assumption that both transformed soil and terrain parameters are normally distributed.

It is often necessary to compare the variability of correlation coefficients and upslope area values calculated for different data sets and grid sizes. For this purpose, the coefficient of variation (CV) was used, based on the following equation (Beckett and Webster, 1971):

$$CV\ (\%) = (\text{standard deviation} / \text{mean}) \times 100$$

The main limitation of the CV to assess variability is it is strongly influenced by the normal distribution. Care should be taken to interpret results, since some of the correlation coefficients are derived from variables with a non-normal distribution.

4. Results and discussion

1) Comparison of algorithms

(1) Spatial distribution and correlation

Figure 2 visualizes the spatial distribution of different upslope areas calculated from the 10 m grid DEM of the Tarrawarra catchment. The first

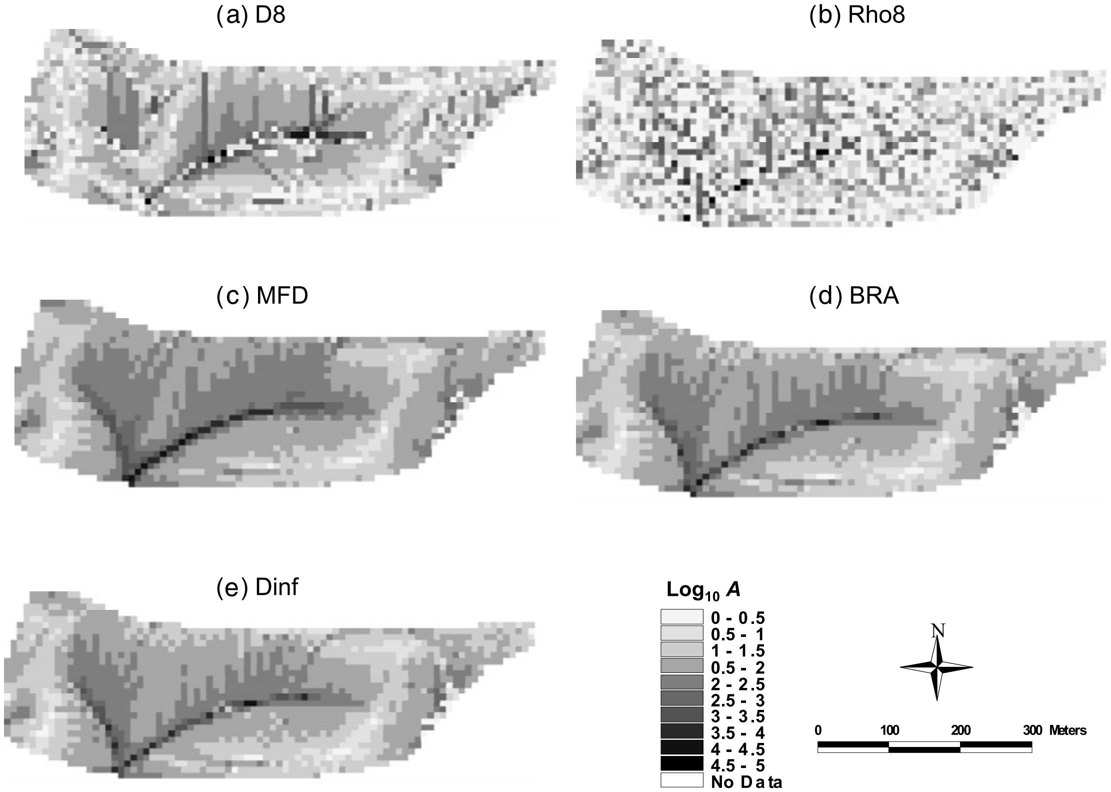


Figure 2. Comparison of different upslope areas, where grid size is 10 m, calculated with five different algorithms, at the Tarrawara catchment (Figure 1(a))

recognizable pattern is the clear difference between single flow algorithms (D8 and Rho8) and the others. Rho8 shows a highly scattered distribution of upslope areas, which is caused by the randomness of downslope direction determination. Consequently, the Rho8 method produced virtually non-interpretable results (Figure 2(b)), despite the rounded and clear surface topography of the catchment (Figure 1). The D8 method also shows a rather scattered pattern in the upslope area distribution, but visualizes relatively clear high flow accumulation along the valley position. The commonly criticized parallel flow paths are also noticeable in the valley (Figure 2(a)).

Unlike D8 and Rho8, the other three algorithms (MFD, BRM, Dinf) produced comparable results with a clear distinction between low and high upslope areas of the valley. MFD resulted in a much smoother distribution (Figure 2(c)), whereas BRM and Dinf closely resemble each other (Figures 2(d) and 2(e)). The 'smoother' upslope area for MFD may be caused by the unlimited downslope flow dispersion (Quinn, 1991). In the correlation matrix of different algorithms for selected grid sizes (Table 4), these three methods are highly correlated with each other (r > 0.85). The correlation coefficient between BRM and Dinf is particularly high (r > 0.90), indicating that these two algorithms behave quite similarly. These three methods show consistent r values over a range of grid sizes.

Table 4. Correlation coefficients between different upslope contributing areas calculated for the Tarrawarra catchment.

	D8	Rho8	MFD	BRM	Dinf
			1m		
D8	1				
Rho8	0.29	1			
MFD	0.61	0.35	1		
BRM	0.54	0.32	0.87	1	
Dinf	0.56	0.34	0.87	0.96	1
			5 m		
D8	1				
Rho8	0.40	1			
MFD	0.70	0.50	1		
BRM	0.69	0.51	0.85	1	
Dinf	0.67	0.54	0.88	0.95	1
			10 m		
D8	1				
Rho8	0.48	1			
MFD	0.75	0.56	1		
BRM	0.74	0.57	0.85	1	
Dinf	0.74	0.62	0.89	0.94	1
			30 m		
D8	1				
Rho8	0.70	1			
MFD	0.84	0.73	1		
BRM	0.86	0.73	0.85	1	
Dinf	0.81	0.80	0.88	0.90	1

note: All r values are significant at $p < 0.01$ level, if states otherwise.

Upslope areas calculated by D8 and Rho8, however, are poorly correlated with those by other methods at finer resolution, but the coefficient (r) increases with increasing grid size.

(2) Scale dependency of upslope area calculation

Figure 3 compares the density distribution of upslope area and the change over different grid sizes examined at the Tarrawarra catchment. In these density plots, there is again a significant difference between D8/Rho8 and the other three methods. D8 and Rho8 commonly show a ‘peak’ in the number of cells computed at the low end of the upslope area. This peak becomes even stronger with coarser grid size. It is already known that the non-dispersive single flow algorithms yield a much higher number of low upslope areas, because many cells do not have a flow (Wilson *et al.*, 2000). Wilson *et al.* (2000) further observed that Rho8 produces a smaller upslope area than D8, due to the breakup of linear flow paths and improves flow concentration at convergent slope sections.

The other three methods resemble each other in the density distribution of the calculated upslope area. The main difference between these three methods is that BRM produced a relatively

Table 5. Mean and standard deviation (STD) of upslope area calculated for soil sampling points for each of eight DEM

	Grid size (m)	1	2.5	5	7.5	10	15	20	30	40	50	mean	STD	CV (%)
D8	mean	1.61	2.17	2.54	2.75	2.86	3.13	3.29	3.56	3.74	3.84	3.00	0.67	22.80
	STD	0.47	0.38	0.23	0.23	0.19	0.17	0.16	0.19	0.17	0.20	0.23	0.11	5.30
Rho8	mean	1.28	1.92	2.36	2.64	2.78	3.09	3.28	3.60	3.79	3.97	2.92	0.81	27.87
	STD	0.45	0.39	0.19	0.22	0.12	0.15	0.15	0.18	0.14	0.14	0.20	0.15	6.37
MFD	mean	2.11	2.58	2.88	3.10	3.20	3.42	3.57	3.80	3.96	4.06	3.31	0.59	17.99
	STD	0.45	0.39	0.28	0.26	0.21	0.20	0.16	0.19	0.18	0.21	0.26	0.12	5.04
BRM	mean	1.97	2.41	2.72	2.94	3.04	3.25	3.40	3.65	3.83	3.93	3.15	0.60	19.37
	STD	0.50	0.39	0.30	0.27	0.24	0.23	0.24	0.28	0.22	0.24	0.28	0.09	4.49
Dinf	mean	1.95	2.40	2.72	2.94	3.05	3.28	3.44	3.72	3.89	4.02	3.18	0.64	20.33
	STD	0.52	0.41	0.30	0.26	0.22	0.20	0.19	0.20	0.16	0.15	0.24	0.12	5.50

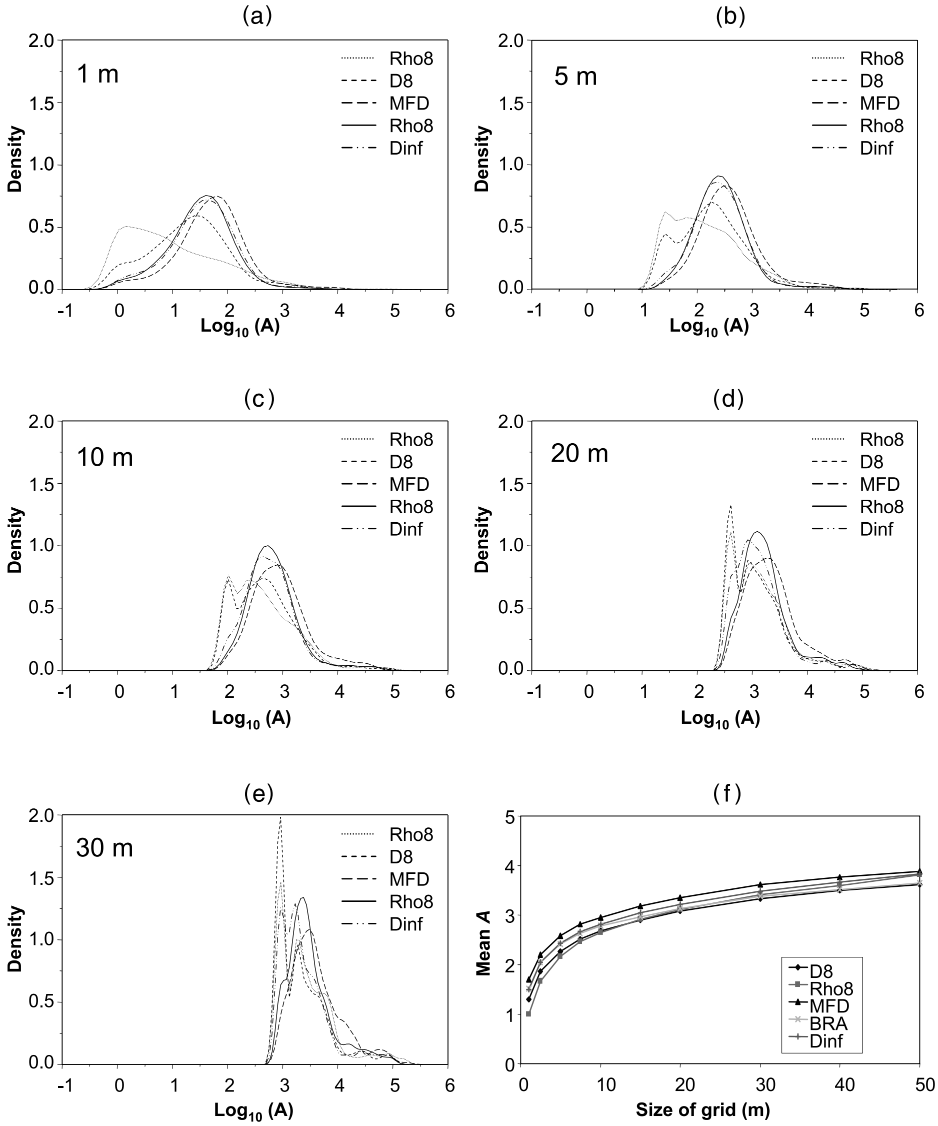


Figure 3. Density function of calculated upslope area at the Tarrawarra catchment (Figure 1(a)) for five different grid resolutions

high density of high upslope area at coarser resolutions (figure not shown here). The increase in the grid size is accompanied by an increase in the average upslope area (Figure 3(f) for the Tarrawarra and Figure 4(a) for all study areas). Among the different algorithms, the mean upslope area is the highest for MFD, followed by BRM and Dinf. Rho8 shows the lowest mean upslope area. In terms of variance within the catchment, BRM shows the highest standard deviation (Figure 4(b)), which is followed by Dinf, MFD, D8, and Rho8. The difference of mean upslope area between different algorithms becomes smaller with increasing grid size (Figure 4(a)). This scale dependency of calculated upslope area is in agreement with previous

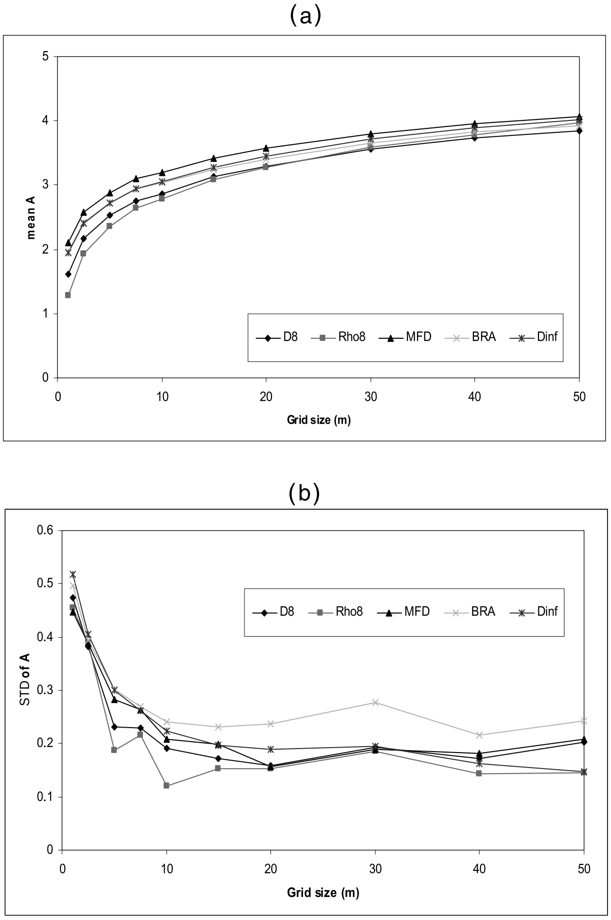


Figure 4. The distribution of mean (a) and standard deviation (b) of upslope area for eight digital elevation models (DEM) used in this research, where the upslope area was calculated for individual soil sampling points at each DEM.

comparisons (Beven and Kirky, 1979; Desmet and Govers, 1995; Quinn *et al.*, 1995; Tarboton, 1997).

Table 5 provides summary statistics of upslope areas derived for all the soil-sampling points within the eight data sets. It shows two interesting comparisons regarding the scale dependency of different algorithms. Firstly, CV calculated for different algorithms show that MFD has the lowest (18 %) variation across different grid sizes. This suggests that MFD is the least sensitive to the change of grid size. The CV increases in the following order; BRM < Dinf < D8 < Rho8. Since a high variation of upslope area with the change of grid size is not a desirable property for any terrain-based modeling, MFD can be considered as the most robust and also preferred method to estimate upslope areas.

Secondly, the average standard deviation of the upslope area is relatively high with finer grid sizes (*i.e.* less than 15 m), but remains constant throughout coarser resolutions (Figure 4(b)). Considering the standard deviation as an indicator to differentiate flow routing elements within the study sites, this indicates that highly disaggregated topographical information is

Table 6. Summary of the correlation coefficient (*r*) between different algorithms of upslope contributing area and soil parameters

Upslope contributing algorithm	Grid size (m)	1	3	5	8	10	15	20	30	40	50
	No. of cases	13	19	19	19	19	19	19	19	19	19
D8	mean	0.06	0.09	0.07	0.05	0.08	0.08	0.09	0.09	0.08	0.06
	std	0.18	0.20	0.23	0.25	0.26	0.30	0.29	0.31	0.30	0.26
	min	-0.29	-0.28	-0.29	-0.34	-0.41	-0.36	-0.39	-0.36	-0.41	-0.40
	max	0.31	0.59	0.66	0.66	0.67	0.70	0.70	0.69	0.59	0.49
Rho8	mean	-0.02	0.02	0.09	0.02	0.06	0.09	0.05	0.07	0.05	0.06
	std	0.06	0.12	0.19	0.20	0.20	0.28	0.23	0.29	0.25	0.26
	min	-0.17	-0.17	-0.26	-0.35	-0.27	-0.43	-0.30	-0.43	-0.36	-0.41
	max	0.05	0.25	0.44	0.46	0.48	0.58	0.60	0.59	0.59	0.51
MFD	mean	0.10	0.07	0.08	0.09	0.09	0.09	0.10	0.08	0.09	0.08
	std	0.31	0.28	0.31	0.34	0.34	0.37	0.36	0.38	0.37	0.38
	min	-0.43	-0.42	-0.42	-0.44	-0.44	-0.50	-0.47	-0.48	-0.49	-0.48
	max	0.76	0.78	0.80	0.81	0.80	0.76	0.72	0.71	0.63	0.68
BRM	mean	0.09	0.03	0.07	0.08	0.11	0.11	0.11	0.10	0.10	0.10
	std	0.28	0.24	0.27	0.32	0.32	0.35	0.35	0.35	0.34	0.31
	min	-0.39	-0.38	-0.43	-0.45	-0.44	-0.47	-0.49	-0.50	-0.49	-0.48
	max	0.76	0.78	0.78	0.80	0.78	0.79	0.75	0.60	0.62	0.62
Dinf	mean	0.10	0.06	0.07	0.08	0.11	0.10	0.11	0.12	0.08	0.09
	std	0.26	0.23	0.26	0.30	0.31	0.35	0.34	0.39	0.33	0.34
	min	-0.28	-0.32	-0.38	-0.40	-0.40	-0.49	-0.49	-0.49	-0.52	-0.49
	max	0.77	0.77	0.76	0.77	0.78	0.78	0.74	0.74	0.59	0.54

captured at less than 15 m grid size, but relatively little difference is seen above this size. This property has significant implications for environmental correlations, which will be discussed in the following section.

2) Correlation with soil attributes

Figure 5 shows correlations between upslope contributing area and selected soil properties from each soil data set. The average correlation coefficients for 19 soil properties for different algorithms and grid sizes are presented in Figure 8 and Table 6. Though the overall correlation patterns are complicated and difficult to interpret, some points are worth mentioning: 1) there is a great difference in the correlation between soil attributes and upslope area, but in general bigger study areas show poorer environmental correlation (e.g. Figures 5(f) and 5(g); 2) single flow algorithms including D8 and Rho8 show relatively low correlation coefficients, whereas MFD yields the highest correlation for most soil attributes; and 3) there are reduced correlation coefficients (*r*) at a scale of less than 15 m, and higher *r* at 15-50 m grid resolutions.

(1) Magnitude of correlation coefficient

The soil attributes analyzed in this research were selected based on the assumption that they have a linear relationship with the potential water flow estimated by the upslope area. This assumption is supported by the linear relationships found between individual soil attributes and upslope area (see Figure 7 as example), even though some of them show highly scattered pat-

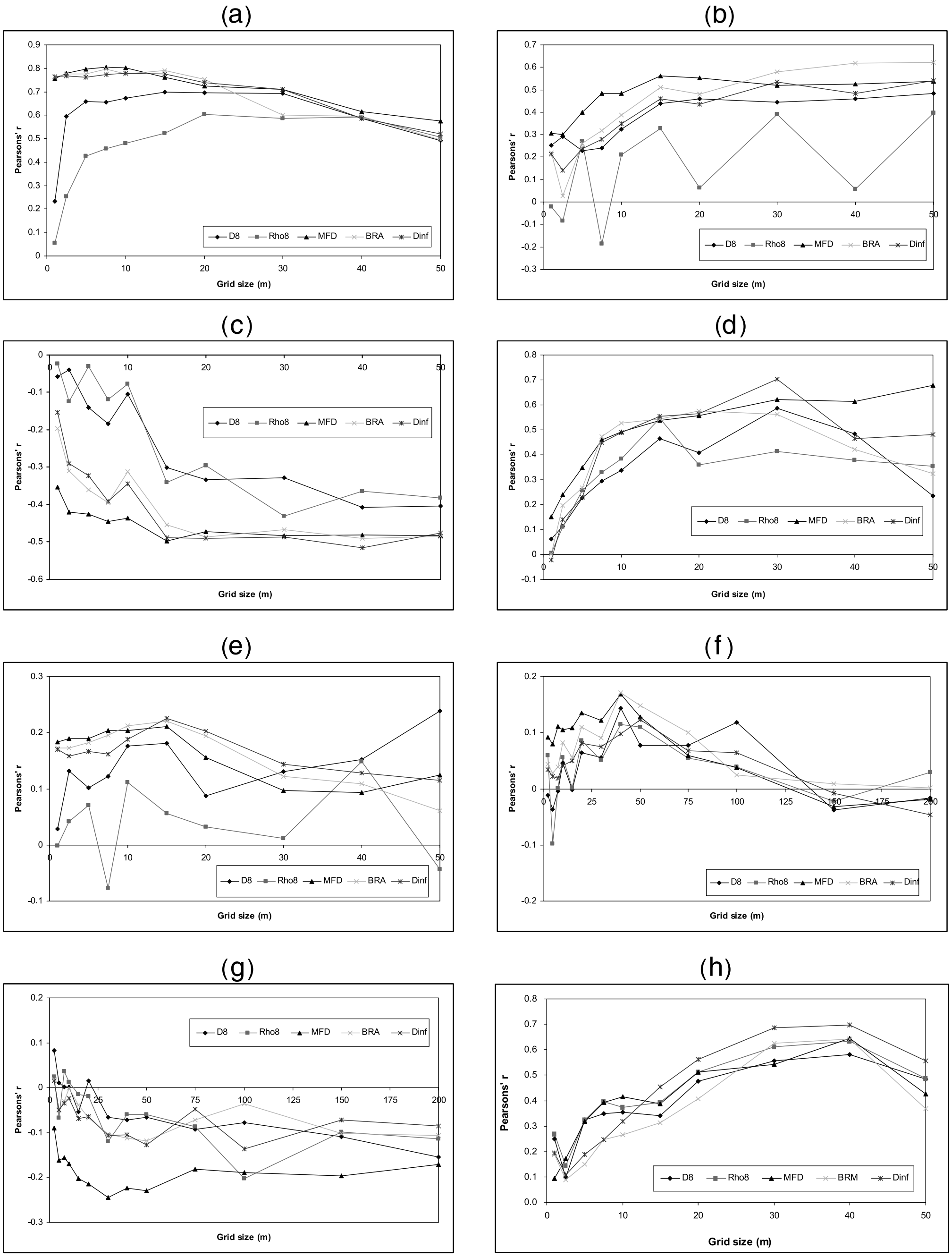


Figure 5. Environmental correlation between selected soil properties and grid-size algorithm to calculate upslope area.

The spatial distribution of each soil attributes corresponds with Figure 1. (a) Soil moisture, Tarrawarra catchment; (b) Clay content, Quantock; (c) Soil pH, Magada hillsope; (d) Loss-on-ignition, Arlington research station; (e) Clay content, Kongta hillsope; (f) Clay content, Nayangpala; (g) Organic matters in the Khiva farm; (h) Soil moisture at the Sindu coastal dune.

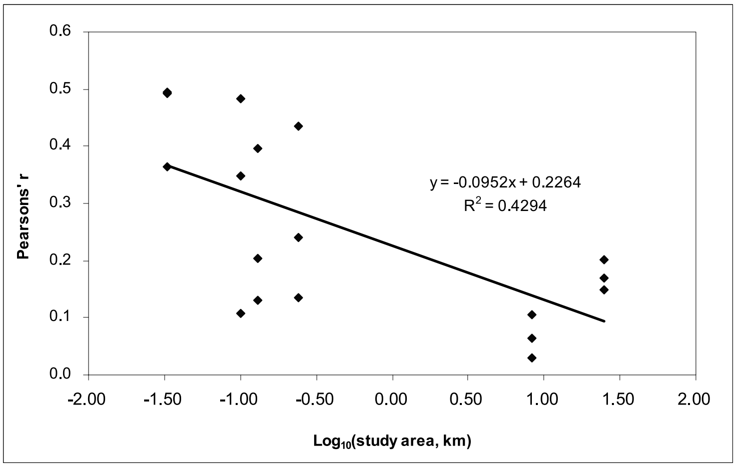


Figure 6. Relationship between Pearsons' *r* and the size of study areas

terns. The intensity of correlation is relatively poor and varies greatly, depending on the study area and the soil attributes selected (Table 6). Interpretation of detailed pedological processes explaining the varying correlation coefficient is beyond the scope of this research, and may be presented elsewhere.

In the comparison of environmental correlation, the larger study areas show poorer environmental correlation (Figure 6). Whereas the relatively small study areas, including Tarrawarra, Arlington, and Quantock, have relatively high correlation coefficients ($r > 0.5$), the r values become much lower for Khiva and Nayankpala. The smaller study areas are mostly single hillslopes or micro-catchments, whereas the bigger areas include several hillslopes and catchments, with a greater heterogeneity of environmental factors within the catchment. In their statistical modeling attempt to characterize the land-use changes in a 100 km by 100 km area in Ghana, Park *et al.* (2005) first observed that there was virtually no significant spatial correlation between land-use change intensity and various dynamic predictors of land-use change. However, when they applied a spatially disaggregated statistical model in which land-use change intensity was regressed against dependent variables within a variable-size moving window, significant spatial patterns of environmental correlation appeared over the study area. They argued that with increasing spatial coverage within the regression model, land-use change processes within the window turned out to be too diverse to establish clear trends. We believe that a similar principle is also applicable for soil-landscape analyses. Thus, the decrease in correlation coefficient together with the increase of the study area is also a result of the increase in the heterogeneity of environmental factors.

(2) Comparison of different algorithms

The visual comparison of correlation coefficients (e.g. Figure 8) leads us to conclude that there are three groups of upslope area algorithms in terms of intensity of soil-environmental correlation. In general, the Rho8 method shows the lowest correlation coefficient and erratic patterns, which comes from the randomness of downslope direction determination. D8 is much more stable than Rho8, but the

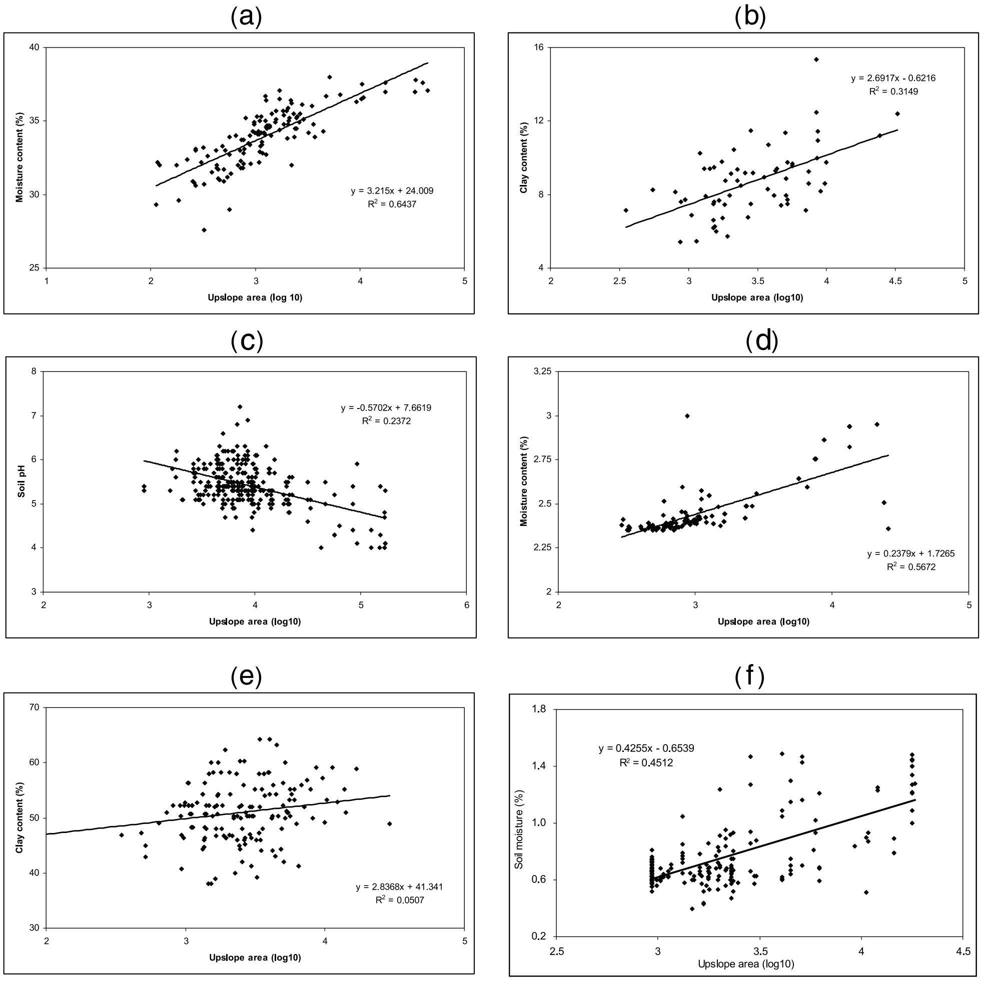


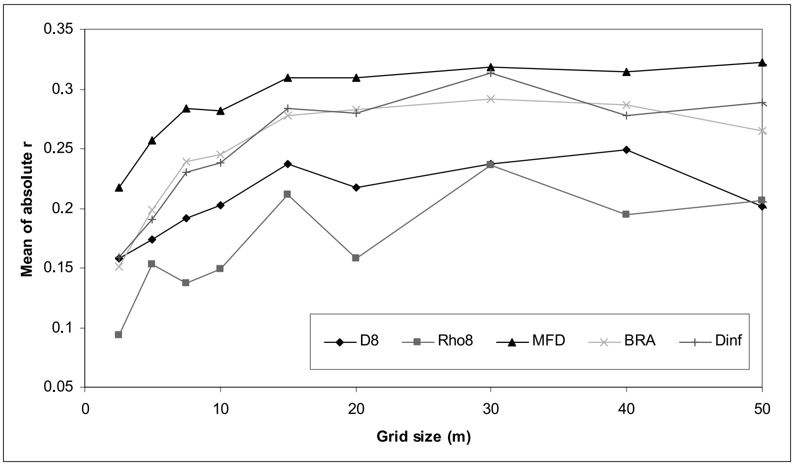
Figure 7. Relationship between soil properties and upslope contributing area

(a) Soil moisture vs. 10 m multiple-flow direction method (MFD), Tarrawarra; (b) Clay content vs. 15 m MFD, Quantock; (c) Soil pH vs. 15 m Dinf, Magada; (d) Soil moisture content vs. 15 m MFD, Arlington; (e) clay Content vs. 15 m Dinf, Kongta; and f) Soil moisture content vs. 30 m Dinf, Sindu.

correlation intensities are much lower than for the other three methods. The clear distinction between dispersion area and accumulation zone in the single flow algorithms as well as the parallel flow paths of D8 on the same slope aspect may greatly reduce the intensity of correlation.

In a comparison of the remaining three methods, the MFD algorithm shows consistently higher correlation coefficients than BRM and Dinf for the majority of the soil attributes considered. As was the case in the comparison of the calculated upslope areas, the results of BRM and Dinf resemble each other, which led to similar correlation patterns with soil attributes. In addition, the MFD method also shows the lowest variation (CV) of correlation for the different data sets (Figure 8(b)). The highest correlation coefficient and the lowest CV lead us to conclude that the MFD method works best for most of the

(a)



(b)

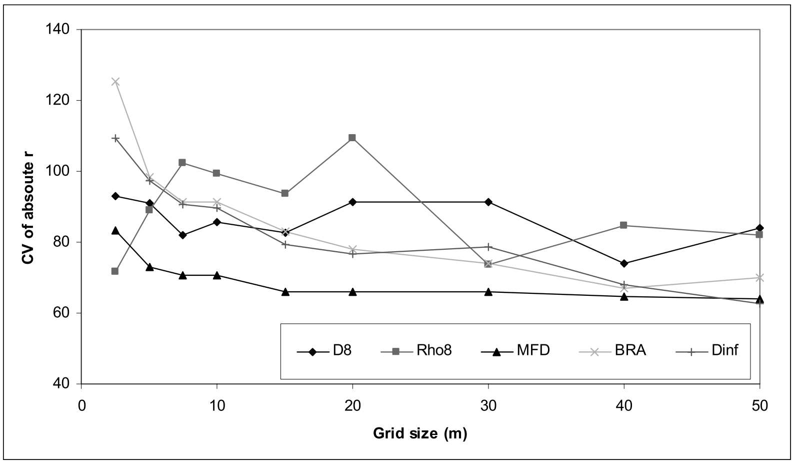


Figure 8. Summary statistics of correlation intensity between different grid size and upslope area algorithms

data sets, covering a wide range of environmental conditions. Despite the often criticized problem of the MFD method - overdispersion of flow (Tarbonton, 1997) - this study shows that MFD is the most adequate algorithm, not only as a result of its robustness at different grid resolutions, but also because of its consistently higher correlation with soil attributes.

(3) Comparison of different grid size

Great differences can be observed in the correlation between upslope contributing area and soil attributes for different grid sizes across the study sites. Some data sets attain maximum values at 10-20 m and decrease afterwards (see Figures 5(a), 5(e), 5(g)), whereas others maintain a stable but higher *r* afterwards (see also Figure 5). Some soil attributes show a progressive increase in *r* with the increase in grid size (figure not shown here). Considering the extreme diversity of soil, topography, land management factors, and the quality of the DEM, such a complex soil landscape is an expected result. This well demonstrates that an empirical functional relationship derived from a specific grid size is not easy to transfer to other grid sizes. The question of how such functional relationships change with different grid size and the question of spatial scale deserve further investigation.

Considering the strong heterogeneity of environmental correlation, we may draw our conclusions regarding the optimum grid size from the statistical summaries of all 19 soil attributes investigated. The comparison of the mean of the 19 correlation coefficients shows that fine spatial resolution (less than 15 m) actually reduces *r* values for all algorithms considered (Figure 8(a)). This is the pattern recognized in all individual soil attributes with little exception (Figure 5). This is a rather contradictory result that has been discussed in previous studies (Mitasova *et al.*, 1996; Quinn *et al.*, 1995). Since the DEM from the Tarrawarra, Quantock, Arlington, and Sindu study areas have a sufficient number of field measurements with a high vertical and horizontal accuracy (Table 1), we can confidently eliminate the accuracy issues of DEM. Instead, we interpret this finding as the result of a discrepancy between the temporal scale of the soils' responses to given hillslope processes governed by surface geometry.

Change within natural systems occurs at different rates, and process scales may vary widely, both in temporal and spatial dimensions. Adding detailed model components is often not necessarily better for modeling system behaviour as a whole despite the resulting more realistic representation of processes components (Beven, 1995). Therefore, it is important that the spatial scale of data collection and terrain modeling should match the scale of the area where the processes are taking place (Blöschl and Sivapalan, 1995; Schulze, 2000). The response of soil properties to a given hydrological and geomorphological process may be rather slow compared to some minor topographical changes in cultivated areas. As an example, small bunds or tillage tracks that might change season after season will be sufficiently included in very detailed DEM, and such micro-topography results in the changes of flow paths calculated from DEM. However, the spatial distribution of individual soil properties over the hillslope will not respond to such short-term topographical changes. Therefore, DEM and terrain parameters should be sufficiently large to override the influence of micro-topography (and also possible measurement errors) in the calculation of flow movements. This observation led us to conclude that highest resolution of DEM may not be necessary for generating useful soil-landscape models.

The comparison of the average *r* values and their variation (Figure 8) reveals that the average *r* reaches a maximum at around 15 m grid size and then remains similar until the 50 m grid size. On the other hand, the CV of the correlation coefficients for the different data sets reaches a minimum at 15 m grid size, and is sustained at this level despite increasing grid size. This is a clear indication that the environmental correlation between soil attributes and upslope area is insensitive to different grid size beyond the 15 m grid resolution, possibly due to the diffusive nature of the soil spatial distribution and soil's slow response to the water flow potential estimated by the upslope area. This observation gives great freedom to soil-landscape modelers, who often experience difficulties in acquiring a detailed DEM. A similar conclusion was drawn from a recent investigation on accuracy issues of DEM in Minnesota, USA, by Thompson *et al.* (2001).

On the other hand, it should also be noted that the coarser grid resolution often leads to a smoothening surface topography and a loss of interpretable topographical representation (Zhang and Montgomery, 1994; Hutchinson and Gallant, 2000; Wilson and Gallant, 2000). The most appropriate DEM grid size for topographically driven hydrological and geomorphological models is somewhat finer than the hillslope scale identified in the field and sufficient to include necessary topographical details (Zhang and Montgomery, 1994). In contrast to the reduced correlation coefficient, we also observed that the correlation coefficient drops for some soil attributes after 15-30 m grid size (see Figure 5). Therefore, we propose that a 15 to 30 m grid resolution might be a good compromise to adopt as an optimum grid size, both in terms of environmental correlation and for maintaining necessary topographical details in further modeling.

5. Conclusions

The influence of horizontal resolutions of DEM and algorithms to calculate upslope area was investigated in a soil-landscape analysis using 19 soil attributes from eight different soil-terrain data sets from systems encompassing a coast and inlands around the world. There was a great difference in the correlation between soil attributes and upslope contributing area, but in general, larger study areas showed poorer environmental correlation due to the additional heterogeneity of environmental factors included in such areas. For environmental correlation between soil attributes and upslope area, the multiple flow algorithm (Freeman, 1991; Quinn *et al.*, 1991) outperformed the other four methods compared in this study, both in terms of correlation intensity and in the scale insensitivity to different grid sizes. There were reduced correlation coefficients at finer scales of less than 15 m, and r was generally highest for the range between 15-50 m grid sizes. The reduced correlation coefficients at the very fine grid size are contradictory to common belief that higher accuracy of DEM is better. We interpret this as a result caused by the discrepancy in the temporal scale of soil responses to given hillslope processes governed by surface geometry. Considering the necessary topographical details governed by the size of grid and environmental correlation with soil attributes, we propose that a 15-30 m grid resolution may be the optimum size range for future soil-landscape analyses.

We also acknowledge that, in addition to the scale effect, the accuracy of DEM itself can also significantly influence results of soil-landform modeling (Bolstad and Stowe, 1994; Holmes *et al.*, 2000). For example, Oksanen and Sarjakoski (2005) performed a GIS analysis-based drainage basin delineation to find that such an approach was very sensitive to uncertainties in DEM acquired. Incorporation of both scale and accuracy issues associated with DEM is thus expected to significantly contribute to the literature of soil-landscape analysis.

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