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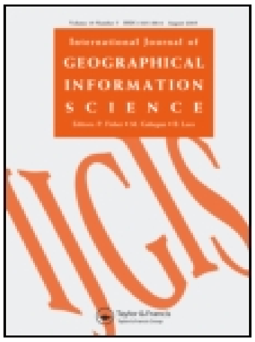

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# DEM resolution dependencies of terrain attributes across a landscape

Y. Deng , J. P. Wilson & B. O. Bauer

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**Research Article**

# DEM resolution dependencies of terrain attributes across a landscape

Y. DENG*†, J. P. WILSON‡ and B. O. BAUER§
†Department of Geography, Western Illinois University, Macomb, IL 61455-1390, USA
‡Department of Geography, University of Southern California, Los Angeles, CA 90089-0255, USA
§Irving K. Barber School of Arts and Sciences, University of British Columbia Okanagan, 3333 University Way, Kelowna, BC, Canada V1V 1V7

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This paper documents resolution dependencies in terrain analysis and describes how they vary across landform location. Six terrain attributes were evaluated as a function of DEM resolution—slope, plan curvature, profile curvature, north–south slope orientation, east–west slope orientation, and topographic wetness index. The research highlights the effect of varying spatial resolution through a spatial sampling/resampling scheme while maintaining sets of indexed sample points at various resolutions. Tested sample points therefore coincide exactly between two directly compared resolutions in terms of their location and elevation value. An unsupervised landform classification procedure based on statistical clustering algorithms was employed to define landform classes in a reproducible manner. Correlation and regression analyses identified sensitive and consistent responses for each attribute as resolution was changed, although the tested terrain attributes responded in characteristically different ways. These responses displayed distinguishable patterns among various landform classes, a conclusion that was further verified by a series of two-sample, two-tailed *t*-tests.

*Keywords*: Resolution effects; Terrain attributes; Landform classes



## 1. Introduction

Concerns pertaining to the effects of spatial scale are ubiquitous, especially in the context of terrain analysis (Moore *et al.* 1993b, Fisher 1996, Wilson *et al.* 1998, Wood 1998) and terrain-based environmental modelling (Band 1986, Wood *et al.* 1988, Beven 1989, 1997, Moore *et al.* 1993a, Zhang and Montgomery 1994, Band and Moore 1995, Quinn *et al.* 1995, Florinsky and Kuryakova 2000). Moore *et al.* (1993b), for example, identified basic element size, choice of attribute algorithm, merging of data sources, and scale differences between model and data as key issues in terrain analysis. With the recent emergence of high-resolution DEMs, two additional concerns have arisen: (1) appropriate demarcation of geomorphic units at different scales and (2) calculation of robust terrain attributes at appropriate scales on high-resolution data (Deng *et al.* in press a). Responding to these issues, this paper seeks to answer the following research question: 'How are calculated terrain attributes dependent upon DEM resolution across different landform classes (types)?'

*Corresponding author. Email: y-deng2@wiu.edu

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The study incorporated a two-step, empirical methodology. First, the study area was partitioned into landform classes using an unsupervised, non-hierarchical clustering procedure. Second, the effect of changing DEM resolution on calculated terrain attributes was assessed using correlation and regression analysis. An assessment was conducted for the entire study area as well as for each landform class.

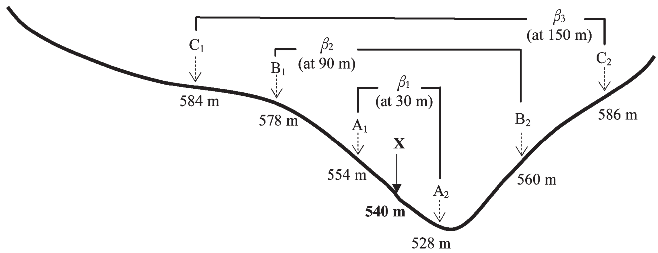
The next section of the paper reviews the relevance of the above research question to terrain analysis. The third section describes the study area, DEM data, as well as the research design and analytical methods, and the fourth section summarizes the major findings and interprets the results. Several conclusions and ideas for future work are offered in the final section.

## 2. Background

Phillips (1988) suggested that biophysical processes operating at vastly different spatial scales may be independent of each other. This possibility poses a fundamental challenge to terrain-based modelling efforts because environmental models may be valid across only a limited range of spatial scales (Zhang and Montgomery 1994, Band and Moore 1995, Florinsky and Kuryakova 2000): either because the studied biophysical processes are scale-dependent or because the models themselves are scale-dependent. As a consequence, it is essential to investigate and define the range of data resolution for which the model is applicable (e.g. Bian and Walsh 1993, Florinsky and Kuryakova 2000). Bian (1997), for example, demonstrated that apparent correspondence between DEM resolution and data resolution of various environmental variables (e.g. normalized difference vegetation index, or NDVI) does not imply that the operational scales of terrain-influenced biophysical processes (e.g. elevation control on vegetation distribution) are well represented. Accurate translations between data resolution and representative spatial scales of the biophysical environment are far from straightforward. This translation process is nonetheless implicit in every terrain-based environmental modelling effort, with important consequences for model reliability and validity (Moore *et al.* 1993b, Phillips 1988).

The effects of altering data resolution are also poorly understood, and tremendous difficulties are encountered when environmental models need to be scaled up or down (Bierkens *et al.* 2000). Beven (1993, 1997) treated DEM resolution as an actual TOPMODEL parameter and noted that 'equifinality' in hydrological modelling—the idea that multiple parameter sets may produce the same simulation outcome—is related to scales of hydrological processes (or 'laws') over the landscape. As a result, it is conceivable that two DEM resolutions can produce the same modelling result, even though it is not generally known how interchangeable the DEM resolutions are.

Wood (1998) suggested that measurement of slope at each landscape point varies with the size of the region over which the slope is derived, and that surface parameters should be recorded as ranges of values depending on the scale of analysis. Gallant and Dowling (2003) have gone further by suggesting that it is problematic to use a single-sized neighbourhood window to estimate terrain characteristics, and scale-explicit, multi-resolution terrain attributes should be considered. Deng *et al.* (in press a) used figure 1 to demonstrate that spatial resolution change may not only cause point-specific effects on calculated terrain attributes but also shift the topographic meanings of the attributes at each point. As




| |
|---|
| $\beta_1$ = (554 m – 528 m) × 100% / 30 m = 87%, $\beta_1$ is the slope gradient for X at 30-m spatial resolution, pointing from $A_1$ to $A_2$ |
| $\beta_2$ = (578 m – 560 m) × 100% / 90 m = 20%, $\beta_2$ is the slope gradient for X at 90-m spatial resolution, pointing from $B_1$ to $B_2$ |
| $\beta_3$ = (586 m – 584 m) × 100% / 150 m = 1%, $\beta_3$ is the slope gradient for X at 150-m spatial resolution, pointing from $C_2$ to $C_1$ |

Figure 1. Scale effects of terrain analysis. Slope gradients ($\beta_1$, $\beta_2$, and $\beta_3$) for the same point X are defined in different ways due to the change of spatial resolution. The resultant slope gradients are different not only in magnitude but also in topographic meaning From Deng *et al.* (in press a); used with permission of the authors.



a consequence, spatially aggregated statistical analysis cannot sufficiently capture the impact of DEM resolution on the calculated terrain attributes, and more spatially explicit approaches need to be developed. An additional consideration is that the adjustment of resolution may induce a dramatic change in the number and location of the evaluated points, implying a shift of the statistical population. This undermines the accuracy of aggregated comparisons between differing resolutions. As implemented in this paper, a sampling/resampling scheme is needed to ensure the spatial coincidence of evaluated points across compared spatial resolutions.

A number of studies have attempted to establish direct, simplified linkages between DEM resolution, data quality, and modelling uncertainty. For example, Florinsky and Kuryakova (2000) recommended a three-step procedure to define an appropriate DEM grid resolution (or resolution range) for the specification of a particular biophysical property (e.g. soil moisture). This procedure was developed in a very small study area of the Eastern European Plain, measuring 58 m by 77 m in size and having a gentle slope (10° on average) and low relief (15 m). The first step was to calculate a series of terrain attributes (slope gradient, slope aspect, plan curvature, profile curvature, etc.) from DEMs of varying resolutions (e.g. 1–7 m for their study area); the second step was to calculate correlation coefficients between the calculated terrain attributes and the targeted biophysical property; and the third step was to plot the change in correlation coefficient against DEM resolution. The resolution range where the calculated correlation coefficients for all tested terrain attributes show a stable variation in value (e.g. 2.25–3.25 m for soil moisture) is then accepted as the optimal resolution range for the modelling of that particular biophysical property.

Zhang and Montgomery (1994) compared cumulative frequency distributions of calculated topographic wetness index and hydrological simulations over vastly different DEM resolutions (2–90 m) in two small (0.3 and 1.2 km$^2$, respectively), moderately to steeply sloped (e.g. 20–40°) western US watersheds. This study showed that 10 m was the threshold resolution for the studied landscape beyond which the model quality deteriorated quickly, but below which no significant improvement in modelling results was observed. A more recent study by Kienzle (2004) emphasized the importance of landscape diversity. Three regular-shaped study areas (15.21 $km^2$ in size) to represent moderately sloped, gently sloped, and flat-relief areas in the Rocky Mountain foothill and Great Plains regions were selected. This study focused attention on the ideal grid DEM resolution that matched information contained in the source data, which includes both regularly sampled elevation measurements at a 100-m interval and measurements on numerous well-selected landmarks. The ANUDEM interpolation method (Hutchinson 1989) was used to generate the DEMs, and a range of 5–20 m was identified as the finest resolution that was supported by these input data for the examined landscape types (i.e. study areas). A similar approach to Kienzle's (2004) was employed by Hutchinson and Gallant (2000) in a roughly 4 $km^2$, high relief (more than 300 m) catchment, who systematically described how the finest-resolution DEMs could be identified from contour data upon a sufficient consideration of the topographic structure.

These and other efforts linking DEM resolutions to the data and model quality have provided valuable 'rules of thumb' for the selection of data resolutions in various landscapes (Moore *et al.* 1993b, Zhang and Montgomery 1994, Quinn *et al.* 1995, Mitasova *et al.* 1996, Florinsky and Kuryakova 2000, Kienzle 2004) and have improved our understanding of, and confidence in, the adopted data, algorithms, and models (e.g. Chang and Tsai 1991, Wolock and Price 1994, Wilson *et al.* 1998, Gertner *et al.* 2002). The results of these studies also suggest that recently emergent fine-resolution DEMs, such as USGS 10 m DEMs or LiDAR/IFSAR 1–5 m DEMs, may have reached beyond certain threshold resolutions for environmental analysis (e.g. Zhang and Montgomery 1994). These new data sources of fine-resolution elevations imply a tremendous opportunity as well as an immediate need to examine the dependency of environmental modelling analyses on DEM resolution and to understand important threshold resolutions in terrain analysis.

Owing to the complexity of the spatial scale problem and the general absence of established guidelines upon which to base decisions, it is often the case that the practical necessity for coping with the scale issue is reduced to a somewhat arbitrary selection of DEM cell size at the onset of model construction (e.g. Beven 1989, Florinsky and Kuryakova 2000, Gertner *et al.* 2002). This avoids the need for dense measurement networks (i.e. ground data) on the one hand, and time-consuming model evaluation on the other. A further expedient is invoked when no consideration is given to the importance of DEM resolution on model performance as a function of landform type or terrain surface roughness. In practice, the effects of spatial scales are often aggregated (averaged) across the entire study area as statistical variations of terrain attributes corresponding to the resolution change (e.g. Chang and Tsai 1991, Wolock and Price 1994). In doing so, most local, possibly site-specific responses to spatial scales are hidden, and it remains unproved as to whether terrain attributes calculated in different parts of the landscape respond to the DEM resolution change in the same way. The ramifications of this issue are most apparent in terrain-based hydrological modelling, where the ability to treat channel cells and hillslope cells differently is often vital because dynamic and site-specific scale effects influence channel–hillslope interactions (Quinn *et al.* 1995, Gallant and Dowling 2003).

Even though it is widely appreciated that there exists a connection between landscape locations and DEM resolutions, a formal treatment of this association is missing in the literature. For DEM data quality evaluations, for example, the location of sample points on the landscape has been viewed as an important factor that is closely related to the accuracy and spatial scale of terrain surface delineations (e.g. Adkins and Merry 1994, Carrara *et al.* 1997, Krupnik 2000). Hence, Zhang and Montgomery (1994) noted the crucial, yet often neglected, role of landscape type in determining the sampling density for topographic mapping. Hutchinson (1989) demonstrated that sparse, but well-selected point elevations could be realistically interpolated to produce high-accuracy DEMs with the assistance of stream network data and a drainage-enforcement algorithm. A fundamental linkage is thus implied between landform structure and the effective DEM resolution (meaning the DEM grid resolution that is well supported by source data or ground-truth). For instance, sample point locations on the terrain surface (e.g. peak, ridgeline, maximum contour curvature) are treated as more important to DEM accuracy than sampling density, and the influence of sampling density should consequently be evaluated in connection with terrain shape representations (Wilson *et al.* 1998). Additionally, not only are sample points viewed as autocorrelated but they should be referenced to the stream channel network to improve the interpolation accuracy.

To minimize the influence of sampling location on the evaluation of data and model quality, relatively homogeneous patterns of terrain shape (e.g. uniform slopes) were sometimes selected for spatial sampling (e.g. Bolstad and Stowe 1994). A more common approach, nonetheless, is to choose several study areas (sites) with different topographic characteristics—usually defined visually and qualitatively using tacit expert knowledge—to represent various landform types (e.g. Moore *et al.* 1993b, Gao 1997, Kienzle 2004). Even though these (and similar) strategies rely heavily on expert knowledge, and there is little guarantee that the results obtained can be reproduced elsewhere, they are still valuable when the effects of landscape type are difficult to define, which in turn is related to the general lack of techniques to stratify the landscape in an objective, meaningful, and reproducible manner. The research reported in this paper addresses this issue within a mountainous landscape in Southern California. First, it identifies natural clusters of sample points based on their topographic attributes, using an unsupervised landform clustering scheme. This classification is data-based and less influenced by human choices but can be interpreted in reference to DEM elevation patterns or in terms of a terrain roughness index. Second, the research links so-defined landform classes to the variation of differences and correlations between attributes that are derived from DEMs of varying resolutions.



## 3. Methodology

### 3.1 *Motivating hypotheses*

It seems reasonable to assume that the values of various terrain attributes (e.g. slope or plan curvature) will vary with a change in DEM resolution, as has been demonstrated in prior studies (e.g. Deng *et al.* in press a). What is not known is whether or not the variation is consistent with resolution change for each attribute (as would happen with continuous increases or decreases of cell sizes) and whether or not these variations are somehow linked to location (i.e. landscape type). Thus, the remainder of the paper is framed around two null hypotheses:

- Terrain attribute values calculated from DEMs do not change in consistent ways when the input DEM resolution is altered.

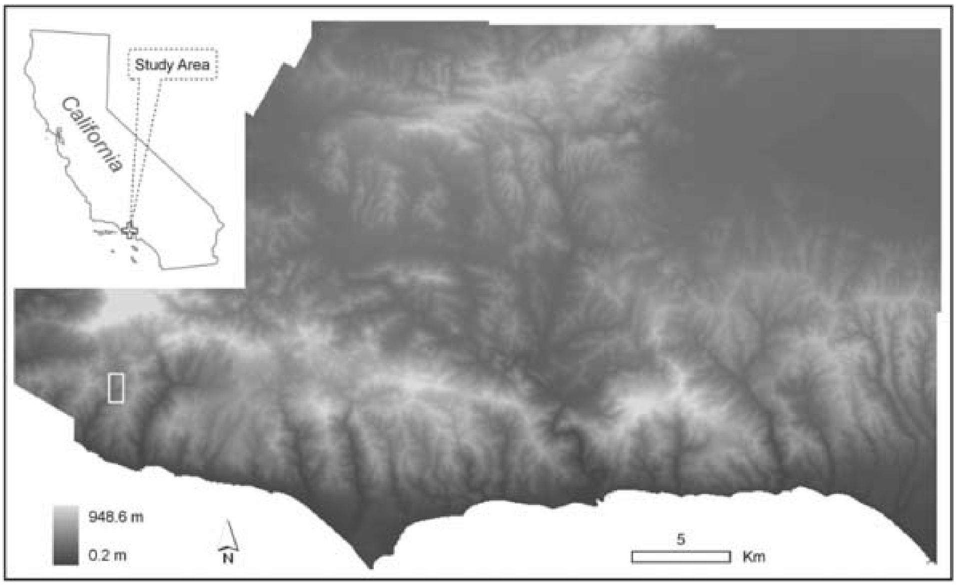



Figure 2. Study area DEM. The white inset box indicates the location of maps reproduced in figures 3 and 4.

- The response of terrain attribute values to DEM resolution change does not vary significantly across landscape locations.

### 3.2 *Description of study area*

The study area covers the eastern Santa Monica Mountains, California (figure 2), which extend in an east–west orientation along the Pacific coast. The study area is 962 $km^2$ in size, which translates into 38 484 560 cells each $5 \times 5$ m in size. The region contains diverse landforms ranging from flat inland basins and coastal plains to steep, rugged mountains. Fluvial topography is dominant, and there are numerous short, narrow stream channels and an occasional wide valley, mostly oriented north–south. The ephemeral streams drain from the central ridgeline of the Santa Monica Mountains either north into the inland valleys or south toward the Pacific Ocean. They constitute the dominant erosive force, and their high density, short length, and deep-cutting character means that the terrain surface is heavily dissected and relatively heterogeneous. From the narrow coastal zone, a relative relief of 950 m with a base at the sea level and top at the central ridgeline is reached progressively within a short distance (about 10 km) and then decreases steadily towards inland basins and plains. The stream network and landform hierarchies are not particularly well developed.

Given that the terrain surface in the study area is of a rather specific (although not unique) nature, it is important to note at the outset that the results of the study may not be generalizable to other landform assemblages that are significantly different in character and geometry. Thus, the findings can only serve to quantitatively define: (1) the extent of the resolution dependency in this particular landscape type; and (2) how the resolution dependency varies within this landscape type. However, the qualitative findings regarding the two null hypotheses should also hold true in other fluvial dominant landscapes that have similar size scales (in $x$, $y$, $z$) and runoff erosion extents. The efforts of grouping the diverse landform components into interpretable classes may also help in extrapolating the findings for individual landform classes to other regions that have landform characters similar to a particular landform class defined in this paper (e.g. flat lowlands or steep slopes).

### 3.3 *DEM source data and DEM sampling/resampling*

Seven bare-ground IFSAR (Interferometric Synthetic Aperture Radar) DEMs of 5-m horizontal resolution (corresponding to equivalent coverage of seven adjoining 7.5-min USGS quadrangles) were used as the source data. Intermap Co., the producer of these airborne DEMs, reports a vertical accuracy (root mean square error or RMSE) of 1 m and a horizontal accuracy of 2.5 m for these data.

The 5-m DEM was resampled using ArcGIS to the following horizontal resolutions: 10, 15, 20, 25, 30, 40, 50, 60, 80, 100, 120, 160, 200, 240, 320, 400, and 480 m. Unless otherwise indicated, most other data pre-processing, attribute calculation, map computation and spatial analysis were also performed in ArcGIS. As indicated in section 2, several analytical challenges arise when comparing terrain attributes across this range of spatial resolutions. First, the exact locations of grid points that are to be compared may not coincide at different spatial resolutions. In this situation, spatially aggregated comparisons of data resolutions are inappropriate, especially in rugged mountainous landscapes where terrain characteristics often display enormous variation over short horizontal distances. Second, the population of grid points is small at a coarse resolution, implying unstable statistics. Third, spatial autocorrelation between neighbouring sample points may be stronger at fine resolutions because of close sample distances (Wilson *et al.* 1998).

The first challenge was overcome by adopting a resampling procedure equivalent to retaining every $n$th grid point after consistently dropping all the other points to produce DEMs of coarser resolutions. As a result, all grid points on a coarser-resolution DEM can be matched to original grid points on finer-resolution DEMs. The second and third challenges were overcome because this resampling procedure limited the output resolution to be an integer multiple of the input resolution. As long as terrain attributes based only on the grid points of the coarsest resolution are compared, the sample size will be constant at all compared resolutions, and the influence of variable spatial autocorrelation is minimized because the distance between neighbouring sample points is uniform for each resolution in the comparison.

Specifically, three mutually independent sets of points were resampled in this research, corresponding to sets of grid points at spatial intervals of 320, 400, and 480 m, respectively. Comparisons of resolutions were made for each set of sample points separately; namely: (1) 5, 10, 20, 40, 80, 160, and 320 m; (2) 5, 15, 30, 60, 120, 240, and 480 m; and (3) 5, 25, 50, 100, 200, and 400 m. Using these coarsest-resolution sets, the entire study area comprises 9378 grid points (320-m intervals), 6002 points (400-m intervals), and 4171 points (480-m intervals). For each coarse-resolution sample point, there is a corresponding fine-resolution point at all resolution pairs in the sample set. After combining results obtained from all three sets of sample points, conclusions can be drawn based on a relatively complete variation of spatial resolutions ranging from 5 m to 480 m.

### 3.4 *Terrain attribute calculations*

Six terrain attributes were evaluated as a function of DEM resolution—slope, plan curvature, profile curvature, north–south slope orientation (NS), east–west slope orientation (WE), and topographic wetness index (W). The first five attributes were computed using the algorithms of Horn (1981) for slope (%) and Zevenbergen and Thorne (1987) for plan curvature and profile curvature. $W$ was calculated as

$$W = \ln\left(\frac{A_s}{\tan\beta}\right) \tag{1}$$

where $A_s$ is the specific catchment area (m$^2$), and $\beta$ is slope (°). $A_s$ was calculated from the 5-m DEM using the D8 algorithm (O'Callaghan and Mark 1984) in PCRaster. Pits in the DEM were removed for the calculation of $A_s$ using the algorithm suggested by Van Deursen (1995).

NS and WE were derived from aspect, where the latter was calculated according to Horn (1981). Aspect was not used because it is calculated as circular degrees clockwise from 0° to 360°, and it is therefore difficult to compare quantitatively (e.g. there is only a 2° difference between aspects of 1° and 359° whereas the numerical difference is 358°). The method suggested by Copland (1998) was used to perform the conversion from aspect to NS and WE, as follows:

$$\text{NS} = \cos(\text{aspect}) \tag{2}$$

and

$$\text{WE} = \sin(\text{aspect}) \tag{3}$$

such that values of NS and WE range from $-1$ to 1 and represent the extent to which a slope faces north (NS=1), south (NS=$-1$), east (WE=1), or west (WE=$-1$).

### 3.5 *Unsupervised landform classification*

Utilizing PCRaster, an unsupervised, non-hierarchical landform classification method was adopted. This method used an iterative clustering procedure to identify the most representative clusters within a group of (random) sample grid points according to their attribute values (Burrough and McDonnell 1998: 283–289, Burrough *et al.* 2000 2001). Each of the other grid points was then assigned to one of the clusters whose attribute distance is the shortest to the grid point, indicating the greatest similarity. This method signifies a more objective means of landform classification because it is data-driven and requires little human intervention.

A total of 690 grid points were randomly sampled from the 5-m DEM and used for clustering on the basis of seven attributes—elevation, slope, ln($A_s$), plan curvature, profile curvature, NS, and WE. Elevation was extracted directly from the original 5-m DEM. The ln($A_s$) was used instead of $A_s$ because the values of $A_s$ cover a wide range of magnitudes. Attribute weighting in the classification was varied such that NS and WE were assigned weights of 0.75 and 0.25, respectively, to represent their different influence on incoming solar radiation. All other attributes were assigned a weight of 1. Three methods were then adopted to facilitate the understanding of the resultant landform classes—by analysing the attribute values in each class, by visually comparing the classification map with the DEM patterns, and by using a terrain roughness index.

It is important to note that a single-resolution landform classification was used to differentiate the landscape in support of a multi-resolution analysis. As will be demonstrated in section 4.1, the partitioned landscape at this resolution can be interpreted in a meaningful way, so as to support conclusions regarding how terrain attribute sensitivity to resolution change may vary across *these* landscape types (locations). However, this approach also poses some limitations to the analysis because the numerical classification results would be different if the classification resolution were shifted, thus producing variable definitions of landscape locations for the same point. In this case, a different landscape structure (e.g. containing fewer topographic details) may be observed at a coarser resolution (e.g. Bian 1997), signifying landscape meanings (processes) that correspond to that resolution. For example, at a very coarse spatial resolution, every point north of the central ridgeline in the Santa Monica Mountains may be categorized as a part of 'north-facing slopes', even though this point may be placed at the bottom of a valley or top of a ridge when observed at the 5-m resolution.

### 3.6 *Terrain roughness index*

Terrain roughness was quantified using the standard deviation calculated using all 5-m elevations within a local $100 \times 100$ m window (containing 400 cells, each of 5 m) centred on a single grid point. It should be noted that the local window size used for the calculation of the terrain roughness index is smaller than the sample intervals that correspond to 320-, 400-, or 480-m grid intervals. As a result, two neighbouring sample points would not share elevation grid points for the calculation of terrain roughness index. This ensured that terrain roughness index values of two neighbouring sample points were independently calculated.

To link terrain roughness to landform class, all grid points whose $5 \times 5$ cell neighbourhood window at the 5-m resolution was completely contained within only one landform class were selected. A 25-cell window was used in this step instead of a 400-cell window because an insufficient number of grid points had their $20 \times 20$ cell neighbourhoods completely contained within a single landform class. Based on these selected grid points, the summary statistics of terrain roughness index were then compared between different landform classes.

### 3.7 *Statistical analyses*

The one-to-one spatial correspondence of grid points across each of the sample sets meant that correlation analysis could be used to assess the effects of changing DEM resolution. For each pair of neighbouring and non-neighbouring resolutions in a set of comparisons, the Pearson correlation coefficient ($r$) was calculated for terrain attribute values derived at these two resolutions. All results for $r$ at the three DEM resolution sets were then represented in a single table or diagram to help evaluate the first hypothesis (section 3.1) and to identify: (1) how $r$ varies between attributes for pairs of resolutions over the wide range of DEM resolutions and (2) how terrain attributes vary in their responses to the resolution change. A linear regression was then applied to each resolution pair. These regression functions, in combination with the frequency distribution histograms of attribute differences caused by the resolution change, explain the variation of terrain attribute magnitudes over various resolutions.

The same statistical procedure was also applied to the sample points contained in each of the landform classes—defined by the procedure described in section 3.5—so as to evaluate the second null hypothesis and identify whether and how responses of terrain attributes to DEM resolution changes show differing patterns among landform classes. To confirm the statistical significance of the above analyses, a series of two-sample (with unequal variance) *t*-tests were performed between pairs of landform classes. Based on the significance of differences between sample means, the *t*-test provides an insight into whether two sample sets are from the same population. SAS was used for all the statistical analyses.

## 4. Results

### 4.1 *Landform classification and interpretation*

Six classification schemes containing 2, 3, 4, 5, 6, or 7 landform classes were generated and evaluated. The 4-class classification was judged the most useful for subsequent analysis because it differentiated the landform surface to the greatest extent on the basis of the seven classification attributes discussed in section 3.4 (see Deng and Wilson 2006, and Deng *et al.* in press b, for a detailed analysis of attribute selection and variable attribute weights). This conclusion was reached by calculating a partition coefficient, $F$, and a classification entropy, $H$, for each classification scheme and then comparing $F$ and $H$ between all classification schemes (cf. Burrough *et al.* 2000). The largest difference between $F$ and $H$ represents the greatest extent of differentiation in attribute space, and this was the case for the 4-class classification.

Table 1 presents the mean attribute values for the four landform classes. Landform classes one and two are distinguished from each other on the basis of oppositely directed NS values, and from landform classes 3 and 4 on the basis of slope steepness. Landform class 1 was therefore interpreted as 'steep north-facing slopes' whereas landform class 2 was interpreted as 'steep south-facing slopes'. Landform classes 3 and 4 both have gentle slopes and similar slope orientations, but class 4 has the gentlest slope gradients, lowest elevations, and greatest $A_s$ values. In contrast, class 3 has higher elevations, negative (i.e. convex) profile curvature, and the smallest $A_s$ values. Therefore, class 3 was interpreted as 'localized highlands' (i.e. ridges, crests, and hilltops), whereas class 4 was interpreted as 'lowland' features such as footslopes, valley bottoms, and stream channels. Interestingly, the mean elevation for class 3 is lower than classes 1 and 2. This is because steep slopes are

Table 1. Mean attribute values within each landform class.

| | Landform classes | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Elevation (m) | 450.43 | 426.32 | 336.91 | 249.58 |
| Slope (%) | 54.02 | 55.12 | 27.30 | 14.05 |
| $\ln(A_s)^a$ | 5.55 | 5.76 | 4.19 | 6.73 |
| Profile curvature | 0.3944 | 0.5145 | −0.4906 | 0.7311 |
| Plan curvature | −0.8024 | −0.9476 | 0.8894 | −0.9180 |
| NS | 0.6523 | −0.6681 | −0.0835 | −0.0652 |
| WE | −0.0421 | 0.0046 | −0.0099 | 0.0417 |

[a] $A_s$ is in $m^2$.

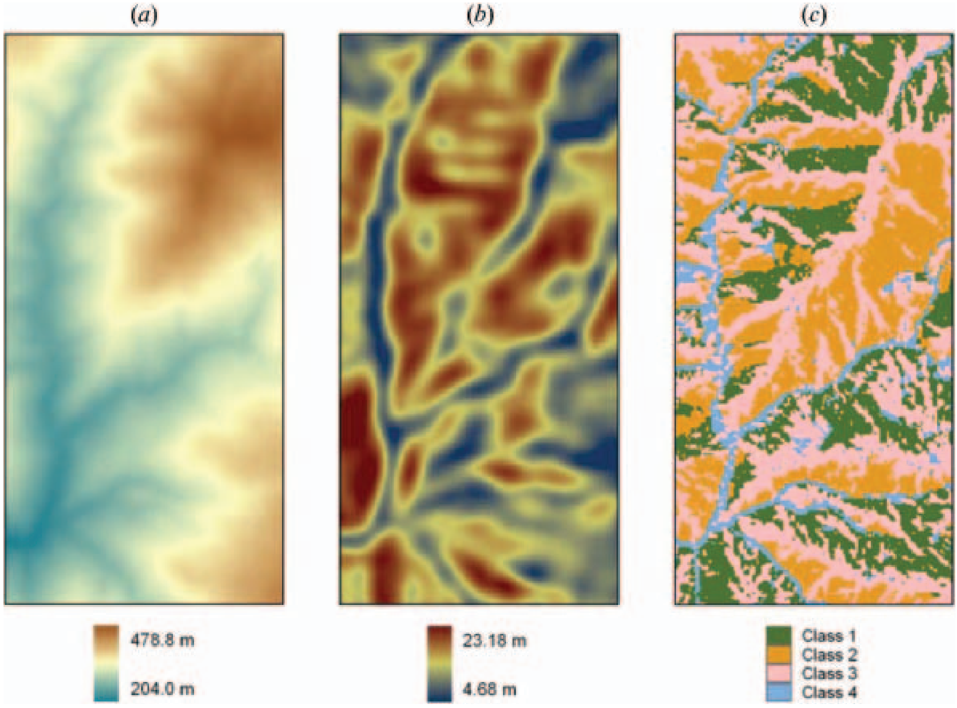



Figure 3. Comparison of 5-m DEM elevation (*a*), terrain surface roughness (*b*), and landform classes (*c*).



mostly located in high-elevation areas, whereas localized highlands occur throughout the landscape in high-, intermediate-, and low-elevation regions.

The above interpretation of landform classes was verified by visually comparing the landform class map (figure 3(*c*)) with the DEM (figure 3(*a*)). Stream channels, ridgelines, and north- and south-facing slopes observed on the DEM map were correctly classified into the aforementioned landform classes. Table 2 and figure 3(*b*) and (*c*) show that the landform classes can also be interpreted in terms of terrain surface roughness. Landform classes 1 and 2 have a much higher mean and maximum terrain surface roughness, indicating that the two steep landform classes display a large variation in elevation. Class 3 and class 4 have a much lower terrain surface roughness, indicating that they are relatively flatter than classes 1 and 2. This

Table 2. Correspondence between terrain surface roughness and landform classes.

| | Terrain surface roughness[a] | | | | |
|---|---|---|---|---|---|
| | Mean | SD | Maximum | Minimum | No. of samples[b] |
| Landform class 1 | 15.561 | 3.848 | 39.492 | 2.966 | 479 |
| Landform class 2 | 16.742 | 4.680 | 36.624 | 1.461 | 616 |
| Landform class 3 | 3.828 | 3.554 | 21.456 | 0 | 3415 |
| Landform class 4 | 1.416 | 1.549 | 15.468 | 0 | 1564 |

[a]Terrain surface roughness was calculated as the standard deviation of elevations in a $20 \times 20$ local window of the 5-m DEM.
[b]These samples include those grid points whose $5 \times 5$ neighbourhoods on the 5-m DEM are completely contained by one landform class.

is especially true for the case of class 4, which displays the lowest mean and standard deviation in terrain surface roughness, implying that this is a relatively homogeneous landform class.

### 4.2 *DEM resolution coarsening*

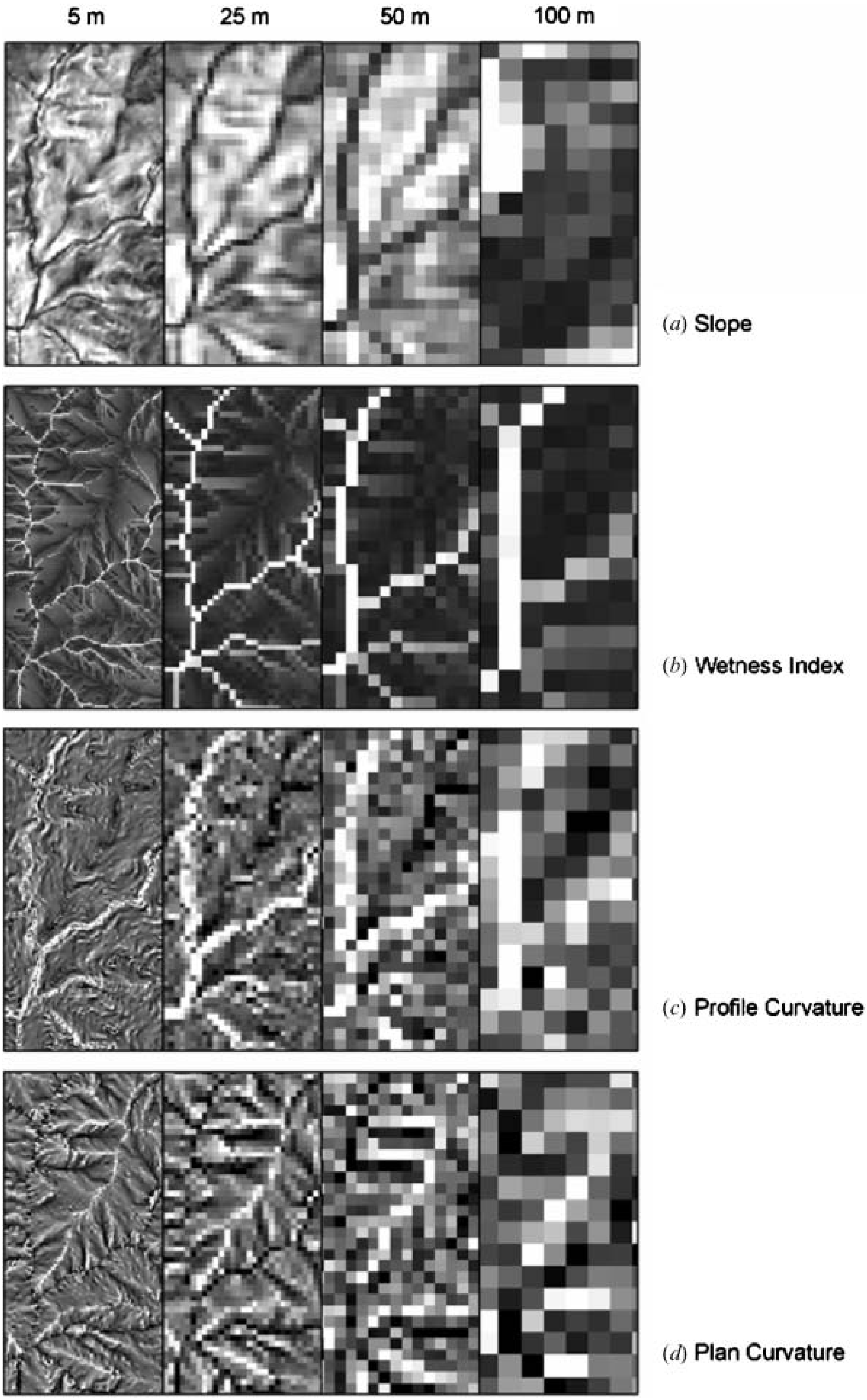
Terrain attributes centred on sample points were calculated for all resampled resolutions while maintaining the same set of 5-m grid-point elevations used at the outset. Hence, the variation in grid-point interval (i.e. resolution) is by default the dominant factor causing the differences in attribute values between DEMs of two resolutions. The effects of spatial sampling, resampling, and interpolation are avoided with this scheme.

Figure 4 shows that attribute values can vary dramatically with a change in resolution, even though the general pattern of attribute distribution is preserved across a range of resolutions. Summary statistics plotted in figure 5 show that terrain attributes vary in predictable ways as a function of DEM resolution. For example, both the mean and standard deviation of slope decrease slowly with the coarsening DEM resolution, while maximum slope decreases sharply. This sharp decrease in maximum slope may be explained, in part, by the small-scale ruggedness of topography in the study area. In contrast, all statistics involving $W$ tend to increase with coarsening resolution, and this is especially true for the mean, minimum, and maximum. This may be related to the fact that $W$ is a ratio and that: (1) calculated slope decreases with coarsening resolution; and (2) minimum $A_s$ increases with coarsening resolution. Large variations in the maximum and minimum profile curvature and plan curvature are apparent in figure 5, although the mean and standard deviation of these two attributes vary little with the resolution change. This indicates that the incidence of convex slopes is similar to that of concave slopes at all resolutions. More importantly, for this landscape type, plan and profile curvatures calculated from coarsening resolutions lead to a false conclusion that the topography is much smoother and gently rounded than it actually is.

### 4.3 *Attribute correlations across resolutions*

The Pearson correlation coefficient ($r$) was used to describe the nature (i.e. positive or negative) and strength (i.e. magnitude) of association between each of the resolution pairs within the three sample data sets (section 3.3). Large positive values of $r$ suggest that there is little difference between attribute values calculated for pairs of spatial resolution. Figure 6 and table 3 show that the coarsening DEM resolution causes a consistent decrease in $r$ for all analysed terrain attributes. This is contrary to the first null hypothesis in section 3.1 and indicates that the values of terrain attributes calculated for coarser grid intervals begin to deviate in a consistent way from those calculated at 5-m grid intervals. Decreasing values of $r$ with coarser resolutions also indicate that the exact manner in which the attribute deviates from the fine-resolution case becomes less predictable (i.e. decreasing correlation). It is noteworthy that for this landscape, all calculated $r$ values between the compared resolutions (5–480 m) were positive for all the evaluated attributes. This finding may

Figure 4. Distribution patterns of terrain attributes at different spatial resolutions. All maps cover the same area as figure 3. Light colours represent larger values, and dark colours represent smaller values.


5 m
25 m
50 m
100 m
(a) Slope
(b) Wetness Index
(c) Profile Curvature
(d) Plan Curvature

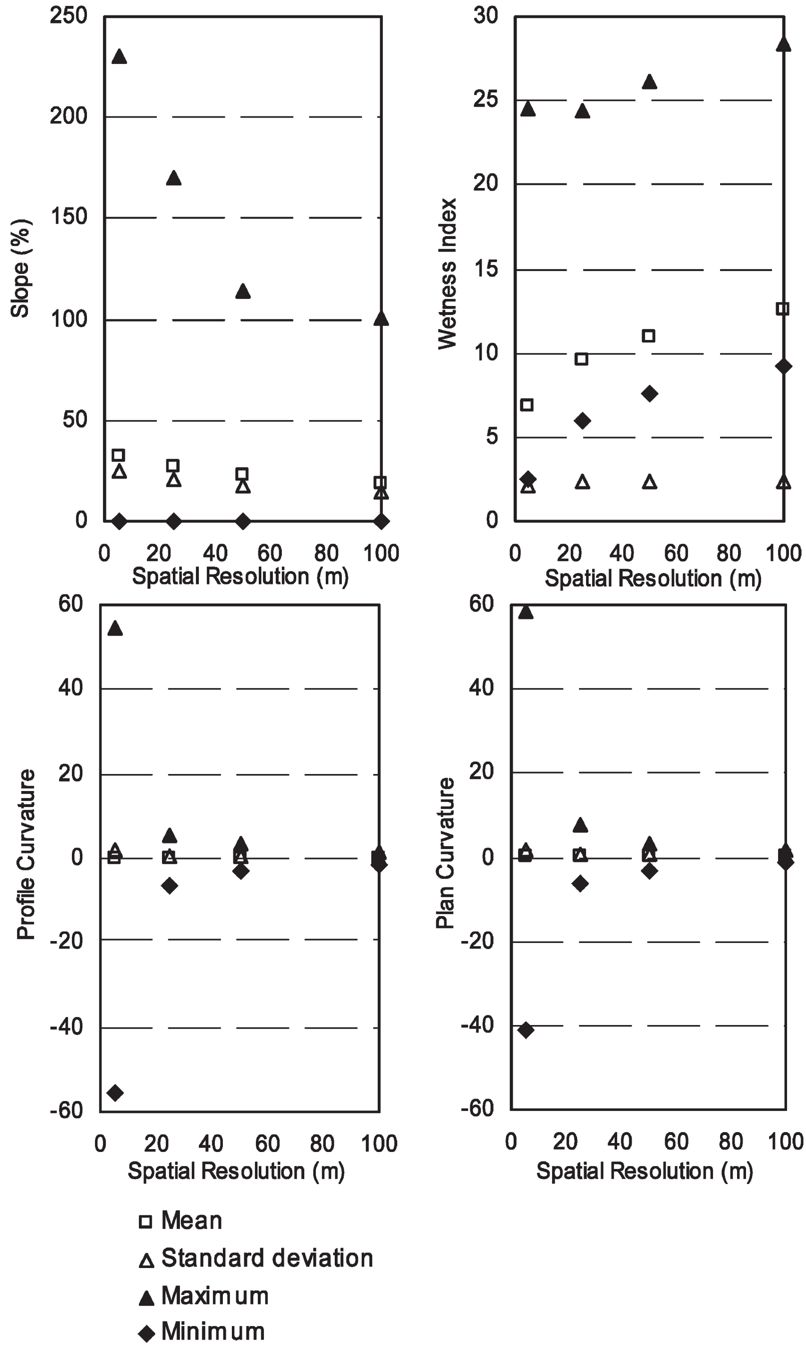



Figure 5. DEM resolutions (5 m, 25 m, 50 m, and 100 m) and statistical variation of terrain attributes—slope (*a*), topographic wetness index (*b*), profile curvature (*c*), and plan curvature (*d*). The statistics were calculated from the same set of points (96 100 samples) that correspond to the DEM grid points at the 100-m spatial resolution.

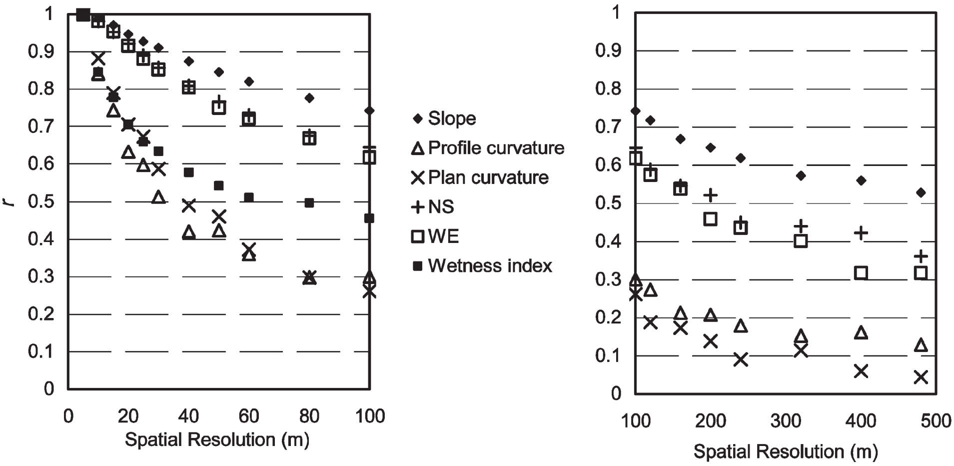



Figure 6. Pearson correlation coefficients ($r$) between terrain attributes of 5 m and other resolutions. Three sets of sample points are used, corresponding to 320-m grid points (9378 samples), 400-m grid points (6002 samples), and 480-m grid points (4171 samples), respectively.



Table 3. Pearson correlation coefficients ($r$) between attributes of different resolutions.

| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 | 80 | 100 | 120 | 160 | 200 | 240 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *(a) Slope* | | | | | | | | | | | | | | | |
| 10 | 0.99 | | | | | | | | | | | | | | |
| 15 | 0.97 | | | | | | | | | | | | | | |
| 20 | 0.95 | 0.98 | | | | | | | | | | | | | |
| 25 | 0.93 | | | | | | | | | | | | | | |
| 30 | 0.91 | | 0.97 | | | | | | | | | | | | |
| 40 | 0.87 | 0.91 | | 0.96 | | | | | | | | | | | |
| 50 | 0.85 | | | | 0.95 | | | | | | | | | | |
| 60 | 0.82 | | 0.87 | | | 0.94 | | | | | | | | | |
| 80 | 0.78 | 0.80 | | 0.85 | | | 0.92 | | | | | | | | |
| 100 | 0.74 | | | | 0.82 | | | 0.91 | | | | | | | |
| 120 | 0.72 | | 0.75 | | | 0.81 | | | 0.90 | | | | | | |
| 160 | 0.67 | 0.69 | | 0.72 | | | 0.77 | | | 0.88 | | | | | |
| 200 | 0.65 | | | | 0.70 | | | 0.76 | | | 0.87 | | | | |
| 240 | 0.62 | | 0.65 | | | 0.68 | | | 0.74 | | | 0.86 | | | |
| 320 | 0.57 | 0.59 | | 0.61 | | | 0.65 | | | 0.72 | | | 0.85 | | |
| 400 | 0.56 | | | | 0.59 | | | 0.63 | | | 0.70 | | | 0.82 | |
| 480 | 0.53 | | 0.55 | | | 0.58 | | | 0.61 | | | 0.67 | | | 0.82 |
| *(b) Profile curvature* | | | | | | | | | | | | | | | |
| 10 | 0.84 | | | | | | | | | | | | | | |
| 15 | 0.74 | | | | | | | | | | | | | | |
| 20 | 0.63 | 0.85 | | | | | | | | | | | | | |
| 25 | 0.60 | | | | | | | | | | | | | | |
| 30 | 0.51 | | 0.82 | | | | | | | | | | | | |
| 40 | 0.42 | 0.59 | | 0.81 | | | | | | | | | | | |
| 50 | 0.42 | | | | 0.81 | | | | | | | | | | |
| 60 | 0.36 | | 0.59 | | | 0.81 | | | | | | | | | |
| 80 | 0.30 | 0.42 | | 0.59 | | | 0.79 | | | | | | | | |
| 100 | 0.30 | | | | 0.58 | | | 0.77 | | | | | | | |
| 120 | 0.27 | | 0.43 | | | 0.57 | | | 0.77 | | | | | | |

Table 3. *(Continued)*.

| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 | 80 | 100 | 120 | 160 | 200 | 240 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 160 | 0.21 | 0.30 | | 0.43 | | | 0.57 | | | 0.75 | | | | | |
| 200 | 0.21 | | | | 0.43 | | | 0.56 | | | 0.74 | | | | |
| 240 | 0.18 | | 0.29 | | | 0.39 | | | 0.55 | | | 0.74 | | | |
| 320 | 0.15 | 0.23 | | 0.32 | | | 0.44 | | | 0.56 | | | 0.73 | | |
| 400 | 0.16 | | | | 0.33 | | | 0.43 | | | 0.55 | | | 0.72 | |
| 480 | 0.13 | | 0.21 | | | 0.28 | | | 0.41 | | | 0.55 | | | 0.72 |
| *(c) Plan curvature* | | | | | | | | | | | | | | | |
| 10 | 0.88 | | | | | | | | | | | | | | |
| 15 | 0.79 | | | | | | | | | | | | | | |
| 20 | 0.71 | 0.88 | | | | | | | | | | | | | |
| 25 | 0.67 | | | | | | | | | | | | | | |
| 30 | 0.59 | | 0.85 | | | | | | | | | | | | |
| 40 | 0.49 | 0.64 | | 0.82 | | | | | | | | | | | |
| 50 | 0.46 | | | | 0.82 | | | | | | | | | | |
| 60 | 0.37 | | 0.57 | | | 0.79 | | | | | | | | | |
| 80 | 0.30 | 0.38 | | 0.52 | | | 0.77 | | | | | | | | |
| 100 | 0.26 | | | | 0.51 | | | 0.74 | | | | | | | |
| 120 | 0.19 | | 0.32 | | | 0.46 | | | 0.73 | | | | | | |
| 160 | 0.17 | 0.22 | | 0.30 | | | 0.45 | | | 0.71 | | | | | |
| 200 | 0.14 | | | | 0.28 | | | 0.44 | | | 0.72 | | | | |
| 240 | 0.09 | | 0.17 | | | 0.27 | | | 0.46 | | | 0.72 | | | |
| 320 | 0.11 | 0.15 | | 0.19 | | | 0.28 | | | 0.45 | | | 0.70 | | |
| 400 | 0.06 | | | | 0.15 | | | 0.26 | | | 0.43 | | | 0.68 | |
| 480 | 0.04 | | 0.09 | | | 0.15 | | | 0.28 | | | 0.46 | | | 0.68 |
| *(d) NS* | | | | | | | | | | | | | | | |
| 10 | 0.98 | | | | | | | | | | | | | | |
| 15 | 0.95 | | | | | | | | | | | | | | |
| 20 | 0.92 | 0.96 | | | | | | | | | | | | | |
| 25 | 0.89 | | | | | | | | | | | | | | |
| 30 | 0.86 | | 0.93 | | | | | | | | | | | | |
| 40 | 0.81 | 0.84 | | 0.92 | | | | | | | | | | | |
| 50 | 0.77 | | | | 0.90 | | | | | | | | | | |
| 60 | 0.73 | | 0.80 | | | 0.90 | | | | | | | | | |
| 80 | 0.68 | 0.70 | | 0.77 | | | 0.88 | | | | | | | | |
| 100 | 0.65 | | | | 0.76 | | | 0.88 | | | | | | | |
| 120 | 0.59 | | 0.65 | | | 0.73 | | | 0.87 | | | | | | |
| 160 | 0.55 | 0.57 | | 0.63 | | | 0.72 | | | 0.86 | | | | | |
| 200 | 0.52 | | | | 0.62 | | | 0.72 | | | 0.85 | | | | |
| 240 | 0.45 | | 0.50 | | | 0.57 | | | 0.69 | | | 0.83 | | | |
| 320 | 0.44 | 0.46 | | 0.51 | | | 0.58 | | | 0.69 | | | 0.83 | | |
| 400 | 0.42 | | | | 0.50 | | | 0.57 | | | 0.68 | | | 0.81 | |
| 480 | 0.36 | | 0.41 | | | 0.46 | | | 0.56 | | | 0.66 | | | 0.81 |
| *(e) WE* | | | | | | | | | | | | | | | |
| 10 | 0.98 | | | | | | | | | | | | | | |
| 15 | 0.95 | | | | | | | | | | | | | | |
| 20 | 0.92 | 0.95 | | | | | | | | | | | | | |
| 25 | 0.88 | | | | | | | | | | | | | | |
| 30 | 0.85 | | 0.93 | | | | | | | | | | | | |
| 40 | 0.80 | 0.84 | | 0.91 | | | | | | | | | | | |
| 50 | 0.75 | | | | 0.90 | | | | | | | | | | |
| 60 | 0.72 | | 0.79 | | | 0.90 | | | | | | | | | |
| 80 | 0.67 | 0.70 | | 0.76 | | | 0.88 | | | | | | | | |
| 100 | 0.62 | | | | 0.74 | | | 0.87 | | | | | | | |
| 120 | 0.57 | | 0.63 | | | 0.73 | | | 0.86 | | | | | | |
| 160 | 0.54 | 0.56 | | 0.62 | | | 0.71 | | | 0.84 | | | | | |

Table 3. *(Continued)*.

| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 | 80 | 100 | 120 | 160 | 200 | 240 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 200 | 0.46 | | | | 0.56 | | | 0.66 | | | 0.81 | | | | |
| 240 | 0.44 | | 0.48 | | | 0.54 | | | 0.65 | | | 0.79 | | | |
| 320 | 0.40 | 0.42 | | 0.46 | | | 0.53 | | | 0.63 | | | 0.78 | | |
| 400 | 0.32 | | | | 0.39 | | | 0.47 | | | 0.57 | | | 0.76 | |
| 480 | 0.32 | | 0.35 | | | 0.39 | | | 0.47 | | | 0.57 | | | 0.74 |
| *(f) Wetness* | | | | | | | | | | | | | | | |
| 10 | 0.85 | | | | | | | | | | | | | | |
| 15 | 0.78 | | | | | | | | | | | | | | |
| 20 | 0.71 | 0.81 | | | | | | | | | | | | | |
| 25 | 0.66 | | | | | | | | | | | | | | |
| 30 | 0.63 | | 0.79 | | | | | | | | | | | | |
| 40 | 0.58 | 0.66 | | 0.78 | | | | | | | | | | | |
| 50 | 0.54 | | | | 0.77 | | | | | | | | | | |
| 60 | 0.51 | | 0.62 | | | 0.77 | | | | | | | | | |
| 80 | 0.50 | 0.55 | | 0.64 | | | 0.78 | | | | | | | | |
| 100 | 0.46 | | | | 0.63 | | | 0.77 | | | | | | | |
| 120 | 0.46 | | 0.54 | | | 0.63 | | | 0.77 | | | | | | |

be explained by the generally rugged terrain surface shape in this landscape, which displays increasing randomness across greater distances. However, this observation needs to be revisited in other landscapes (e.g. flatter landscapes).

The six attributes shown in figure 6 display different trends in $r$ with coarsening resolution. Slope displays the smallest reduction in $r$, from 1.00 to a value of 0.53 at 480 m spacing. This indicates that slope values calculated at very coarse resolutions (such as 400 m and 480 m) are reasonably well correlated to the 5-m slope values in this landscape, which may be explained by the ubiquitous high-relief topography characterized by long, steep slopes. Wetness index, $W$, on the other hand, shows a much sharper decrease in $r$, which is quite pronounced even from 5 m to 10 m ($r$=0.85). Thus, the threshold DEM resolution for the calculation of $W$ in this landscape may need to be defined as <10 m or even 5 m. This finding affirms the previous findings that the calculation of $W$ is very sensitive to DEM resolution (Zhang and Montgomery 1994, Florinsky and Kuryakova 2000). However, this sensitivity may be highly dependent on the type of landscape, a point that will be discussed later. A large amount of variability exists between attributes within the resolution range of 5–20 m, which was identified by Kienzle (2004) as the optimal range for representation of terrain information in the Rocky Mountain foothills and Great Plains. For example, the 20-m $W$ shows a relatively weak correlation with 5-m $W$ ($r$=0.73) in our study area, whereas for slope, $r$ is 0.95 between the 5 m and 20 m resolutions. Correlation trends for aspect (NS and WE) are similar to those of slope with relatively large $r$ up to a resolution of 200 m. Profile and plan curvatures show the sharpest drop of $r$ among all attributes, even at fine resolutions, and at coarse resolutions the correlation is very poor to fine-resolution values. In combination, these results indicate that the depiction of terrain surface shape in this rugged landscape is highly sensitive to spatial resolution of the DEM, which suggests that caution needs to be exercised when extracting landscape characteristics from a DEM for purposes of environmental modelling.

A series of linear regression analyses between all combinations of spatial resolutions were performed using only slope and $W$ to assess terrain attribute value changes with varying DEM resolution. The results for slope show that the gain, $b$, in

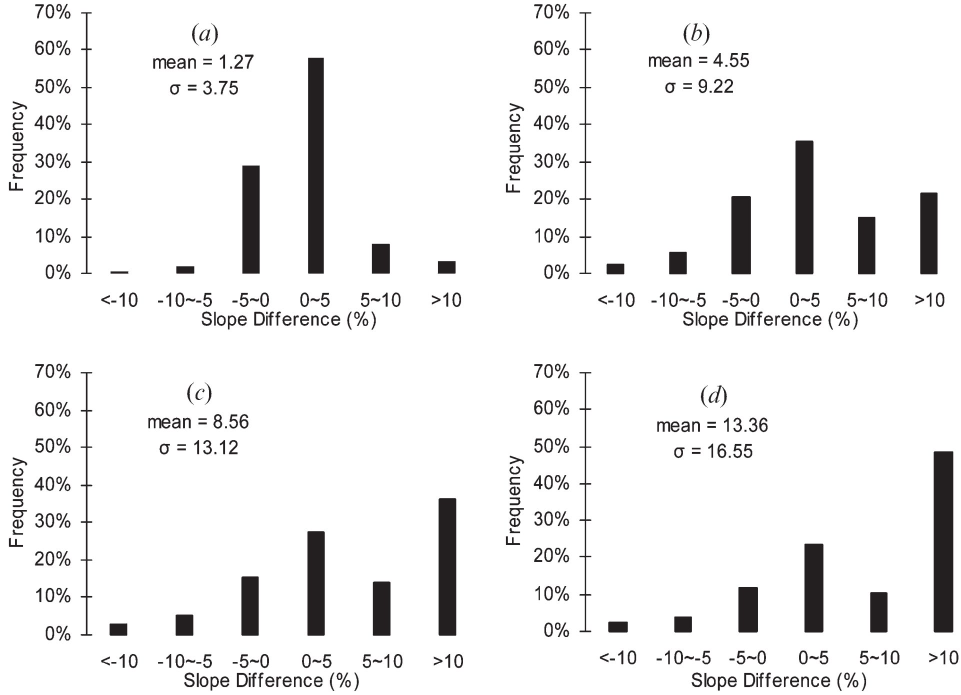



Figure 7. Frequency distributions of slope differences between 5 m and other resolutions: (*a*) 10 m, (*b*) 25 m, (*c*) 50 m, and (*d*) 100 m. The values on the *x*-axis are obtained by subtracting slopes for the aforementioned DEM resolutions from slopes derived with the 5-m DEM on a point-to-point basis.

$y = a + bx$ (where $y$ is the value of slope calculated at fine resolution, and $x$ is the slope calculated at a coarse resolution) is always larger than 1, whereas the offset, $a$, is always positive. In addition, there is a consistent increase in the values of $a$ and $b$ with the coarsening of spatial resolution. This reaffirms that slope values calculated at a coarse resolution (up to 480 m) are consistently smaller than those calculated at fine resolution in this landscape. The results for $W$, on the other hand, show a consistent decrease in $b$ while the change in $a$ is relatively small and inconsistent, indicating a consistent increase in $W$ values with the coarsening of DEM resolution. However, this conclusion (for $W$) is based on a relatively low confidence level (table 3f).

The trends discussed above are supported by frequency histograms of slope and $W$ variations with change in DEM resolution (figures 7 and 8). Figure 7 shows that the difference in slope values between pairs of DEMs at differing resolutions becomes increasingly positive with coarser resolution, which supports the conclusion that calculated slope values decrease consistently with the coarsening resolution. However, the existence of negative differences indicates that this generalization cannot be applied to all grid points. In contrast, figure 8 displays a shift toward negative difference values for $W$, which indicates that $W$ values consistently increase with progressive coarsening of DEM resolution.

### 4.4 *Landform-specific patterns of correlation decrease*

Figure 9 presents the coefficient of determination $r^2$ between terrain attributes of 5 m and the other resolutions for each of the four landform classes separately. $r^2$ (instead

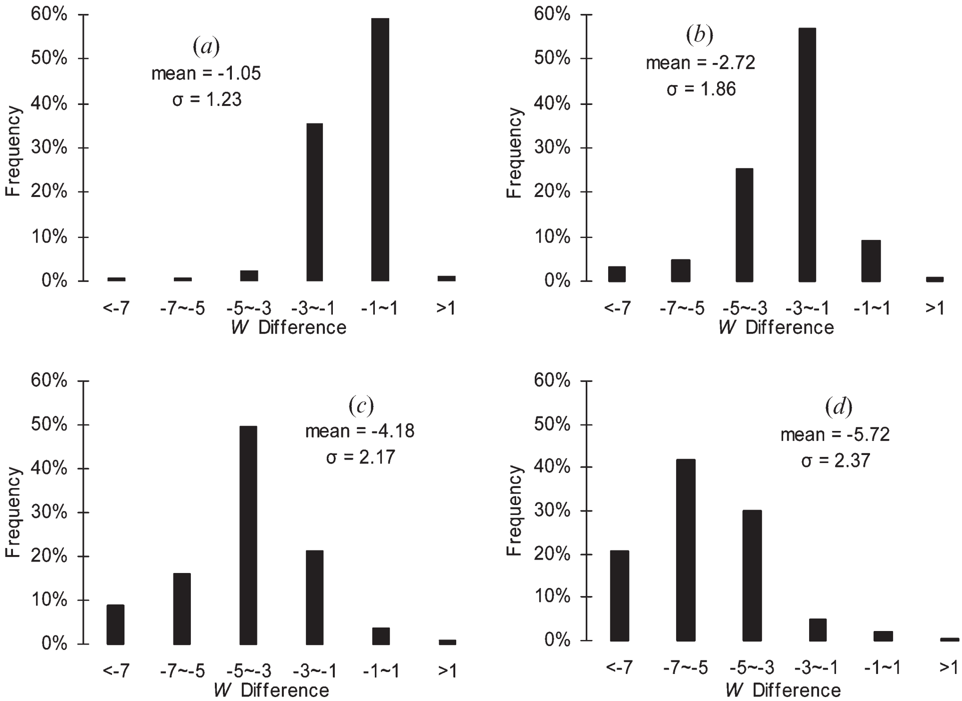



Figure 8. Frequency distributions of $W$ differences between 5 m and other resolutions: (*a*) 10 m, (*b*) 25 m, (*c*) 50 m, and (*d*) 100 m. The values on the $x$-axis are obtained by subtracting $W$ for the aforementioned DEM resolutions from $W$ derived with the 5-m DEM on a point-to-point basis.

of $r$) was used in figure 9 to visually exaggerate the difference in correlation when $r$ is positive and close to 1. Different patterns of $r^2$ decrease are evident between landform classes for all attributes when the DEM resolution is coarsened from 5 m to 480 m. This observation addresses the second null hypothesis and supports the general conclusion that different responses to resolution change occur for different landform classes, at least for the six analysed terrain attributes in the current study area. Tables 4 and 5 contrast the different patterns of correlation ($r$) decrease for landform classes 1 and 3 using slope and $W$ as examples. The general conclusion that $r$ decreases in a different way as a function of landform class holds true not only between 5 m and other resolutions, but also between all compared pairs of resolutions. The same characteristic was observed for other terrain attributes, although those results are not presented here.

Figure 9 shows that very different patterns of decrease in $r^2$ are evident from one terrain attribute to another. Slope displays the largest variation between landform classes. Landform classes 1 and 2, corresponding to steep south- and north-facing slopes, show a similar pattern of $r^2$ decrease pattern, and the same is true for landform classes 3 and 4. Slopes on landform classes 1 and 2 were much more sensitive to resolution change, especially when the resolution was coarser than 15 m. Beyond the 50 m resolution, calculated slopes on classes 1 and 2 show very low correlations with the 5 m slopes. $W$ showed similar patterns to slope: $W$ on landform classes 1 and 2 is more sensitive to DEM resolution change. However, a sharp drop in $r^2$ between 5 m and 10 m was observed on all landform classes, and very low $r^2$

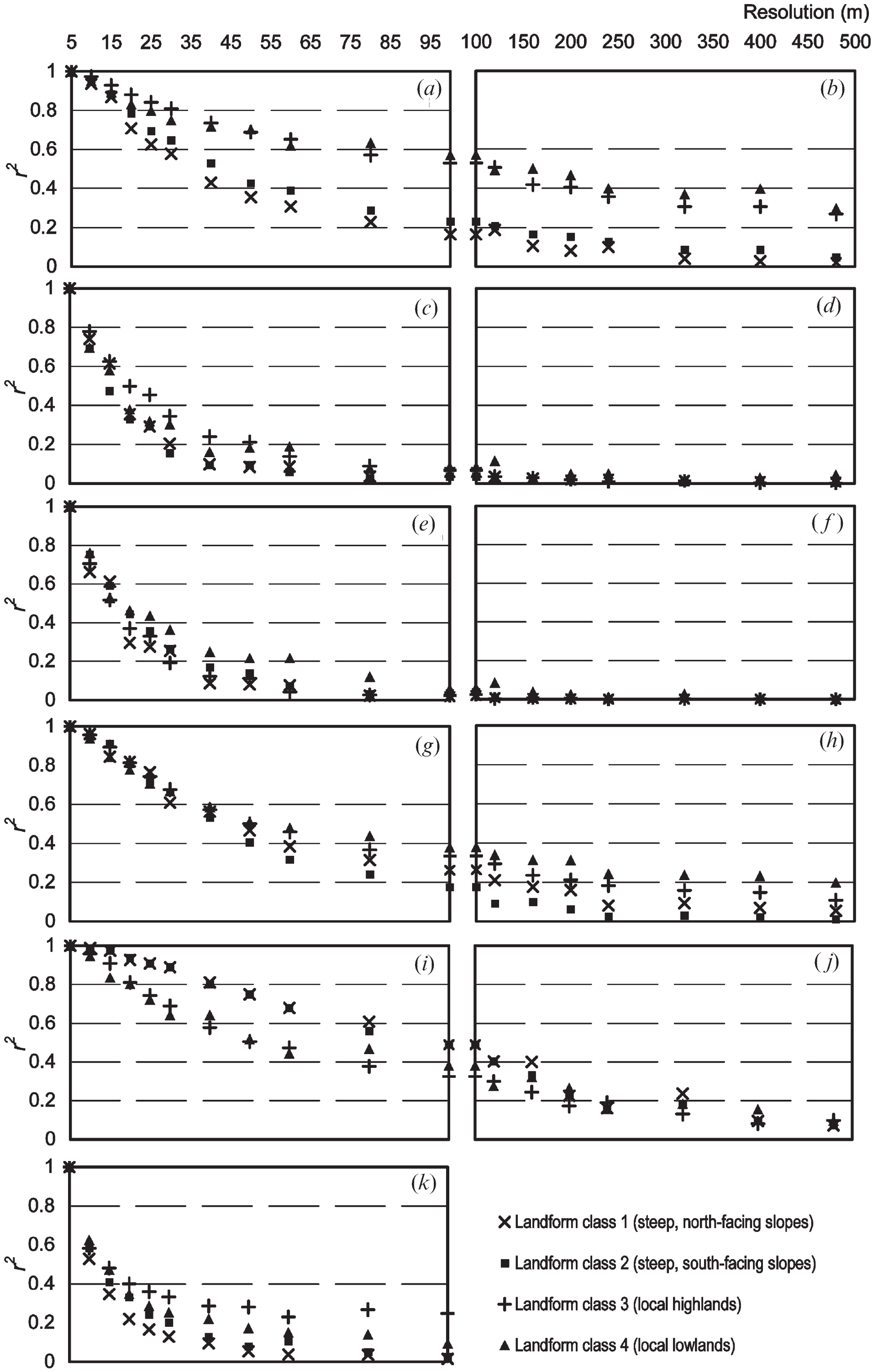



Figure 9. Landscape variation of the coefficient of determination ($r^2$) between terrain attributes of 5 m and other resolutions (all $r$ values are positive). Graphs (*a*) and (*b*) are for slope, (*c*) and (*d*) are for profile curvature, (*e*) and (*f*) are for plan curvature, (*g*) and (*h*) are for *NS*, (*i*) and (*j*) are for *WE*, and (*k*) is for *W*.

Table 4. Correlation coefficients ($r$) between slopes of various resolutions on (a) landform class 1 and (b) landform class 3[a].

| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 | 80 | 100 | 120 | 160 | 200 | 240 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *(a) Landform class 1* | | | | | | | | | | | | | | | |
| 10 | 0.97 | | | | | | | | | | | | | | |
| 15 | 0.93 | | | | | | | | | | | | | | |
| 20 | 0.84 | 0.93 | | | | | | | | | | | | | |
| 25 | 0.79 | | | | | | | | | | | | | | |
| 30 | 0.76 | | 0.90 | | | | | | | | | | | | |
| 40 | 0.66 | 0.75 | | 0.90 | | | | | | | | | | | |
| 50 | 0.60 | | | | 0.88 | | | | | | | | | | |
| 60 | 0.55 | | 0.68 | | | 0.86 | | | | | | | | | |
| 80 | 0.48 | 0.55 | | 0.67 | | | 0.84 | | | | | | | | |
| 100 | 0.41 | | | | 0.61 | | | 0.82 | | | | | | | |
| 120 | 0.43 | | 0.51 | | | 0.62 | | | 0.81 | | | | | | |
| 160 | 0.32 | 0.37 | | 0.43 | | | 0.54 | | | 0.76 | | | | | |
| 200 | 0.28 | | | | 0.42 | | | 0.57 | | | 0.80 | | | | |
| 240 | 0.32 | | 0.39 | | | 0.47 | | | 0.57 | | | 0.77 | | | |
| 320 | 0.20 | 0.22 | | 0.27 | | | 0.34 | | | 0.49 | | | 0.76 | | |
| 400 | 0.16 | | | | 0.26 | | | 0.37 | | | 0.51 | | | 0.74 | |
| 480 | 0.14 | | 0.21 | | | 0.28 | | | 0.35 | | | 0.47 | | | 0.72 |
| *(b) Landform class 1* | | | | | | | | | | | | | | | |
| 10 | 0.99 | | | | | | | | | | | | | | |
| 15 | 0.96 | | | | | | | | | | | | | | |
| 20 | 0.94 | 0.97 | | | | | | | | | | | | | |
| 25 | 0.92 | | | | | | | | | | | | | | |
| 30 | 0.90 | | 0.96 | | | | | | | | | | | | |
| 40 | 0.86 | 0.89 | | 0.95 | | | | | | | | | | | |
| 50 | 0.83 | | | | 0.94 | | | | | | | | | | |
| 60 | 0.81 | | 0.86 | | | 0.93 | | | | | | | | | |
| 80 | 0.76 | 0.78 | | 0.83 | | | 0.92 | | | | | | | | |
| 100 | 0.73 | | | | 0.81 | | | 0.91 | | | | | | | |
| 120 | 0.71 | | 0.75 | | | 0.80 | | | 0.90 | | | | | | |
| 160 | 0.65 | 0.67 | | 0.70 | | | 0.76 | | | 0.88 | | | | | |
| 200 | 0.64 | | | | 0.69 | | | 0.76 | | | 0.87 | | | | |
| 240 | 0.60 | | 0.63 | | | 0.66 | | | 0.73 | | | 0.85 | | | |
| 320 | 0.55 | 0.57 | | 0.60 | | | 0.64 | | | 0.71 | | | 0.84 | | |
| 400 | 0.55 | | | | 0.59 | | | 0.64 | | | 0.70 | | | 0.83 | |
| 480 | 0.52 | | 0.54 | | | 0.56 | | | 0.61 | | | 0.67 | | | 0.81 |

[a]Class 1 represents north-facing slopes, and class 3 represents local lowlands (valley bottoms, stream channels, and coastal plains).

values were calculated for all resolutions coarser than 15 m on all landform classes, indicating that it is probably inappropriate to calculate $W$ at a resolution coarser than 15 m in all landscape types of the study area. The differentiation between landform classes was also less pronounced for $W$ than for slope.

Profile and plan curvatures experienced a relatively sharp $r^2$ decrease for all landform classes. Profile curvature on landform class 3—ridgelines and local highlands—was slightly less sensitive to resolution change than other classes, and plan curvature on landform class 4—valley bottoms and stream channels—was slightly less sensitive to the resolution change than other classes. These characteristics may be explained by the fact that similar concave plan curvatures in the valley bottoms and convex profile curvatures on hilltops and ridgelines can be

Table 5. Correlation coefficients ($r$) between $W$ of various resolutions on (a) landform class 1 and (b) landform class 3[a].

| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 |
|---|---|---|---|---|---|---|---|---|---|
| *(a) Landform class 1* | | | | | | | | | |
| 10 | 0.73 | | | | | | | | |
| 15 | 0.59 | | | | | | | | |
| 20 | 0.47 | 0.65 | | | | | | | |
| 25 | 0.41 | | | | | | | | |
| 30 | 0.36 | | 0.65 | | | | | | |
| 40 | 0.31 | 0.43 | | 0.70 | | | | | |
| 50 | 0.23 | | | | 0.70 | | | | |
| 60 | 0.19 | | 0.39 | | | 0.68 | | | |
| 80 | 0.19 | 0.27 | | 0.48 | | | 0.72 | | |
| 100 | 0.12 | | | | 0.44 | | | 0.67 | |
| 120 | 0.11 | | 0.23 | | | 0.32 | | | 0.52 |
| *(b) Landform class 3* | | | | | | | | | |
| Resolution (m) | 5 | 10 | 15 | 20 | 25 | 30 | 40 | 50 | 60 |
| 10 | 0.76 | | | | | | | | |
| 15 | 0.69 | | | | | | | | |
| 20 | 0.63 | 0.75 | | | | | | | |
| 25 | 0.60 | | | | | | | | |
| 30 | 0.58 | | 0.73 | | | | | | |
| 40 | 0.53 | 0.59 | | 0.73 | | | | | |
| 50 | 0.53 | | | | 0.74 | | | | |
| 60 | 0.48 | | 0.56 | | | 0.73 | | | |
| 80 | 0.52 | 0.54 | | 0.61 | | | 0.76 | | |
| 100 | 0.50 | | | | 0.61 | | | 0.73 | |
| 120 | 0.48 | | 0.51 | | | 0.59 | | | 0.74 |

[a]Class 1 represents north-facing slopes, and class 3 represents local lowlands (valley bottoms, stream channels, and coastal plains).



observed at a wider range of DEM resolutions. The class differentiation for the two curvatures is most pronounced at a resolution range of 20–60 m. However, curvatures at resolutions coarser than 30–40 m have a very low or no correlation with the 5-m curvatures on all landform classes, indicating that coarser-resolution curvatures depict a different terrain shape from that observed at the 5 m resolution.

*WE* experienced two patterns of $r^2$ decrease at a 20–120-m resolution range: landform classes 3 and 4 experienced a greater change (i.e. a higher sensitivity) than classes 1 and 2. This pattern may be a consequence of the density and magnitude of north–south-oriented stream channels and corresponding ridgelines (figure 2) in this particular study area.

### 4.5 t-*tests on selected attributes and resolutions*

In order to address the second null hypothesis, a series of $t$-tests were conducted to confirm the general, empirical observation obtained from section 4.4 that terrain attributes of different landform classes respond differently to the resolution change. The slope difference and $W$ difference between 5-m and several selected resolutions—10, 25, 50, and 100 m—were compared for each pair of landform classes. Only grid points whose entire $5 \times 5$ cell neighbouring areas on the 5-m DEM were completely contained by one landform class were selected for these $t$-tests. This

Table 6. Two-tailed $t$-tests for the slope differences between landform classes using the 5-m and four other resolutions: (a) 10 m, (b) 25 m, (c) 50 m, and (d) 100 m[a].

(a)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 3.06 | | |
| | 3 | 9.25 | 7.17 | |
| | 4 | 13.66 | 12.62 | 8.83 |

(b)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 2.28 | | |
| | 3 | 11.70 | 9.79 | |
| | 4 | 18.03 | 16.80 | 12.74 |

(c)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 1.09 | | |
| | 3 | 15.84 | 15.43 | |
| | 4 | 24.38 | 24.54 | 16.97 |

(d)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 0.74 | | |
| | 3 | 21.83 | 22.10 | |
| | 4 | 31.95 | 32.76 | 19.13 |

[a]All four pairs of variables had unequal variances, and the critical $t$ value is 2.58 ($\alpha$=0.01).

effectively reduces the influence of spatial heterogeneity (noise) present in landform class patterns (figure 3c), which often arises after non-hierarchical clustering of local terrain attributes. The resultant numbers of tested sample grid points are 479, 616, 3415, and 1564 for classes 1, 2, 3, and 4 (section 4.1), respectively. The results of the $t$-tests are reported in table 6 for slope and table 7 for $W$.

The null hypothesis of no difference between the means for slope could not be rejected for landform classes 1 and 2, indicating similarity in response of slope to resolution change. However, the null hypothesis was rejected for all other combinations of landform classes because the differences were so large that they could not have occurred by chance if the two samples were drawn from the same population. This result shows that slope calculations respond differently to a DEM resolution change on steep slopes (classes 1 and 2), local highlands (class 3), and local lowlands (class 4). Table 7 shows that the response of $W$ to DEM resolution change is relatively uniform for landform classes 1, 2, and 4. However, landform class 3—local highlands or ridgelines—gave significantly different responses from all

Table 7. Two-tail $t$-tests for the $W$ differences between landform classes using the 5-m and four other resolutions: (a) 10 m, (b) 25 m, (c) 50 m, and (d) 100 m[a].

(a)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 0.09 | | |
| | 3 | 9.14 | 9.12 | |
| | 4 | 0.81 | 0.88 | 5.95 |

(b)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 0.77 | | |
| | 3 | 11.94 | 13.19 | |
| | 4 | 0.23 | 0.40 | 9.43 |

(c)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 1.43 | | |
| | 3 | 15.94 | 17.85 | |
| | 4 | 1.76 | 0.55 | 14.70 |

(d)

| | | Class 1 | Class 2 | Class 3 |
|---|---|---|---|---|
| Class | 2 | 1.84 | | |
| | 3 | 18.66 | 21.14 | |
| | 4 | 3.25 | 1.73 | 18.23 |

[a]All four pairs of variables had unequal variances, and the critical $t$ value is 2.58 ($\alpha$=0.01).



other classes across all resolutions. This suggests that the topographic wetness index is very sensitive to the resolution used to identify the ridgelines or hilltops where flow accumulation starts, and the second hypothesis in section 3.1 can be rejected for $W$. The different results presented for slope and $W$ also indicate that the landscape variation of resolution dependency varies from one terrain attribute to the next.

## 5. Conclusions

The research reported in this paper documents how scale dependencies in terrain analysis vary across landscape types (i.e. classes). Interpretable landform classes were defined in a reproducible way using an unsupervised landform clustering procedure. Distinguishable responses for various landform classes were described empirically using correlation and regression analyses and tested for significance using $t$-tests. In this way, a formal description of the connection between landform locations and variable scale dependencies of terrain attributes was provided for the studied landscape. The manner in which grid resolution was resampled and the analysed grid points were held constant in location ensures that all statistical summaries and empirical comparisons are based on the same spatial sample sets, even though more than one sample set was used, and the results were combined. This allowed point-to-point comparisons or correlations to be conducted between attributes of various resolutions.

On the basis of this study, the following conclusions for this particular landscape type were reached:

1. Terrain attributes respond to resolution change in characteristically different ways, especially when the resolution is coarsened in the range of 5–50 m. Plan and profile curvatures are the most sensitive among the tested attributes, whereas slope is the least sensitive.
2. Consistently smaller correlations were observed across all terrain attributes when the pairs of DEM resolution compared were increasingly distant from each other.
3. Large differences were observed between 5 and 10 m *W* on all landform classes, signifying that 10 m may be too coarse a resolution for *W* modelling, at least for this landscape.

Further research is required to test *W* variation over a more continuous range of fine resolutions beginning at 1 or 2 m, and in other landscapes. These findings are based on the landscapes that are found in the Santa Monica Mountains, and care should be taken when they are directly applied to other landscapes: further testing or landscape comparisons are recommended.

Taken together, the experimental results presented in this paper provide substantive evidence for scale-dependency issues in environmental modelling. Such evidence is critical when we consider that environmental models developed at a small scale (i.e. on points) are often extrapolated to larger areas over the heterogeneous land surface (Band and Moore 1995), and input data composed of multiple variables (e.g. slope and *W* for TOPMODEL) are often employed for the same model or analysis. In the first instance, models should only be translated to another scale when input data are translatable over various scales or resolutions. Experiments as reported in this paper may assist us in developing reasonable expectations regarding scale-induced variability of modelling results over landscapes that are similar to the Santa Monica Mountains. In the second instance, it is common that a uniform resolution is used for all variables. A better option may exist to choose distinct resolutions for different variables because the scale-dependency varies between these attributes, and multiple resolution combinations may produce better results (Beven 1993, 1997). The diverse responses of different terrain attributes to DEM resolutions and the obvious landscape dependency of these responses indicate that our environmental analysis or modelling may display a very complicated variability when input data resolutions are changed or when the resolutions of variables are combined in different ways.

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