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Topographic uncertainty and catchment-based models

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ABSTRACT

Topographic attributes are key parameters in numerous models to assess sediment or nutrient input into surface waters. A broad range of digital elevation models (DEM) and algorithms bring, however, uncertainty to topographic interpretations. This may raise the question whether empirical, semi-distributed models can cope with such uncertainty. In this study, primary and complex topographic attributes related to soil loss and distributed sediment delivery were computed from DEM with cell widths between 10 and 1,000 m. Correlation and regression analyses were conducted with average values of the catchments of 138 German gauges spanning different terrain. Two slope, single-flow routing and slope-length algorithms were also included to evaluate their effects. Although either choice mostly induces significant changes of catchment means of slope, flow length, slope-length factor and sediment delivery ratio (SDR), Spearman's rank correlation coefficients are generally above 0.9. It is suggested from the data that linear or slightly curved functions are suitable to adapt average topographic attributes computed from differently resolved DEM or by different methods. Empirical catchment-based models can thus cope with topographic uncertainty and model users may implement these equations to compare model outputs. However, the catchment delineation and stream definition may constrain their application.

Keywords: Algorithm; Correlation; Digital elevation model; Resolution; Topographic attribute

1. Introduction

Topography is a fundamental controlling factor for many processes within the landscape [1]. Consequently, primary topographic attributes such as slope and specific catchment area (SCA) or more complex indices have been used in numerous environmental models. However, the wide range of resolutions of digital elevation models (DEM), their inherent accuracy and the algorithms applied to compute topographic attributes are sources of uncertainty in any topographic analysis [2].

The underlying processes of soil erosion and sediment transport are complex and spatially heterogeneous thus limiting the application of physics-based models to comparatively small areas [3, 4]. Empirical approaches are therefore common in large-scale models. The universal soil loss equation (USLE) is widely applied to assess soil loss within catchments and its slope steepness (S) and slope length (L) factors reflect the influence of terrain. However, most mobilised soil particles are deposited along the transportation path and do not reach the outlet. In empirical models, the relationship between observed sediment yield (SSY) at the outlet and modelled gross erosion is called sediment delivery ratio (SDR) and various relationships between the SDR and simple catchment parameters such as area or average slope have been proposed [5]. The complex relationships and the cumbersome prediction of SSY using the catchment area alone are extensively discussed in [6]. Distributed approaches implement therefore environmental information like land use or topography to spatially disaggregate the SDR [7].

Many studies have been conducted to evaluate scale, cell size or algorithmic impacts on topographic attributes. Either choice will significantly alter the derived values and may influence the outcome of subsequent models [2]. The impact thereby depends on terrain complexity. Previous studies mostly focus on cell-based statistics [8–10] or spatial patterns [11, 12]. However, semi-distributed or lumped models use average values for (sub-)catchments. Only few studies have specifically assessed cell size effects on catchment means of topographic attributes. Comparing average values between a 100 m- and a derived 1,000 m-DEM in 1°·1° blocks spatially scattered across the U.S. linear relationships for slope β, SCA and the topographic index defined as $\ln(SCA/\tan\beta)$ are proposed in [13]. Testing areas across China, a more recent study supports these results by covering more pronounced terrain and by comparing a 100 m- and an independent 1,000 m-DEM [14].

Based on these findings, the main problem addressed in this paper is: Can empirical catchment-based sediment or nutrient input models cope with uncertainty in terrain representation? This leads to the following questions:

(a) Can catchment means of topographic attributes be converted between different DEM resolutions?
(b) Is this, in addition to [13, 14], also possible for complex parameters related to soil erosion and sediment delivery and for DEM resolutions below 100 m?
(c) Are results of common GIS algorithms correlated as well?

2. Methods

2.1. Study area and input data

Case study areas are the catchments of 138 gauges in North-Rhine Westphalia (NRW, West Germany) and Bavaria (South Germany). They span various terrains from lowland to alpine conditions as well as a wide range of areas between 20 and 8,800 km^2 (median of 326 km^2) and are partly nested. Official gauge positions and corresponding catchment areas have been provided by [15, 16].

Table 1 lists the available DEM with their horizontal and vertical resolutions. Since DEM correction compromises topographic parameters [18], these DEM were pre-processed as little as possible. Even projections were left unchanged, except for DEM100 whose geographic projection was transformed to UTM using bilinear interpolation. However, bridges are abundant in DEM10 and DEM50 and had to be eliminated prior to any assessment. All GIS operations were performed with ESRI ArcGIS 9.2.

2.2. Bridge removal

Bridges are artificial barriers impeding correctly modelled water flow paths. High-resolution ATKIS polygon data on land use and land cover in 2007 (Germany Survey, NRW) was used to remove obstacles in water bodies after a visual comparison revealed its geometrical agreement with DEM10 and DEM50. ATKIS classes like rivers, wetlands and weirs were reclassified as streams and a local rectangular minimum filter was applied to the elevation of stream cells. The expected maximum width of bridges determined the neighbourhood size. It had to be large enough to contain at least one water cell for each barrier cell.

In mountainous areas, however, roads span valleys that are not characterised as water bodies in ATKIS. So (and if no suitable dataset was available), a simple topographic approach was developed to approximate continuous flow paths. At first, raster cells with a catchment area above 5 km^2 in a minimum-filtered DEM were considered as stream cells. This arbitrary threshold was chosen to limit the removal of potential flow barriers to well-established streams. These preliminary streams were then iteratively expanded to cover neighbour cells below or at the same height in the original DEM. Expanding and shrinking by half of the minimum filter size connected the separate segments and led to the stream mask. All raster cells lower or equal to the local average height were

Table 1
Specifications of DEM.[a]

Name	Resolution XY (m)/Z (m)	Coverage	Source
DEM10	10/0.01	Eastern NRW	NRW Surveying and Mapping Agency
DEM50	50/0.1	NRW	NRW Surveying and Mapping Agency
DEM100	100/1	Germany[a]	SRTM [17]
DEM250	250/1	Germany	Federal Agency for Cartography and Geodesy
DEM1000	1,000/1	Germany[a]	GTOPO30

[a]and adjacent areas

considered as belonging to such a segment. Each cell within the mask higher than a threshold above the local minimum was eventually classified as barrier cells to be filtered. A centreline approximation (THIN function) was implemented to exclude shoreline cells.

2.3. DEM processing

After filling sinks, flow direction and upslope area were calculated for each DEM. As a change of DEM resolution or flow routing algorithm also changes upslope areas of raster cells, gauges then had to be manually adjusted to cells of high flow accumulation. Raster cells comprising an upslope area of at least 2 km^2 were defined as stream cells after a visual comparison with a river net of Germany [19]. These stream cells were thus considered as to be congruent with the river network. If possible, the spatial relations of gauges were also taken into consideration.

Grid-based flow routing algorithms behave differently in distributing the outflow of raster cells to downslope neighbours. The simplest and widely-applied approach is to follow the steepest descent along one of the eight cardinal directions in a raster (D8 algorithm). Disadvantages are the poor spatial congruence [12] and the SCA distribution with a high proportion of raster cells having low values [10]. Therefore, the D∞ (D-infinity) approach [11] was also included. It expresses the flow direction as a continuous angle between 0 and 2π and thus enables the flow to be diverted to a maximum of two neighbour cells. D∞ functionality was provided by the freely available TauDEM extension for ArcGIS [20]. An own flow accumulation routine was developed to circumvent problems with floating-point numbers and for automation purposes.

ArcGIS and TauDEM furthermore implement different slope algorithms. As this may be relevant for soil erosion and sediment input modelling [21], the sensitivity to the choice of methodology was compared against DEM resolution effects. Due to technical constraints, TauDEM could not be applied to DEM10.

2.4. Statistics

Statistics about each topographic parameter listed in Table 2 were calculated for all catchments whose areas deviated less than 25% from DEM100 (slope) or official values (other statistics). Spearman's rank correlation coefficients and regression equations were then determined to assess the relationships between the datasets. Additionally, Wilcoxon tests were applied to estimate the significance of differences. Although STI and LS are only meaningful for land areas, the stream delineation may vary according to the chosen approach (upper catchment area threshold, SCA-slope relationship among others). Therefore, statistics were computed with and without stream cells to obtain a general idea of dependencies on stream cell definition. All statistical analyses were performed using the R-based software Statistical Lab 3.7 [22].

3. Results and discussion

3.1. Catchment area and stream delineation

After bridge removal and manual adjustment of the gauges, the median of the ratios between modelled and official catchment areas is close to 1.0 for all DEM and all flow algorithms. Inter-quartile ranges and the number of outliers, however, increase with raster cell size (Fig. 1).

Table 2
Parameters derived from DEM.

Topographic parameter	Methodology
Catchment area *A*	Flow accumulation including outlet cell
Flow length to outlet and stream	ArcGIS flow length function (D8 flow only, TauDEM D8 flow direction recoded to ArcGIS scheme)
SDR	Ref. [7] without land use factor and d_j = 0.9997/30 m for stream cells
Sediment transport capacity index	$\mathrm{STI} = \left(\frac{\mathrm{SCA}}{22.13}\right)^{0.6} \cdot \left(\frac{\sin\beta}{0.0896}\right)^{1.3}$ [23]
Slope β	Neighbourhood (NS) (ArcGIS) and maximum slope method (MS) (ArcGIS, TauDEM)
Slope length factor L	Ref. [24], with cutoff slope angles of 0.7 (β < 5%) and 0.5 (β ≥ 5%) (D8 flow only, TauDEM D8 flow direction recoded to ArcGIS scheme)
Slope steepness factor S	[25]

Nonetheless, individual errors occur for every DEM and do not follow any clear trend.

The catchment area of each raster cell obviously depends on DEM resolution as larger raster cells also accumulate more area. Consequently, with a given area threshold, the proportion of stream cells in catchments is expected to be proportional to cell width (see Fig. 2). Nevertheless, flow routing algorithms can also have a considerable impact (Fig. 3). The D∞ algorithm of TauDEM returns more stream cells than ArcGIS for DEM1000 (median ratio 1.37). This is not only a bifurcation effect but partly a result of flow routing in flat terrain as TauDEM's D8 algorithm returns streams which are also 19% longer. Such areas are more prominent in the smooth surface of DEM1000 (see Section 3.2). The differences for the other DEM are small and found to be significant for DEM50 ($p < 0.001$) and DEM100 ($p = 0.02$ for D∞, $p = 0.06$ for D8). They are not significant for DEM250.

By contrast to topographic attributes, correlation coefficients are not only relatively low between DEM resolutions (Table 3) but also between flow routing algorithms. For the latter, r_S values depend on DEM resolution being lowest for DEM1000 with $r_S \approx 0.65$ (ArcGIS), $r_S < 0.5$ (TauDEM) and increasing to $r_S \approx 0.8$ for all other DEM. The statistical relationships are linear.

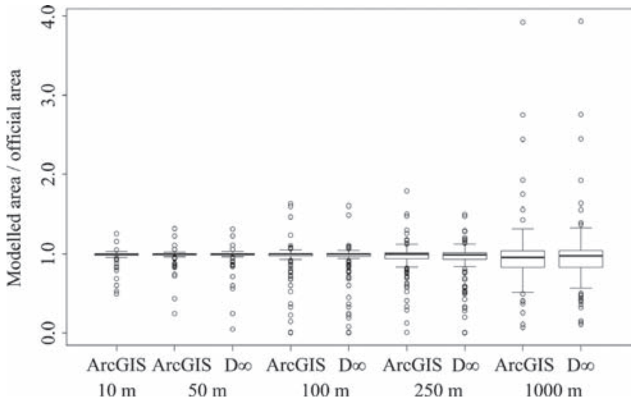

Fig. 1. Modelled area to official area for different DEM resolutions and flow routing algorithms.

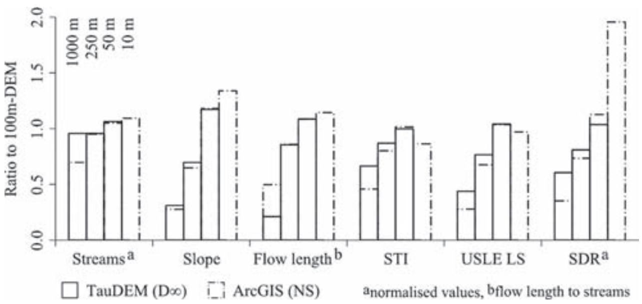

Fig. 2. Effect of DEM resolution on stream delineation and average topographic attributes.

3.2. Slope and flow length

The highly significant increase ($p < 0.001$) of average slope angles with DEM resolution can also be seen in Table 3. With raster cell sizes becoming smaller, average slopes also converge (Fig. 4). This pattern is similar for both slope algorithms, although the impact is slightly lower for the maximum (D∞) than for the neighbourhood slope algorithm (Fig. 2). Correlation coefficients exceeding 0.9 in all cases support the inter-scale correlation of average slopes observed by [13, 14]. Linear regression models describe well the relationships, especially between fine DEM resolutions. Seven virtual gauges with catchment means of slope angles between 10% and 35% have been included in the statistics to increase the sample size for DEM10 and DEM50.

Differences between slope algorithms are comparatively small and proportional to cell width (Fig. 3). They are significant ($p < 0.001$) for all DEM besides DEM10. The D∞ algorithm returns the highest slope angles. This is a flow routing effect because maximum slopes computed with both D8 algorithms do not differ significantly apart from DEM250 ($p = 0.03$). The respective coefficients of linear regression models are 1.00 (0.99 for DEM250).

Average flow lengths prove to be reciprocal to DEM cell size (Table 3) because flow paths meander more if grid cells become smaller. However, the deviations are not as high as for slope angles. The relationships for flow lengths to the outlet are linear and correlation coefficients exceed 0.98. Flow lengths to streams in DEM10 to DEM250 behave in a similar manner, although the impact is larger and r_S values are slightly smaller. In contrast to these DEM, flow lengths in DEM1000 are not only considerably shorter (Fig. 5) but they are also moderately correlated to other DEM resolutions. These correlation coefficients are reciprocal to the proportion of stream cells (Table 3; $r_S = 0.65$ for TauDEM D8).

The choice of methodology plays a marginal role for average slope and flow length to outlet. Flow length values are only slightly higher in TauDEM- than in ArcGIS-processed DEM. Differences are reciprocal to

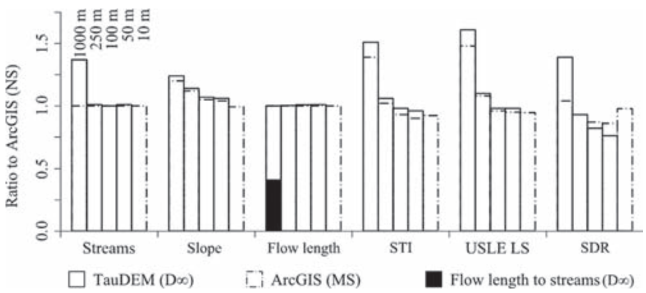

Fig. 3. Method effects on stream delineation and average values of topographic attributes.

DEM resolution and statistically significant ($p < 0.001$) except for DEM1000. Correlation coefficients are above 0.99 for both parameters and linear regression models fit well (Table 4). In contrast, the impact is considerable for DEM1000 when flow lengths are calculated to the streams (Fig. 3). In accordance to Section 3.1, the correlations are only moderate (Table 4; $r_S = 0.76$ between ArcGIS and TauDEM D8). Although the slight differences for all other DEM are also significant ($p < 0.001$, $p = 0.005$ for DEM50 and D∞), r_S values are higher.

Table 3
Coefficients of regression equations $y = a_2x^2 + a_1x$ respectively $y = a_1x$ with x = DEM100.

		Neighbourhood slope				Maximum slope (D∞)		
Parameter	DEM	10	50	250	1,000	50	250	1,000
Streams	a_1	0.11	0.52	2.38	6.89	0.53	2.39	9.60
	N	59	63	112	91	61	108	91
	r_S	0.79	0.90	0.79	0.66	0.80	0.83	0.49
Slope	a_1	1.37	1.23	0.70	0.31	1.20	0.73	0.37
	n	66	71	113	94	61	108	91
	r_S	0.98	0.99	0.98	0.93	0.99	0.98	0.94
Flow length	a_1	1.11	1.03	0.87	0.83	1.04	0.87	0.83
to outlet		(1.16)	(1.08)	(0.88)	(0.51)	(1.09)	(0.88)	(0.21)
(to streams[a])	n	59	63	112	91	61	108	91
	r_S	0.98	0.98	0.99	0.99	0.98	1.00	1.00
		(0.85)	(0.92)	(0.93)	(0.73)	(0.94)	(0.95)	(0.51)
STI[a] (STI)	a_2	0.00	0.00	0.01	0.01	0.00	0.00	0.01
	a_1	0.88	1.05	0.78	0.35	1.02	0.94	0.59
		(0.76)	(1.11)	(0.82)	(0.27)	(1.01)	(0.92)	(0.51)
	N	59	63	112	91	61	108	91
	r_S	0.99	0.99	0.99	0.93	1.00	0.99	0.96
		(0.94)	(0.99)	(0.99)	(0.93)	(1.00)	(0.99)	(0.97)
USLE LS[a]	a_2	0.00	0.00	0.01	0.01	0.00	0.00	0.01
(USLE LS)	a_1	1.02	1.09	0.70	0.21	1.08	0.90	0.38
		(1.05)	(1.11)	(0.67)	(0.19)	(1.10)	(0.86)	(0.27)
	n	59	63	112	91	61	108	91
	r_S	0.99	0.99	0.99	0.93	0.99	0.99	0.95
		(0.99)	(0.99)	(0.99)	(0.94)	(0.99)	(0.99)	(0.96)
SDR[a] (SDR[b])	a_1	0.20	0.56	1.82	3.43	0.50	2.12	5.68
		(0.20)	(0.23)	(2.80)	(13.92)	(0.11)	(2.59)	(22.23)
	n	59	63	112	91	61	108	91
	r_S	0.71	0.97	0.97	0.87	0.95	0.92	0.82
		(0.85)	(0.62)	(0.80)	(0.72)	(0.63)	(0.69)	(0.69)

[a]non-stream cells; [b]TauDEM (D8).

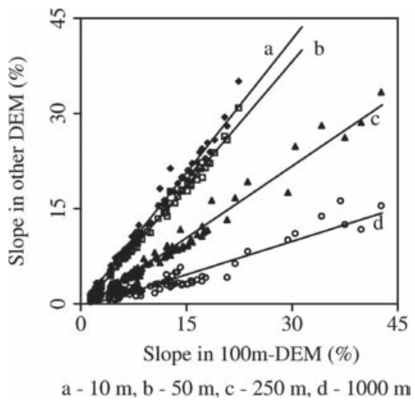

Fig. 4. Average slope (NS) in relation to DEM100.

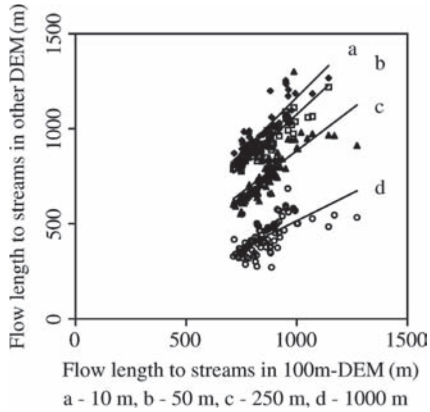

Fig. 5. Average flow length to streams (ArcGIS) in relation to DEM100.

3.3. Sediment transport capacity index (STI) and USLE LS factor

Besides the slope angle, three factors influence the dependency of both attributes on cell size changes. At first, the DEM resolution determines the minimum possible erosive slope length and SCA. Secondly, the terrain-smoothing effect of coarse DEM resolution (Section 3.2) can further increase slope length values. Finally, average slope angles decrease and so does the exponent of the L factor.

The inter-scale correlation of SCA values [13, 14] is supported by the high correlation of average STI values between DEM (Table 3). However, the relationships between coarse and fine DEM are not linear but slightly curved. In accordance to the equivalence of STI and the LS factor [23], both attributes show a similar pattern of resolution dependency, although the impact on LS is higher than on STI (Figs. 6 and 7). They are also highly correlated ($r_S > 0.99$) and second-order polynomial regression models describe the relationship between average LS and STI values.

The largest average values occur in DEM50, nonetheless DEM100 differs only slightly ($p > 0.03$). The reason for the observed drop of average STI and LS in DEM10 has to be the decrease of both SCA and erosive slope length prevailing higher average slopes. This corresponds with observations by [26] on a cell-by-cell basis. In addition, Fig. 2 shows that values calculated by the neighbourhood slope method are stronger influenced by DEM resolution changes, although differences to the maximum slope method decline with raster cell size. The r_S values between DEM are high (Table 3). However, calculated values and differences are somewhat extreme because neither land use patterns nor reasonable slope length caps were applied.

Changing methods has a significant ($p < 0.001$) influence on average STI and LS values aside from DEM1000 (STI) and DEM250 (LS) between both D8 algorithms.

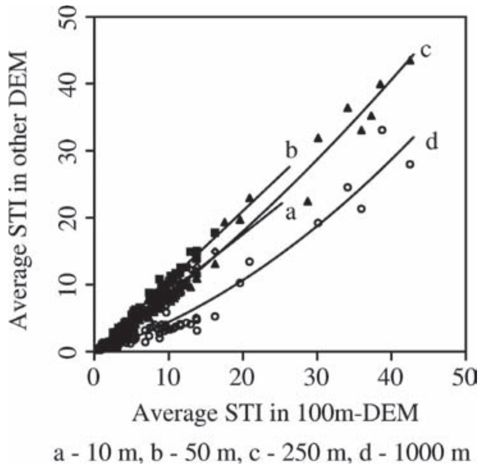

Fig. 6. Average STI (NS) for non-stream cells in relation to DEM100.

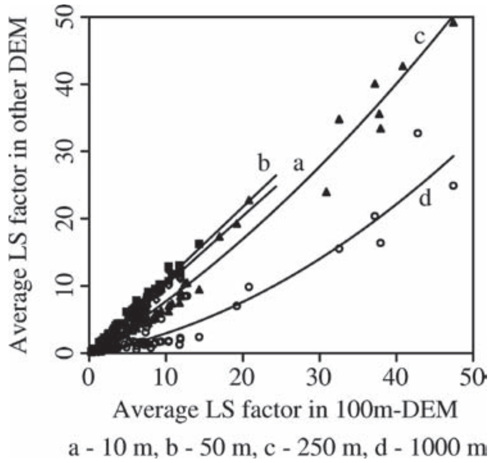

Fig. 7. Average LS (NS) for non-stream cells in relation to DEM100.

Table 4
Coefficients of regression equations $y = a_1 x$ with x = ArcGIS (NS).

		ArcGIS (MS)					TauDEM (D∞)			
Parameter	DEM	10	50	100	250	1,000	50	100	250	1,000
Slope	a_1	0.99	1.03	1.02	1.08	1.21	1.05	1.04	1.10	1.23
Flow length	a_1	1.00	1.00	1.00	1.00	1.00	1.02	1.01	1.00	1.00
(to streams)		(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.99)	(0.98)	(0.99)	(0.40[c])
STI[a] (STI)	a_1	0.93	0.90	0.93	0.97	1.38	0.95	1.00	1.00	1.45
		(0.75)	(0.62)	(0.76)	(0.71)	(0.73)	(0.65)	(0.81)	(0.73)	(0.75)
USLE LS[a]	a_1	0.95	0.95	0.92	0.91	1.46	0.97	0.94	0.91	1.50
(USLE LS)		(0.95)	(0.94)	(0.91)	(0.88)	(1.12)	(0.96)	(0.93)	(0.88)	(1.14)
SDR[a] (SDR[b])	a_1	0.98	0.86	0.87	0.93	1.04	0.76	0.82	0.93	1.39
		(0.83)	(0.53[d])	(0.52)	(0.43)	(0.68)	(0.24)	(0.52[d])	(0.45[d])	(0.69)

[a]non-stream cells; [b]TauDEM (D8); [c]$r_S = 0.55$; [d]$0.85 < r_S < 0.90$.

Following the pattern for slope angles, the effect is proportional to DEM resolution (Fig. 3). While the maximum slope methods (D8 and D∞) return higher STI and LS values for DEM1000, the effect declines and even reverses for finer resolved DEM. Correlation coefficients are also very high ($r_S > 0.98$) and linear regression models describe the observed relationships (Table 4).

Stream cell definition affects both topographic attributes differently. The equations in Tables 3 and 4 for the LS factor generally change a little when stream cells are included in the statistics. Only in DEM1000 with its many stream cells, the inter-algorithmic relationships are affected (Table 4). Besides, the impact on STI is much higher because stream cells have *per definitionem* large SCA values resulting in high STI values if slope angles $\beta > 0°$. This is especially relevant for the neighbourhood slope method which may induce high slope angles along narrow valleys or non-corrected bridge cells. Consequently, the difference is comparatively large and the correlation low for DEM10 (Table 3). The relationship between neighbourhood and maximum slope changes considerably for all DEM, particularly for DEM1000 (Table 4). Nonetheless, correlation coefficients remain high ($r_S > 0.98$; $r_S = 0.95$ for DEM10).

3.4. Sediment delivery ratio

Modifying the DEM resolution or GIS algorithms does not affect many lumped SDR approaches provided that the catchment area does not change. If appropriate, the empirical relationships for average slope may be applied to transform SDR values to other DEM resolutions or methods. Given the high correlations for the STI and USLE LS factor, the sediment input could also be estimated.

By contrast, the distributed algorithm is inherently resolution-dependent as the number of raster cells along each flow path increases with cell sizes becoming smaller. Therefore, the impact of changing DEM resolution is highest among topographic attributes (Fig. 2, $p < 0.001$). If means are corrected for cell width, they are proportional to average slope. Correlation coefficients between DEM are low in comparison to other topographic parameters (Table 3). The moderate values for DEM10 ($0.59 < r_S < 0.71$ for ArcGIS NS; $0.52 < r_S < 0.64$ for ArcGIS MS) indicate an information content that cannot be fully explained by coarser DEM. The relationships are linear (Fig. 8).

Average SDR values also change significantly if flow routing or slope calculation are altered (Fig. 3). Mostly, p is below 0.001 except for DEM10 ($p = 0.01$) and the D8 comparison for DEM250 ($p = 0.003$). At a first glance, the results may contradict the slope pattern. However, higher average maximum slope angles do not mean higher values for each raster cell. At the feet of slopes, for example, the neighbourhood slope algorithm considers the upslope area whereas the maximum slope only includes the flatter downslope relief. Due to the shorter distance to either streams or outlet, the slope angle at a foot of slope has a higher significance than the slope itself where maximum slope returns higher values. Terrain characteristics as well as DEM resolution determine thus the spatial pattern and absolute values of slope differences and, eventually, empirical relationships. The considerably larger average SDR for the TauDEM-processed DEM1000 is equivalent to the larger number of stream cells (Section 3.1).

Without stream delineation, the raster cells next to the outlet are most important and maximum slopes are mostly gentle here. The neighbourhood method can consider (steeper) slopes. This is more probable in coarse DEM, given the fact that the differences between regression equations with and without stream cells are higher there (Table 4). However, the opposed trend of surface smoothing seems to partly overlay. Correlation coefficients are slightly lower between both DEM resolutions and algorithms. The relationships still follow a linear trend although the coefficients change noticeably (Tables 3 and 4).

4. Conclusions

Previous studies suggested that average slope angles and SCA computed from a 100-m DEM can be downscaled to 1,000 m resolution using linear equations [13, 14]. Supporting these findings, the results show that linear or slightly curved regression models are principally suitable to transform catchment means of topographic attributes for DEM resolutions between 10 m and 1,000 m. This is not only possible for simple but also for complex parameters such as USLE's slope–length factor or spatially distributed SDR. Furthermore, linear equations describe sufficiently the relations between outcomes of different single-flow routing and slope algorithms. This is important as often only one version is implemented in standard GIS software. Despite significant changes in absolute values, catchment-based

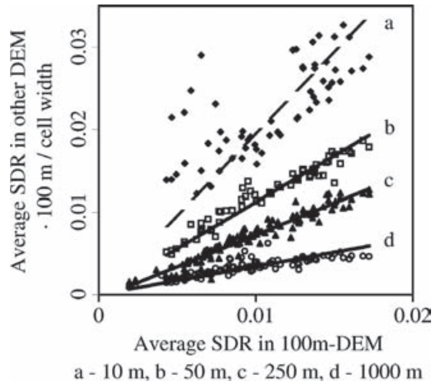

Fig. 8. Normalised average SDR (NS) for non-stream cells in relation to DEM100.

models are thus capable to handle topographic uncertainty. However, there are three constraints.

Firstly, the relations are only valid as long as catchment delineation is not compromised. If catchment areas have to be derived from a DEM, higher resolution means better conformance with official values. Discrepancies here will also affect many lumped SDR approaches. Nevertheless, if DEM become too detailed artefacts may emerge interfering with the calculation of flow directions and catchment area. Secondly, the regression models for the spatially distributed SDR and the STI seem to be susceptible to stream definition. However, the two tested alternatives of a constant threshold of upper catchment area for all DEM resolutions and no streams, respectively, give only a general impression. Finally, the inter-resolution correlations are comparatively low for the distributed SDR approach. The moderate correlations between DEM10 and the other DEM indicate a content being not fully explicable.

DEM and method choice significantly influences estimates of sediment or nutrient input to surface waters. Although it is feasible to expect better results with higher DEM resolution, this study shows that this may not be true for empirical, semi-distributed models. Pre-processing and computing time does not only increase rapidly but benefits of better resolved DEM or elaborate algorithms are marginal. Model users may use the proposed empirical equations to compare model results based on different DEM resolutions or topographic algorithms. Nonetheless, an overall sensitivity analysis of sediment and nutrient models has to include other relevant factors such as land use or soil.

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Nomenclature

SCA	Specific catchment area
β	Slope angle
r_S	Spearman's rank correlation coefficient

References

[1] I. D. Moore, R. B. Grayson and A. R. Ladson, Digital terrain modelling: A review of hydrological, geomorphological, and biological applications, Hydrological Processes, 5(1) (1991) 3–30

[2] S. P. Wechsler, Uncertainties associated with digital elevation models for hydrologic applications: a review, Hydrology and Earth System Sciences, 11(4) (2007) 1481–1500

[3] J. de Vente and J. Poesen, Predicting soil erosion and sediment yield at the basin scale: Scale issues and semi-quantitative models, Earth-Science Reviews, 71(1–2) (2005) 95–125

[4] T. Lenhart, A. van Rompaey, A. Steegen, N. Fohrer, H.–G. Frede and G. Govers, Considering spatial distribution and deposition of sediment in lumped and semi-distributed models, Hydrological Processes, 19(3) (2005) 785–794

[5] D. Walling, The sediment delivery problem, Journal of Hydrology, 65(1–3) (1983) 209–237

[6] J. de Vente, J. Poesen, M. Arabkhedri and G. Verstraeten, The sediment delivery problem revisited, Progress in Physical Geography, 31(2) (2007) 155–178

[7 T. Veith, Agricultural BMP placement for cost-effective pollution control at the watershed level, Ph.D. thesis, Virginia Polytechnic Institute and State University, U. S. A., 2002.

[8] S. Wu, J. Li and G. Huang, An evaluation of grid size uncertainty in empirical soil loss modeling with digital elevation models, Environmental Modeling and Assessment, 10 (2005) 33–42

[9] S. Wu, J. Li and G. Huang, A study on DEM–derived primary topographic attributes for hydrologic applications: Sensitivity to elevation data resolution, Applied Geography, 28(3) (2008) 210–223

[10] J. Wilson, C. Lam and Y. Deng, Comparison of the performance of flow-routing algorithms used in GIS-based hydrologic analysis, Hydrological Processes, 21(8) (2007) 1026–1044

[11] D. Tarboton, A new method for the determination of flow directions and upslope areas in grid digital elevation models, Water Resources Research, 33(2) (1997) 309–319

[12] T. Endreny and E. Wood, Maximizing spatial congruence of observed and DEM-delineated overland flow networks, International Journal of Geographical Information Science, 17(7) (2003) 699–713

[13] D. M. Wolock and G. J. McCabe, Differences in topographic characteristics computed from 100-and 1000-m resolution digital elevation model data, Hydrological Processes, 1 4 (2000) 987–1002

[14] B. Yong, W. C. Zhang, G. Y. Niu, L. L. Ren and C. Z. Qin, Spatial statistical properties and scale transform analyses on the topographic index derived from DEMs in China, Computers & Geosciences, 35(3) (2009) 592–602

[15] Bavarian State Office for the Environment, http://www.hnd.bayern.de/ (accessed 30/07/2009)

[16] NRW State Agency for Nature, Environment and Consumer Production, http://luadb.lds.nrw.de/LUA/wiski/pegel.php (accessed 30/07/2009)

[17] International Centre for Tropical Agriculture, Void-filled seamless SRTM data V3, http://srtm.csi.cgiar.org (accessed 17/10/2007)

[18] J. Callow, K. van Niel and G. Boggs, How does modifying a DEM to reflect known hydrology affect subsequent terrain analysis?, Journal of Hydrology, 332(1–2) (2007) 30–39

[19] Federal Agency for Cartography and Geodesy, Digitales Landschaftsmodell 250 (Digital landscape model 250), scale 1:250000 (2003)

[20] TauDEM V3.1, http://hydrology.neng.usu.edu/taudem/ (accessed 30/07/2009)

[21] S. Warren, M. Hohmann, K. Auerswald and H. Mitášová, An evaluation of methods to determine slope using digital elevation data, Catena, 58(3) (2004) 215–233

[22] Statistical Lab V3.7, http://www.statistiklabor.de/en/index.html (accessed 09/12/2009)

[23] I. D. Moore and J. Wilson, Length-slope factors for the revised universal soil loss equation: simplified method of estimation, Journal of Soil and Water Conservation, 47(5) (1992) 423–428

[24] R. van Remortel, M. Hamilton and R. Hickey, Estimating the LS factor for RUSLE through iterative slope length processing of DEM elevation data, Cartography, 30(1) (2001) 27–35

[25] M. Nearing, A single, continuous function for slope steepness influence on soil loss, Soil Science Society of America Journal, 61(3) (1997) 917–919

[26] R. Sørensen and J. Seibert, Effects of DEM resolution on the calculation of topographical indices: TWI and its components, Journal of Hydrology, 347(1–2) (2007) 79–89